Dominikus Baur, Michael Sedlmair, Raphael Wimmer, Ya-Xi Chen,
Sara Streng, Sebastian Boring, Alexander De Luca, Andreas Butz (Editors)

Trends in Information Visualization

Hauptseminar Medieninformatik WS 2008/2009

Technical Report
LMU-MI-2010-1, Apr. 2010
ISSN 1862-5207

University of Munich
Department of Computer Science
Media Informatics Group

Dominikus Baur, Michael Sedlmair, Raphael Wimmer,
Ya-Xi Chen, Sara Streng, Sebastian Boring, Alexander De Luca, Andreas Butz
(Editors)

Trends in Information Visualization

An overview of current trends, development and research in Information Visualization

Preface

This report provides an overview of current applications and research trends in the field of information visualization. The content ranges from classical information visualization aspects such as network visualization, multivariate data representation and multiple coordinated views to topics beyond the traditional scope such as aesthetics, collaboration or casual aspects in information visualization.

During the winter term 2008/2009, students from the Computer Science Department at the Ludwig-Maximilians-University in Munich did research on specific topics related to information visualization and analyzed various publications. This report comprises a selection of papers that resulted from the seminar.

Each chapter presents a survey of current trends, developments, and research with regard to a specific topic. Although the students' background is computer science, their work includes interdisciplinary viewpoints such as theories, methods, and findings from arts, design and cognitive psychology sciences. Therefore, the report is targeted at anyone who is interested in the various facets of information visualization.

In addition to this report, there are slides from the students' talks available at http://www.medien.ifi.lmu.de/lehre/ws0809/hs/.

Munich, April 2010

The Editors

Dominikus Baur, Michael Sedlmair, Raphael Wimmer,
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Contents

Attractive Visualization

Benjamin Bafadikanya

Abstract— In the course of the proliferation of ubiquitous computing and the continuous price reduction of large displays, people are often confronted with a more or less relevant amount of information. The display designers and content producers solicit the people's attention in a time when people tend to develop a kind of immunity against the steady information overflow. The main goal for designers is to find the essential features to implement an attractive visualization. The following work will give an overview about different possible applications and different spaces displays are or can be introduced to. The consequences for the design and production of attractive visualization are also part of this paper.

Index Terms—attractive visualization, information visualization, public displays, semi-public displays, peripheral displays

1 Introduction

Ubiquitous computing, better graphical processors and constantly falling prices for large displays lead to a relocation of visualization from analog to digital devices. As an example, the vision of modern city centers is closely linked with the presence of large digital displays advertising the newest products or LED-displays at bus stops showing current timetables. Educational institutions use beamers to transport the information to the students. Working groups facilitate meetings and collaborations via SMART Boards [5] or stay aware of their co-working groups via e-mails. Stock traders stay informed about current stock rates with the help of ticker-like displays at the periphery of their private screens. Visualization in the form of displays can therefore be necessary to improve work processes or just be an entertaining gadget. Hence, *attractive* visualization is needed in order to get the attention of the target group.

But attention is achieved differently in public places as opposed to semi-public or private environments. In addition, the attention of a user as the main goal of every form of visualization is not always to be captured at any cost, because of the resulting distraction. Therefore, a closer look is needed as to the aim of certain visualization in a certain environment. Many reported user studies have been carried out about the effect of visualization in different contexts. By summarizing the different results I want to give an overview and conclusion on the design of attractive visualization.

2 Visualization in Attention-Limited Environments

2.1 Peripheral Displays

2.1.1 Distraction and Awareness

In environments that require the undivided attention of people, for example at work, visualization is restricted in terms of size and location. Thus, displays as a form of visualization are mostly located at the periphery of a user view. A good possibility to transport information to the user is by creating peripheral displays which appear whenever a change of the information of interest occurs. Such displays do not urgently have to be restricted to the computer area and can also be traffic signs, timetables or clocks. But in times of ubiquitous computers we focus on peripheral displays such as stock tickers, e-mail notifications *(see figure 1)* , instant messengers or download-status bars. The question now is how much a user gets distracted from his primary task, when confronted with information provided by those displays and how aware of the peripheral display she is. Is a user distracted by a peripheral display at all? Does more than one display have a negative effect on completing the primary task? Is there a difference between graphical and textual displays? In order to make an assumption on these connections, Jacob Somervell, Ragavan Srinivasan, Kim Woods and Omar Vasnaik conducted an experiment [13]. The experiment's setup was as follows: The primary task was a simple browsing task where the user had to answer questions by browsing through a text and gathering the necessary information. The distracting factors were represented by two kinds of peripheral displays. The first one was a graphical display which indicated a scale whose value was decreasing constantly down to a threshold at which the user had to perform an action. This task was entitled as a scale awareness task. The second display was a textual display showing information the way tickers do. It was complemented by a box with information concerning the ticker. This means that the user had to perform an action as soon as the relevant information from the box was shown in the ticker to accomplish the fade/ticker awareness task. The experiment compared the different time periods the four participant groups needed to accomplish the browsing task. The first group (control group) only had to perform the primary task without being interrupted by peripheral displays. In this way a reference time could be generated. The second group, the scale group, saw the scale display in addition to the browser window. The third group was called fade/ticker group and had the browser window, the ticker and the information box on their screen. The last group was a combo group, which means that they had to deal with all displays (browser, scale, ticker and information box) at the same time *(see figure 2)*. The experiment's result was as follows: The control group was the fastest group followed by the scale group. A surprising fact was that the combo group was faster in accomplishing the browser task than the fade/ticker group. This could be explained by the number of awareness tasks the combo group had not mastered which means that at a certain point the participants have chosen to ignore the peripheral displays, resulting in a better browser task time. So in the end one could say that peripheral displays do in fact distract a user but there is no significant difference between graphical and textual ones. As to the question if the number of displays has an effect on the distraction, there could not be made a clear statement since the maximum number of displays or secondary tasks had been limited.

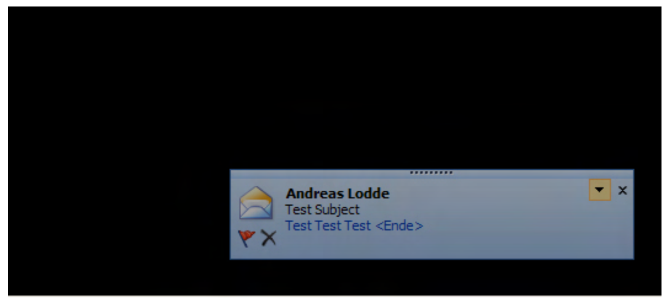

Fig. 1. Example of an e-mail notification at the periphery of the screen

• *Benjamin Bafadikanya is studying Media Informatics at the University of Munich, Germany, E-mail: bafadika@cip.ifi.lmu.de*
• *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

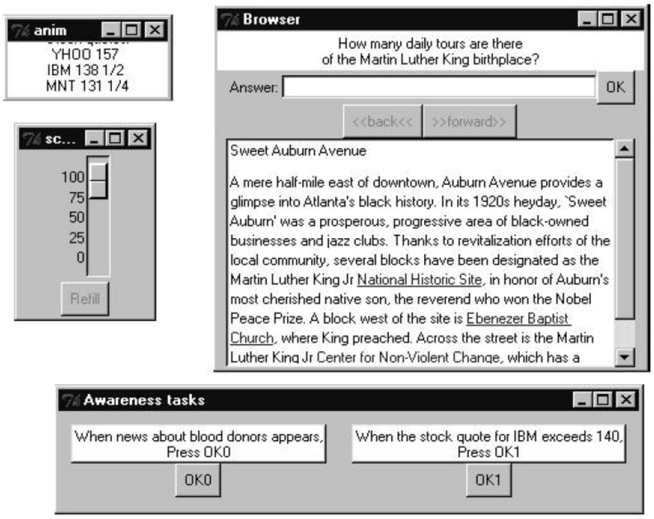

Fig. 2. Screen which was visible for the combo group. A browser window on the top right side, a scale window on the middle left side and a ticker-window/awareness task-window-combo on the top left side and bottom center [13]

2.1.2 Cognition Speed

Under time critical circumstances when the primary task requires the undivided and constant attention of the user, for example when driving a car, it is necessary to create a display which allows the user to get as much information as possible within a very short time [3]. Hence, Jacob Somervell, D. Scott McCrickard, Chris North and Maulik Shukla conducted a similar experiment where they focused on different factors of visualization like visual density, presence time and secondary task type [12]. Their experimental setup included a game as the primary task which required the user's constant attention *(see figure 3)*. Furthermore their peripheral display showed symbols of different shape and color. The variables density, presence time and type of question could be modified as needed. The participants had to find single symbols on the display and name the quarter in which they found them. Another task was looking for clusters of symbols of the same color. The density of symbols could vary from high to low density; the presence time was either one or eight seconds *(see figure 4)*.

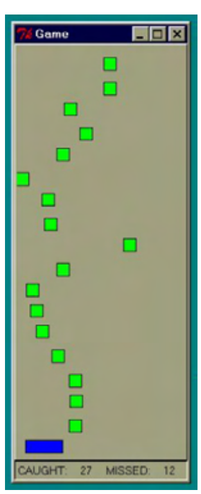

Fig. 3. Primary task: The falling green rectangles have to be caught by moving the blue rectangle from left to right. The game was visible during the whole experiment. [12]

The experimenters found out that the presence of peripheral displays itself do not affect the user's primary task performance. The rate of correct retrieved data increases with the time the visualization is present, because the user is more relaxed and therefore spends several looks on the display. What is more important is the fact that she is able to choose the best moment to risk a glance at the display, which is when her primary task allows it. Lower density displays can give better results in performance since the user has not much information to deal with. And finally, finding clusters was observed to be easier than finding certain single items due to time restrictions.

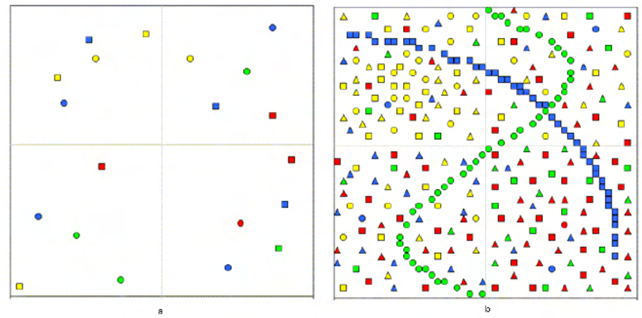

Fig. 4. Box a shows a low density visualization. Box b shows a high density visualization. Participants were shown either box a or b which contained information to answer questions. [12]

2.2 Attraction by Motion

Encoding information in shape and color of icons is a commonly used method but with the advent of better graphic processors *moving icons* are a serious alternative. The advantage is that movements in the periphery can be better recognized by the user in contrast to color and shape information. The cognition of a color or shape detail on the periphery of a user's view falls with a rate of 80%, whereas motion is detectable with a 100% certainty from the view center to the very periphery.

To prove these assumptions Lyn Bartram, Colin Ware and Tom Calvert conducted an experiment [1]. The participants had to perform a primary task which was a simple editing task *(see figure 5)*. As a secondary task the participants were to press a key whenever they detected a change of one of the 15 icons on the screen. Changes could be seen as changes of shape, color or motion. The results confirm the hypotheses that motion detection rates are higher than color or shape detection rates. In addition, motion detection times are shorter than color and shape detection times. And finally shape and color detection rate falls off rapidly when closer to the periphery.

In order to prove their hypothesis that the grade of distraction depends on the motion type, another experiment was conducted. There were three primary task types with different attention degrees. The icons which had random colors and shapes began to move, one at a time. The movement types were either anchored or traveling, that means that a moving icon which changes its size frequently without leaving its location is regarded as anchored. Whereas a moving icon which changes its size while traveling from one screen side to the other is called traveling.

After letting the participants execute the secondary task by performing an action whenever they detected a movement, the experimenters got the following results: Traveling motions are the most distracting, followed by linear but anchored moving icons and the least distracting blinking icons.

3 Visualization in Public Spaces

3.1 Public Displays and Ambient Visualization

Attractive Visualization also refers to displays *in public*, like for example displays in stores which show advertisements or large displays in metro stations which informs passersby about current news. But when

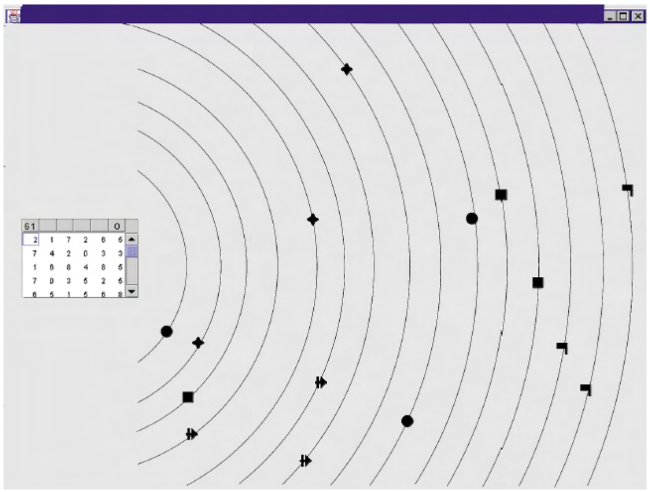

Fig. 5. The window on the left indicates the primary task. The icons on the right are part of the secondary task. [1]

is visualization attractive? That means, when does the public really look at a public display?

Elaine M. Huang, Anna Koster and Jan Borchers conducted a field experiment in three cities in order to get to know more about the people's behaviors towards public displays [4]. After evaluating their results, they found out that the brevity with which passersby look at these displays is very important in regard of position and content of the devices. Most of the people only pay brief attention to the displays and very few passersby make movements towards a display but continue to pass by while turning their heads until the display is too far away. These observations lead to the recommendation to design content so that the important information can be captured within a few seconds; even sentences are unlikely to be read. Another conclusion is that displays should be placed so that passersby walk towards it and do not have to change their directions in order to get a better view at the display. The experimenters also observed that the display's position in general plays an important role in getting the desired attention. Although only a few people really looked at public displays at all, it was especially the ones positioned at eye level that caught the most attention. Therefore displays below or above eye height were never looked at. Figure 6 shows an example of displays in a sub optimal position.

Fig. 6. The displays are above eye-level and therefore not likely to be looked at. [4]

In matters of content type results showed that animated content or videos were more likely to get the passersby's attention than static content or loops of static images. In some cases people even stopped in front of a display or slowed their walk to watch the video or animation until the end, as soon as the video ended they continued their previous walk. This leads to the conclusion that content should be made of animated pictures or videos because human beings are more attracted by motion. Another interesting observation was that people, which are given the choice between digital content presented by a display and the same content in the form of physical presentations like brochures, people tend to choose the non-digital form. An explanation can be that people want to control the amount of information they process by concentrating on certain points of interest while skipping other parts. This control function is not available on public non-interactive displays. Despite the general assumption that large displays are an eye-catcher for themselves, the experiment stated that the displays are only the second link in the chain of attention-catching. Most of the times, other items near the displays are more attractive and lead the passerby's view towards the display. An example can be a stand with brochures where a display is mounted slightly above it. In order to use this fact, the surrounding location of a display should also be considered in regard of an appropriate arrangement of the items that can lead the view towards the large display *(see figure 7)*. Even though

Fig. 7. The wall with special travel offers leads the view towards the display on the right. This is only possible when passersby come from the left side. [4]

in public the focus lies on large displays, small display should also be considered when visualization wants to be attractive. Small displays offer a more private and intimate environment for the viewer in contrast to large displays where the viewer can get a feeling of exposure. This was the conclusion after the experimenters had observed passersby who had preferred watching a video on small display than watching the same video on a large display. This also leads to the recommendation to combine small and large displays when visualizing content.

A different approach to make visualization attractive is by combining aesthetic aspects with computer supported information presentation. This is called *Ambient Visualization* [11]. Compared to peripheral desktop displays, ambient visualization is permanently located in the user's environment. Thus, it has the auxiliary requirement to be visually appealing and serving as a "nice-looking" accessory while it is not being used as an information source. Informative art [8] as a subset of ambient information visualization uses art as a template for the presentation of the required information. The Dutch artist Piet Mondrian painted, among many other pictures, some famous ones, which showed colored fields and black lines, composed on a white canvas. The colors were mainly red, yellow and blue. The reason why these pictures are predestinated as a template for informative art projects is, that the displayed rectangular fields, straight lines and colors are easy to be reproduced by a computer [6]. Besides, the visualized information can be encoded by these shapes and colors without serious problems. Figure 8 and 9 show examples of informative art using Mondrian's style as a template. But in cases when templates do not comply with the requirements of being appropriate for information encoding, some alterations have to be performed to get the possibility to transport all necessary information through the display and to make the cognition phase shorter and more intuitive. But the task of finding the right template is not the only challenge. When designing ambient informa-

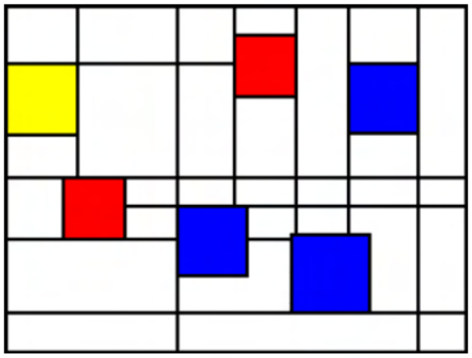

Fig. 8. A visualization showing the current weather in six cities around the world. The positions on the display correspond to the real positions of the cities on the world map with europe as the center. The weather conditions are encoded in the colors and the temperature in the rectangles' sizes. [10]

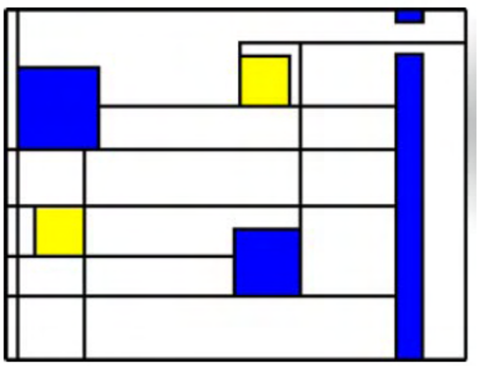

Fig. 9. A visualization representing the bus traffic at a bus stop. The four squares on the left show four busses; the long blue rectangle on the right represents a river. [11]

tion visualization especially informative art, the choice of information type is very important too, since the people who see this visualization find themselves often confronted with the mentioned information, whether they ask for it or not. Thus, the showed type of information has to be of interest for the prospective group of users. This leads to the question where ambient information visualization devices should be installed. Main traffic spots of the target group are preferred locations. For example, bus stops as an installment location for a timetable display. As mentioned above, motion is very powerful when it comes to getting people's attention. Therefore, the rate at which the display changes, should be high enough to make it dynamic and ensure people that the display is still working but low enough to prevent extensive distraction [9]. This is another considerable factor when choosing the right source of information, which gets obvious when you compare weather information update rates with bus timetable update rates.

3.2 Interactive Displays

Unlike one-directional public displays, displays which require a sort of interaction from the user not only have the challenge to attract people but also have to overcome their natural hesitance to become an interacting user. In order to be able to give propositions for designing good interactive displays, Harry Brignull and Yvonne Rogers conducted two experiments where they installed a public display in two different locations and observed the people's behavior [2]. They called their displayed system "The Opinionizer" [2], which is an easy-to-use tool providing the possibility to give an opinion to an interesting topic concerning the on-going event. The opinions could be entered via a laptop, located near the display, and were then shown on a large display legible for everyone. The participants could also add nicknames or cartoon-like avatars to their statements. The first event for their experiment was a book launch party and the second one was a welcome party at a university. The important fact the two events had in common was that most of the people attending those events did not know each other. Hence, the Opinionizer was also supposed to serve as a catalyzer for social connections. The display and the corresponding user-interface, the laptop were placed so that it could be seen from everywhere in the room. In addition, the experimenters paid attention to placing the arrangement near a strategically important spot, like for example the bar in the middle of the location *(see figure 10)*. At the beginning of the party the distance between the on-looking people and the display was long because they did not know what the whole arrangement was all about and therefore were afraid of a possible social embarrassment. In order to entice the people to interact with the display, an instructor demonstrated the functionality, so that the hesitating people could watch and learn the usage. Once the party became more and more crowded the distance between the people and the device got smaller and they started gathering around it after they had seen other participants use the interface. The more people gathered around this "attraction" the more interesting it became for the people who were farer away. This effect was called the "honey pot effect" [2] and made the instructor unnecessary. The big advantage of the location on the book party in contrast to the welcome party was that the bar as a strategically important spot was very close to the display so that people who were standing around the bar could easily observe the ongoing from a safe distance. But the welcome party had no bar and therefore no strategic advantage for the placing. However, the same observation could be made. At the beginning only a few people paid attention to the display and even less people dared to get actively involved. But as the party went on and more people arrived more and more participants interacted with the display by entering their opinions. While trying to evaluate their results the experimenters divided the people at the parties into three groups. The first group who consisted of people who were occupied with eating, drinking et cetera noticed the display only in their periphery. The second group consisted of people who were aware of the display, already took the display into their discussions and even made gestures towards it. People who actually interacted with the display belonged to the third group. In regard to the flow toward the display the experimenters concluded that people traversed the three groups, beginning from the first group *(see figure 11 and 12)*.

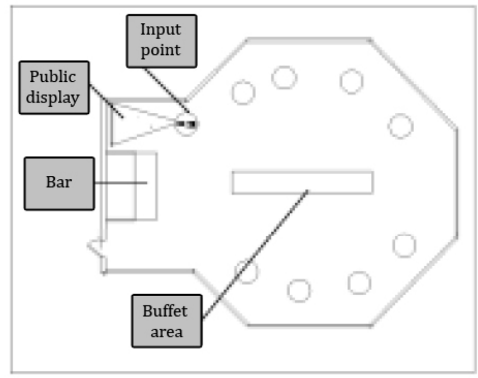

Fig. 10. Floor plan of the book launch party [2]

With each transition the threshold into the next group grew. That means that with the last transition people had to overcome their fear of a possible social embarrassment and stand the pressure of accidentally making a mistake while entering their opinion in front of everybody. There are key information [2] which entice people to cross those thresholds:

- How long will the whole procedure take?

Fig. 11. Photo made at the welcome party which shows the different groups. [2]

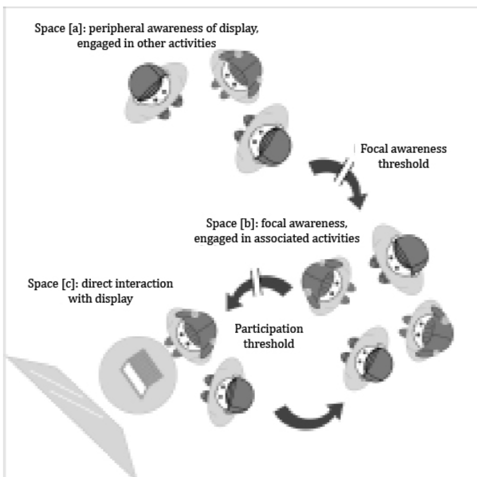

Fig. 12. Diagram which shows the three attention groups and the thresholds between them. [2]

- What is necessary to take part?
- Who has taken part yet?
- Is it possible to stop the interaction without getting embarrassed?
- Is it profitable?

As soon as these questions can be answered the members of the groups are willing to transfer to the next group. In detail, the display has to be able to show all evident information about what is happening in a way so that even people from the first group who only see the display peripherally can become aware. In order to do so, the display has to be located on a high place. Another mean is to place the display near a flow of people, for example the bar from the book party. This also gives people the chance to change their group membership easily. Brochures and free goods are another possibility to encourage people to cross the line. The last step from the second to the third group needs the system to be easy and fast to use without long registration procedures or further instructions. One should be able to learn the functionality only by watching other people using it and should be able to be sure that the participation is enjoyable.

Attractive visualization in form of large interactive tangible displays is also a good possibility to examine people's interaction with a display. A team of experimenters installed a large multi-touch display in a center location in Helsinki, Finland to get more information about the *social activities* their "CityWall" *(see figure 13 and 14)* can initiate [7].

Fig. 13. Screenshot of the City Wall with random pictures. [7]

Fig. 14. City Wall installed in the city center of Helsinki, Finland. [7]

The central location in a highly trafficked street is a good condition to reach the amount of people who will actually interact with the display. The multi-touch functionality and the simple application, in the form of arranging, scaling or throwing of photos on the display were guarantors for simultaneous activities. The results of the experiment mainly focused on how people used the display and how they interacted with each other at the screen. The user's first step before the interaction was the approach. People who stood near the abandoned display did not instantly notice the interactive nature of the device and therefore simply ignored it. This can be explained with the vast proliferation of large displays in big cities which makes people develop some kind of immunity. But like in the book launch party experiment, people began to pay attention to the display as soon as they saw others using it. Akin to the book launch party people who finally noticed the display and its features approached it in a stepwise manner from the peripheral group via the awareness group to the final interacting group. These transitions however were only performed when the people could gather satisfactory information regarding the functionality, own profit and possible social embarrassment in conjunction with the display. The last step from being an onlooker to actually taking part was also influenced by turn-taking factors. People for example use certain closing gestures to signalize their intention to change their focus of activity. Hence, people who stand in an imaginary line wait for these gestures before they can make their move towards the display. But since the display was 2.5 meters wide, there had also been situations when people approached the display even though others were already using it. The experimenters then could observe two types of activities:

- Parallel Use
- Teamwork and playful activities

People used the display parallel by staying on opposite sides of the panel and performed independent actions without interfering with the other side. Teamwork emerged intentionally or accidentally when one sides' actions influenced the other side. Such actions can be maximizing a picture to full screen or throwing a picture into the other side's area. The experimenters even observed situations in which people began using the throwing functionality to simulate a ping pong game or a soccer-like game. However, there are also events that lead to conflict situations that need to be solved. This experiment showed that people who do not know each other tend to solve those kinds of problems with humor or with withdrawal. Whereas it should be mentioned that conflicts not necessarily lead to problems but could also initiate teamwork. Due to the fact that the experimenters had installed cameras which could also make the space behind the active participants visible, interactions between onlookers and users could be evaluated. Most of the time people approached and used the display pairwise but in some cases one of the couple stayed in the background while the other used the display. In conjunction with this behavior people sometimes took different roles, like for example teacher-apprentice or entertainer-audience. In the end it is safe to say that a large multi-touch display entices people to socially interact with each other willingly or unwillingly. It therefore restructures the social space it is installed in.

4 Visualization in Semi-Public Spaces

The city wall experiment shows that people are willing to interact with public displays and handle photos of strangers. But would they also let people, they do not know watch, edit or play with their own photos? If there was a possibility to upload their own photos onto the display in order to exchange them with other users would they allow uninvolved onlookers watch these photos? Public displays hold a great potential for interactions between users but the privacy aspect is hindering. Another problem is the search for possible content that is of interest for as many people as possible. *Semi-public* displays [5] for small, co-located groups try to avoid these problems and instead try to foster awareness and collaboration among the group members. It is easier to find content that is of common interest and displayed user information can be more detailed since co-workers are more likely interested in detailed information about their co-workers. In order to enhance collaboration and awareness among group members it is important to identify already existing ways. Such tools are for example e-mailed status reports, shared schedules or instant messenger status cues. The disadvantage of the e-mailed reports is that requests for long-term help are easily forgotten due to the amount of other e-mails. Viewing other schedules in order to get information about future important events and attendances require a certain active action. Instant messenger status cues are not accurate enough, that means that a person can be currently working on a project without having an ”online” status cue. Attractive visualization in form of semi-public displays has the ability to permanently show the aforementioned content in a space that is frequently visited by members of the co-working groups in order to foster awareness and collaboration. Elaine M. Huang and Elizabeth D. Mynatt developed an application which contained a collaboration space, an active portrait, an attendance panel and reminders. The application was deployed on a tangible display. All the features were viewable at one glance at the display *(see figure 15)*. The reminders and collaboration space was intended to give users the ability to post requests for help by using a stylus. The requests were then displayed constantly in a rotation to maintain a reminder function. The active portrait showed the members of a group in a picture and added different color saturation attributes to single persons according to their current presence status. The attendance panel showed future events in the form of a flower whose petals symbolize the participants. Depending on whether a person attends the event or not, the petal changes its color. In order to keep it anonymous, there are no names and no fixed person-petal assignments. In this way a user can see at one glance how popular an event is. After two weeks of use in a lab the experimenters found out via questionnaires and interviews that the display and its application indeed enhanced collaboration and awareness but had a few flaws regarding following points. The people found the collaboration space not very useful due to difficulties of using the inking on the display. Another negative point was the active portrait where it was difficult to recognize the level of color saturation and therefore the status of the respective person. All in all the experiment could show that interactive displays in semi-public spaces can tap the potential public displays are not able to due to privacy and content paucity.

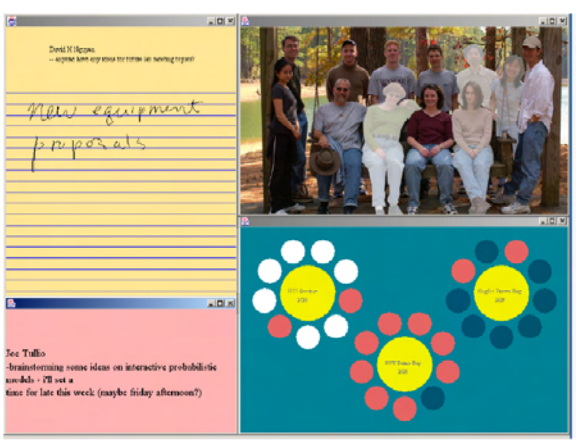

Fig. 15. Screenshot of the semi-public application [5]

5 Conclusion

Displays as a form of visualization have many different possible applications. People get used to being surrounded by displays and to using interactive ones (for example ATM machines) on an everyday basis. The living standard gets higher due to better information visualization. Security systems or car navigation systems are a good example for this fact. But new information visualization devices are waiting to be introduced. In order to make these devices attractive visualization, a few guide lines have to be followed, depending on the application. The following table shows those guidelines.

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Table 1. Guidelines for attractive visualization

Application/Site of Operation	Guideline
Private environment (Peripheral displays)	Low density information visualizations, long presence time, use of travelling motion in order to get the user's attention
Public environment	Position: at eye-level, towards the passersby walking flow, in line with surrounding items that lead the view to the display Size: depends on the event, combination of small and large displays Content: dynamic images, videos, very little text due to the brevity of people's glance
Public environment (Interactive displays)	Position: at strategically important locations, visible for everybody Content: interesting for a large target group, not violating privacy interests Interactivity: easy to use, quickly operation-able, teamwork ability, watch and learn concept, profit promising
Semi-Public environment	Position: high trafficked location Content: useful for the co-working group, as private as possible, improvises present collaboration means

Aesthetics in Information Visualization

Alexander Lang

Abstract— The importance of visualization in conveying knowledge is undisputed. For example, the rise and fall of stocks is processed and understood faster by examining the corresponding line graph than looking at the raw underlying numbers. For the effectiveness of this cognitive process several factors have been identified in research, like for example the background knowledge, as well as its inherent aesthetics qualities. This text focuses on the latter. It has been argued that the higher the aesthetic value of the visualization is, the more engaged the viewer is in trying to decode its meaning. But what does "aesthetics" mean? Does an informative graphic have to be artistic to be effective? Since the perception of aesthetics is a highly subjective matter, what kind of effort should be put into creating a visualization? What connections between aesthetics and information visualization exist anyway? These questions are the subject of the following text. It starts with an introduction to the relevant terms and subfields of aesthetic information visualization research. It then proceeds with a discussion of several examples of information visualization that were created with a strong aesthetic concern. Since these results often resemble works of art, finally their artistic value is debated.

Index Terms—Information, Visualization, Aesthetics, Art

1 Introduction

Our society is defined by information. Every day we create vast amounts of data and transport them through many channels of telecommunication. In order to process the vast amount of data we rely on the power of visualization. With graphs we are able to gain insight in the data, by detecting patterns and trends and are able to check and verify the data.

As computers have become ubiquitous, so has the display of computer-generated and processed data.

Technological advancements in display technology have contributed to that development. The price of liquid crystal displays has fallen dramatically over the last years and even LC- and DLP projectors are affordable to many households. In the near future we can expect technologies like organic displays and E-ink based displays with advantages like less power consumption, less noise, richer contrast and colors and more.

> "The purpose of visualization is insight, not pictures."[28]

As true as this statement is, there has been a rising interest in creating visualization that should have an aesthetic quality. More and more people are able today to create visualizations that are more than bar and pie charts out of MS Excel data.

Software like Adobe *Flash* and the programming environment *Processing* are targeted at the designers with little programming experience and facilitate the process of creating a graphic representation.

Cheap hardware, easy-to-use software tools, growing internet communities and the availability and democratization of data[35] have all contributed to the fact that creating visualizations is as easy as never before.

But are these all *good* visualizations? By what means can the quality of a visualization be measured anyway? Edward Tufte discussed that matter already some 20 years ago in his groundbreaking book *The Visual Display of Quantitative Information*[33].

Aesthetics has been found as an important aspect. Several works of research propose that "enhancing the artistic merit of a visualization can result in a more effective and more productive visual analysis."[31]. There is more to the display than efficiency of communicating data. Visualizations can also be used to convey cultural and social messages and concerns.

- *Alexander Lang is studying Media Informatics at the University of Munich, Germany, E-mail: langal@cip.ifi.lmu.de*

- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

The following text presents an overview of the aesthetic and artistic aspects in information visualization. It first provides an overview of the terms *aesthetics*, *art*, and *information visualization* and then tries to combine them by explaining different models of information aesthetics that have been identified in previous literature. Several subfields with different aims and aspects are presented, namely *Artistic Information Visualization* and *Ambient Information Visualization*. Ambient Information Visualization is about making the display of information more *humane* and integrative to our lives. Several examples of information visualization with aesthetic or artistic concern are discussed. Finally the implications of Aesthetic Information Visualization on art and vice versa are explored.

2 Overview

2.1 Information Visualization

Information visualization is defined as the graphical representation of abstract data. It therefore differs from scientific visualization which visualizes real-world phenomena, like the human body or the flow of air[17]. Several key criteria for an information visualization have been proposed[17]:

- The data are external, that is they were not generated by an algorithm within the visualization program
- The source data are not an image itself
- The graphic must be readable, that is the viewer should be able to transfer the graphic representation back to the underlying values, (that process may require some learning effort, though)

In terms of intended aim two modes can be identified: exploratory and expository aim of use. If the visualization is used to explore the dataset, that is find new hypotheses, then the visualization should display the dataset in its entirety and offer interactivity by zoom and filter mechanisms. If the visualization has the aim to expose a certain issue, then interaction is often limited and only the data necessary to convey the intended message is represented. What qualities should a good visualization have and how can it be qualified? Traditionally, the value of information visualization is measured by how efficiently and effectively knowledge is conveyed [34].

> "Effectively designed visual representations facilitate the understanding of complex phenomena by selectively emphasizing the most important features and relationships while minimizing the distracting effects of extraneous details." [26]

The graphic should present the information in a way that catches the viewer's attention, facilitates reading of the data and enables the user to detect underlying patterns and trends. The key purpose of the graphical representation is thereby to enhance cognition by offloading "the mental internal representations onto an external medium to relieve the cognitive burden and speed up processing." [32] Although several guidelines exist, research strives for a better understanding of the creation of an efficient visualization.

2.2 Aesthetics

What is aesthetics? How is it defined and how can it be measured? No definite answer can be given, in fact these questions have been the topic of philosophic discussions since the 18th century. Kant, Adorno, Goodman, and many more elaborated on aesthetics and its role in society. The term "aesthetics" is well known in everyday-speech and we use it to refer to anything visually beautiful and pleasing our eyes. Aesthetics has been termed as "the measurement of beauty"[27]. Although aesthetics is not only about beauty or vision but of the stirring of any combination of the senses that causes pleasure in the viewer. Beauty has been regarded "as one of the many facets of an aesthetic experience" [8] with other key components being pleasantness, emotions and satisfaction[27]. It has been defined as "pleasurable subjective experience that is directed toward an object and not mediated by intervening reasoning."[24] Studies in perceptual psychology have identified several views on the aesthetic experience[24]:

- The *objectivist view* regards beauty as an imminent property of an object that produces a pleasurable experience to any viewer. Several features are thought to contribute to it and determine it, like symmetry, balance, complexity, figure-ground-contrast and more. For example a symmetrical object would be more beautiful than an asymmetrical one.

- The *subjectivist view* holds that anything can be beautiful, all depends on the viewer and his cognitive and cultural background.

Another view considered more modern is a combination of the previous two. It has been proposed "that beauty is grounded in the processing experiences of the perceiver that emerge from the interaction of stimulus properties and perceivers cognitive and affective processes."[24] The perception of beauty can therefore be explained as function of how fluently a viewer can process an object. Important are hereby the two phases of recognition that have been identified[10][36]:

- The *preattentive phase* denotes the low-level process that happens before the conscious attention and that processes sensory information and

- the *interpretative phase* that processes arbitrary information, that is representation that must be learned, for example the appearance of a word like "dog" has nothing to do with the appearance of the animal[36] or the metaphor color (red as hot/dangerous, green as safe, blue as cold)[6]

Aesthetics therefore has also been described as the "combination of cognitive and sensory modes of experience [..]"[8]. Several cognitive aspects have been proposed and examined, for example in graph design, symmetry, relations according to the Golden Ratio and a minimal number of bends and edge crossings are desirable[8][4]. A minimum of complexity is strongly favoured by E. Tufte. He rejects the use of "chart-junk", that is, elements in a graph that do not convey data. Other researchers argue, based on empirical testing, that the minimal designs are not the preferred ones, thereby indicating a lower aesthetic appreciation[12].

Above guidelines are only hints to follow while creating a visualization. Some like the Gestalt principles can be based on the very human perception. But in the end the highly subjective nature of aesthetic assessment renders it impossible to create a definitely measurable result that is equally appreciated. Integrating aesthetics in information visualization is yet one of the ten most important unresolved questions in this field[3].

So why is aesthetics an important factor in information visualization? Aesthetics has been identified as a key factor to engage a viewer[31]. Once the viewer is analyzing the graphic, it has been shown that a correlation exists between latency in task abandonment and erroneous response time (that is the time until a false information is extracted) in relation to the perceived aesthetic of visualizations [2]. Therefore the more aesthetically a graphic is perceived, the longer the viewer will try to decode the meaning of it or extract a certain information.

2.3 Art

In this section the relation between aesthetics and art is examined. Aesthetics has been termed as the theory of art, as a "critical reflection on art, culture, and nature"[14]. These terms are not to be used interchangeably:

> "Aesthetics is concerned with the theory of sensual perception, while art is a social practice involved in certain forms of research and investigation processes and in the construction of particular types of artifacts." [23]

The aesthetic pleasure, that is the perceived beauty is not be be confused with the aesthetic value. A beautiful object may have little or no aesthetic value: it does not provoke thought or create a new view on culture or society. Accordingly, an object may have aesthetic value without producing aesthetic pleasure [24]. The "subversive and questioning power may act as a substitute for the pure beauty to rate the quality of art."[21].

3 Aesthetic Information Visualization

This section brings the previous sections of information visualization, aesthetics and art together and examines the implications.

Following framework has been created for an assessment of the comprehension of an aesthetic information visualization[30]:

- *That* data are visualized, that is the display is recognized as a visualization, not just as a decorative picture.

- *What* is being visualized, e.g. weather, e-mail traffic, etc.

- *How* to read the visualization, e.g. which metaphor within the visual denotes what

Only if all three criteria are clear to the viewer the visualization is of use to the viewer as information visualization.

It is possible, though, that the data is not readable anymore by the viewer, that is the purpose of the display is not to communicate information but it only uses data to create the picture. This is for example the case in the visualization of music, popularized by the *Winamp* media player [1].

Based on these qualities, aesthetic information visualization therefore can be placed on a continuous scale, ranging from *readable* and *recognizable* and *not readable* and *not recognizable*[17].

Another, more exhaustive model has been created, based on different quantities: According to this, information aesthetics can be placed on a continuous scale based on artistic intentions and interpretative engagement with the extremes of *functional information visualization* (little aesthetic concerns) and *information art* (high aesthetic concerns)[19].

The contrast in their aims and attributes is explained with *Figure 1* displaying a functional representation of stock market data and *Figure 2* displaying an artistic visualization of the same data:

- *Objectiveness vs. subjectiveness*: *Figure 1* is an objective portrayal of facts. It is universal and not based on a personal, subjective point of view. It has been argued, though, that true objectiveness or neutrality is in fact impossible since every visualization is a form of distortion. [35]

[1] `http://www.winamp.com/`

Fig. 1. Market Maven, from the company Ambient Devices.[23]

Fig. 2. Kamila B. Richter and Pavel Němec, I Deal Solution, 3D visualization and sonification application, 2005–2006 [23]

- *Obscuring vs. revealing information*: With *Figure 1* the viewer is able to draw conclusions from the underlying data, whereas *Figure 2* does not allow this. With *Figure 2* not only the underlying values are unclear but even the fact it is a visualization of data.

- *Analysis vs. Emotion*: *Figure 1* is task- and usability-oriented. Emphasis is placed on the efficient transfer of knowledge (that is stock market data). *Figure 2* invokes curiosity and interest because of the enigmatic quality.

3.1 Artistic information visualization

Often when placing emphasis on the aesthetic aspect, the sublime component is very important. It is thought to invoke feelings of awe and inspiration on the viewer. On the one hand, the graphic can be left intentionally ambiguous and thereby open for interpretations. On the other hand, the creator of the visualization is able to communicate a concern by displaying the data in a way a certain trend is made clear or a message is conveyed. It is then more important for the viewer to understand the concern instead of being able to read the data [17][23] The creator can form a statement[35] with strong implications on society and culture. *Figure 3* was displayed in the New York Times in February 2007. It illustrates the deaths of the Iraqi civilians in the month of January. While there would certainly have been a more effective way to show the names or numbers, by this means the immense extend of losses is communicated as an accuse.

> "The task of artistic information visualization is not to resolve but to question or restructure issues pertaining to a topic in a manner that is not possible through any other means, medium or cultural artifact.."[23]

An artistic visualization is therefore defined by the artist's intention to create a work of art [18] [35] and does not have to be beautiful to be artistic [35].

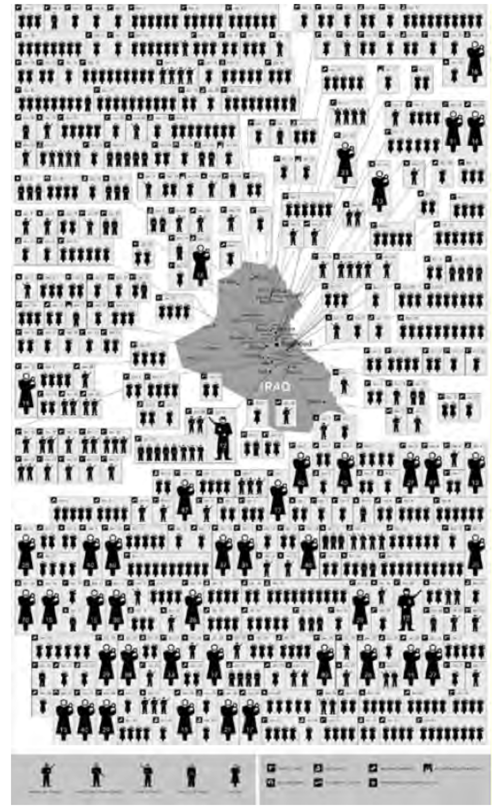

Fig. 3. Adriana Lins de Albuquerque and Alicia Cheng, Iraqian civil losses during January 2007 [5]

3.2 A model on information aesthetics

A recent publication has identified two dimensions for information aesthetics[19]:

- *Mapping Technique* represents the methods by which the visualization was created
  - Direct: the viewer is able to infer the underlying data.
  - Indirect: the viewer is not able to infer the underlying data, that is the graphic is interpretative.
- *Data Focus* represents what is communicated by the graphic.
  - Intrinsic: the graphic facilitates the insight to data by cognitively effective means. The graphic could be considered as a mere tool for analysis.
  - Extrinsic: the graphic facilitates the communication of meaning implied by the data.

Several data visualizations with artistic concern have been arranged according to the their perceived focus on each of the dimensions (see *Figure 4*). It has been observed that a correlation between the mapping technique and the data focus exists: the chosen mapping technique often determines the data focus and therefore resulting in a continuum of information aesthetics between information visualization and information art (see *Figure 5*).

3.3 Ambient Information Visualization and Informative Art

The research field of ambient visualization is closely related to information aesthetics. Ambient visualization researchers try to integrate the display of information in a non-obtrusive, almost unconscious way into our environment. The premise is that in order to communicate non-critical information users should not have to actively search for and stare at a computer screen. Instead, information could be encoded

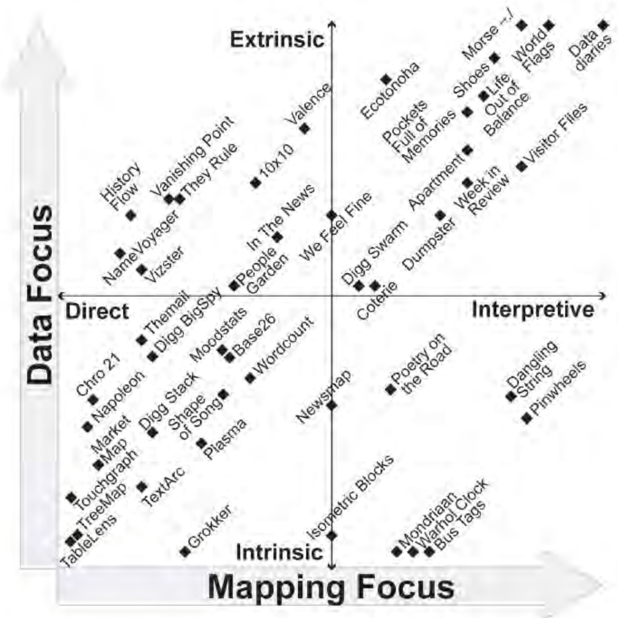

Fig. 4. The proposed model of information aesthetics with *Mapping Technique* mapped on the X-axis and the *Data Focus* mapped on the Y-axis [19]

into things that surround our public or personal daily life: physical elements of architecture or art objects. The off-screen attribute is in fact a criterion for a subfield of ambient information visualization termed *informative art*.

Like a painting the user should be able to hang a display on his living-room wall that tells him, for example, stock market data. The attractiveness is therefore an important factor for the acceptance of these objects. To facilitate this acceptance the metaphors of information that are displayed are often not designed from scratch but based on well-known artistic styles, which creates "art" works that are augmented by information that are interesting to us, therefore termed *amplified* or *augmented art*. [25].

The visualization thereby does not have to be a flat image, physical sculptures with tangible quality have been introduced, too. [20]

Following premises should be considered when designing an ambient visualization: If the display is to be non-distractive, information must be conveyed "at a glance"; the complexity of the data is to be

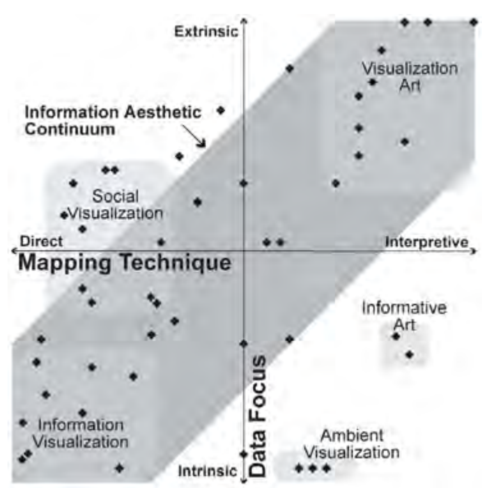

Fig. 5. The various subfields of information aesthetics, [19]

kept simple. Possible quantities to be displayed are mass (e.g. the number of e-mails), growth (e.g. stock market index) and flow (e.g. ratio of incoming vs. outgoing e-mails) [25].

It is often not possible or desirable to display exact numerical values. Therefore the visualization should only present an overview of the data or show trends. [11] And finally, the visualization application has to update the data itself, probably in a regular interval. The interval should be high enough, otherwise a rapid change would appear as animation and would distract the user. It is possible to integrate a slow interpolation between two consecutive values.

Unlike in artistic visualization, ambient visualization systems do not convey meaning beyond the visualized data, they are not to be used to communicate a concern for a certain agenda.

A taxonomy for ambient displays was introduced based on the four dimensions [22]:

- *Information capacity*: holds the number of sources of information conveyed by the visualization.
- *Notification level*: The "designer-intended level of alert" [22] measures how distractive the visualization is. Does the visualization demand for attention e.g. through animation, flashing or blinking or does it blend into the environment?
- *Representational fidelity* represents the degree of how much the graphic metaphor abstracts the underlying data.
- *Aesthetic emphasis* represents perceived importance of the artistic intentions behind the visualization. Does the design follow the style of a certain artist or art movement?

Figure 6 shows the ranking of 19 ambient visualization systems according to aforementioned dimensions.

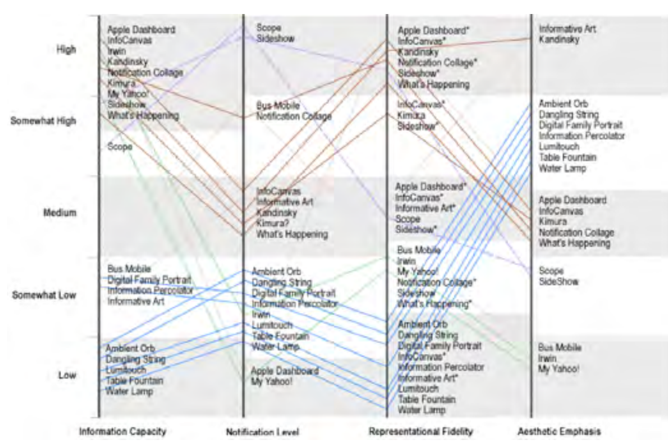

Fig. 6. Parallel coordinate plot of 19 existing ambient information systems across four design dimensions. [22]

Most ambient visualization systems are designed in a fixed way according to the perceived aesthetic of the designer. The effect is evaluated but the aesthetic considerations that went into the design are often not made clear [11]. Some hold that since the perceived aesthetics is so important for the acceptance and appreciation of the display, the user should be integrated in the design process. The user should have full control over which metaphors are used for the display of information and therefore several scientists try to create a system that allows full customization [7].

In ambient visualization research, several additional uses and effects have been examined. Ambient systems have been used as a means for informal communication where, for example, users in a work environment are made aware of the activities of their colleagues [25]. The monitoring of people's activity has also been examined in the *Activity Wallpaper* project [29] that observed the guests of a public café over the time of a week and displayed the number of visitors at a certain time of a day, therefore providing insight about peak-hours, people's habits etc.*(see Figure 7)*.

Fig. 7. A projection of the Activity Wallpaper: each day of the week is mapped to a column, each timeslot is mapped to a row, the amount of people is mapped to the amount of symbols [29]

Works by Skog et al. [11][30] examined the display of bus arrival times and global weather reports. They used the style of Piet Mondrian to create the visualization, encoding information in the color and size and position of the rectangles *(see Figure 8)*.

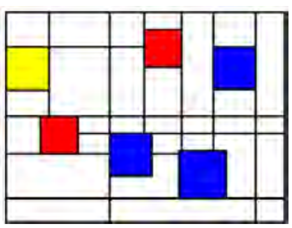

Fig. 8. A visualization of the current weather in six cities around the world: Los Angeles, Gotheborg, Tokyo, Rio de Janiero, Capetown and Sydney. Cities are represented by rectangles, weather is represented by color (red: cloudy, blue: rain- or snowfall, yellow: sunny) [30]

Kosara criticized that these mappings were not easily comprehended, as well as even the fact that the image underlay data [16].

Another use of ambient information visualization has been proposed: persuasive ambient visualization. Like the film *An inconvenient truth* by which the viewer is expected to think about his attitude towards environment, these displays aim to encourage their viewers to change their behaviour or their belief. It was proposed that a display within a shopping environment that showed how many local products were being bought in comparison to foreign products, would encourage clients to buy more local products [20]. The success is debatable. Several ethical issues are raised as well. There is a certain danger of manipulation that should not be neglected, since ambient displays are meant to be perceived almost unconsciously. Also the aforementioned activity monitoring of public spaces is not uncritical, privacy concerns are raised if cameras are used to survey the people [25].

4 Examples

This section presents three examples of visualization projects that were created with an aesthetic concern in mind or involved art practices.

4.1 2D-Fluid Flow, Supernova

Traditional art has been an inspiration for the visualization technique used by Kirby et al. [15] and Tateosian et al. [31].

They use the idea of various layers of paint where underlying layers shine through at certain places on the canvas to construct their visualization that is able to convey multivariate data. The metaphor of brush strokes is used to create the painterly rendering style. Different data dimensions are encoded with different brushes.

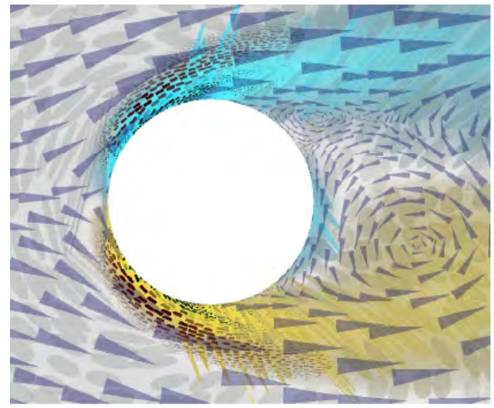

Fig. 9. Visualization of 2D flow hitting a cylinder [15]

Figure 9 shows a scientific visualization of air flow hitting a cylinder in which a total of nine quantities like velocity or vorticity are encoded with different stroke features like shape, color, transparency and orientation. Different layers of brush strokes shine through.

Another idea borrowed from traditional art is the varying degree of abstraction to eliminate unimportant distractions. Higher details are displayed in areas of importance[31]. That aspect is made visible in *Figure 10* in which homogeneous regions receive less detailing than in areas that represent a high data frequency.

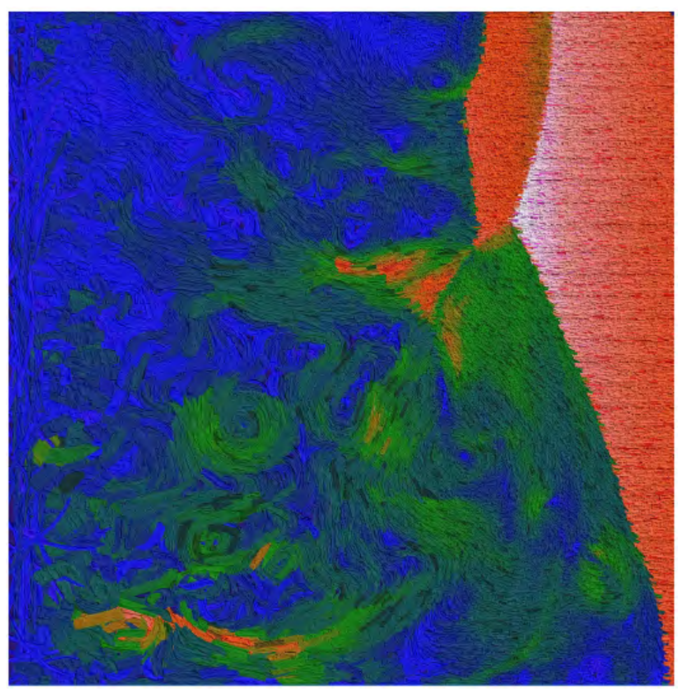

Fig. 10. Visualization of the dataset of a supernova, with Δx and Δy mapped to orientation, magnitude mapped to color, density mapped to size, pressure mapped to aspect ratio. [31]

4.2 Valence

Ben Fry, the author of the popular *Processing* programming environment[2], has created a set of different visualization projects. One of it is called *Valence*, a project to examine huge datasets and the relations embedded within the data. It is described on his website[3] and was used for the visualization of the human genome in the *Genome Valence* project[4], of websites and even ordinary text. The data is presented in 3D and can be interactively turned around and viewed from different angles.

Fig. 11. Valence by Ben Fry, Comparison of Wittgenstein and Goethe at Ars Electronica, 2001 [9]

Figure 11 shows the text version that was exhibited at the Austrian *Ars Electronica*, comparing texts by Wittgenstein and Goethe. The text version reads any input text, and as it reads a new word, it is added to the visualization and connected with the previous through an arc. The words are aligned within the volume of an invisible sphere where the more often a word appears in the text, the further away from the center it is pushed.

The result is a striking visualization of a net of interconnected words, slowly growing in size and complexity; not only beautiful but useful in providing information of relationships and frequency of occurrence, thereby exposing trends in the data.

5 Is it Art?

The mass of new technologies and visualization is viewed sceptically not only by traditional artists [23]. Many fear the dilution of the perception of arts and have criticized that many people make the mistake of the

> "extraction of still images from a moving or interactive screen with the intent of positioning the stills within an art context based on a rather naïve notion about art that sees such a discipline as a marketable exchange of "aesthetic" pictures."[23]

Some researchers do not consider the resulting visualization as art since they have no artistic training themselves and have borrowed the style of finished and established traditional art [11][8]. Others yet do so within the following concept of art:

> "We believe that art needs to engage the users intuition, and that it should allow a person to experience something new. Both of the systems described in this paper achieved this, but in significantly different ways."[1]

Yet art is more than the final resulting image: Depending on the perspective, one can regard visualization as a technology (therefore a task-oriented "tool"), a science or art itself [34]. In the latter case, the whole process of creating a visualization is considered as art, defined by the thought and ideas that went into it. In traditional art that notion has been termed *concept art*, defined by the fact that the idea is more than the final product [8]. This concept is mirrored in the term *Research Art* coined by Gaviria [23]. Like science, artistic visualization should collaboratively investigate new ideas and strive for an innovative art that is beyond decoration.

Many researchers demand a collaboration between artists, designers and scientists [13]. The aim is to integrate science and art as flawlessly as Leonardo da Vinci did. Therefore artists and scientists have come together in interdisciplinary, so-called "renaissance classes" [17][15] for the exchange of ideas.

Several other research fields have absorbed this idea of integration. *Aesthetic Computing* commits to the appliance of art practice to computing [8], and *Algorithmic Art* discovered the use of computer algorithms and programming languages to create art[13].

It has been argued that visualization can learn several things from art. For a better understanding of visualization it is necessary to establish a profession of aesthetic criticism with academic credit like it is done in arts[23]. A basis, that is language and theory, has to be developed in order to be able to discuss the quality of work that is partly subjective [17]. Kosara has therefore launched a website on which constructive criticism of informative graphics is published[5].

6 Conclusion

This text has given an overview of the many different perspectives on aesthetics in information visualization. It has shown that beauty of a visualization is not equal to its artistic quality, and that aesthetics is more than "pretty pictures". Aesthetics has to be recognized as not just being a by-product of science (for example like all these nice images of mathematic fractals) but an integral part of science.

Further reading and up-to-date results from information visualization research are provided by the blogs by Andrew Moere[6], Christian Schmidt[7] and Manuel Lima[8].

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Music Information Retrieval & Visualization

Tim Langer

Abstract—The growing possibilities for digital storage has led to large personal music collections that require new technologies to use and maintain them. There has been a lot of research done related to visualizing music collections in order to improve browsing, exploring and searching of music. While almost every publication in this subject has its own purpose and approach to achieve it there still exist common problems, ideas and methods. In the following I will identify major causes that led to such development, based on state of the art technology, at first. I will then further specify a couple of commonly used ideas to solve those problems as well as techniques to realise them. At last a couple of chosen examples are presented to demonstrate approaches to the prior specification. The ambition of this paper is to identify the development within Music Information Retrieval & Visualization and present a survey of recent research.

Index Terms—MIR, Music, Information Visualization, Music Collections, Music Visualization, Music Similarity

1 Introduction

With the growing impact of technology on everyday life the research field of Information Visualization has developed the new and important topic of Personal or Casual Information Visualization [24] which puts the focus on technologies that try to include visualization into the common daily life cycle. The focus of this paper will be on the domain of music collections by clarifying the current problems within wide-spread music players and giving an overview about recent research that tries to solve those problems and add new functionality to support the user. The next section will summarize existing problems while the third and fourth section will feature new concepts to adopt to the growing demand for development in terms of strategy, ideas and visualization. The fifth section lists a couple of exemplary research and at the end conclusions will be drawn.

2 Status Quo

In today's world digital music collections are usually organized based on a selfmade system by the owner of the collection. Such organisation systems usually vary a lot in their structure - one might sort his collection by artist, by album or by the date of release. Influenced by those heterogeneous structures the current methods for displaying and organzing music in state of the art digital music players [19] are playlists created by the user. People tend to fill such playlists with similar music to create playlists for specific emotional states (for example slow music that helps to relax). This human necessity is one of the main reason why new researches in MIR topic usually rely on similarity-measures to arrange music collections and it has been proved to be a well working concept ([19] [31] [26]).

2.1 Problems

As stated above the tools to listen to music are typically commercial products with a large spread. With the growing size of a music collection it gets harder to find the music you are looking for or simply browse your collection. As the only possibility to search the music, through the file system of the operating system, is based on text, the user has to know at least some part of the file's title to actually find it through the search. When thinking about use cases as described in section 3.1 this gives no opportunity at all to get results related to music a user already knows which is a basic demand. To solve this problem meta data is appended to the digital music to provide further information. The thereby developed problems will be explained by using genres as an example in section 2.1.2

- *Tim Langer is studying Media Informatics at the University of Munich, Germany, E-mail: tim.langer@campus.lmu.de*
- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

2.1.1 Playlists

As stated above the basic systems used nowadays rely on playlists to visualize music collections. But as pictures are easier and faster to recognise for a human, it is quite intuitive that such would be a better choice than text based methods. [31] states this as following: "However this [text] approach by itself is inadequate for effective search and retrieval". Also it is quite hard to put a lot of information into a short text whilst a graphical visualization could present different information by varying itself in terms of size, colour, form or other parameters. On going with a growing music collection and a lot of cross-links information (such as different artists on the same song or one song on different albums) a large amount of playlists is needed to keep up with all this and thereby the clear view gets lost. As mentioned before, some of those music players already try to create automatic playlists. This is done by either studying the users listening behaviour, and grouping favourite tracks together, or by analyzing the metadata. The thereby extracted information is then used to create playlists for different categories, usually distinguished by the genre (see 2.1.2). L As listening to music is correlated to emotions the choice of music tends to depend on our current mood [27]. So searching music that fits this mood would be a quite intuitive feature! But with playlists this is only possible if the user knows what kind of music is stored in a playlists and/or if he already created a playlists that fits this mood. So the system hardly aids the user with his choice.

2.1.2 Tags

The adding of meta information with ID3-Tags brings a whole lot of new problems with it. Firstly, tags provide information appended to and not derived from the music which therefore can obviously contain false information. Secondly, as such tags are added by communities of voluntary users stored in large online databases faults (such as typing errors) are inevitable. Thirdly, the process of assigning the metadata to a musical track is a subjective process ([31] [19]). One person might classify a song simply as "Rock" while another person might go into more detail and categorise it as "Hard-Rock". Hilliges et. al.[19] provide a good example for this when stating that the well-known iTunes music store puts both punk-rockers Anti-Flag and musician James Blunt into the category of Rock. But not only the subjective assignment of Genres (and other tags) is a problem, also the number of possibilities that can be used is problematic field. On the one hand when specifying too many different choices (such as classifying dozens of different subcategories for Rock) the large amount of details makes it almost impossible to still maintain an informational overview. On the other hand tagging is almost futile when putting all your data into the same categories as it provides no further information. And last but not least most musicians develop different styles throughout their musical career. It might usually be possible to categorize one album into a matching genre, but rarely the whole artist based on all his or her releases. And sometimes it even impossible to sum up the different songs in one album into one matching genre as the style of the tracks might vary because of different influences, featured artists or for other reasons. In fact ”few artists are truly a single ’point’ in any imaginable stylistic space but undergo changes throughout their careers and may consciously span multiple styles within a single album, or even a single song” [2]

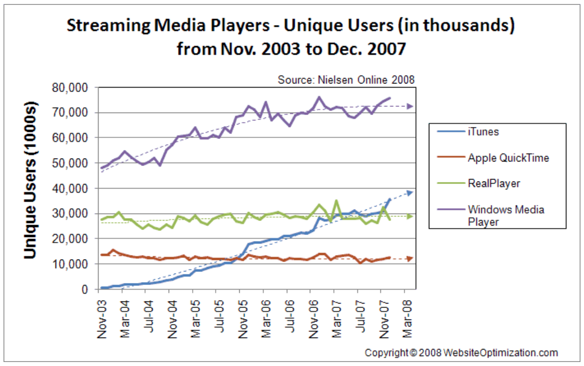

Fig. 1. Streaming Media Players - Unique Users by www.websiteoptimization.com

2.2 Examples

The following section will introduce three state of the art music and media players. They were chosen as a representative of the three biggest operating systems: Microsoft’s Windows, Apple’s Mac and the Linux system. The Windows Media Player and iTunes also posses a large market share within digital media players.

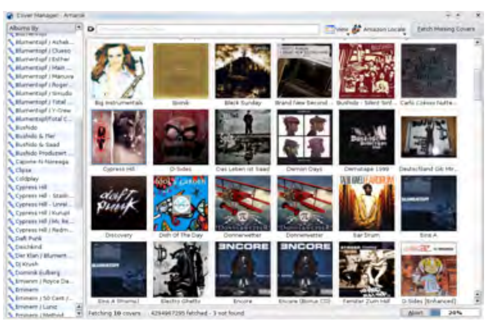

Fig. 2. Visualization using Album Covers (example from Amarok)

2.2.1 Windows Media Player (WMP)

Due to the enormous market share of the Miccosoft operating system Windows [1], the Windows Media Player enjoys a market share of about 50% [18] (and more than 70 million unique streaming users *(see figure 1))*. Currently in its 11th version, it sticks to established structures like playlists and only takes partial advantage of the findings by new research in this topic. But also some of them were taken into account and so WMP offers integration of several (user-made) plugins (for example new track-wise visualizations). The visualization of whole albums *(see figure 2)* is possible and done by presenting the album cover (taken from online databases or added manually by the user). As this also relates to the physical apperance of a music album it is not the worst choice, but still has weaknesses. As said, if the album cover is not available there is nothing but a default image to display unless the user adds the cover manually. The user has the choice between several types of track-wise visualizations *(see figure 4)* that can be added as a plugin and even manually created using a SDK. Grouping of similar music is realised with a stack metaphor *(see figure 5) (top)*.

[1] 80%-90% measured by `http://reseller.co.nz/` at 05.01.2009

2.2.2 Amarok

Amarok[2] is a Linux based music player. Just like the Windows Media Player it uses the album covers to visualize a collection of albums *(see figure 2)*. The playlists view *(see figure 3)* is a bit more advanced though. It does not only list the current tracks of the playlist (or all the playlists available when using another view) but also appends some beneficial information to the whole view like other albums from the same artist or similar artists. It also provides automatical playlists by searching through the whole music collection (as defined by the user) and merging it using the tags chosen by the user. Track-wise visualizations are available by installing a plugin *(see figure 4)*

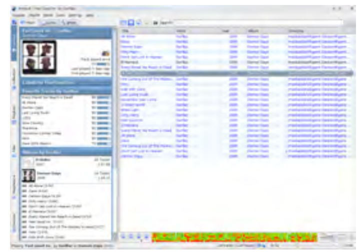

Fig. 3. Amarok Playlist

2.2.3 iTunes

With the spread of the iPod[3], a portable music (and nowadays also media) player developed by Apple, their associated software called iTunes has experienced an increasing distribution as well. Similar to the Windows Media Player it offers a grid-based overview of music albums included to the iTunes library *(see figure 2)* but also a so-called coverflow view that reminds of a jukebox *(see figure 5 bottom)*. Again, just as the Windows Media Player, they use animated art *(see figure 4)* to visualize tracks on their own, the only outstanding difference is the fact that they use 3D. With the integration of the newly developed feature called ”Genius” (more information at section 3.2.3) they approach the research done in the MIR field.

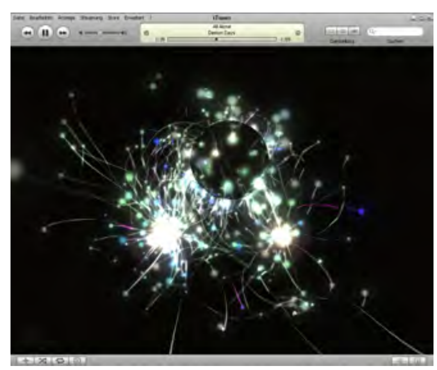

Fig. 4. Track-wise Visualization (example from iTunes)

3 Current Work

”It is one of the manifold goals of Music Information Retrieval to provide new and intuitive ways to access music (e.g. to efficiently find music in online stores) and to automatically support the user in organizing his/her music collection” [14]. But to do this, you first have to identify what is actually relevant, and what is not. As explained before, music and listening to music is a subjective concept, so it is intuitive that human opinion should lead us the way on how to set up the automatism behind our systems. But as [2] stated, it is almost impossible to get human opinion into one consistent basis you could work

[2] regarding version 1.4

[3] market share of 70% - 80% due to [7]

Fig. 5. Clustering (WMP, iTunes)

on. This is one of the main reasons why different research in the MIR field base on different approaches on how to set up their systems. And as no ground truth nor a common evaluation database exists [22] it is yet not possible to say which method works. Even though most publications contain evaluations they can hardly be compared as they only focus on their own approach. Basically when creating new systems there are three main issues to consider that influence the further work.

- What is the purpose of the system (use cases) (3.1)
- What method(s) will be used
- What visualization(s) be used

At the current point of research a couple of common use cases are known and supported by developed systems. Many researches follow the content-based query-by-example (3.1.1) but some also focus on different approaches (3.1.3). After the purpose has been clarified the next step is to decide which method will be used. The predominant method in most proceedings examined in this paper use methods of similarity measuring (3.2). The third issue to consider will then be the choice of the visualization (section 4).

3.1 Music Interaction & Description

This section implies common cases of interaction with music, ideas to improve this interaction, thereby created requirements for music players and different kinds of musical representation and description to fullfil those requirements. As the following will show there is a high relation between the interaction case and the used methods.

3.1.1 Query-By-Example (QBE)

As stated above, much recent research is based on the Query-By-Example paradigm. This means that one musical track or a part of it is used as an example to set up a query for relevant results. This intends to find similar music to the one used as an example. As we have heard before, listening to music is a very emotional and mood-based process. Therefore the choice of the music must be somehow related to our current mood. Since the user, at some point, cannot keep track anymore of a very large and still growing music collection, the search for music that fits special properties gets very difficult. By using known music as an example to find other similar music this process gets a lot easier and supports the user in his aim for music that he likes. But QBE is not only used to find music that a person would like to listen to at the moment. There are some more interesting use cases as following:

- Analyzing a composers evolution and his influences [30]
- Resolving copyright issues [30]
- Query-By-Humming (see 3.1.2)

3.1.2 Query-By-Humming (QBH)

Query-By-Humming is a special use case of Query-By-Example. QBH is used when a user only knows the melody or a tune from a song and hums it into a microphone. The input is then digitized and converted into a symbolic representation and compared with a database. Therefore QBH only works if a symbolic representation (3.2.1) is available for the matching song. ”The conversion of generic audio signals to symbolic form, called polyphonic transcription, is still an open research problem in its infancy” [31]. Further research on QBH has been done by [12] [17] and others.

3.1.3 Query User Interfaces (QUI)

Contrary to the static Query-By-Example paradigm and related user interfaces, Tzanetakis et. al. [31] have developed and presented a couple of new user interfaces. Their goal was to support use cases that vary from the standard QBE and present user interfaces to suit them. While QBE methods base on a music file, a melody (see 3.1.2) or such as an input, and deliver data in context to this input, [31] investigate systems that rely on different data input. They define the term of **Query User Interfaces (QUI)** that sums up ”any interface that can be used to specify in some way audio and musical aspects of the desired query”. The first and simplest technique they present is the use of sound sliders to adjust the parameters for the desired query. While the QBE paradigm already relies on audio input, this technique has numerical input but auditory output. This is called sonification. So-called sound palettes are similar to the sound sliders, the main difference here is that they offer a fixed amount of values (a palette) for each attribute while the rest works just as with sound sliders. The 3D sound effect generator offers a possibility to query music by interaction, thus meaning that the system provides representation of physical objects (such as a can and different surfaces) the user can choose from and make them interact (roll the can on a wooden table). Therefore a use case based on actions or interactions as input is supported. Last but not least they present user interfaces based on midi input. With systems such as the groove box or style machines the user has the opportunity to use symbolic representations (in this case midi data) for a query to search large audio databases.

3.1.4 Query-By-Rhythm (QBR)

[6] propose another technique called Query-By-Rhythm where they support queries based on rhythmic similarity. At first they model a song into a rhythmic string used as a representation and thereby transform the similarity measuring into a string-based process. A rhythm string is created by measuring rhythm patterns (called mubol) and notes as well as their occurence time, ignoring their pitch value. By defining similarity for the mubols they are then able to educe similarity for rhythm strings from it.

3.2 Method

Music itself is generally self-similar [10] (see section 4.3). Together with the fact that similarity measuring is a common technique used to organise data in general it provides one of the basic methods used in MIR. Within music collections it is used to compare different songs and use the output to arrange matching data together and vice versa. This supports use cases like finding new music that still suits the user's taste and/or his current mood. There are different opinions on what is actually relevant to indicate similarity but they all have common principles behind them. Usually the thereby extracted information is then later on used to set up the borders for the visualization. There are three basic ways of measuring similarity. The first one is by looking at symbolic representations of the music such as written notes (3.2.1), another one is by measuring acoustic properties (3.2.2) and the last one is by measuring subjective characteristics (3.2.3).

3.2.1 Symbolic

Using symbolic representations is popular method to compare and extract similar music. It is even indispensable for some ideas such as 3.1.2 and 3.1.4 and often supported by systems that do not only rely on symbolic representation as it expands the possibilities. Symbolic representations usually appear as

- lyrics
- scores

- midi representations
- rhythmic patterns

and the like. Systems that use symbolic data to search through their database usually work with string-based methods, set-based methods or probabilistic matching [30]. With string-based methods it is usually important to grant some divergence as the desired result will not always be an exact match. Set-based methods do not have this problem as they donot rely on a set order. They work with "properties like time, pitch, and duration" [30]. "The aim of probabilistic matching methods is to determine probabilistic properties of candidate pieces and compare them with corresponding properties of queries" [30].

3.2.2 Acoustic

Acoustic based measuring is a technique that is opposite to metadata-based measuring and such, as it relies on data derived from the audio signal and not data appended to the audio. The basic idea behind acoustic measurement is to extract information from the raw audio input and use it to create a model representation. The relevance of the different possible attributes cannot be generalized as it depends on the requirements of the sytem and the subjective opinion of the developers. As we will see in section 5 researchers set up their own choice of relevant properties and measuring methods. The following lists a couple of commonly used attributes as described by [30]:

Loudness: can be approximated by the square root of the energy of the signal computed from the shorttime Fourier transform, in decibels.

Pitch: The Fourier transformation of a frame delivers a spectrum, from which a fundamental frequency can be computed with an approximate greatest common divisor algorithm.

Tone (brightness and bandwidth): Brightness is a measure of the higher-frequency content of the signal. Bandwidth can be computed as the magnitudeweighted average of the differences between the spectral components and the centroid of the shorttime Fourier transform. It is zero for a single sine wave, while ideal white noise has an infinite bandwidth.

Mel-filtered Cepstral Coefficients (often abbreviated as MFCCs) can be computed by applying a mel-spaced set of triangular filters to the short-time Fourier transform, followed by a discrete cosine transform. The word "cepstrum" is a play on the word "spectrum" and is meant to convey that it is a transformation of the spectrum into something that better describes the sound characteristics as they are perceived by a human listener. A mel is a unit of measure for the perceived pitch of a tone. The human ear is sensitive to linear changes in frequency below 1000 Hz and logarithmic changes above. Melfiltering is a scaling of frequency that takes this fact into account.

Derivatives: Since the dynamic behaviour of sound is important, it can be helpful to calculate the instantaneous derivative (time differences) for all of the features above.

This does not claim to be a universally valid list, just some basic possibilites. There will be further information in section 5 on what is actually measured in what research project.

3.2.3 Subjective

As we have heard before, music is subjective. People judge and categorise music differently, based on their taste and their mood. As symbolic and acoustic measuring does not take this into account there is the technique of measuring subjective properties. The basic idea behind this is to analyze people's behaviour and draw logical conclusions from it. A relatively new example for such is the Apple Genius[4] introduced with the 8th version of Apple's iTunes (see 2.2.3). After searching the users music library and the Apple store it provides a playlist of up to 25 similar songs based on the user's initial choice given to Genius. The similarity measuring uses analysis of people's listening behaviour with iTunes amongst other things. Nowadays large communities of music-interested users, providing statistical data of their listening behaviour exist such as Pandora [5], Last.fm [6], Playlist [7] and Imeem [8]. Based on the user-provided data they create playlist for different tastes, moods or events and offer recommendations to the user. This is achieved by collaborative filtering of all the user data assuming with the input from one user assuming that the predictions will then fit his musical taste. Collaborativ filtering means to create links by measuring time-near apperance of artists, albums or tracks in users playlists, numerical apperance in charts and the total occurence of that item within the whole community as well as other features. Even though subjective means are indispensable to measure cultural and other intangible factors it can only be used if a large amount of associated data already exists so it cannot be applied to new or unknown artists and music. Subjective similarity measuring has been used and analyzed on several occasions (see [26] [11] [2])

4 VISUALIZATION

Nowadays there exists an enourmous amount of different visualization techniques. This section will list just a few of them (as proposed by [26]) that relate to visualizing music and music collections.

4.1 Similarity

The following describes a few visualization examples used to describe similarity (for example measured as described in section 3.2) - mainly between artists but it could also be used with other attributes.

Self-Organizing Map (SOM) The Self-Organazing Map ([15] [16]) is a neural-network algorithm to organize data with multi-dimensional feature vectors and map them into a non-linear, low-dimensional (usually 2D) visual representation. The discreet output space is split into so called *map units* from which the best matching unit is chosen for each item to represent it. It tries to map close data from the feature space (thus meaning a high similarity) to close units in the output space and thereby clustering the data. The SOM algorithm is an extremly popular method (over 5000 scientific articles that use it according to [15]) that is also used by some of the examples presented in section 5.

Multi-Dimensional Scaling (MDS) The basic aim behind multi-dimensional scaling is to maintain an appoximate representation of distance from the data itself to its visualization. This means to represent the distance between two data objects by their attributes (similarity in terms of artist, genre and so on) as good as possible. This is usually done by firstly assigning a random position in the output space and then re-arranging the objects by calculating new coordinates to still stick to the given distances and minimize the error rate. Research has developed a couple of different algorithms trying to fulfill the strict specifications of MDS such as *Sammons mapping* [25]. *Figure 6* shows an example of multi-dimensional scaling as presented in [26].

Continuous Similarity Ring (CSR) The Continious Similarity Ring is a novel visualization technique developed by [26] (*see figure 7*). It is based on similarity measuring with anchor references (one prototype artist) for each genre arranged as a circle. Artists similar to the genre prototype are then appended to it while the

[4]Additional information at `http://www.apple.com/de/itunes` December 2008
[5]`www.pandora.com` December 2008
[6]`www.last.fm` December 2008
[7]`www.playlist.com` December 2008
[8]`www.imeem.com` December 2008

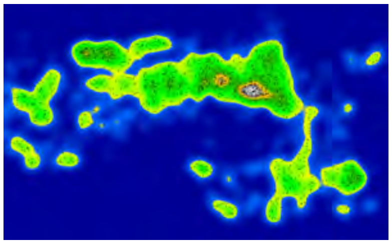

Fig. 6. Multi-Dimensional Scaling Example by [26]

arrangement of the prototype artist tries to preserve the similarity as a distance representation. A thick and colourful edge as well as a close distance between two nodes means a high similarity whilst thin and dark edges connect less similar artists. [26] uses Johann Sebastian Bach and Willie Nelsons as an example to show the functioning (no other prototypes connected to the classic genre - Folk and Country closely connected). He refers the malfunctioning part, as can be seen with the artist Bush, to problems with the measuring algorithm that only occur when using a small amount of data.

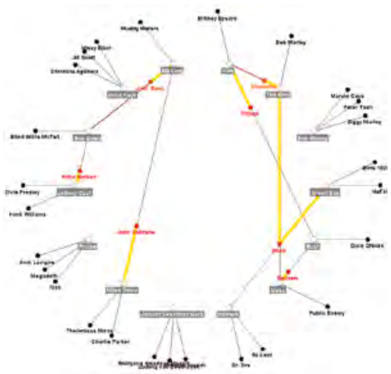

Fig. 7. Continuous Similarity Ring (CSR) by [26]

4.2 Hierarchical

In contrast to the techniques presented in section 4.1 this section will feature techniques used to visualize hierarchical structures.

Treemap Treemaps are a quite common and popular method to visualize hierarchical data. The available space in form of a rectangular layout is recursively divided into further rectangles to indicate the underlying steps in the hierarchy and filled with the associated items of the data set. Even though it is a well-known visualization technique and several further developments have been made ([3] [32]) it is no common technique used for music and music collections.

Hyperbolic Tree The Hyperbolic Tree's original name was Hyperbolic Browser, but due to its tree-like data structure and visual form it is also referred to as a tree [26]. As the name already suggests the tree is is laid out in a hyperbolic plane thus growing with the size of its radius and providing large space at its outer border. Each node of the tree is assigned an equal share of the total angle to arrange its successors. Each child of a node is placed around the arc of the node's angular share and therefore has the same distance. By doing this a possible overlap of children is prevented. The root node is then used as the center item while the other items are arranged accordingly - the further from the center, the deeper the item is in the hierarchy. *Figure 8* shows examples for a hypertree taken from the Sonic Browser (section 5.3) and Musictrails [9]. The Musictrails example shows a good result putting Damon Albarn, lead singer of the Gorillaz, just next to his band.

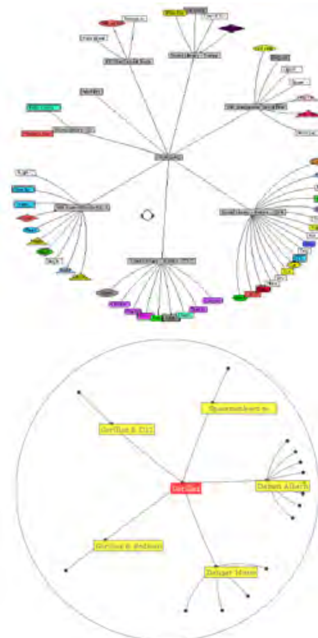

Fig. 8. Hypertree: Sonic Browser (section 5.3) & Musictrails

Sunburst (InterRing) The Sunburst or InterRing (*see figure 9*) is a circular visualization concept developed by [1] and [29]. The top-of-the-hierarchy item is in the center while each sub-level is presented by an arc where the distance to the center again indicates the depth. All children of a node are bounded to the same amount of angular extent their parent had and drawn within those borders. The size of a node is calculated by its proportion to the remaining nodes at the same level. A major disadvantage of the Sunburst visualization is that elements at the bottom of the hierarchy get assigned a very small deal of the arc and therefore are very hard to spot - a problem growing straight proportional with the data size.

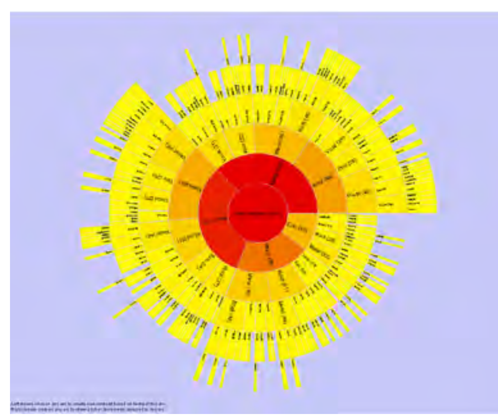

Fig. 9. Sunburst by [1]

Stacked Three-Dimensional Sunburst The Stacked Three-Dimensional Sunburst has been developed by [26] and operates as an extension to the Sunburst concept. The main motivation were the short-comings of the original system which only provided for two-dimensional data to be handled. The support of multi-dimensions is handled by adding the height as a new scale

[9] `http://www.musictrails.com.ar` December 2008

thus making the visualization 3D. With this feature added it is possible to have one layer each to display every data dimension. To prevent an infinite growth the authors introduced a number of limitations for the number of nodes, the depth of the whole stack and the minimal angular extent per node which solves the second deficit of the original system. *Figure 10* shows a non-labeled example of the Stacked Three-Dimensional Sunburst system with three layers where color is used to distinguish the data dimension represented by the arc's angle.

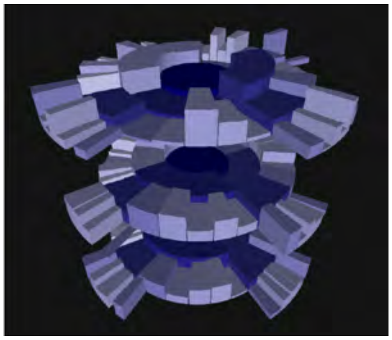

Fig. 10. Stacked Three-Dimensional Sunbursts developed by [26]

4.3 Track-wise

Whilst visualizing music collections has experienced a lot of attention the research field of visualizing single tracks has often been left behind and did not receive much attention. The first attempts to visualize single tracks were done by using timebars which did not only give a visual information but already allowed intra-track navigation [33]. The common strategy to visualize songs nowadays is by using dynamic art depending on the acoustic properties (*see figure 4*). [33] developed a new visualization to aid intra-track navigation called *moodbar* (*see figure 12*) that has already been included in music players like Amarok. The moodbar is a visual track representation that indicates different parts of the song by using different colours. It uses several measuring techniques to extract one and three-dimensional information where the first is used to set the luminosity of a grey shade while the second values are formatted into a RGB colour. Therefore similar clips of one track obtain corresponding coloring and thereby indicate their likeness. [10] developed the concept of self-similarity to visualize the time structure of a musical piece. By comparing it to itself he creates a 2D representation with two time scales where the brightness of each square in the graph represents the similarity. A high similarity is bright while dissimilarity is dark. Because of the identic scales there is a bright diagonal from bottom left to the top right (*see figure 11*). This helps to identify different sections (like verses and chorus) of the song. Unfortunately visualizing tracks seems to be not as popular even though it would provide a lot of possibilities for future research.

5 Related Work

This section will introduce a selection of the mentioned research, shortly explain the methods used to retreive the information and the chosen type of visualization.

5.1 AudioRadar

AudioRadar is a system developed by [19] at the University of Munich. As the name already foreshadows it relates to the metaphor of a ships' radar. The system is intended to aid QBE (see section 3.1.1) use cases and uses acoustic measuring (see section 3.2.2) to calculate the distance between two songs and arrange them accordingly. The example object is in the center (*see figure 13*), appended with some visual controlling options, while the other items are represented by small dots. The system integrates four axes whereby the most dominant difference from the example is chosen to determine the axis that gives the direction. The size of the distance sums up the similarity or difference.

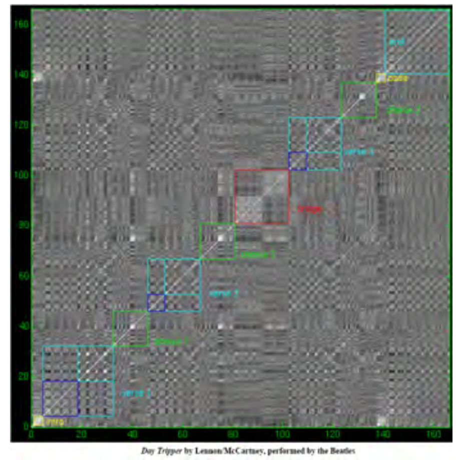

Fig. 11. Self Similarity example by [10]

Fig. 12. Amarok using the moodbar plugin by [33]

The user has the possibility to re-arrange the whole by chosing a new center. The attributes extracted with the automatical acoustic analysis were

- slow vs. fast
- clean vs. rough
- calm vs. turbulent
- melodic vs. rhythmic

by using a given analysis library. The two-dimensional projection of those four attributes is done by picking two of the scales to map them on the four axes. AudioRadar also provides the creation of mood-based playlists by giving the user the oppurtunity to define the range of attributes for the chosen music (similar to the sliders from [31] in section 3.1.3).

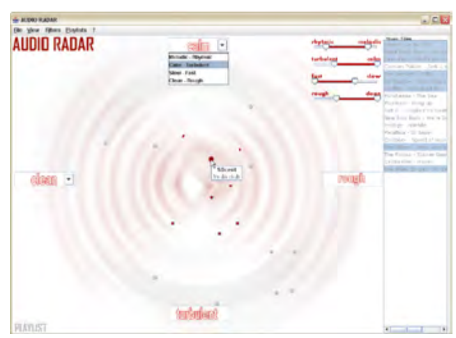

Fig. 13. Audio Radar by [19]

5.2 AudioPhield

AudioPhield is a novel multi-touch tabletop display system created by [27] to support multiple users. It allows for multiple users to interact with each others music collection and easily spot concuring areas. As the whole visual layout is again based on similarity metrics (close means similar, far away means different) such areas are dedicated to a certain kind of music and so a high conformity means a similar musical taste. Each song is represented as a dot and, of course, every user's music collection is assigned a different color to avoid confusion (*see figure 14*). They use a mixture of acoustic and subjective methods to measure similarity and attach meta information about the accuracy to each value. The visualization is based on a SOM with 80 nodes per axis to enable "fine nuances in close proximities" but still "make searches and modifications computable in reasonable time" [27]. Unlike within normal SOM training methods AudioPhield does not recompile the best matching unit but only does it once. This beholds the risk of units "moving away" from an item which is prevented by preimprinting the SOM to define a rough layout. To avoid overlapping of single items they integrated a so-called "*spring-algorithm*" that makes the items push off from each other while they are still connected to their inital place and thereby rearrange themselves until they do not overlap anymore.

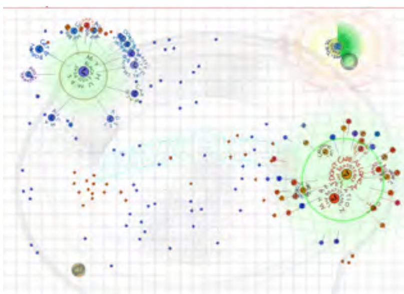

Fig. 14. AudioPhield by [27]

5.3 Sonic Browser

The Sonic Browser has been developed by Eoin Brazil and Mikael Fernstroem and has lived trough several enhancements ([8] [9] [4] [5]). Its main intent is to provide aid to humans for browsing through large audio collections and exploring them. They provide a couple of different views to denote the relationship within the data. The focus lies on the presentation of the content rather than on the classification. The foundation of the design for the Sonic Browser are the "principles of direct manipulation and interactive visualisation interfaces proposed by Shneiderman [28]. The three primary facets of this foundation are "overview first, zoom and filter, then details on demand" [4]. The Sonic Browser integrates many different views *(see figure 15*) such as a basic x-y plot (first implementation), the Starfield Display and a Hypertree View (*figure 8*). The Starfield Display is a scatterplot, with axis depending on the attributes of the dataset, which supports axis remapping (to other attributes), drag & drop as well as object-selection and -editing. Information on the Hypertree can be obtained from [13] & section 4 while a short explanation on the TouchGraph is available at [4]. What is special about the Sonic Browser is the fact that it maps attributes from the data to the representation of an object by adjusting its shape. For example changing symbol size to represent the file size, colour for the sampling rates, symbol shape for the file type and location for the date and time as used in the Starfield Display.

5.4 Islands Of Music (IOM)

Islands Of Music[10] was developed by Elias Pampalk ([21], [23]) as his master thesis [20]. He uses acoustic measuring by dividing a song into time intervals of 6 seconds each and analyzing every third one further. After calculating the loudness sensation per frequency band in a 12ms time interval and then analyzing the loudness modulation in the whole time interval by using a Fourier Transformation as well as several following steps (further detail in [21]) he calculates a median of all sequences (first and last one is cut to avoid fade-in and fade-out effects) to represent the musical piece. Evaluation of alternative combination methods figured for the median to yield likewise results. The

[10] http://www.ofai.at/~elias.pampalk/music/

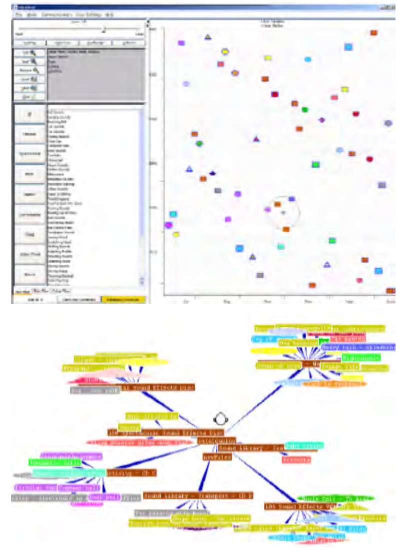

Fig. 15. Sonic Browser Views: Starfield Display & Touchgraph by ([8] [9] [4] [5])

novel user interface represents a music collection as a series of islands (*see figure 16*), each representing a musical genre, with labeled hills and mountains to describe rhythmic properties. Similar genres are locacated close to each other just as the respective tracks on the islands are. Again the arrangement of the music collection is based on similarity metrics while the visualization works with a Self-Organizing Map trained with the received data. [21] developed a new technique that allows each track to vote for a unit that best represents it - giving it one, two or three points - and uses the achieved ranking to set up the geographic maps.

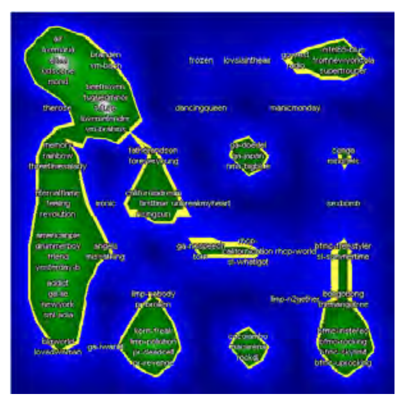

Fig. 16. Islands of Music Example using a 7x7 SOM on 77 songs

5.5 3D User Interface by [14]

The 3D User Interface developed by [14] is an innovative virtual reality like system to browse and explore music collections. The measuring is done with "rhythm-based Fluctuation Patterns that model the periodicity of a audio signal" as presented by [21] and explained in section 5.4. The visualization follows *Islands Of Music* [21] concept but adds additional functionality. While the original layout was in 2D [14] present a 3D approach by using the result from the SOM and feeding it with a Smoothed Data Histogram (SDH) interpreted as a height value to generate the third dimension. The height of the landscape corresponds to the amount of similar items in the specific region thus meaning a high mountain acts for many songs. By creating this virtual reality the user is invited to perform an interactive tour through his music collection which does not only integrate visual information but also auditory. When browsing through the collection audio thumbnails of close songs are played to further strenghten the impression. [14] also included a web-based information retrieval for textual or graphical (covers) information that is appended to the representation *see figure 17*. In total they provide a system based on known ideas ([21]) and enhance it with a new dimension as well as further functionality to support the user.

Fig. 17. 3D User Interface by [14]

6 Conclusion And Future Outlook

The present survey has demonstrated that development in Music Information Retrieval & Visualization has happened and is even partially included into modern music tools already. Most research has a common basis relating to ideas and methods such as using similarity measuring to model a music collection which are than used to create appealing interfaces for the user. As seen within section 5.5 some techniques even rely on previous work which indicates the floating development. Even though the basic principles usually stay the same the exact implementation (chosen method and measured properties) and results differ which can be traced back to individual opinion as well as a missing proven concept for ”the” best-working method. Another problem that adds on constraining the comparing of various developments is the missing of a common dataset to evaluate invented techniques. As almost each developer relies on his own dataset it is barely a miracle that the results vary a lot. For the future a further consideration of track-wise and intra-track visualization will be a possible new issue. With growing social music societies such as last.fm the future focus of measuring similarity will probably lie within subjective means as those platforms provide a large basis.

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Knowledge Visualization

Robert Meyer

Abstract— Knowledge Visualization is a relatively new field of research that focuses on the creation and transfer of knowledge by visualizations with and without the help of computers. It is ought to be a mediator between a lot of different disciplines. This paper gives an overview of the concept of Knowledge Visualization, especially in regard to the definition of Remo A. Burkhard, who worked on the topic in-depth in his dissertation. Therefore the seeds of the concept, its goals and theoretical backgrounds like the Knowledge Visualization model are presented in this work. As it is a very interdisciplinary field of research an overview about the participated disciplines is given. The differences to Information Visualization, which was the key issue of the Media Informatics Advanced Seminar, for which this paper was written for, are also outlined in detail. Additionally the methods to visualize knowledge are categorized and presented as well as three approaches that should help to find the best visualization method for each purpose.

Index Terms—Knowledge Visualization, Information Visualization, Knowledge Management, Overview

1 Introduction

The knowledge of the world increases massively while the half-life of knowledge decreases [22]. Moreover, time gets a rare resource but is needed to communicate the more and more complex knowledge. That is the reason why traditional ways to exchange knowledge among people are probably not sufficient any more. Using mainly text and numbers instead of proper visualizations does not fit the requirements of our knowledge society any more. But it is not enough just to search for ways to transfer knowledge: It is also important to help those who want to use the power of visualization by proposing them advice, which visualization method fits best for the particular problem [8]. The architect Remo Aslak Burkhard analyzed in his PhD thesis [8] the topic of visualization and proposed a new field of research to cope with the mentioned problems: Knowledge Visualization, which is an essential part in knowledge management. Its goals are to transfer and create new knowledge through using visualizations. These visualizations do not necessarily have to run on computers - some visualization methods were used a long time before the invention of information technology. But at least these methods could be supported by visualization software to increase their efficiency. Burkhard analyzed the way how architects communicate information about one object (for example a skyscraper) to the different target groups like engineers, workers, lawyers or clients, which all have different conceivabilities and a different background of knowledge. He found the insight, that architects combine different complementary visualization types to address the mind of every participant with different levels of detail. Based on this conclusion Burkhard tries to build a framework of Knowledge Visualization. It should especially help managers to use and create visual representations of business processes [8].

This paper gives an overview about the topic of Knowledge Visualization - especially in the context of Burkhard's definition - and some related fields of research. It is meant to be a short insight into the topic without the focus on critics or continuative thoughts. Therefore chapter 2 gives an outline of some basic definitions and knowledge background necessary to understand the ideas of Knowledge Visualization. As Knowledge Visualization is not an independent area of research but interdisciplinary grounded, those roots and relationships are presented in chapter 3. Afterwards the main format types of visualization are introduced in chapter 4, which are classified in order to map the optimal visualization to the actual problem in chapter 5. Last but not least chapter 6 concludes this paper with an outlook on the possible future fields of application of Knowledge Visualization

- *Robert Meyer is studying Media Informatics at the University of Munich, Germany, E-mail: meyerr@cip.ifi.lmu.de*

- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

2 Overview

The following subchapters give a short overview about the topic of Knowledge Visualization. After defining the relevant terms used in this paper in subchapter 2.1, subchapters 2.2 to 2.4 shows the need for Knowledge Visualization in consideration of discovering and transferring knowledge. Finally Burkhard's model of Knowledge Visualization is introduced in subchapter 2.5.

2.1 Basic Definitions

A lot of terms like information and knowledge are used in everyday speech synonymously even though they have different meanings. The following basic definitions from Keller and Tergan [21] are based on the concepts of Russell Ackoff, a systems theorist and professor of organizational change [2].

Data consists of symbols and facts, which are isolated and not interpreted yet. It has no relation to other data and has no meaning of itself. For example the sentence "It is raining" describes only a fact that water drops fall from the sky.

Information is more sophisticated. It is data that has been interpreted or processed and therefore contains some meaning and can give answers to questions like "who?", "what?", "where?", "why?" or "when?". For those who do not comprehend the meaning it still stays data [21]. For example if "because the temperature dropped 15 degrees" is added to "It is raining" it becomes information through the understanding of cause and effect for certain people. Abstract information that has no natural visual representation is in the focus of Information Visualization (see chapter 3.1.)

Knowledge is one step further "information, which has been cognitively processed and integrated into an existing human knowledge structure" [21] (p.3). Knowledge is dynamic as "its structure is constantly being changed and adapted to the affordances in coping with task situations" [21] (p.3). A good way to distinguish between information and knowledge is the differentiation, that information is outside the brain whereas knowledge is inside [21]. This means for the rain example, that not only the connection between cause and effect is understood, but also the concept behind this effect (here the relation between temperature and humidity in the atmosphere).

According to Tergan "*Knowledge visualization* is a field of study, that investigates the power of visual formats to represent knowledge. It aims at supporting cognitive processes in generating, representing, structuring retrieving sharing and using knowledge" [31] (p.168). Burkhard offers another definition. According to him Knowledge Visualization "[...] examines the use of visual representations to improve the transfer and creation of knowledge between at least two persons." [7] (p.3). Because this paper focuses mostly on Burkhard's concept of Knowledge Visualization, his definition will be the basis in the following chapters.

2.2 The need for Knowledge Visualization

Burkhard [8] proposes Knowledge Visualization as a new field of research and therefore canvasses for its establishment. First of all the lack of research on transferring knowledge in the domain of business knowledge management was one of the reasons to start researching on this topic and to introduce the term ”Knowledge Visualization”. It is also asserted, that there are a lot of visual formats existing, but only a subset is used for a visual transfer of knowledge in organizations, like clip arts or diagrams. Therefore the existing visualizations must be mapped to real world problems as well as evaluated about their strengths and weaknesses. Burkhard criticizes, that findings in related fields of research are not transferred into knowledge management as an interdisciplinary mediating framework is still missing, that could integrate findings from other domains like visual communication sciences or information design. That is why a theoretical basis of Knowledge Visualization is needed. Furthermore he finds fault with the fact, that Information Visualization researchers succeeded in creating new insights based on abstract data, but they do not concentrate enough on how to transfer these insights to the recipients. In addition the narrowed view of Information Visualization on computer supported methods should be widened to a broader perspective of visualizations, for example on the concepts of visualizations in the architectural context. These problems should be addressed with the introduction of Knowledge Visualization as a new field of research [8].

2.3 Generating Knowledge

According to Burkhard’s definition of Knowledge Visualization it should assist in creating new knowledge. This is relevant on the one hand for individual learners and on the other hand for groups which use visualizations for example in workshops. The working memory of a single person to store information is limited in capacity as well as in time information. Visualizations may help to reduce the cognitive load and enhance the processing abilities by visualizing abstract relationships. They allow to externalize knowledge for example to share it with others or to get an overview about the big picture of the field of interest [31]. Visualizations enable innovation as they offer methods to use the creative power of imagery, for example by using a visual metaphor (see chapter 4.4). In contrast to text based knowledge it is possible to rearrange visualized knowledge very fast and jointly, for example by visualizing the ideas with sketches (see chapter 4.1) [20].

Novak [26] examines the effects of collaborative Knowledge Visualization on Cross-Community Learning and identifies the Knowledge exchange between heterogeneous communities of practice as the critical source of innovation and creation of new knowledge. Individuals participate in communities, which share for example the same needs, goals, problems or experiences. Through interaction and social relationships between the members of the communities new knowledge can be created with the help of visualizations. Novak discusses this on the example of netzspannung.org, a knowledge portal that provides insight in the intersections between digital art, culture and information technology. The heterogeneous user group which consists of for example artists, researchers, designers or journalists can use personalized Knowledge Maps (see chapter 4.3.1) and a shared navigational structure which allow them to explore the relationships between different topics or fields of profession [26].

2.4 Transferring Knowledge

Transferring knowledge is for example necessary to grant access to the achieved knowledge from one person to another one. This could be for example a manager that has to come to a decision on the basis of the knowledge of his consultant. Knowledge Visualization serves as a conceptual bridge to increase the speed and the quality of knowledge transfer among and between individuals, groups or even whole organizations [20]. Knowledge transfer struggles with a few challenges, which need to be solved by the stakeholder who transfers the knowledge to the recipient. First of all the relevant information for the different stakeholders has to be identified. Then a trade off about the depth of information has to be found and it must be decided if an overview is enough or if more detailed information is necessary. This depends on the available amount of time, the attention or the capacity of the recipients. The different cognitive backgrounds of the recipients have to be considered as well because it is only possible to understand something if it can be connected to already available knowledge - maybe the recipients are decision makers that do not understand the new visualization tools [7]. If these challenges are not considered properly they will cause a few elementary problems. One major problem in organizations is information overload, which is caused by the increasing quantity and the decreasing quality of information. This hampers the ability to identify the relevant information. Therefore it is necessary to offer strategies for a better filtering of information concerning quality and relevance [8]. In addition to that the risk of misinterpretation if the decision makers do not understand the information and misuse it by making the wrong decisions is another consequence of false knowledge transfer [7]. During presentations normally only a very limited set of visualization tools is used to transfer knowledge, like Microsoft PowerPoint or business diagrams and these tools are often used wrongly due to the lack of visualization competency. Knowledge Visualization wants to address these drawbacks by offering evaluated visualization tools and by helping to choose the best visualization for each problem [8].

2.5 The Knowledge Visualization Model

Burkhard concludes the findings of his research during his dissertation into a Knowledge Visualization Model. This model is based on the insight that knowledge cannot be transferred directly from one person to another. The recipients of transferred knowledge have to integrate it into their own knowledge depending on their individual backgrounds and experiences. The key strategy is the usage of complementary visualizations for the different steps in the knowledge transfer process to archive an efficient and successful transfer of knowledge from a ”sender” to a ”receiver”. The following five questions should be answered in the model:

- What is the aim and the effect of externalizing knowledge into visual representations?
- What is relevant and should be visualized?
- Which audience should be addressed?
- What is the interest of the recipient?
- What is the most efficient way to visualize the knowledge?

Figure 1 shows a schematic diagram to visualize the idea of the model. The model is divided into three components:

1. The mental model of the ”sender”
2. A medium that is build from the external visual representation of the knowledge
3. The mental model of the recipient

The mental model is in that case an internal representation of knowledge in the memory of a particular person.

The ”sender” wants to transfer a certain part of his knowledge to the ”receiver”. Therefore he externalizes his knowledge into visualizations, which are the source for the recreation process of the ”receiver” who tries to internalize it again into his knowledge. In case of questions or misunderstandings he can use a feedback loop to the ”sender”, who has to modify his existing visualizations or create new ones to serve the needs of the ”receiver”. Burkhard proposes a specific substructure of the visual knowledge representation. There should not be only one type of visualization for the whole transfer process but a few complementary visualizations for different purposes. First of all a visualization must catch the *attention* of the ”receiver” to make him open for the knowledge from the ”sender”. This may be achieved with a provoking image for example. Then in a second stage the *context* of the knowledge must be illustrated to make the recipient aware of the importance of the knowledge for him. Then an *overview* should show the big picture on the topic followed by some *options to act*, which enable the ”receiver” to focus his interests during the presentation of the *details* in the third stage of the transfer process. The author acknowledges that this model has its limitations due to the fact that all humans have different abilities to interpret visual stimuli, but it is at least a general guideline for using Knowledge Visualization [8].

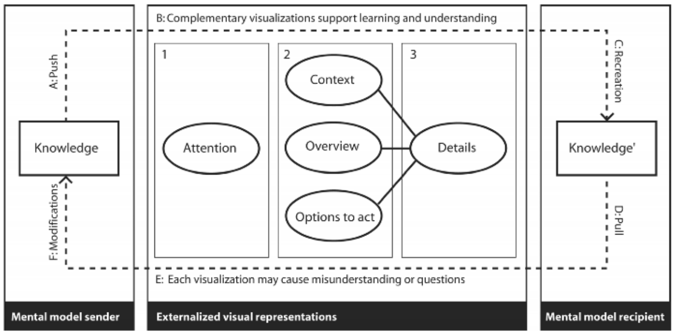

Fig. 1. The Knowledge Visualization Model [8]

3 Connections to other fields of research

Knowledge Visualization is a very interdisciplinary field of research that combines findings of various sciences. Therefore it is not surprising that its concept, which has among others relationships to the communication-, business and computer sciences, was introduced by an architect. This interdisciplinary approach inspires other researchers to study into similar directions. Silke Lang [23] for example uses the ideas of Knowledge Visualization in order to merge knowledge from the different disciplines architecture, engineering, management, and nature sciences to find a common language among these different schools of thinking. This chapter describes the roots of Knowledge Visualization and its relations to other fields of research.

3.1 Information Visualization

There is a big relationship between Knowledge- and Information Visualization as they both help to visualize different abstraction levels of data (see chapter 2.1). Therefore this subchapter discusses the similarities and differences between Knowledge- and Information Visualization.

3.1.1 Definition of Information Visualization

The term ”Information Visualization” is not exclusively used in the context of computer science, for example psychologists use it as ”[...] an umbrella term for all kinds of visualization” [21] (p.7). Card et al. define it as ”the use of computer-supported, interactive, visual representation of abstract non-physically based data to amplify cognition” [14] (p.7). Its methods allow ”to explore and derive new insights through the visualization of large sets of information” [8] (p.23). The theories of Information Visualization are based on information design, computer graphics, human-computer interaction and cognitive science. Users can explore data in real time and discover specific patterns visually with Information Visualization applications. These applications are interactive, dynamic and embed details in context, what means that the user first gets an overview, then the visualized information is reduced by zooming in and filtering and then last but not least details are accessible on demand. Working with Information Visualization methods is much more efficient than working with normal database queries when the knowledge about the data is very low, because the human perception can identify information patterns visually that are very hard to find by working on the pure data [14], [8], [21].

3.1.2 Differences and Similarities

Information- and Knowledge Visualization are both based on the abilities of the human perception system, which is able to process visual representations very effectively, but the content and the process of the respective discipline differ [8]. The major limitations of Information Visualization in contrast to Knowledge Visualization are the very strict focus on computer-based visualizations. Non-computer based visualizations (like sketches) and knowledge types, which cannot be put into a digital carrier (like a database), are ignored [5].

Table 1 compares ten aspects concerning the goals, the origins and the techniques of both fields of research:

Aspect	Information Visualization	Knowledge Visualization
Goal	uses computer supported applications on large amounts of data to get new insights	uses visual representations to improve the transfer and the creation of knowledge
Benefit	improves information access, retrieval and exploration of large data sets	augments knowledge-intensive processes
Content	explicit data like facts and numbers; complex information structures	knowledge types like experiences, insights, instructions or assumptions; social structures, relationship between knowledge and a human actor [26]
Recipients	individuals	individuals or groups to transfer and collaborative settings to create knowledge
Influence	*new insights* for information science, data mining, data analysis, information exploration and *problems* such as information exploration, information retrieval, human-computer interaction, interface design	*new insights* for visual communication science, knowledge management and *problems* such as knowledge exploration, transfer, creation, application, information overload, learning, design, interface design, visual communication
Proponents	researcher with background in computer science	researcher with background in knowledge management, psychology, design, architecture
Contribution	*innovation-oriented*: create technical methods	*solution-oriented*: apply new and traditional visualization problems to solve predominant problems; offers theoretical structures for the whole field of visualization research and aims to improve collaboration
Root	possible through the introduction of computers	grounded in cultural and intellectual achievements for example from architects or philosophers
Means	uses computer supported methods	uses computer supported and non-computer supported visualization methods
Complementary Visualizations	combines different visualization methods which use the same medium in one interface (multiple coordinated views)	combines different visualization methods using one and/or different media to illustrate knowledge from different perspectives

Table 1. Information Visualization vs. Knowledge Visualization [5]

3.2 Visual Perception

The human visual perception system and its vast abilities are the result of the evolution of mankind. In former times it was for example necessary for surviving to improve the skills of motion detection for hunting and color detection for seeking fruits. These perceptions are processed pre-attentively and very fast by the human information processing system and are therefore accessible intuitively without the need for active cognition. After processing the visual information it has to be integrated and perceived in ones mind as a combination of sensory information and previous experiences. Burkhard sums up the findings of some empirical studies with the conclusion, that ”visual representations are superior to verbal representations in different tasks” [8] (p.42). The principles of the Gestalt psychology are good examples for the perceptual phenomena. The viewer of some simple graphics based on these principles recognizes patterns, which are actually not there but added by his perception system [8]. Ralph Lengler [24] identifies the basic visual core competences and refers to them as ”visual literacy”. He also assumes that the ability to process visualizations will raise similar to the finding, that the average intelligence quotient raised over the last decades. The future generations are ought to cope with much more complex visualizations as the processing capabilities for visualizations are for example trained by playing 3D computer games. A deep understanding of the human visual perception system is necessary to enable the creation and the use effective knowledge visualizations.

3.3 Learning Theories

As one of the goals of Knowledge Visualization is the transfer of knowledge where a ”receiver” has to understand the given information from a ”sender”. This can be seen as a learning process and therefore it is obviously useful to consider the findings form educationalists and learning psychologists. Learning theories help to understand how knowledge is created from information and how this process is related to social interaction with others [26]. Three major learning theories propose advises how to design the learning process.

- *Behaviorism* grounds on the assumption, that learning bases on the principle of stimulus and response without respect to the mental model of the learner, which is considered as a ”black box”. It recommends that knowledge should be split up and transferred in small learning steps
- *Cognitivism* goes one step further and opens this ”black box”. The cognitive process, which is necessary to transform information into knowledge, is the focus of this theory. Therefore knowledge should be transferred in a way that it can be used for problem solving.
- *Constructivism* sees learning as an ”active process in which learners construct new ideas or concepts based upon their current/past knowledge” [8] (p.24). Therefore the learner has to create the knowledge based on his own experiences.

The findings of these theories have to be considered when knowledge has to be transferred with the help of visualizations, deepening on the type of knowledge [8], [29].

3.4 Visual Communications Science

In a lot of different isolated research fields people are seeking for the effective design of information, which are summed up here with the term ”Visual Communications Science”.

- *Information design* is the science of preparing information so that it is comprehensible, retrievable and easy to translate into actions. It focuses on mainly static visual formats like maps or posters and not on computer-supported techniques like Information Visualization.
- *Information Architecture* concentrates on graphic-, interface, interaction and human computer design and focuses in contrast to information design more on structural than on presentational matters.
- *Information Art* focuses on aesthetic and emotional issues to show possibilities of digital visual communication design.

All these fields of research contribute to the topic of an effective visual transfer of knowledge, but a framework is necessary to combine their findings [8].

3.5 Communication Science

The communication science offers models that describe the communication of individuals and groups of individuals. As visualizing knowledge is mainly engaged in communicating the knowledge from one stakeholder to another one, an effective transfer of knowledge depends on an effective communication of the content for example concerning the participants, the transferred message and the used channels. The Knowledge Visualization Model, which is introduced in chapter 2.5, is grounded on six different communication models. These models and their respective contribution to the Knowledge Visualization Model are described in detail by Burkhard [8].

3.6 Knowledge Management

Burkhard [8] (p.227) defines that ”Knowledge Management is a management perspective that offers theories, strategies, and methods to manage, i.e., to identify, access, share, and create knowledge in organizations, with the aim to help an organization to compete by being more innovative, effective, and thus more profitable.” This definition shows some similarities with the definition of Knowledge Visualization, especially concerning the tasks of sharing and creating knowledge, but Knowledge Management contains a much broader spectrum of tasks like storing or retrieving knowledge. Thus it is possible to classify Knowledge Visualization as a component of Knowledge Management, particularly because the knowledge transfer process is a key process in knowledge intensive organizations [5], [8].

3.7 Knowledge Communication

Martin Eppler defines Knowledge Communication as an ”activity of interactively conveying and co-constructing insights, assessments, experiences or skills through verbal and non-verbal means.” [18] (p.5). It includes the successful transfer of know-how, know-why, know-what and know-who through face-to-face ore media based interactions. Knowledge Communication focuses on the communication process between domain experts and decisions makers in management and analyzes the difficulties between those two stakeholders. The research area includes Knowledge Management, Communication studies, Expertise and Decision Making. The fields of Knowledge Visualization and Communication have a big intersection in their roots as well as in their goals. This is not astonishing as Eppler and Burkhard share very similar research interests and published some papers together, for example [20]. Knowledge communication is in some respects like the strict focus on decision makers and experts a restriction to the concept of Knowledge Visualization, but on the other hand an extension as it does not concentrate on the visualization topic so much. Nevertheless they are two very related fields of research. Eppler was also involved in developing the tool ”Lets focus”, which is a powerful tool to visualize knowledge in various ways (available at http://de.lets-focus.com) [18].

4 Types of Knowledge Visualization

Until the work of Burkhard [8] a taxonomy of visualizations based on the type of visualization was missing. Therefore he took the most common seven visualization tool categories of architects - which are in his opinion experts in using different visualizations for different target groups and purposes - and evolved them to general categories for types of Knowledge Visualization. These seven types are presented in this chapter in Burkhard’s sequence, enriched with contributions of other authors and some practical examples.

4.1 Sketch

Sketches are simple drawings that help to visualize the key features and the main idea very quickly. They are relatively old since already Leonardo da Vinci used them to visualize his insights and investigations. Sketches can be used in group reflections and communication processes as they make knowledge debatable. Additionally they allow room for own interpretations and thus stimulate the creativity and keep the attention of a group fixed on the discussed object [5], [8].

4.2 Diagram

Diagrams are abstract, schematic representations that are used to display, explore and explain relationships. They reduce complexity, make abstract concepts accessible and amplify cognition. Unlike sketches they are precise and determined. Examples for diagrams are bar- and pie charts, Gantt-, Fenn- or process diagrams [8].

4.3 Map

Maps or plans are in the architectural context used to present entities on a different scale and to bring three-dimensional objects into a two-dimensional visualization. Maps present overview and detail at the same time, help to structure information, motivate and activate employees, establish a common story and ease access to information. Maps are a very busy field of interest in the context of Knowledge Visualization and therefore presented relatively detailed in this chapter by introducing knowledge- and Concept Maps as well as by showing some example usages of maps [11], [8], [20]. Burkhard uses the map visualization of *Figure 6* in a case study for the Knowledge Visualization Framework in chapter 5.1.2.

4.3.1 Knowledge Maps

A Knowledge Map is defined in as a "Guide to, or inventory of, an organization's internal or external repositories or sources of information or knowledge." [12]. According to Eppler [17] Knowledge Maps consist of two components: The *context*, which should be easy to understand for all users of the map, like a network of experts or a project, is represented by a ground layer while *individual elements* like experts and project milestones are mapped within this context. The elements are grouped in order to show their relationships, locations or qualities [11], [8].

Eppler [17] differs between five kinds of Knowledge Maps:

1. *Knowledge source maps* structure a population of company experts along relevant search criteria
2. *Knowledge asset maps* qualify the existing stock of knowledge of persons, groups or organizations
3. *Knowledge structure maps* outline the global architecture of a knowledge domain and its relationships
4. *Knowledge application maps* show which type of knowledge has to be applied at a certain process stage or in a specific business situation
5. *Knowledge development maps* depict the necessary stages to develop a certain competence

Figure 2 shows an example of an Knowledge asset map, which is the stock of knowledge of a consultant company [17].

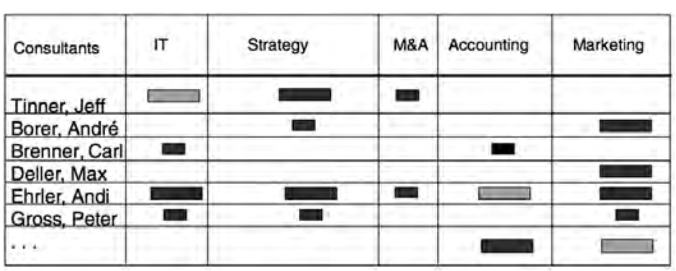

Fig. 2. A exemplary knowledge asset map of a consulting company [17]

4.3.2 Concept Maps

Donald Dansereau [16] describes the principles of Node-Link mapping, which was found already in 1972. Node-Link maps are used in the fields of education, counseling, and business. They consist of nodes, which contain information, and links that show the relationship between the different pieces of information. The idea of maps built from nodes and links are the basis for Concept Maps, which Sigmar-Olaf Tergan [30] utilizes in his approach to use maps for managing knowledge and information. The term "Concept Map" was introduced by Novak and Godwin in their book "Learning how to learn" [28]. Concept maps are intended "to represent meaningful relationships between concepts in the form of propositions. Proposition are two or more concept labels linked by words in a semantic form." [28] (p.15) *Figure 3* shows a Concept Map that recursively displays the the node-link structure of Concept Maps. Tergan [30] analyzes the possibilities of digital Concept Maps to support individual knowledge management and gives an overview about some already existing concepts. He discusses together with Burkhard and Keller if digital concept can be a bridging technology, that could overcome some shortcomings of Information- and Knowledge Visualization [31].

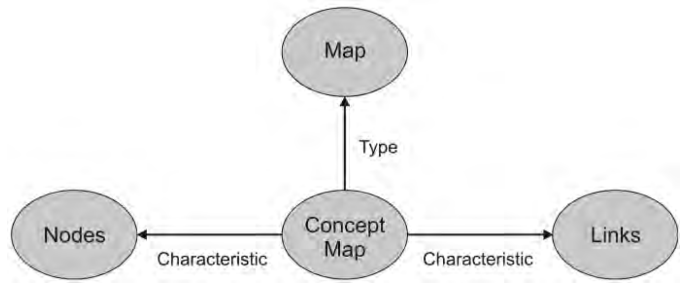

Fig. 3. A Concept Map of the node-link structure of a Concept Map [30]

4.3.3 Example applications for maps

The following paragraphs outline some exemplary usages of maps in the context of Knowledge Visualization

Personal Knowledge Maps: Jaminko Novak et al. [27] discuss an agent-based approach to discover, visualize and share knowledge through personalized learning in large information spaces. Therefore they use a Knowledge Map, which consists of a content map that visually clusters related documents, and a Concept Map, that extracts documents from the content map and visualizes relationships in between them. The ideas are realized on the Internet platform netzspannung.org, which is a knowledge portal that aims to provide insight in the intersections between digital art, culture and information technology.

Kmap: Zhang Yongjin et al. [32] developed the platform and application "Kmap", that supports the creation and visualization of knowledge through Node-Link like maps. They focus on the transformation from implicit / tacit knowledge, which is highly personal and difficult to formalize and thus difficult to communicate and share, into explicit knowledge, which can be expressed symbolically in words and pictures and thus be shared in the form of data or visualizations [21].

CmapTools: Canas et al. [13] introduce a software based on Concept Maps, which empowers users to either individually or collaboratively represent, share and publish knowledge. CmapTools is able to organize repositories of different kinds of information and allows easy browsing of and searching within this organized information. It is available for free at http://cmap.ihmc.us.

Webster: Sherman R. Alpert [1] presents the concept of Webster, which is a Concept Map based tool for personal knowledge management that helps to organize knowledge and information resources for reference and learning purposes. The main idea is to integrate all kinds of digital information like text, sound or video to enable the learner to gain a deep understanding of the domain of interest.

LEO: The Learning Environment Organizer LEO, described by John W. Coffey [15], is a extension of the software tool CmapTools which support courseware design and delivery. It serves as a metacognitive tool for course designers and an advance organizer for students and supports course designers or instructors in visualizing and planning courses, which are afterwards presented to the students.

4.4 Images

Images can be renderings, photographs or paintings that may represent the reality but can also be artistic. They are able to address emotions and can inspire, motivate or energize the audience and thus often used for advertisements. Special kinds of images are *visual metaphors*, which are - as they were already used by Aristotle - ancient, but powerful tools for transferring insights. They are "graphic depictions of seemingly unrelated graphic shapes (from other than the discussed domain area) that are used to convey an abstract idea by relating it to a concrete phenomenon" [20] (p. 15). This can be a natural phenomenon like an iceberg, man-made objects like a bride, activities like climbing or abstract concepts like war. Images can be used to get attention, inspire recipients, address emotions, improve recall or initiate discussions [20], [8].

4.5 Objects

Architects use physical models to show projects from different perspectives. They allow to explore an object in the third dimension, which helps to attract recipients for example on exhibitions and fosters learning. Interactive 3D models can maybe have similiar effects as they allow different perspectives as well. Objects strongly amplify the effect of visual metaphors if these two visualization types are combined [8].

4.6 Interactive Visualization

Computer-based interactive visualizations allow to access, control, explore, combine and manipulate different types of complex data, information and knowledge. They also fascinate the recipients and enable interactive collaborations and thus help to create new insights. Information Visualization makes heavy usage of interactive visualizations as they fit the requirements of this field of research very well. Animations can be interactive visualizations as well. They allow to recognize for example important changes over a certain period of time [8].

4.7 Visions / Stories

Visions or Stories are non physical, imaginary mental visualization, which help to transfer knowledge across time and space. They also help to discuss potential influences of ideas and concepts on future scenarios as well as they enable to establish a shared vision and a coherent story that motivates and activates the recipients [8].

5 Classifying Methods for Knowledge Visualization

Nowadays a lot of different possibilities and methods for visualizing knowledge are existing. But this is both a blessing and a curse: The more methods are existing the more confusing and complex it gets for non-professional visualizers to choose the right tools for each visualizing task. Therefore it is necessary to classify the methods and build models which proposes for each purpose a set of good visualizing methods. Three approaches to do this are presented in this chapter.

5.1 A Framework for Knowledge Visualization

Burkhard introduces a Framework for Knowledge Visualization during the creation of his dissertation [8]. The main reasons for doing this were on the one hand the poor integration of visualization research into knowledge management and communication science research and on the other hand the missing mediating element between the mostly isolated fields of research presented in chapter 3 [8]. Burkhard and Eppler had also in mind not only to introduce the framework to structure the Visualizations but also to give practitioners some aid in choosing the right visualization. Burkhard [7] mentions for this reason the Knowledge Visualization cube and Eppler [20] shows some example relations between the different perspectives of visualization.

5.1.1 Four Different Perspectives

To transfer and create knowledge efficiently Burkhard proposes four perspective types *(see figure 4)* that should be considered in this context. The first perspective concerns the aim or the function that should be achieved. Thus this category is called the function type, that can be coordination, attention, recall, motivation, elaboration or new insights. The second perspective concerns the content type of knowledge that should be transferred. The knowledge can be declarative (Know-What facts are relevant), procedural (Know-How things are done), experimental (Know-Why things occur), orientational (Know-Where information can be found) and individual (Know-Who are the experts). Third there is the recipient perspective type that regards the target group and the context of the recipient, which can be individuals, groups, organisations or networks. The last perspective concerns the visualization types, which form the transporting medium. They are already discussed in detail in chapter 4.

FUNCTION TYPE	KNOWLEDGE TYPE	RECIPIENT TYPE	VISUALIZATION TYPE
Coordination	Know-what	Individual	Sketch
Attention	Know-how	Group	Diagram
Recall	Know-why	Organization	Image
Motivation	Know-where	Network	Map
Elaboration	Know-who		Object
New Insight			Interactive Visualization
			Story

Fig. 4. The Knowledge Visualization Framework [8]

5.1.2 Case Studies for the Knowledge Visualization Model

Burkhard proofed the concept of his framework by accomplishing four case studies, which are shortly presented in the next four paragraphs. An overview about the different test settings is available in *figure 5*.

TYPES	METAVIEW	TUBE MAP	BKV4A	SCIENCE CITY ETH
Function Type	Attention Elaboration New Insight	Coordination Attention Recall Motivation	Coordination Motivation Elaboration New Insight	All types
Knowledge Type	Know-What Know-Who Know-Where	Know-What Know-Why Know-Who	Know-What Know-Why Know-How	All types
Recipient Type	Individual	Organization	Group	All types
Visualization Type	Interactive Visualization	Map	Diagram	All types
Evaluation	User studies	Questionnaire	Expert Interviews	Expert Interviews

Fig. 5. Overview of the Case Studies [8]

Metaview: This case study is about a new approach for a visual document search in digital libraries. While users were able to get an overview about available books by leafing through real books in a traditional library, e-Book libraries normally allow only filtering and searching for keywords or other meta data. Burkhard developed a new search method that combined query driven filtering and a collection overview. Through evaluating he found that the complementary visualization was preferred by users compared to the traditional keyword search [8].

Tube Map: The tube map visualization is a Knowledge Map based on the visual metaphor of a tube plan, where the tube lines represent a group of recipients and the stations project milestones. *Figure 6* shows an example of a tube map. The evaluation showed that the tube map was successful in communication a complex project to different target groups, built up a mutual story, attracted and motivated employees, provided overview and detail in one image, initiated discussions and fostered understanding. It confirmed that it is useful as a complementation to traditional project plans like Gantt diagrams in long term projects with different target groups [11], [8]. A later comparative study of Burkhard et al. [6] shows further that tube maps are even more effective than Gantt diagrams.

Business Knowledge Visualization for Architects (BKV4A): This case study deals with the gap between decision makers and architects, which normally do not use business diagrams. Therefore business diagrams were integrated into the method toolbox of architects. This problem is by the way very similar to the field of interest of

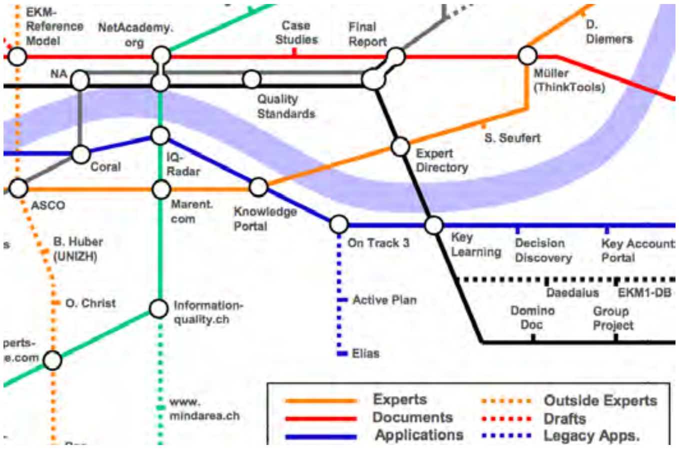

Fig. 6. An example of a Tube map [20]

Knowledge Communication (see chapter 3.7). The result of the case study is again that the use of complementary visualization can improve communication, knowledge transfer and fosters the engagement of decision makers in presentations. Moreover it reduces information overload, prevents misinterpretation, increases the information quality and last but not least improved the making of decisions [8].

Science City ETH: This case study used all visualizations types to find their limitations. The object of interest was the planning process of a "Science City" at the ETH Zürich. It again found evidence that it is reasonable to use different visualization types complementary, especially in early stages of a project [8]. In that context Burkhard introduced the term "Strategy Visualization", which is defined as "the systematic use of complementary visual representations to improve the analysis, development, formulation, communication, and implementation of strategies in organizations" [4] (p. 1).

The conclusion of all case studies is that the framework and the Knowledge Visualization model assist to reflect on a specific visualization problem from different perspectives. This can help to find good strategies for visualizing knowledge in real world problems. The case studies also show an exemplary mapping between different problem settings and possible usages of visualizations.

5.2 A Pragmatic Taxonomy of Knowledge Maps

Eppler [19] tries to find a taxonomy of Knowledge Maps that should give an overview and help to select the appropriate type of a Knowledge Map to a specific purpose. He considers five types of classifications as reasonable: These are the intended purpose or usage, the graphical form, the content, the application level and the creation methods. He created on this basis the "selection matrix" of *figure 7*, which uses the dimension of purpose and format as rows and columns. Letters represent the content type, whereas capital letters imply a strong and small letters in brackets weak recommendations for this combination. The best format of a Knowledge Map for the creation of knowledge through concepts would be metaphoric, while cartographic and diagrammatic formats are a good selection and tables may be used in some cases. According to Eppler this mapping lacks of empiric validation, but can serve as the basic for further studies and discussions.

5.3 Periodic Table for Visualization

Ralph Lengler and Martin Eppler use the visual metaphor of the periodic table of chemical elements to classify 100 different methods of visualization [25]. The original table of chemical elements was found by the Russian chemist Dmitri Mendeleev in order to show periodic trends in the properties of chemical elements. The vertical columns contain groups of elements with similar properties, while the rows correspond to the number of electron shells (period) and thus to the complexity of a chemical element. This idea was transferred into

K Map Format / K Map Use	Table	Cartographic	Diagrammatic	Metaphoric
Creation of Knowledge	(c)	c	c	C
Assessment or Audit of Knowledge	e		e	(e)
Identification of Knowledge		c,d,e	c,d, e	c, d, e
Development or Acquisition of Knowledge		c	c	C
Application of Knowledge	c, d,e	c, d, e	c, d, e	c, d, e
Sharing Knowledge		c,d	c,d	c,d
Marketing of Knowledge		c,d,e	c,d,e	c, d, e

Knowledge Map Content Types:
c = concepts (ideas, theories, insights or their labels, descriptions, references)
d = documents (patents, method descriptions, lessons learned, practice documents)
e = information about experts or groups (photos, coordinates, homepages, CVs)

Fig. 7. A selection matrix for Knowledge Maps [19]

the context of visualization methods. Groups, recognizable through the same background color, contain visualizations of the same application area, which are categorized into data-, information-, concept-, metaphor-, strategy- and compound visualization, while the complexity of the methods is represented by the number of the period. The higher the row number the more complex is the visualization method within its group. Each element contains further information about its task (detail, overview or both), the required cognitive process (convergent vs. divergent thinking) and the represented information (structure vs. process Information) The "periodic table of visualization methods" - poster *(see figure 8)* gives a great overview over a big variety of different visualizations methods and helps to find the different visualization methods for the correspondent problems.

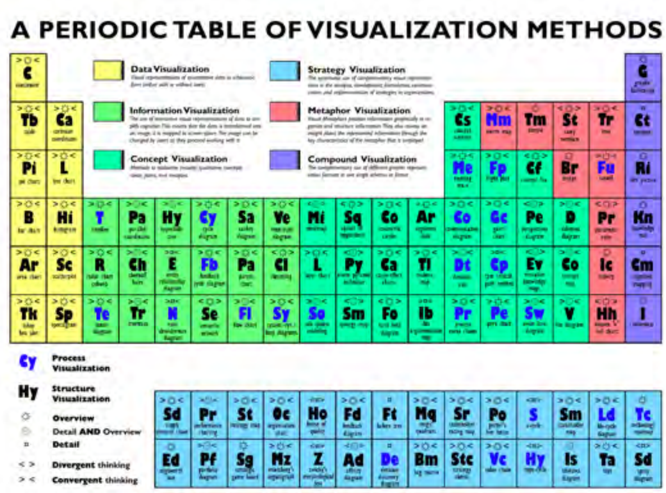

Fig. 8. A periodic table for visualization Methods [25]

6 Conclusion and Outlook

Although Knowledge Visualization is a very young discipline it seems to be a promising approach to support the creation and transfer of knowledge. The proposed concept of Knowledge Visualization as a mediating science between different disciplines might be able to create a synergetic effect that helps all participated fields of research to widen their perspective. Therefore the proposed framework would be a good basis, if other fields of research would accept it. Unfortunately it seems that it did not have the desired success yet as it is only cited in relatively few publications. Nevertheless the call for visualization as scientific discipline on its own by Burkhard [9] should still be considered seriously. The aim of offering help for visualization non-experts to choose the best formats of visualization for each problem is very reasonable, but it is still in the fledging stages. The presented solutions in chapter 5 still need empirical validation and / or firm establishment. Visualization struggles some problems as well which are often ignored. Bresciani and Eppler [3] detect social, cognitive and emotional problems either form the point of the user or from the point of the designer, like the ignoring of economic aspects or the misunderstanding of information. To circumvent those pitfalls of visualization it is necessary that they are categorized and analyzed like it is done in the paper ”The Risk of Visualization” [3]. Nevertheless the methods of Knowledge Visualization are used by researchers and in practice, like the examples in chapter 4.3.3 show. Burkhard points out two main trends for visualization at the end of his dissertation [8]: On the one hand new carrier of information will change the appearance of visualizations. Especially the topics of Ubiquitous Computing and Augmented Realities will enable the users for a much richer multisensory experience and will move visualizations away from screens or projectors. On the other hand visualization will evolve from simple static objects to iterative, collaborative processes, which are able to create visualizations and new knowledge dynamically. He also sees the Semantic Web - an extension to the world wide web that makes it understandable for machines - as possible field of application [10].

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Hypervariate Information Visualization

Florian Müller

Abstract— In the last 20 years improvements in the computer sciences made it possible to store large data sets containing a plethora of different data attributes and data values, which could be applied in different application domains, for example, in the natural sciences,in law enforcements or in social studies. Due to this increasing data complexity in modern times, it is crucial to support the exploration of the hypervariate data with different visualization techniques. These facts are the fundament for this paper, which reveals how the information visualization can support the understanding of data with high dimensionality. Furthermore, it gives an overview and a comparison of the different categories of hypervariate information visualization, in order to analyse the advantages and the disadvantages of each category. We also addressed in the different interaction methods which help to create an understandable visualization and thus facilitate the user's visual exploration. Interactive techniques are useful to create an understandable visualization of the relationships in a large data set. At the end, we also discussed the possibility of merging different interactions and visualization techniques.

Index Terms—informaton visualization, hypervariate data, visualization of hypervariate(multivariate) data, visualization of large data set, interactive visualization methods

1 Introduction

Visualizing data means translating different measurements of a scientific, business, or social topic in a view which facilitates the understanding of the relationship between different data items[28]. Furthermore, the data which needs to be visualized always has high dimension, which means more than three attributes. How to visualize data with high dimension, it is the essence of Hypervariate Information Visualization. Comparing with the uni-, bi- or trivariate data[17] which have less than three attributes, it is difficult to map hypervariate data in a normal cartesian plot or scatterplot without any loss of information or overview. Therefore an understandable and intuitive visualization is very important for the user exploring the hypervariate data[28]. The visualization should support the user to discover the relationship between different data or different attributes of the same data. Different extensive techniques, which will be discussed in later sections, were developed to support visualization of hypervariate information. For example, the parallel coordinate plots[17, 23], star plots[17, 4] and pixel-oriented techniques[9] etc. Due to the data complexity it is not enough and might be problematic in some cases to generate only a static visualization. The user should have options to explore the data set in an intuitive and interactive way. Discussing all these problems and facts, the structure of this paper is organized as follows: Section 2 gives an overview over the different application domains of hypervariate information visualization(HyperInfoVis), and points out how Information Visualization can support the understanding of data with high dimensionality. Section 3 explores and compares the different traditional technical categories concerning hypervariate InfoVis. Section 4 explores the extensive techniques in which system-driven dimension reduction are applied, before visualizing the reduced dimensions with the traditional techniques. Section 5 discussed the problems of the traditional techniques and techniques with system controlled dimension reduction, which leads to interactive methods to create intuitive visualizations, for example the user-driven dimension reduction, brushing, different navigation tools and sharing extracted Informations. Section 6 discusses for further developments.

2 Applicable desire for HyperInfoVis

Most of the collected data in the scientific research, such as natural science and social studies, have more than three attributes. To extract useful information statistical techniques could be applied which work directly with the measured data. One prominent problem of this approach is the compression of the extracted information makes it difficult to comprehend the relationship between all involved data items. That means it is hard to find clusters or outliers. So it is important to translate the data in visual patterns which make it easier to analyze the data and to understand their relations[28]. Figure 1 shows an visualization example for a parallel coordinate plot, which shows the data of different cars, produced between 1968 and 1983. Each axis represents a dimension and each line represents the relation between the dimensions. Based on the information shown in the figure, it is possible to detect at least two valuable information at the first glance. Firstly, it is obvious that the most cars which was produced during these 15 years have more than two cylinders, on the other hand, all cars was produced in Europe, in Japan or in the USA. Using ,for example, a table only showing the pure measured data, it will cost much time to extract the same information. Different application domains,which have to work

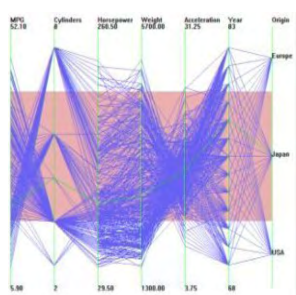

Fig. 1. Parallel Plot created with the XmdvTool[22].

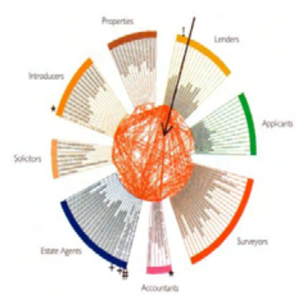

Fig. 2. Unusual mortgage transactions[17].

with and explore increasing large multivariate data sets, have arised the last years. Not only in the natural sciences' research, such as the bioinformatics or earth sciences, but also in law enforcements, social studies or in the engineering which require for methods mapping hypervariate data into an understandable visual pattern[28].In the field of law enforcement visualization techniques are applied to detect cheating delicts or reconstructing crimes with the aid of so called association or timeline style charts[17]. Figure 2, for example, displayed data with unusual activities on the mortgages market. Through the lines it is possible chasing suspicious transactions between different lenders, applicants and institutions. In the field of social studies, most of the census and the surveys produce high dimensional data sets[27], which have to be visualized accurately and intuitively (as figure 3 shows). In

- *Florian Müler is studying Media Informatics at the University of Munich, Germany, E-mail: Florian.Josef.Mueller@campus.lmu.de*
- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

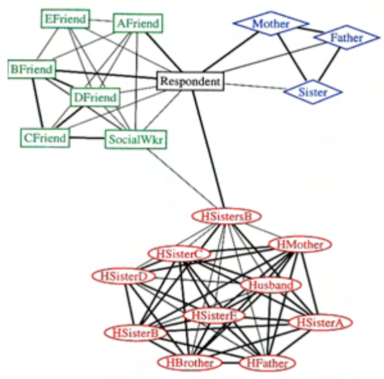

Fig. 3. Social choices and connections of a single mother with her family, her earlier husband's family and her circle of friends[6].

the bioinformatic's research visualizing genome informations is important for understanding the basic structure of the human genotype. On base of these different application domains and advantages of understandability of visual patterns, a multiplicity of more or less extensive multivariate visualization techniques were developed, which will be discussed in detail in sector three and four.

3 TRADITIONAL HYPERVARIATE VISUALIZATION TECHNIQUES

The techniques, which are described in this section were developed in the earlier years in the field of hypervariate visualization. Because of their today's wide dispersion in visualizing high dimensional data, the more extensive techniques use them to display the dimension reduced data set. Due to these facts, these methods are called "Traditional hypervariate visualization techniques". Before discussing the different technical categories of these methods, it is important to explore the existing possibilities of encoding relations among the explorative data items. Several options are given to represent a connection between two or more dimensions or data items. Hence, choosing the appropriate one, is fundamental for creating an intuitive visual pattern. The usage of lines and colour, for example, is often adequate to show a relation between different attributes. The lines associate two related attributes while the colour marks similar data items or attributes. Due to this, it is possible to distinguish very difficult relations with the aid of this simple technique. As shown in figure two and three, this method is applied to visualize social networks and to show complex scenarios for the law enforcements or reveal different business procedures. Other techniques represent relations by an intersection of different plains. Venn-diagrams, for example, display the dimensions as circles that adhere belonging data items. Items which are a member of two or more dimensions get mapped into the intersection of these circles. On the base of the given encoding methods were developed special techniques which are fitted to the hypervariate visualization information problems. They can be subdivided in two different types[17]:

- Techniques supporting attribute visibility
- Techniques supporting object visibility

3.1 Techniques supporting attribute visibility

Methods with attribute visibility point out the apportionment of given object's attribute values in each dimension. So, it is easier for the user, finding clusters or outliers of visualized hypervariate data during the visual exploration process. The most important techniques that fall in this category will be discussed in the following.

3.1.1 Parallel Plot

A widespread attribute visible method is the parallel coordinate plot*(see figure 1)*. Parallel plots are emanated from the cartesian plots, which are not able to visualize data with more than 3 dimensions. For example, a point P in the 5th dimension with the coordinate $\vec{v} = \{5,2,9,7,6\}$,can not be displayed in a cartesian plot. Due to this, the points used as coordinates in the cartesian plots are translated into lines, whereas the axes were conveyed into a parallel constellation. The number of axes depends on the dimension. Regarding the example, there would be five parallel axes in the generated parallel plot. And the point with the given coordinate would be translated into a line which is drawn by points from each axis. A parallel plot is able to contain more than one high-dimensional coordinate. It is obvious that this method can be used for hypervariate information visualization. If P represents the data, for example, of a car, it is possible to map these high-dimensional attributes with the data of many other different cars in the same parallel plot [23].

3.1.2 Scatterplot Matrix

The Scatterplot Matrix is also a established attribute visible technique. A single scatterplot have the same problem as the traditional cartesian plot: It is impossible to visualize data with more than three dimensions. But arranging a number of scatterplots to a scatterplot matrix can solve the problem. The size of the Matrix is conditional to the level of the displayed dimensions. Visualizing data from a n-Dimensional data set needs a $n \times n$-Scatterplot Matrix. Each Scatterplot in the Scatterplot Matrix visualizes the relation of two different dimensions. So, the Scatterplot Matrix is able to show the coherence between all values which are displayed in the different scatterplots[28]. Take the car example with seven dimensions as example, there is generated a 7×7-Matrix*(see figure 4)*.

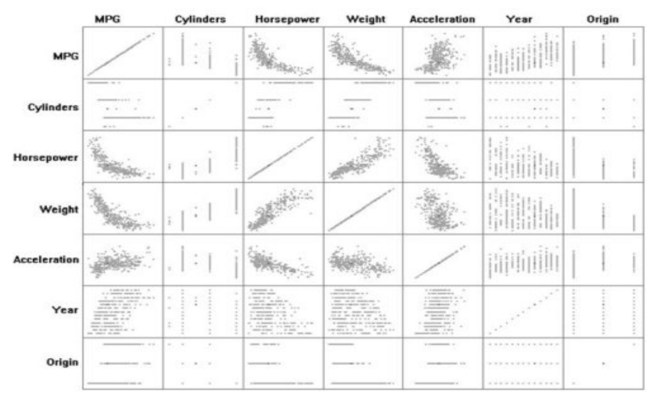

Fig. 4. A scatterplot displaying the relations of seven dimensions[28].

3.1.3 Linked Histograms

Another current technique which falls in the attribute visible archetype is the linked histogram. This method is developed from the normal histogram which is used to visualize two dimensional data. In order to visualize the dimensions and data items as well as the relation between them, a linked Histogram is consisted of multiple single histograms and shows the attribute values of a corresponding dimension. It is also linked with all other histograms. Now, if a user select his/her desired data in one of the histograms, all the others brushes exactly this values, in their own view, which have the same characteristics, like the user‘s desired data[16]. Apparently, the user needs different

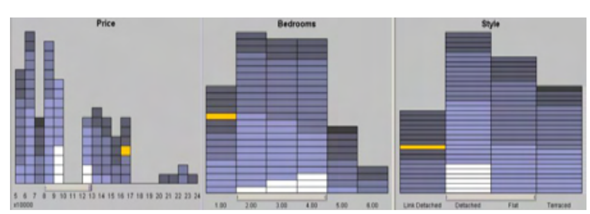

Fig. 5. This linked histogram visualize three attributes of different houses[21].

interaction methods enabling the exploration of the hypervariate data with the aid of linked histograms. These methods, like navigation and brushing will be discussed in section 5. To improve the comprehension of the functionality of linked histograms, an other example should be considered*(see figure 5)*.

3.1.4 Mosaic Plot

The techniques which were presented so far, are all advancements of existing uni-/bi-/ or trivariate visualization methods, whereas the attribute visible mosaic plot has no precursor. Starting with a huge rectangle the mosaic plot is splitted up for every dimension, which he has to visualize additionally. The extent of a splitted part depends on the commonness of the represented attribute values[19]. Visualizing a n-dimensional data set, generated a mosaic plot with n splitted parts of different extents*(see figure 6)*.

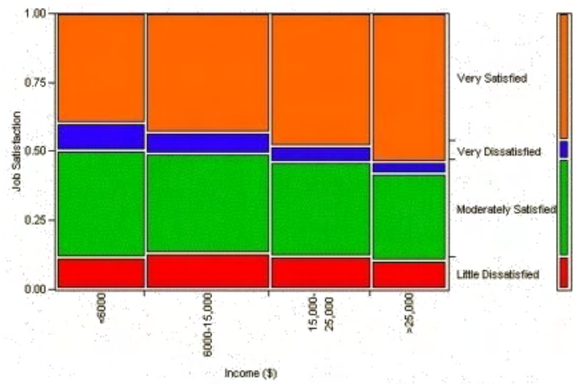

Fig. 6. A exemplarily mosaic plot[20] visualizing employees' Job satisfaction, depending on the income.

3.2 Techniques supporting object visibility

Object visibility techniques display the objects as single glyphs on the screen. Each glyph represents the attributes values of the corresponding object. With the aid of this type of technique, the user is able to compare the relation between different objects in different dimensions[17].

3.2.1 Star Plots

Two representative examples of object visible techniques are the star plots, and the metaphorical icons. The Star plot technique*(see figure 7)* is similar to the Parallel Plots. The attribute values of a object are

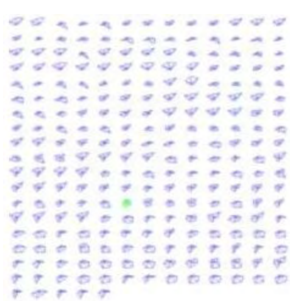

Fig. 7. Exemplary star plot[22] based on the same data like figure 1.

visualized as points on a coordinate axes and they are linked by lines. Every axis represents, like the axes in a parallel plot, a dimension. However, the main difference is, that the axes are arranged radiately from a common root[2], which belongs to one specific object.

3.2.2 Icons

Other object visible methods are the metaphorical icons, which can be divided in two different groups[17]:

- icons with a direct relation between icon and object
- icons with no direct relation between icon and object

The idea behind items out of the first group is simple. A direct related metaphorical icon attempts to display a given object by drawing his attribute values in a direct way. Using the car example again, the created icon would have the shape of a car with attached symbols representing the values of different dimensions. No-direct related icons are, above all, represented through the so called Chernoff faces[17, 1, 3]*(see figure 8)*. Generating a chernoff face, attribute values were encoded into human facial characteristics. The emerging facial expression supports the user to identify interesting objects out of the analyzed data set.

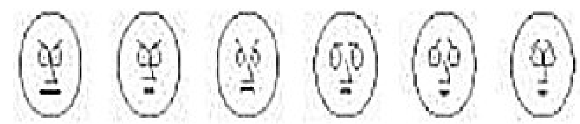

Fig. 8. Five example Chernoff faces[13].

3.2.3 Infocrystals

The Infocrystal*(see figure 9)* is an improved pattern which merges all relations between the attributes within a Venn-diagram to regions inside a specific crystal[18].

Fig. 9. The development process from a Venn-diagram to an Infocrystal[17].

3.2.4 Tree Views

Further possibilities for object visible views are tree representations. Although all of these trees are used to display data out of hierarchical structured data sets, they can be subdivided in different illustrations: In trees, which mirror relations between the data in a noticeable hierarchical form, for example, the cone tree or the Hyperbolic Browser; The other reflecting method is in a plain way, like it is seen in treemaps. One problem which occurs using tree descriptions is the possible huge horizontal display of an ordinary tree. This problem leads to the development of the Cone trees which reconfigure the subordinate nodes to a circle structure in order to create a cone in cooperation with their superordinate node[17]. A Hyperbolic Browser[12] is also a effective to limit the depending space. Every node of an ordinary tree is translated into a corresponding location inside, for example, a circle*(see figure 10)*. The tree's root is in the middle of the generated structure, whereas its child nodes are arranged around it. The distance between an subordinate node to the corresponding superordinate node in the middle is represented through the size of the particular child node. To assure the visualization of all involved data, the user is able to move an interesting node in the center of the hyperbolic browser followed by their subordinate nodes. An alternative technique concerning the trees is the treemap[15]. The root node is depicted as huge rectangle. The direct subordinate nodes are drawn as smaller rectangles within this first one. This process is continued till all nodes are translated into smaller rectangles within their direct superordinate nodes' rectangles.

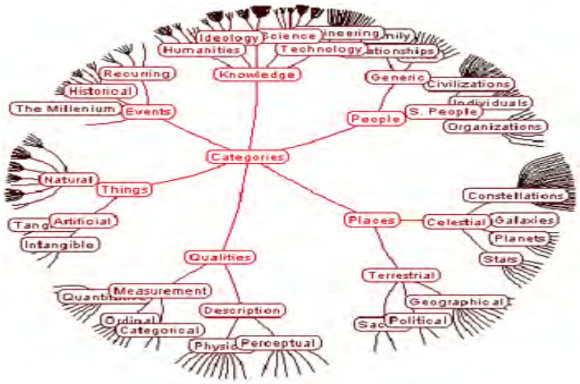

Fig. 10. An ordinary tree was mapped into an Hyperbolic Browser[8].

Because of this method's plain structure, there is no sign relative to the depth of the tree. So the leafs have to be highlighted with the aid of colour encoding.

3.3 Discussion

After the overview of the established traditional techniques it is important to discuss the advantages and disadvantages of the particular types and techniques.So for example, the difference between the attribute visible parallel plot and the object visible Star plot is illustrative. Figure one and seven visualize the same car attributes out of a 7-dimensional data set. In figure one, every car is encoded through one line, in figure seven every car has its own corresponding glyph. The advantage of the attribute visible techniques can be seen in the concept of attribute visibility. The user is able to find clusters or outliers inside the visualized data. The fast identification of those coherences supports the user's exploration of hypervariate data by visualizing an understandable pattern. On the other hand, the attribute visible techniques make it difficult to compare different objects in different dimensions. This can be seen, for example, in the parallel Plot, which encodes every object in different points linked with a line. The disadvantages of the attribute visible methodes could be compensated by the object visible techniques, which supports comparison of different objects. However, these techniques lose the advantage of attribute visible techniques, identifying clusters or outliers. One big problem concerning both maybe the overcoming clutter[28, 24, 27, 25] on the screen by increasing numbers of dimension and data items. From an specific number of visualized dimension or data items, the today's screens are overloaded with informations which makes it impossible analyzing the displayed data or create intuitive visual patterns. Therefore, extensive techniques were further developed to deal with the problem of clutters and to enhance the interactivity.

4 Extensive hypervariate visualization techniques

There are three categories for the techniques which target solving the problem of dimension reduction.[25]:

- System-Driven Dimension Reduction
- User-Driven Dimension Reduction
- Combination of both Approaches

The first category applied automatic process which map a high dimensional data collection on a regular, 2-dimensional pattern[10]. The second category integrates the user in the dimension reduction process. The third category use the system-driven reduction to map the data into a specific view, where the user is able to select the desired dimensions for mapping them in a traditional hypervariate information visualization techniques. On base of the given groups there are different types of developed extensive techniques: The pure system-driven techniques[10, 11], techniques using visual hierarchical methodes[27, 26], techniques using glyphs filled with pixel patterns showing the dimensions relation[25, 9, 14],techniques allowing the user to define his/her own information nuggets[24] and pure user-driven reduction techniques using metaphors[28]. In this section, above all the techniques which use system-driven dimension reduction, will be discussed and the user driven methods will be explored in section 5.

4.1 Techniques using System-Driven methods

The pure system driven techniques,such as the Self-Organizing Maps[10] or the Multidimensional Scaling[11] accrue from the statistic area. These methods use a distance matrix to capture the relation between the given dimensions as similarity or dissimilarity. The equotations, which are used to calculate the similarity of different dimensions will be presented at the end of this section. Then, the system is able to map the high-dimensional data into a two-dimensional view, whereas the dimensions are represented by glyphs and the dimensions' relation is shown by the distance between the visualized glyphs. It is possible to avoid the clutter problem, but due to the reduction from a n-dimensional data set into a two-dimensional view, the output of a pure system-driven technique delivers a rather unintuitive visual pattern[28]. In order to avoid this problem and to assure intuitive visual patterns to facilitate the user's exploration of high-dimensional data sets, there were developed techniques which integrated user in the loop.

4.1.1 Visual Hierarchical methods

One member of these types is the visual hierarchical technique*(see figure 11)*[27, 26]. Using the dimensions belonging to a multidimensional data set, this method generates a so called hierarchical dimension cluster tree. Thereby, all original dimensions get translated into the leaf nodes. The dimensions which are similar to each other get mapped together and form a cluster and similar clusters analogous form cluster on a higher level. Although this approach is completely system-driven, the user is also able to build up the tree manually[27]. After the tree has been generated, the user is able to use several interaction methods to navigate through the cluster tree and therefor has the chance to attain a better understanding and has options to modify the tree. In the third step the user can select the desired dimension cluster, which should be mapped in a lower dimensional subspace. Now, the system generates the so called representative dimension generation(RD), out of the selected clusters, which mirror the attributes of their corresponding dimension. In the end, the system use the RDs to map the high-dimensional data set into the low dimensional subspace, which can be visualized in any existing traditional technique[27]. It is

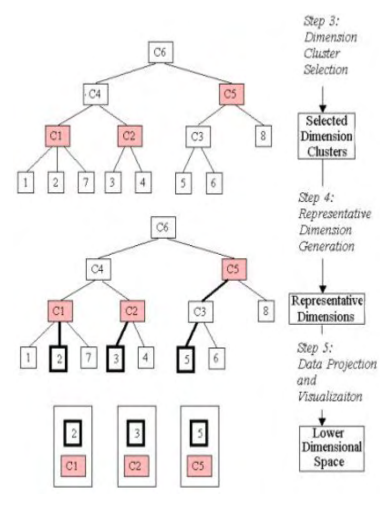

Fig. 11. Overview of the last three steps which shows the user driven part.[27].

obvious, that the visual hierarchical technique combine both existing conceptional reduction approaches, because it alter between system-driven and user-driven dimension reduction during the reduction process.

4.1.2 Glyph representations

The techniques, which apply glyphs for visualizing the dimensions and their relationships, belongs also to the combined group. Examples for applications using this sort of technique are the Glyphmaker[14] or the Value and Relation Display(VRD) [25]. The system-driven part of these methods use Multidimensional Scaling in order to map given dimensions in a two-dimensional view on the screen. So, one glyph encode one dimension of a given data set. The dimension's relation is represented by the distance between the shown glyphs. In order to assure the creation of a understandable visual pattern, there exists different methods which can be user-driven or system driven. Whereas the Glyphmaker-application allows the user to rearrange the glyphs in different structures, like in a Sphere or on a 2D-Grid, the Value and Relation Display use pixel-oriented techniques[9] to map the attribute values of a dimension in the corresponding glyph[14, 25]. Therefore, the glyphs are created as so called subwindows, which contains the relation of the attribute values in form of a specific pixel pattern[9]. Based on these patterns the user is able to compare the relation between the different dimensions by measuring their distance and the specific pixel arrangements in each glyph*(see figure 12)*. Just as the

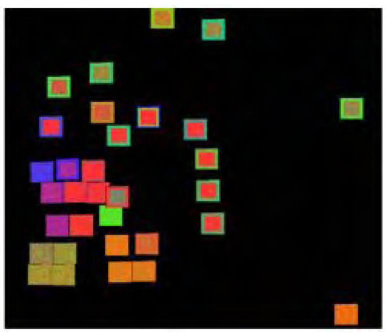

Fig. 12. Visualization of value and relation[25].

system has built up the view, the user is able to navigate through the Value and Relation Display selecting interesting glyphs. Apart from the possibility of selecting a glyph, there are other interactive methods which supports the creation of an understandable visual patterns. The different methods will be discussed in section 5. The chosen dimensions can be mapped in any traditional hypervariate information visualization technique[25]. The Glyphmaker application, however, offers a so called Conditional Box, which the user can move over a interesting subregion of the displayed dimensions[14]. The enclosed dimensions are visualized on a high detail level at a special part inside the application.

4.1.3 Information nuggets

The techniques which allow the user to define his/her own information nuggets, for example the Nugget Management System[24], also applying system and user-driven methods. At first, the user is able to mark interesting values and dimensions intra a traditional technique, in order to create an information nugget which contains the user's valuable information. The marked values are highlighted and possible occurring clusters can be detected easier. If the user don't mark all values belonging to a cluster, the system is able to detect this by calculating the similarity of the data items which are in the area of the defined information nugget. After a detection, the system adds the missing data to the user defined information nugget[24].

4.2 Discussion

In each of the extensive techniques with the participation of the system driven dimension reduction, there was needed a method which calculate the similarity of the corresponding dimensions. In order to work with the attribute values, they have to be normalized in each dimension. Then they could be compared for each pair of dimension. Is the difference of the compared values lower than a given threshold, the dimensions are similar to each other[27, 25]. The extensive techniques are able to solve the clutter problem of the traditional techniques, but,as mentioned above, a new problem appeared caused by the system-driven dimension reduction. The view which is created through this sort of reduction is rather unintuitive and only skilled users are able to extract useful informations out of the visualized data.

5 Integrating the User in the Loop

In the area of HyperInfoVis emerges several issues which have to be solved in order to generate an intuitive and understandable visual pattern. Apart from the problems mentioned in the previous sections, like the overcoming clutter problem by an increasing number of dimensions[28, 24, 27, 25]*(see figure 13)* or the unintuitive views which are generated through a system-driven dimension reduction[28], there are also other problems. A directly consecution out of these difficulties, is that the discoveries which were made only on the basis of visual explorations are not accurate. Additionally, there appear further problems which were not touched upon so far. So, the user needs a specific discovery management mechanism to organize the extracted and valuable informations and to make them available for other users[24]. It is obvious, that static visualizations can not solve these problems. The common interactions supporting the navigations are zooming and panning, showing the name of the corresponding dimension, the extent scaling, comparing the different data items and above all the selection of several interesting visualized dimensions[25]. These interaction methods were applied to avoid the mentioned issues and they also afford a basis for more complex interaction approaches.

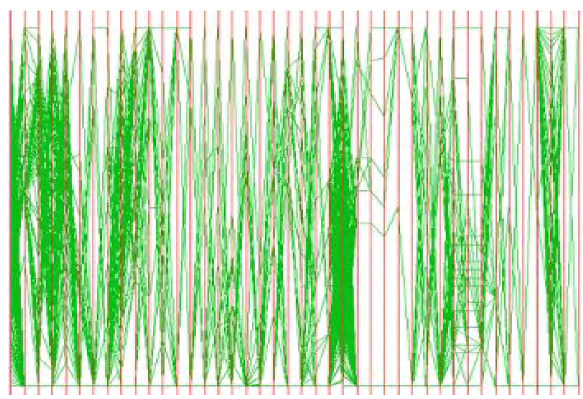

Fig. 13. clutter with increasing number of dimensions[27].

5.1 Brushing

Using the "Pop out" -phenomen[17],brushing is a easy but effective method to encounter the clutter problem and to support the visual exploration process. The user can chose the desired data items and the system highlights the relationship between the different dimensions. Therefore, he/she is able to select the values directly in the view, or enter them into special menus[7]. All presented hypervariate information visualization techniques profit from this technique, above all the linked histograms and the Nugget Management System works with this interaction method. Besides the normal brushing, different ways of brushing can be mentioned[7]:

- Smooth Brushing
- Composite Brushing
- Multiple Brushing

The Smooth Brushing allows the user to define a center-of-interest(COI) inside the used visualization. After selecting the desired point the system denotes the surrounding data. But in contrast to the normal brushing the smooth version highlights the relevant data according to the distance from the COI. The farther the distance of a data item the weaker is the used colour. With the Composite Brush, the user is able to combine different single brushes by using logical operators. The desired data only will get highlighted, if they comply the predefined conditions. At last, Multiple Brushing sets up a entry in a detached brush list, for every normal brush which is initiated by a user. To improve the clarity of the brushing list, every entry can be named. Exploring a visualized data set, the user is now able to browse through this list[7]. All these brushing methods can be combined, in order to increase the understandability of a given hypervariate visualization

5.2 User-driven dimension reduction

The unintuitive visual patterns caused by the pure system driven dimension reduction was attenuated, by introducing the combined methods. Although these techniques already use many interactive elements to support the visual exploration, the system still translated the dimensions into the particular view. Only experienced users are able to extract useful information out of a special data representation. The dimension reduction should be completely user driven, in order to increase the understandability of visual patterns. Additionally, novice users should become acquainted faster with the visualized views. Extensive techniques which base on metaphors apply this sort of reduction method. The developers try to project the functionality of a real-world object into the problem of visualizing hypervariate data sets. So, the dimension reduction approach and the visual pattern itself should be intuitive and understandable. Based on the appropriated metaphor, the user should be able to accomplish the dimension reduction with the given interaction methods[28]. For example, the object visible Dust& Magnet - Application (DM)[28] and "Worlds within Worlds"[5] applies user driven techniques. In DM data items are represented as "dust" in the middle of the display, whereas the user is able to arrange "magnets" around these values. The virtual magnets operate like the real ones and attract those data items which are closely related*(see figure 14)*. Each magnet represents one dimension and can be itemized by the user. So, every step of dimension reduction is comprehensible and leads to an understandable visual pattern.

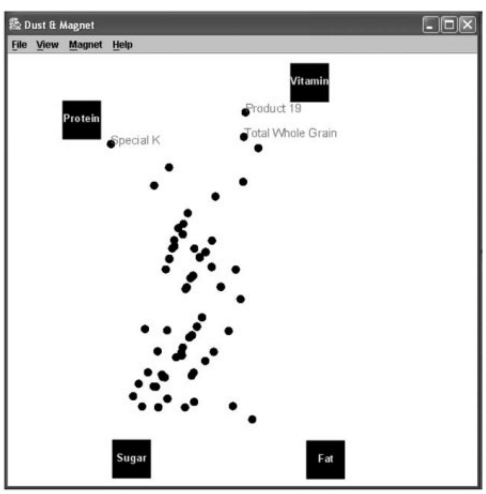

Fig. 14. Here, the dust represents cereals with different attribute values. The magnets represent different attributes.[28].

5.3 Sharing extracted informations with other users

Managing the extracted information is an important point, which has to be discussed. Such a discovery management mechanism has to offer a method, which makes it possible to organize these information and to compare them with other similar data. One possible mechanism could allow the user to store discovered cluster and outlier in a special data-pool. There, the user can work with the stored information and order them according to the importance or commonness of each entry. This approach supports also other users to find valuable information. A good example for such a mechanism is the Nugget-pool, which is applied in the Nugget-Management-System[24]. Another possibility is storing the bindings between the visual patterns and the dimension names. So everyone who loads the stored bindings can explore the same displayed dataset. How the Glyphmaker-Application[14] shows it.

6 Conclusion and outlook

Many application domains which work with high-dimensional data sets need intuitive and understandable visual representations of the hypervariate data. This search for possibilities to extract informations out of such a data set, leads to a multiplicity of hypervariate visualization techniques. Due to the specific problems of the traditional and extensive methods, there were developed different interaction methods supporting the user's visual exploration. But all techniques, which was presented so far, use a two dimensional display. So, one potential advancement could be found in 3D-visualizations. Possible disadvantages of the flat views, for example the overcoming clutter or the specific problems of attribute and object visible techniques, would be avoided. Additionally, a 3D view offers alternative interaction methods. Altogether, a 3D-Display supports the user's visual exploration by generating an understandable visual pattern. Such a technique is represented in a paper, written by Fanea et al[4]:"An Interactive 3D Integration of Parallel Coordinates and Star Glyphs". Fanea presents a new visualization technique by merging the attribute visible Parallel Coordinates and the object visible Star Glyphs into the so called Parallel Glyphs*(see figure 15)*. Translated into a three dimensional view, this combination uses the advantages of both techniques and evades their disadvantages. Due to the gained dimension, the user has different new interaction methods. So, for example, he/she is able to rotate a Parallel Glyph, in order to detect covered relations in a highly cluttered display. Giving different examples for methods concerning the

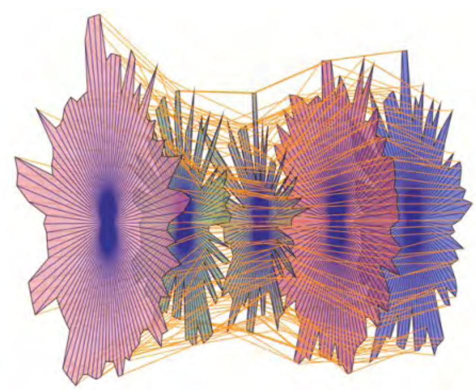

Fig. 15. Each Star Plot in the Parallelglyph replaces an axis of the Parallel Coordinate Plot. So, every dimension is visualized by a Star Plot, and the relations are represented by the Parallel Plot's polylines. [4].

HyperInfoVis, this work should support everybody who looks for hypervariate visualization techniques and to give hints, which technique is appropriate to extract valueable information out of a specific hypervariate data set.

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Multiple and Coordinated Views in Information Visualization

Maximilian Scherr

Abstract— Multiple views are not merely isolated separate views on data but mighty tools which often share a relationship. This relationship is brought to attention and utilized by coordination. Hence, in this paper I present an outline of the field of multiple coordinated views, its reasons, anticipations, jargon and examples. Because of its general nature, a large portion of this text deals with abstract formalizations, models and architecture descriptions. The latter is mainly revolving around user-generated coordination. Here, the works of North and Schneiderman (Snap-Together Visualization), Boukhelifa (A Coordination Model for Exploratory Multiview Visualization) and Weaver (Improvise) get major focus as they address coordination itself in different views and show development in their field. To conclude this paper, a small collections of interesting uses of multiple and coordinated views is presented as well as a brief discussion on recent issues.

Index Terms—multiple views, coordination, information visualization, abstract models, customized coordination

1 Introduction

Sucessfully aiding the seeking and discovery of information, two major purposes of information visualization, not only asks for ingenious ideas for a direct mapping of raw data to pixels. Diversity and the arrangement of such generated views on data also play crucial roles, for however natural or efficient a single specific view might seem, it does not evidently have to fulfill these asumptions for every imaginable situation. This inherent bias can be countered by multiple views.

While multiple views on data appear as an improvement over a single view, they also gives rise to various possible issues concerning screen space, computer performance and user perception[2]. Additionally coordinating multiple views does not necessarily solve these issues but it can compensate for them by facilitating the recognition of previously hidden relationships within the observed data[2].

The concept itself is not quite a novelty. Nowadays an average computer user frequently stumbles upon applications using coordinated multiple views on a regular basis, including file browsers, text editors, 3D modelers and the likes. Though we have to keep in mind that these applications usually do not fall into the category of scientific information visualization, they do however show the same features concerning multiple views and coordination. Even simple and common parts of an application such as a text field with scrollbar can in fact be identified as coordinated views.

In recent years the study of such *multiple and coordinated views* (MCV) has variedly progressed and even spawned a conference (*Coordinated and Multiple Views in Exploratory Visualization*) largely dedicated to this particular field of information visualization. The main subject of this research paper will be an analysis of different concepts and descriptions revolving around MCV, following a description of (historic) ideas to formalize and generalize coordination based on these classifications and an introduction of a small collection of specific MCV systems.

2 Terminology and Guidelines

In order to approach the following concepts a few general definitions are provided here in this section. Along the lines of Baldonado et al.[2] a *single view* shall be defined as the combination of a set of data together with specifications on how to display this data. Imagine a set of pairs, for example, representing time and temperature, size and weight, or coordinates. This kind of data could now be displayed in a single view by utilizing a list, a scatter plot, or some other hopefully appropriate technique. Such type of data representation used by a single view is refered to by the term *form*[14].

Now, a system design in which two or more forms are used to display (the same) data is called *multiform*[14]. If two or more views enable users "to learn about different aspects of the conceptual entity"[2], they may be called *distinct views*. This definition is in some way more general but also more specific than multiform at the same time. For example two scatter plots visualizing the same data in exactly the same way would definitely neither classify as multiform, nor as distinct views. However, if one of these scatter plots displays data in greater detail, users could observe data at a higher granularity and might thus learn about a different aspect. At first sight this may not seem to be in direct accordance with the definition of distinct views but it is actually wide enough to extend to such cases. In the case of multiform, I tend to be believe that such a setup does not fall under the term's definition since in both cases the same technique, that is a scatter plot, is utilized. Argueably this depends on whether such modifications alter a form enough to make it "different".

According to Roberts[14] the term *multiple views* generally refers to "any instance where data is represented in multiple windows"[14] whereas Baldonado et al.[2] strictly require distinct views for a *multiple view system*. I will stick to the former, more general definition here since it is less likely to interfere as easily with potentially stricter definitions used in the following concepts.

2.1 Mutliple Views

The class of multiple views can now be further divided. Usually this is done on grounds of the relationship between two so-called *side-by-side views*. Systems which are only using two such side-by-side views are called *dual-view systems*[14] but the following definitions are not necessarily limited to such:

Overview & detail views use one view to display the whole or at least a very large portion of the dataset and another view for showing a part of the datasets in greater detail. The example earlier of two scatter plots with different resolution falls into this category[14].

Focus & context views is actually not too different from the above. Apart from the semantical focus, stressing the detail before the overview, a context view does not have to display as much data as an overview, but only hint on the context. An example could be a text reader using three views with one being the central, big focus view, displaying several lines of text in an easily readable manner, and two others above and below, showing a certain amount of lines before and after respectively but in a size not quite suited for long reading. As Roberts[14] points out this technique is often used (in single view systems) together with

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- *Maximilian Scherr is studying Informatics at the University of Munich, Germany, E-mail: maximilian.scherr@campus.lmu.de*
- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

distortion, for example fish-eye magnification. There also exists an application of focus & context to virtual reality, called "world in miniature"[17], where the contexting world is shown as a miniature model within or possibly next to a full-sized reality imitating viewport.

Difference views focus on highlighting differences in the observed data, usually achieved by merging several views together[14]. An example for such usage is having two similar, yet different images, wherein differing pixel regions are marked by color. The Subclipse plugin for the popular software IDE Eclipse uses such an approach for sourcecode merging in case of version control conflicts.

Small-multiples are "shrunken, high-density graphics based on a large data matrix"[18]. Encouraging comparison, this choice of arrangement usually implies that the views use the same visualization form. They are "often narrative in content, showing shifts in relatonship between variables as the index variable changes"[18]. Several arranged miniature views representing temperature or rainfall data on top of a map at different times would be an example for this kind of multiple views.

This list is by no means exhaustive. Rather than that it merely represents common appearances of multiple views.

2.2 Coordination

Intuitively, whenever such relationships exist one would expect them to be reflected while interacting with multiple views. In fact, according to Roberts[14], when talking about multiple view systems, coordination is often implied.

The coordination of views requires specifications or mappings that make changes in one view affect the others. Such mappings are specified by so-called *coupling functions*[2]. When exactly or under which conditions these coupling functions are called has to be determined separately in a so-called *propagation model*[2].

Coordination is apparent foremost when user interaction comes into play. A very common coordination is called *brushing*, which means that upon selection of elements in one view the same (or related) elements are simultaneously highlighted in other linked views[2], which is especially useful for *multiform* views to find similarities and anomalies in the data[14]. An extension relying on a repeated brushing technique has been described by Wright et al.[9]. The *brush* metaphor usually refers to how and how much data is selected[14]. When the data to be visualized can be filtered or constrained by sliders, input fields, drop-down menus and such, the term *dynamic querying* is used[14]. This can influence several views and also become part of coordination.

Next to *linking* data across views, *navigational slaving* constitutes yet another common interaction technique[2]. This term describes a relationship between views in which navigational actions in one view are propagated to linked views. For example synchronized scrolling in side-by-side difference views would be a form of two-way navigational slaving. As would be zooming, panning and similar, for example, in a multiple view map application.

Navigational slaving is not restricted to a mapping of navigation in one view to navigation in another. North[11] describes possible occurrences of such case with a 2x3 taxonomy (*see figure 1*). This definition of coordination is restricted to three types (on navigation and data items), that are *selecting items* ↔ *selecting items*, *navigating views* ↔ *navigating views* and finally *selecting items* ↔ *navigating views*. Furthermore he classifies by whether the data collections are different or the same. In the former case, relationships between the collections have to be explicitly specified[11]. Imagine a setup in which one view lists art museums and further information about them, while another view shows a city map. For a coordination that highlights the location of a selected museum in the map, it has to be specified that the adress record in the museum's information is to be used and mapped to the other view. Same data collections already have an implicit relationship[11].

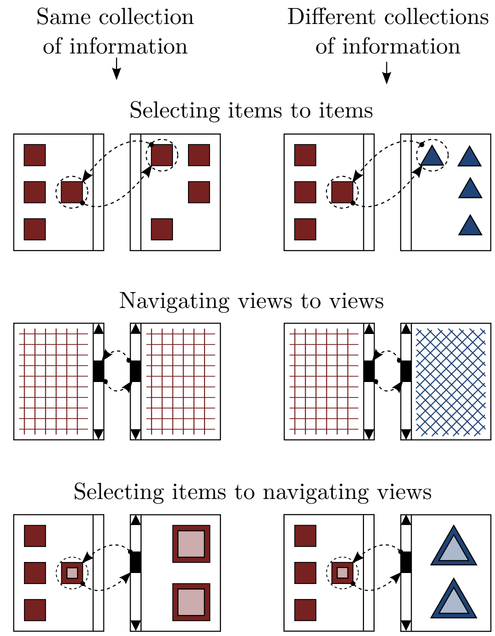

Fig. 1. "2x3 taxonomy of multiple window coordinations" (*modified after North[11], see diagram 1*)

We have to keep in mind, that although interaction is the first that comes into mind, coordination is more general. Whenever an event changes one view (for example an automated update every minute) and this change effects another view, coordination is partaking.

2.3 Issues and Guidelines

If used properly, multiple views can minimize cognitive overhead compared to a data visualization via only a single view. Used in the wrong way multiple views can have quite the opposite effect[2]. Baldonado et al.[2] identify the following aspects that influence utility of an MCV system and could become causes of issues:

- *Learning time and effort* required to use the system properly.
- *Load* on user's working memory when using the system.
- *Comparison effort* required when using the system.
- *Context switching effort* required when using the system.
- *Computational power* required by the system.
- *Display space* required by the system.
- *Design, implementation and maintenance* resources required by the system.

In order to avoid that, several guideline rules have been presented by Baldonado et al.[2]. The *rule of diversity* ("Use multiple views when there is a diversity of attributes, models, user profiles, levels of abstraction, or genres."), the *rule of complementary* ("Use multiple views when different views bring out correlations and or disparities."), the *rule of decomposition* ("Partition complex data into multiple views to create manageable chunks and to provide insight into the interaction among different dimensions."), and the *rule of parsimony* ("Use multiple views minimally.") address the fundamental conditions under which sensible usage of multiple views is recommended, or as Baldonado et a.l[2] put it, they cover the task of selecting views.

The second set of rules covers view presentation and interaction, which involves coordination: the *rule of space/time resource optimization* ("Balance the spatial and temporal costs of presenting multiple views with the spatial and temporal benefits of using the views."),

Table 1. Summary of guideline rules (*modified after Baldonado et al[2].*)

Rule of ...	Major positive impacts on utility	Major negative impacts on utility
... diversity	memory	learning, computational overhead, display space overhead
... complementary	memory, comparison, context switching	learning, computational overhead, display space overhead
... decomposition	memory, comparison	learning, computational overhead, display space overhead
... parsimony	learning, computational overhead, display space overhead	memory, comparison, context switching
... space/time resource optimization	learning, computational overhead, display space overhead	memory, comparison, context switching
... self-evidence	learning, comparison	computational overhead
... consistency	learning, comparison	computational overhead
... attention management	memory, context switching	computational overhead

the *rule of self-evidence* ("Use perceptual cues to make relationships among multiple views more apparent to the user."), the *rule of consistency* ("Make the interfaces for multiple views consistent, and make the states of multiple views consistent."), and the *rule of attention management* ("Use perceptual techniques to focus the user's attention on the right view at the right time.")

When applying these rules tradeoffs have to be considered. Applying the rule of parsimony, for instance, might put a strain on the user's ability to compare relevant data. For a summary of the rules and their possible effects on a MCV system see table 1.

3 Approaches to Abstract Models

Now that multiple views and coordination have been formally introduced I will go about introducing some of the major ideas researchers have come up with in recent years to generalize MCV. Not only can such formalization help implementing visualization frameworks themselves, it also provides a means to allow user defined coordination and thus customization of MCV systems.

3.1 North and Shneiderman.: Snap-Together Visualization

The first approach is the *Snap-Together Visualization* described by North and Shneiderman.[12] It tries to deal with the issue that users might be interested in coordinations not foreseeable by a developer for all possible tasks. It focuses mainly on information exploration and not manipulation/editing tasks.[12]

3.1.1 Ideas and Goals

Snap-Together Visualization both acknowledge user specific needs and "give users the coordinated multiple-view interfaces they want, yet, at the same time, save designers from endless development of coordinations."[12] Especially at the time of this system's devising most MCV systems had been static. Adding new, maybe not so common coordination required custom programming. The goals of this approach are not only simplified custom coordination, but also easy integration into projects, making it easy for developers to add "snap-ability" to their application. If actually performed this could give users a wide range of third party visualizations for utilization in their information exploration tasks[12].

3.1.2 Model and Terms

The model of North and Shneiderman's approach is based on the relational database model, which holds *information*, the basis for visualization, view generation and coordination. One information unit is called *object* and is represented as tuple inside of the database. Building on top of a relational database offers a main advantage in it having already formalized concepts such as unique identifiers (primary key) and relationships. We will see, that it also provides good methods to share queries when coordinating and updating views.

In this system the term *visualization* is used equally to the definition of view in section 2, a visual representation of a set of objects. This visualization can be filled with life by queries on the underlying database, which load the requested data.

North and Shneiderman present three major categories of *user actions*, namely *select* (for example clicking, hovering et cetera), *navigate* (for example scrolling, zooming et cetera) and *query* (as described above).

Finally, *coordination* is here defined on user actions on objects (again a limitation compared to the general definition in section 2) and their mapping across visualizations (views).

3.1.3 Usage

At the basis of this system's usage lies an application that serves as frontend to a relational database. Additionally creating and opening views as well as coordination are all integrated into this application and can be managed there by the user. This application may be regarded as a helper application for (third party) visualization applications.

The standard procedure for using the system is described by North and Shneiderman[12] as follows:

1. A user queries (or in the simplest case merely chooses to retrieve a table of) the database and thus creates a view. Existing views can also be updated with new data by queries. A drag and drop mechanism is employed to do this, as well as throughout most subsequent tasks. I will not discuss the exact usage details here.

2. Coordination is established by "snapping visualizations together" with help of the helper application. At this point the user has to choose what actions to coordinate. Again these coordinations can be modified later on.

3.1.4 Architecture

"[Snap-Together Visualization] is a centralized software system that acts as an intermediary among the visualization tools and the database."[12] The system is supposed to be informed by visualization tools about their snap-able actions upon initialization.

Actual snapping is performed between two visualizations vis_a and vis_b by a mapping of the form

$$(vis_a, action_a, objectid_a) \Leftrightarrow (vis_b, action_b, objectid_b)$$

where $action_a$ and $action_b$ are user defined actions to be coordinated and $objectid_a$ and $objectid_b$ are unique object identifiers, which in most cases are expected to be equal, "as in primary-key to foreign-key joins."[12]

Such information is stored in a coordination graph, the nodes of which are visualizations and the links of which are the described snap mappings for incident visualization nodes. Through inter-process communication the system is notified of user actions by the visualization (application), upon which this coordination graph is traversed and communicates the mapped actions to the snapped visualizations.

As mentioned earlier, applications have to be made snap-able before any of the described tasks can be performed. According to the authors, the role of their system can be compared to copy-and-paste features which are controlled by a centralized process in the background.

Such a system requires applications to implement simple hooks for interoperability. In case of Snap-Together Visualization these hooks are *initialization* (notification of available user actions for coordination), *action notification* (propagating of events upon user action), *action invocation* (interface to methods resulting in an action on a given object) and finally *load* (reading and displaying given data).[12]

3.1.5 Evaluation

When designing such system directed at end-user utilisation it is of utter importance to evaluate acceptance and performance in user studies. As the authors mention in a study on their Snap-Together Visualization (or *Snap*), it is important to study its use for evaluation of usability, benefit, discovery "of potential user interface improvements", and gaining of "a deeper level of understanding about users' ability to understand, construct, and use coordinated-view strategies in general"[13].

This study investigated both, construction of MCV interfaces by users, and its subsequent operation. Participants were given different tasks to fullfil. While observing cognitive trouble spots and user interface problems the team measured the participant's background information, learning time, success, and time to completion[13].

In short, the results of this user-study are:

- Participants were excited to use the system.
- They were overall quick to learn it.
- Several felt satisfaction about being able to create exploration environments and with the ability to effectively use a coordinated visualization.
- They state that exploring with their custom-built system was "effortless compared to the standard tools they [were] used to."[13]
- A variety of solution processes for the given tasks indicated the ability to creatively handle the system, that is adjust them to their very own personal needs.

Despite some issues concerning the user interface (that I have chosen not to describe in detail here anyway) the overall and arguably most important result of this study was that the participants "did not have problems grasping the cognitive concept of coordinating views. They were able to generate designs by duplication and by abstract task description."[13]

3.2 Boukhelifa et al.: A Coordination Model for Exploratory Multiview Visualization

While Snap-Together Visualization provides easy to use methods for building own coordination designs, it is limited by its centering on a relational database backend. Exploratory visualization supports more types of interactions than Snap provides and thus requires a wider approach[3].

Boukhelifa et al.[3] introduce a model that, although similar to Snap-Together Visualization in some parts, "handles coordination from a more general viewpoint and takes in consideration exploratory visualization needs for rich and varied user interactions."[3]

3.2.1 Coordination in Detail

Acknowledging the need for freedom of coordination and an abstract definition thereof, Boukhelifa et al. define essential parts or design issues of a coordination for their system as follows[3]:

Coordination entities: This defines the exact subjects of coordination, for instance view, parameter, data, process, event, and of course aspects of the displaying window.

Type: Very close to the concept of a type in a programming language coordinations have a type as well, be it primitive or complex. Translation between types might also become necessary.

Chronology: This aspect covers a coordination's *lifetime*, dealing with how long a coordination persists and *scheduling*, dealing with matters such as synchronism (or asynchronism).

Scope: The scope of a coordination restricts in terms of link-ability, for example whether any arbitrary entity can be connected.

Granularity of links: This looks at how many entities and how many views there are in a coordination, as well as how many links an "entity contributes to coordination".

Initialization: How a coordination is created (also how links between entities are created) is contained in this aspect.

Updating: Several update models can be applied, for instance user *initiated updating*, *lazy updating*, or *greedy updating*. Updates can lead to inconsistencies that have to be resolved, or even better, avoided from the beginning.

Realization: This aspect decides on general realization matters such as if and how to convey which entities are linked to each other (for example by lines) as well as how users coordinate and interact.

3.2.2 Model

Ideally the model "should be flexible, adoptable, extensible and foster better visual exploration."[3] Additionally, a large degree of freedom to be able to describe all sorts of coordinations is desired, as well as the facilitation of their testing.

At the center of Boukhelifa et al.'s model lie the so-called *coordination objects*, which reside in a *coordination space* and manage (coordination) entities. For each type of coordination a single object is considered to be present, for instance, one object for selecting, responsible for selection-related coordinations (such as brushing), and one for rotation, responsible for all rotation-related coordinations[3].

Views are coordinated when they are linked to a common communication object. Figure 2 shows two views and two (different) coordination objects, which are linked to the maximal possible extent. This linking has two forms in the authors' model, namely translation functions (see $f_{i,j}$ with $i, j \in \{1,2\}$ in figure 2) and notifications, which are invoked in case an event makes changes to the linked coordination object[3].

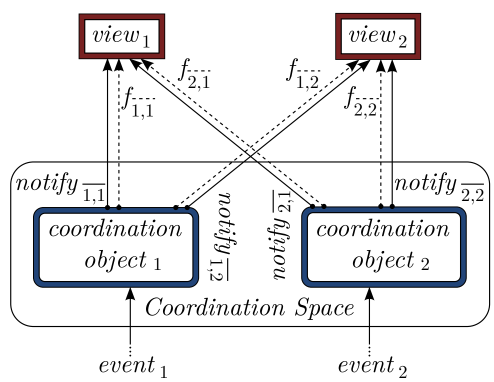

Fig. 2. Example of Boukhelifa et al.'s abstract model (*modified after Boukhelifa et al.[3], see figure 1*)

The authors stress the model's dynamic nature by stating that "views may be added and removed without other views that also access the same coordination object necessarily having knowledge of this activity. Importantly, views do not need to know about other views in the coordination."[3]

They go one step further by extending the abstract model applying it to the several stages of the so-called *dataflow* model. The dataflow paradigm for visualization described by the authors puts data at the first stage or layer. This data is *enhanced*, then *mapped* into an abstract visualization object. Finally this object can be *rendered* and subsequently *transformed* however often it is necessary[4][5]. Applying the earlier, abstract coordination model to the dataflow paradigm,

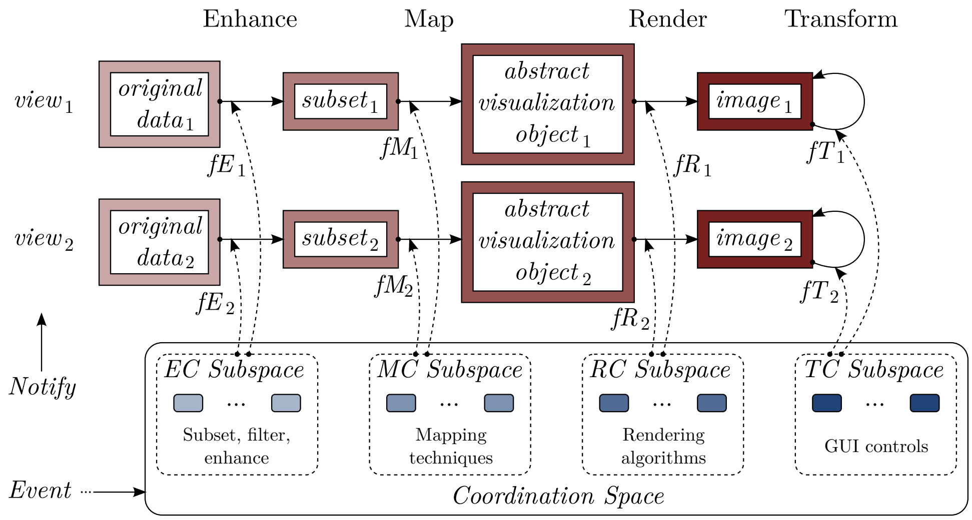

Fig. 3. Boukhelifa et al.'s layered model (*modified after Boukhelifa et al.[3], see figure 3*)

coordination can occur at any of these layers (*see figure 3*). However, it typically tends to happen at the mapping and rendering stages[3].

Since view parameters and coordination object parameters may not be identical, abstract parameters are introduced, which can be passed to translation functions (which in turn convert abstract parameters to view parameters). By these abstract parameters the coordination space can be divided into "four varieties of coordination sub-spaces"[3] (*see figure 3*).

What modifies those abstract parameters? Adequately typed events do, be they user action originated (in which case the views generate them) or occur automatically as result of some background process. As described earlier, notifications are responsible for updating linked views in response to events. It is not only mandatory to define translation functions to each view, it is also mandatory for views "to be registered to receive notify events."

After an event has occurred, the notify handler of a linked view is triggered and finally translation functions (according to the coordination object of origin) are called[3].

3.3 Weaver: Improvise

I have briefly introduced two approaches to MCV, one being simple and limited by its coordination actions and database, the other being a rather theoretical and abstract model. The approach presented by Weaver[19], called *Improvise*, adopts some traits of both and tries to balance between user coordination tradeoffs.

3.3.1 Goals

According to Weaver[19] visualization systems allowing for user controlled coordination are either limited in coordination options but on the other hand let users do this in a simple way (by offering a predefined set of coordinations) or flexible but on the other hand make it more difficult for users to coordinate (by requiring them to write coordination scripts). Thus, "the primary goal of Improvise is to enhance data exploration by offering users fine-grain control over the appearance of visualized data while preserving their ability to work quickly and easily."[19] To do this, the author proposes a visual abstraction language and a coordination mechanism based on shared-objects, which is combined with indirect coordination through a query mechanism[19].

3.3.2 Architecture

Improvise has two concepts that govern coordination, one being direct the other being indirect. The concept associated with direct coordination is called *live properties*.

Coordination in Improvise is performed on *controls*, for instance views, sliders et cetera. For each of these controls one or more live properties are defined. A single (live) property can bind to at most one shared object, called *variable* here (which can, by definition of a shared object, be bound by an arbitrary number of different live properties). A property that only accesses its bound variable is called *passive property*, one that also modifies is called *active property*[19] (*see figure 4*).

Controls are thus never directly modified (by variables) within the coordination mechanism. Instead variable changes are propagated to controls via changes of live properties (and vice versa for the relationship between controls and variables)[19]. Similar to *properties* in object-oriented programming, live properties are a way to conveniently access the control's data from the outside, and in this case data (at least that data, which is relevant for coordination) is actually stored in the property for the control (for instance a slider's position). Live properties are strongly typed and initialized with a default value in case of no variable binding[19]. If we regard control and properties as a single entity, view and variable as coordination object, similarity to Boukhelifa et al.'s abstract non-layered model becomes evident.

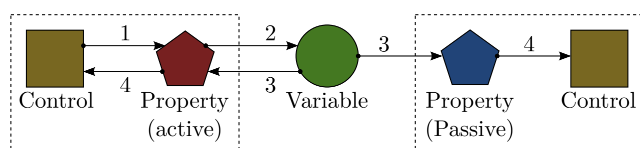

Fig. 4. Direct coordination (*modified after Weaver[19], see figure 1*)

Weaver describes the scenario depicted in figure 4 as follows[19]:

1. "A control modifies the value of one of its (active) live properties in response to interaction."
2. "The live property assigns the new value to its bound variable."
3. "The variable sends a change notification to all live properties bound to it."
4. "The live properties notify their respective parent controls of the change [and the] controls update themselves appropriately."

While live properties are a concept for *direct coordination*, *indirect coordination* can be achieved by so called *coordinated queries*, which "is a visual abstraction language based on the relational database model."[19] Here we can see a similarity to Snap-Together Visualization, yet the concept of coordinated queries appears to be more flexible. The main part of the abstraction language are query operations that are made up by *expressions*. “An expression is a tree of operators that calculates the value of an output field using the fields of a [sic] input record.”[19]

The Improvise implementation provides users with a dedicated expression editor, enabling them to construct complex queries from a variety of operators: *function operators*, *value operators*, *attribute operators*, *aggregate operators*, *constant operators*, *index operators*, and finally *variable operators*[1].

The key to indirect coordination lies in the variable operators, which during evaluation “take on the current value of their corresponding variable.”[19]. A central database, called lexicon stores data, query operations et cetera. Its elements are called *lexicals*.

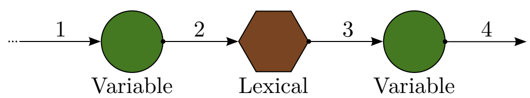

Fig. 5. Indirect coordination (*modified after Weaver[19], see figure 3*)

Weaver describes indirect coordination (situation in figure 5) as follows[19]:

1. “An upstream object propagates a value change to a variable.”
2. “The variable notifies all lexical values that contain expressions which reference the variable.”
3. “Each expression notifies variables to which it is assigned as a value.”
4. “The variable sends a change notification to all downstream objects. Upstream and downstream objects can be live properties (as in [figure 4]), or other lexical values.”

Figure 6 shows an example of direct coordination for a view that displays data in a scatterplot and two axis control views.

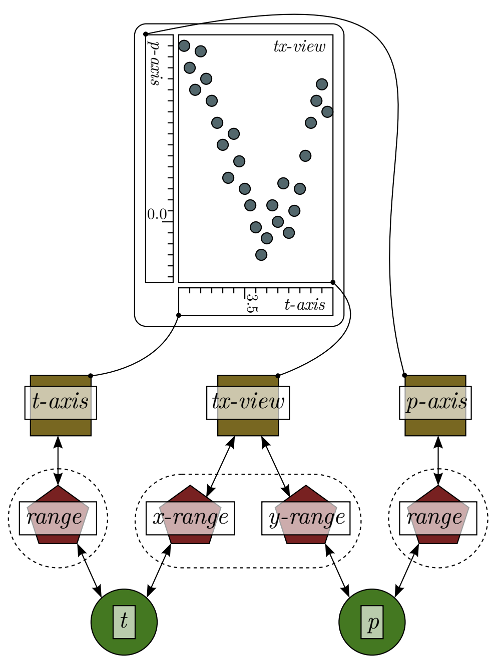

Fig. 6. Direct coordination example (*modified after Weaver[19], see figure 5*)

[1]Please refer to Weaver’s paper[19] for detailed information.

3.3.3 Results

According to Weaver[19] “highly-coordinated visualizations appear to be much easier to build in Improvise than other visualization systems.” He attributes this to indirect coordination, that links every aspect of a MCV system together in a flexible manner. The system was fully implemented, however, as of the time of writing his paper[19] no comparative user studies had been conducted yet.

4 Problem-specific Applications of MCV

Whether all the approaches in the previous section have actually been incorporated into MCV systems or not, one reason I chose to discuss them is, that they present what has to be considered when building a coordinated multiple view visualization and how coordination there can be improved.

Hence, while not directly related to the previous section, I tried to compile a small overview of problem-specific applications of MCV for this last section, to give an idea of what tasks it has been used for explicitly, and what research has resulted in.

4.1 Da Silva Kauer et al.: An Information Visualization Tool with Multiple Coordinated Views for Network Traffic Analysis

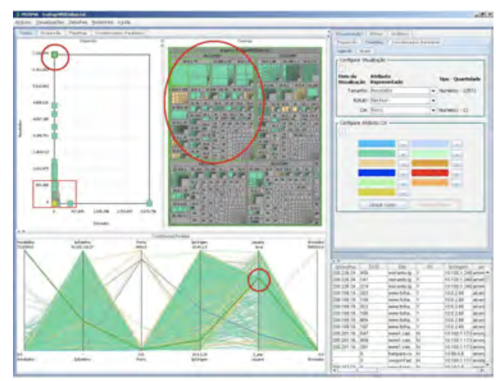

Fig. 7. Screenshot showing brushing (*see da Silva Kauer et al[6]., figure 2*)

The system by Kauer et al. was designed for network traffic analysis. It uses the PRISMA[8] visualization framework and represents a typical MCV design with static coordination between views. As you can see in figure 7, several views containing different types of visualization are used.

4.2 Shimabukuro et al.: Coordinated Views to Assist Exploration of Spatio-Temporal Data: A Case Study

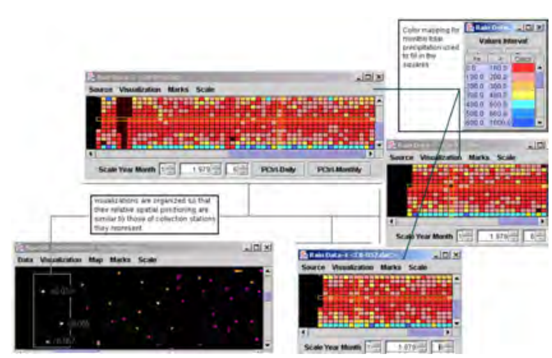

Fig. 8. Window placement reflects location on map (*see Shimabukuro et al.[15], figure 7*)

The system by Shimabukuro et al.[15], is interesting for applying a novel way of visualizing temporal data, and for using multiple views enabling them to effectively combine this data with spatial data. For example, the user sees a map from which he chooses locations, to which certain temporal data has been collected (in this case climate data). Corresponding views are then arranged in a way that their position on screen reflects their locations' arrangement on the map (*see figure 8*).

4.3 Masui et al.: Multiple-View Approach for Smooth Information Retrieval

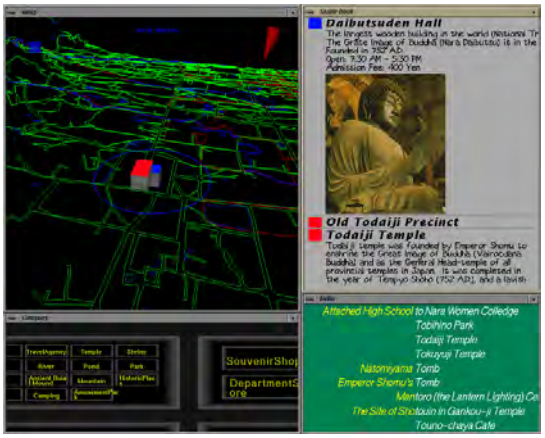

Fig. 9. Screenshot showing all four different views (*see Masui et al.[10], figure 1*)

Masui et al.[10] describe a tourist information system (for Nara, Japan) supporting tourists with a three-dimensional map view showing points of interest, category views and lists to find points of interests. One coordination is for instance, that details about data objects in the three-dimensional view are displayed in a separate window when coming into proximity of the view's center(*see figure 9*). It supports search for points of interest by employing real world search strategies, that is with the help of multiple and coordinated views "any vague knowledge about the data can be utilized to narrow the search space."[10]

4.4 Do Carmo et al.: Coordinated and Multiple Views in Augmented Reality Environment

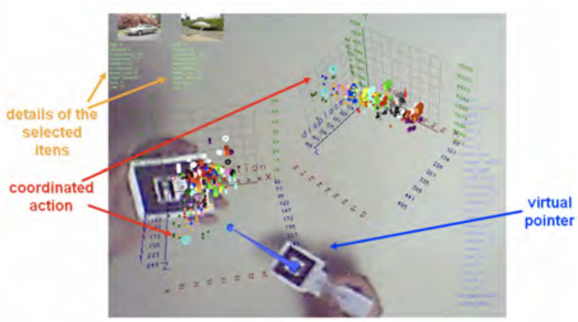

Fig. 10. Two coordinated scatter plots and in the top-left corner coordinated details (*see do Carmo et al[7]., figure 10*)

Combining multiple and coordinated views with augmented reality gives new display options concerning arrangement as well as new user interactions (such as navigation by perspective change). Results of a user study, conducted by do Carmo et al.[7] on their system, showed that most users did not encounter major difficulties adapting to the rather unusual setup. To manipulate views, the system relies on a set of markers and their handling(*see figure 10*). Participants of the user study reported to enjoy the mixture of virtual and real objects, the immersive environment in general, and profited from freedom of movement and manipulation.

5 Discussion and Final Words

In this paper I have tried to introduce the field of multiple and coordinated views. Though the abundance of systems using MCV may have prevented me from choosing the best ones, I hope I was able to give a cross-section through the field.

What struck me the most was that considering that some of the presented ideas are nearly ten years old, progress, especially for customized coordination in commercial systems seems to have been slow. In a recent paper Andrienko and Andrienko[1] attribute this to existing tools and approaches being "insufficiently suited to real-life problems."

To me this comes as a surprise, as approaches like the ones described in section 3 have become more and more general, in fact general enough to cover most cases or at least more and more cases as time passes. Apparently slow processing of large data volume, or in other words, non-scalability of MCV systems is the main cause for Andrienko and Andrienko's judgement. With more data to be visualized visualization itself and coordination come to a limit. In fact, while researching I also felt that most approaches fail to address this issue thoroughly enough.

What their paper also proposes is a deviation from Shneiderman's apparently (in the field of MCV) widely followed *information seeking mantra* "overview, zoom and filter, details-on-demand"[16]. They state that maybe applying "analyse first - show the Important - zoom, filter and analyse further - details on demand" (the *visual analytics mantra*) could be a suitable solution as this procedure "stresses the fact that fully visual and interactive methods do not properly work with big datasets."[1]

For me all the many different, yet not too different formalization approaches and visualization systems give off a general atmosphere of dissatisfaction, and in fact I have personally not come across any commercial application allowing for the described levels of customizability. In the end, one still has to decide what visualization method is best suited for a specific problem, which is not an easy task to begin with[1].

Despite these issues, multiple and coordinates views are still a hot topic and I anticipate further research and development in this area.

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Collaboration in Information Visualization

Simon Stusak

Abstract— This paper describes the current state of research for collaboration in information visualization. It discusses the possible differentiations of collaboration along time and space. Collaborators can work together at the same place, which means co-located or distributed in different places, cities or even countries. Furthermore they can work synchronous or asynchronous, which is the basis for many web applications or required when group members are in different time zones. Because until today the most information visualizations are designed for single-users it is necessary to analyze the requirements and characteristics for collaboration in information visualization. New technologies like wireless networks, higher bandwidth and bigger screens which vary from wall-size displays to interactive tabletops, bring up many new possibilities for collaborative visualizations. But they also raise questions and challenges about how to design and develop these applications. There will be given an overview about supposable design guidelines, both for co-located and distributed environments. It is important to figure out how applications should be developed so that they do not only enable collaboration but rather support it in a way that the advantages have some effects. Some examples for information visualizations, which are used or designed for collaboration will be shown. The paper presents also how single-user oriented applications are used for collaboration and which problems can occur. For synchronous co-located collaboration there will be reviewed an application for interactive tree comparison and DTLens, a multi-lens interaction technique. For the synchronous distributed collaboration the visualization environment CoMotion is described and for the asynchronous collaboration the web-based applications sense.us and Many Eyes.

Index Terms—Collaboration, Information Visualization, Co-located, Distributed, synchronous, asynchronous

1 Introduction

Information Visualization and Collaboration itself are well researched fields, but the body of research that is concerned with the problem of supporting collaborative work around visual information is relatively small until today, although there are many possible areas to investigate [14]. Isenberg [13] enumerates some examples like "a team of medical practitioners (doctors, nurses, physiotherapist, social workers) examining a patient's medical record to create a discharge plan, a team of geologists gathering around a large map to plan an upcoming expedition, or a team of executives looking at charts showing the latest sales trends". Mark et al. [19] write that "organizations are becoming more distributed, which is leading to new forms of collaboration and new technologies to support them".

Working together and to collaborate is common and natural for people in order, to get a job done faster or to share the expertise for a complex task [11]. It is also a way to improve the quality of solutions, because different team members offer different perspectives and insights. Another advantage of collaboration is the possibility to distinguish the work, for example the exploration of the data can be shared among several individuals on a team [14]. Collaboration can help to foster the sharing of knowledge, skills and ideas, and play an important role in areas such as art, academia, business and scientific research [13].

Information visualizations map large amounts of data into a visual form. This is very useful because it is then possible use innate human abilities to explore the data to find patters that would be difficult to identify through automated techniques [11]. Card et al. [3] describe how visualization supports the process of sensemaking, in which information is collected, organized, and analyzed to form new knowledge and inform further action.

Collaboration in Information Visualization makes sense or is even necessary because the data today is often simply too complex to explore in its entirety for an individual or the dataset may be susceptible to a variety of interpretations [14]. It is just unrealistic for an individual to analyze an entire dataset [11]. The probability of finding the correct result is greater for groups than for an individual [19], because groups of users often spend more time in the exploration of data and they ask deeper analysis questions [12]. Both fast network connections and the increase of the web as well as new technologies like wall-sized and tabletop displays introduce new possibilities and challenges for collaborative information visualization.

Current information visualizations have mostly been designed for single-users, which can be very unnatural and awkward for a group, because only one person can make changes and controls the representation [14]. "The challenge to collaboration visualizations is to provide mechanisms to aid the creation and distribution of presentations" [11].

This paper first discusses the possible differentiations in collaboration, then describes some design guidelines for co-located and distributed collaboration and finally gives some example of applications.

- *Simon Stusak is studying Media Informatics at the University of Munich, Germany, E-mail: simon.stusak@campus.lmu.de*

- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

2 Differences of Collaboration in InfoVis

This section provides a description of possible differences of collaboration in information visualization. The first two subsections describe the two main points of differentiation in collaboration. The subsection 3 reports differences in information visualizations systems in general and try to figure out some impacts on collaboration. The last subsection combines some of the differences discussed in the previous sections.

2.1 Co-located vs. Distributed

One big differentiation in collaboration can be made by separating it into co-located and distributed collaboration. [14] defines distributed collaboration as collaborations across distances, so the collaborators are located at varied places. In [6] it is written that today more and more often researchers are working with collaborators at institutions that are shared across the country or even around the world. So one important reason for distributed collaboration is the community need. Group members are working at distance but trying to accomplish a common goal. Distributed collaboration can provide an infrastructure without duplicating the costs and efforts. [11] describes that it is very important for the potential for greater scalability of group-oriented analysis to partition work not only across time, but also across space. And that the scenarios of collaboration and presentation across both time and space are nowadays becoming very common in business. For [23] the today's distance work is very interesting, because the technology which is available changes very often. Also it is possible that every group member has access to another perhaps very different technology. Today there are a lot of possibilities to support and enable distributed communication. The options include for example telephony, meeting room conferencing, desktop video and audio conferencing, chat rooms for text interactions, file transfer or application sharing. [6] means that the evolution of optical networking and thus the multi-gigabit networks played an important role for the development of distributed collaboration. This technology finally allows users to connect remote locations together that can be dedicated to the collaboration task and to information visualization. High bandwith is also very helpful, because visualizations often have a high data volume, which should be transfered to the other members as fast as possible. The rise of the web is also very important for the deployment of distributed collaboration, because it makes it possible for thousands of people to analyze and discuss visualizations together [11], and causes a lot of distributed applications to be web-based [14].

Co-located work means that the team members are at the same physical location. This can be for a short time, because the members traveled to a common location, but also permanent, because the members are at a common site [23]. For [14] it means that the teams share the same workspace or can get to each others' workspaces with a short walk. The co-workers have access to common spaces for group interactions like meeting rooms or lounges. Additionally they have access to shared displays, files, models or other things they are using in their work [23]. An important technology for the co-located collaboration in information visualization was the development of bigger displays like display walls or interactive tabletop displays, because visualizations often need a lot of display space to be readable and useful. Soon there were experiments to support co-located people in information sharing and exploration tasks with tabletop display information visualization interaction techniques [11]. Also the better and faster wireless networks play a role, because they allow laptops and handheld devices to be integral parts of a collaboration environment [6].

2.2 Asynchronous vs. Synchronous

The second big differentiation within collaboration is the time and the separation into asynchronous and synchronous. Synchronous means that the collaborators work at the same time on a project or a solution and can speak directly with each other either face-to-face or for example by audio or video connections. When the team members collaborate asynchronous, they are working at different times. This can be the case when the collaborators for example live in different time zones, which is a common scenario in the business world [11].

The most work on systems supporting collaborative information visualization has been done in the context of synchronous scenarios and interactions. But with the rise of the web the asynchronous collaboration gets new possibilities, like for example different audiences. Besides [11] describes that asynchronous collaboration resulted in higher-quality outcomes, like longer solutions, broader discussions or more complete reports than face-to-face collaboration. I think sites like many eyes and sense.us which are discussed in chapter four are only the beginning in the research for this topic getting more and more important.

2.3 More differentiations

In 2.1 and 2.2 the two main differentiations in collaboration were discussed, but there are still some more possibilities. [19] makes a separation into more and less transparent information visualization systems. The transparency here means that the system is easy to understand and you do not have to be an expert to interact with the system. [14] notes that groups work more effectively with a more transparent system.

It is also possible to distinguish the data for the visualization. [11] names Personal Data, Community Data and Scientific Data. So far information visualization has focused on the scientific data, which is of interest to a small number of specialists and requires multiple specialized skills to analyze. But I think with the advancement of web-based asynchronous applications the personal and community data could get more important. It could be possible for example to share and present your personal photos and videos with your friends in completly new ways. And also the visualization of data that is relevant to a broad of community of users with similar interests can lead to new insights about the data itself, especially when the community discusses it.

[11] differentiates the skills of the users in Novice Users, Savvy Users and Expert Users. Expert users have a lot of experience with graphical software and data representation. But it will become increasingly necessary to provide savvy and even novice users with the capability to explore and analyze data without assistance. This could be again important for web-based systems, which often have users with no experience in information visualization. For example many users arrive directly at the visualizations for the first time via links from external web sites. They only have a little context and no training and if they do not understand what they see it is possible they will simply click away from the site [26].

The different goals can be varied in exploration, analysis and communication according to [11]. In the real world there are often combinations of all three. [18] distinguishes between focused questions and free data discovery. The focused question means that the user has a particular question in mind and uses the visualization to answer it, which is similar to the analysis. The free data discovery by contrast means an exploration without having a predefined question in mind. On the other hand web-based systems have the goal to get a big community, with a lot of users and discussions.

The size of the group is another characteristic. Distributed web-based applications can have thousands of possible collaborators, on the other side it can lead to problems with restricted space when there are more than five people around a tabletop display. Display walls can perhaps be a solution for bigger co-located groups, especially when the visualization is controlled with a handheld or a laptop [4].

2.4 Combinations

This section describes how the previously discussed differentiations can be combined. *Figure 1* shows possible combinations in a time-place matrix.

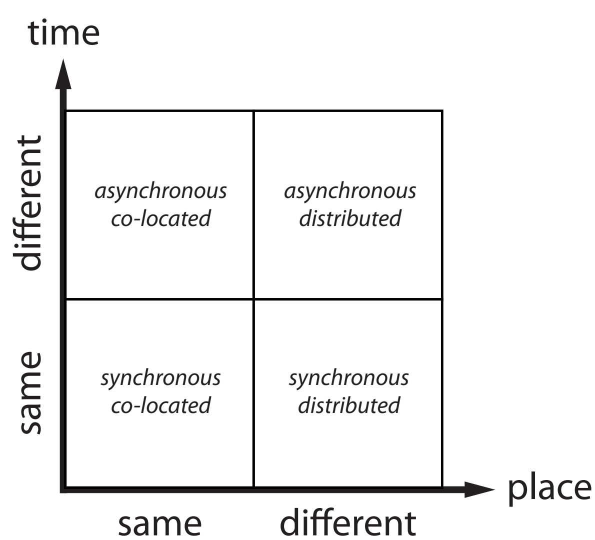

Fig. 1. Time-Place Matrix [2]

The three more important combinations are the co-located synchronous and the distributed asynchronous/synchronous fields. There is not much related work about co-located asynchronous systems. Only some researchers have experimented with asynchronous, co-located visualization in the form of ambient information displays [11].

[11] maps information visualizations tools according to targeted end-user and targeted goal. The skill and effort of the user is divided into Expert Developers, Savvy Designers and Novice Consumers, the goal into Interactive Analysis & Exploration and Communication.

3 Design Guidelines

Isenberg et al. [14] write that "in general, no guidelines, as of yet, exist for the development of collaborative systems specifically tailored for information visualization applications". Also it is yet not clear how interfaces, visualizations and interaction techniques should be designed to support the requirements of collaborators. Some investigations showed that only well designed information visualizations which are easy to use and understand will provide groups an advantage over individuals [19]. To combine the competing requirements of users as individuals and as members of a group is for Gutwin et al. [10] one of the main problems in the design of collaborative systems.

A theoretical basis of the process of collaborative information visualization can also be useful for a good design. Mark et al. discovered in [17] and [18] five stages from parsing the question over mapping the right variables to finding the correct visualization and then validating the visualization and the entire answer (*see figure 2*). The more important stages for the collaboration are four and five, because here the members discuss and validate the solution together. Isenberg et al. researched in [15] also a theoretical understanding of how individuals use information visualizations. They uncovered "the processes involved in collaborative and individual activities around information visualizations in a non-digital setting" and identified eight processes: "Browse, Parse, Discuss Collaboration Style, Establish Task-Specific Strategy, Clarify, Select, Operate, and Validate". With a good theoretical background I think the design and development of new collaborative information visualizations can be easier and better specified to the collaborators and their requirements.

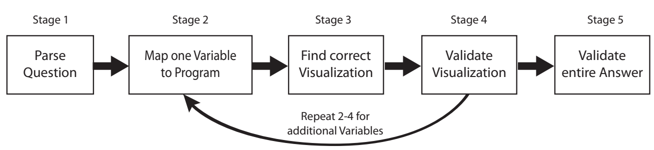

Fig. 2. The 5 Stages of the collaborative visualization process [17]

At lot of design guidelines for single-user information visualizations will still be valid for collaborative environments. The following subsections discuss some new relevant design guidelines for co-located and distributed collaboration.

3.1 Co-located

This section discusses the design guidelines for co-located collaborative information visualization systems. It is a summary of information visualization design advice, co-located collaboration advice and the combination of both. The structure is adopted from [14], which divides this research field into hardware and system setup, designing the information visualization and designing the collaborative environment. It is only an overview, because every application has different visualization and interaction requirements. For example some applications need simultaneous visualization and interaction on the same data across more surfaces other require various displays to show different perspectives of the same scenario [24].

3.1.1 Hardware and System Setup

The display size and the available screen space are very important and are often a problem, when you want to display a large dataset. When the number of group members grows, you also need a bigger display, so that the viewing and interaction area is large enough and gives adequate access to all users [14]. When the members want to work parallel and in an acceptable distance from each other, there should also be enough space to display multiple copies of one visualization [11].

There are a lot of configuration possibilities with advantages and disadvantages. On the one hand only on big display can be availabe, like a display wall or an interactive tabletop, on the other the team members can be connected with their individual displays [14]. A combination is also imaginable, so that the users for example can control the representation on a display wall with their handhelds or laptops [4]. [24] distinguishes the possible connections of the visual elements on different displays. For example there can be a simple file transfer relationship, a synchronous co-related relationship with focused view or a pixel update in unison.

To support collaboration each collaborator should have at least one means of input. Most suitable are inputs that can be identifiable so that the system can give a personalized response. It is also important to coordinate synchronous interactions and the access to shared visualizations and data sets [14].

The display resolution also plays an important role for the legibility of information visualizations. When the display has a low resolution it could be necessary to re-design the representation, so that for example text and color are displayed in proper style. Moreover "interactive displays are often operated using fingers or pens which have a rather low input resolution" [14].

The processing power of the system should also be considered well. Even if the implementations were designed carefully for efficiency, the system is supposed to display several information visualizations that interact with at the same time [14]. This probably needs a lot of capacity and should work without much delay to avoid interferences for the users.

3.1.2 Designing the Information Visualization

Many of the known design guidelines for single-user system will still apply for the use in collaboration. But new questions to answer are for example if certain representations will be better adapted to support small group discussions or if various representations help the users in their different interpretation processes. It is known that people prefer different visualizations on large and small displays [11].

Capabilities to freely move interface items is important for group interactions. "Letting users impose their own organization on items in the workspace may help collaborators create and maintain mental models of a dataset that contains several different representations" [14]. This also allows the users to build their own categorizations on the representations.

It should also be considered that a user can stand at different points and may see quite different visual information or has access to different controls [7]. I think a good design should avoid too many differences, so that the users do not have orientation problems. It can also affect the legibility of information visualizations, when users stand on different sides of the display [14]. [1] describes a system that tracks the head positions of two users and compute four images for every eye of each user. This "allows two people to simultaneously view individual stereoscopic image pairs from their own viewpoints" [1].

An important point is the change between individual and group representations. Every member normally has his own preferences or conventions of how to design and structure a representation. [18] enumeratese several imaginable scenarios. The preferences of one person could dominate and be perhaps adopted by the group or could lead to conflicts. It is also possible that the group successfully negotiate a common representation from the different individual preferences. "Multiple representations can aid the individual but can restrict how the group can communicate about the objects in the workspace" [14]. A solution could be a mechanism to highlight individual data items so that each user can recover his item easily and fast, when he is switching from the parallel to the group data exploration.

"The data analysis history might be of even higher importance in collaborative settings" [14] than in individual. When you know which collaborator has interacted with which objects from a workspace it can help to understand each others' involvement in the task. When the collaborators later want to discuss the data or their results the exploration history can be a big help.

Demspki et al. suggest in [7] that "the classic WIMP (Window, Icon, Menu, Pointer) design paradigm requires reconsideration". This paradigm is oriented for a single-user and a relatively small screen. They concern that important information could be displayed outside the useful viewing envelope by a traditional GUI on a large screen.

[9] describes a method to rank the importance of components. The system then could change dependent on the ranking the size, opacity and contrast of the components. For example more important components could be displayed at specific positions or just larger than others or could differentiate by a chosen color.

3.1.3 Designing the Collaborative Environment

For successful collaboration it is important that the users coordinate their actions with each other. Separating the workspace into shared and personal [4] can be helpful for that. The shared workspace with shared tools and representations is needed for the collaboration. A group can work together, discuss and analyze the visualizations. The personal workspace is necessary to explore the data separately [14]. [4] divides the personal workspace even in public and private.

A fluid interaction is very important for an effective work. The system should be easy to understand and control. "Changing the view or the visualization parameters should be designed to require as little shift of input mode as possible, and as little manipulation of interface widgets and dialogs as possible" [14].

Relevant questions are also who is allowed to modify or delete data or to change the scale or zoom-level of a shared visualization. Policies for the information access might be necessary [14]. [11] means for example that the possibility to filter unwanted data is better than to delete them.

It is required that the system supports the chance to work parallel. When you have access to several copies of one representation, every group member can work individual with his own preferences. "Concurrent access and interaction with the parameters of an information visualization can support a single view of data" [14]. To move and arrange the representation freely around the display could also be helpful.

Very important for the success of collaboration is the communication. Communication helps the group members to understand the intentions of other users and to indicate the need to share visualizations. It is important that the members will be informed when parameters of a shared visualization have changed [14]. Communication can be devided into explicit and implicit communication [11]. The explicit communication means the direct exchange of information through the voice or annotated data. Under implicit communication one understands things like body language, which is often more difficult to understand.

[21] describe cooperative gestures, which are "interactions where the system interprets the gestures of more than one user as contributing to a single, combined command" as another form of communication. Cooperative gestures can increase the users' sense of teamwork and enhance the awareness of important changes or events.

The placement of the control widgets such as menus has another affect on the collaboration. Moris et al. [22] experiment with a central set of controls shared by all users and a distinguish set of controls, where the replicated controls where located at the border of the tabletop display. They came to the conclusion, that the "users strongly preferred the replicated controls". In [4] each participant in a meeting has its own cursor in the shared representation and even an individual avatar to identify them in an easy way.

3.2 Distributed

After the design guidelines for co-located collaboration the guidelines for the distributed collaboration will be described. For Tuddenham et al. [25] "the key issues for remote collaboration will be in resolving the disparity in information orientation and display form-factor between the two sites and in choosing an design to convey presence". Content of the first section are the hardware characteristics of distributed collaboration, the second section illustrates the designing guidelines for a collaborative information visualization.

3.2.1 Hardware and System Setup

The system setup of a distributed collaborative application is similar to the setup of a single-user application. You do not have to share your display directly, so "users will use all available screen space to display their visualizations" [14]. For Kavita et al. [16] a major problem for distributed collaboration is that users may see different versions of the data because of display, network and environment limitations. The collaborators do not have a shared context, which can lead to miscommunication, confusion and other errors. [16] describe heterogeneous network display systems which includes four components with different attributes (*see also figure 3*):

- Images captured from different sensors (satellites, camera, database, ...)
- Networks (bandwidth, latency, reliability, ...)
- Displays (size, aspect ratio, resolution, response time, bit depth, ...)
- Viewers (contrast sensitivity, motion perception, color discrimination, ...)

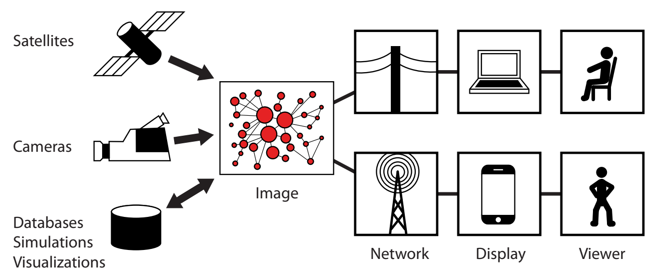

Fig. 3. The components of a heterogeneous network: Images, Networks, Displays and Viewers [16]

The big challenge is to design an application that fits on all possible screens. Visualizations with the same zoom level can look very different on a small and a bigger display. Some details could be only visible on the big display, which could complicate the collaboration. For example on the one hand "modern PDA devices equipped with colour display and wireless network capability are being used in distributed collaborative visualization applications" [2]. On the other hand today a lot of users have large displays at home, which can "provide a shared view of the task in which participants can see each other's gestures and actions" [25]. The network connection is also important, because often visualizations have a lot of data volume and so a high bandwith on both sides is necessary for a good collaboration.

Kavita et al. [16] write that the dramatic advances in networking and electronic display technologies have lead to a range of new distributed collaborative applications "such as emergency response, tele-medicine remote maintenance and repair, reconnaissance, and command-and-control".

3.2.2 Designing collaborative information visualization

As described before in the section about designing the information visualization for co-located collaboration an available history task is very important, this also applies to the distributed collaboration. For example sometimes meetings are interrupted and resumed afterwards. A Software should store the state of these meetings, like the opened visualizations or annotations, and should unproblematically return to any state at a later time [4]. It is also possible that not all collaborators are available at the start of a conference or cannot remain until the end of it [2]. So there should be a comfortable way to join a running collaboration and get an overview about the context and the existing results. If you have to leave earlier you should have the possibility to engage in the solutions afterwards.

To achieve a shared local context is important in distributed collaboration. Users have to communicate findings and bring each other up to the current state of the process quickly [11]. There are a lot of different ways to communicate in distributed environments. Web-based systems for example support sharing through URL bookmarks on different states of visualizations and enable discussion through text comments. It is also possible to tie "threaded comments to specific states of a visualization and retrieved dynamically during exploration" [11]. The synchronous communication is a little more difficult. People have collaborated face-to-face for centuries, they have a lot of experience here, but in the distributed context they have not. For example the implicit communication is an active research field in the distributed collaboration. "Forms of reference are often most easily achieved through speech and written text, deictic reference in particular (like different hand gestures) offers important interface design challenges" [11]. [25] describes a system with linked displays, so both show the same shared view of task. Also a telepointer traces each participant's hand and pen gestures, which makes it possible that each participant sees all other participants' gestures.

For Olson et al. [23] the communication has to be a common ground to be effective, which is very difficult to establish in a distributed environment. For example "when connected by audio conferencing, it is very difficult to tell who is speaking if you do not know the participants" [23]. In contrast to a co-located environment you do not have awareness of the context and the mental state of your partner. The design should take care of this and try to minimize this lack. Cardinaels et al. [4] investigate "how video can enhance (remote) awareness, e.g. by streaming views of a workspace or by low-bitrate video avatars".

Other problems that should be dissolved are that many individuals are overstrained with the capabilities of such technology environments. A lot of people just prefer communicating distributed via telephone or email [6]. Therefore applications should be designed in a way that they are easy to understand. This is especially important for the web-based applications, because they will often be used by users, that do not have much experience in information visualization.

4 Examples of Applications

This section describes different applications designed or used for collaboration. An example of two single-user oriented applications show, how they can be used for collaboration and which problems can occur. The collaborative applications are distinguished again into co-located and distributed. The co-located section gives an overview over an application for tree comparison and the table-top environment DTLens. The distributed section outlines the synchronous systems sense.us and Many Eyes and the asynchronous system CoMotion®.

4.1 Using Single-User Applications for Collaboration [19]

In [19] Mark et al. compare the two single-user oriented visualizations systems InfoZoom and Spotfire both for distributed and co-located collaboration by two users. InfoZoom has three different views, the wide view, the compressed view and the overview (*see figure 4*). In all three the values of attributes are display textually, numerically or symbolically whenever there is enough space, which makes a general view very easy. When you double-click on attribute values you zoom into information subspaces, which is one of the central operations of InfoZoom.

Spotfire supports a lot of familiar visualizations like bar charts, graphs, parallel coordinates or scatterplots (*see figure 4*). Two variables can be chosen for each visualization through pull-down menus for display in the x and y coordinates. Additional variables can be added through a dialog window. A problem of Sportfire is that many functions and significant portions of data are not immediately visible and directly accessible. This also means that users have high planning efforts, because they have to choose in advance what variables and which visualization they want to use. "InfoZoom can therefore be regarded as more transparent than Spotfire, where transparency refers to the system's quality to invoke an easy-to-understand system image in users" [19].

An important point by using single-user oriented applications for collaboration is that the user has to choose roles, like for example who

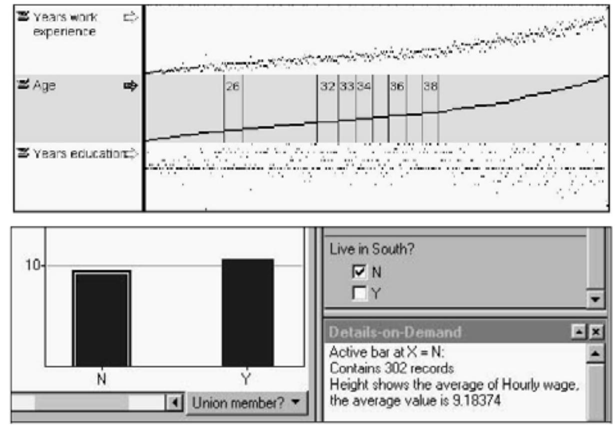

Fig. 4. A compressed view in InfoZoom and a bar chart visualization in Spotfire [19].

will operate the system. In the experiment for distributed collaboration the user communicated via Microsoft NetMeeting and a speaker phone. Here the roles were divided into system operator and system director. The operator manipulated the system and had to explain exactly, what he was doing so that the director could reconstruct everything on his own display. Often the director gave only instructions on how to interact with the system. The roles switched when the operator became lost.

In the co-located collaboration there was a system user and an observer. Because the most controls to manipulate the visualization were located on the left side of the screen, only one user could control the application. Therefore the operator worked basically alone on the visualization until the observer participated to discuss and confirm the final answer. It is interesting to see, that both in the distributed and in the co-located collaboration subjects adopted quite different roles and that there was no equal participation [17]

A product called DecisionSite Posters, which is included in Spotfire, was not used in the experiment. This is "a web-based system that enables users to create bookmarks and comments attached to specific views of a visualization" [26]. Mark et al. [19] came to the conclusion that "bringing people together to view data can have benefits, but they depend heavily on the kind of visualization system used". This statement especially applies to the transparency of the used system. But I think you can expand it to that the benefits will increase, when you use a system which is designed for collaboration instead of single-user.

4.2 Co-located

4.2.1 Collaborative tree comparison software [14]

Isenberg et al. describe in [14] "a information visualization system designed to support collaborative tree comparison tasks". A large digital tabletop display offers an adequate size, configuration, input and resolution for small groups of two to four members. It supports two simultaneous touches by fingers or pens in which the inputs are not identifiable. The system works with hierarchical data, specifically with two different types of tree representations. The radial tree layout places labels in a circular fashion inside the nodes to make reading from different positions around the table easier (*see figure 5*).

Each information visualization is drawn on its own plane which can just like all control widgets be freely moved around the tabletop display. The menu offers scaling, integrated rotation, translation and annotation. To organize the representations it is possible group them and move them as a unit. The free workspace organization allows working individually or coupled, furthermore parallel work is supported by accessing to copies of representations. Communications are possible with annotation directly on the provided visualization and separately on sticky notes.

Fig. 5. A visualization plane with appropriate controls attached on the side. It is showing a radial tree layout with radial labeling [14].

4.2.2 DTLens [8]

In [8] Forlines et al. present DTLens "a new zoom-in-context, multiuser, two-handed, multi-lens interaction technique that enables group exploration of spatial data with multiple individual lenses on the same direct-touch interactive tabletop". Every group member can define an area that he is interested in, called lens here, by creating a rectangle placing two fingers on the table. After opening and locking a lens, a collection of controls around it can be seen. *Figure 6* shows a lens and the controls for minimizing, closing, annotation, resizing and changing the zoom level. Users can also control the zoom level by moving two fingers apart diagonally

Fig. 6. A locked lens with a collection of controls on the right [8].

It is possible to inspect documents from different points of views. That is advantageous for group members who prefer working closely face-to-face around a tabletop more than shoulder-to-shoulder in front of a vertical display. For every command two buttons are placed in the opposite corners of the display, so everybody around the table can always reach one of them. The system provides folding on the tabletop, so users can reposition some interesting part of the data to a more comfortable location and inspect the details of the dataset more conveniently. The identity of every user is represented by a unique color, so any annotations to the data or resizing of a lens is recorded and can be identified. To avoid conflicts only the lens's creator can interact with that lens, anyone else is locked out. The system uses a DiamondTouch table that identifies users by the chair they are sitting in. That enables DTLens to have the controls remain in the same position relative to the point of view of the users and orient them to face each user.

4.3 Distributed

4.3.1 sense.us [11][12]

Heer et al. specify in [12] the asynchronous distributed information visualization application sense.us as "a prototype web application for social visual data analysis". The basis for the visualizations are United States census data over the last 150 years. The primary interface has the visualization on the left and a discussion area on the right (*see figure 7*).

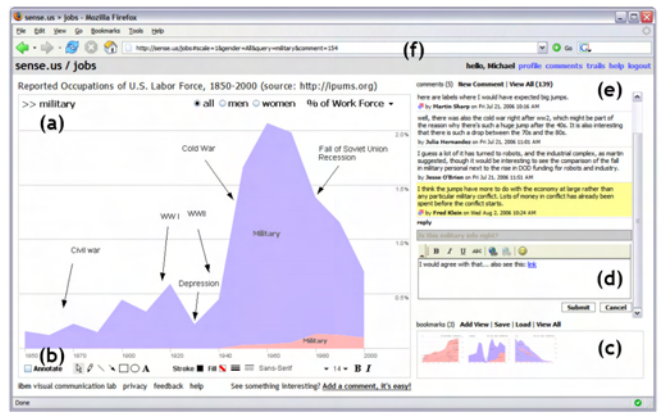

Fig. 7. The interface of sense.us [12].

At the top of the discussion area a commentary associated with the current visualization can be found. A graphical bookmark trail with multiple saved views is displayed under these comments. The possibility to embed several view bookmarks into a single comment enables a better comparison and the chance to tell stories. The application supports a so called doubly-linked discussion. This means that it is possible to link to bookmarked visualizations from the comment panel and also to relevant comments from the visualization. The links are represented by an URL-address. It is also possible to write or draw directly into the visualization using drawing tools like lines, arrows, shapes and text. The comment list shows a collection of all comments which were made within the system. The list includes the text and a thumbnail image and is searchable and sortable. Often the observations about the data were coupled with questions, hypotheses and further discussions. On the other side reading through the comments often brought up some new questions and led the users back to the visualizations.

4.3.2 Many Eyes [11][26]

Vigas et al. describe in [26] "the design and deployment of Many Eyes, a public web site where users may upload data, create interactive visualizations, and carry on discussions". Members can upload data sets, create visualizations of the data with a palette of interactive visualization techniques like bar charts, treemaps or tag clouds (*see figure 8*) and leave comments on both visualizations and data sets.

The two main goals of Many Eyes are enabling users the creation of visualizations and fostering large-scale collaborative usage. Another difficulty was the design choices between powerful capabilities of data-analysis and the accessibility to users with no experience to visualizations. The data can be uploaded as freeform text or as tab-delimited grid. In the first case it is interpreted as unstructured data, in the second as a table. It is possible to flip or reorder the rows and columns of a visualization or even change the data on the fly. This offers a fast way to browse through the different dimensions on a dataset. Many Eyes tries to tap into the often lively discussions in various blogs

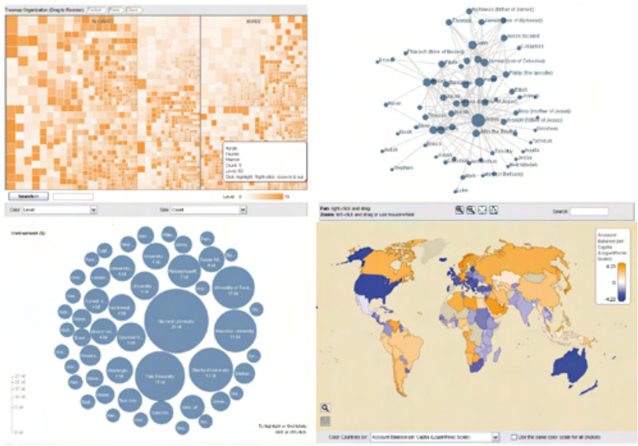

Fig. 8. Some example visualizations from Many Eyes. It shows a treemap, a network diagram, a bubble chart and a world map [26].

and online communities. Therefore it is easy to link to specific views of a visualization with simple URL bookmarks or even subscribe to a RSS feed for visualizations and comments. Another feature to support collaboration is the blog-this button, which generates html code that members can use for the comments section or their blogs. It is interesting to see, that many visualizations have no comments and the deepest analysis of visualizations came from blogs that reference to the site.

4.3.3 CoMotion® [5]

"CoMotion® is a software platform that provides sophisticated visualization components to create interactive, analytic, and collaborative environments that bridge the gap between business intelligence and knowledge management" [20]. It tries to create a common ground for the collaborators by sharing objects, interpretations and tasks. The users collaborate when they share frames, which are window-like containers that give the design and behavior to data. This could be for example visualizations, sticky notes, tables, forms, charts and even application interfaces (*see figure 9*). These frames on the user's desktop are completely interactive, which means collaborators can drag out data of a shared frame.

Fig. 9. Coordinated shared and private visualizations in CoMotion® [20].

Intelligence objects can be specified, which have a yellow point on it until it has been reviewed by a user. This information tells the other team members which data has not been examined. This can be very useful for the collaboration, because collaborators can help out by exploring unexamined data and give it back, if they find something interesting or important. Another feature is the critical-question frame. There, a team member summarizes his goals, which data is important for him and why and also which data could be valuable to share with him. When a user creates a data object the system saves a creation, modification and copy history. "Therefore, on any frame, it is possible to trace the actions being planned, the interpretations motivating them, the data on which interpretations are based, and the goals they all serve" [5]. This helps to understand decisions team members made and can avoid disagreements.

5 Discussion

It is a tacit assumption that learning, communication and discovery will improve when performed collaboratively [19]. I think this is an important statement, because there are only a few experiments, which compare individual and collaborative information visualizations directly. When does collaboration really make sense? I think it is important to figure out, which tools are just nice ideas and which helps on the collaboration in information visualization. For example when collaborators work the whole day with their individual workspace on an interactive tabletop and present at the end of the day their results to the group, the tabletop display is not really necessary for the collaboration. The members could just also work with their own computers and give a presentation with a projector. Or when group members work distributed with a shared window or workspace and everybody has access to everything and can change things, it could be perhaps more confusing to the members than really help them. I think it is also to concern, that today the most collaborative information visualizations are not tailored to the particular needs of the users. An advanced collaboration does not help, if the application misses functions that are necessary for you. On the other side if a great information visualization application has only a bad designed support for collaboration it is perhaps faster and easier to communicate with the good old technologies or just face-to-face without technical help.

6 Conclusion

This paper described that the relatively less research on the field collaboration in information visualization has nevertheless brought some very interesting results. Collaborative information visualization can be very useful in the business and research world, where business people and experts are located all over the world and have to communicate and collaborate, both synchronous and asynchronous.

Investigations on which features are really reasonable in applications and which functions are used by the collaborators are now important. With the access to more and more collaborative information visualizations the users will soon make clear, which applications are helpful and which just make the whole collaboration process more complicated. In an interesting direction are moving the web-based applications. Until today the most information visualization were created and used by experts. Applications like sense.us and Many Eyes have a complete new target group and enable everybody to work with visualizations. I think these applications have a great potential, also for experiments and further investigations. Because you have a lot of different users, with various preferences and skill levels it can be a good way to analyze which features and functions work like they should.

Olson et al. write in [23] that we have perhaps someday virtual reality meeting rooms, where we can see the whole workspace of our partners and that will provide communication on a level of eye contact. They see also as a very interesting possibility "that future tools may provide capabilities that are in some ways superior to face-to-face options" [23].

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Beyond-the-Desktop Interactive Visualizations

Steffen Wenz

Abstract— There are many established information visualizations on desktop computers that rely on a regular screen and the combination of mouse and keyboard as input devices. Mobile devices, however, are becoming more and more widespread. Also, tabletop computers may soon find their way into everyday life. Existing visualizations cannot be ported to these devices due to different screen sizes and input modalities. In this paper, nine exemplary interactive visualizations across different devices are discussed, covering three different areas: photo collections, maps and scatterplots. Then, four different criteria are applied to them. The examples are categorized by data type, screen size, input bandwidth and supported tasks and techniques to reduce screen clutter. The resulting classification leads to some discoveries concerning how the examples deal with the limitations and opportunities of new devices. Photo collection tools, for example, are forced to abandon their typical file browser interface on mobile devices. Maps, on the other hand, profit from innovative methods of input. Altogether, interactive visualizations on devices beyond the desktop have the potential to develop new input and output concepts that increase usability.

Index Terms—Interactive visualizations, mobile devices, tabletop computers, taxonomy

1 Introduction

Information visualizations have been a subject of research for many years by now. Computers are becoming more and more powerful and enable complex scientific visualizations. But moreover, information visualizations have found their way into many everyday application domains. People increasingly use visual tools such as zoomable maps, charts and diagrams to navigate large data sets or visualize data themselves. For example, map visualizations such as Google Maps have found widespread use in recent years. Also, Microsoft Excel and other spreadsheet applications allow users to generate many kinds of diagrams with just a few clicks.

Fig. 1. Small screen space on a PDA [13]

However, these applications usually run on desktop computers and therefore rely on a regular computer screen for output, and a keyboard and mouse for input. Furthermore, they are tailored to the usage behavior associated with desktop computers, meaning that applications can assume that the user is seated at a desk. But nowadays, computers come in all shapes and sizes! Surface computers and large wall-mounted displays offer more screen space than desktop computers and enable new forms of collaboration in applications, but require radically different input devices and methods of usage. Also, mobile devices are becoming ubiquitous and are slowly catching up to desktop computers in terms of processing power and storage capacity, but have limited methods of input and little screen space. This issue is demonstrated in figure 1, where a file browser view, though very compact, can only display 15 data items on a PDA.

Visualizations that are designed for desktop computers cannot simply be ported to other device types. The differences in screen size, methods of input and general usage behavior have to be taken into account [6]. These can either be limiting factors, or they can enable interactive visualizations beyond what is possible on a desktop computer. In this paper, a selection of example interactive visualizations across different devices is discussed. The purpose of this is to find out how common visualizations are adapted to the characteristics of certain devices. Since this discussion should be structured in some way, a set of properties or criteria will be applied to all examples. These criteria, which are introduced in the following section, will make it possible to quickly see differences and similarities between visualizations on various devices.

2 Properties of Interactive Visualizations

There are some requirements for the criteria chosen in this paper. Firstly, they should reflect the properties of the device the visualization was designed for. Visualizations may depend on certain methods of input or output that are not available on other devices. Secondly, the criteria should contain information on how the visualization is adapted to the characteristics of its device. For example, an application on a mobile phone has to deal with the limited screen space, while an application on a surface computer may have to deal with the lack of a keyboard for text entry. The criteria introduced in this section build on previous research in the field of visualization taxonomies, which is discussed in the following subsection.

2.1 Related Work

A relatively early attempt to categorize visualizations is the task by data type taxonomy by Ben Shneiderman [12]. It assumes users are navigating a large set of structured data in search of certain information. Shneiderman proposes two criteria for classifying visualizations: data type and task. The data type describes the attributes of the data set that is to be visualized and can either be 1-, 2-, 3- or multidimensional, or temporal, network or tree data. The tasks are actions which the user may perform within the visualization tool, and can be any combination of the following: Overview, zoom, filter, details-on-demand, relate, history and extract. These tasks may seem familiar as they are based on the information-seeking mantra coined by Shneiderman: "Overview first, zoom and filter, then details-on-demand" [12].

- *Steffen Wenz is studying Media Informatics at the University of Munich, Germany, E-mail: steffen.wenz@campus.lmu.de*
- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

Table 1. Data type criteria [12]

Data type	Typical example
1-dimensional	Textual data, lists
2-dimensional	Images, geographic data
3-dimensional	Architectural models
Temporal	Timelines with (overlapping) events
Multi-dimensional	Database records with more than three attributes
Tree	Hierarchically organized data
Network	Data sets with complex relationships

The tasks proposed by Shneiderman are generic and independent of their technical implementation on different devices. However, technical limitations of input devices are a critical factor for visualizations. In [5], the design space for input devices is analyzed. Devices are modeled as combinations of sensors which measure their position in one of three linear or rotary axes. The model also allows for discrete sensors, such as buttons. Individual sensors are then combined to form devices, using different composition methods. The authors prefer this parametrical analysis over a taxonomy, as the criteria one chooses are not guaranteed to be complete and on the same logical level. The paper also deals with different bandwidths of human muscle groups to be used with input devices, and of course also of the devices itself. Based on this concept, [14] proposes an abstraction layer to allow for substitution of input devices for other, equivalent devices. The authors specifically mention the need to emulate mouse and keyboard on mobile devices. One given example is text entry on mobile phones. The phone's number keypad has to replace a keyboard - the number of keys is of course much smaller, and the model accurately predicts that multiple key presses are needed to type a single letter.

Applications developers for handheld devices have to take great care to utilize the limited screen space efficiently. For this purpose, a number of techniques have emerged. [7] attempts to categorize these techniques for clutter reduction, as the authors call it, in a taxonomy. On the top level, the authors distinguish between techniques that affect appearance of data items, spatial distortion or temporal appearance (meaning animation). Sampling, filtering, changing point size or opacity and clustering are examples for appearance clutter reduction techniques. Point/line displacement, topological distortion, space-filling, pixel-plotting and dimensional reordering on the other hand are techniques working with spatial distortion. Finally, animation can also reduce clutter. The authors also compare these techniques against each other using a set of criteria, for example if they avoid overlap or if they keep spatial information intact.

2.2 Introduction of Criteria

While the taxonomies and models explained in the previous section seem very suitable for this paper, they cannot be applied to visualizations across devices as-is. Therefore, a combination of the criteria is proposed in this subsection.

Data The first criterion is the data type, in accordance with [12]. The data type not only tells what kind of data can be visualized, but is also characteristic of the task the user is trying to solve. Also, it may indicate what kinds of data sets visualizations are compatible with. For example, tools for viewing maps, which are essentially 2-dimensional data, may also be suitable for other types of images. The possible data types are defined in table 1. It should be noted that not all visualizations fit neatly into these categories. As this is a qualitative analysis, combinations of different data types shall simply be identified as such.

Screen size Screen size differs greatly among computers and is thus the second criterion. It is directly correlated with the amount of information that can be displayed at once. But different screen sizes are usually also associated with certain user behaviors. For example, mobile phones are not only characterized by their small screen, but also by their mobility context. Users may be outside in the sun (and low-contrast text thus be hard to read) and have a limited attention span. For this reason, the general device types will be noted alongside the screen size. This criterion will make it possible to identify types of visualizations which have not (yet) been adapted to certain screen sizes and device types. For simplicity, screen sizes are grouped into three categories (see table 2), and resolution is not taken into account. This list is imprecise and by no means complete. It is designed to fit the examples discussed later in the paper and needs to be expanded to include other devices.

Table 2. Screen size criteria

Screen size	Typical devices
Small	Mobile phone, PDA
Medium	Laptop, desktop computer
Large	Tabletop, surface computer, wall-mounted-display

Table 3. Task criteria [12]

Task	Explanation
Overview	Gain an overview over the entire data set
Zoom	Zoom in on interesting data subsets
Filter	Filter out uninteresting data items
Details-on-demand	Show additional attributes
Relate	Show relationships with other data items
History	Keep a history of actions to support undo and refine
Extract	Extract interesting data subsets or query parameters

Input device Applications may also heavily depend on certain input devices. The characteristics of input methods are the third criterion. To quickly characterize an input device, some hints are taken from [5]. A mouse would be described as a combination of two linear sensors (2D), a discrete rotary sensor (the mouse wheel, 0.5D) and three binary linear sensors (the buttons). The authors of the referenced design space analysis include much more detail in their model. However, since this paper constitutes only a qualitative analysis, it can be allowed to be less precise. Given these criteria, it can be determined if a visualization can in theory be ported to a different device which offers compatible methods of input.

Task/Technique Finally, it is interesting to see how applications deal with the characteristics of the device they were designed for. The fourth criterion is a combination of the tasks proposed in [12] and the clutter reduction techniques described in [7]. The tasks are defined in table 3.

The clutter reduction techniques identified in [7] are listed in table 4. The authors explicitly leave out some techniques, such as changing color as an appearance technique. The list of criteria will have to be expanded here.

These two sets of criteria are on slightly different semantic levels. Shneiderman's tasks can be actively performed by the user. The clutter reduction techniques, on the other hand, are generally techniques used by the application to enhance usability. However, there is some overlap: Zooming is both a task and a form of topological distortion, and also, filtering can be found in both taxonomies. Also, the clutter reduction techniques are meant to deal with limited screen space. But these techniques can be universally applied to visualizations, as clutter of information is also a problem on large screens due to cognitive limitations. The application of these criteria is expected to show whether certain devices only allow for visualizations with few supported tasks. Also, applications will be comparable in what techniques they apply to deal with device limitations.

Table 4. Clutter reduction technique criteria [7]

Technique	Explanation
Appearance	
Sampling	Show a random data subset
Filtering	Show a data subset based on query parameters
Change point size	Change size of item representation
Change opacity	Change opacity of item representation
Clustering	Merge items into a cluster
Spatial distortion	
Point/line displacement	Change position of data items
Topological distortion	Distort the background, either uniformly (zoom) or non-uniformly (fisheye)
Space-filling	Arrange items as non-overlapping rectangles (tree map)
Pixel-plotting	Show data items as single pixels
Dimensional reordering	Change attribute axes
Temporal	
Animation	Animate item representation

3 EXAMPLES

In this section, nine example visualizations from three different areas are introduced. The criteria chosen in the previous section are then applied to them.

3.1 Photo Collections

Digital cameras are becoming ubiquitous, and many modern mobile phones are capable of taking high quality photos with built-in cameras. As such, more and more people carry photo collections on their mobile devices. Typical tasks when working with photo collections include finding pictures from a certain time or event, but also organizing the pictures in folders and annotating them with keywords. The data type of photo collections is not immediately clear. Photos are 2-dimensional data, but since the focus for the following applications is on navigating the entire collection, the dimensions of the visualized metadata shall be considered the data type. For example, a tool that organizes photos by their average brightness would be considered to have 1-dimensional data.

Pocket PhotoMesa The first example is Pocket PhotoMesa, a zoomable image browser for PDAs [10]. To gain an overview over a collection of photos, a lot of screen space is usually needed. The authors of Pocket PhotoMesa avoid the need for any scrolling by displaying the entire photo collection in a tree map. The photos are organized in folders, each occupying a rectangular area on the screen which is filled with small thumbnails. The user then interacts with the application using a stylus. By tapping into the whitespace inside a folder, the application zooms in to this folder. By tapping a picture in any zoom stage, it is enlarged and brought to the foreground. Users can then pan and zoom the picture, and return to the collection view by tapping the white space surrounding the picture. Interestingly, Pocket PhotoMesa is an adaptation of an application on desktop computers. The authors mention the difficulties of dealing with the small screen space and the stylus input, which offers fewer input sensors than a mouse.

TiDi Browser TiDi Browser is also an image browser for PDAs, but employs different techniques to efficiently display many pictures on a small screen [3]. It takes advantage of metadata embedded in picture files, specifically time and location information. Users usually group pictures by events which are bound to a certain time and place. TiDi Browser does not require its users to sort pictures in folders themselves. Instead, two small histograms are displayed at the sides of the screen. One of them plots photo frequency over time, the other encodes the distance of each photo to a specified home zone (thus reducing location information to one dimension). Users can then identify events where many photos were taken at the same time in the same place and quickly jump there by tapping with a stylus. The center of the screen is reserved for viewing photos. The current photo takes up about a fourth of the screen area; its file name, time and distance to the home zone are also displayed. Below the currently selected picture, a small number of thumbnails is displayed, showing the temporal context. Users can drag along the time line and bring other pictures into view. Figure 2 shows a screenshot of TiDi Browser in action.

Fig. 2. TiDi Browser plots photo metadata in two histograms to provide an overview [3]

Flux Flux is an application for photo collections that runs on a surface/tabletop computer [2]. Unlike the previous two examples, it is mainly intended for organizing photo collections, rather than just browsing through them in a given structure. Flux makes use of the large available screen area to display many thumbnails at once. It sports a tangible user interface using real-world physical interaction, meaning that users manipulate screen objects directly using their fingers or two pens. Photos can be dragged, resized and rotated at will. They react in a physically plausible way by simulating inertia and friction. Using a circular gesture, photos can be hierarchically organized in clusters or “workspaces”. These are visualized as white rectangles and can themselves be manipulated by touch gestures. The contained photos then behave as they were attached to the workspace. Photos can also be annotated using actual handwriting. In addition to this, Flux supports automatically arranging all photos by time, quality or similarity.

3.2 Maps

The visualization of geospatial data is a common application in many fields. Interactive geographic visualizations can convey more data than static maps, for example by using multiple layers of data. The examples in this section are limited to simple street map visualizations in the likes of Google Maps. In this case, the data type is 2-dimensional, as the maps are basically image data. Typical tasks when viewing a map are locating a certain place, judging distances or finding paths.

Halo + ZUI One common problem of map visualizations is that users lose their context when they zoom in on a point of interest. Several focus plus context visualizations exist to address this problem: Overview minimaps can always keep the entire map in sight, but take up some screen space and may to too small to be useful [6]. Fisheye visualizations make judging distances difficult. The authors of [1] take a different approach: Halo, which is a technique for visualizing off-screen locations. With Halo, the entire screen area is dedicated to the zoomable user interface (ZUI) of the map. It is assumed that points of interest (such as results of a location-based search) are marked with overlays on the map. If one of these points leaves the screen area due to panning or zooming, a circle is drawn around that location. The radius is calculated so that the arc of the circle is visible at the edge of the screen area. In addition to that, the opacity of the arc decreases as the point of interest moves further away. This way, users can quickly and intuitively judge the distance to that point. If the program determines that too many circles would overlap in the same area, they are clustered to form a single halo with double line strength. Halo is a device-independent concept, but it is especially relevant for small screens. As such, for the sake of this paper it is assumed to run on a small screen device using a stylus as input.

PengYo Modern phones allow for interaction methods beyond button and stylus input. Apple's iPhone is a prime example: Its multi-touch screen is the main means of interaction. Several sensors provide additional input: The iPhone has GPS support and also sports an acceleration sensor, allowing it to sense its orientation when at rest [1]. PengYo is an iPhone application for social interaction that takes advantage of these sensors [9]. It displays the position of nearby friends on a street map. (Facebook data is used for this purpose.) Friends can be "penged" simply by tapping their representative icons, upon which they receive a notification, much like Facebook's poke feature. The map is initially centered on the user's position, but can be panned by dragging the finger across the screen, and zoomed by touching the screen with two fingers and then varying their distance. This control scheme is a de facto standard for navigating large images on the iPhone, but PengYo employs another trick to enhance usability. The street maps images are loaded from Google Maps and are thus 2-dimensional, but they are displayed as a plane in 3-dimensional space in PengYo. The user can control the viewing angle by tilting the device: If the iPhone is held parallel to the earth's surface, the map is viewed straight from the top. But if the device is tilted upwards towards the horizon, or rotated, the view changes accordingly (see figure 3). The user interface serves as a metaphorical window to "hybrid space", meaning the enrichment of actual spatial data with abstract information. The user can thus examine his surroundings intuitively while preserving his position or context.

Fig. 3. The viewing angle is controlled by tilting the iPhone in PengYo [9]

DTLens DTLens is a map visualization tool for MERL DiamondTouch tabletop computers [8]. Its approach for providing a focus plus context interface is very different from the previous two mobile solutions. As the screen area of a tabletop computer is quite large, DTLens can afford to display the map in its entirety at all times. DTLens supports multiple users who interact with the tool using a multi-touch interface, as can be seen in figure 4. To view a point of interest in detail, the user creates a small rectangular fisheye lens by tapping once, or by opening and dragging the lens to the desired size with two fingers. The user has to press down both fingers firmly, or else the lens collapses when both fingers are released. These lenses serve as windows to a higher zoom level, while the information normally obstructed is preserved with fisheye distortion. DTLens offers some convenience functions: Users can change the size and zoom level of a lens, move it around on the map, and minimize it. Also, it is possible to draw overlays on objects in the lens view. If the lens is collapsed, the overlay is translated to the overview map. The global zoom level is constant, which greatly aides collaborative work. Also, the DiamondTouch screen is capable of distinguishing multiple users. The authors take advantage of this and allow each user only to manipulate the lenses he or she created.

[1] http://www.apple.com/iphone/features/

Fig. 4. DTLens supports collaboration of multiple users [8]

3.3 Scatterplots

Scatterplots are a quite universal visualization. They plot two (or three) variables of a given data set in a Cartesian coordinate system. Individual data items are displayed as points in the appropriate location. Additional data dimensions can be encoded in the appearance of the points, for example size and color. With scatterplots, it is possible to quickly see correlations between variables by the shape of the cloud made up of single data items.

Scatterplots with geometric-semantic zoom Scatterplots are generally used to visualize large data sets and as such seem unsuitable for small screens. It is vital for a scatterplot visualization to support the overview task as this is required to see trends and correlations. But also, users may be interested in details on single data items. [4] attempts to bring these features to mobile devices. The authors implemented a prototype that visualizes a book database with 7,500 items on a PDA. Two approaches to managing the limited screen size are then compared. The first approach uses geometric-semantic zoom. The user starts out with an overview of the entire collection. The date of publication and sales price are plotted on the two axes. Interaction is realized with a stylus. The user can zoom into a region of interest by tapping and holding near an item he or she wants more details on. At this point, some items may move off the screen. Thus, context is not preserved; only the labels on the axes provide some orientation. As the user zooms further by holding the stylus, the few data items still in sight transform from single pixels to white rectangles. They now contain more details on the books they represent, at first only the book title, then a picture of the cover and eventually other metadata. At the highest zoom level, a single item takes up most of the screen, with only the edges of neighboring items visible. As an alternative to this interface, the authors also developed a scatterplot visualization that uses fisheye distortion to preserve context at all zoom levels. Data item representations remain single pixels up to the highest zoom level, where they take up the entire screen.

Mobile Liquid 2D Scatter Space Another approach for a scatterplot interface on mobile devices is introduced in [13]. The authors created a scatterplot tool named Mobile Liquid 2D Scatter Space, or ML2DSS. The main feature of this visualization is the "liquid browsing" technique. One common problem of scatterplots is that items might overlap. The previous example solved this by letting the user zoom in until individual items were distinguishable. ML2DSS takes a different approach. Data items, in this case entries of a movie database, are represented as circles of different sizes. Instead of zooming, the user taps and holds a stylus near a single item or a cluster of items. The immediate area around the stylus is then magnified using a sort of fisheye distortion. The strength of this effect is controlled by the amount of force on the stylus. But instead of distorting the appearance of the data items themselves, only the distances between the circles are changed. As a result, the selected item stands out as neighboring items move to the side in a smooth animation. Users can receive details on items in a popup window. Also, they have full control over the configuration of the axes. Users can assign different attributes to axes using drop-down list, and also adjust the range using text entry. Since these are quite disruptive changes to the visualization, the transition between two different states is always animated. Figure 5 shows a screenshot of ML2DSS where the user has selected a number of items (marked blue) and is currently holding the stylus near a data item to see additional details.

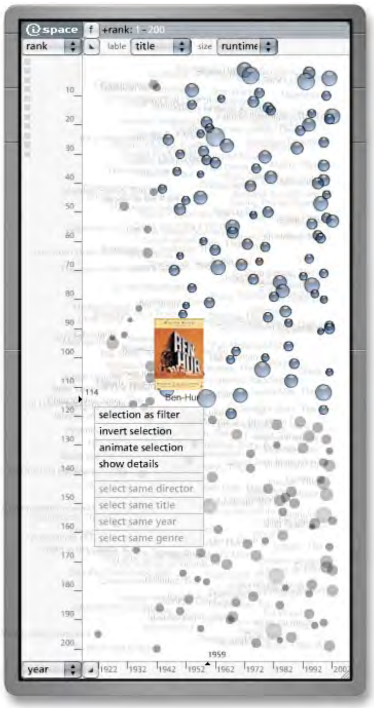

Fig. 5. Mobile Liquid 2D Scatter Space (selected items marked blue) [13]

3D scatterplots 3-dimensional scatterplots solve some of the shortcomings of 2-dimensional ones: A third dimension is added, and as such, yet more information can be visualized, and items that would be overlapping in a 2-dimensional projection are now distinguishable. However, user interaction is quite problematic. The three data dimensions still need to be reduced to two for output on a screen. The user needs to be able to navigate within the "cloud" made up by the data, and be able to select single or multiple data items. [11] shows a prototype of a 3D scatterplot on desktop computers. It allows users to load multidimensional data sets and then visualize up to five selected attributes (three axes as well as color and opacity). The information is then visualized in four linked views, each of which the user can rotate and zoom using a mouse. The prototype allows the selection of data items through brushing. Users can paint on any 3D scatterplot view; the data items that are painted over are highlighted in all views. Since this prototype was designed with Shneiderman's information-seeking mantra in mind, it supports many of the proposed tasks: It is possible to extract details-on-demand by plotting selected items in a separate histogram. Also, users can deduce relations/correlations between data items. For convenience, the prototype keeps a history of performed actions, and allows the extraction of selected data sets.

4 Discussion

In table 5, the results of the previous section are summarized. Altogether, the criteria are applicable for the chosen examples. However, in some cases, applying the criteria is a matter of interpretation and thus not deterministic. The visualizations are always designed specifically for small, medium or large screens and have well-defined methods of input. But the data type criterion is at times not easily applicable to the examples. Photo collections are hard to categorize. Not the pictures themselves, but the context in which they were taken is visualized. This is highly abstract information. In the end, however, all examples reduce this complexity by choosing only a few numerical dimensions to visualize. For example, Flux can sort pictures by their timestamp, quality and similarity, each of which is implemented as a 1-dimensional scalar value. This way, abstract information can be reduced to fit the data type criterion. Although intended for information visualizations by Shneiderman in [12], the data type criteria seem more suitable for scientific visualizations.

A taxonomy is "useful only if it facilitates discussion and leads to useful discoveries" [12]. A quick look at table 5 shows that all examples require at least 2-dimensional input. This is due to the fact that all examples let the user select or manipulate data item representations in 2-dimensional screen space. Examples that require only two dimensions of input are in principle portable to other devices that offer at least the same input bandwidth, for example a desktop computer in combination with a mouse. Pocket PhotoMesa and ML2DSS were ported from a desktop computer to PDAs and thus had to be adapted, since a stylus supports fewer modes of operation than a mouse [10]. Applications that run on tabletop computers, namely DTLens and Flux, take advantage of multi-touch and are not compatible with devices that do not offer this functionality.

The most interesting of the criteria are the tasks/techniques used by the visualizations. As mentioned before, the tasks as defined in [12] are actions the user can perform while seeking information, whereas the techniques as defined in [7] are mostly performed automatically by the application to reduce clutter. Visualizations for large or medium screens support 4 tasks on average, whereas small screen visualizations support only 2.7. On the other hand, small screen visualizations employ 4.3 clutter reduction techniques on average, compared to 3.7 for large or medium screens. This is not a proper statistical analysis, as the sample size is very limited and the criteria are not deterministic. But it is nevertheless an interesting observation. The medium/large screen applications all have more screen space and higher bandwidth methods of input. This seems to enable the support of more tasks. Especially relate, history and extract can be seen as convenience functions and are rarely implemented in the small screen examples. The additional controls needed to support these tasks would take up screen space and complicate the usage of the visualizations. Also, the clutter reduction techniques are intended for small screens by the authors. As such, it seems logical that they are used less frequently on medium and large screens.

Some tasks and techniques are common to all examples: All but one of the visualizations make use of animation of some sort. For example, DTLens animates the closing or minimizing of lenses, while ML2DSS animates selected data subsets to make them stand out from the rest of the data. Also, all examples with the exception of TiDi Browser support the overview task, and all but two support zooming. Some tasks and techniques are specific to certain types of applications. All map visualizations only support the overview and zoom tasks. Additional tasks would only be needed for more complex overlays. But since all examples focus on navigation within the map itself, zooming and panning suffice. Photo collections support more tasks, such as filter and relate. This makes sense, since users may want to filter large photo collections by their attributes, or see which photos relate to each other. The scatterplot examples all supported the details-on-demand task. The reason for this is that items in a scatterplot are only abstract representations of the original data. Once a user has navigated to an item of interest, it is necessary to provide additional attributes that were not visible in the overview visualization.

The visualization of photo collections is a very common task on desktop computers. Many tools for this purpose borrow heavily from the typical interface of file browsers. Figure 6 shows a photo collection viewed in the Microsoft Windows Vista Explorer. Google Picasa may arrange photos in "albums" instead of "folders", but the interface is still similar to that of a file browser, specialized for photo organization tasks [2]. The photo collection examples in this paper run on PDAs or tabletop computers and cannot use a mouse and keyboard for input.

[2]http://picasa.google.com/support/bin/answer.py?answer=93183#organize

Table 5. Visualizations and criteria

Visualization	Data type	Screen size	Input	Task/Technique
Pocket PhotoMesa	Photo collections (folder structure)	Small (handheld)	Stylus (2D)	Overview, zoom; Clustering, uniform topological distortion (zoom), space-filling (tree maps), animation
TiDi Browser	Photo collections (1D temporal, 1D distance)	Small (handheld)	Stylus (2D)	Filter, details-on-demand, relate; Filtering, pixel-plotting (histograms), animation
Flux	Photo collections (1D temporal, 1D quality, 1D similarity)	Large (surface computer)	Multi-touch (2*2D)	Overview, zoom, filter, relate; Filtering, change point size, clustering, point/line displacement (reordering), animation
Halo + ZUI	Maps (2D) + overlay (2D)	Small (handheld)	Stylus (2D)	Overview, zoom; Change point size, change opacity, clustering, uniform topological distortion (zoom), animation
PengYo	Maps (2D) + overlay (2D)	Small (handheld)	Tilt-sensor (3D), multi-touch (2*2D)	Overview, zoom; Change point size, topological distortion
DTLens	Maps (2D) + overlay (2D)	Large (surface computer)	Multi-Touch (2*2D), discrete touch strength (strong/normal)	Overview, zoom; Non-uniform topological distortion (fisheye), animation
Scatterplot with geometric-semantic zoom	2D	Small (handheld)	Stylus (2D)	Overview, zoom, details-on-demand; Change point size, topological distortion, space-filling, pixel-plotting, animation
Mobile Liquid 2D Scatter Space	2D + size/opacity coupled (1D)	Small (handheld)	Stylus (2D), continuous touch strength (1D)	Overview, filter, details-on-demand, relate; Filtering, change point size, change opacity, point/line displacement, non-uniform topological distortion (liquid effect), dimensional reordering (axes assignment), animation
3D scatterplot	3D + color (1D) + opacity (1D)	Medium (desktop computer)	Mouse ("2.5D")	Overview, zoom, details-on-demand, relate, history, extract; Uniform topological distortion (zoom), pixel-plotting, dimensional reordering, animation

Therefore, they are forced to depart from the file browser metaphor and develop completely different interface concepts. For example, Flux simulates physical properties of the photos so that the user is reminded of sorting actual photos on a table. TiDi Browser uses metadata embedded in the photos to cluster them by events and locations, instead of relying on a given folder structure. These new interaction concepts can be more tailored to the specifics of photo collections as a data type and to the typical tasks performed with them. Therefore, the development of photo collection visualizations for small and large screens might result in better interfaces that will in the future influence the way photo collections are visualized on desktop computers.

Fig. 6. Photo collection in Microsoft Windows Vista Explorer [3]

The map visualization examples show that interaction with a map is possible on mobile devices through intuitive methods of input, such as dragging the map to pan. Each of the three examples focuses on a different aspect of map visualizations. Halo is concerned with the visualization of off-screen locations, which in turn is intended to cope with the limited screen space on small screen devices. PengYo uses acceleration sensors to intuitively adjust the 3D viewing angle of the map and thus concentrates on the input method rather than the visualization itself. DTLens enables collaboration through its multi-user, multi-touch interface. Therefore, each example aims to perfect a different component of interactive map visualizations. These could be combined to leverage all of the advantages. In contrast to the photo collection examples, which were mainly driven by input device limitations, map visualizations take advantage of new methods of input which increase usability. An example to support this hypothesis is the multi-touch capability of the iPhone. The iPhone uses multi-touch prominently to pan and zoom images and maps. Since this method of input turned out to be very successful, it has by now been ported to the new generation of MacBooks, which have multi-touch touchpads [4]. Also, Windows 7, the upcoming version of Microsoft's operating system, will support multi-touch input [5].

Scatterplots are still a domain of desktop computers. They are used to visualize large data sets. Examples for scatterplots on mobile devices are still rare. But they show that scatterplots are capable of displaying relatively large data sets on small screens as a lot of information can be shown at once. Therefore, more scatterplot visualizations on small screen devices may be developed in the future. The 3D scatterplot example discussed in this paper was developed for desktop computers, but has the potential to be ported to tabletop computers. It would benefit from the higher screen area and resolution. Also, the main interaction method is brushing to select items, which could be realized with a touch interface.

[3] http://www.microsoft.com/windows/

[4] http://www.apple.com/macbook/

[5] http://www.microsoft.com/windows/windows-7/whats-new-possibilities.aspx

5 Conclusion

The criteria and the examples in this paper led to some interesting insights. Visualizing photo collections is a common application on desktop computers, but existing tools are inspired by file browsers and rely on a keyboard and mouse. This may not be the most effective concept to visualize photo collections, but people are simply used to working with file browsers. Photo collections on other devices are forced to abandon the file browser metaphor due to input and screen size limitations. As a consequence, this could introduce people to new concepts more suitable for photo collections, which might be ported to desktop computers in the long term. Interactive maps are also a very common application on desktop computers and mobile devices alike. Maps can take advantage of new methods of input offered by mobile devices. Multi-touch user interfaces for navigating 2-dimensional data such as images and maps have proven to be very successful on mobile devices. This realization has in turn started to influence desktop computers: Multi-touch will be supported by upcoming Apple and Microsoft operating systems, and has already found its way into some current laptops. Scatterplots are used to visualize large data sets in science and business, but are less common in consumer applications. However, they have potential to increase the usability of small screens since many data items can be visualized at once. Traditional visualizations for large data collections, such as column views, fill up small screens very quickly. In contrast, scatterplots visualize single data items as small circles or even single pixels, and show additional metadata only when an item of interest has been found.

The data type criterion was at times difficult to apply and seems more suitable for scientific visualizations that use numeric data. For example, photo collections are quite abstract data. The photos themselves may be 2-dimensional, but the examples in this paper focus on navigating within entire collections of photos, for example to find certain events. But in the end, this abstract task is accomplished by taking metadata such as a photo's timestamp or location into account - these additional attributes have a concrete data type.

The tasks and techniques supported by the examples were in some cases a matter of interpretation. Many tasks and techniques are somewhat abstract in nature and thus not deterministic. Still, the criteria chosen in this paper led to the desired results. One outcome was that applications on small screen devices seem to support fewer tasks, but apply more clutter reduction techniques. This makes sense since bigger devices have more screen space to position controls for additional functions, whereas applications on small devices have to use the available screen space as efficiently as possible and therefore apply clutter reduction techniques more aggressively.

The clutter reduction techniques proposed by [7] seemed somewhat arbitrary and overall incomplete. Using different colors to encode information was not included in the appearance criteria, but it was used by the 3D scatterplot prototype in [11]. The space-filling technique, described by the authors as a "non-overlapping rearrangement of large, rectangular points" [7], is mostly implemented in tree maps in practice, which is not reflected by its name. Also, it is unclear why the pixel-plotting technique is defined to encode information in single pixels only. The ML2DSS example displays data items as circles, i. e. identical geometric shapes, the only difference to single pixels being that items can vary in size and overlap partly.

These shortcomings could be addressed by conducting a more comprehensive survey of visualizations on various devices, including both scientific prototypes and commercial applications. The list of tasks and techniques could be expanded and refined in this way. Additionally, common techniques to compensate for input device limitations might be discovered. This paper was limited to only three application domains for visualizations. But of course there are many more types of visualizations which are appearing on small and large screen devices. This is an ongoing process, and as such it can be expected that entirely new concepts to visualize information on devices beyond the desktop will emerge in the future.

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Visualizing Sensor Data

Stefan Zankl

Abstract— As costs and size of microprozessors and sensors decrease, interest in using sensor networks for various applications of the most different kinds grows. According to this fact rises the need of exploring best ways of sensor deployement, data acquisition from a network as well as visualizing the sensed data. This paper deals with the last of this needs through the contemplation of sensors and their data delivery, of visualization criterions and the try to merge sensor data and visualization. Sensor networks can vary from very small to very big depending on the number of sensors included and the number of measurands, a sensor node is able to sense. Hence exists a wide range of different applications, sensor networks can be used at, creating an even wider range of possible visualizations. Besides the application the raw sensor data as well as position and time of a measurement are the main aspects when deciding on a visualization.

Index Terms—sensor data, visualization, sensor network, extraction, application

1 Introduction

Due to the technical progress of the last decades, which enables the production of small sized micro processors and sensors at a low cost, a new research area has developed, dealing with wireless sensor networks. These networks mostly consist of a large amount of tiny sensor nodes, which combine sensing, data processing and communicating components [5]. To ensure these three functions the nodes feature a number of sensors, a micro computer and a wireless communication device [8].
The general purpose of such a sensor network lies in its deployment in or very close to a phenomenon a user wants to observe. After a network is deployed the mere act of sensing includes the following three working steps. Step one is the measurement of a physical property by one of the sensors. The second step involves the micro computer which computes the data delivered from the sensor depending on the desired result. In a third step the computed data has to be transmitted from the sensor node to its destination, where it is often stored in a database. *Fig. 1* shows how data from sensor node A could get to the user.

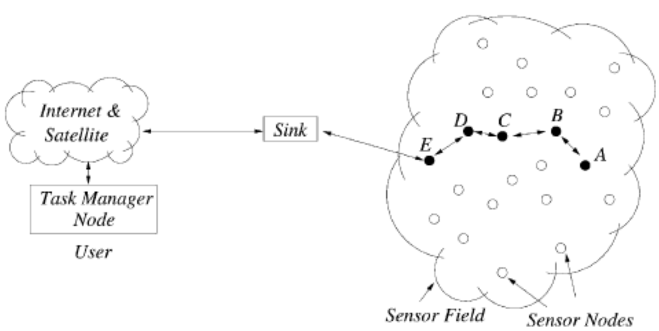

Fig. 1. Sensor nodes scattered in a sensor field [5].

After several hops inside the sensor field the sent information reaches a so-called sink, which communicates with a task manager node via internet or satellite. The sensor network itself is thereby a self-organizing network with a certain protocol stack used by the nodes and the sink.
After these three steps, which have been enquired rather widely, follows a fourth step, which is rather poorly explored, namely the visualization of the sensor data. Just seeing the raw data of a sensor network stored in a database mostly does not fulfill the needs of the users. So the data need to be analyzed and shown to the user in a way, where information can easily be gained from them. Which kind of information can be gathered from a sensor network, depends on the application area the network is used in.
Due to the enormous amount of different sensors (see 2.1) there is a wide range of such application areas for sensor networks. One of these areas are military applications. Sensor nodes are used here for reconnaissance of opposing forces and terrain or targeting. Environmental applications like forest fire detection or tracking of animals represent another interesting area. Even in medicine there can be gathered benefits by the use of sensors for example in monitoring a patients physiological data [5]. An overview of possible application areas is given in *Table 1* adopted from White [21].

Table 1. Fields of application for sensors [21]

Agriculture
Automotive
Civil engineering, construction
Distribution, commerce, finance
Domestic appliances
Energy, power
Environment, meteorology, security
Health, medicine
Information, telecommunications
Manufacturing
Marine
Military
Scientific measurement
Space
Transportation (excluding automotive)
Other (specify)

Only by knowing which kind of sensors are used in a network, which data these sensors deliver and which goal the user wants to reach by sensing a phenomenon, there can be chosen a meaningful visualization.
The remainder of this paper is organized as follows: Section 2 will contain a closer look at sensors and which data they produce. Section 3 provides an overview of what has to be taken into account when visualizing data. A discussion about the assignment of sensor data to a visualization taxonomy is found in Section 4. Section 5 contains the conclusion of the paper.

- *Stefan Zankl is studying Media Informatics at the University of Munich, Germany, E-mail: zankls@cip.ifi.lmu.de*
- *This research paper was written for the Media Informatics Advanced Seminar on Information Visualization, 2008/2009*

2 SENSORS

As mentioned above sensor networks consist of a large amount of tiny sensor nodes. The following section therefor will deal with sensors by looking at several of their aspects. It will be shown different classifications of sensors, ways to gather data from sensors and the relevance of the position of a sensor and the time of its measurement. At the end of the section an existing sensor network will be introduced.

2.1 Different kinds of sensors

A sensor can be defined as "a device that receives a stimulus and responds with an electric signal ... [, whereby] stimulus is the quantity, property or condition, that is sensed" [11].
There exists an enormous variety of sensors, based on their measurands, which are shown in *Table 2*. All these physical properties can be recognized by sensing components. In a sensor node there are often found combinations of different sensors to explore a phenomenon not only by one aspect.
The classification of a sensor can be made simple or complex. An example of a simple classification would be to differentiate between active and passive sensors. A passive sensor responses directly to a physical stimulus without the need of an additional energy source by transforming the stimulus energy into an electric signal. An example here would be a photodiode. On the other hand active sensors are connected to an external power source, which is modulated to create the output signal. For example a thermistor has a certain resistance at certain temperatures. This means the temperature can be measured by detecting variations in the voltage across the thermistor [11].
Sensors can also be classified as absolute or relative, whereby the difference lies in the selected reference a measured value is related to. An absolute sensor would refer on an absolute physical scale, like for example the thermistor mentioned above to the absolut temperature scale of Kelvin, while the signal of a relative sensor has to be seen in perspective to a given value. For a relative-pressure sensor such a value might be the atmospheric pressure to build the baseline for the sensors measurements [11].
A complex classification of a sensor could be a description of all of its properties: Its measurand, its technological aspects (sensitivity, speed of response, ...), its detection means, its conversion phenomena, its materials and its application area. Examples for this classification are found in [21].

2.2 Sensor data

All the different kinds of sensors share the same purpose. They ought to respond to a physical property by converting it into an electric signal, which can be operated on to produce an output [11]. How this physical conversion is managed inside the sensor node is of no importance for our goal of visualization. The importance lies in the delivered data such as for example the momentary temperature at the sensors position.
Depending on the application there are different ways to gather data from the sensors. By having a look at the applications themselves, they can roughly be seperated into two parts: Analysis and event detection. In an analytical application the user wants to access data at a certain time, to watch the status of a phenomenon. For example when tracking an animal the user wants to know what is the animals momentary position. Or the user wants to trace a certain development by looking at fresh data and comparing them to older data. On the other hand sensors are used to detect events. An example here would be a motion sensor of an alarm mechanism that informs the system of an intruder.
So there are two main ways to gather data from sensors: on one side sending a query to a sensor, which answers it, or on the other side getting a message from the sensor itself. Wireless sensor networks mostly use the first method due to numerous constraints like for example the power costs of communication. There have been developed systems to simplyfy the creation and spreading of queries. One of these systems is TinyDB [16], which uses a SQL-like query language called TinySQL and works on sensor nodes using TinyOS [3] as operating system. The user can create simple 'SELECT ... FROM ... WHERE ...' queries and define a certain period in which the query shall be executed by a 'SAMPLE PERIOD' clause [7]. The query is spread over the network and nodes that accomplish the queries goal send back data to the user. If the user wants to collect data to observe a phenomenon over time, it is useful to store the measured data in a database. Otherwise the momentary results have to be shown to the user in an understandable way, as the query only creates a table full of measurements.
TinyDB also supports event detection: If a node shall react to a certain event, it must know what query to start at which event. That means that an 'ON EVENT ... SELECT ... FROM ... WHERE ...' definition must be found in the nodes code. On occurrence of the event a node or several nodes start sensing and send their measured data back to the user, which has to be informed by the system about the detection of the event [15].

2.3 Relevance of position and time

Beneath the data measured by sensors two other values have to be considered as important. On the one hand a user of a sensor network wants to know, where the sensor, that delivers the data, is to be found. On the other hand it is useful to know, when a sensor caught an event. According to Roemer and Mattern [18] there are different use classes of space and time in sensor networks. One of these use classes would be the interaction of an external user with the network. The user, which may be a human operator or a computer system, often defines special "regions of interest in spacetime such as 'only during the night' or 'the area south of ...'" [18] to accomplish a certain goal of an observation. Another use class is the interaction of the sensor network with the real world. As many distributed sensor nodes observe the same phenomenon, it is necessary to use data fusion to gain reliable information, whereby space and time are important components of data fusion. Also different instances of a physical phenomenon detected by a sensor network can only be distinguished by spatial or temporal aspects. These are only some reasons for the importance of position and time in sensor networks.
When looking at the position of a sensor node in a network, there can be distinguished two different kinds of deployement: A node can be installed in a fixed place or distributed arbitrarily in a wide area. The first method is rather suitable for smaller networks with only a few nodes, while a network of some hundred nodes can for example be spread by an airplane over a research area.
When installed in a fixed place, it is no problem to define the position of a node. The application collecting the sensor data can for example hold a table of all the sensors in the network, containing among others the nodes ID and its position. When a node delivers data, it includes its ID, so the application can check, where the node is positioned.
When distributed arbitrarily a node does at first not know its own position, but has to compute it. This can happen either by the nodes sensing components or by making use of the connectivity inside the network. Furthermore a node can on one side achieve its relative position inside the network or on the other side its absolut position in a global coordinate system. There are several different approaches for node positioning explained in [17]. An example for a node positioning system would be the Recursive Position Estimation, where 5 percent of the nodes are GPS-enabled and always know their exact position, while the other nodes gain their position by trilateration to such GPS-nodes or nodes, that already have computed their position [6].
Also time synchronization is important inside the network. Either the nodes are equipped with receivers for time infrastructure, which is not suitable for large networks with tiny sensor nodes due to energy, size or cost constraints, or the time synchronization has to be obtained in the same ways as the node positioning [6]. At this point there can be used a global or a local time scale, whereby the second one might be easier to handle.
In the cases of node positioning and time synchronization the nodes deliver their position and the timestamp of the measurement together with the sensed data to the user.

2.4 An existing sensor network

An example of an existing sensor network would be the collaboration of SensorWare Systems [2] with the Huntington Botanical Gardens in San Marino, California, since June 2000. In August 2001 there were deployed eleven so called Sensor Web pods, which are building a permanent wireless sensor network system for environmental monitoring. The system was extended to a 20-pod system in January 2003 and improved by a newer version of the pods in June 2003. *Fig. 2* is showing such a pod standing in the Huntington Botanical Gardens.

Fig. 2. Sensor Web pod in Huntington Botanical Garden [1].

These pods are equipped with a radio for communication with other pods, a microcontroller, a battery pack with solar panels, a special packaging to ensure weather resistance and a sensor suite. This suite contains different sensors to measure air temperature, air humidity, and light levels as well as soil temperature and soil moisture at two different depths. Additional measurements hold information about the pods health status like its battery status or its own temperature. Measurements take place every five minutes. The Sensor Web is not a typical wireless sensor network as it uses relatively big sized pods and omni- as well as bidirectional communication. This means a pod broadcasts its measurements to all other pods. Thereby a pod itself can gain information from four different types of data: Its own measurements, data from one or more other pods, commands of an external user or commands of another pod. This can for example help a pod to check its own measurements by comparing them to those of surrounding pods. One selected pod thereby acts as portal pod, which is linked to an external web, where the user can access and analyze the collected data [10].
In 4.3 the visualization of the Sensor Web in the Huntington Botanical Gardens, which can be accessed by anyone over the internet, will be shown and discussed.

3 Information Visualization

For the visualization not only of sensor data but any data it is necessary to have a look at well-known and accepted principles of information visualization. So this section introduces a data type taxonomy of information visualization as well as tasks, user normally want to perform on visualizations, based on findings of Shneiderman.

3.1 A data type taxonomy

There are many different ways to visualize data like graphs, charts, maps and diagrams [13]. Depending on the given data there has to be chosen a visualization, that is most suitable.
In this context Shneiderman [19] as well as Card et al. [9] present a taxonomy of information visualization based on data types. Seven such data types are proposed by Shneiderman:

- 1-dimensional
- 2-dimensional
- 3-dimensional
- Temporal
- Multidimensional
- Tree
- Network

Card et al. use the same taxonomy except for temporal data, as they only deal with the use of space when encoding abstract data.
Each item of a data type has among all of its attributes certain attributes, that assign it to this very same data type. Every data type provides certain presentation and interaction techniques as well as problems concerning the user.
1-dimensional data can be regarded as linear data, mostly lines of text arranged sequentially. The presentation depends on chosen font, color or size, while interaction contains overview, scrolling or selection. The users problems include finding an item or items with certain attributes.
2-dimensional data items are placed on a plane or map, whereby the scale is an important factor in presentation and interaction. Finding adjacent items or paths between items as well as accessing an items remaining attributes can become problematic for the user.
A real-world object with volume and relationships to other objects is assigned to 3-dimensional data. It is hard to represent 3-dimensional data due to the many problems in respect of the user like for example orientation in 3-dimensional-space or recognizing above/below and inside/outside relationships.
If an item holds a start and an end time, it belongs into the temporal data type. A common presentation would be a time line where the user has to cope with finding items in a certain time period or moment and with overlapping items.
Multidimensional data can be found in most relational databases, where items have n attributes and are therefor n-dimensional. A way to visualize those data is to lower down dimension to two and use 2-dimensional visualisation in combination with a way to access the remaining attributes like multiple views. This accessing can build a problem for the user besides finding correlations or clusters among the items.
A tree is a hierarchy, where each item is linked to one parent item (except for the root). Attributes can be held by the item as well as by the link. Common presentations are diagrams or treemaps. A user must deal with the number of levels or the number of children of an item as well as with the differences between items on the same or different levels.
Items, that are linked to an arbitrary number of other items, are summarized in the network data type. This type can also be visualized by node and link diagrams, but the problems of the user contain for example the search of the shortest or least costly path between two items.
Additionally there exist several variations and combinations of these seven data types [19].
Looking at 2-dimensional data a very common visualization would be graphs. But still not every 2-dimensional data can be shown in every different kind of graph. It is for example not useful to visualize independent data like the daily average temperature of one week at a certain place with a line graph, as a line graph requires a quantitative variable with continuous values as its x-axis. In this case a bar graph would be reasonable, as relative point values are compared. A third kind of graph would be a scatterplot, in which a relationship between two variables is shown, whereby several items can share the same

value at either axis [13].

3.2 Visualizing for a user

Not only the data, that need to be visualized, are important for the choice of a visualization, but also the person using it.
Besides his seven data types Shneiderman also proposes seven tasks a user generally wants to perform. These seven tasks are [19]:

Overview Gain an overview of the entire collection.

Zoom Zoom in on items of interest

Filter Filter out uninteresting items

Details-on-demand Select an item or group and get details when needed.

Relate View relationships among items.

History Keep a history of actions to support undo, replay, and progressive refinement

Extract Allow extraction of sub-collections and of the query parameters.

When designing a visualization there should always be realized those seven tasks in the presentation and ways of interaction.
Another aspect that needs to be considered is human perception with capabilities like preattentive processing. Preattentive processing means, that the human low-level visual system can detect certain visual properties in an image within 200 to 250 milliseconds. Some of this properties are for example the size, color, shape, density or intersection of items. They can be used to draw attention on a special target. Yet a combination of properties like color and shape should be avoided, as it normally cannot be detected perattentively [12].
A further characteristic of human perception is, that there exist special color encodings for certain properties, like for example the color encoding of temperature. In our culture hot temperatures are linked with the color red, while cold temperatures are linked with blue as for example can be seen on water taps. This encoding is based on psychological reasons like experiences with fire, which is red and hot, or ice, which is blue and cold. When visualizing data of a temperature sensor, it would be reasonable to stick with that encoding, which means to use a blue-to-red color scale, to avoid misinterpretations.

4 Visualizing Sensor Data

After a closer look at sensors and some principles of information visualization both topics have to be combined to achieve a visualization of sensor data. This section therefor shows how to extract usefull data out of the sensor data and how to simplyfy the choice of a suitable visualization. At the end the visualization of the existing sensor network mentioned in 2.4 will be shown and discussed.

4.1 Aggregation and extraction of useful sensor data

When it comes to the visualization of sensor data the first question to be asked is: Which data shall be shown?
In a sensor network that delivers multiple continuous data, it is nearly impossible to show all the data. At this point the needs of the user have to be considered. For example when monitoring a factory process a user is interested in abnormal data like a pressure value, that is too high.
For the extraction of usefull knowledge out of raw sensor data there can be used data mining techniques. But before this techniques can be applied, the data need to be prepared to increase efficiency. This so called preprocessing of the data includes the following four steps:
First there must be selected the relevant attributes, which shall be considered in the data mining process. Often a user is interested in spatially or temporally restricted values like the data out of a special region or period of time.
The second step involves cleaning the data, as sensor networks can produce 'dirty data'. These dirty data can be separated into two fields, namely missed readings and unreliable readings [14]. Missed readings result for example from broken nodes, nodes, which are out of power, or communication losses inside the network, while unreliable readings have their origin in broken sensors, that still deliver faulty values (so-called outliers). There might also be a kind of noise contained in the data caused by minor variations in the individual sensor values.
After the data are cleaned, they have to be reduced for example by aggregation to speed up the later process of data mining.
An additional acceleration of the data mining process will be achieved by the last step, where the dimension of the data is reduced [20].
There are several data mining techniques, which can be used on sensor data. According to [20] there can be distinguished four different tasks, the single techniques can be assigned to, by regarding the purpose of the sensing progress:
The first task would be Predictive Modeling. Thereby values measured in the past are used to design a model, which allows predictions for values in the future like for example the amount of snow in winter.
Cluster Analysis builds the second task. The goal in here is to group items of a data set by similarity of attributes. This leads to the formation of clusters, about which can be made several statements.
In Association Analysis strong co-ocurrence relationships between events are taken into account to create rules at what conditions, which means what kind of data, an event is likely to happen.
The last task is called Anomaly Detection. As its name says, it aims to discover abnormal values in a data set, which mostly allude to unusual activities in the sensed phenomenon.
2.2 contains a description how to gather data from a network. This description referes to a special computational model, namely a centralized model. This means, that all data of the network flow to a central computer, where they are treated. In large scaled sensor networks this leads to a lot of communication and therefor costs of energy and bandwidth. A different approach would be a distributed model of computation. In this case every sensor would have to compute partial results out of its measurements before communicating them to other nodes. This is more reasonable for large scaled sensor networks, but requires every sensor to have an adequate microprozessor onboard [20].

4.2 Visualizing given data

After choosing the relevant data there has to be found a visualization to present these data efficiently.
Due to the enormous variety of application areas (see *Table 1*) it is hard to assign a special visualization to a certain kind of sensed data. Instead the data are classified to narrow the range of possible visualizations and thereby simplyfy the choice. *Table 3* shows such a possible classification of given sensor data depending on their dimensions. The sensed data always have more than one dimension. As mentioned in 2.3 position and time of a measurement always play a certain role when analysing the data. So the columns of the table represent the spatio-temporal dimensions of sensor data. The temporal aspect is thereby divided into momentary, which means an instantanous on-demand value, and continous, which means values of a certain time period, while the spatial aspect is seperated into relative and absolute values (see 2.1). The columns are therefor split into four parts, as they are divided twice. The rows of the table stand for the dimensions of a sensor, which are based on the number of different sensing components a sensor can own. They can differ from 1- to multidimensional. The entries of the table consist of the data types of Shneidermans data type taxonomy [19]. This means, that a certain n-dimensional sensor with regard to the temporal and spatial aspect belongs to one of these data types. Examples for visualizations of the different data types can be found in Shneidermans paper. The temporal data type is not included, as the temporal aspect is encoded as a further dimension of the data.
As can be seen, the dimension of sensor data grows by one, when regarding the temporal progression of the value, and grows by two, when regarding the absolute position of a value, as the absolute position is thought to be given by a x- and a y-value not regarding the z-axis of

Table 3. Classification of sensor data. Columns represent the spatio-temporal aspect of sensor data, divided into relative and absolute position(, whereby the absolute position is given by a 2-dimensional value for the x- and y-axis of space,) and for each of those divided again into momentary and continuos temporal values. Rows represent the dimensions of a sensor, which means the number of its different measurands. Entries refer to Shneidermans data type taxonomy [19].

	Spatio-temporal			
	relative		absolute	
	momentary	continuous	momentary	continuous
1-dimensional	1-dimensional	2-dimensional	3-dimensional	multidimensional
2-dimensional	2-dimensional	3-dimensional	multidimensional	multidimensional
3-dimensional	3-dimensional	multidimensional	multidimensional	multidimensional
multidimensional	multidimensional	multidimensional	multidimensional	multidimensional

space.
Depending on the final dimension of the sensor data, there has to be designed a suitable visualization, that fits the needs of the user. For example a temperature sensor in a factory, that monitors the temperature of a machine to ensure its functionality, would be a 1-dimensional sensor (= temperature) with a relative position (= machine x) and a continuous measurement. Its data are therefor, regarding to *Table 3*, 2-dimensional and could be shown in a line-graph.

4.3 An existing visualization

An example of a visualization of a sensor network is shown in *Fig. 3*. There can be seen the user interface of the internet livestream of the Sensor Web pods in the Huntington Botanical Garden presented in 2.4. This webpage offers three different views on the sensor data: A temporal view, a spatial view as well as an icon view [4].

As can be seen in *Fig. 3* the temporal view shows five line graphs and an interaction panel. The line graphs show the progression of the measurement of air temperature, humidity, light flux, soil moisture and soil temperature done by the four pods 0, 5, 14 and 15 over the last 72 hours. The interaction panel offers the possibility to change the style, scale and data in the graph. Here can be changed the style of the plot (for example from lines to points), the length of the time interval, the number of pods (up to all 20) and charts (between one and five) as well as the parameters shown in the plot out of all possible measurement values mentioned in 2.4.
The location of the pods in the Huntington Botanical Garden can be seen in the spatial view. There is presented a picture of the area taken from the sky, where spots labeled with the number of a pod represent the pods. There may be mentioned, that not all pods are shown. In another interaction panel the user can choose, which value (temperature, humidity, ...) from which point of time shall be shown. The value of a sensors measurement together with its ID and the time of the measurement becomes visible in the upper right corner of the screen, when moving the mouse over the spot representing the sensor. The spots themselves are coloured in red, yellow and green, what indicates, if the measured value lies in a normal range (green), approaches a critical treshold (yellow) or has already crossed it (red). White colour means that the sensor is disabled. A click on an enabled sensor spot shows a line graph of the measurements of the last twelve hours done by this sensor.
In the icon view there can be seen five rows of 20 traffic light, each of them representing a sensor pod and each row representing a sensing parameter, which can again be chosen out of all parameters. The color of a traffic light indicates the same assignment of a value to a range, that was used for the spots in the spatial view. Also moving the mouse pointer over an icon or clicking on it has the same effect as in the spatial view. In the interaction panel there can be chosen the moment of the measurement.
As the pods can measure up to ten values (=multidimensional), have a relative position in the garden and the user is interested in continous values for the temporal view, there are multidimensional data to visualize, regarding to *Table 3*. For gaining an overview over the system and observing single pods the seen visualization is surely suitable. But for a deeper analysis of the conditions in the Botanical Garden or the detection of certain developements other visualizations with aggregational computations might be more useful. But this visualization is open to everybody on the internet, so the scientists at the Huntington Botanical Garden will most surely have their own, better visualizations.

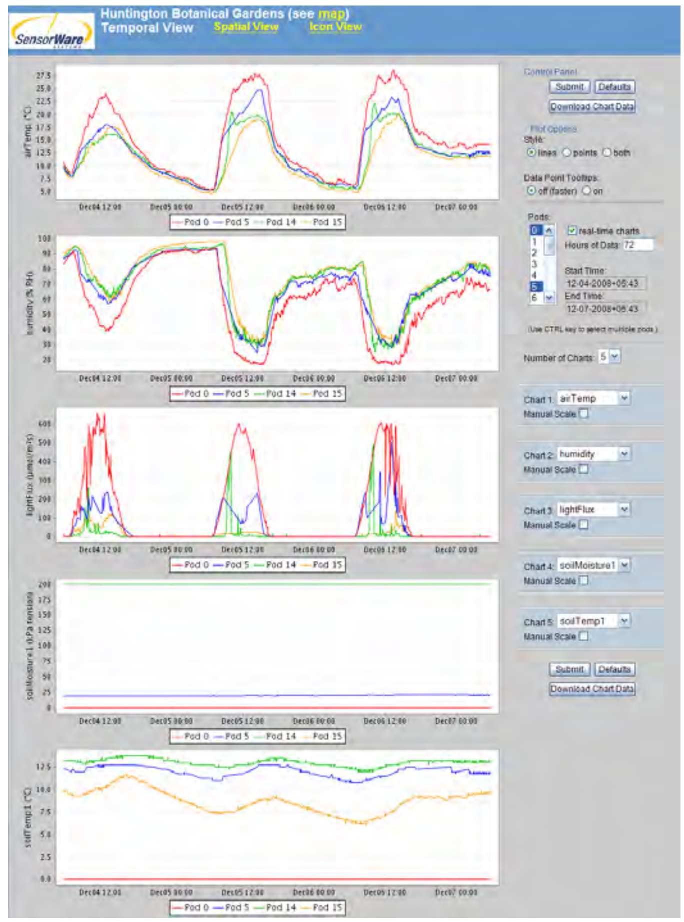

Fig. 3. Visualization of measurements of Sensor Web pods in Huntington Botanical Garden [4].

5 Conclusion

With the growing interest in sensor networks and their wide range of applications rises the need of meaningful visualizations of the sensed data. This paper proposes a classification of sensor data, based on the dimensions of the data and a taxonomy of visualizations by data types adopted from Shneiderman [19].
Before the formulation of such a classification there must be consid-

ered several aspects. There exists an enormous variety of measurands, that can be sensed. As a reaction on a stimulus a sensor produces an electrical signal out of which a special value is computed. Sensor nodes in sensor networks mostly contain more than one sensor and therefor produce different kinds of data. These data have to be acquired from inside the network and to be delivered to an application, which handles them. The handling can thereby consist of the storage of the data in a database as well as the visualization of the data. A visualization of data shall always contain information collected from the data, which has to be presented to the user in an understandable way. So besides the given data a visualization depends on the informations, the user wants to gain. But due to the variety of sensors grows the number of possible applications and therefor the needs of the user. Consequentially it is nearly impossible to give an always valid solution when to use which kind of visualization. Instead the focus lies on looking at the data, a sensor produces, and assigning them to Shneidermans data type taxonomy, in order to choose a visualization based on both the examples provided there and the needs of the user.

For sensor data not only the raw sensed data are of importance. Mostly it is necessary to know where or when a sensor made a measurement. Looking at the example of the Huntington Botanical Gardens in 2.4 it can only be reacted with watering on a low humidity value, which could be harmful for a plant, if it is known, where the sensor stands. The temporal aspect might be necessary to observe light flux over time and to react on a worsening of it, when a plant needs a certain amount of light. When regarding time and location values the dimension of sensor data grows. Considering this fact a classification of sensor data by the data type taxonomy can be done and visualizations realizing the needs of the user can be designed.

Further research on this topic would be necessary, for example looking on the other aspect of visualizations, namely the applications and needs of the user, and combining them with the data type classification to give appropriate solutions, when to use which visualization.

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Table 2. Sensor classification by measurands [21]

super category	*sub category*
Acoustic	
	Wave amplitude, phase, polarization, spectrum
	Wave velocity
	Other (specify)
Biological	
	Biomass (identities, concentrations, states)
	Other (specify)
Chemical	
	Components (identities, concentrations, states)
	Other (specify)
Electrical	
	Charge, current
	Potential, potential difference
	Electric field (amplitude, phase, polarization, spectrum)
	Conductivity
	Permittivity
	Other (specify)
Magnetic	
	Magnetic field (amplitude, phase, polarization, spectrum)
	Magnetic flux
	Permeability
	Other (specify)
Mechanical	
	Position (linear, angular)
	Velocity
	Acceleration
	Force
	Stress, pressure
	Strain
	Mass, density
	Moment, torque
	Speed of flow, rate of mass transport
	Shape, roughness, orientation
	Stiffness, compliance
	Viscosity
	Crystallinity, structural integrity
	Other (specify)
Optical	
	Wave amplitude, phase, polarization, spectrum
	Wave velocity
	Other (specify)
Radiation	
	Type
	Energy
	Intensity
	Other (specify)
Thermal	
	Temperature
	Flux
	Specific heat
	Thermal conductivity
	Other (specify)
Other (specify)	