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Enhancing face recognition using Directional Filter Banks

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ABSTRACT

Face recognition is an increasingly important problem in biometric applications; consequently many recognition algorithms have been proposed during the last three decades. It is accepted that the use of a pre-processing step can extract more discriminating features and increase the classification rates. Although, Gabor filters have been widely employed they do not provide satisfying classification results. This paper proposes the use of directional filters as a pre-processing step to demonstrate that a Directional Filter Bank is capable of enhancing existing face recognition classifiers such as PCA, ICA, LDA and SDA. The proposed method is tested using two different databases: the Yale face database and the FERET database. Experimental results demonstrate that the pre-processing phase enhances the classification rates. A comparative study has also been carried out to demonstrate that a DFB based classification outperforms a Gabor type one.

1. Introduction

Face recognition is one of the most popular applications in image processing and pattern recognition. It plays a very important role in many applications such as card identification, access control, mug shot searching, security monitoring and surveillance.

There are several problems that make automatic face recognition a very challenging task. The input of a person's face to a recognition system is usually acquired under different conditions from those of the corresponding image in the database. Therefore, it is important that an automatic face recognition system can deal with numerous variations of images of a face. The image variations are usually due to changes in: pose, illumination, expression, age, disguise, facial hair, glasses, and background.

Progress has been made towards recognising faces under controlled conditions as described in [14,19], especially for faces under normalised pose and lighting conditions and with neutral expression. The Eigenfaces method [16], based on Principal Component Analysis (PCA), is one of the most popular methods in face recognition. Its principal idea is to find a set of orthogonal basis images (called eigenfaces) so that in this new basis, the image coordinates (the PCA coefficients) are uncorrelated. Independent Component Analysis (ICA) [2] is one generalisation of PCA. It assumes that the data is independent, and not only uncorrelated as in PCA. Fisherface technique [3] based on Linear Discriminant Analysis (LDA) is an other popular method. It considers that each face image in the training set is of a known class and uses this information in the classification step. Subclass Discriminant Analysis (SDA) is a recent algorithm devised by Zhue et al. [20]; each class of the LDA method is subdivided into many subclasses.

However, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains problematic. Researchers have proposed the utilisation of a pre-processing step in order to extract more discriminant features for use in the recognition step. Gabor Filter Bank is one of the most well-known methods used for this purpose and many algorithms have been proposed [5,21,19]. However, as described in [13], the use of a Gabor Filter Bank (GFB) inherently results in some overlapping and missing subband regions. The Directional Filter Bank (DFB), on the other hand, is a contiguous subband representation that preserves all image information. Accordingly, a DFB can represent linear patterns, as found around eyes, nose and mouth area, more effectively, than a Gabor Filter Bank [10].

This paper proposes to employ a DFB pre-processing phase in order to improve the recognition rates of a number of different algorithms. Four algorithms representing both Component and Discriminant Analysis approaches have been selected to demonstrate the efficiency of the DFBs. In this work, the algorithms: PCA, ICA (FastICA [18]), LDA and SDA are chosen for their popularity and efficiency.

The remaining of this paper is organised as follows. Section 2 reviews some well known face recognition classifiers, PCA, ICA, LDA, SDA and the Nearest Neighbour Classifier (NNC) with a

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Euclidean distance. Section 3 presents the proposed method including a review of Directional Filter Banks. Experimental results are shown and discussed in Section 4 while a conclusion is given in Section 5.

2. Face recognition classifiers used for the analysis

2.1. Principal Components Analysis (PCA)

The well-known Eigenface algorithm proposed by Turk and Pentland [16] uses PCA for dimensionality reduction in order to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of the face images (face space). All faces in the training set are projected onto the face space to find a set of weights that describes the contribution of each vector in the face space. To identify a test image, the projection of the test image onto the face space is required to obtain the corresponding set of weights. By comparing the weights of the test image with the set of weights of the faces in the training set, the face in the test image can be identified.

The key procedure in PCA is based on Karhumen–Loeve (KL) transformation. If the image elements are considered to be random variables, then the image may be seen as a sample of a stochastic process. The PCA basis vectors are defined as the eigenvectors of the covariance matrix C:

$$C = E\left[XX^T\right] \tag{1}$$

Since the eigenvectors associated with the largest eigenvalues have face-like images, they also are referred to as eigenfaces. Specifically, suppose the eigenvectors of C are $u_1, u_2, \ldots, u_n$ and are associated respectively with the eigenvalues $\lambda_1 \geqslant \lambda_2 \geqslant \cdots \geqslant \lambda_n$. Then

$$X = \sum_{i=1}^{n} \hat{x}_i u_i \tag{2}$$

The dimensionality reduction can be achieved by letting:

$$X \approx \sum_{i=1}^{m} \hat{x}_i u_i \tag{3}$$

where $\hat{X} = [\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_m]$ and m is usually selected such that λ_i is small for $i > m$.

Since the Eigenfaces method directly applies PCA, it does not destroy any information of the image by exclusively processing only certain points, generally providing more accurate recognition results. However, the technique is sensitive to variation in position and scale. Some serious issues relate to the effect of background, head size and orientation. The change of head size of an input image can be problematic because a neighbourhood pixel's correlation is lost under head size change. Note that variation of light can also be a problem if the light source is positioned in some specific directions.

2.2. Independent Component Analysis (ICA)

ICA is a widely used algorithm in statistical signal processing. It is defined as: having an observed m-dimensional vector $X = (x_1, \ldots, x_m)^T$, find a linear transform A that maps observation X into an n-dimensional vector $S = (s_1, \ldots, s_n)^T$ where the components s_i are as independent as possible:

$$X = AS \tag{4}$$

where A is an $m \times n$ matrix of full rank, called the mixing matrix. In feature extraction, the columns of A represent features, and s_i is the coefficient of the ith feature in the observed data vector X.

There are several methods to compute the ICA. Here FastICA [18] is used because of its fast convergence during the estimation of the parameters.

The FastICA method computes the independent components by maximising non-Gaussianity of whitened data distribution using a kurtosis maximisation process. The kurtosis measures the non-Gaussianity and the sparseness of the face representations [4]. The idea is to estimate the independent source signals U by computing a separating matrix W where $U = WX = WAS$. First, the observed samples are centred and whitened, this means that the data has a mean equal to zero and standard deviation equal to one. Let us denote the centred and whitened samples by Z. Then, one needs to search for the W matrix such that the linear projection of the whitened samples by the matrix W has maximum non-Gaussianity of data distribution. The kurtosis of $U_i = W_i^T Z$ is computed as:

$$K(U_i) = \left|E(U_i)^4 - 3\left(E(U_i)^2\right)^2\right| \tag{5}$$

the separating vector W_i is obtained by maximising the kurtosis.

2.3. Linear Discriminant Analysis (LDA)

PCA constructs the face space without using face class (category) information where training considers the whole face data. However, in LDA the goal is to find an efficient way to represent the face vector space [19,3] by exploiting the class information which can be helpful for the identification task. The Fisherface algorithm [3] is derived from the Fisher Linear Discriminant (FLD), which uses class specific information. By defining different classes with different statistics, the images in the learning set are divided into the corresponding classes. Then, techniques similar to those used in the Eigenface algorithm are applied. The Fisherface algorithm results in a higher accuracy rate in recognising faces when compared with the Eigenface algorithm. The Linear Discriminant Analysis finds a transform W_{LDA}, such that the ratio of the between-class scatter and the within-class scatter is maximised as follows:

$$W_{LDA} = \arg\max_{W} \frac{|W^T S_B W|}{|W^T S_W W|} \tag{6}$$

where S_B is the between-class scatter matrix and S_W is the within-class scatter matrix, defined as:

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{7}$$

$$S_W = \sum_{i=1}^{c} \sum_{x \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{8}$$

N_i is the number of training samples in the class i, c is the number of distinct classes, μ_i is the mean vector of samples belonging to class i and X_i represents the set of samples belonging to class i.

2.4. Subspace Discriminant Analysis (SDA)

The problem with traditional discriminant analysis methods is that they assume that the sample vectors of each class are generated from underlying multivariate normal distributions of common covariance matrix but with different mean values. Many authors have addressed this problem by introducing extensions of LDA, for example Nonparametric DA [6] and Penalised DA [8]. However,

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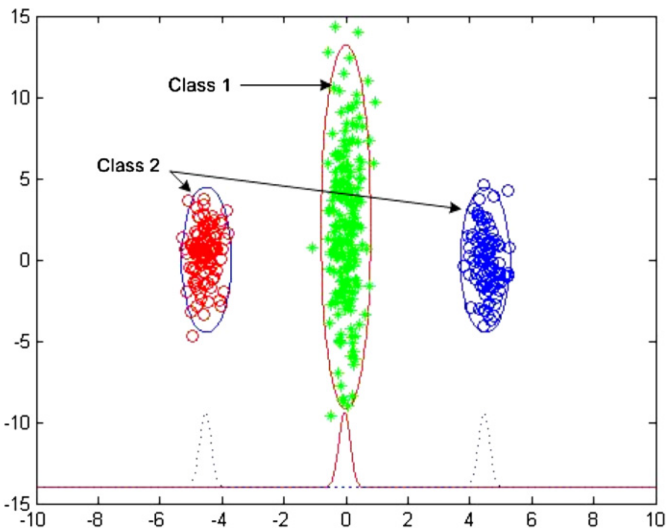

Fig. 1. A two class problem when one of the classes is a mixture of two Gaussians.

these algorithms assume that each class is represented by a single cluster and, therefore, none of them solve the problem posed by nonlinearly separable classes. To solve this problem, one can use nonlinear methods such as Flexible DA [7] and Generalised DA [1]. However, they have two major problems: first, they require a very large number of samples to obtain satisfactory results, and second a high computational cost in the training and testing phases is also needed [20]. One method that addresses the above problems is SDA. Its principal idea is to devise a solution which describes a large number of data distributions, regardless of whether these correspond to compact sets or not [20]. A method to achieve this is to approximate the underlying distribution of each class as a mixture of Gaussians; each Gaussian will represent a subclass.

Fig. 1 shows a two class problem (class of circles and class of stars) where the second class is represented by the mixture of two Gaussians. It can clearly be seen that there exist no direct linear method which can separate the two classes. However, if data distribution of each class is approximated using a mixture of Gaussians, the following generalised eigenvalue decomposition equation can be used to calculate those discriminant vectors that best (linearly) classify the data:

$$\Sigma_B V = \Sigma_X V \Lambda \tag{9}$$

where Σ_B is the between-subclass scatter matrix, Σ_X is the covariance matrix of the data, V is a matrix whose columns correspond to the discriminant vectors where Λ is a diagonal matrix whose elements are the corresponding eigenvalues.

2.4.1. Dividing classes into subclasses

As mentioned in the previous section, the essence of SDA is to divide each class into different subclasses. The first question one may ask relates to how many subclasses each class should have and which clustering approach is best suited in order to divide the samples into a set of subclasses (clusters). Although, there exist many clustering methods, it is accepted that the Nearest Neighbour (NN) method yields superior or equivalent results when compared against other parametric methods such as K-means and Gaussian mixtures; or nonparametric clustering methods such as the Valley-seeking algorithm of Koontz and Fukunaga [6]. In addition, the NN-clustering is efficient because it can also be used when the number of samples in each class is either large or small, and it does not require large computational resources [20].

2.4.2. NN-clustering

In a NN-clustering approach the first step consists of sorting the feature vectors (i.e., face images in our case) so that a set $\{x_{i1}, x_{i2}, \ldots, x_{in_i}\}$ is constructed as follows: if x_{i1} and x_{in_i} are the two most distant feature vectors:

$$\arg\max_{jk} \|x_{ij} - x_{ik}\|_2$$

where $\|x\|_2$ is a norm-2 length of x with x_{i2} being the closest feature vector to x_{i1} and $x_{i(n_{c-1})}$ the closest feature vector to x_{in_c}. In general, x_{ij} is the $(j-1)$th closest feature vector to x_{i1}.

Once this done, the sorted set $\{x_{i1}, x_{i2}, \ldots, x_{in_i}\}$ is divided into M subclasses H_i where $i = 1, \ldots, M$. For example, data can be divided into two equally balanced (in the sense of having the same number of samples) clusters (H_1 and H_2) by simply partitioning the sorted set into two parts: $\{x_{i1}, \ldots, x_{i,n_i/2}\}$ and $\{x_{i,(n_i/2)+1}, \ldots, x_{in_i}\}$. More generally, one can divide each class into h (equally balanced) subclasses; i.e., $H_i = h\ \forall i$. This is suitable for such a case where the underlying distribution of each class is not Gaussian, but can be represented as a combination of two or more Gaussians. Another case is when the classes are not separable, but the subclasses are.

2.5. Distance measure

The problem of finding the closest point in high-dimensional spaces is common in pattern recognition problems. Unfortunately, the complexity of most existing search algorithms grows exponentially with the dimension, making them impractical for dimensionalities higher than 15 [9,11]. However, the Nearest Neighbour Classifier (NNC) remains one of the simplest and most efficient algorithms in pattern recognition. It approximates the minimum error Bayesian classifier in the limit as the number of reference vectors gets large (large database). In this work, we have used a NNC with a Euclidean distance: for two face images i and j, let $f^{(i)}$ and $f^{(j)}$ represent the corresponding feature vectors. Then the distance d_{ij} between the two patterns in the feature space is defined as:

$$d_{ij} = \sqrt{\sum_n \left(\frac{f_n^{(i)} - f_n^{(j)}}{\alpha(f_n)}\right)^2} \tag{10}$$

where $f_n^{(i)}$ is the nth element of the feature vector i and $\alpha(f_n)$ is the standard deviation of the nth element over the entire database. This expression is used to normalise the individual feature components.

3. Proposed method and experimental results

3.1. Directional Filter Bank: A review

A Digital Filter Bank is a collection of digital filters with a common input or output. The DFB is composed of an analysis bank (analysis filter bank) and a synthesis bank. The analysis bank of the DFB splits the original image into 2^n directionally passed subband images (n is the order of the DFB) while the synthesis bank combines the subband images into one image. A diagram of a DFB structure can be given as a tree with two-band splits at the end of each stage (see Fig. 2), where each split increases the angular resolution by a factor of two.

In the analysis section of the DFB, the original image is split into two directional subband images, then each subband image is split into two more directional images, and so on until the order n, where 2^n directional subband images are obtained. At this point, the output is used as the input for the next stage. Each

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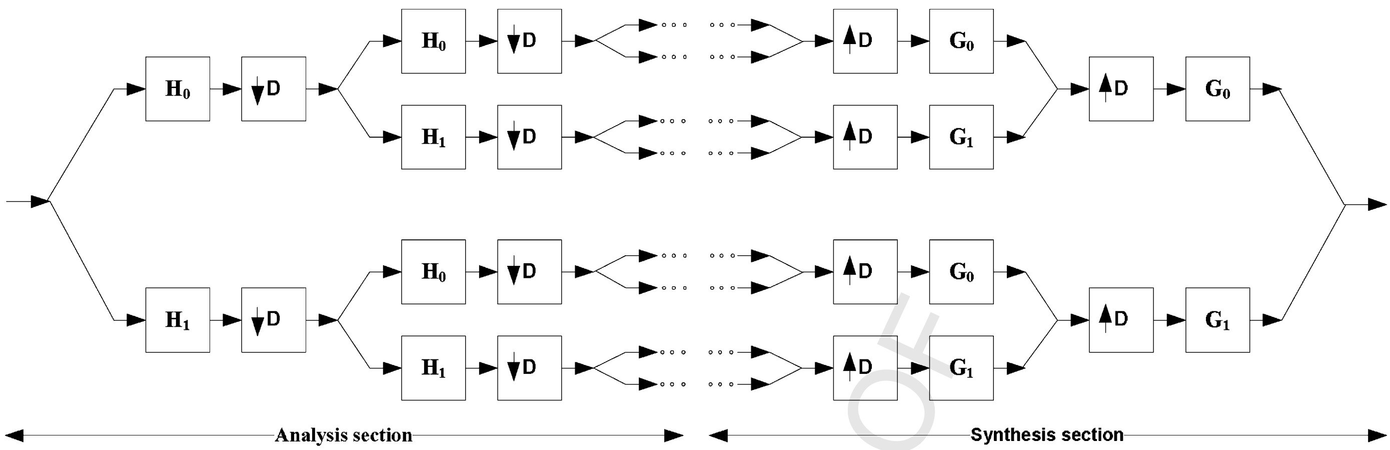

Fig. 2. DFB structure.

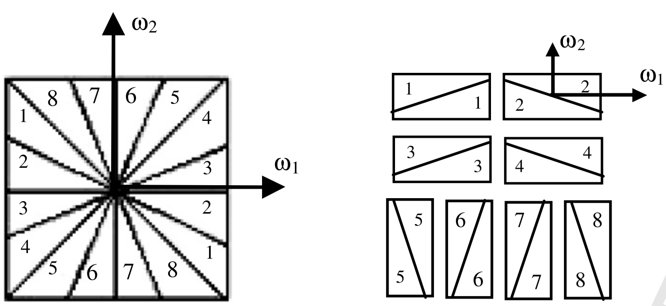

Fig. 3. The frequency partition map for an eight-band DFB. (a) Input. (b) Eight subband outputs.

of the subbands in the analysis part extracts frequency components based on the associated frequency partition map as shown in Fig. 3.

In the synthesis bank, the dual operation is performed, i.e. the directional subband images are combined into a reconstructed image in the reverse order of the analysis stage in order to enable a perfect reconstruction of the signal. However, it is important to mention that, in this work, we are only interested in the analysis section since our goal is to extract only discriminant features from each directional image. The components of the analysis part are the downsampler D and the analysis filters H_0 and H_1.

3.1.1. Analysis filters

One of the attractive features of the DFB is the fact that it can be implemented by one filter prototype only. By using carefully designed unimodular matrices, the filter design process can be reduced to require only one filter prototype $H_0(\omega)$. Therefore, if the unimodular matrices which change the frequency components from $R_0^i(\omega)$ to $H_0(\omega)$, for $i = 1, 2, 3$, and 4, respectively, are determined (see Fig. 4), then the systems in Fig. 5(a) and (b) are identical and only one filter prototype $H_0(\omega)$ is required. Consequently, $H_0(\omega)$ can replace the four remaining filters $R_0^i(\omega)$ using the unimodular matrices.

3.1.2. Quincunx downsampling

Quincunx downsampling uses quincunx 2×2 resampling matrices whose entries are ± 1 so that their determinant equal 2 [12]. There are eight quincunx resampling matrices and the most commonly used is:

$$Q_1 = \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \tag{11}$$

Simply speaking, a quincunx downsampling corresponds to a rotated downsampling. Fig. 6 shows the original Lena image and its corresponding quincunx downsampled image by Q_1.

3.1.3. Overview of 2^n band DFB

The four-band DFB: A four-band DFB is composed of two-band DFBs (see Fig. 7) arranged in a tree like structure. After the modulator, the constituent frequency components are shifted, resulting in a diamond-like shape. Then, via the diamond filters, $H_0(\omega)$ and $H_1(\omega)$, each of the four frequency regions is filtered then downsampled by a quincunx downsampler. By cascading another set of two-band DFBs at the ends of the first two-band DFB, a four-band directional decomposition is obtained.

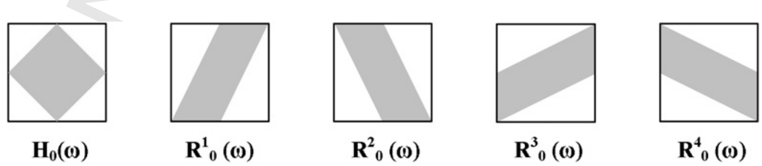

Fig. 4. Five passbands for DFB.

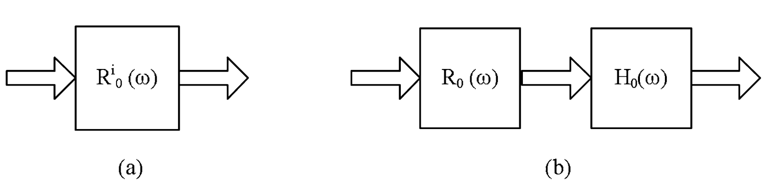

Fig. 5. Two identical structures in a DFB. (a) Using $R_0^i(\omega)$ alone and (b) using a unimodular matrix with $H_0(\omega)$.

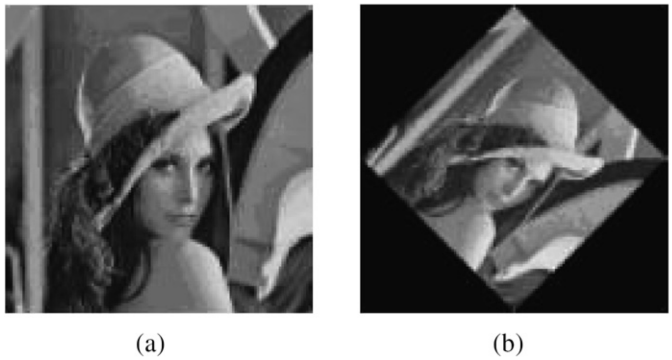

Fig. 6. The Lena image and its quincunx downsampled image by Q_1.

The 2^n-band DFB: Two-band and four-band DFBs lead to 2^n-band extensions. To expand to eight bands, one can apply a third stage in a cascade fashion. With an input whose directional frequencies are labelled as shown in Fig. 3(a), an eight-band DFB generates the eight subband outputs shown in Fig. 3(b). It is worth noting that each of the subband images is smaller than the original input, which is necessary to ensure a maximally DFB decimation.

3.1.4. Directional images

Directional images are obtained by applying all directional filters (as described above). Practical experiments show (see Fig. 10) that better results are achieved when applying a two level DFB design, so four directional images are obtained at the end of the DFB pre-processing. These directional images can be regarded as a decomposition of the original image in four directions. Directional images contain features associated with global directions rather than local directions. By creating directional images, noise in the original image is divided into four different directions, thus reducing noise energy by a factor of four [10].

3.2. Proposed method

Experimental tests have been performed using two different databases: FERET database [15] and Yale face database [17]. The Yale database is a collection of 165 images of 15 different individuals where images belonging to a person (i.e. same class) present variations in expressions and illumination conditions. In this database, 11 images of each individual are available (with different expressions: happy, sad, sleepy… and different lighting sources: centre, left and right), three are randomly chosen to be used as reference faces while the eight remaining as are used as input data (test images).

Fig. 8. Some samples from Yale face database.

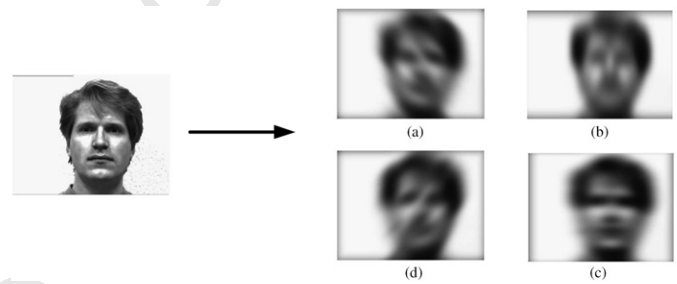

Fig. 9. Directional images generated by DFB. (a) Directional image 1, (b) directional image 2, (c) directional image 3, (d) directional image 4.

The main contribution of this work is to improve the recognition rates of the existing face recognition algorithms, such as PCA, LDA, ICA and SDA, by applying a DFB pre-processing, thus demonstrating their suitability in capturing discriminant information.

First, directional images were generated by applying the DFB to each face image from the database. Fig. 9 illustrates an example of an original face image from the database and its directional images generated by the DFB. To evaluate the effect of the level of DFB decomposition on the ability to capture discriminating information and hence recognition rate, extensive experiments were carried out using both databases with varying levels of decomposition. The experiments show that the best results are obtained when the level of the DFB equals either two or four (see Fig. 10). However, since the time of execution grows rapidly when the order of the filter bank is increased, it makes sense to choose a two level DFB decomposition. Thus four directional images are obtained for each face image in our analysis.

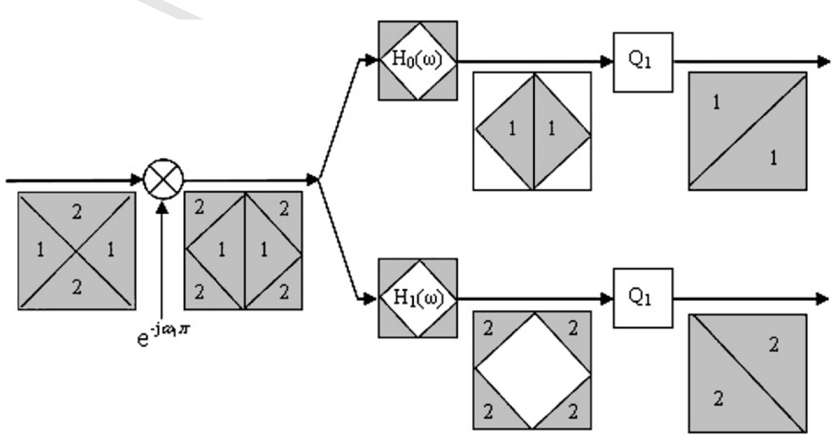

Fig. 7. A two-band DFB structure.

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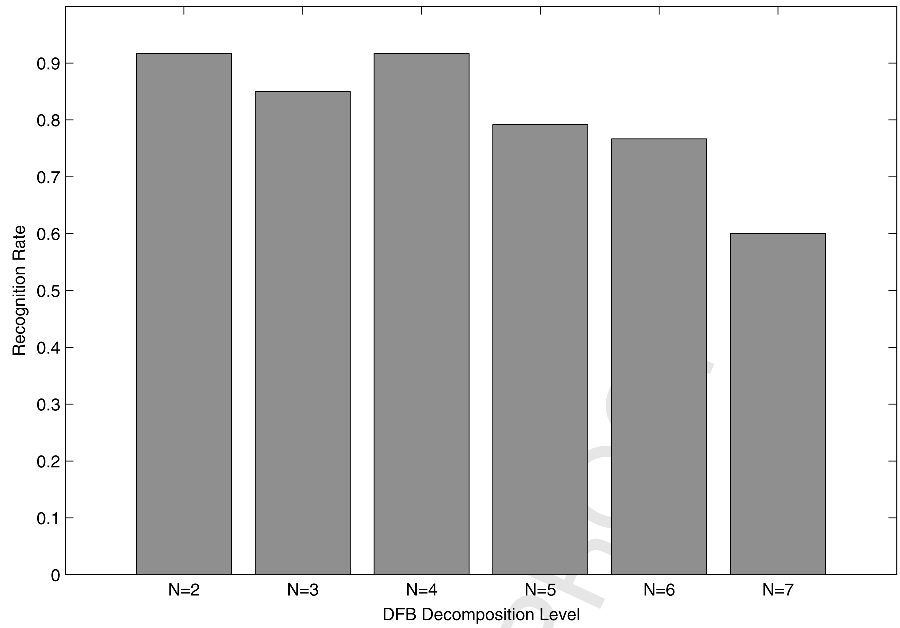

Fig. 10. Recognition rates for different orders of the DFB.

Table 1
Experiment results for the DFB-PCA method and comparison with the PCA algorithm.

Faces	PCA	DFB-PCA	Improvement
Normal	53.33%	86.67%	+62.50%
No glasses	60%	86.67%	+44.45%
Wink	53.33%	86.67%	+62.50%
Glasses	60%	73.33%	+22.22%
Sleepy	60%	86.67%	+33.33%
Surprised	60%	80%	+33.33%
Sad	53.33%	86.67%	+62.50%
Left-light	13.33%	33.33%	+150.04%
Global recognition rate	**51.67%**	**77.50%**	**+49.99%**

4. Result analysis

In order to assess the efficiency of the proposed method, extensive experimentation has been carried out using state of the art face recognition algorithms such as PCA, LDA, ICA and SDA. Experiments were conducted on data with a without the DFB pre-processing step as follows: first, the four methods are applied in isolation, and then combined with.

4.1. PCA

In this experiment the original face database is used to extract features using the traditional Eigenface algorithm. The recognition rate is calculated for all the remaining faces in the database. The same system is maintained and applied to a new database obtained after DFB pre-processing. An NN algorithm using Euclidean distance is used to compute the distances between the different feature vectors. Table 1 shows the results of this experiment over all the different expressions and lighting conditions of the face images in the database.

Note that the improvement mentioned in Table 1 is a relative improvement and can be calculated from the following equation:

$$Improvement = \frac{Rate(DFBSDA) - Rate(SDA)}{Rate(SDA)} \qquad (12)$$

It can be seen from Table 1 that low recognition accuracies are obtained for both methods (i.e. PCA alone PCA with DFB pre-processing). However it is interesting to remark that the worse results are obtained for faces with changes in lighting conditions (only 13% for PCA), but while using the directional filters, the recognition rate have been improved of more than 150%. A general increase in the recognition accuracy of around 50% over all the faces is enough to conclude that a DFB implementation outperforms significantly its Eigenface counterpart algorithm.

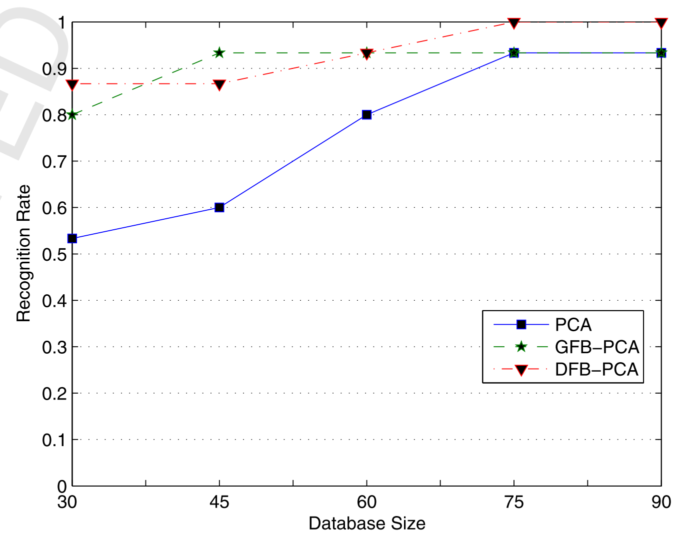

Fig. 11. Recognition rate of PCA-based algorithms.

Fig. 11 illustrates the results of an experiment conducted to show how the database size affects the recognition accuracy. To do so, fifteen image faces are randomly chosen from the Yale database as test images while the number of reference images per person is increased each time by one. A comparison with the Gabor Filter Bank [5] approach has been made to demonstrate that the proposed method clearly outperforms the other pre-processing algorithms even when database size is important.

4.2. ICA

This experiment is performed as with the PCA but using the FastICA algorithm instead of the Eigenface algorithm. The results

Table 2
Experiment results for the DFB–ICA method and comparison with the ICA algorithm.

Faces	ICA	DFB–ICA	Improvement
Normal	80%	93.33%	+16.67%
No glasses	73.33%	80%	+9.10%
Wink	86.67%	86.67%	0%
Glasses	66.67%	73.33%	+10%
Sleepy	93.33%	93.33%	0%
Surprised	66.67%	86.67%	+30%
Sad	93.33%	100%	+7.15%
Left-light	13.33%	33.33%	+150.04%
Global recognition rate	**71.67%**	**80.83%**	**+12.78%**

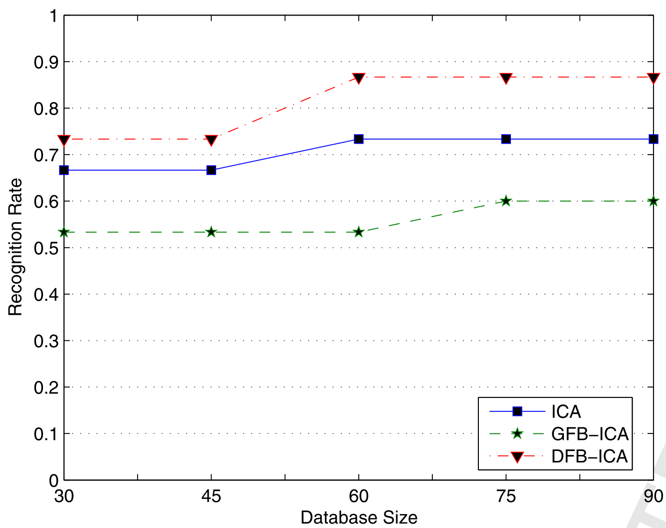

Fig. 12. Recognition rate of ICA-based algorithms.

Table 3
Experiment results for the DFB–LDA method and comparison with the ICA algorithm.

Faces	LDA	DFB–LDA	Improvement
Normal	93.33%	93.33%	0%
No glasses	80%	93.33%	+16.67%
Wink	93.33%	100%	+8.22%
Glasses	80%	86.67%	+8.34%
Sleepy	93.33%	93.33%	0%
Surprised	80%	93.33%	+16.67%
Sad	100%	93.33%	−6.67%
Left-light	80%	80%	0%
Global recognition rate	**87.50%**	**91.67%**	**+4.77%**

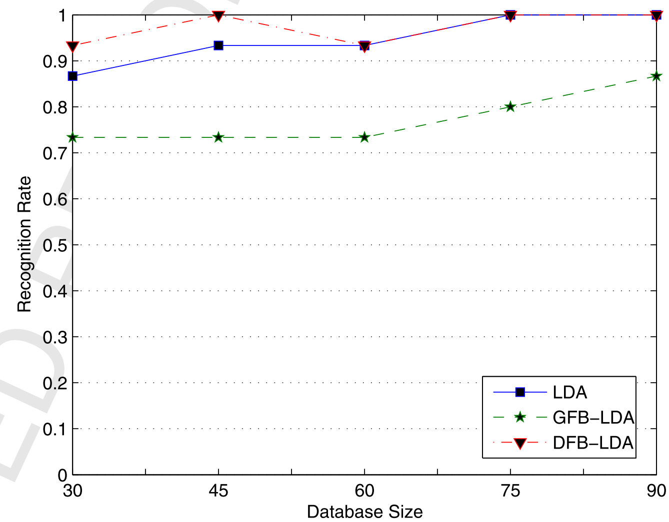

Fig. 13. Recognition rate of LDA-based algorithms.

obtained are reported in Table 2 and the effect of the database size with a comparison with the Gabor Filter Bank approach is showed in Fig. 12. The results obtained for the ICA approach are shown in Table 2. The ICA technique using both approaches significantly outperforms the PCA. In addition, it can also be seen that DFB is able to improve further the ICA especially for situations in which large facial changes occur (e.g., light source, glasses, etc.). For sleepy and wink classes there is little angular variations of the facial features thus making the DFB pre-processing not efficient to capture any extra discriminative features than ICA cannot achieve. This in turn makes DFB pre-processing not useful for these types of face images. An overall recognition rate of 80.83% is obtained for the combined ICA–DFB method with an overall improvement of 12.78%. This result clearly demonstrates the discriminating strength of a DFB pre-processing step.

4.3. LDA

It is well known that the main problem with the principal component methods (PCA and ICA) is the fact that they have no information about the class of each vector in the training database. This means that each face image is treated separately. This disadvantage has been resolved when using the LDA method since all the face images for one person are considered as a class. The same procedure is used as in the previous cases and the results obtained are showed in Table 3. A comparison with the Gabor approach is illustrated in Fig. 13. The results obtained clearly show the LDA technique using both approaches (with and without DFB pre-processing) performs significantly outperforms the PCA. In addition, it can also be seen that DFB is able to improve further the LDA especially when significant changes in the image occur. However, it is noted that normal, sleepy and left-light classes, which are characterised by uniform and slowly varying facial features, can be easily captured by the LDA method. Therefore, DFB pre-processing cannot further enhance these slowly varying features thus making it not useful for these types of images. An overall recognition rate of 91.67% is obtained for the combined LDA-DFB method with an overall improvement of 4.77% which clearly demonstrates the discriminating strength of a DFB pre-processing step.

4.4. SDA

The principal idea of SDA is to divide each class (of the original LDA algorithm) to multiple subclasses. This property is very interesting for our method since we generate from each face image in the database 2^n directional images, when n is the order of the Directional Filter Bank. The best application of the SDA is to put all the directional faces of a person into the same subclass. Fig. 14 shows the proposed scheme for this method. In order to test the method, we follow the same steps as for the previous ones: the original face database is used to extract the features using the SDA algorithm as proposed in [20] and the recognition rate is calculated for all remaining faces in the database. A combined DFB–SDA method is used as illustrated in Fig. 14 to calculate the new recognition rates. The results obtained for both SDA and DFB–SDA methods and the improvement observed for different poses in the database are depicted in Table 4. The results obtained demonstrate that a combined DFB–SDA approach improves the recognition rate obtained when applying the SDA algorithm alone by 4.54%. Since SDA tries to capture and put all discriminating facial features of one class into the same class, DFB pre-processing through its orientation selective directional kernels is

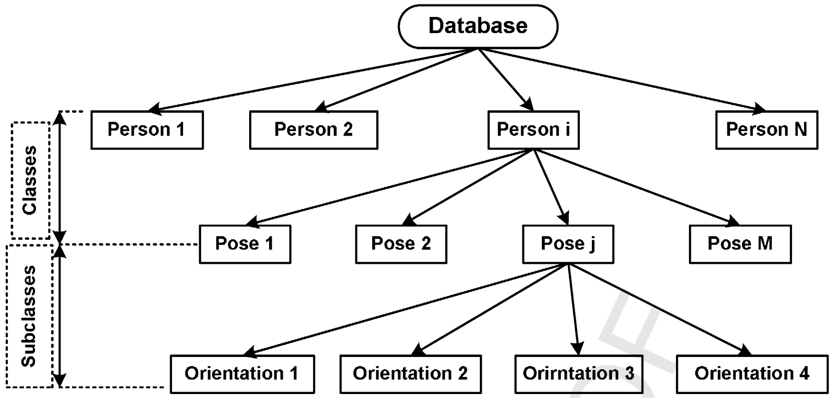

Fig. 14. Proposed scheme for the DFB–SDA method.

Table 4
Experiment results for the DFB–SDA method and comparison with the SDA algorithm.

Faces	SDA	DFB–SDA	Improvement
Normal	93.33%	93.33%	0%
No glasses	86.67%	86.67%	0%
Wink	93.33%	100%	+8.22%
Glasses	93.33%	100%	+8.22%
Sleepy	100%	100%	+0%
Surprised	93.33%	93.33%	0%
Sad	100%	93.33%	−6.67%
Left-light	73.33%	93.33%	+27.27%
Global recognition rate	**91.67%**	**95.83%**	**+4.54%**

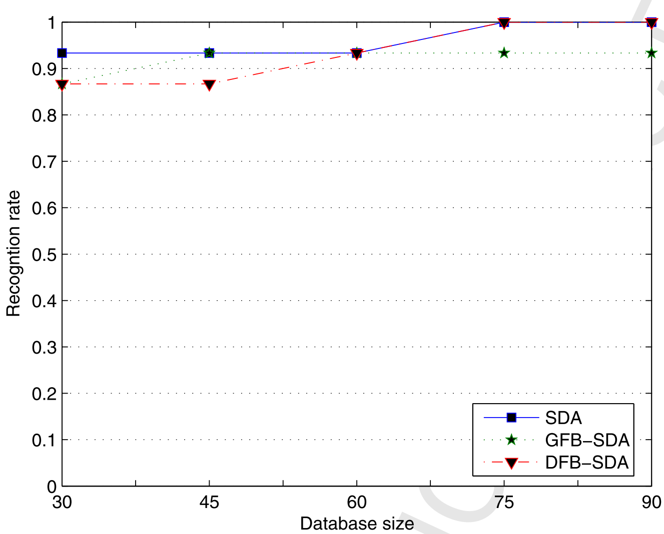

Fig. 15. Recognition rate of SDA-based algorithms.

achieved by a small overall improvement achieved. However, for normal, no glasses, sleepy and surprised images SDA is capable to extract these discriminating features on its own. The DFB on the other hand does not bring much orientation features (which are only slowly varying) thus making the technique not useful in these cases. In addition, in the case of sad images DFB is not able to capture rapidly varying features and as such fails to enhance the classification. In addition, with an overall recognition rate of 95.83%, it can be seen one can also conclude that the idea of dividing the classes into subclasses is compatible with DFB based pre-processing. Fig. 15 shows the effect of database growing on the global recognition rate and a comparison with the Gabor approach.

Fig. 16. Some image samples from FERET database.

Table 5
Experiment results for the different methods with the FERET database.

Method	PCA	ICA	LDA	SDA
Without DFB	72.33%	61.77%	71.67%	74.22%
With DFB	84.89%	74.00%	81.11%	84.90%
Improvements	+17.36%	+19.80%	+13.17%	+14.39%

4.5. FERET database results

To demonstrate the efficiency of the proposed method, similar experiments using the FERET face database (see Fig. 16) have been carried out. The following steps: reference and test databases are constructed from the original FERET database; then the algorithms PCA, LDA, ICA and SDA (alone and pre-processed by the DFB) are applied on the following database sizes: 50, 100, 200 and 300 using only one image by person as reference. The average recognition rate is then calculated for all tests. Table 5 depicts the experimental results obtained. From the table, it can be seen that DFBs improve the results obtained using a larger database with varying conditions such as head rotating and face sizes. Overall, the improvements for the different algorithms are all over 13% which is very satisfying.

5. Conclusion

This paper proposes a new method to enhance some existing face recognition methods such as PCA, ICA, LDA and SDA by using Directional Filter Bank pre-processing. We have shown that this pre-processing step yields robustness against changes in expressions and illumination conditions. This step also can be very helpful when the number of face images in the database is insufficient since the number of images will increase by a factor of 2^n (n is the order of the DFB), thus providing more discrim-

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inant power for the classification phase. It has been shown that this method is at least as good as all the other approaches ones including those with Gabor Filter Bank pre-processing.

The effect of DFB pre-processing is significant for the Yale and FERET databases. This is demonstrated by overall recognition rate improvements varying from 4.54% for the SDA algorithm to 49.99% for the PCA.

The efficiency of the proposed method has been demonstrated by improvements of (Yale = 49.99%, FERET = 17.36%) for PCA, (Yale = 12.78%, FERET = 19.80%) for ICA, (Yale = 4.77%, FERET = 13.17%) for LDA and (Yale = 4.54%, FERET = 14.39%) for SDA. A recognition rate of 95.83% has been obtained for the SDA algorithm combined with DFB pre-processing.

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