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Human Face Recognition using Multi-Class Projection Extreme Learning Machine

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** Regular Paper*

Abstract**:** An extreme learning machine (ELM) is an efficient learning algorithm that is based on the generalized single, hidden-layer feed-forward networks (SLFNs), which perform well in classification applications. Many studies have demonstrated its superiority over the existing classical algorithms: support vector machine (SVM) and BP neural network. This paper presents a novel face recognition approach based on a multi-class project extreme learning machine (MPELM) classifier and 2D Gabor transform. First, all face image features were extracted using 2D Gabor filters, and the MPELM classifier was used to determine the final face classification. Two well-known face databases (CMU-PIE and ORL) were used to evaluate the performance. The experimental results showed that the MPELM-based method outperformed the ELM-based method as well as other methods.

Keywords**:** Extreme learning machine (ELM), Multi-class projection ELM, Face recognition, 2D gabor

1. Introduction

Over the past two decades, face recognition has attracted considerable attention and interest from the research and commercial communities [1-4]. Normally, feature extraction and face classification are very important in real-time face recognition systems.

A large number of face feature extraction techniques, have been proposed in recent years. Principal component analysis (PCA) [1] is a well-known feature extraction technique that involves finding a set of mutually orthogonal basis functions and using the leading eigenvectors of the training samples covariance matrix to characterize the lower dimensional space [2]. Although PCA has the ability to preserve the global structure, the locality of data samples is overlooked. This can lead to a loss of important information of the local geometry of each neighborhood. To incorporate the discriminative information between classes into eigenspace, Linear discriminant analysis (LDA) [5, 6], a supervised method for dimensionality reduction and feature extraction, has been used widely in many applications, such as face recognition [1-6] and palmprint recognition,etc.

In the face recognition field, many graph-based feature extraction methods have been applied successfully and are important approaches. Compared to PCA and LDA, graph-based algorithms do not need to assume that the data obeys a Gaussian distribution. Hence, they are more general for discriminant analysis. Some known graph-based algorithms include locality-preserving projection (LPP) [3], local linear embedding (LLE) [4], local fisher discriminant analysis (LFDA) [5], laplacian faces [6] and unsupervised discriminant projection (UDP) [7], linear discriminant projection (LDP) [8, 9], sparsity preserving discriminant analysis (SPDA) [10], graph-optimized locality preserving projections (GoLPP) [11] and marginal fisher analysis (MFA) [12].

In addition, 2D Gabor filter is a representative texture-based method for face recognition, which provides high recognition accuracy at the cost of speed and memory. 2D Gabor-based methods are used widely in many biometric applications on account of their excellent performance.

Several methods have been developed for face classification. The most representative methods include the classical Bayesian decision theory [1], fuzzy method and its variants, artificial neural networks (ANNs) and its variants, and support vector machine (SVM) and its variants, etc. On the other hand, Huang [13, 14] recently proposed a simple and efficient learning algorithm for single-hidden layer feed forward neural networks (SLFNs) called extreme learning machines (ELMs). ELMs have been applied successfully to a number of real-world applications [15], showing a good generalization performance with an extremely rapid learning speed. In an ELM, input weights and biases can be assigned randomly and the output weights can be determined analytically by the simple generalized inverse operation [17]. Compared to other traditional learning machines [17, 18], ELM not only learns much faster with higher generalization ability, but also avoids many difficulties, such as the stopping criteria, learning rate, learning epochs, and local minima [19, 20]. Owing to these advantages, ELM has been applied successfully to many problems [18-26]. Zhang proposed an extreme learning machine-based method for automatic knee cartilage and meniscus segmentation from multi-contrast MR images in 2013 [24]. Ye proposed a system identification method based on an online sequential extreme learning machine [25]. Zong proposed a weighted extreme learning machine method for imbalance data [26].

Mohammed proposed a new human face recognition algorithm based on an extreme learning machine (ELM) and multidimensional PCA in 2011 [13]. The proposed method is based on the curvelet image decomposition of human faces and a sub band that exhibits a maximum standard deviation that is reduced dimensionally using multidimensional PCA dimensionality reduction technique. The notable contributions of ELM-based work include significant improvements in the classification rate, up to a one hundred fold decrease in training time and minimal dependence on the number of proto types [13]. Extensive experimental results were compared with state of the art techniques.

In 2011, Zong proposed a novel face recognition method based on ELMs and tested it in face recognition applications [17]. The performance of ELM was compared with SVM in both holistic learning and feature-based learning environment, with different dimensionality reduction methods, such as PCA, LDA and Discriminative locality alignment (DLA). The experimental results confirmed the effectiveness of the proposed method in both recognition accuracy and speed.

The ELM classifier overcomes many issues in traditional gradient algorithms, such as stopping criterion, learning rate, number of epochs and local minima. On the other hand, ELMs have some disadvantages: (1) ELMs require more hidden neurons than BP; (2) The generalization performance of the ELM algorithm depends on the appropriate selection of the parameters (For example, input weights) [14-26], particularly for fewer training samples. The best parameters are difficult to find such that the training and testing accuracy was a maximum for a given problem [14-26]. Therefore, it is important to address the existing problem of extreme learning machines.

To address the problem of ELM-based methods, this paper proposed a novel method called a multi-class projection extreme learning machine (MPELM). A face recognition method based on the multi-class projection extreme learning machine and 2D Gabor was proposed. The classical 2D Gabor filter was used to extract the facial features. The multi-class projection extreme learning machine (MPELM) was used to determine the final face image classification. Compared to other ELM-based methods, the proposed method requires less computational time and obtains better accuracy.

The remainder of this paper is organized as follows. Section 2 describes an extreme learning machine. Section 3 presents the face recognition method based on the MPELM. The experimental results and performance evaluation on the CMU-PIE and ORL databases are reported in Section 4. Section 5 discusses the experimental results. The final section summarizes the paper and reports the conclusions.

2. Overview of Extreme Learning Machines

The basic concept of the extreme learning machine and its algorithm in this section are reviewed [14-26].

Firstly, the symbols are defined:

n: Number of samples;

k: Label of samples;

$\tilde{N}$: Number of hidden neurons;

m : Dimensions of the dataset;

$\mathbf{P}_{n\times(m+1)} = \{[\mathbf{x}_k, 1] \mid \mathbf{x}_k \in \mathbf{R}^m\}_{k=1}^{n}$: Input in matrix format;

$\mathbf{w}_{(m+1)\times\tilde{N}}$: Input weights matrix;

$\mathbf{Z}_{n\times\tilde{N}}$: Intermediate matrix into the hidden layer,

$$\mathbf{Z} = \begin{bmatrix} z_{11} & \cdots & z_{1\tilde{N}} \\ \vdots & \vdots & \vdots \\ z_{n1} & \cdots & z_{n\tilde{N}} \end{bmatrix}_{n\times\tilde{N}} = \begin{bmatrix} \mathbf{w}_1\cdot[\mathbf{x}_1,1] & \cdots & \mathbf{w}_{\tilde{N}}\cdot[\mathbf{x}_1,1] \\ \vdots & \vdots & \vdots \\ \mathbf{w}_1\cdot[\mathbf{x}_n,1] & \cdots & \mathbf{w}_{\tilde{N}}\cdot[\mathbf{x}_n,1] \end{bmatrix}_{n\times\tilde{N}};$$

$\mathbf{H}_{n\times\tilde{N}} = \begin{bmatrix} g(z_{11}) & \cdots & g(z_{1\tilde{N}}) \\ \vdots & \vdots & \vdots \\ g(z_{n1}) & \cdots & g(z_{n\tilde{N}}) \end{bmatrix}_{n\times\tilde{N}}$: Output matrix of hidden layer;

$\mathbf{T}_{n\times 1}$: Target in matrix format $\mathbf{T} = \{\mathbf{t}_k \mid \mathbf{t}_k \in \mathbf{R}^l\}_{k=1}^{n}$;

For n samples $\{(\mathbf{x}_k, \mathbf{t}_k)\}_{k=1}^{n}$, where $\mathbf{x}_k = [x_{k1}, x_{k2}, ..., x_{km}]$ and $\mathbf{t}_k = [t_{k1}, t_{k2}, ..., t_{kl}]$, a standard SLFN with $\tilde{N}$ hidden neurons and activation function $g(\cdot)$ is modeled mathematically as follows:

$$\mathbf{o}_k = \sum_{i=1}^{\tilde{N}} \beta_i g(\mathbf{w}_i, [\mathbf{x}_k, 1]), k = 1, ..., n \tag{1}$$

where $\mathbf{w}_i = [w_{i1}, w_{i2}, ..., w_{im}, w_{i(m+1)}]$ is the weight vector connecting the i-th hidden neuron with the input neurons. $\boldsymbol{\beta}_i = [\beta_{i1}, \beta_{i2}, ..., \beta_{il}]$ is the weight vector connecting the i-th hidden neuron and output neurons.

$\mathbf{o}_k = [o_{k1}, o_{k2}, ..., o_{kl}]$ is the k-th output vector of the SLFN, and $w_{i(m+1)}$ is the bias of the i-th hidden neuron. Set $\mathbf{w}_i \cdot [\mathbf{x}_k, 1]$ as the inner product of $\mathbf{w}_i$ and $[\mathbf{x}_k, 1]$. These n equations can be written compactly as

$$\mathbf{O} = \mathbf{H}\boldsymbol{\beta} \tag{2}$$

where $\mathbf{O} = \begin{bmatrix} \mathbf{o}_1 \\ \vdots \\ \mathbf{o}_n \end{bmatrix}_{n\times m}$, $\mathbf{H} = \begin{bmatrix} g(z_{11}) & \cdots & g(z_{1\tilde{N}}) \\ \vdots & \vdots & \vdots \\ g(z_{n1}) & \cdots & g(z_{n\tilde{N}}) \end{bmatrix}_{n\times\tilde{N}}$,

$\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1 \\ \vdots \\ \boldsymbol{\beta}_{\tilde{N}} \end{bmatrix}_{\tilde{N}\times l}$ and

$$\mathbf{Z} = \begin{bmatrix} z_{11} & \cdots & z_{1\tilde{N}} \\ \vdots & \vdots & \vdots \\ z_{n1} & \cdots & z_{n\tilde{N}} \end{bmatrix}_{n\times\tilde{N}} = \begin{bmatrix} \mathbf{w}_1 \cdot [\mathbf{x}_1,1] & \cdots & \mathbf{w}_{\tilde{N}} \cdot [\mathbf{x}_1,1] \\ \vdots & \vdots & \vdots \\ \mathbf{w}_1 \cdot [\mathbf{x}_n,1] & \cdots & \mathbf{w}_{\tilde{N}} \cdot [\mathbf{x}_n,1] \end{bmatrix}_{n\times\tilde{N}}.$$

To train an SLFN, it is important to find some specific $\hat{\mathbf{w}}_i$, $\hat{\boldsymbol{\beta}}_i$ $(i = 1, ..., \tilde{N})$ such that

$\| \mathbf{H}(\hat{\mathbf{w}}_1, ..., \hat{\mathbf{w}}_{\tilde{N}})\hat{\boldsymbol{\beta}} - \mathbf{T} \| = \min_{\mathbf{w}_i, \boldsymbol{\beta}} \| \mathbf{H}(\mathbf{w}_1, ..., \mathbf{w}_{\tilde{N}})\boldsymbol{\beta} - \mathbf{T} \|$,

which is equivalent to minimizing the cost function:

$$E = \sum_{j=1}^{n} \left(\sum_{i=1}^{\tilde{N}} \beta_i g(\mathbf{w}_i, [\mathbf{x}_k, 1]) - \mathbf{t}_j \right)^2 \tag{3}$$

where $\mathbf{H}$ are the unknown gradient-based learning algorithms, which are generally used to search for the minimum of $\| \mathbf{H}\boldsymbol{\beta} - \mathbf{T} \|$.

Huang et al. proposed a SLFN training algorithm called the ELM [14]. As proven by Huang et al. [14], ELMs can work as universal approximators: it is not difficult to find that SLFNs with at most n hidden neurons and with almost any nonlinear activation function can learn n distinct observations. Therefore, unlike traditional gradient-based learning algorithms, the input weights of an SLFN can be chosen randomly (according to any continuous sampling distribution), and the output weights of an SLFN can be determined analytically using Moore-Penrose generalized pseudo-inverse [13, 14]. The ELM can be summarized as follows [14-22].

ELM Algorithm: Given a training set $\aleph = \{(\mathbf{x}_k, \mathbf{t}_k) \mid \mathbf{x}_k \in \mathbf{R}^n, \mathbf{t}_k \in \mathbf{R}^m, k = 1, 2, ..., N\}$, an activation function $g(x)$, and the number of hidden neurons $\tilde{N}$.

(1) Randomly assign the input weights according to some continuous probability density function.

(2) Calculate the hidden layer output matrix, $\mathbf{H}$.

(3) Calculate the output weight $\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{T}$.

For more details, please refer to references [13-22].

3. Face Recognition Algorithm using MPELM

Fig. 1 shows the procedure of the face recognition algorithm based on MPELM.

First, all face images need to be preprocessed, as shown in Fig. 1. Subsequently, 2D Gabor filters were used to extract all the facial image features. Finally, the MPELM classifier was used to determine the final face classification.

The main procedure is detailed as follows.

3.1 2D Gabor-based Feature Extraction

2D Gabor transform is suitable for analyzing the gradually changing data, such as the face, iris and fingerprint images [27-29]. 2D Gabor filter has the following general form:

$$\begin{aligned} \mathrm{G}(x, y, \theta, u, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left\{ -\frac{x^2 + y^2}{2\sigma^2} \right\} \\ \times \exp\{2\pi i (ux\cos\theta + uy\sin\theta)\} \end{aligned} \tag{4}$$

where $i = \sqrt{-1}$, σ is the standard deviation of the Gaussian envelope. Here σ was set as $\{2, 4, 6, 8, 10\}$. u is the frequency of the sinusoidal wave. θ controls the orientation of the function. Here θ was set to $\pi / 8 \times \{0, 1, 2, 3, 4, 5, 6, 7\}$.

This paper used five scales and eight orientations for 2D Gabor transform. Therefore, 40 Gabor filters were used for face feature extraction.

The size of the face images was first resized to 50×50 pixels by bilinear interpolation. The face image was preprocessed using the 2D Gabor transform and 40(=5×8) transformed images were obtained. The face features are expressed by the magnitude values. Fig. 2 presents an original face image and the corresponding transformed images.

To reduce the computational cost and redundant information, the size of each transformed image was resized to 16×10 pixels by bilinear interpolation. Finally, the form of feature vector was taken to represent the 2D Gabor features.

3.2 Multi-class Projection Extreme Learning Machine for Face Classification

In fact, an ELM randomly assigns the input weights $\mathbf{w}_{(m+1)\times\tilde{N}}$ according to the some continuous probability density function. This will cause the output weights, $\boldsymbol{\beta}$, different in every calculation. Therefore, the recognition rate in the biometric applications will be changed dynamically. On the other hand, the ELM requires more hidden neurons than BP [22-26].

For face classification, this paper proposes an algorithm called the MPELM. MPELM requires fewer

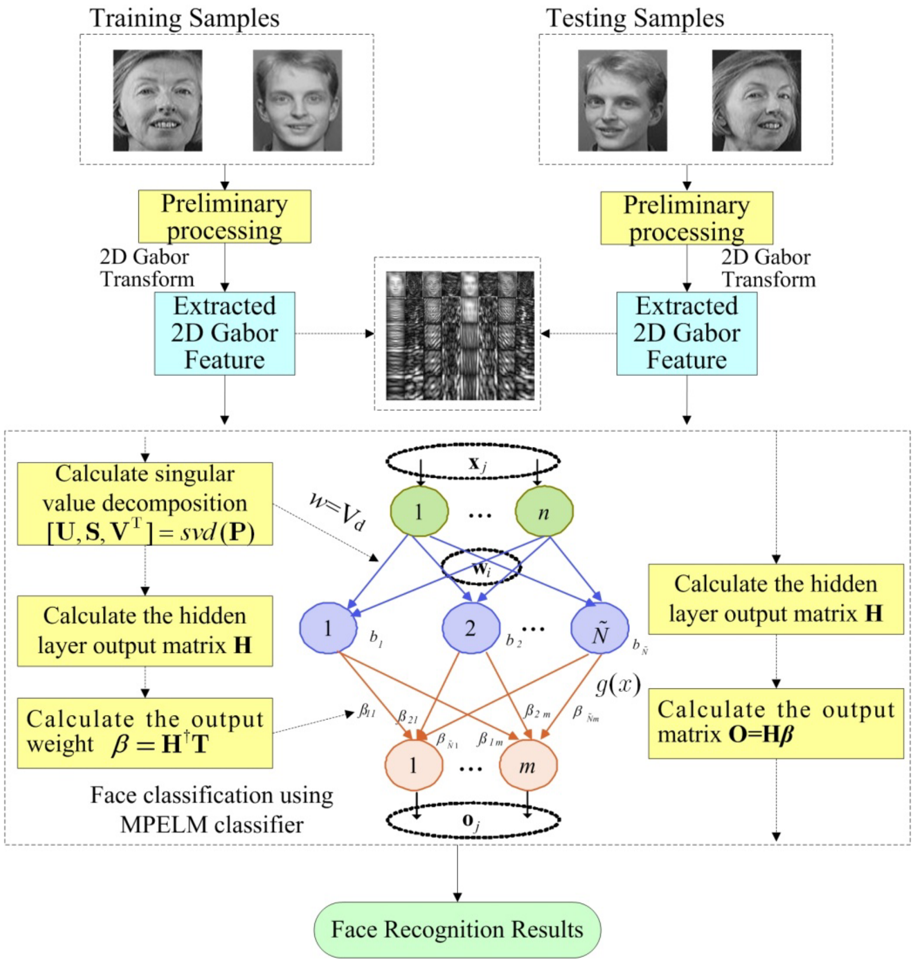

Fig. 1. Schematic diagram of the MPELM-based face recognition method.

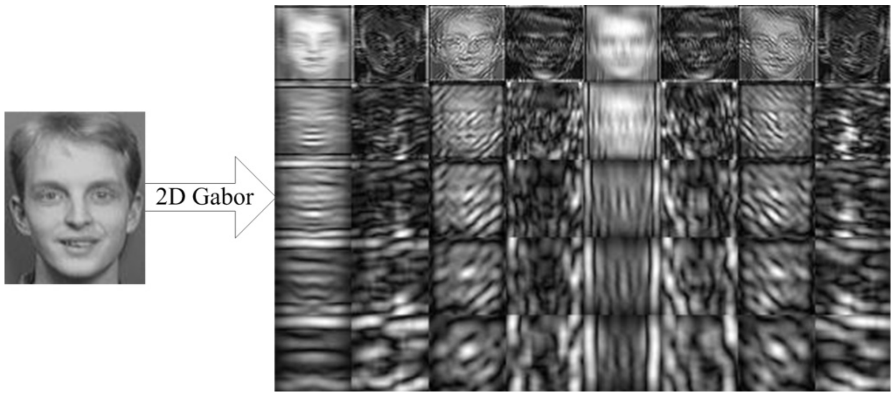

Fig. 2. Original face image and the corresponding 2D Gabor transformed images.

hidden neurons and the recognition rate is explicit in the biometric applications.

First a projection matrix $\mathbf{V}_k \in \mathbf{R}^{m\times k}$ is obtained through a singular value decomposition on dataset $\mathbf{P}_{n\times m}$ and the k singular vector elements in $\mathbf{V}$ corresponding to largest singular values is selected.

$$[\mathbf{U},\mathbf{S},\mathbf{V}^{\mathrm{T}}]=svd(\mathbf{P}) \tag{5}$$

With the matrix $\mathbf{V}_k$, the high dimensional data $\mathbf{P}_{n\times m}$ can be transformed into low dimensional data $\mathbf{Z}_{n\times k}$ by

$$\mathbf{Z}_{n\times k}=\mathbf{P}_{n\times m}\mathbf{V}_k \tag{6}$$

Subsequently, $\mathbf{Z}_{n\times k}$ was applied to SLFN to train network. The input weights $\mathbf{w}_{m\times\tilde{N}}$ and output weights $\boldsymbol{\beta}$ of SLFN were determined using learning algorithms, such as the ELM [14, 22].

The input weights do not need to be learned again. In SLFN, the projection from the input layer to hidden layer by input weights $\mathbf{w}_{m\times\tilde{N}}$ can be can be considered a dimension reduction,

$$\mathbf{Z}_{n\times\tilde{N}} = \mathbf{P}_{n\times m}\mathbf{w}_{m\times\tilde{N}} \tag{7}$$

where $\mathbf{w}_{m\times\tilde{N}}$ can be seen as the projection vectors mapping the data into low dimensions. Therefore, $\mathbf{V}_k \in \mathbf{R}^{m\times k}$ was used directly as the input weights $\mathbf{w}_{m\times\tilde{N}}$. Obviously, couting upon deducing from formulas (6) and (7) the number of hidden neurons is $\tilde{N} = k$, and the column number is $\mathbf{V}_k$.

The procedure of the multi-class projection extreme learning machine (MPELM) is detailed as follows:

MPELM Algorithm： Given a training set $\aleph = \{(\mathbf{x}_k, \mathbf{t}_k) \mid \mathbf{x}_k \in \mathbf{R}^n, \mathbf{t}_k \in \mathbf{R}^m, k = 1, 2, ..., n\}$, an activation function $g(x) = \sin(x)$ or $g(x) = \dfrac{1}{1+e^x}$.

(1) Let $\mathbf{P} = \{[\mathbf{x}_k, 1] \mid \mathbf{x}_k \in \mathbf{R}^m\}_{k=1}^n$, $\mathbf{T} = \{\mathbf{t}_k \mid \mathbf{t}_k \in \mathbf{R}^l\}_{k=1}^n$

(2) Calculate singular value decomposition of $\mathbf{P}$: $[\mathbf{U}, \mathbf{S}, \mathbf{V}^{\mathrm{T}}] = svd(\mathbf{P})$.

(3) Set the number of hidden neurons $\tilde{N}$

(4) Set input weights. Let $\mathbf{w} = \mathbf{V}(:, 1:\tilde{N})$

(5) Calculate the hidden layer output matrix $\mathbf{H}$.

(6) Calculate the output weights $\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{T}$.

(7) Input the testing set. The we can calculate the hidden layer output matrix $\mathbf{H}$ directly.

(8) Calculate the output matrix $\mathbf{O} = \mathbf{H}\boldsymbol{\beta}$ directly. The classification results will be obtained.

In a MPELM algorithm, the input weights have been fixed after singular value decomposition (SVD). Only the output weights need to be calculated using the least square method [14, 22]. In addition, there are no iterative learning steps in the procedure, and their learning speed is quite fast. Obviously, this can be used to build real-time biometric applications, such as face recognition systems, etc.

4. Experimental Results

This section presents the results of a comparative study between the ELM-based methods and MPELM-based methods are presented. Here, 2D Gabor+ELM, MFA+ ELM, LPP+ELM, MFA+NN, LPP+NN methods are used in the experiments. MFA and LPP methods were used instead of the classical PCA,LDA methods in the experiments [12, 30, 31]. The experiments were performed on the two well-known databases: CMU-PIE and ORL face databases.

4.1 Experimental Results using CMU-PIE Database

The CMU-PIE face database provided by Carnegie Mellon University (CMU) contains 68 subjects. The face images were captured from 13 synchronized cameras and 21 flashes under a range of illumination conditions, facial expressions and poses. Each subject has 20 images (Pose C05,C07,C09,C27,C29), which are used in these experiments. All the face images were normalized to 64×64 pixels in these experiments. In the experiments, 68 face subjects (20 images/subject) were used. Fig. 3 shows the image samples.

In the experiments, l (=3,4,5) images of each subject were chosen randomly as training samples. The remaining images were used as the test samples. To evaluate the performance of MPELM, for each l there are 10 random selections of the training samples and the average recognition rate is taken as the final results. Table 1 lists the experimental results using CMU-PIE database.

Table 1 shows that both the MPELM and ELM classifiers outperform the NN classifier. In particular, The performance of the 2D Gabor+MPELM method is better than the other methods. Compared to the 2D Gabor+ELM method, the proposed method can make the average recognition rates increase by 5.28% (3 Train), 4.67% (4 Train), 4.73%(5 Train) for the CMU-PIE database, respectively.

4.2 Experimental Results using the ORL Database

The Cambridge University ORL face database was composed of 400 images from 40 individuals. Some images were captured at different times and had different

Fig. 3. Face image samples from CMU-PIE database.

Table 1. Experimental results using CMU-PIE database.

Methods	Average Recognition Accuracy(%)		
	3Train(Dim)	4Train(Dim)	5Train(Dim)
2D Gabor+MPELM	92.90	95.04	96.52
2D Gabor+ ELM	87.62	90.37	91.79
MFA+NN	72.55(90)	84.94(80)	86.33(51)
LPP+NN	79.85(56)	87.83(63)	90.65(58)
MFA+ELM	73.77(90)	84.85(80)	88.24(51)
LPP+ELM	80.54(56)	89.72(63)	91.90(58)

Fig. 4. Face image samples from the ORL database.

Table 2. Experimental results using the ORL databases.

Methods	Average Recognition Accuracy(%)		
	2Train(Dim)	3Train(Dim)	4Train(Dim)
2D Gabor+MPELM	91.84	96.11	98.29
2D Gabor+ ELM	90.12	94.62	96.95
MFA+NN	82.56(42)	89.14(45)	90.50(53)
LPP+NN	80.53(39)	87.18(39)	94.29(37)
MFA+ELM	83.00(42)	89.29(45)	91.71(53)
LPP+ELM	81.66(39)	88.29(39)	94.42(37)

variations, including facial details (glasses or no glasses), expression (smiling or non-smiling, etc) and different poses. All images were grayscale and had a size of 112 × 92 pixels. For the ORL databases, 40 face subjects (10 images/subject) were used in the experiments. Fig. 4 shows the image samples from ORL database. In the experiments, l (=2,3,4) images of each subject were chosen randomly for training samples. Table 2 lists the experimental results using ORL database.

In Table 2, the 2D Gabor+MPELM method achieves the best recognition accuracy of 91.84% (2Train), 96.11% (3Train) and 98.29% (4Train). Compared to the 2D Gabor+ELM method, the proposed method can make the average recognition rates increase by 1.72%(2 Train), 1.49% (3 Train) and 1.34% (4 Train) for the ORL database, respectively. As listed in Table 2, the MPELM and ELM classifiers also outperformed the NN classifier.

4.3 Relationship between the Recognition Rate and Neuron Numbers

Fig. 5 shows the relationship between the recognition rate and the neuron numbers (3Train, CMU-PIE face database). Here $n \in [1, 204]$. When $n \le 40$, the recognition accuracy was quite low. With increasing neuron numbers n, the recognition accuracy reached the maximum and tended to be steady.

4.4 Computational Time

The computational cost of different methods are reported. Table 3 lists the training time, total classification time and per image classification time using ELM-based and MPELM-based methods. The same facial images were used, as shown in Section 4.1 & 4.2 in the experiments. All the algorithms were implemented by MATLAB 7.12(2011a) and performed on the same computer (Intel

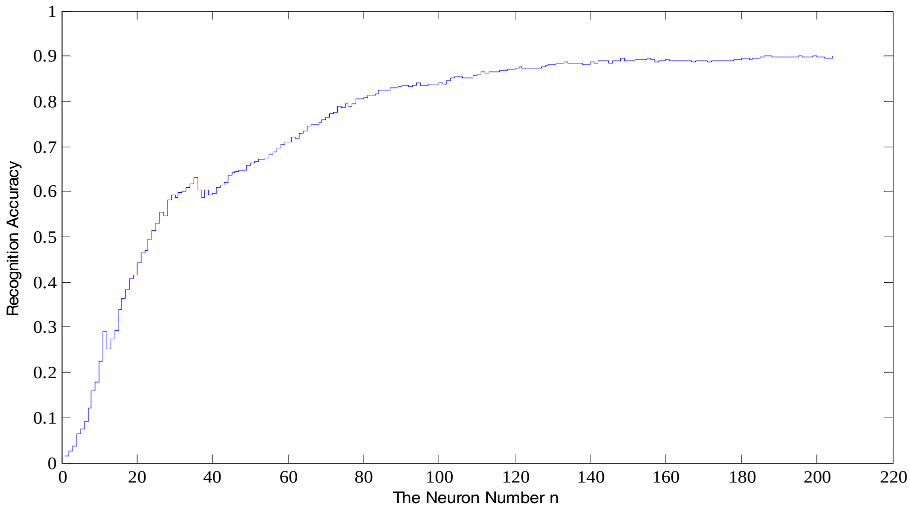

Fig. 5. Relationship between the recognition rate and neuron numbers.

Table 3. Comparison of the computational speed.

Databases/Methods (The neuron numbers)	The Computational Speed		
	Training Time(s)	Total Classification Time(s)	Per image Classification Time(ms)
PIE-2D Gabor+MPELM(80)	0.4781	0.1531	0.13
PIE-2D Gabor+ELM (1500)	0.8141	2.3969	2.07
ORL-2D Gabor+MPELM(80)	0.2313	0.0547	0.19
ORL-2D Gabor+ELM (1500)	0.5516	0.6219	2.22

Core i5-2430 2.8GHz CPU, 4-Core, 2048M RAM, Windows XP SP3). All the experiments were conducted in the same development environment. Three training samples of each subject were used in the experiments. Each experiment was performed 100 times and the average results are reported.

In Table 3, the training time of ELM was 0.8141 s for the CMU-PIE database, whereas the MPELM was 0.4781 s, showing a 41.27% decrease. The classification time of ELM was 2.07 ms, whereas MPELM was 0.13 ms, decreasing by 93.72%. The training time of the ELM was 0.5516 s for the CMU-PIE database, whereas the MPELM was 0.2313 s, showing a 58.06% decrease. The classification time of ELM was 2.22 ms, whereas the MPELM was 0.19 ms, showing a 91.44% decrease. The MPELM-based methods gave the best performance. Both the training speed and classification speed, MPELM-based methods are faster than the ELM-based methods. Therefore, the proposed method requires less computational time and achieves better accuracy than ELM-based methods.

5. Discussion

Compared to the ELM classifier, MPELM showed better performance. Extensive experimental results showed that 2D Gabor + MPELM is a robust and reliable face recognition method, but the MPELM-based methods still have some open problems as follows:

(1) The hidden neuron numbers of ELMs have a large impact on the recognition accuracy. For example, if 100000 hidden neurons are used in ELM, The accuracy of ELM is much higher and stable, but the training speed is very slow. Fig. 5 shows the relationship between the recognition rate and the neuron numbers of MPELM using the exhaust method. Therefore, it is important to decide the hidden neuron numbers of MPELM for higher accuracy and less computational time adaptively.

(2) When the dataset is nonlinear, kernel dimension reduction approaches, such as KLDA will be more effective than linear approaches. Therefore, MPELM should be kernelized for a nonlinear dataset.

These open problems are challenging, and further study will be needed.

6. Conclusions

This paper presents a human face recognition method based on multi-class projection extreme learning machine (MPELM) and 2D Gabor. The experimental results on CMU-PIE and ORL databases confirmed its effectiveness and robustness. Compared to the ELM-based method, MPELM requires less computational time and obtains better accuracy.

The multi-class projection extreme learning machine (MPELM) is a novel and effective classifier for human face recognition, and can be used in other biometrics applications, such as palmprint recognition, iris recognition, etc.

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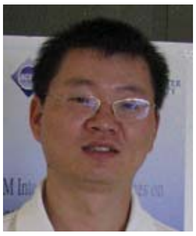

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