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Hand Recognition Using a Fuzzy Classifier

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***Abstract*—This paper proposes a hand recognition method using a fuzzy k nearest neighbor Classifier. Firstly, it obtains the dominant points, and calculate the perimeter of the triangle formed by two consecutive dominant points and the center of gravity of the polygon, and the compactness of the included angle of the triangle formed by three consecutive dominant points, etc. as feature values. Then use the fuzzy k-neighbor cluster analysis method to properly classify the eigenvalues, and then calculate the center of gravity of all the eigenvalues of each category as the representative eigenvalues of the category, so that the number of samples of the eigenvalues tested can be reduced. It can also identify the hands more conveniently and quickly, saving identification time. Some experiments have been conducted and the experimental results indicate that the proposed method can recognize the hand shapes effectively.**

***Index Terms*—hand recognition; fuzzy Classifier; compactness; feature**

I. Introduction

In the past research on hand recognition, most of the methods used can be divided into two categories. The first category is the work of directly recognizing the processed image. However, this method is not suitable for object rotation or scaling. The amount of calculation required for identification is large. The second type further analyzes the processed images, selects the required feature values, and then proceeds to the identification work. In order to identify objects of different angles and sizes, this study adopts the second type of identification method based on image feature values. If the test image is a simple object, the extracted feature values will be less, and the time for identification will be less. But if the test image is a complex image, the extracted feature values will be more, then it may take time. A lot of time is spent on feature comparison. In order to shorten the identification time without affecting the identification results, we consider classifying the captured images. This will not only reduce the number of samples during identification, but also delete redundant and repeated feature data to reduce the accuracy of identification results.

Recognizing hand shape is very important and practical. Hand recognition can be used for person identification. In order to solve these problems, many methods have been proposed [1, 4, 6-7, 9-10, 15]. Egiazarian and Pestana [1] used neural network algorithms for hand recognition. A neural network architecture with a training process is proposed in their paper. Horse etc. al. [4] proposed the B-spline curve method to fit the hand shape. The fitting error is then evaluated to find a close hand shape. Mitome and Ishii [6] compared some hand recognition methods in their paper. They use some evaluation criteria to evaluate the proposed hand shape recognition algorithm. Oden etc. al, [7] use implicit polynomial and geometric features to recognize hands. Geometric features of hands have been used as important classification features. Savic and Pavesic [9] proposed a hand recognition method for the human body recognition problem. Hand shape recognition is an important and critical task for identification. Sun and Qiu [10] used the HMM algorithm to solve the hand recognition problem. Yoruk et al, [15] discussed some hand biometrics in their paper. Hand biometrics can be used as a feature in the recognition phase.

Gesture recognition is a special problem in pattern recognition. It is agreed that representation and matching are the two main problems involved in pattern recognition. These two issues are also key issues in hand recognition. Fuzzy Classifier algorithm is an effective matching method in pattern recognition problems. Several reports have been introduced in the past years.

The inverse of shape compactness is used as a feature in the matching process. It is considered to be an effective feature in the recognition problem. In this paper, the inverse of compactness is also used as a feature for hand shape recognition. This feature is calculated based on extracting some important points of the five fingers in the hand shape. A loop fuzzy Classifier is then performed. The input shape is matched to the reference shape with the smallest dissimilarity measure among all reference shapes. The inverse of compactness is translation-invariant, rotation-invariant, and scale-invariant (TRS-invariant). Hand recognition results will also be TRS invariant.

In terms of eigenvalue classification, the previous studies include the fuzzy average method to classify eigenvalues, which mainly consists of a set of n samples, according to the m-dimensional eigenvector space in the sample and the membership Function, divided into c groups of clusters, so that the value of the objective function is the smallest, so after classification, the Euclidean distance of each sample in the same cluster is the shortest, and the distance between the centers of different clusters is the largest. The fuzzy k-neighbor cluster analysis method is used to classify the eigenvalues. Its algorithm is very similar to the fuzzy c-average method. The difference is that it must first set the number of adjacent areas as K. Whether it is the shortest or not, you must first check whether the sample has K samples in the adjacent area. If so, calculate its weight according to its adjacent sample data, and then calculate the membership function and judge whether the sample belongs to this cluster.

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II. Feature and Classifier

The features used for object recognition must have characteristics that do not change with the size, position and direction of the object. In this study, we use the polygon approximation method to find the dominant point of the edge image of the object, and use the dominant point as the feature point of the object. After connecting the obtained feature points, calculate the two consecutive feature points and the polygon center of gravity. The compactness of the triangle angle formed by the adjacent three feature points are used as feature values. Because the compactness of the polygon will not be different due to the displacement or rotation of the image, these two values are taken as feature values to adapt to object recognition in different environments.

Suppose that r_i is the i th reciprocal of the compactness, then r_i is defined as (Figure 1)

$$r_i = a_i / p_i^2, \tag{1}$$

where $p_i = |\overline{V_i V_{i+1}}| + |\overline{V_i C}| + |\overline{V_{i+1} C}|$ is the perimeter and a_i is the area of the triangle.

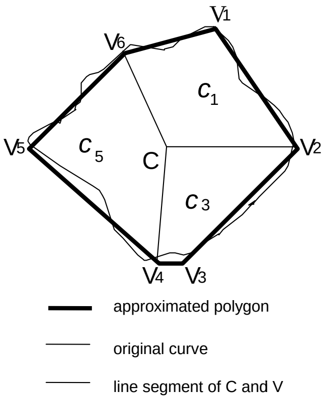

Fig. 1: The compactness of the polygon: $c_i = p^2/a_i$, for i = 1, 2,..., M.

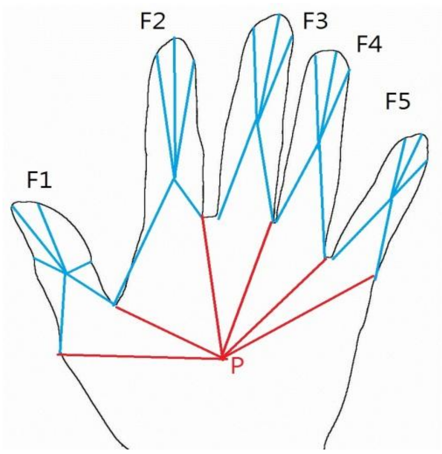

Fig. 2. The reciprocal of compactness: five fingers and one palm

The hand shape has five fingers and a palm. We can find the centroid of each finger. The centroid of the palm can also be found, as shown in Figure 2. The reason we use the reciprocal of compactness instead of compactness is the same reason we use modified compactness. In this case, compactness is not well defined. For each finger and palm, we can find the inverse of the compactness of the shape.

In terms of feature classification, fuzzy k-neighbor cluster analysis method (FKNN) is the main method, mainly to classify feature value clusters in advance to simplify the complexity of the identification process. Fuzzy cluster analysis is a commonly used classification method. It provides a simple step, using the evaluation of the degree of correlation of each sample in the feature vector space, to divide the highly correlated into a group. A group is expressed by the degree of membership, so that the analyzed samples are not simply belongs to or does not belong to a certain group. But it becomes the degree of belonging to a certain group. Compared with traditional hard clustering, fuzzy grouping can describe the data points in the middle zone through the processing of membership degree, and it can also describe more data points.

It is important to define a cost function in Classifier. Suppose that the value of λ is zero. We can define the classify cost function that is both suitable for the one-dimensional or higher dimensional features.

$$\varepsilon \quad (s_i \quad \rightarrow \quad t_j \quad) = \quad \left\| s_i - t_j \right\| \quad , \tag{2}$$

where $\|*\|$ is the norm of the vector *.

In the conventional classify approach, the input shape can then be classified as the reference shape with the minimum matching cost. However, due to the uncertainty principle, the edit costs can be defined as the triangular fuzzy numbers as seen in Fig. 3. The triangular fuzzy number A=(r, a, b) is a fuzzy number with membership function f_A defined as

$$f_A(x) = \begin{cases} (x-r+a)/a, & r-a \le x \le r. \\ -(x-r-b)/b, & r \le x \le r+b. \\ 0, & otherwise. \end{cases} \tag{3}$$

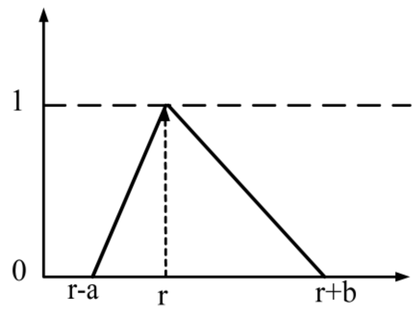

Fig. 3. A triangular fuzzy number A=(r, a, b).

Instead of the crisper definition in equation 2, the classify cost is represented as a fuzzy number in this paper. In fact, the fuzzy cost is defined as

$$\varepsilon \ (s_i \rightarrow t_j) = (r, a, b) \tag{4}$$

where $r = \left\| s_i - t_j \right\|$ and a=b=r/40.

In addition, an addition of two triangular fuzzy numbers can be defined as follows:

$$(r_1, a_1, b_1) \oplus (r_2, a_2, b_2) = (r_1 + r_2, a_1 + a_2, b_1 + b_2). \tag{5}$$

The fuzzy edit costs in equation (4) are defined as fuzzy numbers. They represent the weights. Therefore, the edit distances are also the fuzzy numbers. In each stage of finding the shortest path, the fuzzy edit distances should be ranked to find the shortest path. Thus, the fuzzy shortest paths can be found by ranking fuzzy numbers.

The method for ranking fuzzy numbers can be done by a simple method [3]. It used the integral values of the inverse of membership functions to rank fuzzy numbers. For a fuzzy number A=(r, a, b), the total integral value can be constructed from the left integral value and the right integral value are two values. The total integral value $I_T(A)$ with index of optimism α is then defined as:

$$I_T(A)= \alpha\, I_L(A) +(1-\alpha)\, I_R(A) \tag{6}$$

The left integral value $I_L(A)$ and the right integral value $I_R(A)$ of a triangular fuzzy number A=(r, a, b) can be found as:

$$I_L(A)=r-a/2 \tag{7}$$

And

$$I_R(A)=r+b/2 \tag{8}$$

From equations (6) to (8), the total integral value is defined as

$$I_T(A)= r+(b-(a+b)\alpha)/2 \tag{9}$$

For two triangular fuzzy numbers, they can be ranked by finding their integral values for the inverses of the membership functions. For triangular fuzzy numbers, it is very effective to find the inverse of the membership functions. Therefore, the integral values can be found effectively.

In order to facilitate the description of the algorithm process, the symbols used are listed as follows [2]:
n: the number of feature vectors to classify.
c: number of clusters.
K: the number of nearest neighbors of the feature vector, $1 \le K \le n$
m: calculate the weighted value of the degree of membership.
S_i: the set formed by the i-th cluster.
f_j: j th featurer
d_{ij}: distance between i th and j th features, $d_{ij} = \| f_i - f_j \|$
KNN_j : K nearest neighbors of jth feature vector
n_{ij}: the number of ith feature vector n KNN_j
u_{ij}: membership of j th feature vector in i th cluster

$$u_{ij} = \frac{\sum_{f_s \in KNN_j} u'_{is}\left(1/d_{js}^{2/(m-1)}\right)}{\sum_{f_s \in KNN_j}\left(1/d_{js}^{2/(m-1)}\right)} \tag{10}$$

where

$$u'_{is} = \begin{cases} 0.51 + \dfrac{n_{is}}{K} \times 0.49, & f_s \in S_i \\ \dfrac{n_{is}}{K} \times 0.49, & f_s \notin S_i \end{cases} \tag{11}$$

The steps of the fuzzy K-neighbor cluster analysis method used in this paper are:

Step 1: Set the required parameters m and K; and let c=1, j=1.

Step 2: Calculate the distance d_{ij}, i=1, 2, ... ,n, i≠j.

Step 3: Find the K smallest values from $d_{i,j}$, and the set of their relative eigenvectors is KNN_j.

Step 4: Use the equation (10) to calculate the membership function u_{ij}, i=1, 2, .., c of f_j in each existing cluster.

Step 5: If $u_{sj}=\max\{u_{ij}, i=1, 2, .., c\}>0.5$, classify f_j into the s th cluster; otherwise separate f_j into another new cluster, and add 1 to the value of c.

Step 6: If j=n, end; otherwise, add 1 to the value of j and return to Step 2.

III. Experimetnal Results

To evaluate the proposed method, an experiment is designed to test the performance of the new features. In this experiment, 100 hand shapes were used for evaluation. Hand shapes include male and female hands. Figure 4 shows an example of a test hand image.

Furthermore, since a good object recognition method should be robust to different orientations and scales, for each hand image, 16 different orientations and 4 different scales are performed in the experiment. Different orientations and scales are used to evaluate the robustness of the proposed method.

Fig. 4. One example of the testing hand shape image.

Choose from any of 16 different orientations by rotating your hands while changing the position of your hands. For each orientation, generate three additional images by downscaling the image to 90%, 80%, and 70% of the original image in the x and y dimensions. Therefore, there are 64 (=16x4) test images for each hand. They are used for hand recognition tasks. A total of 6400 (=100x64) test images were used for evaluation in the experiment.

For each hand image, an edge detection algorithm is used to find a rough sketch of the hand. Then do a dominant point algorithm to find the important points of the hand. Then find the inverse of the compactness of each finger and palm. The inverse of compactness is used as a feature in the proposed fuzzy Classifier algorithm to find the membership. Use the fuzzy k-neighbourhood cluster analysis method to properly classify the features, where the K value is set as the number of feature vectors.

One can find the minimum matching cost and then identify candidates for the recognition hand.

Apply the fuzzy Classifier algorithm to each of the 6,400 hand recognition test images. If an incorrect classification is made, an error will be logged. And the recognition rate can be calculated. Experimental results show that the correct recognition rate is about 94.3%. From the analysis of the reasons for the recognition errors, it is found that most of the wrong recognitions are due to the problem of overlapping fingers. That is, two or more fingers overlap when the hand image is captured. Overlapping fingers cause hand shape distortion.

IV. CONCLUSIONS

Hand recognition is an important step in the use of human biometrics. An effective hand recognition algorithm will help reduce the complexity of the human body recognition problem. Fuzzy classifier is a useful tool for 2D object recognition, but is susceptible to the uneven segmentation problem. In this paper, we evaluate a fuzzy Classifier technique for hand shape recognition. The inverse of compactness is used as the feature in recognition. The input hand shape is classified as the reference hand shape with the least discrepancy. Experimental results show that the proposed method can effectively recognize hand shapes. Another advantage of using new features is that it does not require any parameters to be used in the hand recognition process.

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