Technical Report

Pattern Recognition and Image Processing Group
Institute of Computer Aided Automation
Vienna University of Technology
Favoritenstr. 9/183-2
A-1040 Vienna AUSTRIA
Phone: +43 (1) 58801-18351
Fax: +43 (1) 58801-18392
E-mail: axel.pinz@tugraz.at, bischof@icg.tu-graz.ac.at, {krw,yll,ion}@prip.tuwien.ac.at, {gschweig,opelt}@emt.tugraz.at,
URL: http://www.prip.tuwien.ac.at/

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Representations for Cognitive Vision: A Review of Appearance-Based, Spatio-Temporal, and Graph-Based Approaches[1]

Axel Pinz[a], *Horst Bischof*[b], *Walter Kropatsch*[c], *Gerald Schweighofer*[a], *Yll Haxhimusa*[c], *Andreas Opelt*[a], *Adrian Ion*[c]

Abstract

The emerging discipline of cognitive vision requires a proper representation of visual information including spatial and temporal relationships, scenes, events, semantics and context. The goal of this review article is to summarize existing representational schemes which might be useful for cognitive vision, and to discuss promising future research directions. We structure the various approaches into appearance-based, spatio-temporal and graph-based representations for cognitive vision. The representation of objects has been covered extensively in computer vision research, both from a reconstruction as well as from a recognition point of view. Cognitive vision, however, will also require new ideas how to represent scenes. We introduce new concepts for scene representations and discuss how these might be efficiently implemented in future cognitive vision systems.

[a]EMT - Vision-based Measurement Group, Institute of Electrical Measurement and Measurement Signal Processing, Graz University of Technology
[b]ICG - Institute of Computer Graphics and Vision, Graz University of Technology
[c]PRIP - Pattern Recognition and Image Processing Group, Vienna University of Technology

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1 Introduction

Cognitive vision is an emerging discipline that brings together such diverse fields of research as digital image analysis, computer vision and cognitive sciences. From a computer scientists point of view, several major issues have to be solved in engineering a cognitive vision system: embodiment, learning, recognition, and reasoning. At the basis of all these efforts, we require a proper *representation* of visual information, spatial and temporal relationships, scenes, events, semantics, and context. This report gives an overview of existing representations that should suit some of the requirements of a cognitive vision system, and outlines promising research directions. Special emphasis is put on appearance-based, spatio-temporal, and graph-based representations, including a comparison of these rather diverse approaches.

Even though there is no generally accepted definition of cognitive vision yet, presumptions about the cognitive capabilities of a system can be made by comparing it's results with that of an entity, already 'known' and accepted to have these capabilities, the human. The *Research Roadmap of Cognitive Vision* [161], presents this emerging discipline as 'a point on a spectrum of theories, models, and techniques with computer vision on one end and cognitive systems at the other'. Potential definitions of a cognitive vision system range from 'visually enabled cognitive system' to 'cognitively enabled vision system'.

Typical results that we would expect from a cognitive vision system are for instance to be able to correctly answer queries regarding the relative position of occluded objects or to recognize previously unseen objects of a learned category. Based on this brief discussion of 'cognition' in a vision system it clearly arises that suitable representations of objects and scenes are a principle basis. It also follows that it would on one hand be desirable to enable the easy extraction of data for human comparison. On the other hand it will be necessary to bridge the gap between high level and low level abstraction data used for computer vision and cognitive processes (see also [80]).

The first complete theory of a *computational* approach to vision has been presented by the late David Marr [104]. This seminal work has not only significantly influenced a decade of Computer Vision research, but is still used by researchers from related fields as the reference framework in setting up new theories (see e.g. Palmer [135]). Marr distinguished between a *reconstruction* and a *recognition* approach, which has been further detailed by Aloimonos and Shulman [5]. He also initiated work on representations when he introduced what he called a 'primal sketch' (local 2D saliency), a '2-1/2–D sketch' (visible surface depth and orientation), and a '3D object model' (volumetric object representation, typically Marr's 'generalized cones'). Primal sketch and 2-1/2–D sketch are 'viewer centered' in image coordinates, and the 3D model is 'object centered' in a specific object coordinate system. This allows to build a scene model (in scene coordinates), which is composed of individual objects, and their poses (position and orientation) and scales. The idea also supports nicely the decomposition of an object into (volumetric) parts, and Marr's book has triggered a 'Recognition by Components' (RBC) school, which has been

advocated by Biederman [19] from a cognitive psychology viewpoint, and was supported by Dickinson and others in the computer vision community (e.g. [40]).

Some computer vision researchers have reviewed Marr's theory from a more critical point of view. One interesting aspect is provided by Medioni et al. [110]. They concentrate on the limitations of a 2-1/2–D sketch, which may even complicate the problem of reconstruction when many different views are used. Instead, they propose to use *layers*, a layered representation of visible curves and surfaces, and they present tensor voting as the appropriate computational framework. Other researchers, including Ullman [158] and Edelman [43], advocate view-based approaches, which avoid computationally expensive and sometimes ill-posed 3D reconstruction. View-based recognition also has strong support from cognitive scientists (e.g. [154]) and biologists [151].

Computer Vision has seen a rapid and fruitful development of 3D reconstruction from multiple images and image sequences (stereo, structure from motion), and also of 2-1/2–D (shape from X), with an especially concise treatment of algebraic projective geometry (see [46, 64, 103], but also [148]). While it seems now possible, to reconstruct a 3D scene in terms of visual features and their positions in scene coordinates, the automated assembly of 3D object models has turned out to be more difficult. RBC, especially geon-based recognition suffered from the problem of insufficient low-level image analysis - while higher level algorithms worked nicely, the necessary segmentation had to be circumvented by line-drawings [39]. Some success was reported for very narrowly limited cases, for instance, by Zerroug and Nevatia [170] for a few special types of generalized cones under orthographic projection.

On the other hand, appearance-based object recognition (without requiring 3D reconstruction, and working purely in the 2D image domain) has been very successful, and still has not reached its limitations, over the past 10 years (e.g. early work by Murase and Nayar [122] or robust PCA by Leonardis and Bischof [92]). Recently, Nistér and Stewénius [126] presented a vocabulary tree, and claim that they can recognize a specific object out of 110 million candidates in less than 6 seconds. While global PCA and related subspace approaches (e.g. LDA, ICA, etc.) work on the 2D images themselves, i.e. on well defined pixel arrays (including certain size and brightness normalization), recent developments are relating back to Marr's primal sketch and try to reduce the complexity of the problem by looking only at salient points. The theoretical foundation for this work is scale space theory [96] and some of the saliency detectors are invariant to scale and/or affine distortions [75, 116, 99, 108]. They have been successfully used to represent, detect, and recognize individual objects and even object categories by a collection of object specific local features (e.g. [164, 48, 129, 1, 51, 90]).

Perceptual grouping approaches may be considered somewhere in the middle between purely appearance-based and 3D reconstructionist approaches. Starting from basic primitives (points, lines, curves), these approaches work toward grouping these primitives into higher-level entities (closed contours, surfaces, volumes). Seminal work in this area has been contributed by Lowe [101], Dickinson [40], and Sarkar [142]. Grouping

may be either data- (bottom-up) or model-driven (top-down). Recently good results for object recognition were achieved with object representations using curves as primitives (e.g. [17, 86, 49, 149, 131]).

Up to this point, we did not explicitly mention time in our discussion. Early work in computer vision was mainly based on the interpretation of individual images or on stereo pairs, which were captured at a certain instance in time. A reconstructionist approach for dealing with time will include a history, object trajectories, and prediction of future motion. The straightforward way is to extend 3D reconstruction techniques toward 4D (3D space + time), which has partly been covered for static scenes (see e.g. work by Pollefeys, Nistér and others [121, 125, 2]). There are many applications of tracking in videos which are recorded by a stationary camera and deal with the 3D space-time domain (2D image coordinates + time, for instance person tracking and traffic monitoring). A recognition point of view is to extend scale-space theory toward scale in space and time, and to detect salient space-time events. This formal extension toward space-time scale space has been presented by Laptev and Lindeberg [87].

Table 1: Abstraction Levels

	addressing and axis	entities	neighborhood
image-based	2D (row, column)	pixel	4,8-neighborhood
appearance (view) -based	)$n \times m$-D subspaces	points in subspace	distance to subspace
part-based	part-whole relation	properties, parts	semantics
object/model-based	name, location	sub-objects/models	
scene-based	(x,y,z,t,...)	objects	spatio-temporal semantics
topology-based	relational paths	topology domain	explicitly encoded

Multiple abstraction levels have been identified, spanning from the low, image-based (pixels) to the high, object, model, and topology based. Table 1 shows the main abstraction categories and some of their properties.

A suitable representation for computer vision has to bridge the representational gap between raw images and high level interpretations of scenes [79, 81]. Computer Vision over the past 30 years has followed a path from generic (prototypical) models (generalized cylinders, superquadrics and geons) to individual (exemplar-based) models (starting with 3D CAD based models, appearance based models, generative probabilistic models). There is evidence that some mechanisms in human visual cognition are view-based and do not require the reconstruction of a 3D object model, or a 3D scene model [154]. However, to

a certain extent, when we have to reason with objects, their motion, and their relations to each other in space and time, we will require to explicitly represent these entities.

1.1 Terminology

In this subsection, we look at the main concepts involved in representation (and reasoning), discuss the related terms, and indicate their dimensionality in space and time (boldface numbers). We deal with *images* (**2:** 2D space), *image sequences* (**3:** 2D space + time), *scenes* (**3:** 3D space), and *objects* (**3:** 3D or **2:** 2D projections) Objects can be represented by one or more *view(s)* (**2:** 2D space), or by a *3D model* (**3:** 3D space), and their motion can be described by *trajectories* (**3:** 2D space + time, or **4:** 3D space + time). Depending on the type of the objects and their motion, these trajectories can be simpler (e.g rigid objects) or more complex (e.g. articulated motion of a human). Furthermore, we might want to represent *events*, which are characterized by spatial extent (2D or 3D), and occur at a certain instance in time. Events have a *duration* (time interval).

It turns out, that one case is not well grounded in this terminology: while an image sequence (video **3:** 2D space + time) is a common term, we do not have anything comparable for a sequence of scenes. How should the successive states of a scene be called? In Computer Graphics, there is the term of an *animation sequence*. In this report we will use the term *scene sequence* for a 4D development of a scene (**4:** 3D space + time). A scene sequence is certainly more than an object trajectory. A scene sequence could be represented by a number of independently moving objects (thus resembling a number of simultaneous trajectories), or, depending on the scene representation, it might be represented by a sequence of occupancy grids or graphs (as proposed by [71]).

Further terms that will be used include *history* (knowledge about the past states of an object/scene), *prediction*, *topology* (adjacency, containment and decomposition/part relations), and *behavior* of an object, parts of an object, or a group of objects (e.g. hiding, seeking, a certain motion pattern, etc.).

1.2 Problem Statement

This is a joint report by three groups: EMT, ICG, and PRIP. These groups are investigating into representations within a joint research project on 'Cognitive Vision for Personal Assistance'[1]. Emphasis is put on a review of spatio-temporal methods (EMT), appearance-based methods (ICG), and graph-based methods (PRIP). We search for new representations (or combinations of already existing representational schemes) which can deal with 4D scene sequences in order to represent spatio-temporal relations and to support spatio-temporal reasoning for Cognitive Vision.

A reconstructionist view of this problem (also called 'cognitivist approach' in [161]) would focus at the loss of one dimension in the imaging process. The real world can be

[1] Joint Research Project JRP S91, funded by the Austrian Science Fund FWF

described by a scene sequence which has a dimensionality of four, but the captured image sequence has only a dimensionality of three.

The reconstructionist's goal will be to use reasoning-techniques to estimate a representation of the scene sequence from an image sequence (video stream), which is captured from a moving (or stationary) camera. The first step to estimate a representation of a scene sequence will be to detect the objects in the scene. To obtain the relationships between the objects (e.g. which object is behind the other) one needs to estimate the positions/trajectories of all objects in the scene.

From the 'emergent systems' (see also [161]) point of view, it is possible to learn and to reason about objects, spatio-temporal relations, and even scene sequences without requiring an explicit 4D reconstruction. But there might be a potential tradeoff between recognition and reconstruction that should be researched.

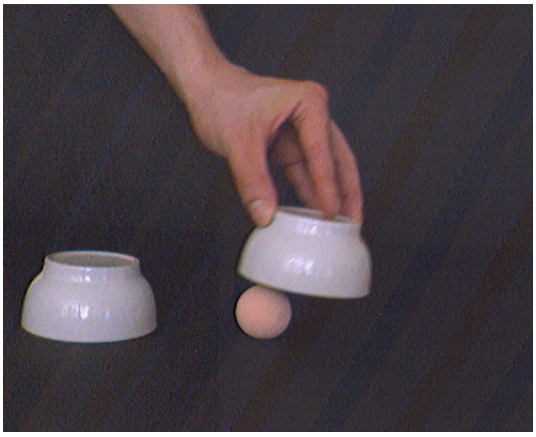
EMT investigates into spatio-temporal relations with very little geometry, and into the amount of geometry which is required to recognize certain object categories or to localize an object instance in an image. ICG researches into global and local appearance-based representations of objects with an emphasis on robust, incremental learning of such representations. Both groups are interested in using spatio-temporal (e.g. tracking) information to improve object models. A further idea, pursued by PRIP, is the development of new representations that combine geometry and topology to handle 'structured geometric objects'.

One fundamental question is: How much geometry do we need? To what extent do we need to perform reconstruction? Avoiding reconstruction would ease some tasks considerably, but it is not clear at all if reconstruction can be avoided all together.

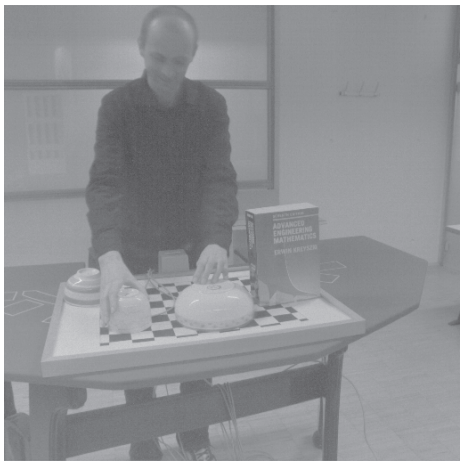
While the research of the three groups is well-covered by their individual and joint scientific publications on structure and motion, tracking, segmentation and object recognition, the unique constellation within our joint project on 'Cognitive Vision' offers the possibility to cover these contributions at a broader scale. The goal of this article is to present the state of the art and to compare various representational schemes with respect to their use in cognitive vision.

1.3 Cognitive Vision – Personal Assistance – Hide and Seek: A Scenario-based Approach to Basic Research

Within the very broad field of cognitive vision, our project is focused at the development of fundamental vision techniques that should aid future personal assistance systems. Such systems have to reason about dynamic scenes and their changing content in terms of user pose and trajectory, objects and their trajectories, events and their impact on the user, etc. Specifically, reasoning about dynamically moving objects will require to represent objects which may be temporarily hidden (partially or fully occluded, out of the current field of view or simply not recognized under the current viewing conditions). We have started the systematic investigation of such cases in a number of 'Hide and Seek' videos. Figure



(a) Two cups and a ball



(b) More complex scene

Figure 1: Two example frames taken from 'Hide and seek' videos. In these videos, objects are manipulated (e.g. cups) and can temporarily hide or even contain other objects (e.g. shell game).

1 shows two simple example frames taken from such videos. In these videos of varying complexity, a number of objects are manipulated by a human operator, including cases of casual hiding (when an object in the foreground may temporarily hide another one behind) and of deliberate hiding (e.g. placing a cup upside down over a ball, and shifting several such cups around in a 'shell game' of sorts). Such videos have been collected, including ground truth, both 'metric ground truth' in terms of positions and trajectories of the objects involved, and 'cognitive ground truth' by description in a scenario language. While this scenario is sufficiently constrained to support us in completing our research agenda, we feel that it is at the same time sufficiently general to point out general principles that are valid to many directions in cognitive vision research.

1.4 Human Description of Videos - An Experiment

Based on these hide and seek videos, we have conducted a small set of experiments focusing on human description of the videos. As a first step, 7 students (mother tongue

German, descriptions made in German[2]) were shown 2 videos ("two cups and yellow ball") containing 2 identical black cups, a ball, a table (support for the cups and ball), and a hand that acts only on the cups by changing their position (on the table by pushing/shifting and in the air by picking up and holding). The 2 videos are approximately 15 and 31 seconds long.

A description of the experiments is as follows: Each of the students was given one piece of paper (size A5). The students were told that they would be shown 2 videos which they should describe, with one half of the piece of paper available for each video. After watching each video a limited amount of time (5 minutes) was given to them to describe it. No additional cues were given. Of course, one can say, that seeing the hand hiding the ball using one of the cups is enough for a human (knowing the shell game) to focus on the ball. Which is probably true, and can be seen on the produced descriptions.

One of the first things that should be mentioned is that there were two constraints for the descriptions: one intended, which was the time allowed to write the description (2 of the descriptions are not finished), and the other one noticed, the space available on the paper for the description (more then 70% of the descriptions use up all the allocated half of the A5 paper). We can easily associate the 2 constraints with processing power vs allowed processing time and available memory, and notice that humans handle this very well the problem of adapting to them.

Now, getting to the $7 \times 2 = 14$ descriptions themselves. Except one, all of the participants have produced narrative descriptions, with very short sentences of the form *object action direction/position*, focusing on the movement of the cups and on the position of the ball at the end of the videos. The remaining participant has used a bullet-ed list with subsections and very schematic description.

All descriptions follow a 2 section pattern:

1. - initial configuration: contains the 3 objects initially visible (2 cups + ball), and for 8 descriptions also the spatial arrangement using words like "left", "right", and "center"

2. - actions: short sentences of the form *object action direction/position* using "left cup", "right cup", "ball", and "hand" to identify objects, a whole variety of verbs for actions (e.g "pick up", "raise", "move", "shift", "push", "slide", etc.) and expressions "over *object*", "behind *object*", "place of *object*", "between 2 *objects*", "left", "right", "center" to identify positions.

One of the descriptions refers to one of the cups as "the cup with the ball" for all the time the cup is hiding the ball. On the other hand, the bullet-ed list descriptions (2, made by the same person) refer to all objects as "object" (colors are used at the initial configuration description, but only there). They contain no more then 3 actions to describe all the changes in the video and clearly state the final outcome. There is one

[2]It would be interesting to compare with other languages.

description containing the wrong result, and some contain interesting hypotheses like the diameter of the ball in centimeters and the gender of the person that the hand belongs to. The original descriptions, in German, can be found in [71].

After looking at the descriptions, the main observations are that:

- all the participants focused on the "implicit" problem statement (where is the ball?) and most of them basically ignored the hand;
- objects that cannot be identified easily by aspect are referred to using positions relative to the scene limits or relative to other objects;
- if the result of a position change is an interaction with another object, then this is used to describe the action, if not, then the final position is used and described relative to the scene limits or relative to other objects using qualitative measures (left, right, front, middle, etc.);
- the descriptions focus on interaction between the objects, that could be considered relevant for the task, and
- they could be extended to map human description to the different technical representations presented in this document.

Having in mind the abstraction levels presented in Table 1 and looking at the descriptions produced by the students, we can see that the following abstraction levels were used: object-based, topology-based, and scene-based (note that due to the content of the videos, the usage of part-based abstraction was not really adequate).

As can be seen from the experiments [69, 71], humans tend to abstract as much as possible to obtain a high simplification of the descriptions (minimum description length). Abstraction is done when observing a scene and storing it into our memory or when processing it, and when extracting the stored information in order to describe it. Humans also seem to create a model of the audience and describe only the differences between the perceived events (observed scene) and the expected understanding (interpretation of the transmitted information) in the audience. The descriptions are not complete i.e. we cannot reconstruct the whole scene based on these descriptions. They focus on the (implicit) task, solve it, and throw away all the unnecessary data, and this is exactly the point we wanted to stress. Two important questions that one has to ask are to what extent and how these descriptions are corelated with the human internal representation, and what kind of properties of the internal representation could we derive from these descriptions.

Further experiments could be devised to check the cognitive plausibility of the representations. To our knowledge this would be the first such experiment.

1.5 Outline of the paper

As we have already seen in the previous introductory sections, the topic of representation in vision is broad and will be subsequently reviewed from several viewpoints. We start with two brief and rather general aspects on visual abstraction (section 2) and representational levels (section 3), and focus then on object representations in section 4. The extension from objects to scene representations is covered by section 5, and we conclude with a dedicated section on promising future research directions (section 6) and a summary.

2 Visual Abstraction

Recognition, manipulation and *representation* of visual objects can be simplified significantly by "abstraction". By definition abstraction extracts essential features and properties while it neglects unnecessary details. Two types of unnecessary details can be distinguished: redundancies and data of minor importance.

Details may not be necessary in different contexts and under different objectives which reflect different types of abstraction. In general, four different types of abstraction are distinguished [85]:

isolating abstraction: important aspects of one or more objects are extracted from their original context.

generalizing abstraction: typical properties of a collection of objects are emphasized and summarized.

idealizing abstraction: data are classified into a (finite) set of ideal models, with parameters approximating the data and with (symbolic) names/notions determining their semantic meaning.

discriminative abstraction: only aspects discriminating one object from the other are considered.

These four types of abstraction have strong associations with well known tasks in computer vision: recognition and object detection tries to *isolate* the object from the background; perceptual grouping needs a high degree of *generalization*; and classification assigns data to *"ideal"* classes, *discriminating* between them, disregarding noise and measurement inaccuracies. Such generalization allows to treat all the elements of a general class in the same way. When applied successively, the four types of abstraction imply a hierarchical structure with different levels

- of concepts for representing knowledge about the world, e.g. the conceptual hierarchy in [8],
- of representation,

- of processing stages, e.g. hierarchies of invariance in cognition [10], and
- in the complexity of processing images.

In all cases abstraction drops certain data items which are considered less relevant. Hence the *importance* of the data needs to be computed to decide which items to drop during abstraction. The importance or the relevance of an entity of a (discrete) description must be evaluated with respect to the purpose or the goal of processing. The system may also change its focus according to changing goals after knowing certain facts about the actual environment, other aspects that were not relevant at the first glance may gain importance. Representational schemes must be flexible enough to accommodate such attentional shifts in the objectives. With respect to cognitive vision, abstraction can help in obtaining compact but still very descriptive representations. It is one of the known ways to connect low level data with high level processes such as high level reasoning (Where is the cup?), and is needed to communicate with humans in their natural language.

3 Representation Levels

To build a scene representation one needs at the basis techniques for the semantic interpretation of images, in particular to localize and name objects contained in a scene and to assess their mutual relationships. A general topic within this interpretation is the question of the representation levels. Different aims (tasks) and different scenes might need more or less detail.

Some of the pictorial entities, their information content, and the operations that can be performed at different processing levels are summarized in Table 2.

In [156], the *connection table* allows the transition between the different levels of abstraction. Five different representation levels are identified from the real to the cognitive world: 2D image (image-based), 3D skeleton (feature-based), connection table (part-based), object description language (model-based), natural language (language-based) (see Table 1). Basic descriptive notions are: objects - parts - primitive parts. The *connection table* describes the way in which parts form an object.

While visualization generates an image from a computer stored description, digital image analysis is supposed to produce descriptions of a digital image. Still, both fields have at the basis descriptions at different levels of abstraction. The following levels are identified:

1. 2D digital image with pixels;
2. image segments such as region, edge, or texton [74];
3. image segments with specific properties such as generalized cylinders;

Table 2: Pictorial entities at different levels of processing

Entity	information content	examples for operations
Picture	imaging conditions, geometry	sampling, rectification
Pixel	gray value / color vector	enhancement, classification
Neighborhood	spatial locality	shrink, expand
(Step) edge	magnitude, orientation	edge detection and linking
Region	homogeneity, connectivity	segmentation
Boundary	shape	connecting continuous curve segments
Image Part	specific image properties	property measurement
Object Part	specific object properties	property matching
Object	functionality	relational matching
Situation	specific configuration of objects	interpretation
Scene	visible situations of the world	description

4. fragments, parts of objects, 'GEON' [20];
5. objects, models;
6. functional areas [109];
7. natural language like in [156].

4 Object Representations

One of the most important decisions that have to be taken when designing a vision system is how objects and their properties are represented. This determines the classes of features that could be used, how they are grouped, and how they are matched. Current object representations, depending mostly on the task, span from prototypical (high abstraction level, used mainly for generic object recognition) to exemplar-based (low abstraction level, used mainly for recognizing particular instances). We give here a summary of existing object representation frameworks and discuss their advantages and disadvantages.

4.1 Global Subspace Methods

The basic idea underlying subspace methods for visual learning and recognition is that an image can be represented as a point in a high-dimensional space (the space spanned by its pixels), a change of the object in the image (e.g., object rotation) has not an arbitrary effect on the point in the high-dimensional space. Therefore, an object (or even an object

class, e.g. faces) can be characterized by the set points (the subspace) they occupy in the high-dimensional space. Since this subspace is usually of much lower dimensionality than the original space a considerable amount of compression can be achieved by characterizing this low dimensional subspace. The difficulty is to find a compact representation of this usually highly non-linear space. A common approach is to choose a linear approximation:

$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

where, $\mathbf{x} \in \mathbb{R}^n$ is the original image, $\mathbf{y} \in \mathbb{R}^m$ its low dimensional subspace representation and $\mathbf{A} \in \mathbb{R}^{n \times m}$ the linear subspace. Depending on the required properties of the subspace we can obtain different (linear) subspace representations. Among the most commonly used representations are:

Principal Component Analysis (PCA): The most commonly used technique for compression of training images is based on *principal component analysis* (PCA) [67]. PCA requires that the reconstruction error (the error obtained when reconstruction $\mathbf{x}$ from its low dimensional representation $\mathbf{y}$) over all training images is minimal. To achieve this goal, the directions with the largest variance of input data are found in the high-dimensional input space. The dimension of the space can be reduced by discarding the directions with small variance of the input data. By projecting the input data into this subspace, which has the principal directions for the basis vectors, we obtain an approximation with an error, which is minimal (in the least squares sense) among all linear transformations to a subspace of the same dimension. It turns out that the correlation between two images can be approximated by the distance between their projections in the principal subspace. Thus, the recognition can be carried out by projecting an image of an unknown object into the principal subspace and finding the nearest projected training image [122].

Independent Component Analysis (ICA): [68, 7] is a powerful technique from signal processing known also as *blind source separation*. Contrary to PCA it does not only find uncorrelated components, but it delivers a linear transformation $\mathbf{A}$ such that the projections are as statistically independent as possible. This can be seen as an extension of PCA, where the projections of the input data into the subspace are not only uncorrelated but also independent. Independent representations lead to sparse codes which is considered as one goal of sensory coding in the brain (cf. [11]).

Linear Discriminant Analysis (LDA): PCA and ICA are *unsupervised* methods, which means that no additional information about the training images is necessary to build the representation. If, for instance, PCA is used for classification, no information on classes is used, thus the discriminant information might be lost. In this case, rather than maximizing the variance of all projections, one would prefer to maximize the distance between the projected class means, which increases the discriminant power

of the transformation. This is the goal of *linear discriminant analysis* (LDA) [105]. Furthermore, next to maximizing the distance between the classes, *Fisher's linear discriminant* [15] minimizes the distances within classes by minimizing within-class variance of the projections. It has been a popular tool in the field of pattern recognition, where it is frequently used to reduce the dimensionality of the input signal to alleviate the subsequent classification step.

Canonical Correlation Analysis (CCA): If the task is regression (not classification), *canonical correlation analysis* (CCA) [111] is the method of choice. It relates two sets of observations by determining pairs of directions (canonical factors) that yield maximum correlation between the projections of these sets. Thus, it is suitable, for example, for estimation of orientation, where one set of observations consists of observed images, while the observations in the second set are object orientations from which the corresponding images were acquired.

Non-negative Matrix Factorization (NMF): Another subspace technique is *non-negative matrix factorization* (NMF) [89]. It is similar to PCA (finds the representation with the minimal error) with the constraint that the factors consist of non-negative elements only. Due to this non-negativity constraint it tends to decompose the input images into parts (e.g., learn from a set of faces the parts a face consists of, i.e., eyes, nose, mouth, etc.), leading to a part based representation.

Kernel methods: As explained above the subspace of images is usually not linear, and all the methods discussed so far provide only a linear approximation. They can, however, be extended to *nonlinear* feature extractors [32, 145, 112, 111]. This can be done by first mapping input vectors using a nonlinear mapping into a high-dimensional feature space and then performing a linear method on the obtained high-dimensional points. This procedure is equal to the employment of a non-linear method in the original space. To avoid computing a nonlinear mapping into a space of a very high (possibly infinite) dimension, the so called *kernel trick* can be applied [32]. This method was originally proposed in the context of Support Vector Machines (SVM) [160]. It can be applied whenever it is possible to formulate the algorithm in such a way that it uses only dot products of the transformed input data. The dot products in feature space are then expressed in terms of kernel functions in input space, thus all operations can be performed in the original lower-dimensional input space.

The major advantage of the subspace approach is that both learning as well as recognition are performed using just two-dimensional brightness images without any low- or mid-level processing. However, due to the direct use of two-dimensional images there are various problems associated with the direct application of the methods, in particular, robustness against occlusion, scaling, varying background, illumination changes etc. Recently some new methods that can cope with these problems have been proposed (e.g., [92]

has demonstrated how to handle occlusion, varying background and other kinds of non-Gaussian noise in PCA, [22] has demonstrated how to handle severe illumination variations). Also the problem of learning these representations in a robust manner has been addressed recently [152].

Besides using these methods on whole images they can also be applied locally to image patches [128] or local descriptors, a recent example is the so called PCA-SIFT [78] descriptor.

Another characterization of the subspace approaches is to distinguish, whether a generative model (i.e., the ability of reconstruction and generation of samples), or a discriminative model is employed [124]. Each of them offers distinctive advantages. Generative models such as PCA, ICA, etc. enable robustness in model construction due to their ability to reconstruct the input from partial data Their representation is also not task dependent and can be used for different purposes. On the negative side, generative representations are usually wasteful in the resources and do not scale well. On the other hand discriminative methods such as LDA, SVM, etc. achieve in general higher recognition rates. Their representation is tailored for the specific task and they are usually faster. On the negative side, discriminative representations do not enable reconstruction, therefore, robust methods cannot be easily used. Furthermore, the representation is less flexible and cannot be adapted to new tasks. Since these two representations have quite complementary properties it makes sense to combine them, and recently people have started to work on such combinations, e.g., [53].

4.2 Local Detectors and Descriptors

As there are many problems with global representations (sub-space methods, aspect graphs) of an object (e.g. outliers, occlusion, varying background) recent research focuses on a local description of the object. The basic idea is to first extract distinguished regions in an image (such that the regions can be re-detected with a high probability), then describe the region and/or its local neighborhood with a possibly invariant photometric descriptor and use the descriptor for matching with new images. The advantage of these approaches is that they do not require a segmentation and can deal with occlusions and clutter. Using photometric descriptors the approaches are discriminative (see [118, 119] for a comprehensive review and evaluation of different approaches). There is a wide variety of different distinguished region detectors.

Simple detectors: A large class of detectors is based on measures of cornerness, among those the well known Harris corner detector [63]. The idea is reformulated using the structure tensor [21] and the second moment matrix respectively, leading to different variants of corner detectors [54, 155, 140, 83]. Other approaches use the second derivatives (Hessian matrix) instead of the first derivatives. All these approaches can be considered belonging to one class of simple interest point detectors. They all detect only a location. Therefore, for a subsequent task like image matching via

cross-correlation the size and orientation of the necessary matching window has to be chosen independently. This is a severe limitation when dealing with differently scaled or affinely transformed regions.

Scale and Affine invariant detectors: This limitation was addressed by estimating a proper scale for every detected interest point. The first work going into this direction was presented by Tony Lindeberg [97] in 1998. Other approaches followed shortly by David Lowe [102] or Krystian Mikolajczyk [114]. This class of interest operators is usually called scale-invariant interest operators.

However, research again went one step further. According to the success of interest operators which are invariant to scale changes, methods were sought to create interest operators invariant to a larger class of image transformations. This was driven mostly by developments in wide baseline image matching were significant perspective distortions occur. Research therein led to a new class of interest detectors, affine-invariant detectors. In most cases such a detection consists of a point location and an elliptical delineation of the detection. The ellipse representation captures the affine transformation of the detection. By normalizing the ellipse to an unit-circle the affine transformation can be removed. This method was first suggested in 2000 by Baumberg et al. [12]. This has lead to a wide variety of affine-invariant detectors [117, 107, 76, 157]. The common property of these approaches is that they provide information how the region around the detection can be normalized to allow image matching. The detections themselves, however, may not be simple point locations anymore. In the case of the MSER detector [107] a detection is a whole image region showing similar gray-values. Approaches like that are usually referred to as interest region detectors, moreover as every affine detector defines its own support region too.

Besides the detection of local regions we need also a description of local photometric content of the regions, which is then in turn used for matching. The descriptors can be roughly divided into three classes:

Distribution-based: Distribution based methods represent certain region properties by (sometimes multi-dimensional) histograms. Very often geometric properties (e.g. location, distance) of interest points in the region (corners, edgels) and local orientation information (gradients) are used. In this class falls the well-known SIFT descriptor [100] that uses histograms of local edge orientations. Ke and Sukthankar [77] modified the SIFT-key approach by reducing the dimensionality of the descriptor by applying principal component analysis to the scale-normalized patches. A rotation invariant version of SIFT is obtained by the Gradient location-orientation histogram (GLOH) descriptor, which divides the patch into a radial and angular grid [113]. Other well known distribution based descriptors are the spin image [73, 88] and the shape context [16] that uses the distribution of relative point positions and corresponding orientations collected in a histogram as descriptor.

Filter-based: The basic idea of filter-based methods is to use the response of a set of filters as a description of the region. Properties of local derivatives (local jets) are well investigated and can be combined to sets of differential operators in order to obtain rotational invariance. Such a set is called "differential invariant descriptor" [144]. "Complex filters" is an umbrella term used for all filter types with complex valued coefficients. In this context, all filters working in the frequency domain (e.g. Fourier - transformation) are also called complex filters, examples are [13, 143, 29].

Other methods: The simplest method that can be used as a descriptor is to take the gray-value patch as it is and use cross-correlation for matching. To obtain invariance, moments can be used [159].

Local descriptors are also used for object categorization. The idea is to learn local descriptors which are category-specific. Various methods are used to learn the features which are best for classification: Boosting [129], Naive Bayes [167], SVM or PCA on local features ([167]), and others.

A problem with all these approaches is the fact, that the learning algorithms do not know where the objects are in the image, so that they also learn features on the background which are related to the object (e.g. [130]).

We have shown in [146] that such learned classifiers give good classification rates on images which are similar to the images used for learning, but they give poor recognition rates on ground truth data (just the object without any contextual information). We have also shown that object localization based on spatio-temporal reasoning is one method, which can improve the learning procedure to give also good recognition rates on ground truth data.

In recent work we have studied the problem of learning local descriptors from image sequences for specific objects [57] and object categories [134]. In particular, local features are tracked in image sequences leading to local trajectories containing dynamic information. Based on these trajectories the quality and robustness of the local feature can be evaluated (and only those that are stable enter the representation). In addition the most representative local description can be selected based on the information obtained from the trajectory. This approach shows that by using dynamic information compact and distinctive local object descriptions can be obtained.

4.2.1 Models Based on Local Descriptions

The biggest problem in using collections of local features for object categorization is the fact that the features can be located anywhere in the image. We know for instance that there has to be a nose between two eyes to be a face, but the algorithms listed above do not take this information of spatial relation between features into account. Many papers exist in face detection which have a pre-learned representation of the model of the face, which consists of eyes, mouth, nose and also ears [65, 169]. These are only useful in

limited cases where we know the model of suited features (namely the parts of the face). Nowadays people try to learn the model also from the training images.

In [164, 48], for extensions see [47, 49], the model is learned as a flexible constellation of features, where the variability within a class is represented by a probability density function. The main problem with this approach is that the images used for learning must look similar, which means that the objects in the images must be roughly aligned, resulting in similar position, orientation and scale of the objects. This approach can only learn 2D models from rather aligned images.

An enhancement to this approach was made by [66] to be translation and scale invariant in both learning and recognition of the objects. Results are only reported for face images, where the learned parts look like eyes, chin and eyebrows.

The constellation model is probably the most prominent out of several similar representations. The constellation model proposes a fully connected graph of all model parts. Crandall et al. [35] presented their k-fan model, where k denotes the number of parts that are fully connected to all other parts in the model. A 1-fan can be regarded a star-shaped model, as was also presented by Fergus et al. [50].

Constellations and similar representations model object shape explicitly by a limited number of salient parts and their spatial constellation. Leibe et al. [90] presented a codebook of local appearance (local salient features and their descriptors) that is used together with an implicit shape model (the location of each salient point is mapped relative to the object center).

4.3 Curves, Boundaries, Fragments

Although there has been significantly more recent work on object representation by local, salient patches and their descriptors, 2D object shape can often be efficiently represented by an object's internal and external contour. When shape is a dominant cue (e.g. in distinguishing cows from horses), such models may be better suited than patch-based methods. On the other hand, patch-based representation can emphasize texture (e.g. to distinguish horses from zebras, which is impossible based just on the external contour). It is slightly more difficult to represent boundaries at varying scales, orientations and other spatial transformations, but together with the idea of a codebook with object centroid votes, there is recent success in representing codebooks of contour fragments [150] or boundary fragments [132]. An obvious, promising direction of future research will be to combine patch and boundary representation into a unified model (as we report in [133]).

4.4 3D Object Representations

There is a vast amount of literature on shape from X methods that recover 2-1/2-D representations and on the recovery of 3D object models either from images, or from 2-1/2-D. Photogrammetric methods include calibrated stereo and block bundle adjustment

methods, while the Computer Vision approach is rather directed toward the recovery of scene structure from uncalibrated video [121, 125], or from potentially very disparate views [108]. The typical object representation that emerges from such approaches is a 3D point cloud of salient points. It is not only necessary that a certain saliency detector responds above threshold, but it is also required that point correspondences between views can be established. One way to obtain high quality point clouds is to texture the objects (when this is possible, e.g. by spraying them with a random pattern), another one to mount them on a rotating table. Tracking of feature points while the object is rotated, or while the camera is moved around the object can substantially ease correspondence search.

There are cases, when 3D point clouds, either in scene coordinates, or in object-centered coordinates, are a sufficient 3D model. For instance, in computer graphics, point based rendering attaches a grey-, color- or texture-value to each point and obtains very realistic rendering results when the point cloud is sufficiently dense. In computer vision, however, the necessary next step is to aggregate metric 3D point clouds into more abstract models. One obvious way is to try to fit parametric models to the 3D data. This can be the fitting of dominant planes, or of higher order parametric surfaces such as superquadrics (e.g. [153], obtained from dense 3D range images). Another idea is to model 3D objects and to try to recover their 2D projections in the images, e.g. by geometric hashing [168].

The above approaches all obtain metric 3D models from metric 3D reconstruction. While this is an important research goal on its own, cognitive vision will probably require other kinds of 3D object representations, which are more qualitative, but at the same time may generalize well to represent object categories as well as individual objects. However, the research landscape in qualitative 3D object representation is far more sparse than for 3D reconstruction.

Marr proposed to recover generalized cones and cylinders from single intensity images. This has been achieved for a limited number of specific types of generalized cylinders, based on clues like curvilinearity, symmetry, and low- and mid-level geometric reasoning [170].

Geons have been introduced based on a cognitive theory [19] and have been recovered from intensity images [40], but many open problems remain [39]. However, geons would be attractive, because they constitute *qualitative* models, which eases their use for generalization and categorization. The graphs produced in [40], however, lack a proper representation of spatial configuration. A workaround has been presented in [137], which might also work for representing spatial and temporal relations.

A very different approach is advocated by Medioni, who argues that the Marr paradigm has been very influential. It triggered numerous reconstructionist research in shape from X and in 2-1/2-D. Medioni prefers a more direct, layered representation, which circumvents the necessity of reconstructing 2-1/2-D (tensor voting [110]).

4.5 Graph-Based Representations

Handling "structured geometric objects" is important for many applications related to Geometric Modeling, Computational Geometry, Image Analysis, etc.; one often has to distinguish between different parts of an object, according to properties which are relevant for the application (e.g. mechanical, photometric, geometric properties). For instance for geological modeling, the sub-ground is made of different layers, maybe split by faults, so layers are sets of (maybe not connected) geological blocks. For image analysis, a region is a (structured) set of pixels or voxels, or more generally a (structured) set of lower-level regions. At the lowest level, such an object is a subdivision[3], i.e. a partition of the object into cells of dimensions 0, 1, 2, 3 ... (i.e. vertices, edges, faces, volumes, ...).

The structure, or the topology, of the object is related to the decomposition of the object into sub-objects, and to the relations between these sub-objects: basically, topological information is related to the cells and their adjacency or incidence relations. Other information (embedding information) is associated to these sub-objects, and describes for instance their shapes (e.g. a point, a curve, a part of a surface, is associated with each vertex, each edge, each face), their textures or colors, or other information depending on the application.

4.5.1 Aspect Graphs

The use of Aspect Graphs (see e.g. [55], chapter 20) as an object representation is a generalized method, representing the view space. The main idea is to combine different viewing directions, where the object looks alike, to one aspect. The object is represented by a number of aspects, a representation of these aspects and a graph which describes the possible transitions between them. Aspect Graphs were used in the early 90's to recognize simple polyhedral objects, or objects which could be decomposed into generalized cones.

[137] sketches an extension of Aspect Graphs using CAD prototypes and a view-sphere for generic object recognition. This work is also based on simple geometric objects where the generality of the method deals only with small variations of the parameters of the used models (generalized cones).

An aspect graph is defined only for polyhedral objects, but the concept can be generalized for arbitrary objects. In this case one is interested in partitioning the view sphere of on object, such that the view of the object changes only slightly within the partition. An example how this can be done using a PCA based representation is the multiple eigenspace algorithm [91].

One advantage in using aspect graphs and related representations is that with the recognition of an object we not only know the object, but also its corresponding aspect, and the possible next aspects. This aspect gives us an idea of the viewing direction i.e. the pose of the camera.

[3]For instance, a Voronoi diagram in the plane defines a subdivision of the plane

4.5.2 Characteristic View

The concept of a characteristic view (CV) is useful in appearance-based object recognition [162]. Characteristic views are intended to help obtain a representative and adequate grouping of views, such that a given level of recognition accuracy may be achieved using a minimum number of stored views [42]. Clearly, this has important implications for the storage space needed to represent each object, and the number of matches which must be performed at run-time for the purpose of recognition. View grouping has been addressed using CVs and aspect graphs. An extension to the original idea of Koenderink et al. [82], the so called appearance graph uses the appearance of the object under consideration as well as information like illumination, texture etc. Problems in building aspect graphs occur when the object under consideration has curved surface, non-uniform illumination, etc, since it is hard to find stable views. Instead of building a complete aspect graph one can build an approximate of the object's appearance [25].

4.5.3 Generic Models based on Graphs

In learning a prototype from a set of noisy examples of the same object the goal is to find a representative model. If the examples are given as graphs, Jiang et.al. [72] introduced a concept of set median and generalized median graphs and a genetic algorithm to obtain the prototype graph. The generalized median concept is more powerful since it does not constrain the resulting graph as being one of the example graphs. Spectral methods were utilized to cluster graphs of different views [98].

Recently, Keselman and Dickison [80] introduced a novel approach based on graph shortest paths approximation to close the representation gap in the domain of automatic acquisition of 2D view-based models. The harder task of recognition is not tackled.

Cyr and Kimia [37] introduced a 3D object recognition algorithm based on 2D views. The aspects are based on a notion of shape similarity between views.

4.5.4 Dual Graphs and Combinatorial Maps

Dual graphs [84] can be seen as an extension of the well known region adjacency graph (RAG) representation. In 2D space a dual graph representation consists of a pair of the primary planar graph and its dual (called also geometric dual [62]). This representation is able to encode any subdivision of the 2D topological space. Encoding higher dimensions with graphs is a difficult problem. Combinatorial maps or generalized maps are well-suited representations to overcome this problem. In 2D space simple dual graphs are equivalent to 2D combinatorial maps.

N-dimensional combinatorial maps [93] may be seen as a graph with an embedding in an N-dimensional space, i.e., in the case of 2D [27], combinatorial maps are planar graphs encoding the orientation of edges around vertices. The base elements of an N-dimensional combinatorial map are the darts, also called half edges, which are connected

(sewed) together by the orbits of 1 permutation and $N-1$ involutions. In the case of 2D [27], the permutation is called σ and forms vertices, and the involution is called α and specifies edges (other attributions for the permutations exist). One of the advantages of combinatorial maps is that in the 2D case, unlike dual-graphs, they explicitly encode the orientation of the plane, correctly handling all the complicated cases with self-loops and parallel edges.

Like combinatorial maps, n-dimensional generalized maps [93, 94] are defined in any dimension and correctly represent all topological configurations of the n-dimensional space (including 2D). Their base elements are darts and use only involutions to represent the connections between them. With these relations they describe cells in any dimension.

4.6 Geometry and Topology

Many topological models have been conceived for representing the topology of subdivided objects, since different types of subdivisions have to be handled: general complexes [30, 36, 45, 166] or particular manifolds [6, 14, 165], subdivided into any cells [58, 41] or into regular ones (e.g. simplices, cubes, etc.) [52, 136]. Few models are defined for any dimensions [18, 141, 26, 95]. Some of them are (extensions of) incidence graphs or adjacency graphs. So, their principle is often simple, but:

- they cannot deal with any subdivision without loss of information, since it is not possible to describe the relations between two cells precisely if they are incident in several locations;
- operations for handling such graphs are often complex, since they have to handle simultaneously different cells of different dimensions.

Other structures are "ordered" [26, 95, 45], and they do not have the drawbacks of incidence or adjacency graphs. A comparison between some of these structures is presented in [94]. A subdivided object can be described at different levels. For instance, a building is subdivided into floors, each floor is subdivided into wings, each wing is subdivided into rooms, etc. Thus, several contributions deal with hierarchical topological models and topological pyramids [38, 18, 84]. For geometric modeling, there are often only few levels. For image analysis, more levels are needed since the goal is to derive information which is not known a priori.

Since a geometric object is represented by a topological structure and its embedding in a geometric space we distinguish: (i) topological operations which modify the structure; (ii) embedding operations which modify the embedding; and (iii) geometric operations which modify both topology and embedding. For the animation of articulated objects, the object structure is not modified. Therefore, animation can be performed by applying embedding operations. Local operations can be easily defined and performed (e.g. chamfering, contraction, removal, extrusion, split, etc.), and this plays an important role when wanting to simultaneously (in parallel) apply them when an image is analyzed.

Moreover, topological features can be computed from the topological structure: orientability for pseudo-manifolds [28], genus for surfaces, and homology groups which provide information about the "holes" in the object for any dimension [3]. Such information can be used to control the construction of the object. For instance, when simplifying an image and constructing a pyramid, one often wants to keep some properties like connectedness invariant. When an object is made of many parts, one requires tools in order to check it. Topology and shape are complementary, and it is very useful to compute both types of information.

The use of geometry and topology for a generally valid representation should also incorporate the local object appearances. This third cue increases the use for a real world scene representation. Different scenarios can be conceived: for instance, a box with a picture of a lion on top might be represented by two layers in topological means (top and bottom of the box). Each of these layers is again represented by a topological description combined with its geometric appearance. One can imagine that the use of the surface appearance (here the picture of the lion) increases the discriminative power of such a representation.

5 Scene Representations

We can regard the scene representation as the internal state of a cognitive vision system. This representation should correspond as accurately as possible to the real scene which is observed by the system.

Some of the previously discussed methods for object representation in 2D extend quite naturally toward appearance-based scene representation. These can be global methods modeling brightness, contrast, color, texture, or integral features, which have for instance been applied in image retrieval, but also local methods. Bags of keypoints (and their descriptors) can be similarly used for object recognition (and, thus, object representation) [56], and for image retrieval (and, thus, scene representation) [115].

There is also a straightforward extension of the above explanations on 3D object representations to a type of scene representation, which works either in the 2D ('viewer centered') image coordinates, or in a 3D scene coordinate system, where each individual object in the scene is represented by a 3D vector that points at the origin of an 'object centered' coordinate system, which in turn is used to properly represent the individual object.

A scan of literature on scene representations has led to several results, which either do not originate from computer vision (artificial intelligence, linguistics, topology, geometry) and are hard to adapt to cognitive vision, or they have been tailored for a very specific vision application (navigation, tracking, surveillance, brain atlas, geographic information systems) and are not sufficiently general. Obviously, there is still plenty of room for future research in this area, as will be seen from the subsequent sections.

In general, a scene representation for cognitive vision should address the following topics:

1. The scene representation is not independent of the object representation, therefore it is important how objects are represented.

2. Time is an essential factor of the scene representation, especially the time resolution defines what types of events need to be represented (i.e., what type of object interactions can we resolve?).

3. The question of a purposive and qualitative representation should be addressed. It is clear that we do not need a full representation of every detail (reconstructive), but we must address the question of the purpose of the representation (cf. purposive and qualitative vision).

5.1 4D-Coordinates

Masunaga and Ukai [106] propose a database of 3D, moving objects, which is a 4D (Euclidean space+time) representation. The representation is at the object level and consists of:

- A list of all objects.
- For every object and every time instance: 6 DoF of object pose (3D position + orientation).
- A set of primary relations like velocity of an object, distance between objects and a set of topological relations: Disjoint, Contains, Inside, Overlaps, Touches, Equals, Covers and CoveredBy.

As a difference to the topology-based representations this (4D) scene representation has the advantage that one can use history information. This could be useful as discussed in section 1.1.

5.2 Appearance-based scene representations

Similar to object representations we could also use the appearance of the scene as a representation of it. In the simplest case we just store some snapshots of the scene. In more sophisticated approaches (mainly used in a robotics context) more complex appearance-based representations are used. Similar to object recognition we have global appearance based scene representations. A typical example is a robot equipped with an omni-directional camera and global PCA as a representation, e.g. [120]. Another class of appearance-based representations are local ones. Similar to the object recognition case,

only distinguished regions in the scene are represented. A recent approach for this type of representation can be found in Se et al. [147]. In this paper, a vision-based mobile robot localization and mapping algorithm (cf. SLAM) that uses SIFT descriptors as a scene representation is presented. It is interesting to note that visual landmarks are also used by a variety of animals for navigation purposes.

5.3 Occupancy Grids

Occupancy grids [44] are different from the scene representations discussed above. The world is divided into fixed grid cells. In every cell there is a value stored, which stands for the probability that this cell is empty / occupied. Thus, this representation does not deal with different objects and their motion in the scene, but with the space they occupy. From the nature of this representation, it will also be difficult to distinguish between objects and static background.

Occupancy grids are mostly used in robotic applications. Here the grid is a 2D floor plan of the scene, which describes where the robot can move around in the world. In most applications the grid is estimated with sonar sensors or laser-range finders, but there exist also applications where stereo vision is used.

There have also been attempts to model imperfect knowledge about the scene (ignorance, imprecision, and ambiguity), e.g. within a complete representational framework for fuzzy mathematical morphology by Isabelle Bloch [23]. Probabilistic, possibilistic, and fuzzy occupancy grids have been proposed [139, 24]. One problem with these approaches is their static description (description of one frame) of the scene.

5.4 Topology-based

Topology-based approaches often relate to linguistics or artificial intelligence and try to simplify the representation based on relations. Such a representation may consist of a list of objects plus a list of relations between these objects. Interval calculus [4] is used in systems that require some form of temporal reasoning capabilities. In [4] 13 interval-interval relations are defined: 'before', 'after', 'meets', 'met-by', 'overlaps', 'overlapped-by', 'started-by', 'starts', 'contains', 'during', 'ended-by', 'ends' and 'equals'. In [138], motivated by the work in [4, 33, 34], an interval calculus-like formalism for the spatial domain, the so called region connection calculus (RCC) was presented. In (RCC-8) [138], the set of 8 possible relations between two regions are: 'is disconnected from', 'is externally connected with', 'partially overlaps', 'is a tangential proper part of', 'is non-tangential proper part of', 'has a tangential proper part', 'has non-tangential proper part', and 'equals'. A more expressive calculus can be produced with additional relations to describe regions that are either inside, partially inside, or outside other regions (RCC-15). There exist also extensions of RCC to 3D space and time ([163]).

Different graph based representations have been used to describe the changes / events

in a dynamic space. In [31] graphs are used to describe actions (vertices represent actions). Graphs are also used in [9], but here vertices represent objects. Balder [9] argues that arbitrary changes can be best described by a state approach: the state of the world before and after the change characterizes the change completely. The Unified Modeling Language (UML), in its state diagram, also defines a graph based representation for tracking temporal changes.

5.5 Event Representation

Representing objects and their spatio-temporal behavior in a scene can be done in different ways on different levels. For a cognitive vision system it might be interesting to detect events in a video sequence instead of just behavior. For instance, lifting a cup, moving it and finally putting it over a smaller item might be described by the events: 'lift', 'move', 'put down'. It could also be represented by the event 'hide'. For example, for a short video with a hand using 2 cups to hide a ball, such a description would be: 'hand from left', 'grasps left cup', 'moves it over ball', 'releases cup', 'shifts it to the left', 'releases cup', etc.

Event representation from video sequences has broad interest (e.g. video surveillance). There is a vast amount of literature and we give only a very brief overview to state-of-the-art research. Recently a consortium of researchers developed a formal language to describe the ontology of events in videos which they called 'VERL' (Video Event Representation Language) [123]. In [70] a proposal on spatio-temporal graphs is presented. The authors proposed to use new relations (like grasp, move and release) to describe events as the changes in the scene and to build a hierarchical graph-based representation to keep track of actions, events, and relations. Hakeem et al. [60] presented an extension of the 'CASE' description method which bridges the representational gap between low level vision and human scene description. Such representations can be learned by e.g. the method of Hakeem and Shah [59] which uses a video event graph and a video correlation graph on a set of training videos.

6 Promising Research Directions

It is a hard task, to try to list promising directions of research for a field as active and developing as cognitive vision is today. However, we subsequently identify a number of evident research goals, and we also present our more specific ideas. Some of them are reflected by current research activities at our labs (EMT, ICG or PRIP), others will probably be addressed in the near future. We use the context of our joint research project on Cognitive Vision as outlined in section 1.3.

Representational concert: It is quite clear that for a versatile cognitive system we need a multitude of representations to have to work together. Probably all (and maybe more) that have been discussed in this paper. But this requires to answer several hard questions, like how we can keep these representations consistent? What happens if they are inconsistent? Should we jointly update them or keep them separate? How do we decide with representation is the most appropriate to solve a task?

Recognition versus reconstruction: To which extent is an explicit metric representation of space and time required? What are the limitations of purely appearance-based approaches? It seems that a hybrid representation might be most appropriate. This could cover the approximate reconstruction of objects and their trajectories (spatio-temporal reconstruction, including camera and object pose), a qualitative (graph-based) representation of spatial and temporal relations and events, and purely appearance-based recognition.

Object versus background: What is a relevant object for the current state of representation and reasoning in the cognitive system? What is 'background'? Attention may switch, and an object may gain importance and be separated from the surrounding background, for instance by grasping it. On the other hand, some object may loose importance. Having not been used for an extended period of time, it might be merged with the background. This kind of approach has for instance been followed by the EU-IST project VAMPIRE, where a 'visual active memory' served the purpose of storing and retrieving relevant visual information at various levels of abstraction [61].

Spatio-temporal representation: The EMT research group considers a 4D scene representation similar to the one described in section 5.1 well-suited to represent spatio-temporal relationship. Using such a scene representation one could answer the following important questions:

- Where are the objects? This information is directly available from the representation.
- Object trajectories? This information is directly available from the history of the representation.
- Which object hides which object? This information can be inferred from the topological relations of the representation.

At the object level, a certain amount of metric representation will be required to represent camera-to-object pose, object and camera trajectories in scene coordinates etc. At a base representational level, objects could be represented as a 3D point cloud, and motion by the correspondence of moving points between subsequent frames. This representation

might serve as the basis for an increasingly complex representational framework. One can think about attaching local descriptors to points of interest, combining point and contour information, thus representing an object as a collection of loosely related pieces of information. Even the boundary of an object might be represented in a fuzzy manner. First experimental results in this direction show that a representation based on a point cloud is sufficient to improve learning and recognition of object categories [146], but for a proper object representation and for spatio-temporal analysis, this can only be considered a starting point.

Appearance-based representation: Currently appearance-based representations are quite popular in the object recognition community, but there are some obstacles that need to be overcome. First of all we need to address the issues of scaling (i.e., how can we build a system that can recognize thousands of objects). It is clear that one-to-one matching is not useful, we need proper ways to hierarchically structure the object representation. A recent approach in that direction can be found in [127], but this approach is not the solution because it needs too much storage space. Very recently Nistér and Stewénius [126] presented a hierarchical system with that scales to many specific objects. It remains to be shown how the generalization and accuracy is influenced by the approximations introduced. Another interesting issue is how we can combine local and global appearance-based representations in a coherent framework in order to use the best of both worlds. Ideally we would like to have a seamless integration between these two representations so that we can always select the most appropriate one. A question closely related to learning is how we can build a hierarchy of appearance-based representations, starting with simple patches based on interest points to more complex constellations and expressive representations. It is clear that such a representation needs to be learned (in an unsupervised manner).

Graph-based representation: Existing graph based representations support any number of dimensions but the question of minimum required complexity is still open. Do we really need more than $2D + time$ and represent everything in maximum detail or should we focus more on the advantages of representations which keep embedding information, structure, and topology? Preliminary experimental results show that in most of the cases humans do very well using simple descriptions enhanced by the power of relations. RCC is definitely something that should be considered in the future, along with n-dimensional graph based representation like combinatorial maps and generalized maps, for which many properties in $3D$ and $4D$ still need to be studied. Staying with qualitative measures, landmark based addressing, mosaicking graph based patches, and, graph and shape matching should enforce the way to human like generic object recognition capabilities and, thus, will certainly be part of our future research.

7 Summary

This report presents an overview of historical developments as well as the current state of the emerging field of cognitive vision (confluence of recognition and reconstruction school in computer vision, cognitivist vs. emergent systems approach to cognitive vision). Proper schemes of representation for objects, scenes, and motion are at the core of cognitive vision research, constituting de-facto an enabling technique for learning, reasoning, and acting, as well as fundamental research in itself.

Our taxonomy of representations is structured into appearance-based, spatio-temporal and graph-based approaches. Even though more still needs to be done, we can conclude that the representation of objects has been researched in depth, both from a recognition and from a reconstruction point of view. But cognitive vision requires also the representation of dynamically changing scenes. We have developed the notion of 'scene sequence' and proposed 3D (2D + time) and 4D scene representations to deal with scene sequences. And we have shed light on the use of graphs, hierarchies and description languages for scene representation in cognitive vision.

We have conducted a simple cognitive vision experiment that yielded human descriptions from video. Humans tend to abstract as much as possible. They focus on the (implicit) task, solve it, and throw away all the unnecessary data.

In section 6 we have presented a number of promising research directions. We think that there still is an open problem of generating proper object descriptions from image sequences (and scene descriptions from scene sequences).

Especially the area of multiple coexisting representations has been hardly touched. Of course we also have not addressed the question how these representations can be obtained (i.e. learning) which is closely related but would require at least another paper.

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