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VISUAL MOTION PERCEPTION
BY INTELLIGENT SYSTEMS

by

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Abstract

The focus of this study is to develop an understanding of the state of the art in visual motion perception by intelligent systems. We examine diverse theoretical and empirical approaches to visual motion analysis, perception, and understanding. We survey the literature applicable to visual motion perception as discussed in scene analysis techniques, hardware-based vision systems, computer animation,artificial intelligence techniques, and human motion perception. We focus primarily on issues of observed object and image sequence description, representation, and perceptual control strategies. We next introduce two concepts in visual motion perception: motion vantage perspective and object motion coherence. We then suggest the emerging trends, problems areas, and alternative directions for research in visual motion perception by intelligent systems.

Introduction

The focus of this study is to develop an understanding of the state of the art in visual motion perception by intelligent systems. We do not restrict our attention to a particular problem domain for examining motion perception. Rather, we seek to derive a general understanding of motion perception tasks in different situations and then unify, generalize, and extend some of the disparate findings that have appeared in the literature.

Our general interest is to develop understandings of the relationship of motion information to the general activity of visual perception in a variety of different viewing situations. Continuous visual motion analysis is useful for visual control of braking or collision avoidance [29], for an autonomous roving robot vehicle, for flight path analysis, and for observing and interacting with industrial parts moving along a slowly moving conveyor belt [20]. But, in general, visual motion analysis is not well understood.

Correctly perceiving images or scenes with motion is a complex task for any intelligent system. A recurrent set of problems must be confronted and resolved. A vision system must reduce the bandwidth of the in-coming visual data to avoid computational (i.e., visual analysis) saturation. Processing strategies which deal with saturation when it occurs are necessary. Specifying the different functions of motion analysis tasks including feature extraction and development of multi-level object descriptions are topics that merit attention. Likewise, for motion understanding, processing different levels scene description, making inferences on observed or unobserved visual phenomena, and utilizing knowledge of prior visual experiences all appear to be necessary system processing capabilities. We will explore these and other related issues.

This paper is organized into four remaining sections. The next section presents a survey of recent work in the areas of Scene Analysis, Computer Animation, Artificial Intelligence, and Human Motion Perception. This section outlines the current state of the art in these respective fields as they may relate to the task of visual motion perception and understanding. In the third and fourth sections, we introduce two issues related to visual motion analysis not well developed in the current literature. Here we attempt to identify linkages between the relevant findings discussed in the second section. In addition, we assume a knowledge-based approach to visual motion perception and understanding. The fifth section presents a set of topics which point to present dilemmas and possible research directions for developing computer systems for visual motion analysis.

Survey of Visual Motion Analysis and Related Topics

Scene Analysis Techniques

Our discussion of scene analysis will primarily focus on motion analysis. We find that motion analysis is usually taken to mean object motion tracking by a stationary observer. Most strategies for motion tracking have been based on tracking idealized planar objects (such as aircraft sihlouettes) which are not occluded by other intersecting object boundaries [4,6,10,13,15]. Some approaches track objects moving in three-dimensional space from a stationary observation position [3,7]. If visual occlusion of objects is known not to occur in a observation setting, then such procedures are useful. However, if partial occlusion of objects can arise in the observation setting, then some other strategy must be pursued. Techniques for recognizing stationary objects that may partially occlude each other include model-based and cooperative template matching approaches to scene analysis [5,14].

Tracking moving objects in a scene sequence can be directed by following the "significant" or interesting features of the object of interest [3]. The specification of these features may be provided either by the interactive user or by the scene analysis system if it is model-based.

Another approach for tracking the motion of planar objects in a scene is also useful for scene segmentation tasks [15]. However, these approaches to segmentation are restricted once again to non-occluding objects. The extent to which object motion tracking of occluding objects can be completed or aided by model-based visual analysis is a current research question.

A related direction in visual motion analysis research concerns the analysis of changes that occur in comparative scenes. Probably the most interesting aspect of this work can be seen in the move from analyzing low-level changes in image pixel clusters [6,7,13] to a higher symbolic level. At the symbolic level, a strategy for describing and explaining the observed changes in the compared images can be followed [1,16,18].

Change analysis at a symbolic level is an effective strategy for dealing with very slow changes in a visual environment. For example, analyzing the movement of selected regions of a stereo image pair can provide information useful for determining the distance of viewed objects from a stationary observer [11]. However, symbolic change analysis as now practiced may not be the best research direction for visual motion analysis. The computational resources required to follow this approach when comparing scenes arriving in real-time rates (e.g., 30 images per second) are not available. This is not to say that use of symbolic descriptions of observable objects in a scene is impractical. Rather, the generation and implied processing of high-level descriptions of objects is impractical for <u>each</u>

image arriving at real-time frame rates.

More and more we are seeing the emerging uses of high-order knowledge representations and supporting control strategies to assist single-scene analysis tasks [2,8,9,12,17]. The representations in use span from geometric to symbolic representations of objects and their features. Popular representations utilize generalized cones for geometric information and structured or partitioned semantic networks for symbolic information [2,8,9,12]. The use of high-order knowledge representations to assist in visual motion analysis has not yet been pursued though it has been suggested [18].

Most hardware approaches to visual motion analysis focus on tracking and determining the relative velocities of a small number (1-4) of non-occluding moving objects [7,18,19]. The imaging devices in use are inherently limited in their ability to accurately record object motion in a scene. This problem is especially acute when imaging fast-moving or momentarily bright visual objects. In short, these vision systems are subject to "motion illusions." Computer vision systems with newer imaging devices (such as CCD sensor arrays) are less subject to certain of these motion illusions, but they too may be subject to yet some other kinds of motion illusions.

"Slippage" techniques are used for tracking non-rigid object motions such as those exhibited by clouds or active micro-organisms [24]. With slippage techniques, when complex or rapid motions are observed the system follows a procedure that softly degrades motion analysis[1] as the image complexity increases. Conversely, as the image complexity decreases, so does the amount of slippage. Slippage routines are currently the only technique capable of tracking arbitrary complex motions.

In brief, we see that current approaches to motion analysis follow scene analysis techniques primarily directed to tracking known or specified features of idealized, non-occluding planar objects [10]. The use of object representations with higher-order feature descriptions, symbolic object representations, and procedures accounting for motion behavior appear to be an emerging trend in scene analysis research.

Computer Animation Techniques

Many image processing techniques in computer animation are complementary to those in scene analysis. Both scene analysis and computer animation techniques depend on the use of internal image descriptions and representational organization.

One of the most common techniques used in the production of animated films is "key-frame" interpolation [22]. With this technique, the animator specifies a pair of images which represent the starting and finishing image for an image sequence. The animator specifies the association between object segments in

[1] When complex images or object motion occur, the system will require greater amounts of processing time to perform analysis to an image. The system thus will let an interval of images bypass or slip analysis.

the two images and then specifies the number of interpolated images to be filled-in by the animation system. The animation system then generates an image sequence displaying the interpolated dynamics of the objects in the scene.

The animation system must be capable of dealing with partial occlusions or overlap of objects or object parts to achieve more natural object motions [23]. Currently, the visual dynamics representing metamorphic changes between initial image pairs can be easily captured with the key-frame technique. In an effort to achieve greater realism of objects and their motion dynamics, the key-frame techniques can incorporate the use of generalized cone and skeletal object representations [9,12,22]. This strategy can help reduce potential computational load at least as experienced by the system user.

One way to further enhance the processing capabilities of an animation system is through the use of extensible data structures [21,25]. These data constructs, together with their attached procedures, can be used to represent the motion dynamics of multi-part objects.

Artificial Intelligence Techniques

In choosing to discuss some of the recent work in Artificial Intelligence (AI), we examine those topics closely related to the issues or techniques for developing intelligent vision systems.

Currently, a topic of broad interest within the AI community concerns the content, construction, and use of high-level knowledge representations [8,9,35,36,40-43]. Many issues center around the development and use of _models_ of some aspects of the problem domain. Models can be use to direct system control, to suggest expected events or situations, to structure knowledge acquisition activities, and to explicitly model the structure and contents of the intelligent system itself [35-43]. However, model building can be very difficult for ill-defined problem domains. It is also difficult to build effective general-purpose models. Some recent scene analysis systems have adopted the use of models as one strategy for recognizing partially occluded objects [14,36].

A related issue in the use of models concerns the organization of descriptive information incorporated in a given knowledge representation. Recent work is directed at developing strategies for organizing knowledge of a problem domain at different _levels of description_ [8,39-41,43]. This leads to the use of models organized into multiple knowledge sources or modules supporting the different levels of object description. The showcase AI system that directly addresses this topic is the HEARSAY-II speech recognition system [39]. This approach to knowledge organization is also useful in learning situations [35,43]. This notion of organizing the various levels knowledge of some problem environment or situation appears to be quite amenable as a strategy for organizing visual information.

The effective use of knowledge organized at different levels requires efficient control mechanisms. Two related strategies are useful here. The first is based on cooperative interaction with an intermediate knowledge structure: a globally viewed "blackboard." This knowledge structure serves as a short term data base for storing active knowledge chunks clustered at different levels. However, deciding which chunks of information are useful for a given understanding task depends on selectively attending to available information. This is where the second control strategy comes into play.

A system which must choose among multiple or diverse knowledge sources needs some mechanism to focus its attention. A knowledge-based system can utilize an attention focusing scheme which cooperatively or competitively draws upon either in-coming low-level information or high-level symbolic information about the situation. These control strategies are respectively labeled data-driven and model-driven[2] [37,39,41]. The extent to which alternative focusing strategies can be embedded in different levels of system knowledge (such as in schematized production systems [40]) is likewise related to the information source selection process.

[2] When a knowledge-based system is data-driven, the occurrence of observed events (such as recognizing a characterizing feature of an object) directs the system's processing attention. This control strategy is most viable in task domains with high "signal-to-noise" ratios [41]. When the system is being model-driven, the system relies on its existing knowledge to suggest or hypothesize the occurrence of objects or events.

The global blackboard structure together with the attention focusing schemes provide a working control strategy for an understanding system that utilizes multiple knowledge sources organized at different levels. It seems that a knowledge-based vision understanding system could be developed along these lines.

Human Motion Perception

Our investigation of this literature focuses on topics that appear to be closely related to the work in computer vision [cf. 33,34]. Visual psychologists report that in certain viewing settings, motion information can act as the primary cue for recognizing objects in a scene [28]. Also, motion information is found to override static indicators (e.g., converging texture gradients and perspective) when perceiving the slant of the observed environment [26,27].

People exhibit the ability to recognize object motion signatures [26-28]. Recognizing motion signatures seems especially useful when viewing objects that exhibit motions familiar to the observer. These perceptual capabilities are useful when viewing partially occluding objects. Furthermore, people can recognize non-rigid motion signatures.

Johansson and Braunstein suggest that people perceive non-rigid object motions as a hierarchy of rigid motions [26,28]. People apparently can more easily understand rigid object motions. Thus people decompose and organize perceived non-rigid motions into manageable chunks of rigid motions. Such clustering occurs about the signficant features of objects as perceived by a human observer [30]. Furthermore, this clustering of object-features may be organized in hierarchical levels in a global-to-local manner [32]. But the available evidence suggests localized or partial hierarchies are a better characterization.

There are no apparent perceptual models which claim to organize or integrate visual and spatial knowledge of multiple domains. However, people may utilize symbolic knowledge representations similar to "Scripts" [40] to recognize and understand object motion signatures. But presently, this is an unexplored topic.

Motion Vantage Perspective

Different viewing situations imply different flow of control issues for a visual motion analysis system. Visual motion analysis by any intelligent system is yet to be examined from three object motion vantage perspectives. These three different viewing situations are:

1. Stationary observer (with stationary background) with the object(s) in motion in the foreground
2. Moving observer (with known trajectory information) viewing stationary objects
3. Observer moving (with background following the same motion trajectory) while visually tracking a moving foreground object.

These various viewing situations may require three different motion analysis strategies. This observation suggests the need to understand the appropriate control strategies and attached planning mechanisms necessary to affect the transformations in visual analysis processes. Part of our concern here is to determine what visual processes follow procedures that are viable in one viewing situation but not in another.

In attempting to specify the naturalness of motion vantage perspective state transitions, we also must consider how alternative control strategies or other system limitations give rise to certain visual motion illusions. We believe that certain motion illusions will be experienced with current computer vision systems if extended to undertake visual motion understanding tasks. Motion illusion problems may arise due to the limiting characteristics (such as bloom, lag, alaising, and image smearing) of real-time imaging devices. One strategy to mitigate these illusions is to adopt an approach to scene understanding that allows motion slippage to occur [24]. Slippage would be tolerated for specified times depending on the nature of the hardware-induced motion illusion. However, the extent that such a strategy is effective given knowledge-based motion illusions is yet to be determined.

The different visual motion vantage perspectives lead us to consider the knowledge-control interface requirements for a vision system. We address the following conjectures to these requirements:

1. A vision system capable of robust visual motion perception and understanding must make use of "long-term" memory of the features and spatial relationships of known or observed static objects. In addition, the vision system must account

for the relative location of the observer vis-a-vis the observable environment.

2. A vision system should possess some kind of working "intermediate" memory where a focusing mechanism can interact with the current knowledge-base perspective[3] and in-coming visual data.

3. A vision system should utilize a "low-level" (iconic) visual memory to support a hardware based capability for extracting and labeling the features of objects (such as color, texture, and boundaries) or events of interest in the visual scene.

4. A vision system should use an attention-directed "retina" or viewing window to selectively observe objects or object features within the image. The retina thus acts as a knowledge-base process.

5. These vision system structures and processes will interactively work both for and against each other. No single predetermined order shall prevail.

While these suggestions may imply formidable engineering undertakings, the research literature suggests the mutual dependence of these vision system considerations. Are we merely suggesting the need for an integrated system approach? Yes in the sense that the HEARSAY-II speech recognition system represents an integrated system. And no in the sense that integrated systems require centralized control for managing operations. The approach to system integration we are referring to is achieved through <u>distributed control</u>: control of knowledge sources and processing activities which emerges from

[3] By knowledge-base perspective, we mean the current working knowledge about imaged objects arrangement within their environmental context as internally "viewed" from the observer's motion vantage point.

knowledge-base transactions.[4] This implies that an intelligent system's ability to analyze, understand, and react to a bounded, though not necessarily predictable, range of situations arises from conflicting, competing, and cooperating interactions.

New Directions in Visual Motion Research

The established object of analysis in computer vision research is the single image. Research in image understanding indicates that large amounts of "world" or contextualized knowledge improves a vision system's ability to understand a single image. Continuous image sequences from real-time imaging devices, however, can consist of large numbers of individual yet semantically similar images [10]. Analyzing image sequences by adopting a repetitive "single image" perspective may not be the best strategy to pursue.

In intelligent vision systems, high-level knowledge representations support inferential computations which facilitate visual recognition tasks. Likewise, when analyzing image sequences, knowledge representations can be utilized to inferentially bind moving objects to their knowledge-base descriptions.

[4] this model of control is similar to that suggested by Hewitt [43].

Image sequences exhibit properties of coherence. Image sequences contain objects that are semantically identical within the bounds of space and time. For example, when people view an image sequence, they use the knowledge that an object recognized at a given moment is still the same object in sight until the scene changes. People apparently do not need to re-recognize objects viewed moment to moment. This is often the case even when the object is viewed from different motion vantage perspectives. An intelligent vision system can exploit the visual knowledge embedded in a coherent image sequence. We refer to this property of visual motion semantics as <u>object motion coherence</u>. We further note that this appears to be a lower-level property of visual motion knowledge.

A visual motion analysis system that utilizes knowledge of object motion coherence de-emphasizes the need to analyze a visual setting on a frame-by-frame basis. This implies that such a vision system relies more on high-order knowledge descriptions, representations, and processing in understanding an image sequence. For example, with a "smart" vision system, key-frames -- those frames in which object features change "unexpectedly" -- are the primary images for analysis. Recognizing key-frames is the essential task. Frames between key-frames exhibit object motion coherence. Thus, such a vision system could focus its attention to understanding key-frames or just the unexpected objects in those frames. Furthermore, if the system recognizes a known object motion signature, then it can attend to pertinent object features or to their consistency with an object's motion script.

The low-level processing of images is influenced by the needs of higher-level analysis in the vision system. Low-level image processing should support the symbolic processing activities of recognizing and describing of object features particularly color, texture, and boundary information. These low-level features cohere between key frames. When new object features appear or when the existing order of object features in an image changes, then a key-frame is indicated. The intelligent vision system needs to acquire image-based information selectively. However, this information must be be continually accessable. The selection of pertinent low-level symbolic information will thus be driven by the processing of models in the knowledge-base in the presence of in-coming visual data.

We consider low-level symbolic image pre-processing to be a necessary intelligent vision system capability. Such a capability is needed to support feature extraction or image data compression to avoid saturation of the visual analysis processes. Computational saturation can occur due to high bandwidth data rates from real-time imaging devices. Image preprocessors serve to reduce the raw bandwidth of data flowing through the vision system. Furthermore, the image preprocessors should gracefully accomodate low-level analytical slippage when processing capacity is exceeded.

With low-level knowledge, we also need to indicate how visual knowledge processes are organized about multi-level vision knowledge and knowledge descriptions. These multi-level knowledge processes and descriptions are to be staged in partial hierarchies -- not according to a single hierarchical ordering. The ordering of these structures is determined in part by the current "cognitive" model of the imaged objects, the objects dynamics, and the descriptive data that is available. As such, the composition of multi-level knowledge processes is built from the following components: object features, object representations, object motion scripts, the perceived spatial organization of the visual environment [38], and the vantage perspective of the observer.

Current Problem Areas in Visual Motion Understanding

Given the representational power of multi-level visual knowledge organization, there are still many poorly understood practical problems. These problems must be confronted and resolved in order to develop vision systems which understand motion. The following list of problem areas in visual motion understanding merit further investigation:

-- We expect the next generation computer vision will utilize high-level knowledge representations. These representations are yet to be incorporated into vision systems which interactively utilize low-level symbolic information with knowledge of an environment where objects and the observer can change location.

-- The use of high-level knowledge representations is predicated on the use of various models of object features, objects and object behaviors. While such models are useful for analyzing and understanding a situation, we still don't have good strategies for establishing what information should be represented in a model. Also, our understanding of how an intelligent system can learn or be taught models of new domains is minimal.

-- The kinds of computational inferences that bind the multi-level descriptions of entities in an image sequence to their representations are not widely known. Likewise, the deductions that can be drawn from these representations regarding "missing" or occluded information are not widely known.

-- Tracking objects with linear or curvilinear trajectories is an established capability. But the notion that complex object motion patterns recur in ways that can be succinctly described, represented and recognized by a computer vision system is not well understood.

-- Our understanding of high-level knowledge-base management and low-level image-base management is limited. Our understandings of distributed control schemes which lets these data-bases interact is also limited. In addition, experience with multi-level knowledge organizations is limited, though this appears to be an emerging approach in knowledge-based system research.

-- The ability to use motion information as a cue for determining the spatial relationships of objects and their surface slant orientations is yet to be explored for computer vision systems. Similarly, for intelligent vision systems, the presence and effects of motion illusions -- due to processing or device constraints -- are poorly understood. Here there is a need to identify the different conditions under which certain kinds of motion illusions will be experienced and to suggest different strategies for minimizing adverse effects.

In order to develop solutions to these research problems, we need to consider alternative strategies for acheiving these goals. Present strategies are adequate but not necessarily extendable to visual motion analysis. Rather, in examing this list of alternatives, we see that the solutions to these problems all impact the design, organization, and processes of a knowledge-based computer vision system.

Summary

In this document, we examined diverse empirical and theoretical approaches to visual motion analysis, perception, and understanding. This work began from an interest to see what is known about these topics, what research findings have been derived, and what the range of research problems appears to be. We examined the extant visual motion literature as discussed in scene analysis, computer animation, artificial intelligence techniques, and human motion perception. We examined selected topics central to visual motion recognition tasks, which did not appear in the literature. Finally, we suggested emerging trends and problem areas in visual motion research.

If there is single point to assert about the direction of visual motion research, it is that a visual motion analysis and understanding system must be organized about descriptive multi-level knowledge sources whose interactions are directed by continually emergent, distributed control processes.

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