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From Knowledge based Vision Systems to Cognitive Vision Systems: A Review

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Abstract

Computer vision research and applications have their origins in 1960s. Limitations in computational resources inherent of that time, among other reasons, caused research to move away from artificial intelligence and generic recognition goals to accomplish simple tasks for constrained scenarios. In the past decades, the development in machine learning techniques has contributed to noteworthy progress in vision systems. However, most applications rely on purely bottom-up approaches that require large amounts of training data and are not able to generalize well for novel data. In this work, we survey knowledge associated to Computer Vision Systems developed in the last ten years. It is seen that the use of explicit knowledge has contributed to improve several computer vision tasks. The integration of explicit knowledge with image data enables the development of applications that operate on a joint bottom-up and top-down approach to visual learning, analogous to human vision. Knowledge associated to vision systems is shown to have less dependency on data, increased accuracy, and robustness.

Keywords: Computer Vision; Knowledge; Cognitive Vision

1. Introduction

Modern computer vision research and applications were first approached as part of the Artificial Intelligence (AI) agenda to create systems that could autonomously understand the visual world. The lack of resources in early research time and the need for automation in a variety of industrial, scientific and military tasks narrowed down the goals of computer vision. Subsequent research adopted mathematically oriented approaches to specific tasks in more practical applications[1,2]. Most recently, the development of new techniques in fields such as machine learning has contributed to significant progress in computer vision, enabling systems to outperform humans in certain tasks.

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However, the performance of current systems is highly data dependent, lack generalization beyond the training datasets, and requires major adaptations to include new conditions[3]. Therefore, the ongoing challenge in vision systems is to create robust and flexible systems that can recognize complex object classes under poorly controlled environments[4], and do not require prohibitive amounts of training data to solve unconstrained computer vision problems[5,2].

In this context, human vision has been used as a reference model for excelling under these conditions for which machines still fall short. In recent years, approaches have been proposed to mimic the human intelligence capabilities by combining prior knowledge and visual information in knowledge vision based systems, which is a step towards cognitive vision. These systems may perform recognition under conditions that pose limitations to computer vision systems, such as the presence of geometrical variation, unideal lighting conditions, occlusion[6], among others. It usually relies on top-down contextual knowledge acquired from visual experiences, combined with the bottom-up information constantly collected. For instance, in the human mind, the same object will be known, by experience, to exist in a variety of different forms, sizes or shapes. This accumulation of experiences allows human vision to comprehend and classify new images [4,2]. Therefore, knowledge based vision systems may integrate the bottom-up data-driven approaches that perform computer vision tasks through machine learning algorithms with the top-down approach offered by prior knowledge into an inference process inspired by biological vision[3].

This paper is organized as follows. In Section 2, we present a brief overview of current vision systems, their tasks and limitations. Section 3 introduces knowledge-based systems. Section 4 describes how explicit knowledge has been applied in vision systems and surveys applications developed in the last ten years, as a step towards cognitive systems, organized by their pertaining fields. Finally, Section 5 summarizes the findings in this paper.

2. Vision Systems and Current Limitations

The universal goal of computer vision is to provide visual information for a given application[7]. To achieve this, vision systems can be comprised of different subtasks which are grouped under three categories: Low-level Vision, Intermediate-level Vision and High-level vision. Low-level vision tasks comprise operations such as image acquisition and pre-processing. Intermediate-level tasks pertain to segmentation, symbolic representation, classification and recognition. High-level vision tasks are concerned with achieving conceptual understanding of information acquired from lower-level vision modules.

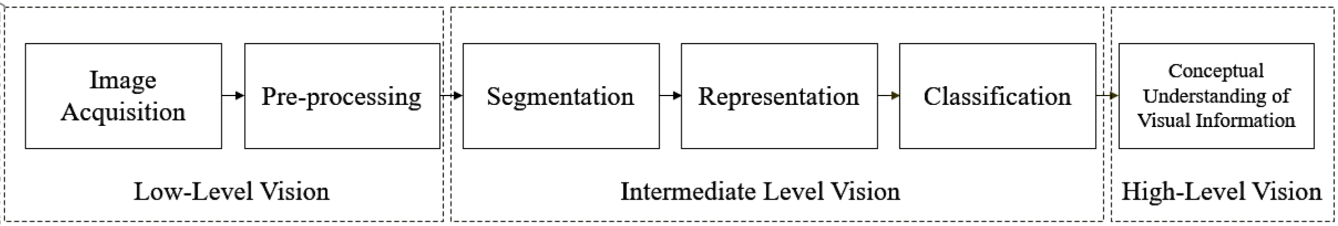

Fig. 1 – Block diagram of a typical cognitive vision system

A complete cognitive vision system (Fig.1) is the result of the integration of these three levels, including all the tasks required to identify image elements and establish relationships between themselves or between elements and the viewer.[8,9] However, this definition arises from a functional/architectural approach, which is based on the set of minimal tasks that a system is required to perform in order to be classified as a cognitive vision system. Researchers have addressed some issues with this approach, as a good definition "should be neutral to any underlying model", advocating for a universal definition of cognitive vision that is independent of structure.[57] Such generic definition remains elusive.

Currently, computer vision is a well-established field of research, with noticeable focus on intermediate level applications, such as the automation of tasks in production lines in industrial settings. For many of these vision problems, solutions can be attained based on mathematical descriptions without the use of prior knowledge[2]. The issues with this approach is that it often cannot match real-world conditions and it is not able to estimate unknowns. The ongoing challenge is to develop systems that are robust to noise and deviations from data-driven models, as well as efficient in terms of computational requirements and memory space[10]. Other challenges involve reducing the reliance on large training data sets, invariance, and handling degradations in training data[11].

3. Knowledge Based Systems

Knowledge based systems are often employed for performing tasks using an explicit form of knowledge representation to handle information encoding and inference processes according to the corresponding inference engine implemented. Therefore, a knowledge based system consists of a knowledge base and an inference application mechanism[12]. Knowledge bases have been employed in applications that require flexibility to be gradually advanced[13], to replace or reduce input in tasks for which factors such as fatigue and boredom can impact performance[14], and to integrate human expertise and machine learning methods to reduce time, efforts and cost[15].

Designing knowledge based systems impose the challenge of obtaining knowledge. Such can be done both by integration in design or reuse of experience. Other design considerations concern with the reuse and exploitation of knowledge. Ideally, in a knowledge based system architecture, ontological, domain-specific and problem specific knowledge are separated and easily identifiable within the inference system, to improve reusability and help to establish formal properties[16].

4. Knowledge Based Vision Systems

The ultimate goal of computer vision systems is the capability of generic image interpretation and semantic description[7]. For this purpose, the limitations of geometrical representations were early identified (as they cannot handle the large amount of variations an object can have and models including additional information on the function of an object (known as affordances) was proposed[1]. These models were based on psychologist James J. Gibson's concept of affordances, stating that humans understand objects according to the ways it is usable[2]. In addition to enabling better object recognition, affordances can provide information about the scene context. The understanding about scene composition in an image (which set of objects are present) can improve recognition performance about the scene where they are inserted. For instance, the presence of multiple cutlery items in an image can aid the recognition of a kitchen image. This relationship is held both ways, as contextual knowledge can also offer insights about the function of an object in a scene, reducing the impacts of sensor noise or occlusions. In this case, the recognition of an individual cutlery item could be enabled by recognizing the kitchen environment, and therefore the affordance of the individual object[17].

Research from other cognitive science fields have also shown that visual understanding of the surrounding world goes beyond vision, and the integration of conceptual knowledge cannot be overlooked. Conceptual knowledge aggregates what we know about the world, such as what is learned from previous experiences[18]. Marvin Minsky argued that frames could provide a global theory of vision, by proposing that, memory structures called Frames, could encode knowledge similarly to how humans remember the information needed to identify new situations based on previous experiences. With structured and concise ways to organize knowledge, information can be revisited and adapted to fit reality[2].

4.1 Applications of Knowledge Bases in Vision Systems

In addition to enable computers to interpret images, knowledge has been proposed for integration in individual modules of vision systems. Early knowledge based vision systems were mainly concerned to low and intermediate level vision tasks such as segmentation[9]. Moreover, contextual knowledge has been proposed to reduce computational resources as it places a smaller burden in the system as compared to storing the geometrical representation of every single variant of the same object[2,9].

Finally, the use of explicit knowledge representation in vision systems offer several benefits present in conventional knowledge-based applications, such as the flexibility to add rules without the need for any major alterations in existing code, the extraction of information from example and the reuse of acquired knowledge[9].

A cognitive vision achieves four levels of computer vision tasks[2,57]:

- *Detection* of a particular item in the visual stimulus;
- *Localization* of the detected item;
- *Recognition* of which class the item belongs to
- *Understanding* the role of an item present in the scene

These functionalities can be achieved through[57]:

- A faculty for learning semantic knowledge;
- The retention of contextual knowledge, and how it relates to the system;
- Reasoning about objects and events in the environment

In this session, applications of knowledge bases in vision systems are surveyed. In the context of this paper, the systems that aim to perform "subtasks" of cognitive visions are defined as knowledge based vision systems.

4.1.1 Image Understanding, Processing, Annotation and Retrieval

Automatic annotation of image datasets has gained interest given the large amount of training data required for machine learning classifiers. For instance, automatic annotation for images has been achieved by acquiring knowledge automatically from data[19] by using a fuzzy knowledge representation scheme based on the Fuzzy Petri Net formal representation, the proposed system uses an inference mechanism to understand scenes and concepts that cannot be linked to images without the use of domain knowledge. A similar approach using a feature-engineering inspired framework was used to find intrinsic data structural information. This data structural knowledge was exploited using labeled and unlabeled images in a supervised-learning based model, boosting image annotation performance[20].

In image processing, the use of knowledge instead of raw data has been employed in Transfer Learning to improve segmentation performance in texture images. While this is usually achieved using referable information between the source and target domains' raw data, the use of prior-knowledge extracted from other texture images was found to be insightful and less susceptible to noise than other approaches. This was achieved by establishing pairwise relationships of clustering prototypes between the source and target domains[21]. Prior-knowledge has also been used in image registration (matching image regions from different images) to reduce computational requirements imposed by area-based methods while maintaining high accuracy in performance[22].

Finally, in retrieval systems, the performance is dependent on their understanding of high-level features within images. A novel technique for automatic query interpretation of image using lexical and common-sense knowledge was shown to outperform traditional query expansion methods[23]. Another knowledge based image retrieval system was developed to organize the image database into all different domains covered by the database, by integrating semantic and visual features[24].

4.1.2 Image Classification

In order to improve performance in image classification, researchers proposed the integration of prior-knowledge encoded in graphs with a Graph Search Neural Network (GSNN)[25]. Using features from the image to efficiently annotate the graph, selection of a relevant subset of the input graph enabled the prediction of outputs on nodes representing visual concepts.

Using Genetic Programming and Transfer Learning researchers have been able to improve the performance in classification of rotated and noisy images[26]. Transfer Learning extracts knowledge from a source task and apply to more complex (but still related) tasks. Genetic programming (GP) is a computational approach to automatically develop solutions for a given problem. The images from the training set of the GP program were used to generate knowledge base vectors. Finally, a Nearest-Neighbor classifier was applied to classify the images using feature vectors generated from testing images and the set of knowledge vectors.

Explicit knowledge has also been integrated to improve different aspects of machine learning based approaches. To improve classification accuracy, domain knowledge was encoded in a Probabilistic Ontology to express the spacial relationship between image objects in terms of probability[27]. Prior knowledge was proposed as a way to reduce the required training data from deep networks, using Sematic Based Regularization (SBR) to represent prior knowledge as a set of first-order logic clauses (FOL). The knowledge base and the tasks to be learned were correlated and translated into a set of constraints that is integrated in the learning process. The results showed reduction in the amount of training data required and increased accuracy[28].

4.1.3 Object Recognition

In the object recognition field, researchers have proposed the use of circumstantial knowledge to improve the performance of traditional Support Vector Machine methods, with more pronounced boost in accuracy when the amount of training data available was small[3]. Contextual knowledge was also employed as an acting supervision for a conventional supervised statistical learning algorithm (Vector Quantisation based nearest neighbour classifier). The proposed system builds and uses models autonomously from sensory input, encapsulating information in a way that can be applied to new datasets[29].

To mitigate performance issues caused by changes in illumination, difference in backgrounds, noise and discrepancy in image resolutions, prior knowledge and context information have been used. A framework was proposed to integrate image process techniques and knowledge representation to develop a system that can automatically identify real unsafe activities in industrial environments. In this system, knowledge was acquired and structured in order to obtain and reuse formal decision events. Visual information acquired from camera images and context-based data are represented as Set of Experience Knowledge Structure (SOEKS), a knowledge structure capable of storing formal decision events for later reasoning and risk evaluation. Then, grouped sets of decisions from the same category are stored as decisional experience named decisional DNA (DDNA) to support future decision-making events in similar input images[30]. These structures of knowledge representation were later shown to be effective in improving accuracy performance and solving scalability issues, providing a framework that can be adapted to different conditions, clients, and situation without the need for major changes to the code[31]. Similarly, in order to deal with real world scenarios that lack resolution, a fine-to coarse knowledge transfer approach was proposed for applications such as surveillance or satellite images, where image resolution is low at test time, but high resolution labelled photos are available[32].

Although the importance of using affordances has been early addressed, the issue of collecting the semantic knowledge as affordances remains. This has been addressed by using Latent Semantic Analysis to convert words to semantic vectors. Researchers counted the frequency of the appearance of verbs and nouns together representing the action-object affordance to query an image search engine and developed a more effective way to mine affordance knowledge, as compared to mining from texts and images[33].

4.1.4 Human Activity Recognition

Knowledge based human activity recognition systems (KBAR) use a priori knowledge (such as knowledge of which activities are expected to be performed and knowledge of human anatomy) and context information (the location where images are being collected from) for activity recognition. These applications can be grouped into three categories: statistical approaches, syntactic approaches, and description-based approaches[34].

A survey showed that knowledge exploitation has been used to select suitable classification techniques and improve overall performance. Statistical approaches have been increasing in recent years, with predominance in use of Bayesian Belief Networks, Probabilistic Petri Nets and Hidden Markov Models. Syntactic approaches define a set of domain-dependent bases, with entities that are formed by attributes, functions and relationships. Different authors have exploited this approach through representing knowledge as logic rules (first-order logic), approximate reasoning (when represented knowledge is characterized by a certain degree of uncertainty, for instance, expert domain knowledge possessed by humans), grammars (theoretical basis for modelling structured processes) and ontologies (formal description of the knowledge within a domain). Lastly, description-based approaches rely on spatio-temporal structures of human activities. These approaches involve the description of temporal structures of activities in terms of sequential and current subevents[34].

Visual semantic planning, which predicts a sequence of actions that achieves a desired goal, has been employed to encode affordances in human activity recognition. A proposed framework showed promising cross-task knowledge transfer capabilities, which could enable the system to achieve generalizable solutions[35]. Commonsense knowledge has also been used to improve activity recognition. Given the GPS position of the user, the neighboring commercial activities were identified using a reverse geo-coding service to classify the satellite image of the area[36].

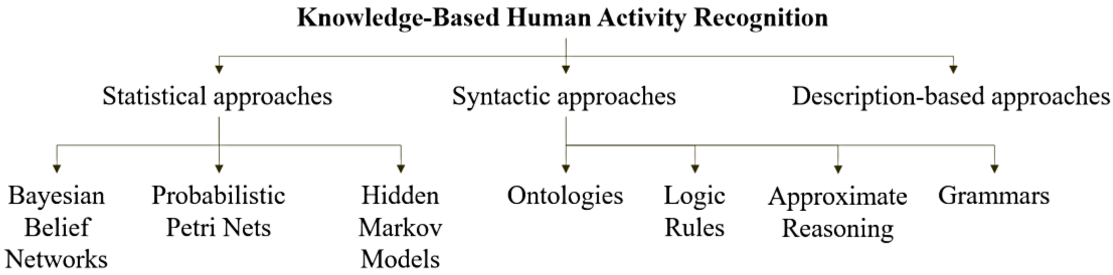

Fig. 2 – Summary of surveyed approaches commonly used in KBAR[34]

4.1.5 Face Detection and Face Recognition

Traditional methods used in facial action units (AU) are data-driven, ignoring any knowledge/theories that govern the facial muscles movements. Exploiting domain knowledge and integrating them with image data results in robust AU recognition, in an approach that can generalize to different people and datasets[3]. A new data-driven approach was proposed to describe facial expressions converting features to semantic knowledge. The method based on axiomatic fuzzy set (AFS) theory acquires sematic knowledge from data distribution, and links this acquired knowledge to facial expressions using optimized criterion selections[37].

4.1.6 Medical Images Analysis

The integration of expert and domain knowledge in the field of medical images analysis has been exploited in several applications.

Anatomical information was seen to improve the quantification and contrast-to-noise ratio (CNR) of small lung nodules. Combining the use of an anatomical prior knowledge with the post-reconstruction partial volume correction (PVC) method greatly increased CNR without a clear impact on the quantitative accuracy when compared to using the PVC method alone[38]. Similarly, inter-structure relational knowledge was used to reduce the number of false positives in the detection process of anomalies present in retinal images[39]. Medical knowledge in breast cancer grading (BCG) improved current manual annotation procedures for semantic indexing of histopathology images[40] and to reduced time in annotation of cellular nuclei[41]. A cognitive computing technology was used to perform corrective post-processing and remove artifacts (such as discontinuous blood vessels or two vessels shown merged when they are not) from MRIs[42]. In low-dose computed tomography (LdCT) that presents noise, classical techniques such as Markov Random Field (MRF) may compromise tissue texture information that is important for differentiating malignant from benign lesions. Researchers incorporated priori knowledge from full-dose computed tomography to achieve texture preserve reconstruction of LdCT[43].

Some medical applications pose challenges due to the nature of the images used. For instance, automated prostate segmentation in magnetic resonance imaging (MRI) images is a challenge, as the shape of the prostate can present wide variations among different people. In addition, boundaries of regions of interest are not easily distinguished from the background. To deal with these issues, researchers proposed an approach that acquires local intensity features using a random walker (RW) algorithm and prior knowledge from an atlas probability map. This approach outperformed that of the conventional RW in both accuracy and robustness[44]. Prior knowledge was also shown to increase segmentation accuracy in prostate MRI[45] and enable boundary-based semi-automated segmentation for the colon wall in Computed Tomography Colonography (CTC)[46].

Finally, some applications are concerned with exploiting knowledge from available datasets. Computer-aided diagnosis (CAD) using big data and deep learning was achieved by design and implementation of a medical image knowledge base (KB). The medical image KB proposed is capable of storing thoracic CT image and its diagnostic information effectively and structurally for pulmonary nodule diagnosis[47]. Semantic annotations storing structural and anatomical information was used to acquire knowledge in computer aided dentistry detection[48].

4.1.7 Traffic Monitoring and Public Surveillance

The performance of current algorithms for image recognition in outdoor setting degrades under challenging illumination conditions. This poses portability issues, where consistent performance in varying environmental lighting is required. Researchers proposed a novel guided deep network that distills knowledge from a multi-modal pedestrian detector. The proposed network learns to extract both RGB and thermal-like features from RGB images alone, eliminating the need for costly automotive-grade thermal cameras. Quantitative results show the model could better detect pedestrians which are only marginally visible. The system outperformed a model trained only from ground-truth annotations with improvement of 12% over the existing state-of-the-art methods[49]. A knowledge-driven system was also designed to control unidirectional traffic on highways and freeways through the use of knowledge on traffic conditions[50].

4.1.8 Remote Sensing

Several types of knowledge related to sensing image understanding has been identified. A proposed knowledge representation (KR) architecture for remote sensing image understanding systems grouped explicit knowledge in six categories: object knowledge, image knowledge, environment knowledge, algorithm knowledge, task knowledge, and integrated knowledge, which combine knowledge from symbolic representations and computational intelligence[51].

In other applications, environmental knowledge is seen to be the most commonly exploited type of knowledge. A study proposed a method of road damage detection based on the road knowledge. Three key procedures were carried out in this study: the road centerline extraction, the post-disaster road extraction and the damage detection based on road knowledge[52]. Environmental knowledge has also been employed for a bridge detection system[53] and building detection, in which the information on solar angles was used to overcome shadow masking effects[54]. Other types of knowledge such as prior information about scene components evolution and expert geoscientist knowledge encoded in semantic representations was used in a new approach to achieve automatic Satellite Image Time Series analysis for land cover monitoring[55].

5. Conclusion

The integration of knowledge into vision systems has been early proposed to achieve generic image understanding analogous to human vision. Subsequent research moved away from artificial intelligence methods onto pragmatic goals for constrained scenarios, using statistical and mathematical approaches. Despite the research advancements, computer vision systems still face many limitations that can be resolved with the integration of a knowledge base.

Although the use of explicit knowledge has been initially proposed to design truly autonomous and cognitive vision systems, different types of explicit knowledge have been integrated in various modules of image understanding architectures. Predominantly, semantic knowledge, contextual knowledge and expert domain knowledge have been exploited. A prominent topic in knowledge based vision systems is Transfer Learning, as there are increasingly more available labelled datasets that can be used to overcome limitations in real life situations where data is incomplete or of low quality.

Among the applications surveyed for this review, only a very limited amount uses a formal architecture of knowledge representation. This segregation between Computer Vision and Knowledge Representation communities may be due to predominant focus in research on lower-level vision[56]. This may pose a hindrance in the progress of cognitive vision systems, as the design of knowledge bases is frequently application-oriented, and therefore not portable.

Several authors have addressed the problem of lack of standardisation in knowledge based vision research. This offer numerous challenges to the development of new applications, like the identification of resourceful prior knowledge, the capture of the knowledge of interest and the process of encoding knowledge into visual learning. By exploiting the use of formal knowledge representation architectures, the integration of knowledge into visual learning can mitigate ongoing issues in vision systems such as overfitting, and too much reliance on quality and quantity of training data. There is a multitude of application domains and subtasks among vision systems. The integration of knowledge representation architectures is of interest for the computer vision community, as portability can lead to further progress towards the development of vision systems that are robust out of laboratorial environment and able to generalise to novel data and visual learning tasks[3,9].

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