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Recognition of Partially Obscured Family of Objects Stretched along Axis of Symmetry [1]

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ABSTRACT

A data-driven approach is proposed to recognize a family of planar objects, which are stretched along the axis of symmetry and are partially obscured, using high-curvature points, sampled boundary distances (SBD) and a statistical method, cross correlation. In this work, the SBD's are the distances measured to the boundary points of an object from points equally spaced along a line which is either a symmetric axis or assumed to be a symmetric axis. A method for detecting symmetry and finding axis of symmetry of partially obscured objects is presented. The experimental results are also presented.

1. Introduction

The partial planar shape recognition has elaborated by many research works. Ansari and Delp[1] used landmarks and sphericity. Their matching method is known as hopping dynamic programming[1]. Wolfson[2] developed a string matching algorithm for finding the longest common subcurve of two 2-D curves. Chaudhury et al[3] used an feature-independent, admissible heuristic function to search the curve of an object in the state space. Han and Jang[4] used the distance between the locally maximum curvature points, the graph-theoretic optimization method with maximal cliques, and a weight matching algorithm. Grimson[5] used a constrained search process to recognize parameterized objects. Knoll and Jain[6] used local features and feature indexed hypothesis method to handle the cases with a large number of possible objects. Their prototype system can recognize 2D objects with known scale. Ayache and Faugeras[7] used the longest line segments and angles between adjacent segments of the polygonalized object as description, and developed generation and recursive evaluation of hypotheses. Huttenlocher and Ullman[8] investigated alignment method to handle 2D and 3D cases. Kalvin et al[9] used footprint and geometric hashing to effectively work with large database of models. Mehrotra and Grosky[10] used high-curvature points to polygonalize the objects, and developed an algorithm for generating and testing data-driven indexed hypothesis using angles at the vertices and distances between vertices of the polygons. Grimson and Lozano-Pereze[11] used local measurements of positions and surface normals to search for consistent matches in the interpretation tree and efficiently discard inconsistent matches. Hong and Wolfson[12] studied the geometric hashing technique with weighted footprint, which can achieve better recognition than Kalvin et al[6]. Koch and Kashyap[13] developed polygon moments and used association graph. Wang et al[19] used fast Fourier transform on the sampled boundary distances (SBD)[17,18] to show that partially obscured objects can be recognized provided that the endpoints of major axis are visible and that partially obscured object family (stretched along axis of symmetry) can also be recognized provided that the endpoints of major axis and symmetric axis are not obscured.

The research in partial shape recognition of parameterized object is rare. Most of the aforementioned works used local features that are changed with respect to stretching transformation and therefore, can not be used to recognize stretched objects. In this area, Grimson's approach[5] is complicated and approximate and Wang et al's work[19] is too much constrained. In this paper, a data-driven recognition process is introduced, in contrast to the slow model-driven approach used in most of the previous works. This process applies to both the curved boundary and polygons, and the constraint in [19] is removed. In addition, the proposed process does not have to use polygon representations of an object which are non-unique and the representation are used by many previous works.

The detection of symmetry and finding of axis of symmetry (AOS) at a shape of image has been studied by Attalah[14], Friedberg[15], Marola [16] and Wang et al[19]. The first three works[14-16] are based on the centroid of an object, which cannot be located precisely if the object is partially occluded or obscured. However, the major axis is used in the approach of [19]. The advantage of [19] over [14-16] is that, in [19], the AOS can still be found for partially obscured objects provided that the endpoints of major axis are not obscured. Although the approach is more flexible than the approach in [14-16], it is still limited by the strong constraint. In this paper, the proposed process can recognize more generalizedly obscured objects. That is, the endpoints of major axis need not be visible.

The organization of this work is as follows: Section 2 describes the sampled boundary distances (SBD); Section 3 presents the detection of symmetry and finding of AOS, and Section 4 investigates the recognition of partially obscured objects stretched along the AOS. Section 5 gives the experimental results and Section 6 summarizes this work.

2. Sampled Boundary Distances

The smple boundary distances (SBD's) are the ordered samples of distances defined from a line to the points located on the boundary of an object image. In [17] and [18], the line from which the SBD's are measured is the major axis. In [19], both the major axis, and the AOS are used. In this work, the SBD's are measured from the AOS or the possible AOS. The SBD's measured from the AOS of [19] and of this work are depicted in Fig. 1. As shown in Fig. 1(a), the SBD's are measured from the entire length of AOS. In Fig. 1(b), however, the SBD's are measured from part of the AOS, starting from one pair of high-curvature points (HCP), A_1 and A_2, and ending at another pair of high-curvature points, B_1 and B_2. In this work, the endpoints of AOS do not have to be visible, which is in contrast to that the endpoints of AOS connot be covered in [19].

3. Detection of Symmetry and Finding of Axis of Symmetry

In many cases, the AOS in a symmetric object can be obtained by determining the major axis of the object [19]. That is the reason why the endpoints of a major axis must be visible for finding the AOS of a partially obscured objecta in [19]. In this paper, the HCP's, generated by using the work in [20], instead of the major axis, are used to detect the symmetry for the

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shape of an object and this can certainly handle more general cases. Consider an object to be partially obscured as shown in Fig. 2(a) and Fig. 2(b). The detection of its symmetry and finding of its AOS can be proceeded as follows:

Step 1. Find HCP's from the partially obscured object. [e.g. points 1, 2, ..., n of Fig. 2(b)]

Step 2. Measure the distances between the consecutive HCP's. [e.g. dist (1, 2), dist(2, 3), ..., dist(n-1, n) of Fig. 2(b)]

Step 3. Sort these distances.

Step 4. Find the distances with closer values. [e.g. dist(n-2, n-1) and dist(5, 6), or dist(6, 7) and dist(n-3, n-2) of Fig. 2(b)]

Step 5. Check the parallelism between the lines connecting the correspoinding endpoints of line segments with similar distances. [e.g. lines L_1 and L_2 of Fig. 2(b)]

Step 6. If the two lines are approximately parallel, [e.g. lines L_1 and L_2 of Fig. 2(b)], obtain the midpoints of these two parallel lines [e.g. points P_1 and P_2 of Fig. 2(b)]

Step 7. Obtain SBD's perpendicular to the line connecting the two midpoints of approximately parallel lines [e.g. line $\overline{P_1P_2}$ of Fig. 2(b)] from equally spaced points on this midpoint connecting line [e.g. lines l_{ij}, i=1, 2, j=1, ..., n of Fig. 2(b)]

Step 8. Compute the correlation coefficient of SBD [CCSBD] between the SBD's on the one side and the SBD's on the other side [e.g. l_{1j} and l_{2j}, j=1, ..., n] as follows:

$$CCSBD = \frac{\sum_{j=1}^{n}(l_{1j} - \bar{l}_{1j})(l_{2j} - \bar{l}_{2j})}{[\sum_{j=1}^{n}(l_{1j} - \bar{l}_{1j})^2\sum_{j=1}^{n}(l_{2j} - \bar{l}_{2j})^2]^{1/2}}$$

If CCSBD=1, this implies that the two sets of SBD, l_{1j} and l_{2j}, j=1, ..., n, are linearly correlated the part under testing [e.g. the area (n-1)59(n-5) of Fig. 2(b)] is symmetric. If, on the other hand, this criterion is not satisfied, the part of image under consideration is asymmetric. That the value of CCSBD equals one is certainly an ideal case, this cannot be achieved in the real cases. Therefore, a threshold is used and, in this work, 0.98 is chosen as the minimum value of CCSBD for determination of symmetry.

4. Recognition of Object Family Stretched along AOS

After the symmetry is detected and AOS is found, as described in Section 3, the SBD's l_{1j}, j=1, ..., n, are used to correlate with four sets of SBD models and four values, $(CCSBD)_{1-m}$, m=1, 2, 3, 4, are obtained. These four $(CCSBD)_{1-m}$ are used as the keys to search respectively for the region of an object from the four arrays corresponding to the four sets of SBD models. Each entry in the arrays contains a search key and a pointer to the corresponding section of an object in the object base. The search key is the CCSBD between the SBD's of that section of object and a SBD model. The object region with the closest key value to the target key is choosen as the candidate. If at least three candidate are the same, that candidate is the object region matched by the input object region. Otherwise, the SBD's of those candidate regions are fetched and correlated with the input SBD's to be matched. The candidate regions generating largest CCSBD value, which is also greater than a minimum allowable value (e.g. 0.95 in this work), belongs to the object matched by the input object region.

5. Experimental Results

The camera used to take pictures in this work is JVC TK-870U color video camera. An ATV is a Video-graphics Adapter is used to digitize the pictures and a Fountain PC, an IBM PC/AT compatible, is used to store the digitized pictures. The pictures are then transferred into a Sun Workstation. A software named KOVIS, which is under development in this Institute is used to process the pictures.

The images of Fig's 4 and 5 are the picture of drawings drawn using FIG software on the Sun Workstation. Images 1 through 6 of Fig. 4 are the original images, and images 1p through 6p of Fig. 5 are the partially obscured, stretched (or shortened), rotated, translated and scaled images of the corresponding images of Fig. 4, in which the area between two consecutive pairs of high curvature points is called region. The number of regions of images 1 through 6 are listed in Table 1. Two consecutive regions are a unit to be correlated with the SBD models and the generated CCSBD's are presented in Table 2. In Table 2, there are sixteen units A consecutive regions. Therefore, there are four 16-entry arrays to be searched during the course of matching. The matching results for images 1p through 6p, are given in Table 1, in which, the symmetry of each one of the two consecutive regions is checked first. Their SBD's are then correlated with the four SBD models, respectively, in both straight and reverse ways; the latter is for the possible reversal of order of SBD's when they are correlated with the SBD models. The candidate object regions are selected and the SBD's of an input object are correlated with the SBD's of the candidate regions if there are no more than two same candidates. The matching results are presented in the bottom row of Table 3. It should be noted that the partially obscured stretched objects along axis of symmetry can be easily recognized, using this method.

6. Summary

In this work, a new approach is presented for recognizing partially obscured family of objects with polygonal or curved boundary stretched along axis of symmetry, using sampled boundary distances. The process is data-driven recognizing for partially obscured objects. This can reduce the time for an object database with a large number of objects. A method for detecting symmetry and finding axis of symmetry of partially obscured objects is presented.

The experimental data indicates that this approach performs satisfactorily. It should also be noted that, to improve the discriminative capability of this approach, and more SBD models may be used. The use of this approach to recognize the partially occluded objects whose images cannot be separated by the segmentor and the robustness of this approach against noises will be investigated.

7. References

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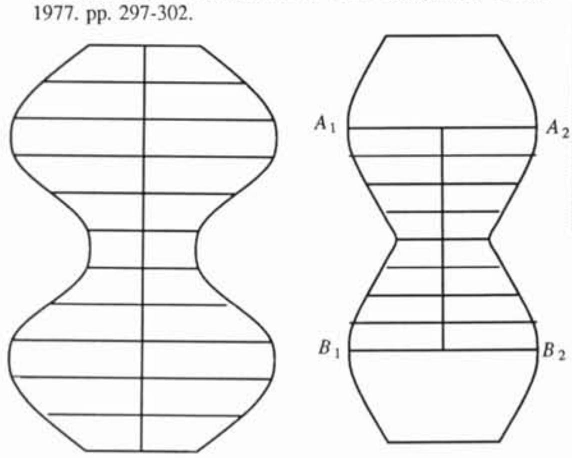
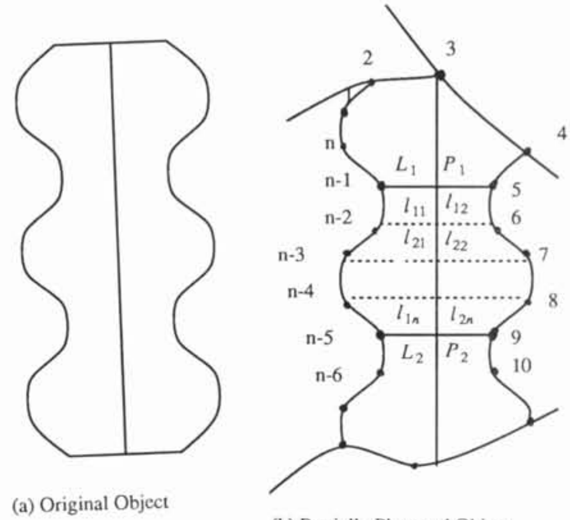


(a) SBD's Measured from Axis of Symmetry in [19]

(b) SBD's Measured from Axis of Symmetry of this work.

Fig. 1. The SBD's Measured from Axis of symmetry in [19] and This Work.

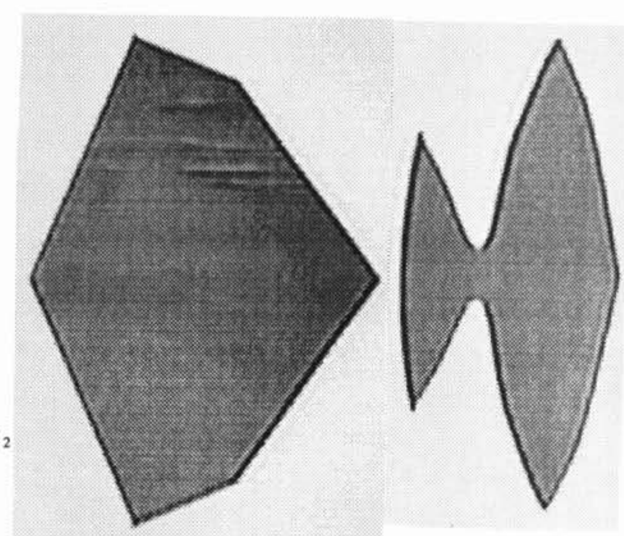
Table 1. Number of Regions of Images 1 through 6.						
Image	1	2	3	4	5	6
Number of Regions	3	3	6	3	4	3



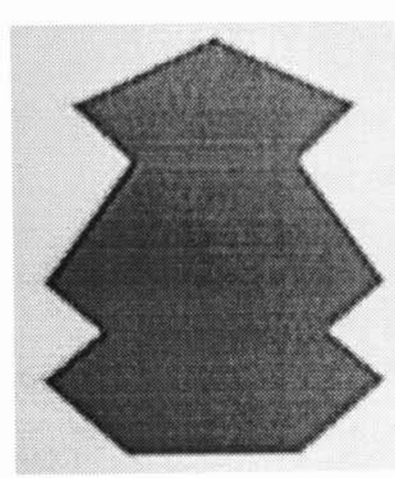
(a) Original Object

(b) Partially Pbscured Object

Fig. 2. An Original and Partially Obscured Object.

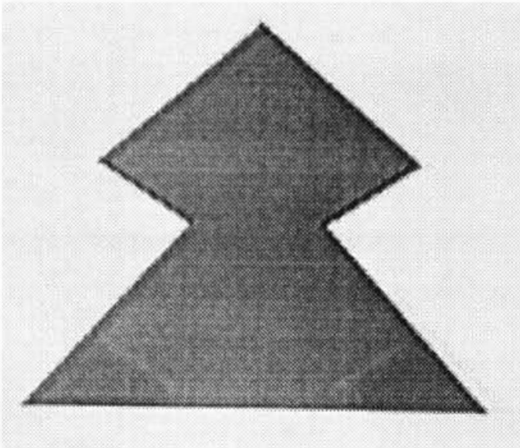


(a) Image 1 (b) Image 2

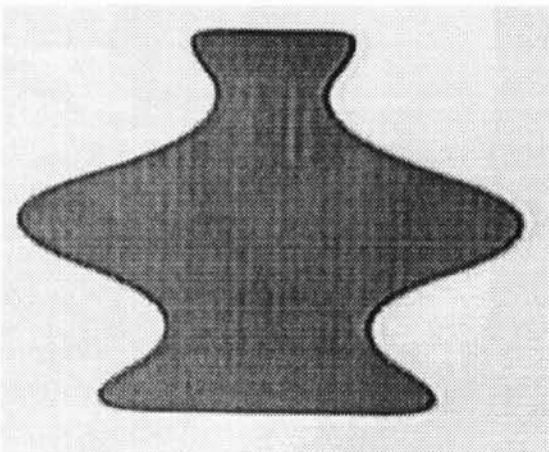


(c) Image 3

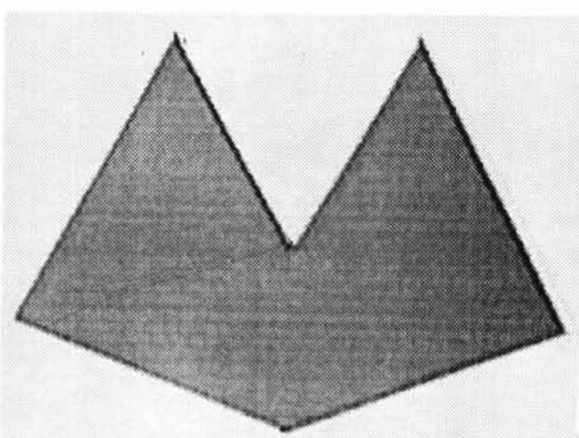
Fig. 3. Original Base Images.



(d) Image 4

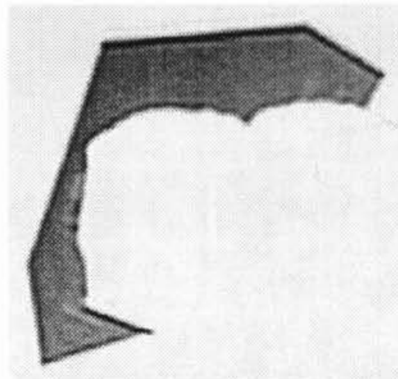


(e) Image 5

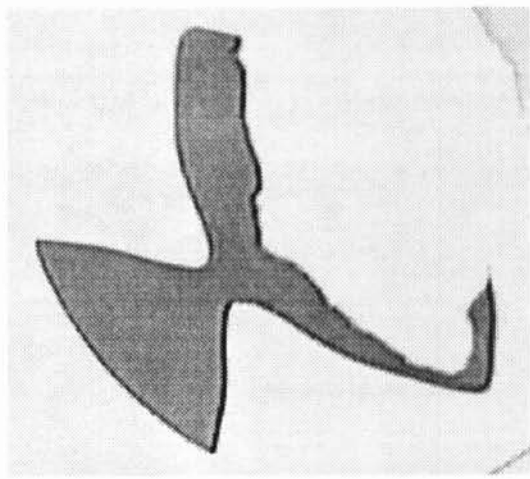


(f) Image 6

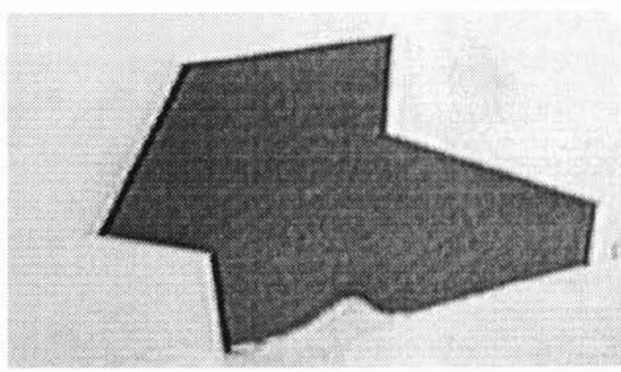
Fig. 3. Original Base Images (cont'd).



(a) Image 1p (shortened)

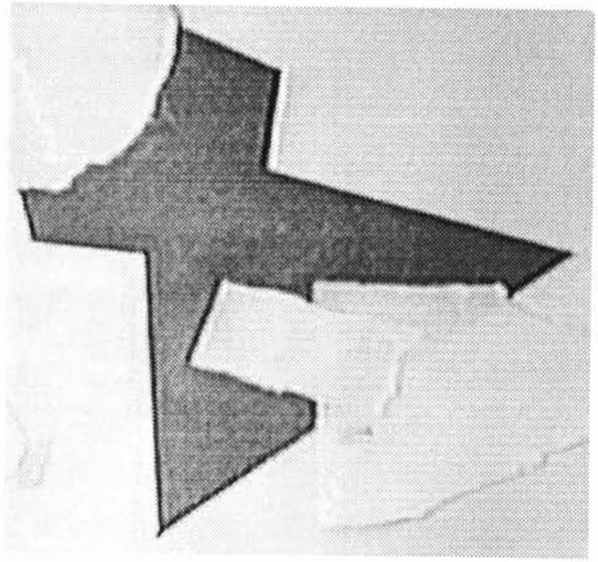


(b) Image 2p (stretched)



(c) Image 3p (stretched)

Fig. 4. Partially Obscured, Stretched, Rotated, Translated, Scaled Images of Fig. 4.

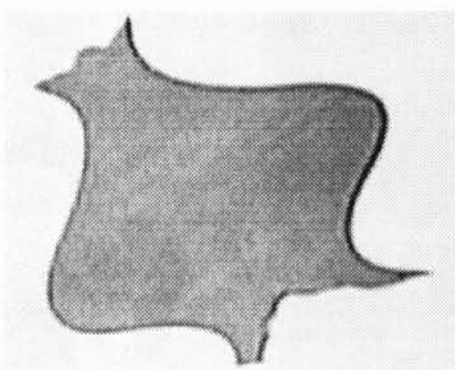


(d) Image 4p (stretched)

Fig. 4. Partially Obscured, Stretched, Rotated, Translated, Scaled Images of Fig. 3.

Table 2. Coefficent of Cross Correlation between SBD Models and SBD of Regions of Original Images.

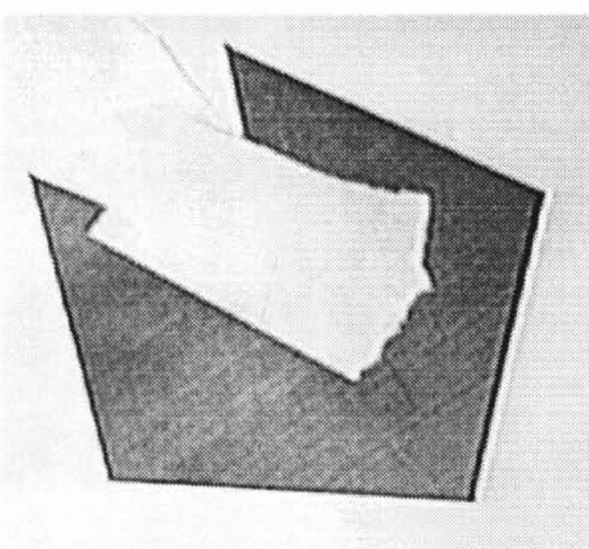
Image Regions	SBD Model	1	2	3	4	5	6
1-2	1	0.6033	0.6095	0.6371	0.5577	-0.0123	0.3564
	2	-0.3162	0.2858	-0.2419	-0.1823	-0.6315	-0.5722
	3	0.3843	0.6174	0.4778	0.4577	-0.2322	0.0525
	4	-0.3242	0.2018	-0.2417	-0.1705	-0.4728	-0.4473
2-3	1	-0.1681	-0.5746	-0.2072	-0.0907	0.6160	0.3979
	2	0.6263	0.2162	-0.6132	-0.6106	0.0980	0.3295
	3	0.0992	-0.4883	-0.3167	-0.2587	0.5265	0.5598
	4	0.4493	0.2601	-0.5352	-0.6025	-0.1346	0.2317
3-4	1			0.5198		-0.6350	
	2			-0.1581		0.1173	
	3			0.4540		-0.4569	
	4			-0.1592		0.2350	
4-5	1			-0.5889			
	2			-0.1139			
	3			-0.5185			
	4			0.1583			
5-6	1			0.2286			
	2			0.6019			
	3			0.3199			
	4			0.4840			



(e) Image 5p (stretched)

Table 3. The Process and Results of Matching

Input Image	SBD Model	1	2	3	4	5	6
Sym-CCSBD-1		0.9994	0.9983	0.9925	0.9827	0.9996	0.9997
Sym-CCSBD-2		0.9976	0.9979	0.9977	0.9978	0.9994	0.9994
Model (Straight)	1	-0.2063	-0.5840	0.6465	-0.0052	0.1655	0.3360
	2	0.6195	0.2051	-0.1811	-0.6084	-0.5969	-0.5633
	3	0.0432	-0.4824	0.4918	-0.2002	-0.0735	0.0515
	4	0.4680	0.2709	-0.2285	-0.6029	-0.4811	-0.4512
Model (Reverse)	1	0.4726	-0.2289	0.2026	-0.4714	-0.4536	-0.3436
	2	-0.4850	-0.5607	0.5935	0.3673	0.4524	0.5749
	3	0.2071	-0.3463	0.3675	-0.2932	-0.2058	-0.0483
	4	-0.4131	-0.2868	0.3435	0.2899	0.4140	0.4514
Candidate Object (from straight)	1	3(2-3)	3(4-5)	3(1-2)	5(1-2)	3(5-6)	6(1-2)
	2	1(2-3)	2(2-3)	4(1-2)	3(2-3)	6(1-2)	6(1-2)
	3	1(2-3)	2(2-3)	3(1-2)	5(1-2)	6(1-2)	6(1-2)
	4	3(5-6)	2(2-3)	3(1-2)	4(2-3)	5(1-2)	6(1-2)
Match CCSBD (if necessary)		0.9954 1(1-3) -0.8396 3(2-3) 0.8258 3(5-6)			0.9572 5(1-2) 0.9583 3(2-3) 0.9916 4(2-3)	-0.8560 3(5-6) 0.9243 6(1-2) 0.9568 5(1-2)	
Matching Result		1(2-3)	2(2-3)	3(1-2)	4(2-3)	5(1-2)	6(1-2)



(f) Image 6p (stretched)