EXPERIMENTS ON SHAPE RECOGNITION USING MULTISCALE STRUCTURE MATCHING

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Abstract: This paper addresses the problem of finding a common structure to many deformed samples of the same class. The algorithm used is the multiscale structure matching. We have experimented a new distance measure, based on the curvature of the contour.

I. INTRODUCTION

Learning visual models from samples of the same class is one of the central problems in pattern recognition and computer vision. This paper addresses the problem of generating a model from given samples, using a multiscale convex/concave structure of the shapes, and the extraction of the optimum scale structure common to shape samples of the class.

There are many previous works in which shapes are described by symbolic representations, which means those parts and parts relationships are in the form of attributed relational graphs.

The method described here does not need apriori knowledge about object shapes, reduces the computational complexity about graph models.

II. THEORETICAL FRAMEWORK

A shape contour can be expressed as two periodic functions $C(t)=(x(t),y(t))$, where x,y are the coordinates along the contour. An evolved version of this contour is defined using the convolution between c(t) and the Gaussian kernel:

$$\Gamma_\sigma=((X(u,\sigma),Y(u,\sigma)),\quad u\in(0,1)$$
$$X(u,\sigma)=x(u)\otimes g(u,\sigma);$$
$$Y(u,\sigma)=y(u)\otimes g(u,\sigma); \qquad (1)$$

$g(u,\sigma)$ is the gaussian kernel.

The curvature along the contour is:

$$k(u)=\frac{x_u y_{uu}-x_{uu}y_u}{(x_u^2+y_u^2)^{3/2}}$$

where u is the normalized length along the contour, and x_u, yu, xuu, yuu, are the derivatives of the functions x(t) and y(t).

The points where $k(t,\sigma)=0$ are inflection points, and the segments between them are convex/concave structures.

The shapes can be represented as sequences of segments that have some characteristics. In our case these characteristics are the ratio l_i/L, and DKci, where

l_i = the length of the segment
L = total length of the contour
DKci = the variation of the curvature along the contour.

We consider two shapes A and B defined as two sequences of segments:

$$A^h=a_1^h,a_2^h,...,a^h_N$$
$$B^k=b_1^k,b_2^k,....,b_M^k$$

h and k are associated with two different scale factor σ_h, σ_k.

Increasing the value of σ, odd consecutive segments can be replaced by one segment. For the two shapes it can be two different scales for which there exist an optimum matching according to a distance measure defined between the two shapes.

The problem is to match segments of different shapes by finding corresponding segment pairs between them.

The matching procedure involves the definition of a dissimilarity measure between a_i, and b_j segments as:

$$d(a_i^h,b_j^k)=\frac{|DK_{ci}^h-DK_{cj}^k|}{|DK_{ci}^h|+|DK_{cj}^k|}\cdot\frac{|l_i^h-l_j^k|}{|l_i^h|+|l_j^k|} \qquad (2)$$

where DK_{ci}^h is the signed difference between the maximum and the minimum value of curvature along the l_i segment.

We denote a sequence of (2n+1) consecutive segments of a shape, $a(i-2n|i)$ and a sequence of (2m+1) segments of shape B, $b(j-2m|j)$.

We consider that, $a(i-2n|i)$ at the finest scale can be replaced by a_i^h.(segment i at scale h), and similarly $b(j-2m|j)$ with b_j^k.(segment j of shape B, at scale k).

The multiscale segment dissimilarity between a(i-2n | i) and b(j-2m | j), can be formulated as:

$$D(a(i-2n|i),b(j-2m|j))=d(a_i^h,b_j^k)+ \quad (3)$$
$$+d_A(a(i-2n|i\dashrightarrow a_i^h)+d_B(b(j-2m|\dashrightarrow b_j^k)$$

The first term is the one to one dissimilarity between segments a_i and b_j, and the others represent the cost of replacing a(i-2n | i) with a_i and b(j-2m | j) with b_j.

Given many samples of the same class of shapes we can find a common structure of segments.

We consider a shape A_i within N samples. This shape is partitioned into n_{ij} subsets (each subset contains an odd number of segments). Then matching shapes A_i to A_j is performed by finding a correspondence between the two sets.

$$P_{ij}=\{a_{i,w} \mid w=1,n_{ij}\}$$

P_{ij} is a partioned segment family of sets.
$a\in P_{i,j}$ consists of one or an odd number of segments of the finest scale on the shape contour. Similarly we can define $P_{j,i}$ as the family of subsets that best describe the matching of A_j by A_i. In the case of N samples of the same class, the matching is performed N(N-1)/2 times.

We consider the union of P_j:

$$Q_i=\bigcup_{j=1N} P_{ij}$$

Q_i is named a partially ordered set. The interpretation for shape generalization is equivalent to find the maximal elements in Q_i. The maximal element $q\in Q_i$ is an element for witch there is no q' with $q\subset q'\in Q_i$.

III. EXPERIMENTATION

We have tested this method on deformed industrial shapes made by a small number of segments (<15). We have used the curvature for the dissimilarity measure, reducing the computational effort.

The minimization of the criterion function (2) is performed for a value of σ=5-7.

The algorithm for obtaining pairs of segments has 2 stage:

Firstly we match the segments using the dissimilarity measure formulated in (2).

Then we calculate the dissimilarity between the replaced segments (at the finest scale) and the corresponding segment at the scale σ.

In the second recognition stage the dissimilarity used is in the form:

$$d_A(a(i-2n|i)=\omega(d(a(i-2n|i-2n+1))+$$
$$+d(a(i-2n+1|i-2n+2)),.....+d(a(i-1|i)) \quad (4)$$

where ω is a weighting factor.

A ω value of 0.6 reduces the effect of noisy contour.

In the case of models generation, given N samples of the same class, The matching procedure used are described in the Fig. 1.

The model generation is performed in many stages, and finally the class model M12.N is find. The matching between samples uses the equation (2).

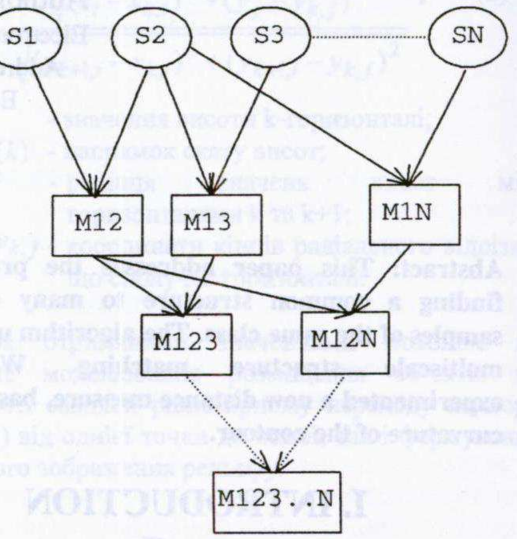

Fig. 1

IV. CONCLUSIONS

The method of shape recognition using a multiscale matching is suitable for deformed objects, and very robust with respect to position, orientation and scale change.

This method is computational less expansive than others such as those based on the curvature scale space which have the same objective.

V. REFERENCES

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