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Visibility Enhancement in Bad Weather

►Dehazing and Defogging

Vision-Based Control

►Visual Servoing

Vision-Based Feedback

►Visual Servoing

Visual Cognition

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Synonyms

Visual Inference

Related Concepts

►Cognitive Vision

Definition

Visual cognition is the branch of psychology that is concerned with combining visual data with prior knowledge to construct high-level representations and make unconscious decisions about scene content [1].

Background

Although the terms visual cognition and cognitive vision are strikingly similar, they are not equivalent. Cognitive vision refers to goal-oriented computer vision systems that exhibit adaptive and anticipatory behavior. In contrast, visual cognition is concerned with how the human visual system makes inferences about the large-scale composition of a visual scene using partial information [1–3].

Theory

Visual cognition, often associated with high-level vision and top-down visual processing, constructs visual entities by collecting perceived parts into coherent wholes, determining which parts belong together. Since the sensory data on which the processes of visual cognition operate are typically incomplete and insufficient to specify the percept of which we are aware, there are many possible solutions or interpretations. Consequently, additional extraretinal information, often referred to as object information, is used by visual cognition to infer what the percept is.

The entities that are constructed by visual cognition include both static structures, such as perceived surfaces and objects, and dynamic entities that emerge over time, such as patterns of biological motion. The dynamics of these visual entities can be used to infer a causal relationship between events or to attribute some sense of intentionality to the entity. Thus, the unconscious inferences of visual cognition also impact on the construction of a theory of mind for other cognitive agents, i.e., the inference of the goals of other agents [4].

A key role of the representations of visual cognition is their use to communicate with other centers of the brain. Thus, visual cognition provides a bridge to general high-level cognitive function while still making its own independent cognitive inferences. In essence, visual cognition constructs a representation of the visual world which is constantly updated on the basis of new visual data and which encapsulates knowledge about the world in a high-level descriptive manner that can be exchanged with the rest of the brain.

Visual cognition addresses several distinct areas such as visual attention (including spatial attention, selective attention, visual search, change detection, and the control of eye movements) [5–8], short-term and long-term visual memory [9], and object, face, and scene recognition [10, 11].

The processes of visual cognition are held to be principally unconscious, operating rapidly on the flux of visual data sensed by the retina in order to choose the conscious percept of which we become aware. Consequently, visual cognition embraces both the selectivity of visual attention and unconscious inferential decision-making.

Although the primary concern of visual cognition is human visual perception and not computer vision, the two fields share some common ground. For example, many of the theories of visual cognition have their roots in cognitivist psychology which asserts that cognition is intrinsically computational [12, 13]. This has led to several computational models of visual cognition, combining relevant aspects of computer and human vision.

Open Problems

There is some debate in the psychology community as to where one should draw the line between vision and cognition and how sharply one should draw it; for comprehensive discussion, see the paper by Pylyshyn [14], the many commentaries on it (e.g., [15]), and his response [16]. The issue revolves around the cognitive impenetrability of visual perception: whether or not any cognitive functionality such as inference or rationality is involved in visual perception, especially early vision. Cavanagh's recent review [1] suggests that the visual system does have its own independent cognitive processes, quite apart from the more general cognition that occurs in other parts of the brain and with which the processes of visual cognition interact.

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Visual Cortex Models for Object Recognition

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Related Concepts

▶Object Class Recognition (Categorization)

Definition

Visual cortex model-based methods aim to develop algorithms for object detection, representation and recognition that attempt to mimic human visual systems.

Background

Object recognition is difficult Like other natural tasks that our brain performs effortlessly, visual recognition has turned out to be difficult to reproduce in artificial systems. In its general form, it is a highly challenging computational problem which is likely to play a significant role in eventually making intelligent machines. Not surprisingly, it is also an open and key problem for neuroscience.

Within object recognition, it is common to distinguish two main tasks: identification, for instance, recognizing a specific face among other faces, and categorization, for example, recognizing a car among other object classes. We will discuss both of these tasks below, and use "recognition" to include both.

Models of the visual cortex Over the last two decades, some of the best performing recognition systems have come from research at the intersection of computational neuroscience and computer vision. Recent models of visual cortex based directly on known functional anatomy [20, 21] and building on earlier attempts (e.g., [1, 6, 15, 19, 22–24]) were able to account for and predict a number of physiological data from areas of the ventral stream from V1 and V2 to V4 and IT. This family of models was able to mimic human performance in rapid categorization tasks [20]. Surprisingly, some of these models of visual cortex were among the best computer vision systems at the time [16–18, 21].

Computer Vision and the Visual Cortex: Fundamental Differences

The recent past has shown convergence of computational schemes and brain modeling. There still are, however, major differences between models and the cortex, as well as large differences in performance between models and the brain. We will discuss below two examples of prominent features of cortical structure which have only a minor role in current computational models.

Why Hierarchies

The organization of visual cortex is hierarchical, with features of increasing complexity represented at successive layers. Models of the visual cortex have naturally adopted hierarchical structures. In contrast, in computer vision, the large majority of current schemes are nonhierarchical, with no clear difference in performance between hierarchical and nonhierarchical models. Some computational schemes, however, may be implicitly hierarchical and possibly derive some of their power from their hierarchical organization. For instance, SIFT [13] can be regarded as a three-layer network with the output roughly corresponding to intermediate units in a hierarchical cortical model [19]. What is the possible advantage of hierarchical visual representations, and can artificial systems benefit from adopting such representations?

Scale and position invariance One possible role of feature hierarchies is the need to achieve a useful trade-off between selectivity to complex patterns and sufficient tolerance for changes in position and scale, as seen in the response of IT neurons [10–12]. While scale and position invariance can be achieved quite