A New Fuzzy Linear Mapping Technique for Facial Feature Extraction and Recognition

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ABSTRACT

Fast feature matching process and high recognition rates are two important issues in face recognition systems. In this paper, a fuzzy neural network based face recognition system which addresses on these two subjects is proposed. This face recognition system uses a fuzzy linear mapping (FLM) for feature extraction and a fuzzy neural network (FNN) for fuzzy feature matching. Experimental results show that the proposed face recognition system has two advantages. First, higher recognition rates are achieved in comparison with statistical feature extraction methods. Second, feature matching process using fuzzy neural network is faster than minimum distance classifier.

Keywords: Face recognition, feature extraction, fuzzy linear mapping, fuzzy neural network.

1. Introduction

Face recognition systems have many real world applications, such as criminal detection, security system, and access control systems. Usually, these applications require real-time performance, therefore, it is important to design a face recognition system with high recognition rate and fast matching speed.

It is well known that feature extraction and pattern identification are two major processing stages in a face recognition system. Principal Component Analysis(PCA) and Linear Discriminate Analysis(LDA) are two promising statistical feature extraction techniques[1]. PCA extracts features such that variance information enclosed in population can be preserved as much as possible. Usually, PCA does not use class information and is not suitable for classification purpose. On the contrary, LDA adopts class information and maximizes the ratio of between class distance and within class distance. Because the within class distances of real patterns are not reliable, LDA has the risks of poor generalization ability. Features extracted by PCA or LDA need a nearest neighbor classifier to conduct pattern classification. However, a nearest neighbor classifier must compare an input pattern with all templates so that an appropriate output class can be chosen. It is well known that the searching time increases when the number of templates is increased. In this paper, we propose a new transformation-based feature extraction technique and a fuzzy neural network based pattern classifier. The new feature extraction technique can solve the drawbacks of PCA and LDA simultaneously while fuzzy neural network can speed up the pattern matching process. The proposed feature extraction method first applies a new linear mapping to maximize the between class distances of extracted features. Then, the within class distances of extracted features are used to define fuzzy feature ranges. The new linear mapping technique together with fuzzy feature ranges are called fuzzy linear mapping (FLM). Empirical results demonstrate that features extracted by FLM indeed have better discriminating power than those extracted by PCA-based [4] or LDA-based [2] approach due to the introduction of class information and the fuzzy represenation of class boundaries. In the pattern identification stage, the proposed fuzzy neural network can process fuzzy information and can learn from training examples. The architecture of the proposed FNN is basically a coarse-to-fine search mechanism. In the coarse search stage, candidate classes are selected if the features of an input pattern falling in the fuzzy class boundary. In the fine search stage, templates of the previously selected candidate classes are compared one by one with the unknown input and finally only the best matched template will be selected. The class that contains the best matched template

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will be chosen as the output class. Since a class may contain large number of templates, the coarse-to-fine search strategy can significantly accelerate the matching process of the proposed system.

The remaining parts of this paper are organized as follows. In Section 2, the concept of fuzzy linear mapping is discussed. Architecture and operation of the proposed fuzzy neural network are discussed in Section 3. Experimental results are shown in Section 4. Section 5 is conclusion of this paper.

2. Feature Extraction

The proposed fuzzy linear mapping technique is described in this section. Let $p_j^{(i)}$ denote a d dimensional training image vector, where $i = 1, \ldots, c$ is the class index, c is the total number of classes in population, $j = 1, \ldots, n_i$ represents the pattern index in class i, and n_i is the number of images in class i. There are totally n training images in population, where $n = n_1 + n_2 + \ldots + n_c$. Let $x_j^{(i)}$ denotes zero mean pattern vector of $p_j^{(i)}$, and every class has its own class mean vector $\bar{m}_i$. In the analysis of linear mapping techniques, the within class, between class, and total covariance matrices are denoted as C_w, C_b, and C_t respectively. The proposed fuzzy linear mapping consists of two elements. The first one is projection axes on which patterns project having the largest between class distances. The second one is fuzzy feature range which is used to predicate class boundaries. Let $W^f = \{w_k^f\}$ denote projection axes, where $k = 1, \ldots, n_f$, and n_f is the number of features. Projecting class mean vector $\bar{m}_i$ onto axis w_k^f yields feature $\bar{y}_k^{(i)}$, that is

$$\bar{y}_k^{(i)} = (w_k^f)^t \bar{m}_i.$$

To measure discriminating ability of projection axis w_k^f, the variance z_k of features can be calculated as follows:

$$z_k = \sum_{i=1}^{c} \sum_{j=1}^{c} (\bar{y}_k^{(i)} - \bar{y}_k^{(j)})^2 = (w_k^f)^t C_B (w_k^f). \tag{1}$$

The total variance Z of extracted features thus can be defined as:

$$Z = \sum_{k=1}^{n_f} z_k = tr((W^f)^t C_b (W^f)). \tag{2}$$

To maximize between class distances is equivalent to maximizing Z. Equation (1) is an eigen problem, let w^f be eigenvectors corresponding to the n_f largest eigenvalues of C_b, then W^f is KL-transform.

The within class distances of original pattern space are not reliable to perform discriminant analysis, because density and shape of class variate significantly. However, the largest ranges of between class distances can be calculated from training samples to predicate class boundaries. Let $y_{jk}^{(i)}$ denote the projection of pattern vector $p_j^{(i)}$ on axis w_k^f, that is

$$y_{jk}^{(i)} = (w_k^f)^t p_j^{(i)}.$$

Define the kth within class *perimeter* of class i as

$$r_k^{(i)} = \max_j \{y_{jk}^{(i)}\} - \min_j \{y_{jk}^{(i)}\},$$

then the largest within class distances on the kth projection axis can be calculated as

$$f_k = \max_i \{r_k^{(i)}\},$$

where f_k is called *fuzzy feature range* of the kth feature. Performing fuzzy linear mapping on pattern vector $p_j^{(i)}$ obtains fuzzy features $\tilde{y}_{jk}^{(i)}$, which is defined as follows:

$$\tilde{y}_{jk}^{(i)} = (y_{jk}^{(i)}, f_k),$$

where f_k is fuzzy feature range associated with the kth extracted feature. This definition of fuzzy features let trained or unknown feature points of the same class fall in the same class boundary with high probability. Using fuzzy features, and a coarse-to-fine searching mechanism can accelerate the process of pattern identification. This issue will be discussed in the following section.

3. Pattern Classification

The proposed FNN consists of multiple Super Class Neurons (SCN) which have coarse-to-fine search mechanism to accelerate pattern identification.

Super Class Neuron A Super Class Neuron is designed to store and process information of a class of patterns. Information in an SCN includes boundaries and templates of a class. Basically, SCN is a hybrid modular neural network, which consists of two types of neurons, class neuron and template neuron. Figure 1(a) shows an exemplar Super Class Neuron. An SCN is characterized by class neuron C^i, template neurons T_j^i, compound class boundary weights l_k^i,r_k^i, and template weights w_{jk}^i, where $i = 1, \ldots, c$ is class index, $j = 1, \ldots, n_i$ is template index, and $k = 1, \ldots, n_f$ is dimension index of inputs. Input signal I_k is features produced by fuzzy linear mapping discussed in the previous section. The fuzzy feature range f_k is constant and put in input terminal of SCN. In training process, fuzzy feature ranges are used to extend class boundaries. The output signals are status λ^i of SCN and membership degree μ^i of input signals relative to the specified class of SCN. When signals I_k is put on input terminals, the dynamics of SCN are as follows. Basically the dynamics of SCN consists of two time steps. In the first time step, input signal compares with compound class boundary weights. If input signal fully contained in class boundaries, then class neuron is activated, otherwise class neuron is disabled. The activation function of class neuron is as follows:

$$C_i = \Pi_k sgn((I_k - l_k^i)(r_k^i - I_k)), \tag{3}$$

where

$$sgn(x) = \begin{cases} 1 & \text{if } x \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

The value of C_i is then sent out of SCN as status λ^i and transmitted to template neurons. In the second time step, template neurons calculate the membership degree of input signals. The dynamics of template neuron is characterized by:

$$T_j^i = C_i(e^{-h\sum_k (I_k - w_{jk}^i)^2}), \tag{4}$$

where h is constant for all template neurons. Note that C_i dominate the output values of T_j^i. If C_i is zero, T_j^i always has zero values, i.e. the remaining parts in right hand side of Equation (4) need not be calculated further. The maximum of template neurons then output as membership degree of SCN, that is:

$$\mu^i = C_i \max_j \{T_j^i\}. \tag{5}$$

Note that C_i also dominates calculation of μ_i. If $C_i = 0$, the calculations of T_j^i can be omitted. The dynamics of SCN can thus be thought of as a coarse-to-fine searching process. In coarse searching, activation value of C_i is calculated by checking if class boundary contains input features. If $C_i = 1$, a fine searching process is performed by comparing input feature with those stored templates. If $C_i = 0$, the fine searching process can be omitted, so the computation load can be reduced significantly. The SCN can be aggregated as a hybrid neurons conceptually as shown in Figure 1(b). The inputs of the aggregated SCN is features I_k as well as the constant fuzzy feature ranges f_k. The outputs of the aggregated SCN are status λ^i and membership degree μ^i.

Architecture of the proposed FNN The proposed FNN uses a set of SCNs and a MAXNET to perform pattern identification in the proposed face recognition system. Figure 2 demonstrates the architecture of the proposed FNN. The number of SCNs in FNN depends on classes of training samples. When signals put on input terminal, all SCNs perform coarse-to-fine searching operation simultaneously. Status and membership degrees of each SCN then fed into MAXNET in output layer to make final decision.

Learning in Fuzzy Neural Network FNN dynamically constructs its structure through training process. Training samples comprise feature vectors and class label. Feature vectors as well as fuzzy feature range in input terminal are applied to extend class boundary. Class label guides the construction process of FNN. When input training sample, FNN compares class label with SCNs'.

If there is no SCN corresponding to the specified class label of training sample, then a new SCN is added into FNN. The new SCN consists of a class neuron and a template neuron. Let a training feature vector be $I = (I_1, I_2, \ldots, I_{n_f})$, and class label be i^*. An FNN constructs a new SCN which includes a class neuron C^{i^*} and a template neuron $T_1^{i^*}$. The class weights of C^{i^*} are set as

$$l_k^{i^*} = I_k - \alpha f_k,$$

$$r_k^{i^*} = I_k + \alpha f_k,$$

where α is a constant and f_k is a fuzzy feature range in input terminal. The template weights of $T_1^{i^*}$ is set as input feature vector, that is

$$w_{1k}^{i^*} = I_k,$$

for every k.

If an FNN has an SCN corresponding to the specified class of input vectors, then the FNN updates class boundaries of SCN and stores the new template into SCN. Assume the target class label is i^*, the class boundary will be adjused as follows:

$$\begin{aligned} l_k^{i^*(new)} &= \min\{l_k^{i^*(old)}, I_k - \alpha F_k\}, \text{and} \\ r_k^{i^*(new)} &= \max\{r_k^{i^*(old)}, I_k + \alpha F_k\}, \end{aligned}$$

where $0 \leq \alpha \leq 0.5$ is constant. Assume there are already j templates in the i^*th SCN, store the input vector as the $(j+1)$th template, that is:

$$w_{j+1,k}^{i^*} = I_k,$$

for each k.

Recall in Fuzzy Neural Network The recall process of an FNN contains three stages. They are coarse searching, fine searching, and output response. In the coarse search stage, Equation (3) is used to calculate the status of an SCN. For those SCN whose class boundary can cover input feature are activated and chosen as candidate classes for fine searching. If more than one SCN is activated, a fine searching on templates is needed to calculate the best matched output class. In the fine searching process, Equation (4) is used to calculate the similarity degree between input features and the stored templates. The Gaussian function in template neuron is used to calculate a fuzzy similarity degree which value ranges from 0 to 1. Each SCN outputs the maximum membership of its templates to compete the final output class. That is, the best similarity degree of SCN is fed into MAXNET so that the final decision can be made. The lateral inhibition mechanism of MAXNET suppresses SCN with smaller output membership degree. When equilibrate, only one SCN which has nonzero output response is chosen as output class.

4. Experimental Results

To test the effectiveness of proposed face recognition system, a face database provided by Olivetti Research Laboratory[3] is used to conduct experiments. Face images in face database are normalized in advance. That is: the size, orientation, and position of a face are roughly the same. Two measures, recognition rates and matching speed, are used to compare the performance of the above mentioned linear mapping techniques.

The experimental results of recognition rates are shown in Table 1. It can be found that an FLM has minimum error rates among three feature extraction methods. Only an exception occurred when training number is 8, PCA has smallest error rates. So, better generalization ability of new linear mapping (LM) is verified.

Table 2 lists the searching rates of Nearest Neighber Classifier (NN) and Fuzzy Neural Network (FNN). The lower the searching is, the faster the matching process is. Because NN calculate distances between input feature and all stored templates, so the searching rates is 100 percent. The proposed fuzzy neural network need not search all templates. However, searching rates of FNN depends on fuzzy class boundaries.

Table: 1: Error rates of three linear mapping technique

No. of Training Face	*No. of Testing Face*	*PCA*	*LDA*	*FLM*
80	400	15.06	21.35	14.10
120	400	7.95	12.78	7.60
160	400	4.90	8.92	4.30
200	400	2.80	4.90	2.45
240	400	1.70	1.70	1.45
280	400	0.95	0.85	0.65
320	400	0.25	0.40	0.30
360	400	0.10	0.15	0.10

Table: 2: Comparison of searching rates of three linear mapping technique

No. of Training Faces	*No. of Testing Faces*	*NN*	*FNN*
80	400	100	37.97
120	400	100	54.74
160	400	100	55.79
200	400	100	55.64
240	400	100	58.23
280	400	100	59.97
320	400	100	63.07
360	400	100	64.75

5. Conclusion

In this paper, a fuzzy linear mapping is proposed to perform feature extraction with better generalization ability than the conventional statistical methods, PCA and LDA. A fuzzy neural network is proposed also to accelerate the feature matching process. Experimental results shows that the proposed fuzzy linear mapping and fuzzy neural networks has two advantages. First, higher recognition rates are achieved. Second, fast matching process can be expected. Thus, this face recognition system can fulfill the two requirements, high recognition rates and fast matching speed.

References

[1] Fukunaga, *Introduction of Statistical Pattern Recognition,* 2nd edition, Academic Press, New York, 1990.

[2] K. Liu, Y.-Q. Cheng, and J.-Y. Yang, "Algebraic feature extraction for image recognition based on optimal discriminate criterion," in *Patt. Recogn.,* vol. 26, no. 6, pp. 903-911, 1993.

[3] F. Samaria and S. Young, "HMM-based architecture for face recognition," in *Image and Vision Computing,* vol. 12, no. 8, pp. 537-543, October 1994.

[4] M. Turk and A. Pentland, "Eigenfaces for recognition," in *J. of Cognitive Neurosci.,* vol. 3, no. 1, pp. 71-86, 1991.

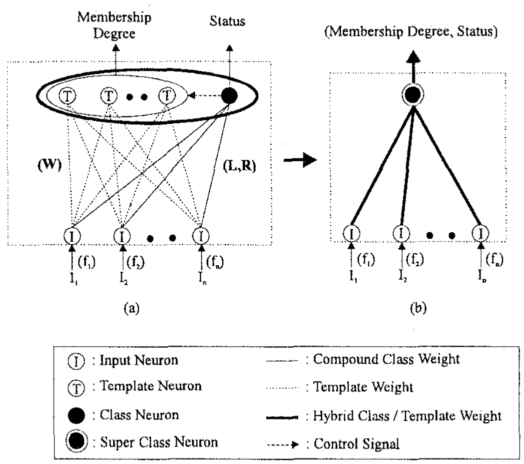

Fig. 1: Illustration of Super Class Neuron (SCN). (a) is detail architecture of SCN, while (b) is aggregrated SCN conceptually.

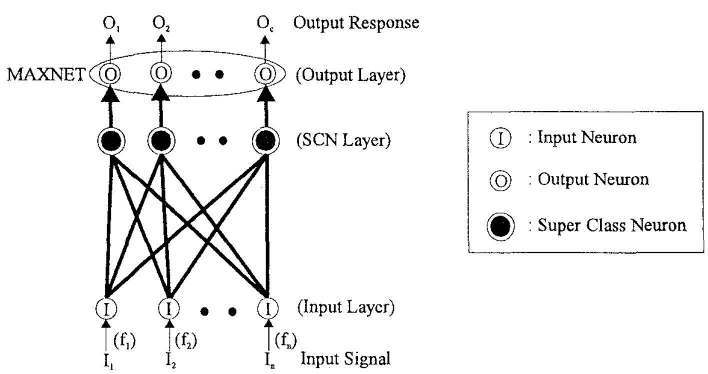

Fig. 2: Architecture of Fuzzy Neural Network.