# Contour-based Partial Object Recognition using Symmetry in Image Databases

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## ABSTRACT

This paper discusses the problem of partial object recognition in image databases. We propose the method to reconstruct and estimate partially occluded shapes and regions of objects in images from overlapping and cutting. We present the robust method for recognizing partially occluded objects based on symmetry properties, which is based on the contours of objects. Our method provides simple techniques to reconstruct occluded regions via a region copy using the symmetry axis within an object. Based on the estimated parameters for partially occluded objects, we perform object recognition on the classification tree. Since our method relies on reconstruction of the object based on the symmetry rather than statistical estimates, it has proven to be remarkably robust in recognizing partially occluded objects in the presence of scale changes, rotation, and viewpoint changes.

## Keywords

Object, Image, Contour, Recognition, Symmetry

## 1. INTRODUCTION

Most existing methods for object recognition are based on full objects. However, many images in electronic catalogs contain multiple objects with occluded shapes and regions. Due to the occlusion of objects, image retrieval can provide incomplete, uncertain, and inaccurate results. To resolve this problem, we propose new method to reconstruct objects using symmetry properties since most objects in a given image database are represented by symmetrical figures.

Even though there have been several efforts in object recognition with occlusion, currents methods have been highly sensitive to object pose, rotation, scaling, and visible portion of occluded objects [12] [9] [17] [3] [15]. In addition, many appearance-based and model-based object recognition methods assumed that they have known occluded regions of objects or images through extensive training processes with statistical approach. However, our approach is not limited to recognizing occluded objects by pose and scale changes, and does not need extensive training processes.

Unlike existing methods, our method finds shapes and regions to reconstruct occluded shapes and regions *within objects*. Our approach can handle object rotation and scaling for dealing with occlusion, and does not require extensive training processes. The main advantage of our approach is that it becomes simple to reconstruct objects from occlusions. We present the robust method, which is based on the contours of objects, for recognizing partially occluded objects based on symmetry properties. The contour-based approach finds a symmetry axis using the maximum diameter from the occluded object.

In experiments, we demonstrate how our method reconstruct and recognize occluded shapes and regions using symmetry. Experiments use rotated and scaled objects for dealing with occlusion. We also evaluate the recognition rate of the reconstructed objects using symmetry and the visible portion of the occluded objects for recognition.

The rest of this paper is organized as follows. In Section 2, we briefly review work related to this study. In Section 3, we describe a method to recognize partial objects from given classes. In Section 4, we describe experimental results for partial object recognition. Finally, we summarize this paper in Section 5.

## 2. RELATED WORK

There have been several research efforts in object recognition for dealing with occlusion. Krumm [13] proposed a new algorithm for detecting objects in images which uses models based on training images of the object, with each model representing one pose. Williams [23] proposed a method for the reconstruction of solid-shape from image contour using the Huffman labeling scheme. For object recognition, Chang and Krumm [3] used the color cooccurrence histogram based on pairs of pixels. Schiele et al. [20] proposed a method to perform partial object recognition using statistical methods, which are based on multidimensional receptive field histograms. In addition, Rajpal et al. [17] introduced a method for partial object recognition using neural network based indexing.

In appearance-based object recognition, Edwards and Murase [6] addressed the occlusion problem inherent in appearance-based methods using a mask to block out part of the basic eigenimages and the input image. Leonardis and Bischof [14] handled occlusion, scaling, and translation by randomly selecting image points from the scene and their corresponding points in the basis eigenvectors. Rao [18] applied the adaptive learning of eigenspace basis vectors in appearance-based methods. Ohba and Ikeuchi [16] were able to handle translation and occlusion of an object using eigenwindows.


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Current methods for dealing with occlusion have been based on template matching, statistical approaches using localized invariants, and recognition of occluded regions based on local features. In addition, there are many efforts in ellipse construction and detection [7][9][22]. In this paper, we propose unique methodologies in object recognition for dealing with occlusion based on symmetry properties through the ellipse reconstruction.

Even though there have been several efforts in object recognition with occlusion, current methods have been highly sensitive to object pose and scaling. In addition, many appearance-based and model-based object recognition methods assumed that they have known occluded regions of objects or images through extensive training processes. However, our method is not limited to recognizing occluded objects by pose and scale changes, and do not require extensive training processes.

## 3. THE PROPOSED METHOD

We discuss the object reconstruction and the parameter estimation method to find the best matching class of input objects using the classification tree method [4]. We extracted shape parameters from reconstructed objects using RLC lines, such as roundness, aspect ratio, form factor, surface regularity [5].

The approach tries to find occluded shapes within partially occluded objects. The basic assumption is that most objects are represented by symmetrical figures. When a symmetric object is partially occluded, we use the symmetry measure to evaluate the symmetric shape. We estimate the most similar parameters of occluded shape and region of objects, and we retrieve objects that have the estimated parameters of occluded objects.

A basic idea of reconstruction and estimation of occluded objects is to use symmetry properties within objects and use to the contour of objects. Fortunately, most products in electronic catalogs have symmetry in their shapes and they are represented by symmetrical figures. Symmetrical descriptions of shape or detection of symmetrical features of objects can be useful for shape matching, model-based object matching, and object recognition [2] [1].

In the given database, we have elliptical and roughly-rounded objects such as plates, cups, pans, and pots, depending on their poses and shapes. First, we consider elliptical objects in which the occlusion changes values of measurements and parameters related to diameters. We assume that we can get diameters from elliptical objects, which are partially occluded.

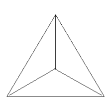

**Figure 3.1 Three-Spoke from the Triangle.**

However, the elliptical objects are limited to the shape of objects. Therefore, it may not be applied to other types of shape such as irregular shapes. In this case, since we cannot easily detect the symmetry axes, we introduce the three-spoke type symmetry method as shown in Figure 3.1. We apply this approach to roughly-rounded objects such as cups.

For roughly-rounded objects, we use the three-spoke type method, which is derived from the triangle. The triangle is a basic model to represent figures such as circle, rectangle, and polygon. We use extended lines of the triangle to make axes as shown in Figure 3.1. The three-spoke type symmetry axes, which are equally assigned by 120 degrees, provide the possibility to detect proper symmetry axes on roughly-rounded objects. Therefore, this method can detect symmetry axes in roughly-rounded objects.

In order to perform the following procedures, we assume that objects are represented by symmetrical figures.

1. We have an occluded elliptical object in Figure 3.2 and roughly-rounded object in Figure 3.6, we can get cutting points of the occlusion *(x,y)'* and *(x,y)''*, that are given by overlapping or cutting.

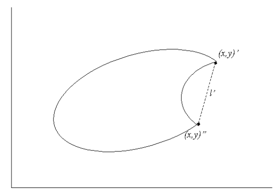


**Figure 3.2 The Occlusion Area Estimation using Symmetry: Get cutting points *(x,y)'* and *(x,y)''* and get a distance *l'*.**

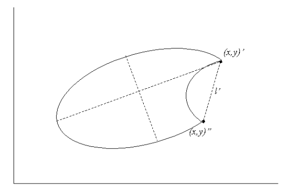


**Figure 3.3 The Occlusion Area Estimation using Symmetry: Get the maximum diameter and the symmetry axis.**

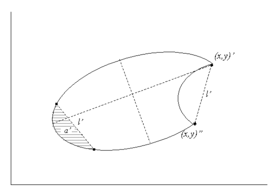


**Figure 3.4 The Occlusion Area Estimation using Symmetry: Get the estimated region *a'* using a line *l'* and the symmetry axis.**

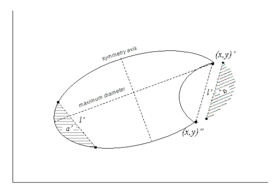


**Figure 3.5 The Occlusion Area Estimation using Symmetry: Add region a' to occluded shape and region and re-captured the estimated shape of an object.**

2. Compute a distance between two cutting points from *(x,y)'* and *(x,y)''*, which is called a line *l'* as in Figure 3.2 and 3.6.
3. Based on a line l', make a connection between two points, fill the concave region and re-captured the shape. It is important to compute a centroid in an object.
4. Get the maximum diameter from re-captured shape using extremal points as shown in Figure 3.4 and 3.7. Two extremal points *(r, l)* and *(r, l)'* from re-captured shape as in Figure 3.7. The distance between two extreme boundary points are represented by the maximum diameter.
5. In elliptical objects, one of the maximum and minimum diameters can be a symmetry axis. In roughly-rounded objects, we use the three-spoke type symmetry, one spoke can be a

symmetry axis to find occluded region within an object.

6. Centroid Detection: In case of elliptical objects, we find a centroid based on the maximum diameter and a line perpendicular to the maximum diameter, which is located in the center of the length of the maximum diameter. We select symmetry axes based on one of these lines as in Figure 3.3. In roughly-rounded objects, we get a centroid, based on whole region of an object. Equation 2 is adapted from Russ [19]. If the centroid is calculated by equation 1 using the boundary pixels only, the results may not be correct. The calculated points will be biased toward whichever part of the boundary is most complex and contains the most pixels. The correct centroid location uses the pairs of coordinates $x_i$ , $y_i$ for each point in the shape boundary. The centroid of an irregular shape is calculated correctly using all of the pixels in an object.

$$C_x = \frac{\sum_{i=0}^{k} x_i}{Area}, C_y = \frac{\sum_{i=0}^{k} y_i}{Area} \quad (1)$$

$$C_x = \frac{\sum_{i-0}^{k} (x_i + x_{i-1})^2 (y_i - y_{i-1})^2}{Area}, C_y = \frac{\sum_{i-0}^{k} (y_i + y_{i-1})^2 (x_i - x_{i-1})^2}{Area} \quad (2)$$

7. In roughly-rounded objects, a centroid is put at the same position at the center of the three-spoke type symmetry axes.

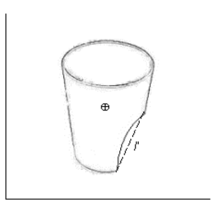

**Figure 3.6 The occlusion of a cup: Get a centroid after re-captured a shape.**

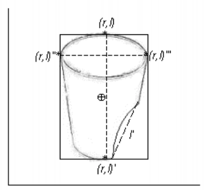

**Figure 3.7 Get extremal points *(r,l)*, *(r,l)'* and *(r,l)''*,*(r,l)'''* and the maximum diameter of an object.**

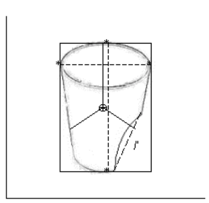

**Figure 3.8 Use the three spoke type symmetry: Match a center of the spoke to a centroid and parallel one of axes to the maximum diameter.**

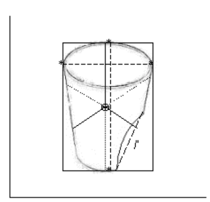

**Figure 3.9 Extend axes and make symmetry axes.**

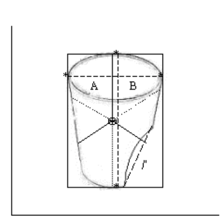


**Figure 3.10 Select a symmetry axis based on two regions, which are A and B.**

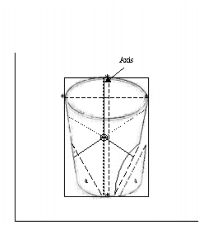


**Figure 3.11 Find a region *a'* of occluded shape using a symmetry axis and add to a occluded shape.**

8. Axis Detection: The midpoint of the major axis is called the center of the ellipse. The minor axis is the line segment perpendicular to the major axis which also goes through the center and touches the ellipse at two points. In elliptical objects, we detect a symmetry axis based on the maximum diameter or the minimum diameter. To find a symmetry axis in roughly-rounded objects, one of axes of the three-spoke type symmetry axes is in parallel with the maximum diameter of an object as shown in Figure 3.8.
   Based on occluded shape and region, we select a symmetry axis to estimate this region within an object. Figures 3.9 and 3.10 show how to select a symmetry axis. When we select an axis in roughly-rounded objects, we consider conditions as follows:
   - Select axes, which don't intersect the occluded region.
   - 3.9 and 3.10 show how to select a symmetry axis. Select axes, which have a region with the maximum diameter $\geq$ *l'*.
   - Area and perimeter are invariants as in equation 3, compare the proportion of region A and B.

$$\left(\frac{Perimeter}{Area}\right)^A \cong \left(\frac{Perimeter}{Area}\right)^B \quad (3)$$

9. Using mirror symmetry, we can get points across an axis. We find points on the contour across an axis which have the same length *l'* and the same angle corresponding to the axis that is perpendicular to a symmetry axis, but the distance between axis and points may or may not be the same.
10. Capture a region *a'*, move the captured region to the occluded shape using the mirror symmetry, and add to these regions as shown in Figure 3.4, 3.5, and 3.11.
11. Re-compute shape measurements such as area, diameters, and perimeter using RLC lines from re-captured shape of an object. Then, re-compute shape parameters based on measurements.
12. Apply to a classifier.

From the above discussions, we described how to reconstruct and estimate the partially occluded shape and region of an object and how to find the best matching class of partially occluded objects after the estimation.

## 4. EXPERIMENTAL RESULTS

In the sections, we evaluate and describe the results of partial object recognition by our proposed a method. We have selected 190 partially occluded objects of images from electronic catalogs on the Internet as well as manipulated images. We assume that occluded objects have more than 50% visibility of objects, and images of catalogs contain partially occluded objects. The objects are categorized by semantic meanings such as cup and plate. In addition, our approaches and experiments are limited to cups and plates since we use roughly-rounded or elliptical objects. More precisely, the database contains 32 objects from different viewpoints and images of 97 objects comprising image plane rotations and scale changes.

In sample images, we have extracted image features of partially occluded objects such as shape and texture. We experimented with shape reconstruction based on the contour of objects using symmetry properties. We assumed that inputs are not correctly classified and have occlusion.

We experimented with samples such as plates and cups to reconstruct the occluded shape of objects as shown in Figure 4.1 and 4.2. In Figure 4.2, it is correctly classified after the reconstruction with an occlusion about 30%. On the other hand, Figure 4.1 is not correctly classified after the reconstruction since the width of plate is too narrow. This experiment shows that our method heavily relies on shape of objects.

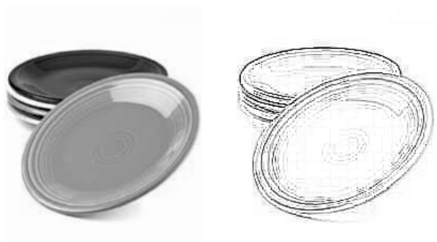

**Figure 4.1 Example of the occlusion with a Plate.**

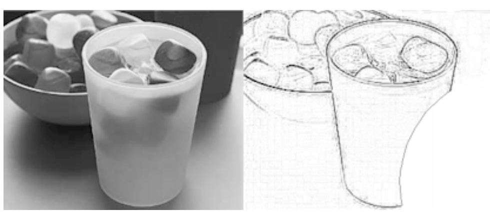

**Figure 4.2 Example of the manipulated occlusion with a Cup.**

Finally, we performed an experiment for the relationships between visible portion of objects and recognition rates. In order to evaluate the visibility of objects, we used manipulated images of cups and plates. Figure 4.3 shows the pattern of object recognition in the presence of partial occlusion of objects and the results obtained by the symmetric recognition. A visible portion of approximately 67% is sufficient for the recognition of objects based on the contour.

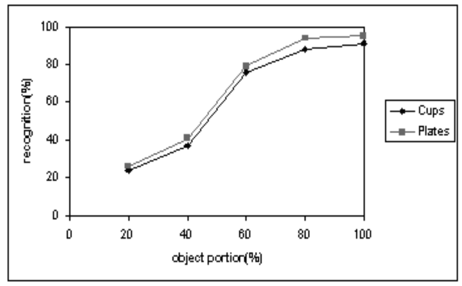


**Figure 4.3 Object recognition in the presence of the occlusion of objects based on the contour.**

There are many efforts in object recognition for dealing with occlusion. The visible portion of objects required to recognize occluded objects are shown in Table 4.1. Table 4.1 shows a simple comparison between our method and other existing methods. The probabilistic method based on local measurements requires small portions of objects to recognize the whole objects, but it required extensive training processes to recognize occluded objects [21] [20]. Our method shows good visibility of partial object recognition and do not need extensive training processes.

**Table 4.1 The visibility of object recognition in the presence of partial occlusion.**

| Methods | Visibility | Training processes |
|---|---|---|
| Appearance matching techniques using adaptive masks | 90% | not required |
| Probabilistic technique using Chi-square | 72% | required |
| Probabilistic technique using local measurements | 34% | required |
| Contour-based approach using symmetry | 67% | not required |

In order to measure the influence of occlusion and compare its impact on the recognition performance of the different methods, we performed an experiment as follows.

Figure 4.4 summarizes the recognition results for different visible object portions. For each test object, we varied the visible object portion from 20% to 100% and recorded the recognition results using Chi-square divergence and our method.

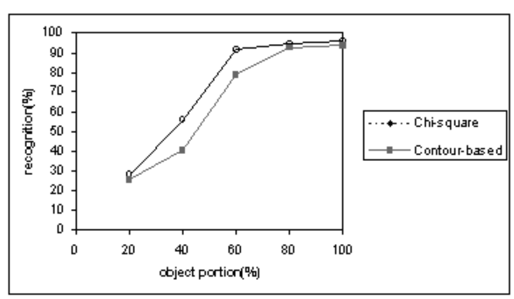


**Figure 4.4 Experimental results with occlusion.**

The results show that our method clearly obtains better results than Chi-square divergence. Using only 60% of the object area, almost 80% of the objects are still recognized. This confirms that our method is capable of reliable recognition in the presence of occlusion.

**Table 4.2 Summary of Object Recognition Methods for dealing with Occlusion.**

| Methods | Occlusion | Scale changes | Object Pose | Rotation |
|---|---|---|---|---|
| Bischof et al. [1] | Yes | Yes | No | No |
| Edwards et al. [6] | Yes | Yes | No | Yes(limited) |
| Ohba et al. [16] | Yes | No | Yes | No |
| Rao [18] | Yes | No | Yes | No |
| Jacob et al. [11] | Yes | No | Yes | No |
| Krumm [13] | Yes | No | No | NO |
| Contour-based using symmetry | Yes | Yes | Yes(limited) | Yes |

Table 4.2 summarizes the various object recognition methods. The table indicates whether the methods can handle occlusion, rotation, pose, and changes in the size of objects in the database. Unlike the other methods, our method can handle scale change, object pose, and rotated objects with occlusion, even though our method has minor limitations of object poses.

## 5. CONCLUSION

In this paper, we have discussed how to estimate parameters and to reconstruct the occluded shape of partial objects in image databases. In order to reconstruct occluded shapes, we used symmetry, which provides powerful method for the partial object recognition. Unlike the existing methods, our method tried to reconstruct occluded shapes and regions within objects, since most objects in our domain have symmetrical figures. However, we have limitations in the shape of objects and the occluded region of objects. For example, if a pan has an occlusion in handle, it cannot correctly reconstruct and be recognized.

Another minor limitation of our method is that a method is sensitive to the pose of an object. For example, if we cannot see an ellipse due to the object's pose, we cannot recognize the object. After estimation, we have applied inputs, which include estimated parameters, to the existing classification trees, to get to the best matching class.

All experiments are performed based on the classifier in earlier work. In experiments, the results show that the recognition of the occluded object is properly reconstructed, estimated, and classified, even though we have limited to the size of samples. In addition, we have experienced the power of the symmetry through experiments.

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