Landmark based shape representation scheme for recognition of two dimensional shapes

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Abstract

This paper presents a novel fuzzy-symbolic approach for the recognition of two-dimensional shapes. The proposed method represents a binary shape using symbolic (multi interval valued) features. The representation scheme is based on the landmark points (dominant points) of the shape and the concept of fuzzy equilateral triangle membership function. A similarity measure to estimate the degree of similarity between two shapes is proposed. The proposed method is shown to be invariant to rotation, translation and scale.

Keywords: Shape analysis, Shape representation, Fuzzy equilateral triangle, Multi interval-valued features.

1 Introduction

Shape is an important visual feature for distinguishing an object from its surroundings in an image. Shape can be used to complete the information provided by other local properties in an image such as gray level, texture or colour. Accurate recognition of a shape depends on its representation. Therefore an efficient representation of shape information is a basic task in many areas of computer vision, video processing and analysis, and computer graphics. An ideal shape representation scheme makes it easier for a shape to be stored, retrieved, transmitted, compared against, learned and recognised.

The concept of symbolic data provides a more natural and realistic analysis to problems. It has been has been well studied in data analysis and data clustering [1],[3],[4],[5],[6],[7],[8] and shown theoretically as well as experimentally that approaches based on symbolic data outperforms conventional approaches, but its inherent capabilities in preserving shape properties of an object have not yet been explored. To the best of our knowledge, there has been no attempt in proposing an unconventional approach based on symbolic data for shape analysis. However, there are several approaches for shape analysis based on conventional data types. Moment based features [12]; signature based centroidal profile method [2], Fourier Descriptors [15], Curve Bending Function (CBF) method [4], Curvature Scale Space (CSS) method [14], recognition of shapes by editing shock graphs [17] have been proposed. A detailed survey on shape analysis can be found in [3], [13].

As the approaches based on symbolic data types are shown to perform much better than the conventional techniques in data clustering, we feel that an approach based on symbolic data types may outperform other existing conventional techniques for shape analysis. Hence we feel that the shape representation scheme based on fuzzy-symbolic approach may show a better performance than existing conventional shape representation schemes. With this background, in this paper we propose a simple and a novel method of extracting symbolic (multi interval-valued) features from a shape by making use of the concept of fuzzy equilateral triangle membership function. A novel similarity measure for matching shapes represented by symbolic features is proposed. Experiments are conducted on several standard shapes to demonstrate the feasibility of the proposed method. The proposed method is invariant to rotation, translation and scale and computationally less expensive.

2 Proposed methodology

In this section, we present in detail the proposed unconventional shape representation scheme, the proposed similarity measure and the shape matching algorithm.

2.1 Concept of fuzzy triangle membership function

The concept of fuzzy triangle [16] is employed to identify the type of triangle formed by the given three non collinear points. In identification of a triangle, let α, β and γ be the inner angles of a triangle, in the order $\alpha \geq \beta \geq \gamma$, and let U be the universe of triangles; i.e.,

$$U = \left\{ (\alpha, \beta, \gamma) / \alpha \geq \beta \geq \gamma \geq 0;\ \alpha + \beta + \gamma = 180^{0} \right\} \qquad (1)$$

We can define an approximate equilateral triangle fulfilling the constraints given in (1). For this purpose we use fuzzy equilateral triangle membership function, which assigns a value in the interval [0, 1] and approximate the equilateral triangle depending on the inner angles of a triangle formed by the three non collinear points. The membership function is given by the following equation:

$$\mu_E(\alpha, \beta, \gamma) = 1 - \tfrac{1}{180}(\alpha - \gamma) \qquad (2)$$

The Membership value (μ_E) of the fuzzy equilateral triangle is used to characterize the shape as described in the next section.

2.2. Feature extraction and shape representation

The proposed shape representation scheme identifies the local descriptors called dominant points. The images of the shapes to be represented are pre-processed to extract the boundary curves. The dominant point detection algorithm [9] is employed to locate dominant points on the extracted boundary curves. Once the dominant points are identified, the shape boundary is traversed in clockwise direction and at each dominant point the triangular spatial relationship existing among the predecessor, successor and the dominant point is perceived by using the fuzzy equilateral (μ_E) triangle membership function as described in the section 2.1. The value μ_E is invariant to (translation, rotation and scale). It shall be observed that the three successive dominant points forming a triangle may possess similar spatial relationship for both concave as well as convex parts of the shape as shown in the Fig. 3. If the dominant point is concave then the associated fuzzy equilateral triangle membership value is considered as negative else positive. This idea is very much useful to distinguish shapes efficiently. In order to decide the concavity or convexity of a dominant point, we consider the predecessor and the successor of a dominant point under consideration. Let P_{i-1} and P_{i+1} be the predecessor and successor of a dominant point P_i then we choose the midpoint Q of the line drawn between P_{i-1} and P_{i+1}. If the point Q belongs to the shape region then the dominant point P_i is considered as convex otherwise it is concave.

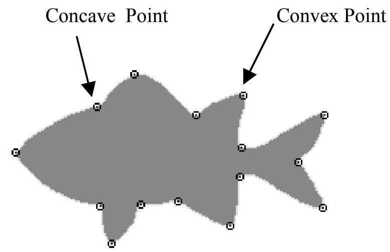

Fig. 1 Shape with dominant points

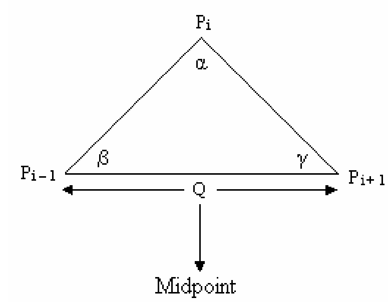

Fig.2. Triangle formed by three consecutive dominant points

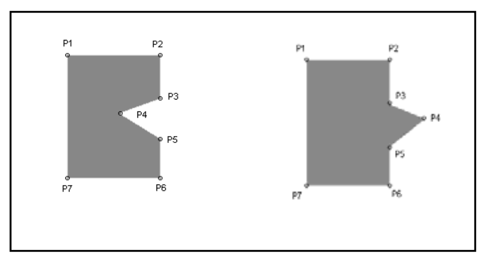

Fig. 3 Shapes whose dominants points possessing same spatial relationship

In addition to approximating the type of triangle formed by the three consecutive dominant points using a fuzzy equilateral triangle membership function, we also measure the steepness of the convexity and the depth of the concavity using the following relation.

$$\eta = 1 - \left[\frac{d_3}{(d_1 + d_2)} \right] \qquad (3)$$

where $d_1 = \overline{p_i p_{i-1}}$, $d_2 = \overline{p_i p_{i+1}}$, and $d_3 = \overline{p_{i-1} p_{i+1}}$ be the Euclidean distances between their respective points. The value η is considered as negative for concave dominant point and positive for convex dominant point and is invariant to liner image transformations..

Thus, if the shape contour has n dominant points then the set of all n values $\{\mu_E, \eta\}$ extracted forms the feature vector of dimension n to represent the shape at a particular instance. However, the value of n can vary from shape to shape depending on the number of its dominant points. In order to make our representation scheme more robust to noise and to efficiently handle pragmatic errors caused due to limitations of computing system in handling floating point operations, we consider several possible instances like (rotated 30^o interval and scaled up by 125% scaled down by 75%) of a shape during feature extraction process (offline) and the obtained features are aggregated to form an interval which reflects the variation in each feature values. Unlike conventional shape representation schemes where a shape feature vector is a collection of merely a crisp data, our proposed representation scheme is unconventional in the sense each model shape in the database is represented using an n-dimensional vector with each element is of multi interval-valued type data.

If S is the shape to be represented and n is the number of dominant points identified on the shape contour, then the feature vector F representing the shape S is of the general form

$F_i = \{f_1, f_2, f_3, \ldots, f_n\}$ where $f_i = \{[\mu_E^-, \mu_E^+],[\eta^-, \eta^+]\}$, μ_E^-, μ_E^+ and η^-, η^+ are, respectively, the lower and the upper bound of the interval μ and η

2.3. Shape matching

In this subsection, we propose a similarity measure to estimate the degree of similarity between a query shape and a model shape in order to recognize the given query shape as one among the shape stored in the model shape database

Given a query shape Q, the proposed retrieval scheme computes the dominant points on Q and then extracts the feature values and forms a feature vector F_Q as described in section 2.2. It shall be observed that the obtained feature values of Q are simply a vector of real values instead of a vector of interval values as we have only one instance of Q. i.e., $F_Q = [f_{Q1}, f_{Q2}, f_{Q3}, \ldots, f_{Qn}]$ where the k^{th} feature, $f_{QK} = \{\mu_{QE}^k, \eta_Q^k\}$ is simply a multivalued type data rather than multi interval valued.

Let $f_{MK} = \{[\mu_{ME}^{k-}, \mu_{ME}^{k+}][\eta_M^{k-}, \eta_M^{k+}]\}$ be the k^{th} feature component of a model shape described by the feature vector, $F_M = [f_{M1}, f_{M2}, f_{M3}, \ldots, f_{Mn}]$ which is of multi interval valued type. The degree of similarity between Q and M is defined as the average of the degree of similarities between their respective features.

The similarity between the query shape Q and the model shape M with respect to their k^{th} feature is defined as

$$v_\mu^k = \begin{cases} 1 & \text{if } \mu_{ME}^{k-} \le \mu_{QE}^k \le \mu_{ME}^{k+} \\ \max(\mu_L, \mu_U) & \text{otherwise} \end{cases}$$

$$v_\eta^k = \begin{cases} 1 & \text{if } \eta_M^{k-} \le \eta_Q^k \le \eta_M^{k+} \\ \max(\eta_L, \eta_U) & \text{otherwise} \end{cases}$$ where

$$\mu_L = \left[\frac{1}{1 + \left|\mu_{QE}^k - \mu_{ME}^{k-}\right| * \delta} \right],$$

$$\mu_U = \left[\frac{1}{1 + \left|\mu_{QE}^k - \mu_{ME}^{k+}\right| * \delta} \right],$$

$$\eta_L = \left[\frac{1}{1 + \left|\eta_Q^k - \eta_M^{k-}\right| * \delta} \right],$$

$$\eta_U = \left[\frac{1}{1 + \left|\eta_Q^k - \eta_M^{k+}\right| * \delta} \right]$$ and

δ is the normalizing factor.

$$Sim(f_Q^k, f_M^k) = \frac{(v_\mu^k + v_\eta^k)}{2} \quad (4)$$

It shall be noticed that if the value μ_{QE}^k, η_Q^k lie, respectively, within the interval $[\mu_{ME}^{k-}, \mu_{ME}^{k+}]$ and $[\eta_M^{k-}, \eta_M^{k+}]$ then the similarity value is 1 (high); otherwise the similarity value depends on the extent to which the values μ_{QE}^k. η_Q^k are, respectively, closer to the lower bound μ^-, η^- or to the upper bound μ^+, η^+.

Once the degree of similarity between the k^{th} features is computed, the total degree of similarity between the query shape and the model shape is estimated to be the average of the degree of similarities computed for each feature. Since the number of features used to describe a shape depends on the number of dominant points detected on its boundary, the dimension of the feature vector describing a query shape and a model shape may be different. So our algorithm will find the best association (by preserving features sequence) of all the features of a model shape to all or to a subsequence of features of a query shape (i.e., part of Q may be left unmatched) and vice versa. The matching process is described as below.

Let $F_Q = \{f_{Q_i}\}\ for\ i = 1,2,3,...,n$ and $F_M = \{f_{M_j}\}\ for\ j = 1,2,3,...,m$, respectively, be the query and the model feature vectors.

While performing matching, we need to consider three cases.

(i) If $m < n$, we compare all the m features of F_M with the first m features of F_Q and estimate the degree of similarity with respect to these m features using the formula $sv = \frac{1}{n}\sum_{K=1}^{m} Sim\left(f_Q^k, f_M^k\right)$. However, we are not sure that this itself is the best correspondence between the query and the model feature vectors. So to know the best correspondence, we perform n cyclic shifts of the model feature vector and find the corresponding similarity values. Thus, we obtain n similarity values say, $sv_1, sv_2, sv_3, ..., sv_n$ due to n cyclic shifts. The maximum of these similarity values $\max(sv_1, sv_2, sv_3, ..., sv_n)$ is taken as the similarity value between the query shape and the model shape under consideration.

(ii) If $m = n$, we compare all the m features of F_M with all the n features of F_Q and the degree of similarity between query and model shape is estimated by performing cyclic shifts in order to obtain maximum similarity value as explained in the step (i).

(iii) If $m > n$, we compute the similarity between the query and the model shape as explained in step (i) but by interchanging the role of F_M and F_Q.

Given a query shape Q in the form of its feature vector, we compute its degree of similarities with the feature vectors of all the model shapes M present in the database and then to select the model shape, which posses more similarity value with the query shape. A threshold can be fixed to reject a query shape if it is not visually very similar to the model shapes stored in the shape database.

3 Experimental results

We have conducted several experiments on standard shapes to demonstrate the feasibility of the proposed methodology. In this section, we present the results of selected shapes used in the experiment. We considered 25 shapes of 5 categories with 5 shapes in each category. Each of the shapes is used as a model to which other shapes are compared and also some independent transformed queries (scaled up, scaled down, rotated versions) are also considered, thus nearly 750 shape comparisons are made for each repetition of the experiment. Ideal results would be that the 5 closest matches (including the model itself) be of the same category as the model as well as a sharp decrease in similarity for the shapes outside the category.

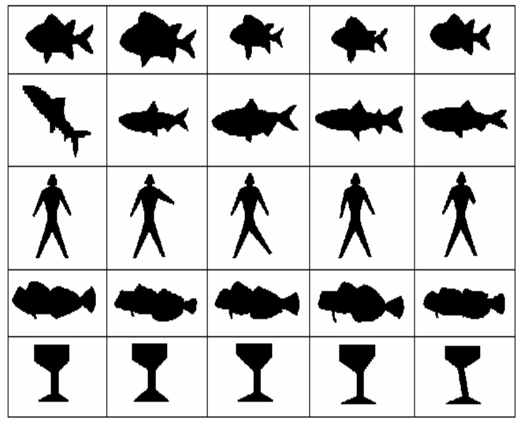

Fig. 4. Images of shapes used in the experiment.

Fig. 4 shows the images of 25 shapes used in experiment and Fig. 5 shows the results of the top eight shapes retrieved for the query shape along with their matching value. Matches 6, 7 and 8 are shown only for the completeness. It can be observed that the top 5 shapes retrieved for the query shape in each category are from the same category. In order to verify the performance of the proposed methodology for linear transformations, we considered some independent transformed queries (200% scaled up version, 50% scaled down version, 90^o rotated, 180^o rotated, 270^o rotated versions of shapes) which are not in the model shape database. Even for such transformed queries, our method has shown good recognition rate. It can be observed form the retrieval results shown in Fig. 5 that the shapes retrieved for original query (Serial No. 5) and its transformed versions (Serial No. 6, 7) are same except their matching values, which are different in second decimal places. Similar results can be observed for other transformed queries also. We can also observe that, in most cases, the largest difference in consecutive similarity values lies between the last shape of the category and the first shape outside the category, thus allowing a broad margin for thresholding. As we have normalized the feature values to lie between 0 and 1. The parameter δ is set to 10 to have a clear separation between matching values.

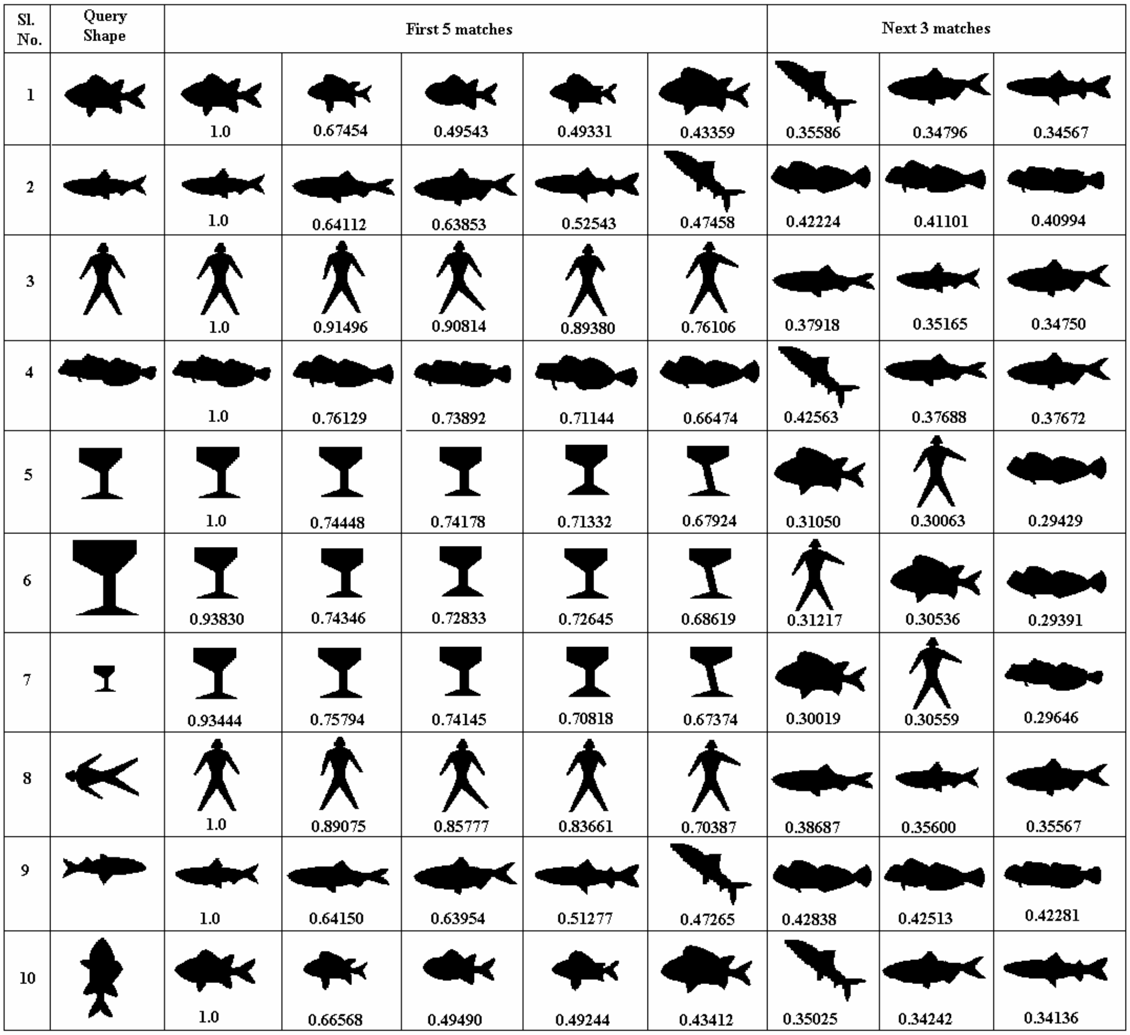

Fig. 5. Selected results of shape matching.

4 Conclusions

In this paper, we have presented a novel unconventional method of representing a shape using a symbolic (multi interval-valued) features. The method makes use of landmark (dominant) points and the concept of fuzzy equilateral triangle membership function to extract symbolic features. A new similarity measure to estimate the degree of similarity between shapes is also proposed. The proposed method shows very good recognition rate and can also handle minor deformations in addition to being invariant to linear image transformations. Exploring the possibility of employing this idea for shape based image retrieval is our future work.

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