# Face Recognition Using Gabor Filter Bank, Kernel Principle Component Analysis and Support Vector Machine

Saeed Meshgini, Ali Aghagolzadeh, and Hadi Seyedarabi

***Abstract*—This paper presents a novel face recognition method based on the Gabor filter bank, Kernel Principle Component Analysis (KPCA) and Support Vector Machine (SVM). At first, the Gabor filter bank with 5 frequencies and 8 orientations is applied on each face image to extract robust features against local distortions caused by variance of illumination, facial expression and pose. Then, the feature reduction technique of KPCA is performed on the outputs of the filter bank to form the new low-dimensional feature vectors. Finally, SVM is used for classification of the extracted features. The proposed method is tested on the ORL face database. The experimental results reveal that the proposed method has a maximum recognition rate of 98.5% which is higher than the other related algorithms applied on the ORL database.**

***Index Terms*—Face recognition, Gabor filter bank, kernel principle component analysis, support vector machine.**

## I. Introduction

The technology of automatic face recognition involves computer recognition of personal identity based on the geometric or statistical features derived from face images [1]. This technology can be used in wide range of applications such as identity authentication, access control, and surveillance. Interests and research activities in face recognition have increased significantly over the past few years. A face recognition system should be able to deal with the various changes in face images. However, the variations between the images of the same face due to illumination and the viewing pose are near always larger than the image variations due to change in face identity [2]. This problem causes a great challenge in face recognition. Two issues are important when a face recognition system is designed. The first is what features should be extracted from face images. The selected features have to represent the discriminating properties between different faces in an effective manner. They should also be robust against the different variations within the images of one face such as changes in viewpoint, illumination and expression. The second issue is how to classify a new face image using the selected features [3].

In recent years, extracting the effective features according to the human visual sense principles has been a hot research topic. Recently, researchers show that Gabor wavelets whose kernels are similar to the response of the two-dimensional receptive field profiles of the mammalian simple cortical cell, exhibit the desirable characteristics of capturing salient visual properties such as spatial localization, orientation selectivity, and spatial frequency [4]. Now, more and more researches are being conducted on face recognition approach which uses Gabor wavelets to extract the human face features. But the size of Gabor face feature dimensions computed by each pixel is very large; so the complexity is very high. To reduce the dimensions, many researchers utilized simple down sampling technique to select feature points [5]. However these methods which used down sampling strategy still have high dimensions of feature matrix and, in addition, can lead to partial loss of feature discriminative information. Therefore, it causes accuracy reduction in the classification stage. So, researchers used PCA or other feature extraction approaches to reduce the size of dimensions [6].

After the stage of feature extraction, the extracted features have to be entered to a powerful classifier. Support Vector Machines (SVMs) have been proposed by Vapnik [7] as a very effective method for general purpose pattern recognition. Intuitively, given a set of points belonging to two classes, a SVM finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. According to Vapnik [7], this hyperplane is called Optimal Separating Hyperplane (OSH) which minimizes the risk of misclassifying not only for the examples in the training set, but also for the unseen examples of the test set.

According to the above discussion, this paper presents a novel face recognition system by integrating the Gabor wavelet representation of face images, the kernel PCA method and SVM classifier. At first, the Gabor filter bank with 5 scales and 8 orientations is used for feature extraction from raw face images because the Gabor filters remove most of the variability in image caused by changes in lighting conditions and contrast and create robust features against illumination and pose variations. Then, the KPCA technique is applied to reduce the dimensionality of the filtered images. Finally, a multi-SVM (multi class support vector machine) is used for classification. We examine the performance of our proposed method over the ORL face database and compare the obtained results with those in the latest published papers. The experimental results show that our proposed method has a maximum recognition rate of 98.5% which is higher than the other similar algorithms tested on the ORL database.

The rest of this paper is organized as follows. Section 2

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gives the background information about the Gabor filter bank, KPCA, and SVM. Section 3 presents the proposed algorithm. Experimental results are given in Section 4 and Section 5 concludes the paper.

## II. Background Information

### A. Gabor Filter Bank

As mentioned before, the characteristics of the Gabor wavelets (filters), especially for frequency and orientation representations, are similar to those of the human visual system and they have been found to be particularly appropriate for texture representation and discrimination. The Gabor filter-based features, directly extracted from gray-level images, have been widely and successfully applied to different pattern recognition problems [8]. In the spatial domain, a 2-D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. It can be represented by

$$\Psi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x'^2+y'^2}{2\sigma^2}\right)\exp(j\omega x') \quad (1)$$
$$x' = x\cos\theta + y\sin\theta \;,\quad y' = -x\sin\theta + y\cos\theta$$

where $(x, y)$ is the pixel position in the spatial domain, $\omega$ is the central angular frequency of a sinusoidal plane wave, $\theta$ is the anti-clockwise rotation of the Gaussian function (the orientation of the Gabor filter), and $\sigma$ represents the sharpness of the Gaussian function along both $x$ and $y$ directions. We set $\sigma \approx \pi/\omega$ to define the relationship between $\sigma$ and $\omega$ in our experiments [9].

The Gabor filters with the different frequencies and orientations, which form the Gabor filter bank, have been used to extract features of face images. In most cases, a Gabor filter bank with 5 frequencies and 8 orientations is used [10]. Fig. 1 shows the Gabor filter bank with 5 different scales and 8 different orientations.

The following equations give 5 frequencies ($m = 1,2,\ldots,5$) and 8 orientations ($n = 1,2,\ldots,8$) for the Gabor filter bank:

$$\omega_m = \frac{\pi}{2}\times\sqrt{2}^{-(m-1)} \quad , \quad \theta_n = \frac{\pi}{8}(n-1) \quad (2)$$

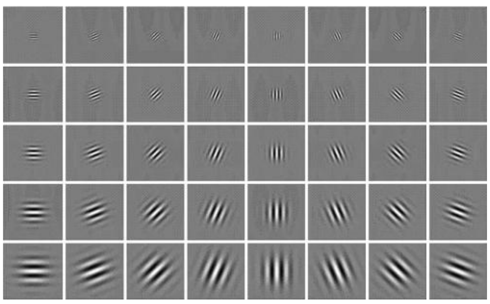

Fig. 1. Real parts of the Gabor filters at 5 scales and 8 orientations.

The input image $I(x,y)$ is convolved with the Gabor filter $\Psi_{\omega,\theta}(x,y)$ to obtain Gabor feature representation as

$$G_{m,n}(x,y) = I(x,y) * \Psi_{\omega_m,\theta_n}(x,y) \quad (3)$$

The phase of $G_{m,n}(x,y)$ changes linearly with small displacement in the direction of the sinusoid, but its magnitude changes slowly with the displacement [11]. Hence, we use the magnitude of the convolution outputs.

### B. Kernel PCA

Principal Component Analysis (PCA), a powerful technique for reducing a large set of correlated variables to a smaller set of uncorrelated components, has been applied extensively for both face representation and face recognition. Kirby and Sirovich [12] showed that any particular face can be effectively represented along the eigenpictures coordinate space. Therefore, any face can be approximately reconstructed by using just a small collection of eigenpictures and the corresponding projections. Applying PCA technique to face recognition, Turk and Pentland [13] developed a well-known eigenfaces method, where the eigenfaces correspond to the eigenvectors associated with the largest eigenvalues of the face covariance matrix. The eigenfaces thus define a feature space, or "face space" which drastically reduces the dimensionality of the original space, and face detection and recognition are then carried out in the reduced space.

PCA algorithm, however, considers only the second order statistics (variances and covariances) of the input data. Since these second order statistics provide only the partial information on the statistics of face images, it might become necessary to incorporate the higher order statistics as well. Toward that goal, PCA is extended to a nonlinear form by mapping nonlinearly the input space to a feature space, where PCA is applied [14]. In other words, a pattern in the original input space is mapped into a potentially much higher dimensional feature vector in the feature space. An initial motivation of KPCA is to perform PCA in the feature space. However, it is difficult to do so directly because it is computationally very extensive to compute the dot products in a high dimensional feature space. Fortunately, kernel techniques can be used to avoid this difficulty. The algorithm can be actually implemented in the input space by virtue of kernel tricks. The explicit mapping process is not required at all [15]. Now, let us describe KPCA formalization as follows.

Given a set of $M$ samples $x_1, x_2, \ldots, x_M \in \mathbb{R}^N$ in the input space, suppose $\Phi$ be a nonlinear mapping between the input space and the feature space such as $\Phi: \mathbb{R}^N \to \mathcal{F}$. Note that, for KPCA, the nonlinear mapping $\Phi$ usually defines a kernel function. Assume $D$ represents the data matrix in the feature space: $D = [\Phi(x_1)\ \Phi(x_2)\ \ldots\ \Phi(x_M)]$. Let $K \in \mathbb{R}^{M\times M}$ define a kernel matrix by means of dot product in the feature space as in

$$K_{ij} = \Phi(\mathbf{x}_i)\cdot\Phi(\mathbf{x}_j) \quad (4)$$

Scholkopf and Smola [16] showed that the eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_M$ and the eigenvectors $V_1, V_2, \ldots, V_M$ of KPCA can be derived by solving the following eigenvalue equation

$$KA = MA\Lambda \quad \text{with} \quad A = [\alpha_1\ \alpha_2\ \ldots\ \alpha_M]$$
$$\Lambda = diag\{\lambda_1, \lambda_2, \ldots, \lambda_M\} \quad (5)$$

where $A \in \mathbb{R}^{M\times M}$ is an orthogonal eigenvector matrix, $\Lambda \in$

$\mathbb{R}^{M\times M}$ is a diagonal eigenvalue matrix with diagonal elements in decreasing order ($\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_M$) and $M$ is a constant (the number of training samples). In order to derive the eigenvector matrix $V = [V_1\ V_2\ \ldots\ V_M]$, of KPCA, first, $A$ should be normalized such that $\lambda_i\|\alpha_i\|^2 = 1$, $i = 1,2,\ldots,M$. The eigenvector matrix, $V$, is then derived as

$$V = DA. \tag{6}$$

Let $\mathbf{x}$ be a test sample whose image in the feature space is $\Phi(\mathbf{x})$. The KPCA features of $\mathbf{x}$ are derived as

$$F = V^t\Phi(\mathbf{x}) = A^tB \tag{7}$$

where $B = [\Phi(x_1)\cdot\Phi(x)\ \Phi(x_2)\cdot\Phi(x)\ \ldots\ \Phi(x_M)\cdot\Phi(x)]^t$.

### C. SVM

As mentioned before, SVM is a pattern classifier which aims to find the Optimal Separating Hyperplane (OSH) between two classes of the classification problem. The OSH is the hyperplane that separates the positive and negative training samples with the maximum margin. Also, SVM tries to minimize the number of misclassified training samples. Both of these are obtained by solving an optimization problem. Thus, we can obtain a classifier that has the best generalization ability.

Suppose training samples are given as a set of pairs, $\{(x_1,y_1),(x_2,y_2),\ldots,(x_M,y_M)\}$, where $x_i \in \mathbb{R}^N$ indicates a feature vector and $y_i \in \{-1,1\}$ shows its label. In other words, if $y_i = 1$, then $\mathbf{x}_i$ belongs to the positive class, otherwise it belongs to the negative one. The kernel function $K(x_i,x_j)$ is used to map the training data from the input space to the feature space. SVM aims to obtain a decision function $f$ such that it can automatically recognize the label of a test feature vector $\mathbf{x}$. To do this, SVM has to solve the following optimization problem

$$\underset{\alpha}{\text{Maximize}} \quad W(\alpha) = \sum_{i=1}^{M}\alpha_i - \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\alpha_i y_i \alpha_j y_j K(\mathbf{x}_i,\mathbf{x}_j) \tag{8}$$

$$\text{subject to} \quad \sum_{i=1}^{M}\alpha_i y_i = 0,\ \alpha_i \in [0,C],\ i = 1,2,\ldots,M$$

where $\alpha_1,\alpha_2,\ldots,\alpha_M$ are Lagrange coefficients and $C$ is a constant. Lagrange multipliers are obtained by solving the above problem. Support vectors are the training samples which their corresponding Lagrange coefficients are not zero. After determining support vectors and their corresponding Lagrange coefficients, the decision function, $f$, is given by the following equation

$$f(\mathbf{x}) = \operatorname{sgn}\left(\sum_{\mathbf{x}_i \in S}\alpha_i y_i K(\mathbf{x}_i,\mathbf{x}) + b\right) \tag{9}$$

where $S$ is the set of support vectors and $b$ is the bias term.

SVM was originally designed for binary classification. Some methods have been proposed where typically construct multi-class classifier by combining several binary classifiers like One-Against-All (OAA) and One-Against-One (OAO) methods [17]. OAA constructs $k$ SVM models where $k$ is the number of classes. The $i^{\text{th}}$ SVM is trained with all of examples in the $i^{\text{th}}$ class with the positive labels, and all other examples with the negative labels. But, OAO constructs $k(k-1)/2$ classifiers where each one is trained on data from two classes. Another method to generalize binary SVM classification to multi-class state is all-together method which solves multi-class SVM in one step [17].

## III. The Proposed Algorithm

Block diagram of the proposed algorithm is shown in Fig. 2. The input face images from the ORL database are given to a Gabor filter bank at 5 scales and 8 orientations for feature extraction. Each face image of the ORL database has resized to the size of 70×80 pixels. After applying the Gabor filter bank, 40 (5×8) outputs (each one with size 70×80 pixels) are obtained for every input image. Then, each of these 40 outputs is down sampled with a factor of 20 (4×5) and normalized to zero mean and unit variance (whitening transform). At the next stage, they are concatenated to each other resulting in a feature vector of size 11200 (40×(70×80)/20) for every input image. Before applying SVM classifier on feature vectors, KPCA algorithm is used for further reduction of feature data dimensionality. There are several different kernel functions which can be used in the KPCA method. This paper uses radial basis function (RBF) as

$$K(\mathbf{x}_i,\mathbf{x}_j) = \exp\left(-\|\mathbf{x}_i - \mathbf{x}_j\|^2 \big/ (2\sigma^2)\right) \tag{10}$$

In this research, three kinds of multi-class SVMs are used containing OAO, OAA, and all-together methods. Each of them uses the different kernel functions including RBF kernel, polynomial kernel, and linear kernel which are described at (10), (11), and (12), respectively.

$$K(\mathbf{x}_i,\mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^n \tag{11}$$

$$K(\mathbf{x}_i,\mathbf{x}_j) = \mathbf{x}_i \cdot \mathbf{x}_j \tag{12}$$

The next section presents the results of implementing the above proposed techniques.

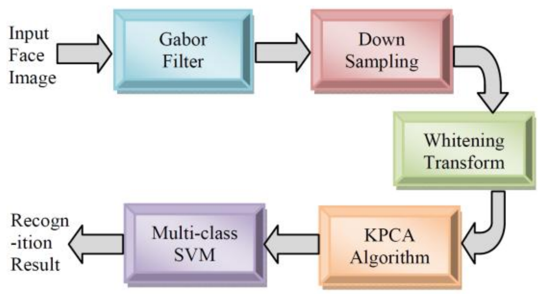


Fig. 2. Block diagram of face recognition procedure by the proposed algorithm.

## IV. Experimental Results

Face images from the Cambridge Olivetti Research Lab (ORL) database are used to train and test the proposed face recognition system. The ORL database contains face images from 40 distinct persons. Each person has 10 different images, taken at different times. We show four individuals (in four rows) from the ORL face images in Fig. 3. There are variations in facial expressions such as open/closed eyes, smiling/no smiling, and facial details such as glasses/no glasses. All the images were taken against a dark homogeneous background with the subjects in an up-right, frontal position with tolerance for some side movements. There are also some variations in scale [3].

Fig. 3. Four individuals (each in one row) in the ORL face database.

In our experiment, 400 face images of the ORL database from 40 persons (all images in the database) are used for training and testing. We randomly divide them into 2 sets with equal number of images for each class i.e. each set consists of 200 images (5 images for every person). One set is used for training and the other one is used for testing. This is performed for 3 times and in each time, the new training and testing sets is chosen. The final result is obtained by averaging the results of these 3 experiments. This replacement strategy makes our results more reliable.

For each kernel function of SVM classifier, we estimate the kernel parameter ($\sigma$ for RBF kernel and $n$ for polynomial kernel as described by (10) and (11), respectively) and cost parameter ($C$ in (8)) with 5-cross-validation method explained in [17]. Also, the number of eigenvectors which are used in KPCA algorithm affects the recognition rate. Experimental results showed that the recognition rate is maximized when the number of selected eigenvectors is set to 180. So, we chose 180 eigenvectors in the KPCA algorithm in all experiments. TABLE I contains the average recognition rates of our proposed method. This table shows that the highest average recognition rate of the proposed algorithm is 98.5% which is acceptable.

TABLE I: AVERAGE RECOGNITION RATES FOR GABOR+KPCA+SVM ALGORITHM (PROPOSED METHOD) OVER THE ORL FACE DATABASE (IN %)

| Method | RBF | Polynomial | Linear |
|---|---|---|---|
| OAO | 94.83 | 94.50 | 94.50 |
| OAA | 98.00 | 98.17 | 98.50 |
| All-together | 98.50 | 98.33 | 98.33 |

For the next experiment PCA is used as feature reduction algorithm instead of KPCA in order to compare the results with the proposed method. The experiment is based on the same 5-cross-validation technique as used in KPCA. For this experiment, the maximum recognition rates are achieved when the number of eigenvectors is set to 152. TABLE II indicates the results for PCA. This table shows that the highest average recognition rate for PCA is 96.83%. Therefore the proposed algorithm achieves better recognition rate than the PCA algorithm.

TABLE II: AVERAGE RECOGNITION RATES FOR GABOR+PCA+SVM ALGORITHM OVER THE ORL FACE DATABASE (IN %)

| Method | RBF | Polynomial | Linear |
|---|---|---|---|
| OAO | 92.83 | 94.67 | 94.50 |
| OAA | 95.83 | 96.33 | 96.33 |
| All-together | 95.67 | 96.83 | 96.83 |

In order to compare the performance of our proposed scheme with the other related methods, we also bring the results of some recent papers below.

In [18], a face recognition algorithm based on non-negative matrix factorization (NMF) and SVM was presented. The first row of TABLE III shows the performance of their proposed algorithm on the ORL database. As we can see, the highest recognition rate of our proposed method which is 98.5% is more than the highest recognition rate reported by [18] which is 97.3%.

TABLE III: RECOGNITION RATES OVER THE ORL DATABASE (IN %) OBTAINED BY [18]

| Method | 3 training | 4 training | 5 training |
|---|---|---|---|
| NMF-SVM | 89.2 | 96.5 | 97.3 |
| Fisherfaces | 85.4 | 91.6 | 93.8 |
| Eigenfaces | 78.3 | 83.7 | 87.5 |

Wavelet transform, PCA and SVM are combined in [19] to form a face recognition system. Their experiments over the ORL face database indicated a maximum accuracy of 92% while the maximum accuracy achieved by our proposed algorithm is 98.5%.

In [20], a feature extraction method (HMAX) was introduced and then SVM was used for classification. TABLE IV shows the results of their suggested algorithm over the ORL database. As we can see from this table, the maximum recognition rate of their method is 96% which is lower than the results obtained by our proposed method.

TABLE IV: RECOGNITION RATES OVER THE ORL DATABASE (IN %) OBTAINED BY [20]

| Class Number | SVM Kernel = 1 | SVM Kernel = 2 | SVM Kernel = 3 | kNN |
|---|---|---|---|---|
| 10 | 94 | 94 | 96 | 95.2 |
| 20 | 93 | 93 | 94 | 90 |
| 30 | 91.6 | 92 | 92.1 | 88 |
| 40 | 87 | 87 | 88.3 | 81.5 |

Finally, a face recognition algorithm was presented in [21] by using 2DLDA method for feature extraction and SVM for classification. Their experiments over the ORL database result in the maximum recognition rate of 98.33% which is less accurate when compared with the maximum recognition rate of our proposed algorithm (98.5%).

In summary, our proposed algorithm can be an effective and reliable method for the technology of automatic face recognition.

## V. CONCLUSION

In this paper, we have proposed an efficient face recognition algorithm based on the Gabor filter bank for feature extraction, KPCA algorithm for feature reduction, and SVM for classification. Applying the Gabor filter bank causes to remove most of image variations due to changes in lighting conditions and contrast, and the extracted features are robust against small shifts and deformations. Comparisons between our proposed algorithm and the other related face recognition methods are conducted over the ORL database. The experimental results clearly demonstrate the effectiveness of our proposed algorithm.

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