Development of Fuzzy Objective Function for Establishing the Region Correspondence

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ABSTACT

One of the challenging problems in dynamic scene analysis is the correspondence problem. Points and lines have been two major entities for establishing the correspondence among successive frames and gave rise to discrete approach to dynamic scene analysis. Some researchers take continuous approach to analyse the motion. There it is usually usually assumed that some sort of region correspondence has already been established. In tis paper, we propose a method based on fuzzy membership function for solving region correspondence problem.

1. INTRODUCTION

The correspondence problem is concerned with matching a point(or a group of points) in one frame to a point(or a group of points) in another frame. The basic entities commonly used for matching include feature points(such as corners), lines(edges), and regions. If points/lines/regions are used in the correspondence process, we term it as "point/line/region correspondence."

There are several methods for establishing point and line correspondences between sets of points in successive frames. Among them are the correlation method and the edge-match method. In the correlation method, give a patch in one frame, we move that patch around on other frame to find out the one with the best match. This process may also be called template matching.

In the edge-match method, we concentrate only on abrupt changes in brightness. Here an attempt is made to match symbolic description of one image to that of another. The primitive used as a description is an edge along with some information associated with it. This primitive is also referred to as a "token" by Aggarwal, Davis, and Martin[2].

There are several frameworks that may be used for establishing the region correspondence. Among them are graph matching[1], fuzzy tree automation[10], and relational matching[3, 13]. Ambler *et al* [1] propose the match graph method where, given two graphs G and G", they build the match graph such that each node of the match graph is an assignment of a pair of nodes from G to G″, an and arc is drawn between two nodes of the match graph if the two corresponding assignments are compatible. With this match graph, graph matching is just finding a maximal clique.

Lee [10] applied the concept of fuzzy languages and tree systems to pattern recognition through the use of fuzzy tree automaton. Given a fuzzy binary input tree, the corresponding fuzzy binary tree automaton is constructed. This machine is capable of processing fuzzy binary trees with various membership values associated with the leaves. The machine accepts only those fuzzy binary input trees with exactly the same structure as the one on which the construction is based. The degree of acceptance is the intersection of membership values associated with the leaves of fuzzy state tree.

Haralick and Shapiro[13] formalize the process of finding the correspondence between relational descriptions. Given two relational descriptions D_A and D_B, a relational distance metric, termed as structural error, is defined. The goal here is to find the optimal mapping that minimizes the total structural error. Boyer and Kak[BoK88] adopt a similar formalism of relational descriptions, but incorporate a probabilistic scheme to solve structural stereopsis.

A scene may contain multiple objects experiencing independent motions. Thus, it is quite possible that one object is obscuring another(dynamic occlusion) and/or the object obscured by another is emerging (dynamic disocclusion). It is dubious how the graph matching technique and fuzzy tree automata scheme handle such cases. The relational model used in[13] basically assumes no occlustion, otherwise the metric property of their relational distance measure is violated. The structural model presented in [3] uses the concept of nilmapping to take care of occlusion. However this scheme is restricted to stereo matching where, if converted to a viewer-centered situation, all objects are experiencing a uniform motion.

In this work, we allow two things which are not generally allowed in other works:

(1) Multiple independently moving objects in a scene and

(2) dynamic occlusion and disocclusion.

2. THE PROPOSED METHOD

As was mentioned in section 1, we allow the independence of motion for objects in a scene. Thus the spatial relationship (arc information) among regions(nodes) is of no use. Therefore the matching in our method is a pure node mapping. However, some useful arc information, if any, may be used to constrain the search for an optimal mapping. In this section, we propose method utilzing fuzzy membership function for region correspondence. we describe the a preprocessing stage first and the method for the mapping stage in turn.

PREPROCESSING STAGE

First, given a sequence of color pictures CP_1, $CP_2 \cdots$, CP_K, we use an iterative fuzzy image segmentation scheme [6] to obtain from each CP_i the p color classes CC_1^i, $CC_2^i, \cdots, CC_p^i$. We use color for classification to ease the subsequent mapping process in such a way that we break one big problem(analogous to mixture of colors) into several, usually small, problems(analogous to homogeneous color classes) and work on them independently.

For each color class j=1, 2, ⋯, p, we have a sequence of k frames $CC_j^1, CC_j^2, \cdots, CC_j^k$. Next we extract regions from each of these k frames using a boundary followre [12]. Regions are encoded in runs. Sets of regions $R_j^1, R_j^2, \cdots, R_j^k$ are input to the mapping stage.

MAPPING STAGE

We use fuzzy membership to compute the degree of similarity among regions. Here each region is descrived by two fratures. They are x and y coordinates of centroid. Now define the fuzzy membership function as follows:

$$\mu_{pq}^{i} = \frac{1}{\sum_{r=1}^{c} \left[\frac{d_{pq}^{i}}{d_{pr}^{1}} \right]^{\frac{2}{(m-1)}}},$$

where μ_{pq}^{i} = degree of similarity between p^{th} region in i^{th} frame and q^{th} region in $(i+1)^{st}$ frame, d_{pq}^{i} = Euclidean distance between the centroid of p^{th} region in i^{th} frame and the centroid of q^{th} region in $(i+1)^{st}$ frame, c=min{ number of region in i^{th} frame, number of regions in $(i+1)$ st frame}, and m=2.0. Note that $\sum_q \mu_{pq} = 1$.

Let us assume for a moment that each frame has the same number of regions. Now our procedure to find and optimal mapping is to search for a mapping h that maximizes the global fuzzy objective function defined as :

$$G\_OPT\_FUZZY(h) = \sum_{i=1}^{k-1} \sum_{p->q \in h_i} \mu_{pq}^{i}$$

By "global," we mean "across all the frames." By "local," we mean "between successive frames." Here we require the mapping to be both 1-1 and onto. The optimal mapping h^{opt} satisfies $G\_OPT\_FUZZY(h^{opt}) > G\_OPT\_FUZZY(h)$ for all h. Let h^i be the optimal mapping from i^{th} frame to $(i+1)^{st}$ frame and local fuzzy objective function $L\_OPT\_FUZZY(h_i) \sum_{p \to q \in h_i} \mu_{pq}^{i}$. Then we have the following theorem.

Theorem : h is h^{opt} iff $h_i = h_i^{opt}$ for all i.

Proof: We first suppose $h = h^{opt}$ and there exists at least one i such that $h_i \neq h_i^{opt}$. Then there exists i' such that $h_i \neq h_i^{opt}$ and $L\_OPT-FUZZY(h'_i) > L\_OPT-FUZZY(h_i)$, contradicting $h = h^{opt}$. Conversely, we suppose $h_i = h_i^{opt}$ for all i and $h \neq h^{opt}$. Since $G\_OPT\_FUZZY(h^{opt}) > G\_OPT\_FUZZY(h)$, there exists at least one i such that $L\_OPT\_FUZZY(h_i) < L\_OPT\_FUZZY(h_i^{opt})$, thus $h_i \neq h_i^{opt}$ again a contradiction.

So far we have assumed that each frame in the sequence has the same number of regions. Now we release this restriction so that different frame may have different number of regions as might

Fig 1. Original image sequence

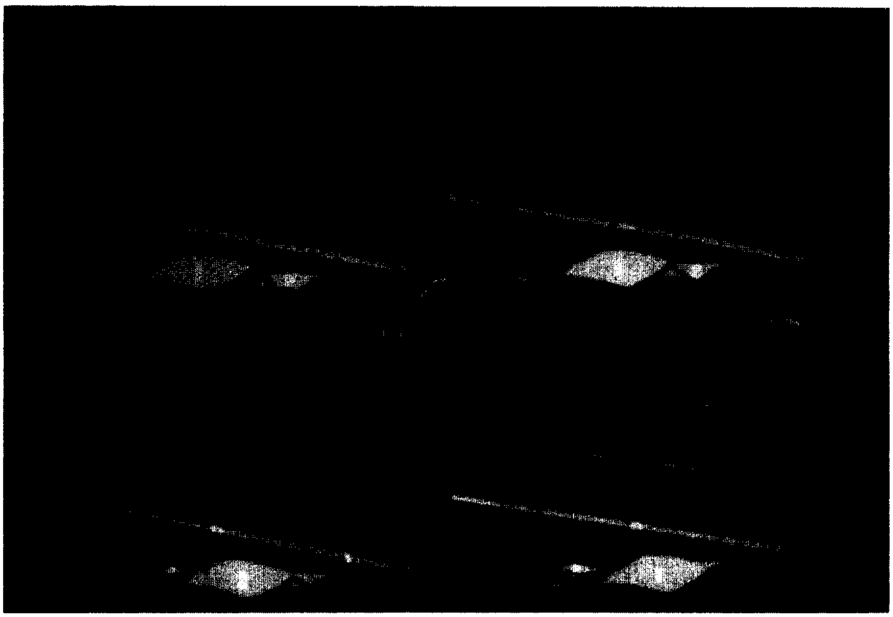

Fig 2. Regions identified for a particular color class

Region ID	Frame 1	Frame 2	Frame 3	Frame 4
0	(169.45,117.50)	(168.91,115.91)	(166.57,106.10)	(169.38,117.71)
1	(197.52,96.59)	(200.60,108.04)	(186.25,190.21)	(206.89,132.08)
2	(205.00,155.89)	(204.41,159.82)	(203.73,122.73)	(200.57,79.40)
3	-	-	(199.11,74.80)	-

Fig 3. Centroid coordinates

Frame 1(row)--> Frame 2(column)			
	0	1	2
0	.996	.003	.001
1	.012	.868	.030
2	.005	.007	.988

Frame 3(row)--> Frame 4(column)				
	0	1	2	3
0	.879	.015	.071	.034
1	.136	.023	.699.	.143
2	.122	.421	.384	.073

Frame 3(row) --> Frame 4(column)			
	0	1	2
0	.836	.039	.012
1	.022	.023	.002
2	.099	.912	.012
3	0.44	0.27	.974

Fig 4. Mapping obtained

happen when there is dynamic occlusion and/or disocclusion. Thus the mapping is now 1-1 but not necessarily onto. We use the same objective function to find an optimal mapping and, supposing the number of regions in frame i is greater than the number of regions in frame (i+1), those elements in frame i which do not have conterpart in frame(i+1) are considered to be empty mapping, also referred to as nilmapping in [3]. The same theorem can easily be proven in this case also since the independence among local mappings are still preserved.

3. EXPERIMENTAL STUDIES

To test the method, real world image sequence was generated by taking an outdoor traffic scene. The original sequence(Fig.1) is in color with one car moving in left upward direction and the other in right-downward direction. Fig.2 depicts the regions identified for a particular color class. Fig.3 shows the corresponding centroid coordinates for four frames. Fig.4 describes the optimal mapping obtained.

All regions were correctly mapped even in the presence of dynamic occlusion and disocclusion except that the front part of the arrow in the second frame is mapped onto the fraction of the center line in the third frame. This false mapping happened since we force every region in domain D to be mapped onto some region in range R if $|D| \leq |R|$.

The false mapping could have been avoided if we have used the a-cut [6] at say 0.5. That is, if the degree of similarity between two regions is less than 0.5, we say that they are different.

4. DISCUSSION

In this paper, we present the method for region correspondence. The method work well even in the presence of dynamic occlusion and disocclusion. We prove that both schemes can be run in parallel on all pairs of images in the sequence. This greatly reduces the search space size and time. The detailed description of a parallel computer application of the method is given in[14, 15].

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