RECOGNITION OF OCCLUDED TWO DIMENSIONAL OBJECTS

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The problem of recognizing occluded or partially seen objects is becoming more and more important in applications such as biomedical image analysis, industrial inspection and Robotics. In this contribution we propose a hierarchical stochastics labeling technique to identify parts of two dimensional shapes represented by their polygonal approximations.

I) HIERARCHICAL STOCHASTIC LABELING :

We work with two polygons. One is the model $M = \{M_1,\dots,M_N\}$ and one is the observed object $O = \{O_1,\dots,O_{L-1}\}$ where M_i and O_j are line segments, $i=1,\dots,N$ and $j=1,\dots,L-1$. We are trying to identify part of the model M within the observation O. We are therefore trying to label each of the segments M_i $(i=1,\dots,N)$ either as a segment $O_j (j=1,\dots,L-1)$ or as not belonging to O (label O_L=NIL). Each segment M_i has therefore L possible labels.

Using a technique described in Section II we compute for every segment M_i a set of L positive numbers $p_i(\ell), \ell=1,\dots,L$ forming a vector $\vec{p}_i = [p_i(1),\dots,p_i(L)]^T$. $p_i(\ell)$ can be thought of as the probability of labeling the segment T_i, O_ℓ. The set of vectors $\vec{p}_i$ is called a stochastic labeling of the segments M_i.

Initially the stochastic labeling is ambiguous (except in some very special cases) and we make it evolve toward a less ambiguous labeling by comparing the local structures of M and O.

From now on indexes i are taken modulo N. To every segment M_i, we associate the two neighboring segments M_{i-1} and M_{i+1}. In order to compare the local structures of M and O we define two compatibility $c_1(M_i,O_k,M_j,O_\ell)$ (j=i-1 or i+1) and $c_2(M_i,O_k,M_{i-1},O_\ell,M_{i+1},O_m)$ which we denote more simply by $c_1(i,k,j,\ell)$ and $c_2(i,k,i-1,\ell,I+1,m)$.

c_1 and c_2 take values between 0 and 1. $c_1(i,k,i-1,\ell)$ measures the ressemblance of the set $\{M_i,M_{i-1}\}$ with the set $\{O_k,O_\ell\}$, for example. A good (bad) match means that the value of c_1 is close to 1,(0).

As we describe in [1,2,3] we can associate to everv segment M_i a compatibility vector $\vec{q}_i = [q_i(1),\ldots,q_i(L)]^T$. Intuitively, this vector represents what the neighbors of segment M_i (that is to say segments M_{i-1} and M_{i+1}) "think" about the way it should be labeled whereas $\vec{p}_i$ represents what the segment M_i "thinks" about is own labeling.

Mathematically speaking, we compute

$$Q_{ij}(k) = \sum_{\ell=1}^{L} c_1(i,k,j,\ell)\, p_j(\ell) \qquad \begin{array}{l} j=i-1,i+1 \\ i=1,\ldots,N \\ k=1,\ldots,L \end{array}$$

$$Q_i^{(1)}(k) = \frac{1}{2}\left(Q_{i\ i-1}(k) + Q_{i\ i+1}(k)\right)$$

$$Q_i^{(2)}(k) = \sum_{\ell_1,\ell_2=1}^{L} c_2(i,k,i-1,\ell_1,i+1,\ell_2)\,p_{i-1}(\ell_1)\,p_{i+1}(\ell_2)$$

The numbers $Q_i^{(1)}(k)$ and $Q_i^{(2)}(k)$, k=1,...,L are positive. The idea is that they are large when the probabilities of the labels of the neighbors of M_i compatible with the label O_k are large and small otherwise. The numbers $Q_i^{(1)}(k)$ and $Q_i^{(1)}(k)$ are normalized so that they they add up to 1 yielding two vectors $\vec{q}_i^{\,(1)}$ and $\vec{q}_i^{\,(2)}$ such that

$$q_i^{(j)}(k) = \frac{Q_i^{(j)}(k)}{\sum_{\ell=1}^{L} Q_i^{(j)}(\ell)} \qquad \begin{array}{l} j=1,2 \\ k=1,\ldots L \end{array}$$

The idea is to decrease the discrepancy between what every segment M_i thinks about its own labeling ($\vec{p}_i$) and what its neighbors think about it ($\vec{q}_i^{\,(j)}$, j=1,2). We have shown elsewhere [3,4] that a good "local" measure of compatibility and nonambiguity is the inner product $\vec{p}_i \cdot \vec{q}_i^{(j)}$ (j=1,2). By computing the average over the set M of these local measure we obtain two global criteria :

$$J^{(j)} = \sum_{i=1}^{N} \vec{p}_i \cdot \vec{q}_i^{(j)} \qquad j=1,2$$

The problem of labeling the segments M_i is therefore equivalent to an optimization problem : given an initial labeling $\vec{p}_i^{(o)}$, $i=1,\ldots,N$, find a local maximum of the criteria $J^{(j)}$ (j=1,2). Since c_2 is a better measure than c_1 of the local match between M and O we are actually interested in finding local maxima of the criterion $J^{(2)}$. On the other hand maximizing $J^{(1)}$ is easier from the computational standpoint. We therefore use the following hierarchical approach : starting with an initial labeling $\vec{p}_i^{(o)}$ we look for a local maximum $\vec{p}_i^{(1)}$ of the criterion $J^{(1)}$. This labeling is less ambiguous than $\vec{p}_i^{(o)}$ in the sense that many labels have been dropped (their probabilities $p_i(k)$ are equal to zero). We then use the labeling $\vec{p}_i^{(1)}$ as an initial labeling to find a local maximum of criterion $J^{(2)}$. The computational saving comes from the fact that the values $c_2(i,k,i-1,\ell_1,i+1,\ell_2)$ corresponding to probabilities $p_{i-1}(\ell_1)$ or $p_{i+1}(\ell_2)$ equal to zero are not computed. Details about the maximization procedure can be found in [2,3,5,6]

II) COMPUTING THE INITIAL PROBABILITIES AND THE COMPATIBILITY FUNCTIONS :

The initial probalities are computed from a set of feature values such as length of a segment, angle between a segment and the horizontal axis, angle between two segments,etc. Let P be the number of features used. We measure the quality of the correspondance between the segments M_i and O_k as

$$C(M_i,O_k) = \sum_{p=1}^{P} | F_{mp} - F_{op} | W_p$$

where F_{mp} and F_{op} are the values of the p-th features of the model and the observation, respectively, W_p is a weight factor. The initial probabilities are then chosen proportional to $\frac{1}{1+C(M_i,O_k)}$.

The definition of the compatibility functions c_1 and c_2 is guided by the type of deformation that we allow our polygones to undergo. We have restricted ourselves to rotation and scaling. For c_1 for example, given two segment M_i and M_j in M and two segments O_k and O_ℓ in O we compute the best transformation (composition of a rotation a change of scale and a translation) in the least squares sense that takes the pair (M_i,M_j) as close as possible to the pair (O_k,O_ℓ). If $C_1(M_i,O_k,M_j,O_\ell)$ is the corresponding error we define

$$c_1(i,k,j,\ell) = \frac{1}{1+C_1(M_i,O_k,M_j,O_\ell)}$$

c_2 is defined in a similar fashion. The problem of defining c_1 and c_2 when some of the segments in the observed object are equal to NIL is solved in [6].

III) RESULTS, CONCLUSIONS :

In figure 1 we show the outline of a piece of a car shocks absorber. In figure 2 we show the outline of the superposition of two such pieces, the one below being the one of figure 1. From a practical standpoint, it is important to identify in the shape of figure 2 (the observation) the visible part of the shape of figure 1 (the model). Figures 3 and 4 show the corresponding polygonal approximations (N=L=28). Table I shows the results of the hierarchical stochastic labeling algorithm at different iterations. We display only the label with the highest probability. The run time is 20 seconds on a DEC 10 machine.
In conclusion we have shown how the techniques of stochastic labeling could be successfully applied to the problem of recognizing partially visible 2D objects. We are in the process of extending our results to 3D.

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Table 1. Labels of segments of M at different iterations of the maximization of criteria $J^{(1)}$ and $J^{(2)}$.

Segments M_i	Labels at different iterations					
	0	4	8	4	8	12
1	1	1	1	1	1	1
2	28	28	28	28	2	2
3	28	28	28	28	28	28
4	28	28	28	28	28	28
5	28	28	28	28	28	28
6	28	28	28	28	28	28
7	28	28	28	28	28	28
8	28	28	25	25	25	25
9	28	26	26	26	26	26
10	27	27	27	27	27	27
11	28	1	1	28	28	28
12	8	8	8	8	8	8
13	28	28	9	9	9	9
14	28	28	28	28	28	11
15	28	28	28	28	28	28
16	28	28	28	28	28	28
17	28	28	28	28	28	28
18	28	28	28	28	28	28
19	28	28	28	28	28	28
20	28	28	28	28	28	28
21	28	28	28	28	28	28
22	28	28	28	28	28	28
23	28	22	22	22	22	22
24	23	23	23	23	23	23
25	24	24	24	24	24	24
26	25	25	25	25	25	25
27	26	26	26	26	26	26
28	27	27	27	27	27	27
Values of criteria	-	3.58	3.88	3.57	4.07	4.64
	$J^{(1)}$			$J^{(2)}$		

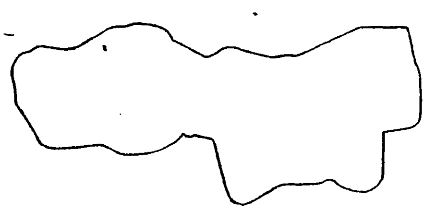

Figure 1.

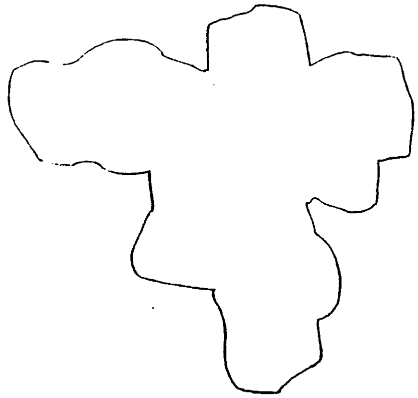

Figure 2.

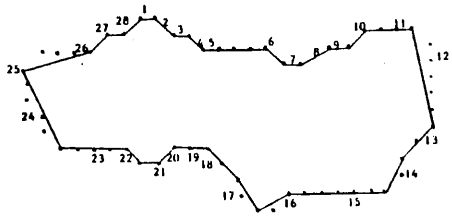

Figure 3.

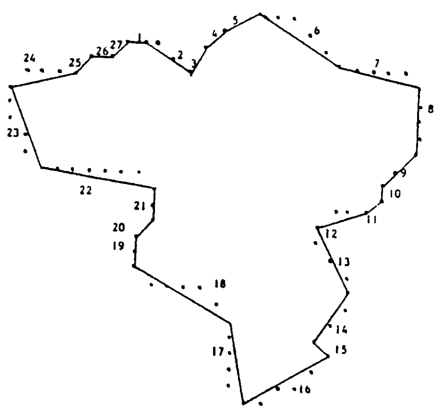

Figure 4.

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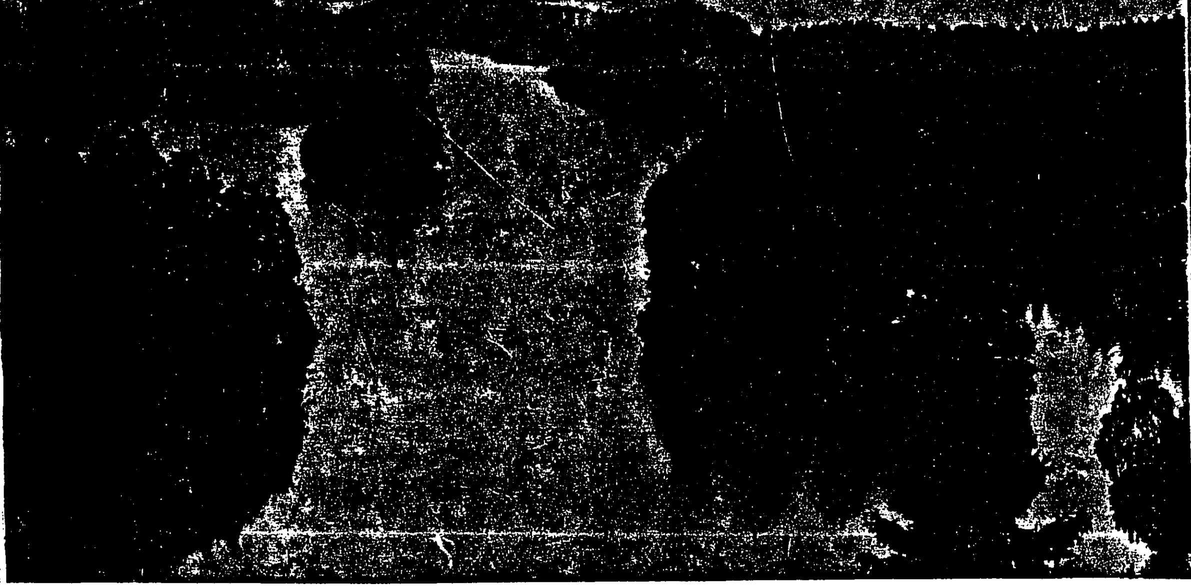

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