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A GABOR FEATURE BASED HORIZONTAL AND VERTICAL DISCRIMINANT FOR FACE VERIFICATION

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Abstract. *In this paper, a novel discriminant analysis method for a Gabor-based image feature extraction and representation is proposed and then implemented. The horizontal and vertical two-dimensional principal component analysis (HV-2DPCA) is directly applied to a Gabor face to reduce the redundant information and preserve a bi-directional characteristic as well. It is followed by an enhanced Fisher linear discriminant model (EFM) generating a low-dimensional feature representation with enhanced discrimination power. By the most discriminant features, different types of classes of training samples are made widely apart and the same category classes are made as compact as possible. This novel algorithm is designated as the horizontal and vertical enhanced Gabor Fisher discriminant (HV-EGF) in this paper. By use of various dimensions of features as well as various numbers of training samples, our experiments indicate that the proposed HV-EGF method provides a superior recognition accuracy relative to those by the Fisher linear discriminant (FLD), the EFM and the Gabor Fisher classifier (GFC) methods. In our proposal, the recognition accuracies up to 99.0% and 97.7% are reached with images of features dimensions* $38 \times 38 \times 2$ *and* $10 \times 10 \times 2$ *on the ORL and the Yale databases, respectively.*

Keywords: Gabor Fisher classifier (GFC), Fisher linear discriminant (FLD), Enhanced Fisher linear discriminant model (EFM), Horizontal and vertical enhanced Gabor Fisher discriminant (HV-EGF)

1. **Introduction.** Face recognition has recently attracted wide attention of the researchers in the field of biometric authentication. There are a great number of techniques developed to extract textures from face data, such as Fourier transformation, wavelet transformation and Gabor filtering, among which the Gabor filtering is demonstrated as an effective approach for face recognition [1,2], sustaining face recognition performances under varying illuminations and poses. The Gabor filtering representation is validated able to capture salient visual properties such as spatial localization, orientation selectivity and spatial frequency [3,4].

In the face representation and recognition with Gabor filtering, five different scales and eight orientations Gabor filters are used in most cases to extract different spatial frequencies and orientation textures, which leads to a large dimensional Gabor face. The identification recognition is turned into a complex task full of challenges due to the high dimensional face image data. In an effort to circumvent the above mentioned problem, there have been plenty of methods proposed for face representation and recognition, one of which is the Principal Component Analysis (PCA) [5-9] aiming to preserve a global structure and reduce the dimensionality based on the shared characteristics among the transformation methods. It is firstly indicated by Sirovich and Kirby that an arbitrary human face can be represented along an eigenvector coordinate space [5], and Turk and Pentland further proposed the well-known Eigenfaces method for face recognition based on PCA [6]. Dagher and Nachar [7] found a fast incremental principal non-Gaussian directions analysis algorithm, referred to as IPCA-ICA, which is done by merging the runs of two algorithms based on PCA and independent component analysis (ICA) running sequentially. A high average success rate rendered by this algorithm is reached in contrast to others by simulations on various databases. Furthermore, Xie and Lam [8] describe a novel improved version of PCA in terms of nonlinear mapping, which is performed in an original feature space. Taking into account the statistical property of the input features, the proposed nonlinear mapping adopts an eigenmask to emphasize the facial feature points of interest. By Vaswani and Chellappa in [9], a novel classification algorithm is proposed on the basis of the principal component subspace (PCA space) for the entire data, which is designed for classification problems, such as object recognition where different classes are of distinct and nonwhite noise covariance matrices.

Although the PCA has been proven to be one of the most effective methods in face recognition, it still undergoes the problem of a high dimensional vector space due to the vector operation therein. In a vector operation mode, the computation of the eigenvectors of a covariance matrix is highly time consuming. In the event that the training sample size is much smaller than the dimensionality of the images, the singular value decomposition (SVD) technique is found effective in the reduction of computational complexity. Yet it is seen not as effective to a large size of training sample. PCA in face recognition has not been extended to two dimensions until recently. As a popular technique widely used in many applications providing more effective and accurate results, the two-dimensional Principal Component Analysis (2DPCA) method is a straightforward image projection technique [10]. In PCA, it is requested that the 2D image matrices be mapped into pattern vectors. Instead, the 2DPCA extracts directly image features based on 2D image matrices rather than a 1D vector. In this way the image matrices do not need to be transformed into vectors. Due to the smaller size of the image covariance matrix required than that in the original PCA, 2DPCA requires less amount of time to extract image features and achieves a superior recognition accuracy.

Having been used successfully as a statistical feature extraction in a number of classification problems, another popular method for face recognition is the Fisher linear discriminant (FLD), also known as the Linear Discriminant Analysis (LDA) [11,12]. The FLD solves a generalized eigenvalue problem so as to maximize the ratio between the traces of the between-class and the within-class scatter matrices. In face image recognition applications, there are often a large number of pixels or features needed. However, there is a limited number of training samples in total, which is commonly less than the dimension of the feature space. The within-class scatter matrix will be singular in case its rank is found less than the number of feature. A considerable amount of research has been devoted to the design of Fisher-based methods, for targeting small sample and high dimensional problems. In this regard, one popular technique proposed is a combined version of PCA and FLD [13,14]. In this way, the 2DPCA is first used for dimensionality reduction to remove the singularity of the within scatter matrix, and then the FLD is implemented in the 2DPCA subspace. In addition, the conventional 2DPCA method is operated on row vectors of image, but the information might be contained in column vectors of image. Therefore, both kinds of information are needed in the representation for face recognition. Based on this concept, a horizontally and vertical PCA-based discriminant analysis (HVDA) was proposed [15,16], in which 2DPCA is firstly applied horizontally and vertically on the image matrices in order to achieve a lower computational complexity, and then the FLD analysis is used for further feature extraction. As a significant feature in recognition, HVDA can preserve the covariance information between the horizontal and the vertical geometric structures in image representation.

One major drawback of FLD is that it requires a large size of training sample to reach a good generalization. An enhanced Fisher linear discriminant model (EFM) method, as presented in [17], improves the generalization performance of an FLD-based scheme by balancing the spectral energy criterion for sufficient representation and the eigenvalue spectral requirement. Applying the EFM to the integrated shape and texture features, an Enhanced Fisher Classifier (EFC) is developed by Liu and Wechsler [18]. At the onset, the dimensionalities of the shape and the texture spaces are reduced by the use of 2DPCA, and then constrained by the EFM for enhanced generalization.

An excellent face recognition system must acquire the following properties, i.e., simplicity, robustness and a high recognition accuracy. On the simplicity property, it requires low-dimensional features of the face object with enhanced discriminatory power. On the robustness property, it should be less sensitive to facial expressions, occlusions and the illumination variation. Based on these properties, a novel algorithm, referred to as the horizontal and vertical enhanced Gabor Fisher discriminant (HV-EGF), is developed in this paper. As illustrated in Figure 1, the Gabor features of different scales and orientations are firstly extracted in the algorithm by the convolution of the face image with a set of Gabor filters. The extracted features are then reorganized to form a new feature matrix, designated as a Gabor face capturing the local structure corresponding to the spatial frequency, the spatial localization and the orientation selectivity [19,20]. Based on the Gabor face, the horizontal and vertical 2DPCA are used subsequently to reduce the dimension and to preserve bi-directional characteristics. The use of the horizontal and vertical 2DPCA makes a difference between our proposal and [21,22]. It is followed by EFM generating a low-dimensional feature representation with enhanced discrimination power. By the most discriminant features, different types of classes of training samples are made widely apart and the same category classes are made as compact as possible. Finally, the nearest neighbor classifier is used for classification. In the experiments, the face recognition tasks were performed based on two well-known face databases, namely ORL and Yale. The ORL database is composed of 400 images taken from 40 individuals, each with 10 different images containing variations in facial expression and in some other details, e.g., wearing eyeglasses or not. However, the Yale face database is made up of images from 15 individuals, each providing 11 distinct facial expression images with illumination variations. Our proposal is demonstrated to not merely require less amount of computation but also outperform a number of existing popular face recognition methods, i.e., the FLD [23,24], the EFM [17] and the Gabor Fisher classifier (GFC) methods [21,22].

The rest of this paper is outlined as follows. The proposed algorithm is detailed in Section 2. Section 2.1 presents the Gabor filtering for feature extraction, Section 2.2 presents the horizontal and vertical 2DPCA to reduce the dimensionality of a Gabor face, and the EFM analysis is presented in Section 2.3. Compared with other methods, the experimental results, including the performance analysis, based on ORL and Yale face databases, are exhibited in Section 3. Concluding remarks are given in Section 4 at the end of this paper.

2. **The Proposed Algorithm.**

2.1. **Gabor feature analysis.** A Gabor representation is optimal and gives good performance for classifying facial actions. Daugman pioneered the use of the Gabor wavelet representation in computer vision in the 1980s [19,25]. In this paper, the Gabor wavelet

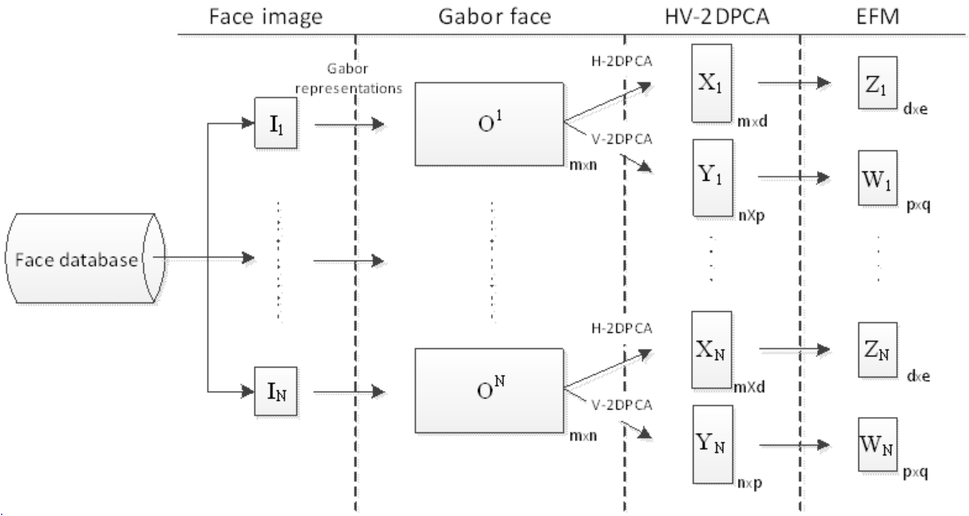


FIGURE 1. Block diagram of the proposed face recognition scheme

representation is introduced because it could provide a superior performance for classifying facial expressions [1].

2.1.1. *Gabor filtering.* Gabor filters correspond to a family of bi-dimensional Gaussian functions modulated by an even (cosine function) and odd (sine function) part. In this paper, Gabor wavelets (kernels, filters), as defined in [21,26], are expressed as

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

where $z = (x, y)$, and μ and v define the orientation and scale of a Gabor filter, respectively. $e^{ik_{\mu,v}z}$ is a function of oscillation, and $e^{\left(-\|k_{\mu,v}\|^2\|z\|^2/2\sigma^2\right)}$ is a Gaussian function reflecting the localization of the Gabor filter and confining the range of the oscillation function, where σ denotes the standard deviation of the Gaussian, $\|\cdot\|$ the norm operator, and the wave vector $k_{\mu,v}$ is defined as

$$k_{\mu,v} = k_v e^{i\phi_\mu}, \quad k_v = \frac{k_{\max}}{f}, \quad \phi_\mu = \mu\frac{\pi}{8} \tag{2}$$

where $k_{\max}$ represents the maximum frequency, and f the spacing factor between filters in the frequency domain. The Gabor kernels in Equation (1) are all similar since they can be generated from a filter, the mother wavelet, by scaling and rotation via the wave-vector $k_{\mu,v}$. Our proposal is implemented with 40 Gabor wavelet filters, i.e., combinations of eight orientations $\mu \in \{0, \ldots, 7\}$ and five scales $v \in \{0, \ldots, 4\}$, on a condition that

$$k_{\max} = \frac{\pi}{2}, \quad f = \sqrt{2}, \quad \sigma = 2\pi \tag{3}$$

Shown in Figure 2 are the real parts of the 40 Gabor filters. All the filters have a strong representation of spatial locality and orientation, making them a proper choice in an image feature extraction for face recognition.

2.1.2. *Gabor representation.* Letting $I(z)$ be the gray level distribution of the input image, the Gabor transform of I is defined as

$$O_{\mu,v}(z) = I(z) * \psi_{\mu,v}(z) \tag{4}$$

where $*$ denotes a convolution operator, and $O_{\mu,v}(z)$ the convolution result corresponding to the Gabor filter at the frequency v and the orientation μ. A set $S = \{O_{\mu,v} : v \in (0, \ldots,$

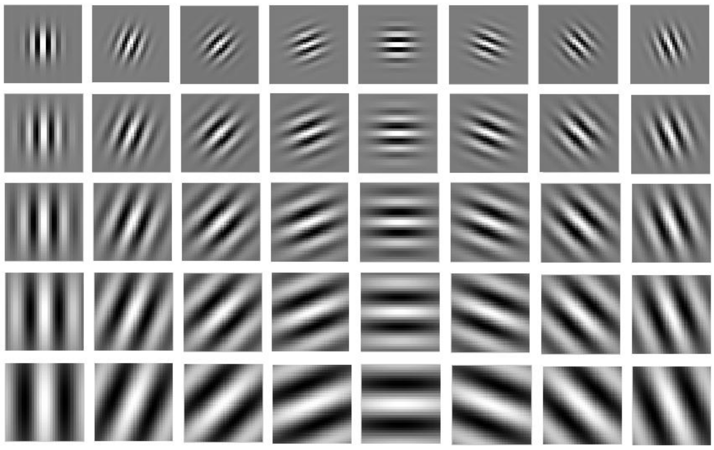
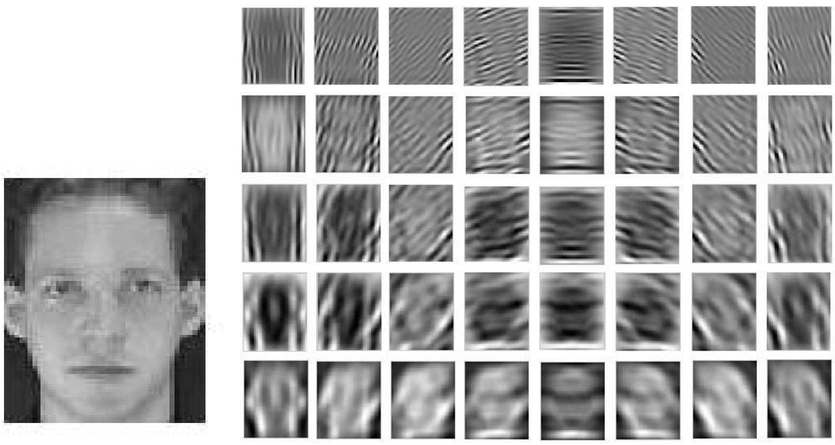


FIGURE 2. Real parts of the Gabor filters along eight orientations on five scales



(a) (b)

FIGURE 3. Illustration of a facial image response to 40 Gabor filters for (a) an original face image and (b) the Gabor representation of the face image (Gabor face)

$4), \mu \in (0, \ldots, 7)\}$ is formed as the Gabor transform representation of the gray level image $I(z)$. Now, the Fast Fourier Transform (FFT) of $O_{\mu,v}(z)$ is given as

$$F\{O_{\mu,v}(z)\} = F\{I(z)\}\, F\{\psi_{\mu,v}(z)\} \tag{5}$$

and taking the inverse transform leads to

$$O_{\mu,v}(z) = F^{-1}\{F\{I(z)\}\, F\{\psi_{\mu,v}(z)\}\} \tag{6}$$

where F and F^{-1} denote the Fourier and the inverse Fourier transform operators respectively. As the response $O_{\mu,v}(z)$ to each Gabor filter is a complex function, the real part, $Real\{O_{\mu,v}(z)\}$, is employed to represent the original face image.

Using a family of 40 Gabor filters, the Gabor representation of a face image is shown in Figure 3. The 40 $O_{\mu,v}$, as seen in Figure 3, are treated as an entity and referred to as a Gabor face O. Salient local features, such as eyes, nose and mouth that are suitable for visual event recognition [27], are characterized in a Gabor representation. Since it consists of different localities, scales and orientation features, it makes sense to perform operation on a Gabor face directly.

2.2. **The 2DPCA.** Low dimensionality is a requirement for learning and computation in practical applications. Since a Gabor output is expressed in a two-dimensional matrix form, it is required to reduce the dimensionalities accordingly. In comparison, 2DPCA is a preferred choice in face recognition, aimed at the dimensional reduction and efficient to represent a face image. Yang et al. [10] proposed a novel technique, coined 2DPCA, in which face recognition is directly performed on a 2D matrix representation, that is, there is no need to transform the image matrix into a one-dimensional vector. The eigenvectors of the original image covariance matrix are directly evaluated in the absence of a matrix-to-vector conversion. Hence, it requires a much smaller size of image covariance matrix than the PCA. Suppose that there are N training samples, O^i $(i = 1, \cdots, N)$, where O^i is an $m \times n$ Gabor representation matrix of a face image. The N training samples are then applied to the 2DPCA, which is followed by EFM generating a low-dimensional feature representation with enhanced discrimination power. The following section outlines two versions of 2DPCA, namely, the horizontal and the vertical 2DPCA.

2.2.1. *Horizontal 2DPCA.* The goal of the horizontal 2DPCA is to find a set of orthogonal projection axes $U = [u_1, u_2, \cdots, u_d]$ satisfying an identity matrix constraint $U^T U = I$. In this way the projected vectors $x_k = O^i u_k$ $(k = 1, 2, \cdots, d)$ achieve a maximum total scatter. Denoting the mean of all Gabor face image samples as $\bar{O}$, G_t, the image covariance matrix of the horizontal 2DPCA, is given as

$$G_t = \frac{1}{N} \sum_{i=1}^{N} \left(O^i - \bar{O}\right)^T \left(O^i - \bar{O}\right) \tag{7}$$

The optimal projection axes, $u_1, u_2, \cdots, u_d$, are the orthonormal eigenvectors of G_t corresponding to the first d largest eigenvalues. The image linear transformation of the horizontal 2DPCA is defined as

$$X_i = \left(O^i - \bar{O}\right) U \tag{8}$$

Thus, an m-by-d projection feature matrix $X_i = [x_1, x_2, \cdots, x_d]$ is formed with column vectors x_k $(k = 1, 2, \cdots, d)$, referred to as the project feature vector of an image O^i, where d is the number of the horizontal projections waiting to be found. The matrix $X_i = [x_1, x_2, \ldots, x_d]$ is the principal component containing the horizontal 2DPCA features of the image O^i.

2.2.2. *Vertical 2DPCA.* By analogy with Equation (7), the image covariance matrix of the vertical 2DPCA is defined as

$$H_t = \frac{1}{N} \sum_{i=1}^{N} \left(O^i - \bar{O}\right) \left(O^i - \bar{O}\right)^T \tag{9}$$

Letting $V = [v_1, v_2, \ldots, v_p]$ be the orthonormal eigenvectors of H_t corresponding to the p largest eigenvalues, the image linear transformation of the vertical 2DPCA is given by

$$Y_i = \left(O^i - \bar{O}\right)^T V \tag{10}$$

where $Y_i = [y_1, y_2, \ldots, y_p]$ denotes the principal component containing the vertical 2DPCA features of the image O^i.

2.2.3. *Properties.* There are three properties in both the horizontal and the vertical 2DPCA, i.e., the invariance, the uncorrelation and the minimal mean square error (MSE) properties. The transform matrix of horizontal (vertical) 2DPCA is invariant to any change in image row (column) sequence. Any change in the sequence of image rows (columns) of a training image demonstrates no effect on G_t (H_t). The invariance property

(a) $d = 3$ (b) $d = 10$ (c) $d = 20$ (d) $p = 3$ (e) $p = 10$ (f) $p = 20$

FIGURE 4. (a)-(c) Images reconstructed by the horizontal 2DPCA, and (d)-(f) images reconstructed by the vertical 2DPCA

is an advantage of 2DPCA over PCA in the aspect of image representation. The uncorrelation property of 2DPCA is due to the fact that the projection axes of 2DPCA are the set of orthonormal eigenvectors of the covariance matrix. Thus, the projection feature vectors satisfy the conditions $Cov\left(x_i, x_j\right) = 0$, $i \neq j$, $i, j = 1, \cdots, d$ and $Cov\left(y_i, y_j\right) = 0$, $i \neq j$, $i, j = 1, \cdots, p$.

As in PCA, the original face O^i in the 2DPCA method can be reconstructed by

$$\tilde{O}^i = \sum_{j=1}^{d} x_j u_j^T \tag{11}$$

where $\tilde{O}^i$, the same size as O^i, denotes a reconstructed image of O^i. Illustrated in Figure 4 is the invariance property of the reconstruction of the horizontal and vertical 2DPCA methods. The reconstruction MSE can be computed as

$$\varepsilon^2 = E\left\|O^i - \tilde{O}^i\right\|^2 \tag{12}$$

where $\|\cdot\|$ denotes the Frobenius norm of a matrix. The optimal projection axes, u_1, u_2, $\cdots, u_d$ $(v_1, v_2, \cdots, v_p)$ are the orthonormal eigenvectors of G_t (H_t) corresponding to the first $d(p)$ largest eigenvalues. The reconstruction MSE is thus minimized by use of the first $d(p)$ eigenvectors to represent O^i.

2.3. **The enhanced Fisher linear discriminant model (EFM).** As illustrated in Figure 1, an HV-2DPCA is cascaded with an EFM to generate a low-dimensional feature representation with enhanced discrimination power. By this most discriminant features, different types of classes of training samples are made widely apart and the same category classes are made as compact as possible. Viewed as an enhanced FLD, the EFM method employs a more efficient numeric by which the FLD procedure is decomposed into a simultaneous diagonalization of the within-class and the between-class scatter matrices. Assuming that the principal components of the horizontal 2DPCA, X_i, $i = 1, \cdots, N$, as defined in Equation (10), are clustered into classes $\prod_1, \cdots, \prod_c$, and that there are N_j images in the class $\prod_j$, then there is a total of $N_1 + \cdots + N_c = N$ images. Define the between-class and the within-class scatter matrices respectively as

$$S_b = \sum_{j=1}^{c} N_j\left(M_j - M\right)\left(M_j - M\right)^T \tag{13}$$

and

$$S_w = \sum_{j=1}^{c} \sum_{X_i \in \prod_j} \left(X_i - M_j\right)\left(X_i - M_j\right)^T \tag{14}$$

where $M_j = \frac{1}{N_j}\sum_{X_i \in \prod_j} X_i$ denotes the mean of the jth class, and the global mean M is given by

$$M = \frac{1}{N}\sum_{j=1}^{c}\sum_{X_i \in \prod_j} X_i \tag{15}$$

The EFM method first whitens the within-class covariance matrix as

$$S_w \Xi = \Xi\Gamma \text{ and } \Xi^T\Xi = I \tag{16}$$

$$\Gamma^{-1/2}\Xi^T S_w \Xi\Gamma^{-1/2} = I \tag{17}$$

where $\Xi \in R^{m\times m}$ represents the eigenvector matrix of S_w, I the unitary matrix and $\Gamma \in R^{m\times m}$ the eigenvalue matrix of S_w with diagonal elements in descending order. The EFM then computes the new between-class scatter matrix as

$$K_b = \Gamma^{-1/2}\Xi^T S_b \Xi\Gamma^{-1/2} \tag{18}$$

Now, the new between-class scatter matrix is diagonalized as

$$K_b\Psi = \Psi\Lambda \text{ and } \Psi^T\Psi = I \tag{19}$$

where $\Psi \in R^{m\times m}$ denotes the eigenvector matrix of K_b and $\Lambda \in R^{m\times m}$ the eigenvalue matrix of K_b. The overall transformation matrix of the EFM can be defined as

$$T = \Xi\Gamma^{-1/2}\Psi \tag{20}$$

and the ith horizontal feature matrix Z_i of dimension $d \times e$ is defined as

$$Z_i = X_i^T T \tag{21}$$

By analogy with Equation (21), the ith vertical feature matrix, denoted by W, of EFM can be expressed as

$$W_i = Y_i^T R \tag{22}$$

where Y_i is defined as in Equation (10), and the overall transformation matrix R is obtained by replacing S_b and S_w in Equations (16) and (18) with S_b' and S_w', respectively. (S_b' and S_w' are the between-class and the within-class scatter matrices obtained by replacing X_i in Equations (13) and (14) with Y_i, respectively). W is a feature matrix of dimension $p \times q$.

3. **Experiments and Discussions.** In this section, the performance of the proposed HV-EGF is evaluated in comparison with a number of popular face recognition methods, i.e., the FLD [23,24], the EFM [17] and the Gabor Fisher classifier (GFC) methods [21,22], for a face recognition task based on the well-known ORL and Yale face databases.

3.1. **ORL database.** The ORL database consists of 400 images taken from 40 individuals, each with 10 different images. These 10 images were taken at different time instants, containing variations in facial expression (open or closed eyes, smiling or non-smiling), facial position (there are slightly rotated faces) and variations in some other details like wearing eyeglasses or not. In the experiment, each original input image is of the size 56×46 pixels. Through the Gabor filters, there are 40 Gabor feature images to form a Gabor face with a spatial resolutions of 280×368 pixels, namely, the Gabor face is of the dimension 280×368.

The first performance analysis is made with a focus on the dimensionality reduction of the HV-EGF method because a low dimensionality representation is critical for learning [6]. Tabulated in Table 1 is a series of experimental results obtained by applying different dimensions of feature space of size $d \times e(= p \times q)$, where $d(p)$ and $e(q)$ respectively denote the numbers of projection vectors of $U(V)$ and $T(R)$. For each recognition evaluation, five training samples are selected randomly and the remaining five are used as a testing set. Eight tests were performed with successive subspace dimensions varying as 10, 15, 20, 25, 30, 37, 38 and 39. As can be seen in Table 1, dimension 38×38 is the case with the best recognition accuracy and training efficiency at the same time. Therefore, in the subsequent sets of experiments, the same choice of the dimensionality is made on the ORL database.

Tabulated in Table 2 are the best average recognition accuracies of various algorithms on a condition that all the training samples are fixed for each class. In the first test, the first two samples of each class are chosen as a training set and the remaining are used as test set. In each of the following tests, the numbers of the training and the testing samples are added and decreased by 1 respectively in each class. This process was repeated until the same number of the training and the testing samples are seen. It is demonstrated that the proposed HV-EGF scheme outperforms the others in every test.

In comparison with FLD and GFC on the ORL face database, the recognition performance of the proposed HV-EGF approach is plotted in Figure 5 against the dimension of the feature vectors. Five samples of each class are randomly selected for training and the

TABLE 1. The recognition accuracy (%) of HV-EGF on the ORL database against feature dimension under five training samples selected randomly

Dimensions	10×10	15×15	20×20	25×25	30×30	37×37	38×38	39×39
Recognition accuracy (%)	92.5	93.5	94.0	94.5	96.5	98.5	99.0	99.0

TABLE 2. Comparison of the recognition accuracy (%) of some fixed training samples using the ORL database

Training samples/class	1	2	3	4	5
FLD	–	82.5	84.5	90.0	93.0
EFM	–	83.5	89.5	91.5	93.5
GFC	–	85.0	89.5	92.0	97.5
HV-EGF	–	91.0	93.5	94.0	99.0

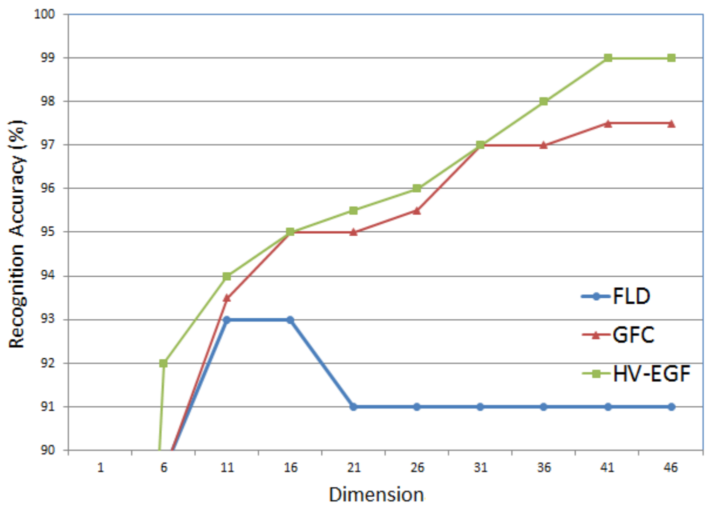


FIGURE 5. A plot of the recognition accuracy vs. the dimension of the feature vectors

Table 3. The recognition accuracy (%) of HV-EGF on the Yale database against feature dimension under training samples randomly selected

Dimensions	8×8	9×9	10×10	11×11	12×12	20×20	30×30	40×40
Recognition accuracy (%)	92.2	94.4	97.7	96.6	95.5	97.7	94.4	91.1

Table 4. Comparison of the recognition accuracy (%) among different training samples using the Yale database for some sampled fixed

Training samples/class	1	2	3	4	5
FLD	–	80.0	84.4	85.6	90.0
EFM	–	81.1	85.6	86.7	91.1
GFC	–	78.8	88.8	90.0	95.5
HV-EGF	–	83.3	91.1	92.2	97.7

remaining are for testing. It is clearly seen that the proposed HV-EGF approach outperforms the other two due to the reason that the integrated Gabor filters, the HV-2DPCA and the EFM are all combined. The Gabor transformed face images are localized and vary in frequencies and orientations in contrast to the original face images. The HV-2DPCA method then eliminates redundant features and forms a discriminant representation that is more compact. The EFM module adopts an eigenvalue spectrum analysis criterion in the determination of the number of principal components to avoid over-fitting.

3.2. **Yale database.** The Yale face database contains the images taken from 15 individuals, each individual providing 11 different facial expression images with illumination variations. In an attempt to test the sensitivities of the horizontal and the vertical displacements by the proposed HV-2DPCA method, most of the background remains intact. All images are displayed in grayscale and normalized to a resolution of 61×80 pixels.

The recognition accuracy of our proposal against feature dimension is given in Table 3 for the Yale database. Among the 11 different facial expression images taken from an individual, five are chosen randomly as the training samples (75 images in total) and the remaining are as the testing (90 images in total). Tabulated in Table 3 are the experimental results against dimensions (8, 9, 10, 11, 12, 20, 30 and 40) of features. It is seen that a very high recognition accuracy approaching 98% is reached in the case of a very low subspace dimensions 10×10 by our proposal.

Next, a performance comparison of some fixed training samples is made among the FLD, EFM, GFC and the proposed HV-EGF. In the first test, the first two images of each class containing the 11 different facial expression images of an individual as mentioned above is used as a training sample, and the remaining nine images are used as test samples. In each of the following tests, the numbers of the training and the testing samples are increased and decreased by 1 respectively in each class. This process was repeated until test 4. It is clearly seen that the proposed HV-EGF scheme outperforms the others in every test.

Finally, the proposed HV-EGF method is plotted in Figure 6 against the dimension of the feature vectors and compared as well with FLD and GFC on the Yale face database. The HV-EGF method is demonstrated to characterize most of the effective discriminative information by use of merely 10 feature dimensions.

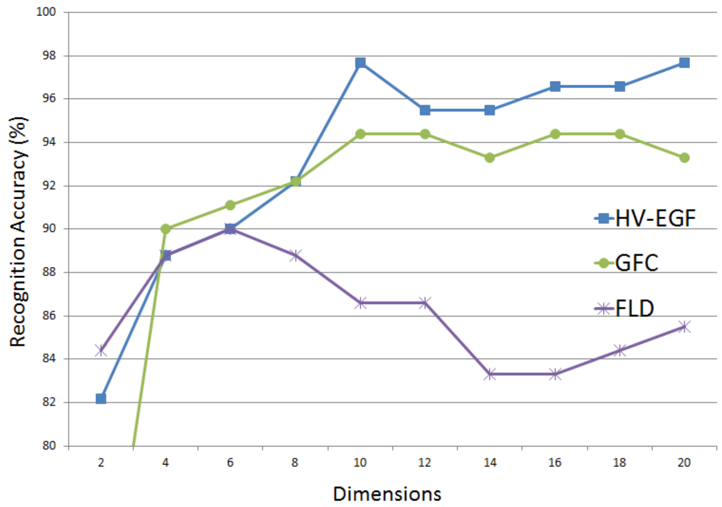


FIGURE 6. A plot of the recognition accuracy vs. the dimension of the feature vectors

TABLE 5. The best accuracy (%) and the corresponding dimension on the ORL and Yale databases

Method	ORL Database		Yale Database	
	Best recognition accuracy (%)	Corresponding dimensions	Best recognition accuracy (%)	Corresponding dimensions
FLD	93.0%	11×11	90.0%	6×6
EFM	93.5%	10×10	91.1%	3×3
GFC	97.5%	39×39	95.5%	15×15
HV-EGF	99.0%	$38 \times 38 \times 2$	97.7%	$10 \times 10 \times 2$

3.3. **Summary.** In summary, Table 5 tabulates the best recognition accuracies and the corresponding dimensions thereof for the FLD, EFM, GFC and HV-EGF methods on the two databases. It is noted that the GFC and HV-EGF methods are both of higher recognition accuracies in situations with different head poses, facial expressions (ORL database), and illumination variance (Yale database) is Gabor-based. The performances of the GFC and the proposed HV-EGF methods are analyzed in the same context. Taking into account the horizontal and vertical sensitivities of the features, the HV-EGF method outperforms the GFC. The HV-EGF method achieves the highest recognition rates up to 99.0% and 97.7% on the ORL and the Yale databases, respectively. By contrast, the best results provided by FLD are merely 93.0% and 90.0% on the ORL and the Yale databases, respectively. The HV-EGF method takes advantage of the horizontal and vertical 2DPCA-based properties and the generalization capability of FLD of the Gabor features to enhance the recognition accuracy for all training/testing percentages. In short, the HV-EGF method outperforms the FLD, the EFM and the GFC methods in any case.

4. **Conclusions.** In this paper, a novel discriminant analysis method of the Gabor features for an image feature extraction and representation is proposed and then implemented. In the method, the horizontal and vertical 2DPCA is directly applied to a Gabor face derived from the Gabor wavelet representation of an image. The 2DPCA reduces the redundant information and preserves a bi-directional characteristic as well. It is followed by an EFM obtaining the discriminating features, according to which classification

is made more reliable. The feasibility of the novel HV-EGF method has been successfully tested for face recognition using a data set chosen from both the ORL and the Yale databases, treated as two standard testing beds for face recognition technologies. In our experiments, the HV-EGF method is tested by using various dimensions of features and various numbers of training samples. The experimental results show that our proposed method not only requires less amount of computation but also outperforms a number of popular face recognition methods, i.e., the FLD, the EFM and the Gabor Fisher classifier (GFC) methods. It is also exhibited that best recognition accuracies up to 99.0% and 97.7% are reached by our proposal for the ORL and the Yale databases, respectively. In addition, the features required for the proposed HV-EGF method on the ORL and Yale are of the dimensions $38 \times 38 \times 2$ and $10 \times 10 \times 2$, respectively.

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