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A Survey on Object Location with Imaging System

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Abstract- *Object recognition is a basic application domain in computer vision. For many decades, it is considered as an area of extensive research especially in 2D. 2D object recognition can be defined as the task of finding and identifying objects in the real world from an image or a video sequence. It is still a hot research topic in computer vision because it has many challenges such as viewpoint variations, scaling, illumination changes, partial occlusion, and background clutter. Many approaches and algorithms are proposed and implemented to overcome these challenges.*

In this paper, we will discuss the current computer vision literature on 2D object recognition. We will introduce an overview of the current approaches of some important problems in visual recognition, to analyze their strengths and weaknesses. Finally, we will present particular challenges in 2D object recognition approaches that have been used recently. as well as, possible directions for future research will be presented in this field.

I. INTRODUCTION

Space programs on space robot, debris removing, rendezvous and docking, satellite formation, and other on-orbit service applications all involve the technology of moving body control [19–22]. The precondition for moving body control is to a first be acquainted with the body movement information, such as inertia, position, attitude, and velocity. Figure 1 shows several examples of on-orbit service application with vision system.

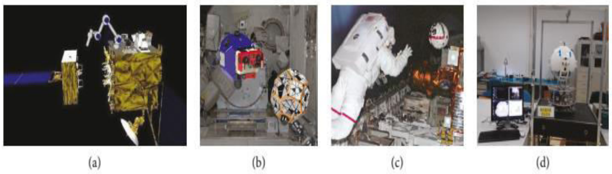

Figure 1: Examples of on-orbit service application with vision system. (a) On-orbit servicing, (b) SHPERE, (c) minCAM, and (d) our system on the ground

Generally, there are many techniques for measuring the relative position and attitude between two objects. Sensors such as GPS, gyroscopes, accelerometers, and star sensors are commonly used for self-navigation, and their position information is sent to each other by wireless communication. Optical-electronic sensors such as laser radar and vision based system may be more suitable to measure relative position and attitude when the two objects are at the close range, especially in autonomous vehicles or aircrafts [23–25]. In addition, the vision-based system based on computer vision is also widely used for object localization in industry manufacturing lines, medical instruments, and some intelligent applications. Since the vision-based measurement is of low cost and flexible to setup, vision system is increasingly applied in space body control. Vision system also has many schemes such as monocular vision [26], stereo vision [27], and active vision with structure light [28]. Besides, the active cameras such as Flash LIDAR's can be used to detect the unknown object [29]. For the noncooperative system localization, stereo vision and monocular vision [30] can both recognize the unknown objects by edge detection and feature matching. Active vision with structure light obtains the object 3D information when structure light scans the object surface, and it can not only help to recognize the object but also reconstruct the 3D information of unknown object. While monocular vision is more difficult to handle the unknown object, its precision and speed is not worse than stereo vision or active vision in applications of known target and environment. This work is involving in an on-orbit service application. A free-floating robot can move inside the spacecraft, and the function of the robot includes routing inspection, astronaut assistant, and autonomous docking and charging. Many similar programs have been carried out in the satellite or Space Station such as the SHPHEREs [31], SCAMP [32], mini AERCam [33], and Astrobee [34], which are shown in Figure 2.

This kind of robot does not require space orbit control but only serves for relative movement inside the spacecraft. However, once the environment suitability permitted, it can also work out of the spacecraft. In this work [35], a vision navigation camera is configured on a robot, and another camera is fixed at the docking place to recognize this robot. These two kinds of vision system above have the same function to measure the relative position and attitude. The main problem of the positioning system is that the complex background and light environment may influence the image recognition. Another problem is the requirement of real-time processing speed and high precision in the control system.

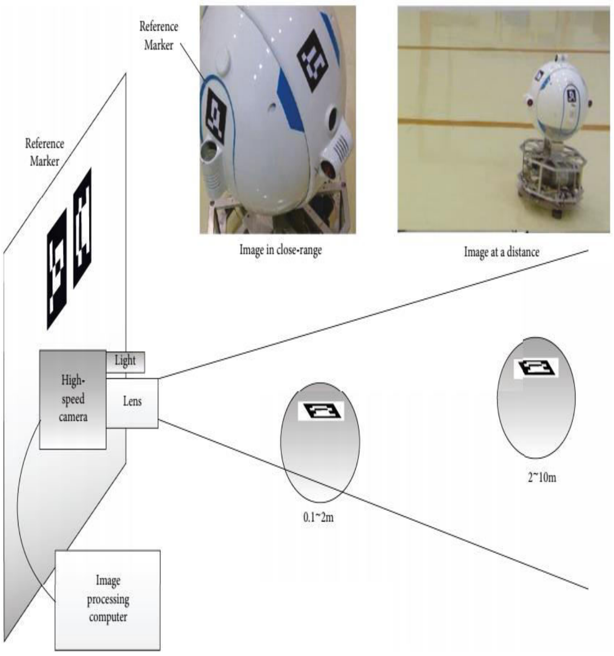

Figure 2: System working mode: long-distance navigation and close dock in.

To resolve these problems, firstly, the deep learning method is introduced robust for object detection and localization in the image sequence. Secondly, after the object is detected, the geometry of object position and attitude calculation is solved by P4P (perspective in 4 points) method, and the explicit calculation is gotten. The embedded electronic platform driven by GPU is applied for accelerating the image processing speed. The ground test platform is established, and its testing result indicates that our measures greatly improved the recognition accept rate so that the precision of object localization is up to 1% and the embedded platform can process the image sequence at best by 70 frames per second. The works aimed at making such vision-based system more practicable in the real dynamic environment.

To evaluate an object recognition technique, each application imposes different requirements and constraints, such as [3]:

1) Evaluation time: Especially in industrial applications, the data has to be processed in real time. Of course, evaluation time depends strongly upon the number of pixels covered by the object as well as the size of the image area to be examined.

2) Accuracy: In some applications, the object position has to be determined very accurately. The error bounds must not exceed a fraction of a pixel.

3) Recognition reliability: All recognition techniques try to reduce the rates of “false alarms” (e.g., correct objects erroneously classified as “defect”) and “false positives” (e.g., objects with defects erroneously classified as “correct”) as much as possible.

4) Invariance: Virtually, every algorithm has to be insensitive to some kind of variance of the object to be detected. Depending on the application, it is worthwhile to achieve invariance with respect to [4]:

a) Illumination: Gray scale intensity appearance of an object depends on illumination strength, angle, and color. In general, the object should be recognized regardless of the illumination changes.

b) Scale: The area of pixels, which is covered by an object, depends on the distance of the object to the image acquisition system. Algorithms should compensate for variations of scale.

c) Rotation: The rotation of the object is not known a priori and should be determined by the system.

d) Background clutter: Especially natural images don’t show only the object, but also contain background information. This background can vary significantly for the same object. The recognition technique shouldn’t be influenced by background variation.

e) Occlusion: Sometimes, the system cannot rely on the fact that the whole object is shown in a scene image. Some parts might be occluded by other objects.

f) Viewpoint changes: The image formation process projects a 2D-object located in 2D space onto the image plane. Therefore, the 2Dappearance depends strongly on the relative position of the camera to the object (the viewpoint), which is unknown for some applications. The design of the object recognition algorithm should aim at ensuring at least partial invariance for a certain viewpoint range.

II. RELATED WORK

OBJECT RECOGNITION APPROACHES.

Many object recognition techniques have been implemented over multiple decades. Object recognition approaches can be classified according to number of characteristics. In this paper, we focus on model acquisition (learning) and invariance to image formation conditions. Therefore, the object recognition techniques are categorized into four groups: geometry-based methods, appearance-based methods, three-dimensional object recognition schemes, and descriptor-based methods [3, 5, 6, 7].

In geometry- or model-based object recognition, the knowledge of an object's appearance is provided by the user as an explicit CAD-like model. Typically, this model only describes the 3D shape and omits other properties such as color and texture [3, 5, 6]. Appearance-based methods do not require explicit user provided model in object recognition. The object representations are usually acquired through an automatic learning phase, and the model typically relies on surface reflectance properties [6]. Some methods intend to locate the 3D position of an object in a single 2D image, essentially by searching for features which are invariant to viewpoint position. Descriptor-based approaches represent the object as a collection of descriptors derived from local neighborhoods around characteristic points of the image [3].

A. *Geometry-Based Methods*

Early attempts of object recognition were focused on using geometric models of objects to account for their appearance variation due to viewpoint and illumination changes. The main idea is that the geometric description of a 3D object allows the projected shape to be accurately predicate in a 2D image under projective projection, so facilitating recognition process using edge or boundary information (which is invariant to certain illumination changes). Most attention was made to extract geometric primitives (e.g., lines, circles, etc.) that are invariant to viewpoint change. It has been shown that such primitives can only be reliably extracted under limited conditions (controlled variation in lighting and viewpoint with certain occlusion) [5].

Geometry base techniques for object recognition have many advantages, such as [8, 9]:

• Invariance to viewpoint: Geometric object descriptions allow the projected shape of an object to be accurately predicted under perspective projection.

• Invariance to illumination: Recognizing geometric descriptions from images can be achieved using edge detection and geometric boundary segmentation. Such descriptions are reasonably invariant to illumination variations.

• Well-developed theory: Geometry has been under active investigation by mathematicians for thousands of years. The geometric framework has achieved a high degree of maturity and effective algorithms exist for analyzing and manipulating geometric structures.

• Man-made objects: A large fraction of manufactured objects are designed using computer-aided design (CAD) models and therefore are naturally described by primitive geometric elements, such as planes and = spheres. More complex shapes are also represented with simple geometric descriptions, such as a triangular mesh.

B. *Appearance-Based Methods*

In contrast, most recent efforts have been centered on appearance-based techniques as advanced feature descriptors and pattern recognition algorithms. The core idea of these techniques is to compute eigenvectors from a set of vectors where each one represents one face image as a raster scan vector of gray-scale pixel values. Each eigenvector, dubbed as an eigenface, captures certain variance among all the vectors, and a small set of eigenvectors captures almost all the appearance variation of face images in the training set. Given a test image represented as a vector of gray-scale pixel values, its identity is determined by finding the nearest neighbor of this vector after being projected onto a subspace spanned by a set of eigenvectors. In other words, each face image can be represented by a linear combination of eigenfaces with minimum error, and this linear combination constitutes a compact reorientation [5].

Appearance based methods typically include two phases [10, 11, 12]. In the first phase, a model is constructed from a set of reference images. The set includes the appearance of the object under different orientations, different illuminants and potentially multiple instances of a class of objects, for example faces. The images are highly correlated and can be efficiently compressed using e.g. Karhunen-Loeve transformation (also known as Principal Component Analysis - PCA) [13]. In the second phase, parts of the input image (sub images of the same size as the training images) are extracted, possibly by segmentation (by texture, color, motion) or by exhaustive enumeration of image windows over whole image. The recognition system then compares an extracted part of the input image with the reference images (e.g. by projecting the part to the Karhunen-Loeve space) [6].

A major limitation of the appearance-based approaches is that they require isolation of the complete object of interest from the background. They are thus sensitive to occlusion and require good segmentation [14, 15].

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C. Descriptor-based Methods

When object recognition has to be performed in "real-world" scenes, characterization with geometric primitives like lines or circular arcs is not suitable. Another point is that the algorithm must compensate for heavy background clutter and occlusion, which is problematic for global appearance methods. In order to cope with partial occlusion, local evaluation of image information is required. Additionally, gradient-based shape information may not be enough when dealing with a large number of similar objects or objects with smooth brightness transitions. To this end, Schmid and Mohr [16] suggested a two-stage strategy for the description of the image content: the first step consists of the detection of so-called interest/key points i.e. points exhibiting some kind of salient characteristic like a corner. Subsequently, for each interest point a feature vector called region descriptor is calculated. Each region descriptor characterizes the image information available in a local neighborhood around one interest point, as shown in Figure 3.

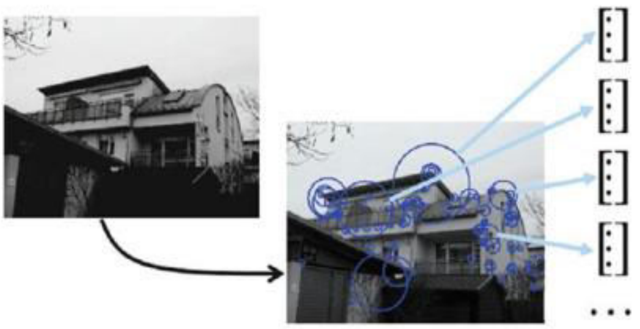

Figure 3: Illustrative example of the strategy suggested by chmid and Mohr [15]: first, interest regions are detected (middle part, indicated by blue circles). Second, a descriptor is calculated for each interest region (right part) [3].

Object recognition can then be performed by comparing information of region descriptors detected in a scene image to a model database. Usually the model database is created in an automated manner during a training phase. During the last decade, there has been extensive research on this approach to object recognition and many different alternatives for interest point detection and region descriptors have been suggested [17, 18].

FEATURE-BASED OBJECT RECOGNITION TECHNIQUES

Extracting the points from an image that can give the best definition for an object are called keypoints/features and they are very important and valuable. These features have many applications in image processing like object detection, object and shape recognition, and object tracking. By extracting the features, we can use them for finding objects in other images. If the keypoints are correctly identified, they achieve the best information from the image [26].

A. Harris Corner Detector

Harris and Stephens [37] developed an approach to extract corners and infer the contents of an image. Corner detection is frequently used in many applications, such as motion detection, image registration, video tracking, panorama stitching, 3D modeling, and object recognition. Corner detection overlaps with the topic of interest point detection [38]. The Harris corner detector is popular because it is independent to rotation, scale, and illumination variations. However, the Shi-Tomasi corner detector [39], the one implemented in OpenCV library [40], is an improvement of this corner detector. A corner is so special because, since it is the intersection of two edges, it represents a point in which the directions of these two edges change. Hence, the gradient of the image (in both directions) has a high variance, which can be used to detect it [41].

B. The SIFT Algorithm

Lowe [42] developed a feature detection and description technique call SIFT (Scale Invariant Feature Transformation). This means that an image is looked for important points. These points, called keypoints, are then extracted and described as a vector. The resulting vectors can be used to find reliable matches between different images for object recognition, camera calibration, 3D reconstruction, and many other applications [43].

SIFT consists of three basic stages. First, the keypoints are extracted from the image. Then, these keypoints are described as 128 vectors. Finally, the last step is the *matching* stage. Several stored vectors in the database are matched against the calculated vectors of the tested image using the Euclidian distance.

Fig. 4 gives an overview of the three main stages of the SIFT technique. In the top figure, the extracted keypoints are drawn on the image using arrows. The length of the arrow represents the scale of the keypoint, while the angle of the arrow represents the orientation of the keypoint. The middle figure shows how a keypoint is described. The third figure shows another example in which the box in the right image has to be found in the left image [43].

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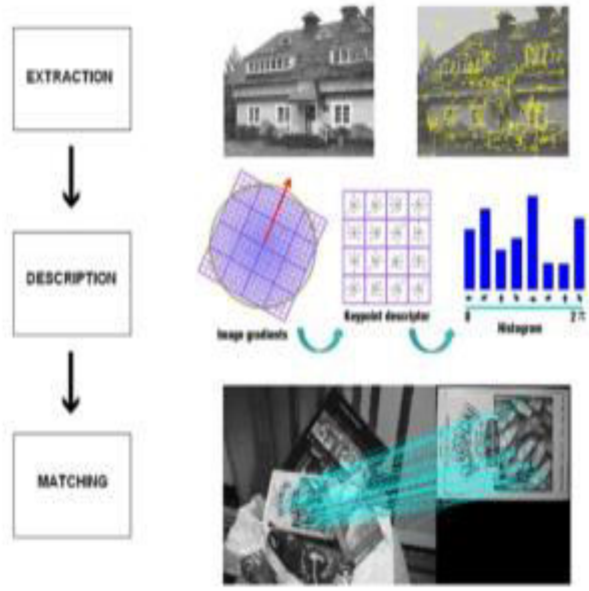

Figure 4. Graphical representation of the SIFT algorithm and a matching example

The SIFT is used as a benchmark for many propositions of interest point detectors and region descriptors. It is a strong hint of its good performance, especially in situations with heavy occlusion and/or clutter. A particular strength of this technique is that each step is carefully designed and, additionally, all steps work hand in hand and are well coordinated [3]. However, this technique only works well if a significant number of keypoints can be detected in order to generate enough descriptor information and therefore relies heavily on the keypoint detector performance [3].

C. The SURF Algorithm

SURF is developed by Bay et al. [44] and it stands for Speeded Up Robust Features. SURF algorithm is actually based on the SIFT algorithm [42]. It uses integral images and approximations for achieving higher speed than SIFT. These integral images are used for convolution. Like SIFT, SURF works in three main stages: *extraction*, *description,* and *matching*. The difference between SIFT and SURF is that SURF extracts the features from an image using integral images and box filters. The extraction of the keypoints from an image is a process that requires image filtering. SURF implements these filters using box filters. A very interesting pre-processing step is the conversion of the original image into a so-called integral image [43].

Integral images are very easily computed by adding the right pixel values. In an integral image every pixel is the sum of all pixels located in a rectangular window formed by that pixel and the origin, with the origin being the most top-left pixel. Box filters are used as an approximation of the exact filter masks. By using integral images together with box filters a major speed up is realized. Another difference in the extraction of keypoints is that SIFT rescales the image, while SURF changes the filter mask. The term box-space is used to distinguish it from the usual scale-space. While the scale space is obtained by convolution of the initial images with Gaussians, the discrete box-space is obtained by convolving the original image with box filters at several different discrete sizes. In the detection step, the local maxima of a Hessian-like operator, the Box Hessian operator, applied to the box-space are computed to select interest point candidates. These candidates are then validated if the response is above a given threshold. Both box size and location of these candidates are then refined using an iterated procedure fitting locally a quadratic function. Typically, a few hundreds of interest points are detected in a digital image of one mega-pixel [45]. Therefore, SURF builds a descriptor that is invariant to viewpoint changes of the local neighborhood of the point of interest. Like in SIFT, the location of this point in the boxspace provides invariance to scale and provides scale and translation invariance. To achieve rotation invariance, a dominant orientation is defined by considering the local gradient orientation distribution, estimated with Haar wavelets. Making use of a spatial localization grid, a 64-dimensional descriptor is then built, corresponding to a local histogram of the Haar wavelet responses [47].

III. CHALLENGES OF OBJECT RECOGNITION

In recent times, the most popular approaches to object recognition represent an object by feature vectors, and the recognition problem is framed as one of supervised learning - training a classifier given a set of positive and negative examples.

On the other hand, matching and learning visual objects is a challenging problem. Instances of the same object category can generate very different images, depending on confounding variables such as illumination conditions, object pose, camera viewpoint, partial occlusions, and unrelated background "clutter". Different instances of objects from the same category can also exhibit significant variations in appearance.

Furthermore, in many cases appearance alone is ambiguous when considered in isolation, making it necessary to model not just the object class itself, but also its relationship to the scene context and priors on usual occurrences.

In addition, scalability concerns also arise when designing a recognition system's training data: while unambiguously labeled image examples tend to be most informative, they are also more expensive to obtain. Thus, methods today must consider the tradeoffs between the extent of costly manual supervision an algorithm requires versus the advantages given to the learning process.

There are other issues that add to the challenge of solving the problem of 2D object recognition and they include:

• Occlusion: A part of the 2D object is always hidden due to self-occlusion or occlusion by other objects in the scene.

• Clutter: A scene may include many closely spaced objects, making it difficult to determine the source object of a data point.

• Noise: Sensors are not perfect and therefore a 2D representation of the same view of an object is never exactly the same and can possibly include missing parts depending on the quality of the sensor.

• Sampling Resolution: The 2D data of objects in the database might be captured using a different sensor with a different sampling rate than the one used to capture the 2D scene data.

In support of better object recognition, we can expect a full function tool kit that will have a framework for interchangeable interest-point detection and interchangeable keys for interest-point identification. This will include popular features such as SURF, HoG, Shape Context, MSER, Geometric Blur, PHOG, PHOW, and others. Support for 2D features is planned.

IV. CONCLUSION

We have presented an overview of the literature of the 2D object recognition, pointed out some of the major challenges facing the community and stressed some of the characteristic approaches attempted for solving the recognition problem. Through this survey we noticed that a great deal of the research focused on passive recognition, to some extent, on the feature selection stage of the recognition problem without taking into consideration the effects of various cost constraints discussed in the survey.

V. FUTURE WORK

We are seeking to build system of the 3D object recognition based on depth map. So this system is used to recognize real 3D objects. The conventional local feature based object recognition methods, such as SIFT, SURF, and ORB, that are used to retrieve the strong features of the object.

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