Face Recognition using Gaborface-based 2DPCA and (2D)²PCA Classification with Ensemble and Multichannel Model

Lin Wang, Yongping Li, Chengbo Wang, Hongzhou Zhang

Shanghai Institute of Applied Physics, Chinese Academy of Sciences

2019 Jialuo Road, Jiading, Shanghai, China

Tel.: +86 21 5955 4646; fax: +86 21 5955 2037; E-mail:wanglin@sinap.ac.cn

Abstract-**This paper introduces Gaborface-based 2DPCA and (2D)²PCA classification method based on 2D Gaborface matrices rather than transformed 1D feature vectors. Two kinds of strategies to use the bank of Gaborfaces are proposed: ensemble Gaborface representation (EGFR) and multichannel Gaborface representation (MGFR). The feasibility of our method is proved with the experimental results on the ORL and Yale databases. In particular, the MGFR-based (2D)²PCA method achieves 100% recognition accuracy for ORL database, and 98.89% accuracy for Yale database with five training samples per class.**

I.   INTRODUCTION

As one of the computational intelligent techniques, face recognition has an active development in the past few decades due to its potential applications in automated video surveillance, identity authentication, access control, and law enforcement, etc. In 1991, Turk and Pentland presented the principal component analysis (PCA) based eigenface method [1], which has become a baseline for various approaches. In recent years, many methods based on Gabor filters have been proposed. The Gabor filters exhibit desirable characteristics of spatial localization and orientation selectivity, and the Gabor filter representations of face image (termed also as Gaborfaces) are robust for illumination and expressional variability, so are used extensively in face recognition [2-6]. However, the dimensionality of the Gabor feature space is overwhelmingly high, because the Gaborfaces are obtained by convolution of the face image with dozens of Gabor filters. Therefore, many sampling or compressing methods are proposed to reduce the space dimension to avoid dealing with the enormous data. In [7], each face was represented as convolution results of the face with 40 Gabor filters at 48 predetermined fiducial points, which were located at face landmarks (e.g. the eyes, nose and mouth, etc), so that the dimensionality was reduced to 48×40. And in [8], a SVM face recognition method based on manually labeled Gabor-featured key points was proposed, where a face was represented by a 87×40-dimensionality feature vector rather than the total $256 \times 384 \times 40$ feature data. One disadvantage of fiducial-points sampling is that manual annotation is required, which is inconvenience for automatic face recognition. Another sampling method is Fixed-grid sampling [9], where a grid of 64 points at regular intervals was used to sample Gabor-filtered handwritten numerals.

Recently, a novel adaptive sampling algorithm was introduced to reduce feature vectors. It selected sample-point sets that maximized inter-object distance [10]. Another method is to downsample the Gaborfaces by factor ρ and concatenate its rows (or columns) to form one augmented feature vector [4,5].

Unlike the aforementioned methods, in this paper we try to make use of the total enormous feature data for face recognition instead of extracting a feature vector by sampling. Inspired by the 2D representation idea from 2DPCA [11], we develop 2D Gaborface representation method, which is based on 2D Gaborface matrices rather than sampled 1D feature vectors, i.e. the 2D Gaborface matrices are straightforward used as the feature representation of the image without any sampling or compressing. As will be shown in Section III, we have introduced two kinds of strategies to use the bank of Gaborfaces: ensemble Gaborface representation (EGFR) and multichannel Gaborface representation (MGFR). Although many researches have been done on multichannel filtering approaches [12-14], no work, to the author's knowledge, has been done on 2D multichannel Gaborface representation. In [12], a multichannel subsampled filter bank was used for texture segmentation. And in [13], a multichannel texture analysis approach using localized spatial filters was described. The method to apply 4 orientation Gabor channels for face recognition was proposed in [14]. All the methods are based on 1D sampled Gabor feature vectors, however, our MGFR method is based on 2D Gaborface matrices as mentioned above. Due to the 2D Gaborface representation from different channels seems to provide complementary information [14], so we simultaneously apply classification algorithm on these channels and perform the decision level fusion. For measuring the recognition performance we adopt some commonly used fusion rules, i.e. sum rule, product rule, max rule, min rule, median rule and majority vote rule.

In addition, we propose a scheme to yield optimized Gabor filter bank in terms of linear correlation criterion. The attempt is desirable in that optimized filter bank may reduce redundancy of feature sets. By analyzing the correlation matrices of Gabor filters with different sets of scales, an optimal Gabor filter bank with scales, $v \in \{-2, \cdots, 5\}$, is obtained by achieving the minimal values in the correlation matrix.

The feasibility of our method has been successfully tested with a series of experiments on ORL and Yale databases. In

particular, the MGFR-based $(2D)^2PCA$ method achieves 100% recognition rate using only 6×1 feature coefficients on ORL database.

The rest of this paper is organized as follows: In Section II, we briefly review the Gabor filter and describe how to select Gabor filter bank based on linear correlation criterion. The proposed EGFR and MGFR methods are introduced in Section III. Section IV briefly reviews the 2DPCA and $(2D)^2PCA$ method. Experiments and analysis are conducted in Section V. Finally, Section VI summarizes the main results of this paper and offers concluding remarks.

II. GABOR FILTER BANK

A. Gabor Filter

Gabor filters are now being used extensively and successfully in various computer vision applications including face recognition and detection due to their biological relevance and computational properties [2-6]. Because the Gabor kernels can model the receptive fields of the orientation-selective mammalian cortical simple cells, the Gabor filters, which are generated from a wavelet expansion of the Gabor kernels, exhibit desirable characteristics of spatial locality and orientation selectivity, and are localized in the spatial and frequency domains optimally. The Gabor filters take the form of a complex plane wave modulated by a Gaussian envelope function [4,5]:

$$\psi_{\mu,\nu}(z) = \frac{\left\|k_{\mu,\nu}\right\|^2}{\sigma^2} e^{(-\left\|k_{\mu,\nu}\right\|^2\|z\|^2/2\sigma^2)} \left[e^{ik_{\mu,\nu}z} - e^{-\sigma^2/2} \right] \quad (1)$$

where $k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$, $z = (x, y)$, μ and ν define the orientation and scale of the Gabor filters, $k_\nu = k_{max}/f^\nu$ and $\phi_\mu = \pi\mu/N$, k_{max} is the maximum frequency, and f is the spacing factor between kernels in the frequency domain. $\sigma = 2\pi$, $k_{max} = \pi/2$ and $f = \sqrt{2}$. The first term in the brackets in (1) is the oscillatory part of the kernel and the second compensates for the DC value.

B. Correlation-based method to select Gabor Filter Bank

For extracting discriminating information of different orientations and scales as much as possible, a bank of Gabor filters with eight orientations, i.e., $N = 8$, and eight scales is chosen to extract the feature data of a facial image. Hence the total number of filters in our experiments is 64. In most cases the choice of 8 orientations $(0, \pi/8, \cdots, 7\pi/8)$ is sufficient for differentiating the local orientation of the image features, so the undetermined parameters of filters are 8 scales. As we all known, the Gabor wavelets (filters) are nonorthogonal wavelets. This means that a wavelet transform based on the Gabor wavelet is redundant [3,15,16]. From this point of view, we need to select the scale set ν to obtain an optimal filter set as uncorrelated as possible to reduce redundancy. We adopt a scheme that is based on linear correlation criterion. In this scheme, the orientation set $U = \{\mu : 0 \leq \mu \leq 7\}$ is fixed and different scale sets are tested from $V_1 = \{\nu : -4 \leq \nu \leq 3\}$ to $V_5 = \{\nu : 0 \leq \nu \leq 7\}$ as illustrated in Fig.1.

We consider the real part of the filters and the similar results are obtained with imaginary part. We first concatenate the rows (or columns) of the real part of filter, $\text{Re}(\psi_{\mu,\nu}(z))$, to construct a vector $\phi_{\mu,\nu}$, then the linear correlation between two filters $\psi_{\mu,\nu}(z)$ and $\psi_{\mu',\nu'}(z)$ is evaluated by

$$r = \frac{\sum(\phi_{\mu,\nu} - \overline{\phi}_{\mu,\nu})(\phi_{\mu',\nu'} - \overline{\phi}_{\mu',\nu'})}{\sqrt{\sum(\phi_{\mu,\nu} - \overline{\phi}_{\mu,\nu})^2}\sqrt{\sum(\phi_{\mu',\nu'} - \overline{\phi}_{\mu',\nu'})^2}}, \quad (2)$$
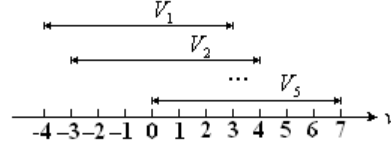

Figure 1. Different scale sets.

the correlation matrix of the total 64 filters is a 64×64 symmetric matrix with all elements on the diagonal equal to unity. In order to get a better understanding of the correlation matrix, we display it in a form of visual representation. Since the elements of the correlation matrix are in the interval [-1, 1], we take the absolute value of these correlation coefficients and map them from [0, 1] to the gray-level scale [0, 255]. The correlation matrices are shown in Fig.2. The numbers below each correlation matrix represent the different scale sets, respectively.

For explicating the correlation characteristics between the filters with different orientations and scales, we take two permutations of the 64 filters to form correlation matrices. In Fig.2 (a)-(e), the 64 filters are arranged in order of orientation and then scale, i.e., every 8 consecutive filters are assigned with different orientations of the same scale ν, and then the scale is increased. On the other hand in Fig.2 (f)-(j), the 64 Gabor filters are arranged in order of scale and then orientation, i.e., every 8 consecutive filters are assigned with different scales of the same orientation μ, and then the orientation is altered.

Each correlation matrix has two lines in parallel with the diagonal, which suggests that the correlations are particularly strong between two filters with neighboring scales ν of the same orientation in Fig.2 (a)-(e), and two filters with neighboring orientations μ of the same scale in Fig.2 (f)-(j). And it's obvious to see that those high correlation coefficients are particularly concentrated on the low scales $\nu = \{-4, -3\}$ region in Fig.2 (a) and $\nu = -3$ region in Fig.2 (b) and the high scales $\nu = 6$ region in Fig.2 (d) and $\nu = \{6, 7\}$ region in Fig.2 (e). On the other hand in Fig.2 (f)-(j), we note that the top left corner of each 8×8 sub-block indicates the correlations between filters with the low scales, and the bottom right corner indicates the correlations between filters with the high scales. Similarly we find that those high correlation coefficients are especially concentrated on the top left corner of sub-block on the low scales $\nu = \{-4, -3\}$ region in Fig.2 (f) and $\nu = -3$ region in Fig.2 (g) and the bottom right corner on the high scales $\nu = 6$ region in Fig.2 (i) and $\nu = \{6, 7\}$ region in Fig.2 (j), which are in good agreement
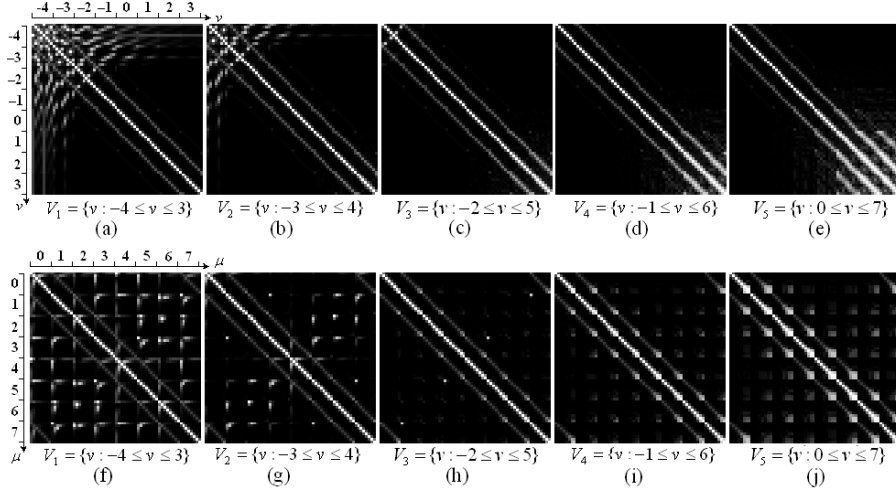
Figure 2. The correlation matrices of 64 Gabor filters.

with the observations of Fig.2 (a)-(e). And when the scale set is, the total correlation coefficients arrive at minimal values both in Fig.2 (c) and in Fig.2 (h). Therefore we select $V_3 = \{v : -2 \le v \le 5\}$ as the scale set of Gabor filter bank to extract feature sets as uncorrelated as possible. Fig.3 shows the real part of the 64 Gabor filters at 8 scales and 8 orientations and their magnitude.
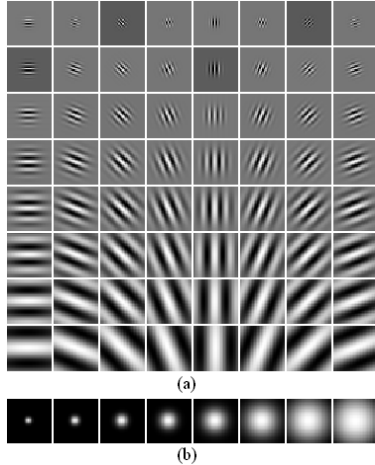

(a)

(b)

Figure 3. (a) The real part of the Gabor filters at eight scales and eight orientations (b) The magnitude of the Gabor filters at eight scales.

III. GABORFACE REPRESENTATION

Let $I(z)$ ($z = (x, y)$) be a $m \times n$ facial image, the Gaborface representation is the convolution of the image with a filter in the bank, and is defined as follows:

$$O_{\mu,v}(z) = I(z) * \psi_{\mu,v}(z) \qquad (3)$$

where $O_{\mu,v}(z)$ is the convolution result corresponding to the Gabor filter at orientation μ and scale v. Therefore, the set $S = \left\{ O_{\mu,v}(z) \mid 0 \le \mu \le 7, -2 \le v \le 5 \right\}$ forms the Gaborface representations of the image $I(z)$. If we combine the set S into a vector, the length of the vector is $64 \times m \times n$, it is difficult to deal with such a high-dimensional vector space. So the method to reduce the

space dimension by downsampling each $O_{\mu,v}(z)$ and concatenating its rows (or columns) to form a 1D feature vector is proposed and used extensively [4,5].

In this paper, 2D Gaborface representation method is proposed. It is based on 2D Gaborface matrices rather than transformed 1D feature vectors. That means the image is represented by 64 $m \times n$ matrices. We combine the 2D Gaborface representation method with 2D feature extraction algorithms, i.e., 2DPCA and (2D)^{2}PCA [11,17], thus the needed feature coefficients for efficient face recognition are reduced dramatically, which will be discussed in detail in Section IV. We now describe two kinds of strategies to use the bank of 64 Gaborfaces: ensemble Gaborface representation (EGFR) and multichannel Gaborface representation (MGFR).

A. Ensemble Gaborface Representation Model

The set $S = \left\{ O_{\mu,v}(z) \mid 0 \le \mu \le 7, -2 \le v \le 5 \right\}$ forms the bank of Gaborfaces, and we define the following matrix:

$$\Re = \begin{vmatrix} o_{0,-2}(z) & o_{0,-1}(z) & \cdots & o_{0,5}(z) \\ o_{1,-2}(z) & o_{1,-1}(z) & \cdots & o_{1,5}(z) \\ \vdots & \vdots & \ddots & \vdots \\ o_{7,-2}(z) & o_{7,-1}(z) & \cdots & o_{7,5}(z) \end{vmatrix} \qquad (4)$$

where each $O_{\mu,v}(z)$ is a 2D matrix, capturing some facial properties corresponding to orientation μ and scale v, so the integration of the ensemble set S in the form of matrix $\Re$, an $8m \times 8n$ matrix, encompasses the overall facial discriminating information of all orientations and scales. We shall term this representation method as 2D ensemble Gaborface representation (EGFR).

B. Multichannel Gaborface Representation Model

We take each filter $\psi_{\mu,v}(z)$ as a Gabor channel, the 64 filters form a set of parallel and quasi-independent channels which are sensitive to visual signal with some specific scale v and orientation μ [18-20], thus the 2D Gaborface representations from different channels seems to provide an observer with multiple cues and this in itself facilitates data

fusion [14]. Consequently we shall study three approaches to divide the 64 Gaborface representations from different channels into groups, and simultaneously apply classification algorithm on these feature groups, and then perform the decision level fusion to obtain the final classification results. The groupings are as follows:

1. all Gaborfaces to one group and form 64 Gaborface channels.

2. all Gaborfaces to 8 groups according to their respective orientation and each group is formed by averaging 8 Gaborfaces with different scale of the same orientation, i.e.,

$$\zeta_\mu(z) = \frac{1}{8}\sum_{v=-2}^{5} O_{\mu,v}(z), 0 \le \mu \le 7 .$$

3. all Gaborfaces to 8 groups according to their respective scale and each group is formed by averaging 8 Gaborfaces with different orientation of the same scale,

i.e., $\Xi_v(z) = \frac{1}{8}\sum_{\mu=0}^{7} O_{\mu,v}(z), -2 \le v \le 5 .$

We shall refer to these methods as 2D multichannel Gaborface representation (MGFR). The framework of the grouping 1 and 2 are illustrated in Fig.4. And we apply a number of common fusion rules as mentioned in [21], i.e. sum rule, product rule, max rule, min rule, median rule and majority vote rule, to evaluate the performance of the MGFR method with experiments in Section V.
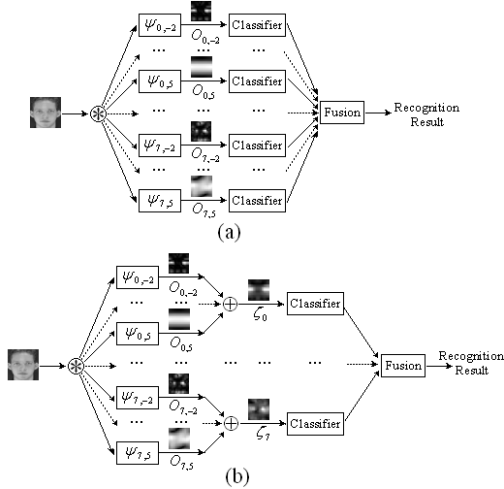

(a)

(b)

Figure 4. The frameworks of the proposed MGFR method. (a) 64 Gaborface channels (b) 8 orientation Gaborface channels.

IV. GABORFACE-BASED 2DPCA AND (2D)^{2}PCA CLASSIFIER

In this section, we describe our Gaborface-based 2DPCA and (2D)^{2}PCA classifier method for face recognition. We take the ensemble Gaborface representation method as an example. The ensemble Gaborface representation matrix $\Re$ is an $8m \times 8n$ matrix, projecting $\Re$ onto X by the linear transformation:

$$Y = \Re X \qquad (5)$$

In 2DPCA, the total scatter of the projected samples characterized by the trace of the covariance matrix was used to determine a good projection matrix X. That is, the forllowing criterion is adopted:

$$J(X) = tr(S_x) = tr(E[Y - EY][Y - EY]^T)$$
$$= X^T E[\Re - E\Re]^T[\Re - E\Re]X \qquad (6)$$

Define the Gaborface covariance matrix $G_n = E[\Re - E\Re]^T[\Re - E\Re]$, which is an $8n \times 8n$ nonnegative definite matrix. Suppose that there are M training image samples in total, the jth image can be represented by an $8m \times 8n$ ensemble Gaborface matrix $\Re_j$, and the average of the set $\{\Re_j \mid j = 1,2,\cdots,M\}$ is defined by $\overline{\Re}$, then G_n can be evaluated by

$$G_n = \frac{1}{M}\sum_{j=1}^{M}(\Re_j - \overline{\Re})^T(\Re_j - \overline{\Re}) \cdot \qquad (7)$$

So we can select the optimal projection axes, $X_1,\cdots,X_d$, subject to the orthonormal eigenvectors of G_n corresponding to the first d largest eigenvalues, and project $\Re$ onto X, yielding an $8m \times d$ matrix $Y = \Re X$. This is the so-called 2DPCA technique [11].

If we transpose the matrix $\Re$, then (7) can be rewritten as

$$G_m = \frac{1}{M}\sum_{j=1}^{M}(\Re_j^T - \overline{\Re}^T)^T(\Re_j^T - \overline{\Re}^T) = \frac{1}{M}\sum_{j=1}^{M}(\Re_j - \overline{\Re})(\Re_j - \overline{\Re})^T \quad (8)$$

It is easy to verify that G_m is an $8m \times 8m$ nonnegative definite matrix. In the same way, we can select the optimal projection axes, $Z_1,\cdots,Z_q$ by computing the eigenvectors of G_m corresponding to the q largest eigenvalues.

Now we project $\Re$ onto X and Z simultaneously, yielding a $q \times d$ matrix $C = Z^T\Re X$. This is the so-called (2D)^{2}PCA technique [17].

By applying the (2D)^{2}PCA on the ensemble Gaborface matrix $\Re$, the feature coefficients for classification are reduced dramatically due to $q << 8m$ and $d << 8n$. So it is tractable to make use of the total enormous Gaborface feature for face recognition without any sampling or compressing.

V. EXPERIMENTS RESULTS AND ANALYSIS

We test the EGFR-based and MGFR-based 2DPCA and (2D)^{2}PCA method against conventional 2DPCA and (2D)^{2}PCA method for face recognition. Frobenius distance is used for similarity measure. Here, the distance between two feature matrices, $A = (a_{i,j})_{q \times d}$ and $B = (b_{i,j})_{q \times d}$, is

defined by $d_F(A,B) = (\sum_{i=1}^{q}\sum_{j=1}^{d}(a_{i,j} - b_{i,j})^2)^{1/2}$. Two

publicly available face databases: the ORL face database and the Yale database are used.

A. Experimental results on ORL face database

The ORL database consists of 400 frontal faces: the size of each image is 112×92 pixels, and each face image is rescaled to 32×32 using a bicubic interpolation to facilitate the Gaborface representation and reduce the computational complexity. The first 5 images of each subject are used for training, the rest are left for testing. Hence there are 200

training images and 200 testing images and no overlap between them.

Fig.5 shows the experiment results of EGFR-based 2DPCA and $(2D)^2$PCA method against conventional 2DPCA and $(2D)^2$PCA method. Without any optimized algorithm, the recognition performance is improved by a margin. In addition, we compared the results with the Gabor-based PCA method and conventional PCA. Table 1 presents the comparisons of six methods on top recognition rate, dimension of feature vector and running time. From Table 1, we can see that the Gabor-based PCA, EGFR-based 2DPCA and $(2D)^2$PCA method achieves the same improvements in accuracy (98%), while the latter needs much reduced dimension of feature vector and less running time than the former two.
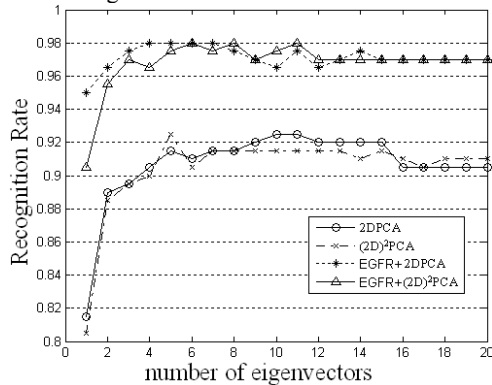

Figure 5. Face Recognition Rate Curve.

Table 1 Comparison of fix methods on ORL database

Method	Recognition Rate(%)	Dimension	Time(s)
PCA	91.0	89	5.58
2DPCA	92.5	10×32	2.64
$(2D)^2$PCA	92.5	5×10	2.48
Gabor+PCA	98.0	137	180.70
EGFR + 2DPCA	98.0	4×256	149.84
EGFR + $(2D)^2$PCA	98.0	12×6	137.19

The Time is CPU Time for the total process including train and test based on a 2.99 GHz Intel Pentium 4 computer with 1.99GB RAM.

We apply six classifiers combination rules and six groups of channels to evaluate the performance of the MGFR-based $(2D)^2$PCA method, and the results obtained are shown in Table 2. Besides the three groups of channels discussed in Section III, we introduce another three groups by appending the intensity images to the three original groups to form channels with odd numbers (65, 9, 9), which are better choices for majority vote rule.

Table 2 Recognition rate (%) for different combination rules and different groups of channels

Rule	Groups of Channels					
	64	64+1	8O	8O+1	8S	8S+1
Sum	100(1)	100(1)	99(2)	99(2)	97(2)	97(2)
Product	99.5(1)	99.5(1)	99(2)	99(2)	97(2)	97(2)
Min	85.5(6)	85.5(6)	92.5(6)	92.5(6)	86.5(4)	86.5(4)
Max	88.5(8)	88.5(8)	94(4)	94.5(9)	93.5(2)	94(2)
Median	99.5(1)	99.5(3)	97(2)	97.5(2)	98(2)	98(2)
Majority Vote	99(3)	99(3)	97(5)	98.5(6)	95(4)	96(4)

The values in parentheses denote the dimension d for the best recognition rate, while the dimension q is fixed as 6. The six groups are 64 Gabor channels (64), 64 Gabor channels plus the intensity images (64+1), 8 channels with different orientation (8O), 8 channels with different

orientation plus the intensity images (8O+1), 8 channels with different scale (8S) and 8 channels with different scale plus the intensity images (8S+1).

The experimental results lead to the following findings: 1) the MGFR-based $(2D)^2$PCA method achieves 100% correct recognition accuracy when using only 6×1 feature coefficients with 64 and 64+1 channels in sum rule and 2) the average results of the three groups by appending the intensity images are a little better than the three original groups and 3) the dimension d for the best recognition rate are less than 10, i.e., the method has good performance in low-dimension condition and 4) the average results in 8O and 8O+1 channels are better than the ones in 8S and 8S+1 channels, i.e., the orientation channels contain more discriminating information than the scale channels and 5) the worst results are achieved when using the min rule, and the sum rule has the best classification results followed in order by the product rule, the median rule, majority vote rule and max rule. The results are consistent with the analysis in [21] except for the product rule, which is the worst combination rule there.

B. Experimental results on Yale face database

The Yale dataset consists of 165 images of 15 subjects under various facial expressions and lighting conditions. Each image is cropped according to the eye positions and rescaled to 32×32 pixels in our experiments. We carried out a series of experiments to compare the performance of EGFR-based and MGFR-based $(2D)^2$PCA method against $(2D)^2$PCA method under conditions where the sample size is varied. In MGFR-based $(2D)^2$PCA method the group of 64+1 channels is selected. Table 3 demonstrates the top recognition accuracy (%) achieved by different methods for varying number of training samples.

Table 3 Recognition rate (%) for different combination rules on Yale dataset

Method		Number of Training Samples per Class			
		2	3	4	5
$(2D)^2$PCA		84.44	87.50	89.52	91.11
EGFR+$(2D)^2$PCA		85.19	88.33	95.24	96.67
MGFR +$(2D)^2$PCA	Sum	83.70	91.67	95.24	96.67
	Product	82.96	91.67	95.24	96.67
	Min	82.96	84.17	91.43	84.44
	Max	83.70	88.33	93.33	92.22
	Median	80.00	91.67	95.24	96.67
	Majority Vote	92.59	92.50	98.10	98.89

We can see from Table 3 that 1) the performance of EGFR-based and MGFR-based $(2D)^2$PCA method are better than $(2D)^2$PCA method except for few cases 2) the worst results are achieved when using the min rule, and the majority vote rule has the best classification results and 3) the sum rule, product rule and median rule have the approximate performance except for the condition in which the number of training samples per class is 2.

VI. CONCLUSION

In summary, the main contribution of this paper is in two respects. First of all, we propose a scheme that is based on linear correlation criterion to select Gabor filter bank as uncorrelated as possible, which directly results in a

reduction of redundancy of feature sets. And we obtain the optimal Gabor filter bank to achieve the minimal values in the correlation matrix. In addition, we introduce two kinds of 2D Gaborface representation methods: EGFR and MGFR. As opposed to conventional Gabor-based method, our method is based on 2D Gaborface matrices rather than 1D sampled feature vectors. Therefore, there is no loss of information due to downsampling.

From our experimental results on ORL and Yale databases, we can see that the MGFR-based $(2D)^2PCA$ method achieves the best face recognition performance as compared with the others. Moreover, the method shows good performance in the low dimension. In addition, we apply six commonly used classifier combination rules to evaluate the performance of the MGFR-based $(2D)^2PCA$ method, and find that no rule is superior to others in all conditions and the sum rule, product rule, the majority vote rule and median rule have the approximate excellent performance, whereas the min rule has the worst classification results. In [21], Kittler and Hatef proved that the sum rule outperformed other rules and the worst one was product rule, which are a little inconsistent with our results. However, it should be pointed out that the multiple Gaborface channels have parallel and mutual complementary characteristics and the number of classifiers in our MGFR method is much higher than the one in [21] and these may be some explanations of the varieties in the performance of different fusion rules. Comparing the results of different groups of channels, we find that the orientation channels contain more discriminating information than the scale channels.

REFERENCES

[1]. [1] M. Turk, A. Pentland, Eigenfaces for recognition, Journal of Cognitive Neuroscience, 3(1), 1991, 71-86.

[2]. D. Field, Relations between the statistics of natural images and the response properties of cortical cells, J. Opt. Soc. Amer. A, Vol. 4, No. 12, 1987, pp. 2379-2394.

[3]. T. S. Lee, Image Representation Using 2D Gabor Wavelets, IEEE Trans. On PAMI, Vol. 18, No. 10, October 1996.

[4]. C. J. Liu, H. Wechesler, Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition. IEEE Trans. On Image Processing, Vol. 11, No. 4, 2002, pp. 467-476.

[5]. C. J. Liu, Gabor-Based Kernel PCA with Fractional Power Polynomial Models for Face Recognition, IEEE Trans. On PAMI, Vol. 26, No. 5, 2004.

[6]. O. Ayinde, Y. H. Yang, Face recognition approach based on rank correlation of Gabor-filtered images, Pattern Recognition. Vol. 35, 2002, pp. 1275-1289.

[7]. P. Kalocsai, C. von der Malsburg, etc, Face recognition by statistical analysis of feature detectors, Image and Vision Computing. Vol. 18, No. 4, 2000, pp. 273-278.

[8]. J. Qin, Z. S. He, A SVM Face Recognition Method Based on Gabor-Featured Key Points, Proc. 4th IEEE Conf. on Machine Learning and Cybernetics, 2005, pp. 5144-5149.

[9]. Y. Hamamoto, S.Uchimura, etc, A Gabor Filter-Based Method for Recognizing Handwritten Numerals, Pattern Recognition. 31(4), 1998, pp. 395-400.

[10]. R. Alterson, M. Spetsakis, Object recognition with adaptive Gabor features, Image and Vision Computing, Vol. 22, 2004, pp. 1007-1014.

[11]. J. Yang, D. Zhang, etc, Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition, IEEE Trans. On PAMI, Vol. 26, No.1, 2004, pp.131-137.

[12]. T. Randen, J.H. Husøy, Multichannel filtering for image texture segmentation, Optical Eng., Vol. 33, 1994, pp. 2617-2625.

[13]. A. C. Bovik, M. Clark, W. S. Geisler, Multichannel Texture Analysis Using Localized Spatial Filters, IEEE Trans. On PAMI, Vol. 12, No. 1, 1990, pp.55-73.

[14]. W. Fan, Y. H. Wang, etc, Combining Null Space-based Gabor Features for Face Recognition, Proc. 17th IEEE Conf. On Pattern Recognition, Vol.1, 2004, pp. 330-333.

[15]. F. Farrokhnia, A. K. Jain, A multi-channel filtering approach to texture segmentation, IEEE Conf. on Computer Vision and Pattern Recognition, 1991, pp. 364-370.

[16]. S. G. Mallat, Multifrequency channel decompositions of images and wavelet models, IEEE Trans. Acoust., Speech, Signal Process., Vol. 37, No. 12, 1989, pp. 2091-2110.

[17]. D. Q. Zhang, Z. H. Zhou, $(2D)^2PCA$: 2-Directional 2-Dimensional PCA for efficient face representation and recognition, Neurocomputing, Vol. 69, 2005, pp. 224-231.

[18]. S. Bi, D. Liang, Texture Segmentation using adaptive Gabor filters based on HVS, SPIE, Vol. 6057, 2006.

[19]. Z.R. Long Puhui, A new texture segmentation method based on visual perception and phase feature, Proc. 3rd International Conf. On Signal Processing, 1996, pp. 1015-1018.

[20]. A. P. Ginsburg, Specifying relevant spatial information for image evaluation and display design: an explanation of how we see certain objects, Proc. of the SID. 21 (3), 1980, 219-227.

[21]. J. Kittler, M. Hatef, etc, On Combining Classifiers, IEEE Trans. On PAMI, Vol. 20, No. 3, 1998, pp.226-239.