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# Recognition of Partially Occluded Objects Using Maximum Curvature Points

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*Abstract* : Partially occluded objects are recognized from a 2-D image through the use of maximum curvature points on the image boundary. The vertices of high curvature on an occluded object are classified by the objects which are hypothesized to be involved in the occlusion. A heuristic method is developed for computational speed. Two typical examples are given to illustrate the accuracy as well as the simplicity of the heuristic method.

## 1.0 Introduction

An occlusion takes place when an object is either touched or overlapped by other objects. When an occlusion takes place, the resulting image will not match any of the involved objects because some of the image information will be lost due to the occlusion. In this paper, an object image refers to the image of an object free of any occlusion, whereas the occluded image refers to an image of multiple occluded objects. Figure 1 shows examples of images of occluded objects.

Price [4] has developed a method which compares the boundary segments of an object image to the occluded image and creates a disparity matrix. From this disparity matrix, the sequence of compatible segments is found and the transform information is calculated. Bhanu and Ming [1] have used the length of boundary segments, in addition to vertex angles, to create a disparity matrix and then formed clusters for the objects which might be involved in the occlusion.

In this paper, we present a heuristic method of identifying objects from an image of occluded objects using the vertices of local maximum curvature.


(a) (b)
Figure 1. Partially Occluded Objects

## 2.0 Local Maximum Curvature Points

In this paper, we have adopted a different approach which uses vertices of local maximum curvature. A vertex of local maximum curvature is defined as a vertex at which the local curvature is greater than the local curvatures at adjacent vertices.

Using the split method by Duda and Hart [2], which is later extended for computational efficiency by Han et al.[3], the curved boundary is approximated by a polygon with the vertices marked by crosses in Figure 2. Each vertex is given a sequential number starting from one. The starting vertex is marked by a square.

At each vertex, the interior angle value as well as the length of the two adjacent edges are calculated. Column 3 of Figure 2- (a) shows the values of the interior angles, which is denoted by $\alpha$, and column 4 shows the right edge length at a vertex, which is denoted by $l_r$. The left edge length at the vertex (to be denoted as $l_l$) is the same as the right edge length of the left adjacent vertex.

The curvature at a vertex point $\nu$, $k(\nu)$, is defined as:

$$k(\nu) = (\pi - \alpha)/\Delta s\,, \qquad (1)$$

where we adopt $\Delta s = l_l + l_r$ at vertex point $\nu$. Column 2 of Figure 2-(a) shows the value of curvature at each vertex point.

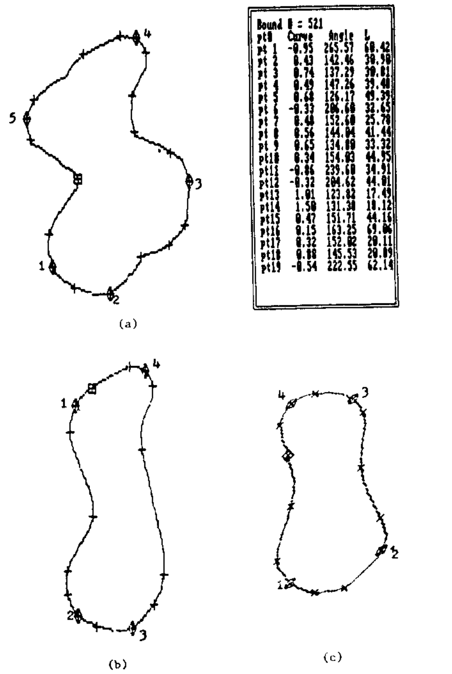


Figure 2. Vertices of Local Max Curvature

### 3.0 Heuristic Method

Using the curvature values in column 2 of Figure 2, those vertices of local maximum curvature are easily identified. Among those identified vertices, those with values greater than a given threshold value are selected for consideration. Those vertices will be called local-max points hereafter. The local-max points are indicated by oblongs on the image boundary and they correspond to vertex points *pt* 3, *pt* 5, *pt* 9, *pt* 14, and *pt* 18. For convenience, the local-max points are renumbered by the numbers shown next to each oblong.

Let $d(i,j)_k$ represent the distance between the local-max points $i$ and $j$ of object image $k$. In this paper, $k$ is assigned the value zero for the occluded image, one for object 1, two for object 2, and so on. Tables 1-a, 1-b, and 1-c show the distance matrices between the local-max points for the images shown in Figures 2-(a), 2-(b), and 2-(c), respectively.

An index is introduced to measure a disparity between $d(i,j)_0$ and $d(p,q)_k$, and is denoted as $D_{(ij)(pq)k}$, which is defined as follows:

$$D_{(ij)(pq)k} = \frac{abs[d(i,j)_0 - d(p,q)_k]}{U}\,, \qquad (2)$$

where $U$ represents a scaling factor.

For object recognition requiring speed and minimal software resources, a quick heuristic method is developed using the disparity indices. The heuristic method orders the values of $d(i,j)_k$ for object $k$ in a non-increasing order. Then, for each entry of $d(i,j)_k$, the entries of the occluded image are scanned to identify those entries for which the disparity index value, defined by Eq.(2), is less than a prescribed threshold value. In this example. the threshold value is set to 1.0 with $U$=10.

The first row of Table 2 represents the entries from Table 1-b for object 1. The entries in each column under the first row represent the entries selected from Table -a for which the disparity index values are less than the threshold value. Within each column, those entries are reordered with the smallest disparity index value first.

| $\nu$ | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0 | 67.5 | 170.8 | 235.7 | 141.6 |
| 2 | 67.5 | 0 | 138.0 | 244.3 | 187.5 |
| 3 | 170.8 | 138.0 | 0 | 148.3 | 187.4 |
| 4 | 235.7 | 244.3 | 148.3 | 0 | 142.8 |
| 5 | 141.6 | 187.5 | 187.4 | 142.8 | 0 |

Table 1-a. Distance Between Local Max Points, Occluded Image

| $\nu$ | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 0 | 197.3 | 218.8 | 70.1 |
| 2 | 197.3 | 0 | 65.1 | 238.6 |
| 3 | 218.8 | 65.1 | 0 | 242.4 |
| 4 | 70.1 | 238.6 | 242.4 | 0 |

Table 1-b. Distance Between Local Max Points, Object 1

| $\nu$ | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 0 | 91.6 | 180.2 | 178.3 |
| 2 | 91.6 | 0 | 157.5 | 186.1 |
| 3 | 180.2 | 157.5 | 0 | 60.2 |
| 4 | 178.3 | 186.1 | 60.2 | 0 |

Table 1-c. Distance Between Local Max Points, Object 2

| $(4,3)_1$ | $(4,2)_1$ | $(3,1)_1$ | $(2,1)_1$ | $(4,1)_1$ |
|---|---|---|---|---|
| $(4,2)_0$ | $(4,1)_0$ | | $(5,2)_0$ | $(2,1)_0$ |
| $(4,1)_0$ | $(4,2)_0$ | | $(5,3)_0$ | |

Table 2. Edge Association Based on Disparity Index

The first matching attempt is made between edges $(4,3)_1$ of Table 1-b and $(4,2)_0$ of the occluded image. The center of rotation is taken at the middle of each edge, and the difference in the slope of the two edges with respect to a common reference axis provides rotation information. After all vertices on the boundary of object 1 are translated and rotated upon the occluded image, the resulting image looks like Figure 3. As a matter of fact, this matching happens to be a correct one, satisfying hypothesis testing statistics. Therefore, it is declared that object 1 is recognized in the occluded image.

If the first matching attempt had been unsuccessful, the next matching attempt would have been with edges $(4,3)_1$ and $(4,1)_0$ in the next row, which would result in an incorrect matching. This procedure will continue either until the hypothesis is accepted or all possible matchings shown in Table 2 are attempted. The same procedure applies to the identification of object 2.

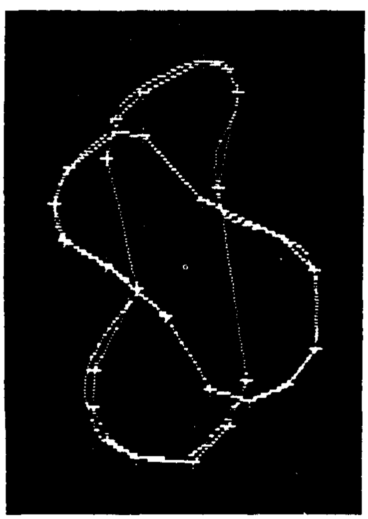

Figure 3. Image Superposition

**Example 1**

Suppose two objects are involved in a partial occlusion which results in the occluded image shown in Figure 1-(b). Figure 4 shows the polygonized images, the local-max points for the occluded image, and the local-max points for the two object images.

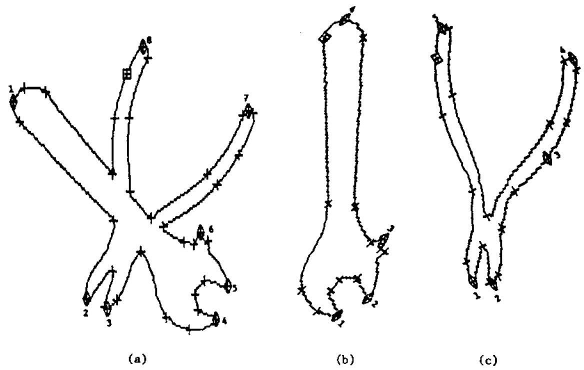


Figure 4. Image of Occluded Objects

For the time being, we will pretend that we have no prior knowledge of the occluded image, as well as of the object images, other than the distance values between the max curvature points. When distance matrices are created as described earlier, a table of object association can be created. Using this table, objects, a pair of pliers and wrench, could be recognized as indicated by superimposed polygon in Figure 5

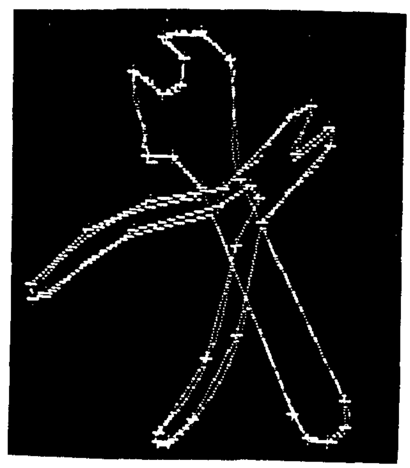

Figure 5. Object Images Superimposed on the Occluded Image

## 4.0 Conclusion

Use of maximum curvature points proves to be computationally speedy and accurate for the recognition of partially occluded objects from a 2-D image. The subroutines used in the program are the improved split method for image polygonization. The experimental results show that the objects with a natural polygon shape are very efficiently recognized, whereas curved objects take more time and matching accuracy decreases.

## References

[1] Bir Bhanu and John C. Ming, Recognition of Occluded Objects: A Cluster-Structure Algorithm, *Pattern Recognition*, vol 20, no. 2, pp. 199-211, (1987).

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