

# Effectively Crowdsourcing the Acquisition and Analysis of Visual Data for Disaster Response

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**Abstract**—Efficient and thorough data collection and its timely analysis are critical for disaster response and recovery in order to save peoples lives during disasters. However, access to comprehensive data in disaster areas and their quick analysis to transform the data to actionable knowledge are challenging. With the popularity and pervasiveness of mobile devices, crowdsourcing data collection and analysis has emerged as an effective and scalable solution. This paper addresses the problem of crowdsourcing mobile videos for disasters by identifying two unique challenges of 1) prioritizing visual-data collection and transmission under bandwidth scarcity caused by damaged communication networks and 2) analyzing the acquired data in a timely manner. We introduce a new crowdsourcing framework for acquiring and analyzing the mobile videos utilizing fine granularity spatial metadata of videos for a rapidly changing disaster situation. We also develop an analytical model to quantify the visual awareness of a video based on its metadata and propose the *visual awareness maximization* problem for acquiring the most relevant data under bandwidth constraints. The collected videos are evenly distributed to off-site analysts to collectively minimize crowdsourcing efforts for analysis. Our simulation results demonstrate the effectiveness and feasibility of the proposed framework.

**Keywords**—Crowdsourcing, Disaster Response, Geo-tagged Video

## I. INTRODUCTION

Enhancing situational awareness is of great importance for disaster response and recovery. In the event of disasters, situational awareness can be enhanced by data acquisition and analysis. Data acquisition refers to the efficient collection of data in timely manner while data analysis represents the process of identifying and understanding the critical incidents from the collected data. Prompt and accurate data acquisition and effective analysis empower decision makers, which in turn can expedite disaster recovery, minimize damages, and potentially save lives. For example, after the 2010 Haiti earthquake, the Ushahidi-Haiti project (i.e., Mission “4636”) gathered more than 80,000 text messages from on-site users (on-site rescuers, local people, etc.) of which nearly 60,000 were translated into English by Haitians and were sent to the first responders for search and rescue and other emergency activities [10]. Using the collected data,

off-site volunteers created a post-disaster map of Haiti to help on-site workers, revealing undamaged roads, buildings, hospitals, and shelters.

Disaster data can be acquired in many ways such as from automatic sensor readings, reports from field workers and civilians, etc. In contrast to sensor readings, which is limited to a fixed set of locations and suffer from infrastructure damages, crowdsourcing has been shown to be a cost-effective and time-efficient way to acquire disaster data [9], [5] and then to analyze the collected data [17], [19], [20], [21]. Among various media types (text, image, video, graphics, etc.) from multiple data sources, videos and images are most effective in understanding the disaster situation. Videos can be watched and easily understood by international analysts, independent of language and cultural barriers, without wasting time for inaccurate interpretations [10]. However, there is little study in utilizing a large amount of videos, especially from ubiquitous mobile devices, for disaster situations. Hence, the primary focus of this paper is on devising a unified crowdsourcing framework aiming for both collection and analysis of user-generated mobile videos.

There exist platforms for crowdsourcing the mobile video collection along with fine granularity of spatial metadata, such as MediaQ (mediaq.usc.edu) and GeoVid (geovid.org). However, similar to aforementioned studies [9], [5], these platforms neglect to consider **prioritizing data acquisition** and thus may be subject to data overload, which is critical especially under limited network resources due to catastrophic outage [13], [16], [14]. Data triage is a central issue in disaster data collection since video data is large and often redundant. During the critical first response time, redundant data collection wastes not only communication bandwidth to transmit unnecessary data but also analysts’ valuable time for manual verification. In sum, more data do not necessarily mean more effective situational awareness.

Once data are acquired, the next challenge is to analyze the collected data in a timely manner and there exist several studies in this area [17], [19], [20]. However, these studies have focused on processing and integrating data, rather than on assigning analysis tasks to analysts. An effective analysis

refers to the **assignment of analysis tasks** to a number of off-site analysts in a balanced way such that no analyst becomes a bottleneck in a collective situational awareness. To the best of our knowledge, the only system that distributes the analysis tasks among the available analysts is GeoQ ([geo-q.com/geoq/](http://geo-q.com/geoq/)). GeoQ is a crowdsourcing platform for disaster data developed by US National Geospatial-Intelligence Agency. However, GeoQ statically assigns an analyst to a certain geographical region and he will be in charge of analyzing all the corresponding data. In this case, the amount of data within each region represent the workload assigned to each analyst. However, such a static assignment is hardly effective as non-uniform distribution of data may introduce regions with a wide variation of data, leading to unbalanced workload per analyst. Thus, an effective task assignment should consider the data distribution across geospatial regions and among the analysts.

Combining MediaQ and GeoQ, while overcoming their shortcomings, we introduce a new four-step framework that seamlessly fuses fast and efficient data collection with effective analysis (Figure 1). First, to facilitate the real-time data sensing, analysis and consequently time-sensitive decision-making, we propose the so-called *metadata first* mechanism, in which the geospatial metadata of videos such as camera location and camera viewing direction [4] are automatically captured and uploaded at the time videos are taken by on-site users (Step 1). The geospatial metadata, which represent the geographical properties of the captured videos with a far less number of bytes than the actual videos, are transmitted to the server first without delivering the large amount of the corresponding video data. Next, we identify the problem of prioritizing data transmission under bandwidth constraints (Step 2), i.e., only relevant videos selected based on their metadata will be transmitted in a priority order. Thereafter, the collected data are assigned to *analysts* by partitioning a large disaster area (e.g., the earthquake damage area can be obtained from ShakeMap) into manageable regions, so called *work cell* (Step 3); each work cell and its enclosed collected data are assigned to one analyst. Finally, the analysts watch the videos corresponding to their work cells to identify *incidents* (e.g., a building on fire, a collapsed house, road block) from which they evaluate the importance/urgency of their assigned work cells in the form of an *urgency map* (Step 4), i.e., the higher the assigned value, the more urgent the situation in the cell.

Subsequently, we develop an analytical model to quantify the situational awareness of a particular video, namely *visual awareness*. In practice, the visual awareness of a video (or a frame<sup>1</sup>) indicates how relevant the video is to the disaster incidents. Whether the video covers the actual incidents' locations or not is unknown to the control center at the time when only metadata are uploaded. Hence, we define

<sup>1</sup>A video is represented by a sequence of its frames (Figure 2).

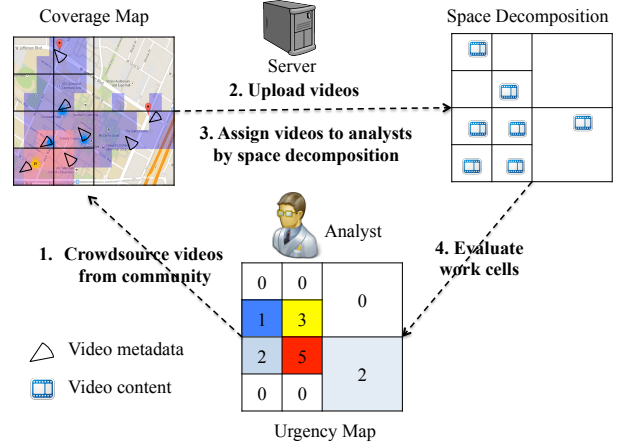


Figure 1: The crowdsourcing framework for disaster response. The loop is necessarily for dynamic data awareness, which may be critical in a rapidly evolving situation.

the relevance of a video based on its coverage with respect to the enclosed work cell and regional importance of the cell. Consequently, we define the *Visual Awareness Maximization (VAM)* problem that only selects a set of videos or frames with maximum total visual awareness without exceeding the bandwidth constraints. This maximizes the amount of useful information obtained from a limited amount of videos delivered under constrained bandwidth.

The bandwidth limit at a given time interval, referred to as *budget*, determines the amount of content that can be uploaded to the server. Our solutions consider the budget constraints with two variations: entire video content needs to be uploaded or individual video frames can be extracted on mobile clients (i.e., keyframes to reduce the data size) and then uploaded. Due to the budget constraints, an approach that simply ranks videos/frames and selects the ones with the highest information does not yield the optimal result. Thus, we study the problem complexity of both variants and prove that they are NP-hard. Particularly, when individual frames can be selected, we propose a solution that minimizes overall redundant coverage of the overlapped frames, therefore, achieve the maximum total visual awareness.

The visual awareness of a video depends on the importance of its containing work cell. The challenge with the spatial decomposition step is to ensure the maximum total visual awareness of the selected videos, using any optimal VAM solution. The baseline technique is to use a uniform grid, in which the number of grid cells is determined by the number of analysts. However, the shortcoming of the uniform grid is that, similar to GeoQ, some analysts may be overloaded while the others are underutilized. Therefore, considering the spatial distribution of the videos, we propose two partitioning techniques based on point Quadtree and Kd-tree. These techniques not only result in almost equal number of videos assigned to each analyst but also increase the total visual awareness of the uploaded videos, as shown

in Section VI. To summarize, the specific contributions of this paper are as follows.

- (i)) We identify two specific challenges in disaster response, *fast and efficient data acquisition* and their *effective analysis* with regards to two existing crowdsourcing projects, MediaQ and GeoQ, and propose a unified crowdsourcing framework to overcome such challenges by leveraging geo-tagged videos.
- (ii)) We propose an analytical model to measure the probability that a video covers an actual disaster incident without knowing the locations of the incidents, termed *visual awareness* of the video. We formulate an optimization problem to select a set of videos with the *maximum visual awareness* under bandwidth constraints, and propose to use a dynamic programming algorithm to solve the problem.
- (iii)) We extend our solution to the case where individual video frames can be uploaded. The improved solution minimizes the redundant coverage in overlapped frames, thus, yields an order of magnitude higher visual awareness in comparison to the case of transmitting the entire video.
- (iv)) We propose adaptive spatial decomposition techniques considering the spatial distribution of the videos to automatically assign the uploaded videos within a particular work cell to the corresponding analyst.
- (v)) We conduct experiments on various synthetic datasets to show the effectiveness and efficiency of the proposed framework. We conclude that the data-dependent partitioning techniques outperform the baseline by two orders of magnitude.

The remainder of this paper is organized as follows. In Section II, we review the related work. Section III discusses the preliminaries necessary to present our framework. In Section IV, we introduce the framework and define the constraint optimization problem, VAM. Thereafter, in Section V, we present an enhancement to the VAM problem. We present the experimental results in Section VI and make the conclusion of the paper in Section VII.

## II. RELATED WORK

**Crowdsourcing Disaster Response:** Crowdsourcing has been widely regarded as a cost-effective and time-efficiency means in disaster management, especially in data collection and analysis under disaster situations [9], [5], [17], [17], [19], [20], [21]. Firstly, early efforts in disaster data collection focused on geographic information provided voluntarily by individuals [9]. Chu et al. [5] developed a disaster surveillance and response system that provides the global view of the situation of the off-site users (e.g., analysts) with the help of on-site users (field commanders, local people, etc.). Secondly, regarding crowdsourcing the analysis of disaster data, Ortmann et al. [17] conducted a study on processing and integration of data associated with disasters

by leveraging Linked Open Data (linkeddata.org). Schulz et al. [19] proposed to combine human and machine intelligence for enhancing the situational picture of the off-site users, resulting in an increased situational awareness. In [20], the authors discussed the feasibility of harnessing collective knowledge in disaster relief and presented a generic system architecture with examples of how this could be accomplished. Yang et al. [21] proposed a platform that provides real-time assistance to on-site users by leveraging off-site users' efforts. Despite of efficient data collection and analysis, the credibility of the crowdsourced disaster data is still a major concern [10], [9]. Our study aims to focus on both efficient data collection and effective analysis of user-generated videos concerning disasters to advance capabilities for situational awareness. Fast and efficient data collection is achieved by prioritizing data transmission under limited bandwidth while effective analysis is obtained by evenly distributing the collected data to the analysts.

**Anti-disaster Systems:** Recently, there has been a growing research interest in improving the resilience and responsiveness of emerging computer systems to facilitate real-time data sensing [13], [16], [14], which is critical for time-sensitive decision-making. In [13], the author presented the infrastructure damage caused by the Great East Japan Earthquake such as transmission cables, mobile stations, etc., and Japan's efforts in restoring such telecommunication network. Liu [14] showed a comparison between typical outages and catastrophic outages caused by disasters, i.e., inaccessible power, damaged or unavailable communication network facilities. In [16], the authors surveyed several studies on resilient information and communication technologies, such as satellite network platform and anti-disaster information distribution platform. Among such systems, unmanned aerial vehicles (UAV) have emerged as effective controlled/autonomously systems in disaster imagery collection, especially in areas that are inaccessible on the road. For example, Google built aerial drones that can deliver medical equipments, food to people in need across the country. Skybox (skyboximaging.com) developed a satellite acquisition technology to collect real-time satellite imagery and full-motion video from space on demand. In contrast to these studies, our framework shows the possibility of an anti-disaster information distribution platform that collects a vast amount of videos concerning disasters. The collected data, which can come from various sources, such as mobile phones, UAVs, conventional CCTVs, facilitate comprehension of the situation and better decision-making.

## III. PRELIMINARIES

As this study was inspired by the two existing platforms, MediaQ [12] for data acquisition and GeoQ for data analysis, in this section, we introduce them and related concepts.

### A. MediaQ for Data Acquisition

Crowdsourcing disaster data contribute to stages of disaster response in a scalable, cost-effective and real-time manner. However, verifying crowdsourced information is critical for decision-making in disaster response as time lost responding to inaccurate reports may outweigh the benefit of the provided information. For example, less than 6% of the text messages published on the Ushahidi-Haiti crisis map were tagged as “verified” by field reporters [10]. Fortunately, visual data such as images and videos with spatial metadata and content can be verified easily by off-site analysts without the need of the field reporters. Thus, we developed MediaQ for collecting videos with their metadata from community, voluntarily or on-demand manner. With crowdsourcing, off-site analysts can outsource their content requests at particular locations that will automatically generate push messages to nearby workers, i.e., individuals with mobile devices that perform the requests by physically traveling to the specified locations and taking videos.

**Geo-tagged Videos:** Mobile videos can be captured at a fine granular level (e.g., frames) and their geospatial metadata (e.g., camera location, viewing direction) are transparently associated with each frame. This capability is referred to as geo-tagged videos. Particularly, we represent a video as a sequence of video frames, or frames for short, and each frame is modeled as a field of view (FOV) [4]. In 2D space, the field-of-view of a camera at a particular time forms a pie-slice-shaped area as illustrated in Figure 2a. We formally define a field of view.

**Definition 1 (Field of View (FOV)):** A FOV  $f$  is denoted as  $(p, \vec{d}, R, \theta)$ , in which  $p$  is the camera location of  $\langle \text{latitude}, \text{longitude} \rangle$  coordinates, the camera direction  $\vec{d}$  is obtained based on the orientation angle provided by a digital compass, the camera viewable angle  $\theta$  describes the angular extent of the scene imaged by the camera. The angle  $\theta$  is calculated based on the camera and lens properties for the current zoom level,  $R$  is the maximum visible distance at which a large object within the camera’s field-of-view can be recognized.

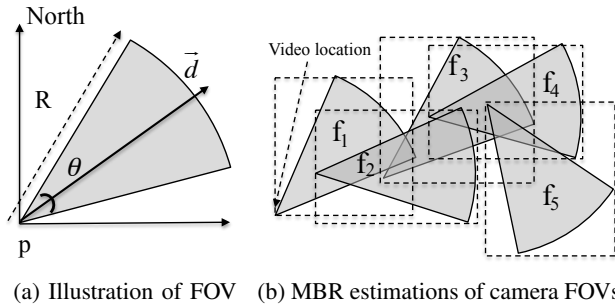


Figure 2: The Field Of View (FOV) model.

The viewable scene of a camera changes as it moves or changes its orientation. In order to keep track of the FOVs of

a moving camera over time, we need to record its location  $p$ , direction  $\vec{d}$  and viewable angle  $\theta$  with a certain frequency and produce time-stamped metadata together with time-stamped video streams. Our meta-data streams are analogous to sequences of  $(p, \vec{d}, R, \theta, t)$  quintuples, where  $t$  is the time instant at which FOV information is recorded. Figure 2b depicts FOVs of a 5-seconds video; one frame is sampled per second. For simplicity, we assume that the video location is the first point of a trajectory of video.

As shown in [4], one issue with such a representation is the computational overhead. A more appropriate approach is to define the FOV in the spatial domain with a pie-slice-shaped area and then estimate it with a minimum bounding rectangle (MBR) as shown in Figure 2b. Consequently, we estimate the coverage area of a video as the overall coverage of its FOVs’ MBRs. To efficiently compute the coverage of the MBRs, we use *cascaded union* which is available in various languages such as PostGIS and Python.

### B. GeoQ for Data Analysis

The disaster data are often analyzed on a crisis map to provide the overview of the disaster situation at the control center. Crisis mapping techniques often evaluate and annotate damage based on a geographical (district) map imported from popular geospatial vector data formats such as Shapefile. For instance, Figure 3a shows the color-coded damage levels in Nepal Earthquake 2015. The darker the color, the more damaged the districts. However, district-based evaluation fails to represent the damage at fine granular level due to rigid pre-defined geographical regions. Therefore, GeoQ uses a grid-based partition of the space to enable fine-grained evaluation as illustrated in Figure 3b.

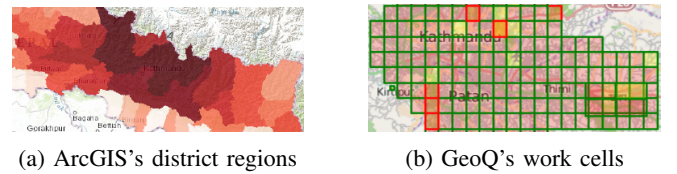


Figure 3: Crisis mapping tools used in Nepal Earthquake 2015.

GeoQ allows the analysts to collect geographic structured observations across a large area, but manage the work in smaller geographic regions. That is, a disaster area can be partitioned into small regions (e.g., 1km squares), so called *work cells*, and be assigned to the analysts. GeoQ also assists the analysts to aggregate and analyze information from the data concerning disasters. The role of the analysts is to evaluate the available data sources in their allocated work cells (e.g., video data from MediaQ, social data from Twitter and Youtube, imagery data from satellites) to determine any relevant incident associated with disasters (e.g, a building on fire, road block) that needs to be marked on the GeoQ’s crisis map. To become an analyst, volunteers need to pass

required training classes on a particular disaster type (e.g., earthquake, wildfire).

We formally define a work cell and an analyst.

*Definition 2 (Work Cell):* A work cell  $w$  is a region with an urgency value  $U$  that can be rated by an analyst.

*Definition 3 (Analyst):* An analyst is a trusted personnel with expertise in situational crisis. By analyzing data within a work cell, the analyst measures the severity of the disaster and sets an urgency value to his assigned work cell.

#### IV. CROWDSOURCING DISASTER RESPONSE

We propose a unified framework that empowers MediaQ and GeoQ, but overcomes their limitations in crowdsourcing disaster data and data analysis. We first focus on efficient mobile video acquisition and transmission.

##### A. Data Acquisition

1) *Acquisition of Video Metadata and Content:* First, one critical issue in acquiring videos is the timely delivery of data, especially under a potential catastrophic disruption of communication during and after disaster. For example, in 2010 Haiti Earthquake, 85% of Haitians could still access to their mobile phones but 70% of cell towers were destroyed [10]. Therefore, we propose “metadata first” mechanism that prioritizes uploading metadata of videos (the quintuples in Section III-A) over their content, in which metadata are automatically captured and uploaded when the videos are taken without delivering a large amount of the corresponding video data themselves. The reason for this is to enable time-sensitive acquisition and analysis on the uploaded metadata, such as real-time data sensing, visualization (e.g., video coverage map in Figure 1) and decision-making (e.g., crowdsource more data in sparse-video areas such as the Northeast in Figure 1). Other reasons for separately handling metadata first includes supporting data governance as metadata often lives longer than its content, preserving privacy and strict access control [7].

Due to the small size of metadata with respect to the content<sup>2</sup>, they can be transmitted through various channels such as Internet, SMS and WLAN. The acquired metadata can be used in data management applications, which enable other applications to access the metadata via RESTful APIs. For example, using the RESTful metadata services, a range query can find all video frames that overlap with a user-specified region, or a direction query can find the objects that are covered by a video with a specific viewing direction. This kind of queries are particularly useful when analysts have identified an incident and in search for more videos that cover the event.

<sup>2</sup>The size of metadata of one FOV is around 300 bytes [1], thus, the metadata of a ten-seconds video, with a sampling rate of one FOV per second, is only 3KB. However, the size of a video is typically a few MBytes, which is thousands times larger than its metadata.

Second, by leveraging the spatial metadata, the server periodically selects a set of videos to be uploaded, e.g., every five minutes. Once the videos are identified by the server, to be discussed in the next sections, their contents can be requested. That is, the server sends push notifications to the mobile phone clients that hold the selected videos, triggering the service to upload the videos. Mobile phone users can choose to opt-in/opt-out the option of automatically transmitting the video content when receiving the notifications; otherwise, the users can directly upload the content. The content once uploaded is matched to the corresponding metadata stored in the server.

The above selective on-demand data collection efficiently uses network bandwidth by minimizing redundant data transmission. The total volume of uploaded videos, within a time interval, is limited by the network capacity, namely *budget*  $B$ . In practice, budget  $B$  captures the bandwidth constraints from either the communication network or the cloud server that stores the videos [1]. We formally define the budget.

*Definition 4 (Budget):* Budget  $B$  is the maximum amount of data (MB) to be transmitted in a given time interval.

2) *Visual Awareness of a Video:* Given uploaded metadata, videos will be prioritized for their transmission so that relevant or urgent ones can be delivered first. We develop an analytical model that allows the server to quantify the importance of a particular video or frame, namely *visual-awareness*. In practice, the visual awareness of a video indicates the probability that it covers any interesting incidents in the enclosed work cell. Whether the video covers an actual incident or not can be confirmed only when the video is uploaded and evaluated by the analysts. Thus, it is intuitive to define the visual awareness of the video based on its geospatial metadata. Particularly, it is proportional to the coverage ratio of the video with respect to the containing cell, formally defined as follows.

$$VA(v) = U(w) \frac{area(v)}{area(w)} \quad (1)$$

where  $area(v)$  is the coverage area of video  $v$ , calculated using *cascaded union* as described in Section III-A;  $U(w)$  is the *urgency value* of work cell  $w$  that encloses video  $v$ , either manually entered by the analyst associated with  $w$  or automatically computed as will be shown in Section IV-B2 (Equation 2). The intuition for Equation 1 is that  $VA(v)$  is high if both the urgency of the containing work cell  $U(w)$  and the coverage ratio  $area(v)/area(w)$  is large. Note that we assume the video region is entirely enclosed within the work cell that covers the video location  $v.l$ . This assumption is reasonable as the work cell’s area is generally much larger than the video region.

3) *Visual Awareness Maximization:* To decide the order of video transmission, the server selects a set of videos with the maximum total visual awareness without exceeding the budget constraint.

**Problem 1 (Visual Awareness Maximization ( $VAM_V$ )):** Given budget  $B$  for a time interval and the video set  $V = \{v_1, v_2, \dots\}$  the budget-constraint maximization of visual awareness is the problem of selecting a set of videos such that the total visual awareness  $\sum_{i=1}^{|V|} VA(v_i)d(v_i)$  is maximized while satisfying  $\sum_{i=1}^{|V|} size(v_i)d(v_i) \leq B$ .  $d(v_i)$  represents a decision to select the  $i^{th}$  video:  $d(v_i) = 1$  if video  $v_i$  is selected and  $d(v_i) = 0$  otherwise. By restriction, we prove that the  $VAM_V$ <sup>3</sup> problem is NP-hard by a reduction from the 0-1 knapsack problem [2].

**Theorem 1:** The  $VAM_V$  problem is NP-hard.

*Proof:* Suppose that the maximum weight we can carry in the bag is  $W$ . With 0-1 knapsack, given  $n$  items,  $z_1$  to  $z_n$  where  $z_i$  has a value  $value(z_i)$  and weight  $weight(z_i)$ , we need to maximize the sum of the values of the items in the knapsack so that the sum of the weights must be less than or equal to the knapsack's capacity. More formally, we maximize  $\sum_{i=1}^n value(z_i)d(z_i)$  while satisfying  $\sum_{i=1}^n weight(z_i)d(z_i) \leq W$  and  $d(z_i) \in \{0, 1\}$ .

We prove the theorem by providing a one-to-one correspondence from 0-1 knapsack to the  $VAM_V$  problem. That is, given an instance of the knapsack problem, there exists a one-to-one mapping to an instance of  $VAM_V$ . For every item  $z_i$ , we create a video  $v_i$  with  $VA(v_i) = value(z_i)$  and  $size(v_i) = weight(z_i)$ . Also, the maximum weight  $W$  is mapped to budget  $B$ . This simple mapping completes the proof. ■

By a reduction from the 0-1 knapsack problem, we can use any algorithm that computes 0-1 knapsack to solve the  $VAM_V$  problem. It has been shown in [15] that the greedy algorithm gives 0.5-approximation ratio. Fortunately, there is a pseudo-polynomial time algorithm using dynamic programming to optimally solve 0-1 knapsack. This solution runs in  $O(|V|B)$  time and  $O(B)$  space, where  $|V|$  is the number of videos and  $B$  is the budget.

## B. Data Analysis

Once the data are acquired, they are distributed to analysts who then evaluate them (Step 4 in Figure 1. In this section, we present the problems of task distribution and task analysis in turn.

1) **Task Assignment:** To facilitate timely evaluation on the acquired data, we investigate various partitioning techniques to evenly assign work cells and the enclosed videos to the analysts. We propose to adaptively partition a large disaster region into work cells and automatically assign each work cell to an analyst. As a result, each analyst is assigned the videos within his work cell that have not been yet reviewed. For simplicity, we assume that the disaster region is a rectangle and one analyst is responsible to one and only one work cell. In the following, we present the uniform grid as a baseline and two other techniques based on Quadtree

and Kd-tree which take the spatial distribution of the videos into consideration.

**Data-independent Partitions:** Given  $A$  analysts, we partition the disaster region into an equal-size grid of size  $\lfloor \sqrt{A} \rfloor \times \lfloor \sqrt{A} \rfloor$  so that each work cell is assigned to at least one analyst. For example, the disaster region will be split into  $6 \times 6$  grid given 36 analysts. As a data-independent technique, the equal-size grid may suffer unbalanced allocation of videos, i.e., some work cells have many videos while the others are empty. Consequently, the analysts with empty work cells are idle while the others may be overloaded.

**Data-dependent Partitions:** To enable balanced assignment, we propose data-dependent techniques based on Quadtree and Kd-tree [18]. The point quadtree algorithm recursively decomposes the space into adaptable cells. A cell is split into four equal quadrants or regions if the number of data points within the cell is larger than a maximum capacity.

We propose an algorithm for space partitioning based on Quadtree and Kd-tree structures with a customized stop condition (Algorithm 1). Unlike the stop condition of the point quadtree, Algorithm 1 terminates when the number of cells is greater than or equal to  $A - 3$  (Line 5). This is to ensure that all work cells are assigned to the analysts. Furthermore, at each stage of Algorithm 1, we split the cell with the highest number of videos to maintain balanced workload between the analysts (Line 6). When a parent node is split into four equal quadrants, we move the data from the parent into the corresponding child nodes,  $NW, NE, SW, SE$  (Line 9). Finally, Line 11 updates the current number of work cells. Note that a work cell cannot be further partitioned if it has no more than one video (Line 7).

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### Algorithm 1 QUADTREE (KD-TREE) ALGORITHM

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- 1: Input: uploaded videos  $U = \{u_1, u_2, \dots\}$ , analyst count  $A$
  - 2: Initialize root work cell  $ROOT.data = U$
  - 3: Initialize work cell count  $cell\_count = 1$
  - 4: Initialize priority queue  $Q = \{ROOT\}$ , ranked by video count
  - 5: While  $cell\_count \geq A - 3$  and  $size(Q) > 0$ :
  - 6:   Work cell with highest video count  $CELL \leftarrow Q$
  - 7:   If  $CELL$  has more than one video:
  - 8:     Split  $CELL$  into four quadrants  $NW, NE, SW, SE$
  - 9:     Move  $data$  from  $NODE$  to its children
  - 10:    Update queue  $Q \leftarrow Q + \{NW, NE, SW, SE\}$
  - 11:    Update work cell count  $cell\_count \leftarrow cell\_count + 3$
- 

The Kd-tree construction algorithm is similar to that of Quadtree, except the splitting criteria in Line 8 needs to be tailored with respect to the point kd-tree algorithm. Instead of midpoint splitting as Quadtree, median splitting is used, which results in approximately the same number of videos per quadrant. The obvious advantage of Kd-tree over Quadtree and the simple grid is that each analyst has roughly the same number of videos, thus, facilitating concurrent data analysis among them.

<sup>3</sup>The subscript  $V$  denotes the video-level optimization problem.



2) *Work Cell Analysis*: With GeoQ, the analysts measure the severity of the disaster by analyzing the data within their corresponding work cells, then assign urgency values to them. In the same fashion, we extend the idea of geographic tasking in GeoQ to analyzing the video data. For example, the analysts can count the number of damaged buildings or mark emergency cases by watching their assigned videos. In addition to these specific tasks, analysts can provide an overview of the situation for the decision makers by assigning an urgency value (i.e., priority) to each work cell, e.g., zero means no damage while five means heavily damaged (urgency map in Figure 1). The urgency values may change over time as more videos are available and to be watched by the analysts.

Due to the complexity of the disaster, we argue that detecting critical incidents, such as fire, flood, smoke and explosion should be semi-automatic. Either the analysts manually watch the uploaded videos in their work cells to identify the incidents, or the server automatically provide descriptions of the events by means of computer vision or machine learning techniques that analyze the videos. These issues are beyond the focus of this work. However, the urgency of the work cells can be automatically recommended based on their *importance* and *geosocial* factors, weighed as follows.

$$U(w) = \text{Importance}(w)\alpha + RE(w)\beta \quad (2)$$

While the former one is provided in form of a pre-defined priority map, e.g., nuclear plant areas have higher priority than residence areas, the geosocial factor is represented by region entropy (RE) (entropy of a region is high if many people visit the region). Intuitively, a high-population work cell is more important than the one with fewer people, and the priority of a work cell is high if many people visit, such as schools and hospitals. Location entropy [6], which measures the diversity of unique visitors of a location, can be used to measure the spatial “popularity” of a location. A location has a high entropy if many people visit that location with equal proportions. We extend the concept of location entropy to *region entropy* of a work cell.

For a given work cell  $w$ , let  $O_w$  be the set of visits to  $w$ . Also, let  $P_w$  be the set of distinct people that visited  $w$ , and  $O_{p,w}$  be the set of visits that person  $p$  has made to the region  $w$ . The probability that a random draw from  $O_w$  belongs to  $O_{p,w}$  is  $P_w(p) = \frac{|O_{p,w}|}{|O_w|}$ , which is the fraction of total visits to  $w$  that belongs to person  $p$ . The region entropy for  $w$  is computed as follows:

$$RE(w) = - \sum_{p \in P_w} P_w(p) \times \log P_w(p) \quad (3)$$

$RE(w)$  can be computed based on any geo-social dataset such as Gowalla<sup>4</sup>. Consequently, we can associate a geosocial priority to every work cell as shown in Equation 2.

<sup>4</sup>snap.stanford.edu/data/loc-gowalla.html

## V. MINIMUM REDUNDANT COVERAGE

Thus far when a video is selected, the entire video content needs to be uploaded. However, transmitting the content is not only costly but also may render many frames useless, i.e., redundant frames are generated when either users do not move their cameras or videos cover the same area. To reduce the bandwidth usage and therefore maximize the total visual awareness, we propose to upload only keyframes and their metadata to the server and simultaneously minimize redundant coverage of these frames. While the acquisition of metadata and content of a video frame (i.e., an image) is similar to Section IV-A1, in the following, we focus on identifying the keyframes across all videos.

### A. Visual Awareness of a Frame

To compute the overlap regions, we divide the space into small grid cells (e.g., 20m squares), so called *unit cells*; each is identified by a number as shown in Figure 4a. With this discretization, one FOV can be represented by a set of covered unit cells. A unit cell is covered by a FOV (or a work cell) if the unit cell’s center is within the FOV (or the work cell). For instance, the FOV is represented by the set of gray unit cells in Figure 4a.

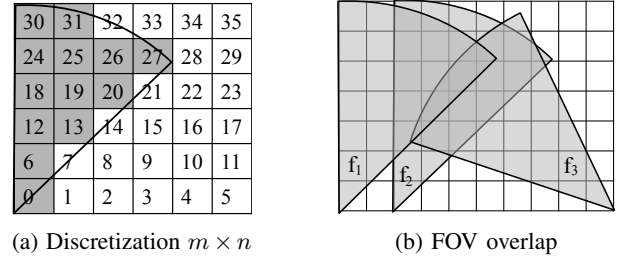


Figure 4: Optimization at the frame level.

Intuitively, visual awareness has composition property, which means that the visual awareness of a FOV is equal to the sum of the enclosed unit cells’:

$$VA(f) = \sum_{c \in f} VA(c) \quad (4)$$

where the visual awareness of the enclosed unit cell  $VA(c)$  is similar to Equation 1.

$$VA(c) = U(w) \frac{\text{area}(c)}{\text{area}(w)} \quad (5)$$

where  $w$  is the work cell that encloses unit cell  $c$ .

### B. Visual Awareness Maximization

To prioritize the video frames for transmission, the server selects a set of frames that maximizes the total awareness without exceeding budget  $B$ . With the assumption that the size of all video frames is the same, budget  $B$  is equivalent to the maximum number of frames that can be transmitted,  $K = \lfloor B / \text{size of a frame} \rfloor$ . We formally define the problem as follows.

*Problem 2 (Visual Awareness Maximization ( $VAM_F$ )):* Given a budget  $K$  for a time interval and a collection of video frames  $F = \{f_1, f_2, \dots\}$ , each frame  $f_i$  containing a set of unit cells  $c_k$ , the budget-constraint maximization of visual awareness is the problem of selecting a set of frames, denoted by  $L$ , such that the total visual awareness of the covered unit cells  $\sum_{c_k \in \bigcup_{f_i \in L} c_k} VA(c_k)$  is maximized while satisfying  $|L| \leq K$ .

By restriction, we proof that the  $VAM_F$ <sup>5</sup> problem is NP-hard by a reduction from the weighted maximum coverage problem (MCP) [11].

*Theorem 2:* The  $VAM_F$  problem is NP-hard.

*Proof:* We proof the theorem by providing a one-to-one correspondence from MCP to the  $VAM_F$  problem, or  $MCP \leq_p VAM_F$ . Toward that end, given an instance of MCP, denoted by  $I_m$ , there exists an instance of the  $VAM_F$  problem, denoted by  $I_v$ , such that the solution to  $I_v$  can be converted to the solution of  $I_m$  in polynomial time. The reduction is straightforward by matching from  $I_m$  components to  $I_v$  components. ■

In Figure 4b, given  $K = 2$  and the visual awareness of all unit cells is the same,  $VAM_F$  selects  $f_1$  and  $f_3$  to minimize redundant coverage.

As MCP is strongly NP-hard, a greedy algorithm is proposed to achieve an approximation ratio of 0.63 [8]. The algorithm chooses a set (i.e., a frame) at each stage that contains the maximum weight (i.e., visual awareness) of *uncovered* elements (i.e., unit cells). Feige and Uriel [8] show that the greedy algorithm is the best-possible polynomial time approximation algorithm for MCP.

## VI. PERFORMANCE EVALUATION

We conducted several experiments on synthetic datasets to evaluate the performance of our proposed approaches. Below, we first discuss our experimental setup and then we present our experimental results.

### A. Experimental Methodology

We used the source code in [3] to generate synthetic video metadata with realistic geospatial properties, based on the behavioral patterns of mobile cameras when they move and rotate. We generated three spatial distributions of the video locations, *Uniform*, *Gaussian* and *Zipfian*, in a region of  $10 \times 10$  square km at Los Angeles, USA. *Uniform* dataset is randomly generated while *Gaussian* and *Zipfian* datasets follows Gaussian ( $\mu = 0$ ,  $\sigma = 0.1$ ) and Zipfian (skew parameter  $s = 1$ ) distributions, respectively. We discretized the space into  $500 \times 500$  unit grid cells; the size of each unit cell is 20 square meter. We used a reasonable assumption of pedestrian camera moving with speed limit is between 5 and 20 km per hour. We fixed the video sampling rate to one frame per second, which means the metadata of a

five-seconds video has five FOVs. We fixed the horizontal viewable angle  $\theta$  to 60 degrees and the visible distance  $R$  to 200 m. We calculated the average rotation (in degrees/s) of the camera at each trajectory point is about 12 degrees while the maximum rotation is 55 degrees.

In all of our experiments, we varied the number of analysts  $A \in \{16, 25, \mathbf{36}, 49, 64\}$  and the bandwidth constraint  $B \in \{10, 15, \mathbf{20}, 25, 30\}$  MBs per time interval. We fixed the number of videos with metadata only  $|V| = 1000$  and the number of videos with content  $|U| = 250$  whose locations are randomly sampled from  $V$ . The video size follows Zipfian distribution with skew parameter  $s$ . We varied the skew parameter  $s \in \{1.6, 1.8, \mathbf{2.0}, 2.2, 2.4\}$ , resulting in the corresponding mean values  $\{16.7, 8.2, \mathbf{4.6}, 2.9, 1.4\}$  MB. Default values are shown in boldface. With such default settings, the total coverage area of all FOVs is about 15 square km. Also, we assume one-second video weighs 1MB and the size of each frame image is 100KB. We assigned the urgency to each work cell by generating a random number between 0 and 5. All measured results are averaged over ten random seeds.

### B. Experimental Results

We evaluate the performance of the proposed partitioning techniques in terms of maximizing *visual awareness*. We first present the results where the entire video needs to be uploaded.

1) *Visual Awareness Maximization:* Figure 5 illustrates the results by varying the number of analysts  $A$ . We observe that with the increase of  $A$ , higher visual awareness is obtained. The reason is that the higher the number of analysts, the smaller the work cells; leading to the increase in the visual awareness of the enclosed videos. Also, Kd-tree generally performs best in terms of maximizing visual awareness. As shown on *Uniform* (Figure 5a), Kd-tree increases the visual awareness by up to 3 times in comparison to Grid. The improvement is 6 times higher on *Gaussian* (Figure 5b). In the same fashion, Figure 6 shows the similar results when the urgency map is computed based on region entropy (RE) (from Section IV-B2) rather than randomly generated. The reason is that, unlike Grid and Quadtree, Kd-tree produces roughly equal number of videos per work cell, which contributes to the balanced workload of the analysts (Figure 7). In contrast, it is almost certain that Grid and Quadtree produce empty and over-populated cells. While empty cells waste analyst resources and thus contribute to the smaller visual awareness, highly populated cells are susceptible to redundant coverage of the containing videos.

Figure 8 measures the impact of increasing budget  $B$ . As expected, a higher budget yields higher visual awareness, as more videos can be selected. Also, Kd-tree and Quadtree outperform Grid, particularly in the *Gaussian* dataset (Figure 8b), which shows that Kd-tree and Quadtree adapt better

<sup>5</sup>The subscript  $F$  denotes the frame-level optimization problem.



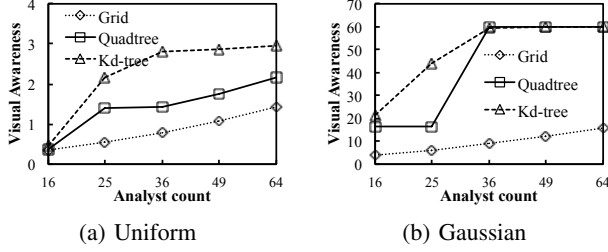


Figure 5: Varying the number of analysts  $A$ .

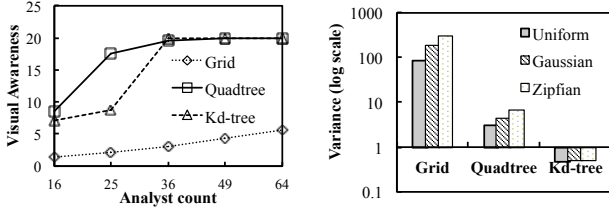


Figure 6: Gaussian. RE is calculated from Gowalla dataset. Figure 7: Variance of the number of videos per analyst.

to the non-uniform datasets. Figure 9 depicts this adaptation by showing their structures on *Gaussian*.

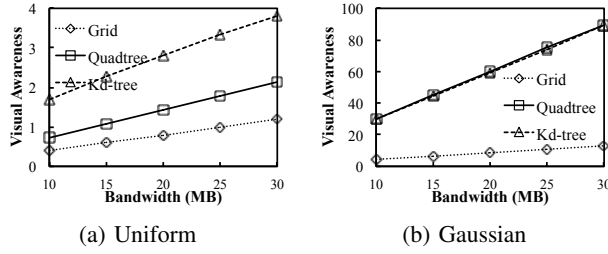


Figure 8: Varying the bandwidth constraint  $B$  (MB).

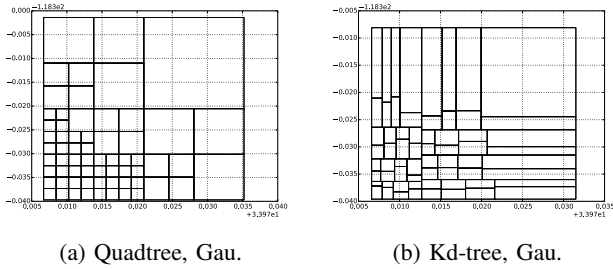


Figure 9: Structures of Quadtree, Kd-tree on Gaussian ( $A = 64$ ).

2) *Minimum Redundant Coverage*: We evaluate the performance of the Greedy algorithm from Section V where individual video frames can be uploaded. Figure 10a shows the results by varying the number of analysts on *Uniform* dataset (similar results were observed for *Gaussian*). We observe similar trend as in Figure 5a, except that the obtained visual awareness is an order of magnitude higher. The reason is that, for the same amount of bandwidth and analyst count as in the video-level problem, frame-level optimization selects the frames with minimal overlap and thus maximizes the visual awareness. We also show the results by varying

the budget  $B$  in Figure 10b and observe similar trends as in Figure 8a.

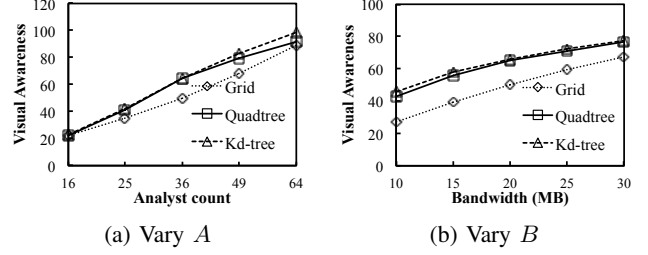


Figure 10: Performance of greedy algorithm on Uniform.

3) *The Effect of Skewed Data*: We evaluate the performance of partitioning techniques on the highly skewed *Zipfian* dataset. We observe from Figure 11a that the obtained visual awareness of Quadtree and Kd-tree is much higher than that of the baseline by nearly two orders of magnitude. The reason is that Quadtree and Kd-tree produce many tiny work cells and less large work cells in *Zipfian* when compared with *Uniform*; and these tiny work cells lead to excessive high visual awareness of the enclosed videos. Similar results are revealed from frame-level optimization (Figure 11b), the gap between Kd-tree and Grid is higher when compared to that in Figure 10.

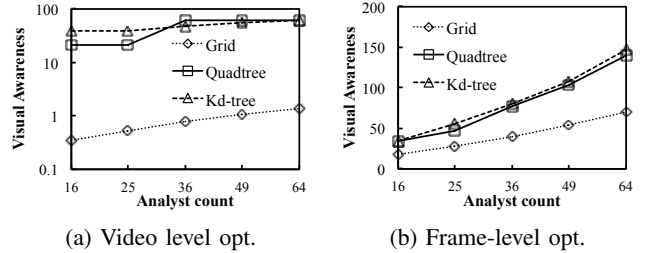


Figure 11: Varying the analyst count  $A$  on the Zipfian dataset.

4) *The Effect of Video Size*: Figure 12a evaluates the performance of the partitioning techniques on *Uniform* by varying the skew parameter  $s$ . The figure shows that increasing  $s$  or equivalently decreasing the average video size marginally increases the visual awareness. This unexpected result can be attributed to the fact that regardless of the skew parameter most videos are small in size, which are highly likely to be selected by the server.

5) *Runtime Measurements*: Figure 12b compares the construction time of the partitioning techniques (Algorithm 1). Their construction times are small and the differences are insignificant. In addition, the average runtime of the dynamic programming algorithm from Section IV-A3 is 1.1 seconds while that of the greedy algorithm from Section V-B is 10 seconds. These results show the practicality of our proposed framework.

## VII. CONCLUSION

We introduced a crowdsourcing framework for collection and analysis of video data under disaster situations. The

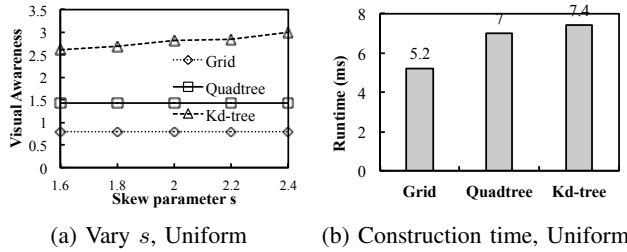


Figure 12: The effect of skew parameter  $s$  for generating video size and the construction times of the partitioning techniques.

framework automatically divides a large disaster area into small work cells, each assigned to one analyst. We developed an analytical model to quantify the visual awareness of a particular video or frame and introduced the visual awareness maximization problem. Two problem variants have been studied, one with uploading the entire videos, the other with uploading individual frames to reduce bandwidth usage and avoid redundant coverage. Our experimental results on synthetic data demonstrated that the proposed decomposition techniques are effective and the optimization solutions are practical. As future work, we will study crowdsourcing strategies that collaboratively involve both the analysts at the command center and the controlled workers at the disaster site to answer some open questions, including who to ask and where to collect data in disasters.

## VIII. ACKNOWLEDGMENTS

This research has been funded by NSF grants IIS-1320149, CNS-1461963 and the USC Integrated Media Systems Center. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of any of the sponsors such as NSF.

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