A REVIEW ON 3D OBJECT REPRESENTATION AND RECOGNITION

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Abstract

The recognition of objects is one of the most challenging goals in computer vision. The problems increase when the process of recognition involved three dimensional (3D) objects. To deal with this problem, many researchers have proposed their own solution. This paper gives a short review of some of the researches in the area in representing their 3D models. It is intended to be a summary of the important research issue and approaches that researchers have taken and how these techniques are related.

Keywords

3D object recognition, object representations, robotic vision, computer vision.

1. Introduction

Technological development of modern society has led to increase research on methods and systems to automate human tasks. For the last 30 years, computer vision had been a large and productive research field. Included within the field of computer vision are many problem subdomains such as image enhancement and restoration, text recognition, tracking and motion estimation, and object recognition [Procter 1998].

A model based object recognition system finds objects in the real world from an image of the world, using object models which are known a priori [Jain et al., 1995]. The process of object recognition is one of the hardest problems in computer vision. Human performs object recognition effortlessly and instantaneously but an algorithmic description of this task for implementation on machines has been very difficult. Since our life deal with 3D space, it is important to have a system that have an ability to recognize 3D objects. However, developing a 3D object recognition system is much harder compared to "flat" 2D recognition system. Büker & Hartmann [Büker and Hartmann, 1996] had underlined 3 reasons referring to this problem. First, the handling of 3D scenes allows additional degrees of freedom for the orientation of the object in space. Second objects may partially occluded each other and third, only one side of an object can be seen from any given viewpoint, which is sometimes insufficient to distinguish similar objects from each other. According to Jain et al. [Jain et al., 1995] a model based object recognition system must have the following components:

1. Model database - contains the information of all the models known to the system.
2. Data acquisition - converting scene object in 3D world coordinate into 2D image.
3. Feature extraction - Applies operator to images and identifies locations of features that help in forming object hypotheses. Example of features such as area, parameter length, compactness, etc.
4. Hypothesizer - It assigns likelihoods to objects present in the scene using the detected features in the image. This step is used to reduce the search space for the recognizer using certain features.
5. Hypothesis verifier - It uses object models to verify the hypotheses and refines the likelihood of objects.

Figure 1 depicts the interaction and information flow among different components of the system.

In discussing object recognition methods, there are some important criteria for judging how well a method performs. Most researchers have been concerned with the following criteria, as summarized by Grimson [Grimson, 1990]:

1 Scope - kinds of objects can be recognizes, and in what kinds of scene.
2 Robustness - Does the method tolerate reasonable amounts of noise and occlusion in the scene, and does it degrade gracefully as those tolerances are exceeded
3 Efficiency - time and memory required to perform the recognition.
4 Correctness-accuracy of the recognition

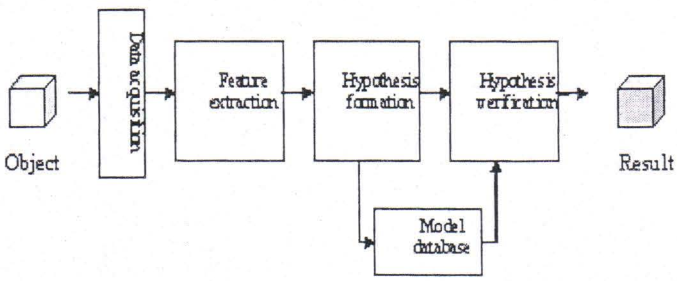

Figure 1: Different components to perform object recognition task

Many researchers had proposed their own approach and solution regarding this problem. To simplify these, our review will be focused on two parts. The first part is object representation and modeling in 3D, and the second part is the method of classification.

2. Object Representation

Before any work can be done on the subject of object recognition, a representation must be choosen. Object representation is a term for decribing an object or some aspects of it [Marr and Nishihara, 1978]. Different techniques have been used depending on shapes of real objects and the types of sensors utilized in the recognition process. Consequently, designers must consider the parameter in their design problems to select the best representation for their task. There are two main types of object representation, object centered representations and view centered representations.

2.1 Object Centered Representations

An object centered representations uses description of objects such as boundary, curve, surface, volume etc. in a coordinate system attached to objects [Jain et al., 1995]. This description is usually based on three-dimensional features or description of objects. It should have enough information to produce object images or object features in images for a known camera and viewpoint.

Some early works use wire-frame representation. A wire-frame model represents an object using a dictionary of possible edge junctions [Brady et al., 1989]. Cheng and Zong [Cheng and Zong, 1998] use a revised wire-frame representation to model their objects. However, this method is computational expensive because it required stereo matching process before 3D contour can be derived. Lowe [Lowe, 1991] uses line segments as its primitives, with the features of proximity, parallelism, and collinearity being extracted from the segments. These features are invariants under a perspective projection. However, this method is not robust to noise since it relies heavily on the ability to extract the primitives.

Besl and Jain [Besl and Jain, 1988] segment surfaces into eight fundamental types; peak, ridge, saddle, ridge, minimal, pit, valley, saddle valley and planar. Surface classification is generally performed by calculating the functions H (Mean curvature) and K (Gaussian curvature) in any point and labeling the surface pixels according to the values of those functions. Pieroni and Tripathy [Pieroni and Tripathy, 1989] divide the surface into triangular tiles and thereafter use H and K parameters to segment the surfaces. York et al. [York et al., 1981] use B-spline bounding curves and Coon's patches to model the surface representation. The spline curves are represented by a set of points on the curved and its corresponding vertex polygon. Farias and de Carvalho [Farias and de Carvalho, 1999] uses surface attributes such as area, parameter, normal vector, number of vertices and centroid to recognize 3D polyhedral objects. They had used three 2D views to extract 3D surface attributes. This method yield low processing time and robust to occlusion.

In volumetric representation, there are some methods to represent volumetric description such as spatial occupancy, constructive solid geometry (CGS), super-quadrics, and generalized cylinders. CSG represents an object as a binary tree where each leaf represents an instance of a primitive and each internal node represents an operation on its descendents [Roth, 1982]. Primitives such as spheres, blocks, cylinders, and cones are first transformed (i.e. translated, rotated and scaled) and then combined by using the Boolean set operators (union, intersection and difference) from the bottom to the top of the tree. The internal nodes specify the types of Boolean operations on their immediate children. The final shape is constructed at the roof of the tree. Figure 2 shows a CSG representation for a simple object. Since arbitrarily curved objects cannot be represented using just a few chosen primitives [Jain et al., 1995] and required large amount of memory for storage [Haralick and Shapiro, 93], CGS approaches are not very useful in 3D object recognition.

Super-quadrics introduced by Barr [Barr, 1981] are geometric bodies that can be understood as a generalization of basic quadric solids. Superquadric volumetric primitives can be deformed by bending, twisting and tapering, and Boolean combination of simple entities can be used to represent more complicated shapes [Terzopoulos and Metaxas, 1991]. Generalized cylinders, or generalized cones are also called sweep representations approximate a 3D object using globally parameterized mathematical models. Brooks et al. [Brooks et al., 1979] has developed a vision system, *ACRONYM*, that recognised three-dimensional objects occurring in two dimensional images. The examples given in the papers involve recognizing airplanes on the runways of an airport from aerial photographs. He uses a generalized cylinder approach to represent both stored model and objects extracted from the image.

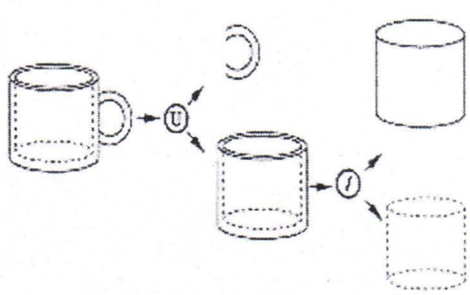

Figure 2: An object and its CSG representation

2.2 View Centered Representation

View centered representations model 3D objects through a set of images or views, taken ideally, in all possible conditions (viewpoint, illumination and sensor parameters) [Trucco and Verri, 1998]. It summarizes the set of possible 2D appearances of a 3D object.

Koenderink and van Doorn [Koenderink and van Doorn, 1979] proposed the use of graph structure known as aspect graph. An aspect graph represents all stable 2D view of a 3D object. Figure 3 shows a simple object, a box and its aspect graph. Stewman and Bowyer [Stewman and Bowyer, 1987; Stewman and Bowyer, 1988] proposed an algorithm for constructing the perspective projection aspect graph of 3D objects and is applicable to general convex polyhedral. Other related works based on this method are [Bowyer et al. 1988, Dorai and Jain, 1997; Sripradisvarakul and Jain, 1989]. However, the extraordinarily large in size and complexity of aspect graphs for even simple objects has prevented the use of this representation in recognition problem [Denzler et al., 1994].

Paggio and Edelmen [Paggio and Edelmen, 1990] show that 3D objects can be recognized from raw intensity values in 2D images, called pixel-based representations. Pixel-based object recognition uses pixel information directly as input data. Elsen et al. [Elsen et al., 1997] also used pixel based representations for their system. The recognition of 3D objects is achieved by providing arbitrary 2D views of each object. Invariance against affine transformations such as translation or scaling is achieved by precoding in pixel space.

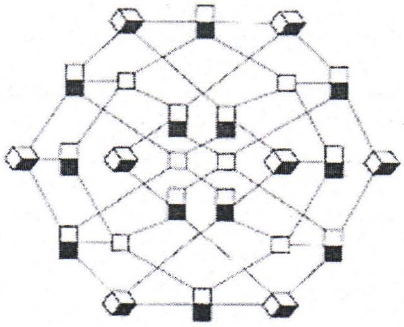

Figure 3: An object and its aspect graph

Murase and Nayar [Murase and Nayar, 1995] and Nayar et al. [Nayar et al., 1996] developed a parametric eigenspace method to recognize 3D objects directly from their appearance. This method encodes the variations of an object shape and reflectance with respect to its pose and the illumination conditions. It has been applied successfully to the tasks of face recognition [Turk and Pentland, 1991], illumination planning [Murase and Nayar, 1994] and object recognition in the presence of occlusion [Bischof and Leonardis, 1998]. However, this technique does not provide indication on how to optimize the size of the database with respect to the types of objects considered for recognition and their respective eigenspace dimensionality.

Ulman and Basri [Ulman and Basri, 1991] show that object's silhouette can be use as an image feature. In their approach, 3D object is represented by the linear combination of 2D views. They have shown that with three views of rigid object whose contours are defined by surface tangent discontinuities, one can interpolate among the three views with a linear operation to produce a fourth view. Other works that use object's silhouette such as Vijayakumar et al. [Vijayakumar et al., 1996] and Mokhtarian [Mokhtarian, 1997].

3. Classification

Classification is a process to recognize objects based on features. In this section, some methods for classification are briefly discussed. We have listed five popular methods: graph matching, interpretation tree, fuzzy, statistical method and neural networks.

3.1 Graph matching

This method has been the basis and earlier way of classification. A graph consists of a set of nodes connected by links (also called edges or arcs). Each node represents an object feature for example a surface. Nodes can be labeled with several of the feature's properties such as size, shape, area, compactness, type of surface etc and links of the graph represent relationships between features. Classification task is performs by finding similarity between object graph and model graph. Some works that used this method such as in [Bowyer et al., 1988; Brooks et al., 1979; Dorai and Jain, 1997; Koenderink and van Doorn, 1979; Sripradisvarakul and Jain, 1989; Stewman and Bowyer, 1987; Stewman and Bowyer, 1988].

3.2 Interpretation tree

In interpretation tree, each node represents an association between one scene and one model feature. Object recognition can be viewed as matching an object's features against an interpretation forest consisting of a tree for each object model in the database. The set of valid mappings from the object features to the corresponding model features that survive the pruning constraints from a collection of hypotheses indicating which object is present in the scene [Newmann et al., 1992]. Classification using interpretation tree can be found in [Ettelt and Schmidt, 1998; Flynn and Jain, 1991; Greenspan, 1998; Minovic et al., 1993; Newmann et al., 1992].

3.3 Fuzzy

Fuzzy sets were introduced by Zadeh [Zadeh, 1965]. It was designed to represent or manipulate with diverse, non-exact, uncertain and inaccurate knowledge and information. Fuzzy approach is based on the premise that key elements in human thinking are not just numbers but can be approximated to tables of fuzzy sets [Pal and Mitra, 1999]. Much of the logic behind human reasoning is not the traditional two-valued or even multivalued logic, but logic with fuzzy truths, fuzzy connectives and fuzzy rules of inference. Since fuzzy is the powerful tool for decision making, several previous studies in 3D object recognitions have given attention in applying this technique [Fukushimura and Minoh, 1995; Ngan and Kang, 1992; Ramirez et al., 1995; Walker, 1996].

3.4 Statistical method

In this approach, each pattern is represented in terms of *d*-features or measurements and is viewed as a point in a *d*-dimensional space. The goal is to choose those features that allow pattern vectors belonging to different categories to occupy compact and disjoint regions in a *d*-dimensional feature space. The effectiveness of the representation space (feature set) is determined by how well patterns from different classes can be separated. Given a set of training patterns from each class, the objective is to establish decision boundaries in the feature space which separate patterns belonging to different classes. In the statistical decision theory approach, the decision boundaries are determined by the probability distributions of the patterns belonging to each class, which must either be specified or learned [Jain et al., 2000]. Some works that used this method such as in [Denzler et al., 1994; Horegger and Niemann, 1995; Honnegger, 1997; Krebs et al., 1998; Malik and Whangbo, 1997, Hetzel et al. 2001]

3.5 Neural networks

Recent research in 3D object recognition focused on using neural networks as a classifier. A neural networks consists of many processing elements joined together to form an appropriate network with adjustable weighting functions for each input. These processing elements are usually organized into a sequence of layers with full or random connection between layers. A neural network works by pattern matching. It must be trained by presenting a set of cases to the input layer, and then providing feedback about how closely the output layer predicts the actual outcomes. The weights of the connections are adjusted to make the prediction better (to minimize error in prediction). The most common algorithm for doing this is called back propagation. The training set is repeated until the network performs sufficiently well. Then, the network is validated with an independent set of data (with outcomes) to see how well it has generalized the training set. If it performs well enough, the network can be used as a decision aid -- data with unknown outcomes can be fed in and the predicted outcome used to make decisions. Some works related to this method such as [Büker and Hartmann, 1996; Carpenter and Ross, 1996; Park and Cannon, 1996; Sahambi and Khorasani, 2003; Wang and Cohen, 1991].

4. Conclusion

Since 3D object can be observed by different viewpoints, representing objects in 3D recognition system can be based on object centered or view centered. Object centered representation uses description of objects based on three dimensional features. Since representations are intrinsically feature-based, they generate the most concise shape descriptions, and usually the most accurate. In addition, features are local, so this method offers some robustness against occlusion and invariance against illumination and pose variations. However they cannot be compared directly with images and required feature extraction Sometimes a shape maybe too complex to be represented in terms of features. In view based representations, images and models can be compared directly. As a result, any shape can be represented no matter how complex it is. However illumination, pose and location variations will alter the images. In addition, this method required large size of database, so the processing speed will be decreased.

Conventional methods used interpretation tree and graph matching for classification task. However, these methods required large training sets, and the algorithm becomes complex when the number of objects and the complexity of object shape increase. Recently, most researchers are focusing on applying fuzzy, neural network or statistical methods in their works. The increasing popularity of these methods, especially neural networks to solve classification problems is due to low dependency on domain-specific knowledge (relative to model-based and rule-based approaches), easy implementation and availability of efficient learning algorithms.

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