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Biologically Inspired Computer Vision

Fundamentals and Applications



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Foreword

Since the mid-twentieth century, our scientific world of information technology has become more and more multidisciplinary, combining the knowledge and experience of many disciplines such as biology, psychophysics, mathematics, and engineering.

The first attempts to widen their field of view came from engineers and mathematicians who were fascinated by the tremendous faculties of our brain to process and extract information from the noisy and changing world of our environment: would it be possible to mimic our brain to build a novel kind of machines for signal, images, and information processing? This opened the era of artificial neural networks.

Among the pioneers of this new approach are the seminal works of McCullogh and Pitts (1943) for their *Formal Neuron*, Von Neuman (1948) for his *Automata Networks*, Hebb (1949) for his famous *Synaptic Learning Rule*, Rosenblatt (1958) for his *Perceptron*, Widrow and Hoff (1960) for the *Adaline*, inspired from a combination of the perceptron, and Hebb's learning rule in the framework of linear predictive filters in signal processing.

Later, in the following decades, Minsky and Papert (1969) revisited the perceptron and its limitations, opening the way to the *multilayered perceptron* with a new learning rule: the *gradient back-propagation* suggested by Werbos (1974) and extended by Rumellart and McClelland (1986). We also cite the Hopfield networks (1982) derived from some statistical physics considerations. The common feature of all these networks is that they are taught to classify or recognize items according to an *ad hoc* learning rule.

In the mean time, a new concept of artificial neural networks, called "selforganization" emerged from the pioneering work by Kohonen (1984) with his *self-organizing maps*. In this framework, the neural network rather than to be taught what to do, was left able to evolve with respect to the input information structure, according to some general learning rule. With this concept, artificial neural networks acquired some scent of "intelligence" and many researchers worked around this idea of self-adaptive networks: among them, in nonlinear dimensionality reduction and data visualization Demartines and Herault (1999)

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with *curvilinear component analysis*, Tenenbaum (2000) with *isomap*, Lee and Verleysen (2004) with *curvilinear distance analysis*. We also cite the *sources separation network* also called *independent component analysis* (Herault, Ans, and Jutten, 1986) widely used as a signal processing technique to extract signals from unknown mixtures of them, provided that these signals are statistically independent and that the mixtures are different.

During this period, many international workshops and conferences concerning neural networks (ICANN, NIPS, IWANN, ESANN, etc.) were launched, gathering researchers mainly from mathematics and engineering. However, several biologists and psychophysicists progressively attended these conferences, often under the solicitations of the early participants.

Since the beginning of the 1980s, some researchers turned themselves toward more "realistic" models of neurons, among them Carver Mead (1988) who defined the concept of *neuromorphic circuits*, with his famous CMOS electronic model of the retina: he mimicked the retinal electric synapses by means of simple resistors and capacitors. He designed an analog electronic integrated circuit which exhibited the main properties of the vertebrate retina. This circuit was much more efficient than the usual digital approaches: fast, robust, continuous-time, and low energy consumption are the most important qualifying terms of this approach.

Maybe because this work was about the retina, it has motivated a renewal of interest in the biological model as an alternative – or rather as a complement – to computer vision. Hence, many researchers in engineering began to consider and study the biology of vision, asking for help from their colleagues in biology and psychophysics. This led to the creation of several multidisciplinary teams around the world, acting in the framework of cognitive science. A new era was thus born.

This book is the congregation of internationally renowned scientists in biology, psychology, mathematics, electronics, computer science, and information technology. They have made a number of major contributions in biological vision, computer vision, and cognitive science. The book addresses the most important aspects of the fields, from visual perception to technology at a high scientific level. Across its chapters, it offers a comprehensive view of biological motivations, theoretical considerations, as well as application suggestions.

On going through the chapters, the reader will discover in-depth studies of the state-of-the-art statements in various disciplines and cross-disciplinary topics related to vision and visual perception. Without any order of precedence, the following subjects are of interest: electronic neuromorphic circuits, retinal and color processing, insect vision, visual psychophysics, visual attention, and saliency, Bayesian inference in visual perception, detection of scale-invariant features, object recognition, spiking neurons, sparse coding, plenoptic cameras, motion detection, visual navigation.

Far from being a simple list of topics, this book offers the opportunity to consider a global approach to vision and invites the reader to make his (her) own point of view on a synthetic basis. It will be of great importance for researchers who

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are interested in the fundamental principles of biological vision and in computer vision, hardware, and autonomous robotics. Bringing together scientists of different disciplines, and bi- or three-disciplinary scientists, the book offers an example for future organization for academic and even industrial research teams.

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Jeanny Herault