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Cognitive Vision

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Related Concepts

▶Cognitive System; ▶Visual Cognition

Definition

Cognitive vision refers to computer vision systems that can pursue goals, adapt to unexpected changes of the visual environment, and anticipate the occurrence of objects or events.

Background

The field of cognitive vision grew from the broader area of computer vision in response to a need for vision systems that are more widely applicable, that are able adapt to novel scenes and tasks, that are robust to unexpected variations in operating conditions, and that are fast enough to deal with the timing requirements of these tasks [1]. Adaptability entails the ability to acquire knowledge about the application domain, thereby removing the need to embed all the required knowledge in the system when it is designed. Robustness allows the system to be tolerant to changes in environmental conditions so that system performance is not negatively impacted by them when carrying out a given task. Speed and the ability to pay attention to critical events are essential when providing feedback to users and devices in situations which change unexpectedly [2, 18]

While computer vision systems routinely address signal processing of sensory data and reconstruction of 3D scene geometry, cognitive vision goes beyond this by providing a capability for conceptual characterization of the scene structure and dynamics using qualitative representations. Having knowledge about the scene available in conceptual form allows the incorporation of consistency checks through the use of, e.g., logic inference engines. These checks can be applied both to the knowledge that is embedded in the system at the outset and the knowledge that the system learns for itself. Consistency checking applies across several scales of space and time, requiring cognitive vision to have an ability to operate with past, present, *and* future events. These consistency checks are one way in which the robustness associated with cognitive vision can be achieved [3]. Furthermore, the conceptual knowledge generated by cognitive vision can, if required, be communicated to a human user in natural language [4]. This linguistic communication is one manifestation of an autonomous system demonstrating its understanding of the visual events in its environment [3].

Theory

Cognitive vision entails abilities to anticipate future events and to interpret a visual scene in the absence of complete information. To achieve this, a cognitive system must have the capacity to acquire new knowledge and to use it to fill in gaps that are present in what is being made immediately available by the visual sensors: to extrapolate in time and space to achieve a more robust and effective understanding of the underlying behavior of the sensed world. In the process, the system learns, anticipates, and adapts. These three characteristics of learning, anticipation, and adaptivity are the hallmarks of cognition, in general, and cognitive vision, in particular [6, 7].

A key property of cognitive vision is its capacity to exhibit a robust performance even in scenarios that were not anticipated when it was designed. The degree to which a system can deal with unexpected circumstances will vary. Systems that can adapt autonomously to arbitrary situations are unrealistic at present but it is plausible that they should be able to deal with new variants of visual form, function, and behavior, and also incremental changes in context. Ideally, a cognitive vision system should be able to recognize and adapt to novel variations in the current visual environment, generalize to new contexts and application domains, interpret and predict the behavior of agents detected in the system's environment, and communicate an understanding of the environment to other systems, including humans.

A cognitive vision system is a visually enabled cognitive system, defined in this encyclopedia as "an autonomous system that can perceive its environment, learn from experience, anticipate the outcome of events, act to pursue goals, and adapt to changing circumstances." Since cognitive vision is principally a mode of perception, physical action – with the possible exception of the camera movements associated with active vision – usually falls outside its scope. However, speech acts may be involved when communicating an interpretation of the scene in conceptual terms through language [5]. Since cognitive vision is a particular type of cognitive system, all the issues identified in the cognitive system entry in this encyclopedia apply equally to cognitive vision. They will not be revisited here apart from noting that there are several scientific perspectives on the nature of cognition and on how it should be modeled. Among these differing perspectives, there are two broad classes: the *cognitivist* approach based on symbolic information processing representational systems, and the *emergent systems* approach, encompassing connectionist systems, dynamical systems, and enactive systems, all based to a lesser or greater extent on principles of self-organization. A third class – *hybrid systems* – attempts to combine something from each of the cognitivist and emergent paradigms. The vast majority of cognitive vision systems adopt either a cognitivist or a hybrid approach, with matching cognitive architectures [8].

The term *visual cognition* is strikingly similar to the term *cognitive vision*. However, they are not equivalent. Visual cognition is a branch of cognitive psychology concerned with research on visual perception and cognition in humans [9, 10, 19]. It addresses several distinct areas such as object recognition, face recognition, scene understanding, visual attention (including visual search, change blindness, repetition blindness, and the control of eye movements), short-term and long-term visual memory, and visual imagery. It is also concerned with the representation and recognition of visual information currently being perceived by the senses and with reasoning about memorized visual imagery. Thus, visual cognition addresses many visual mechanisms that are relevant to cognitive vision but without necessarily treating the entire cognitive system or the realization of these mechanisms in artificial systems.

Application

Several applications of cognitive vision may be found in [11–13]. Examples include natural language description of traffic behavior [5], autonomous control of cars [14], and observation and interpretation of human activity [15, 16].

Open Problems

All of the open problems associated with cognitive systems apply equally to cognitive vision. Three which are particularly relevant are highlighted here.

The first concerns embodiment [17]. There is no universal agreement on whether or not a cognitive vision system must be embodied. Even if it is, several forms of embodiment are possible. One form is a physical robot capable of moving in space, manipulating the environment, and experiencing the physical forces associated with that manipulation. Other forms of embodiment do not involve physical contact and simply require the system to be able to change the state of its visual environment, for example, a surveillance system which can control ambient lighting. These alternative forms of embodiment are consistent with the cognitivist and hybrid paradigms of cognition but do not satisfy the requirements of the emergent approach.

Learning in cognitive vision presents several significant challenges. Since cognitive vision systems do not have all the knowledge required to carry out their tasks, they need to learn. More specifically, they need to be able to learn in an incremental, continuous, open-ended, and robust manner, with learning and recognition being interleaved, and with both improving over time. Since the learning process will normally be effected autonomously without supervision, the learning technique needs to be able to distinguish between good and bad data, otherwise bad data may corrupt the representation and cause errors to become embedded and to propagate. Furthermore, the use of learning in several domains is required, including perceptual (spatiotemporal) and conceptual (symbolic) domains, as well as in mapping between them. The mapping from perceptual to conceptual facilitates communication, categorization, and reasoning, whereas the mapping from conceptual to perceptual facilitates contextualization and embodied action. Learning may be interpreted in a restricted sense as the estimation of the parameter values that govern the behavior of models that have been designed into the system, or in a more general sense as the autonomous generation of mappings that represent completely new models.

The identification and achievement of goals in cognitive vision presents a further challenge. With cognitivist approaches, goals are specified explicitly by designers or users in terms of the required outcome of cognitive behavior. With emergent approaches, goals are more difficult to specify since cognitive behavior is an emergent consequence of the system dynamics. Consequently, they have to be specified in terms of constraints or boundary conditions on the system configuration, either through phylogenetic configuration or ontogenetic development, or both. It is a significant challenge to understand how implicit goals can be specified and incorporated, and how externally communicated goals can be introduced to the system from its environment or from those interacting with it, e.g., through some form of conditioning, training, or communication.

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Color Adaptation

►von Kries Hypothesis

Color Appearance Models

►Color Spaces

Color Balance

►White Balance

Color Constancy

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Definition

Color constancy is the ability to perceive colors as approximately constant even though the light entering the eye varies with the illuminant. Color constancy also names the field of research investigating the extent of this ability, that is, the conditions under which a color is actually perceived as constant and which factors