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Face Recognition Using Wavelets Transform and 2D PCA by SVM Classifier

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Abstract

Among the various biometric methods, face recognition has become one of the most challenging tasks in the pattern recognition field during the past decades. An integrated algorithm for face recognition is proposed based on the respective advantages of wavelets transform (WT), 2D Principle Component Analysis (PCA) and Support Vector Machines (SVM) in this paper. At first stage, the original images are decomposed into low frequency images by applying wavelets transform, the high-frequency components were ignored, while the low-frequency components which contains the primary information can be obtained. And then 2D PCA algorithm is used to deal with feature extraction. After generating feature vector, distance classifier and SVM are used for classification stage. Experiments with two face databases show that the proposed method has accuracy and robust for face recognition.

Keywords: *Face Recognition, 2D DWT, 2D PCA, SVM*

1. Introduction

Face recognition is the biometric identification of a human's face and matching the image against a library of known faces. It has become the important area of research in computer vision and one of the most successful applications of image analysis and processing. Face recognition task is actively being used at airports, employee entries, criminal detection systems, etc. classifier and they shows very good performance.

On the analysis of face recognition system, some of the important studies on face recognition systems are discussed, PCA method is also known as Eigen face method; PCA approach reduces the dimension of the data by means of basic data compression method [1] [2] and reveals the most effective low dimensional structure of facial patterns [3]. LFA method of recognition is based on the analysis the face in terms of local features, *e.g.*, eye, nose, *etc.*, by what is referred LFA kernels. Recognition by Neural Network [4] is based on learning of the faces in an "Example Set" by the machine in the "Training Phase" and carrying out recognition in the "Generalization Phase". Support Vector Machines (SVM) technique is in fact one of the binary classification methods. The support vectors consist of a small subset of training data extracted by the algorithm given in [5]. Face recognition based on template matching represents a face in terms of a template consisting of several enclosing masks the projecting features, *e.g.*, the mouth, the eyes and the nose [6]. In reference [7], a face detection method based on half face-template is discussed. Recognition technique formulated on Partitioned Iterated Function System (PIFS) [8] makes use of the fact that human face shows self-similarity region-wise, which is utilized for encoding the face to generate the PIFS code, by matching the PIFS codes recognition is performed. In [9] the face recognition system based on partitioned Iterated Function System is discussed, in which face recognition based on PIFS representation and matching is carried out in the domain of PIFS code. In [10] Bayesian approach to face recognition based on wavelet transform is discussed.

Moreover, Wavelet Transform is a signal analysis method of the time scale and has a advantage of multi-resolution analysis. It is the time-frequency localization analysis which has the capacity of local features in the time domain and frequency domain. As opposed to PCA, 2DPCA represents face images by using matrices or 2D images instead of vectors. Clearly, using 2D images directly is quite simple and local information of the original images is preserved sufficiently, which may bring more important features for facial representation. SVM belongs to kernel methods, Kernel algorithms map data from an original space into a higher dimensional feature space using non-linear mapping [13]. An original algorithm from the original space is used in the feature space. Although the high-dimensional space increases the difficulty of the problem (curse of dimensionality), a trick for computing the scalar products in the feature space exists.

In this paper, we combine the advantages of WT, 2D PCA and SVM for an integrated method of face recognition. Wavelet decomposition is a multilevel dimension reduction process that makes time–space–frequency analysis. Unlike Fourier trans-form, which provides only frequency analysis of signals, wavelet transforms provide time–frequency analysis, which is particularly useful for pattern recognition. 2D PCA is an efficient and long term studied method to extract feature sets by creating a feature space. 2D PCA also has low computation time which is an important advantage. On the other hand because of being a linear feature extraction method, 2D PCA is inefficient especially when nonlinearities are present in the underlying relationships. For the classification step, we consider Support Vector Machines (SVM) and nearest distance classification and all results obtained are evaluated.

2. Decomposing Images using 2D-DWT

In our study, the input images are decomposed into low frequency images by applying wavelet transform and ignored the high-frequency components, the related contents are described as following.

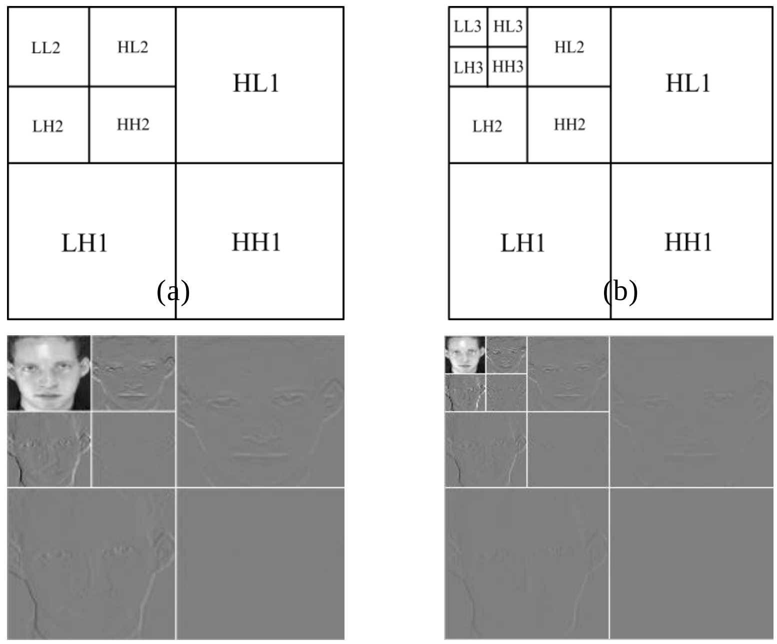
Wavelet Transform is a popular tool in image processing and computer vision, because of its ability to capture localized time-frequency information of image extraction. The decomposition of the data into different frequency ranges allows us to isolate the frequency components introduced by intrinsic deformations due to expression or extrinsic factors (like illumination) into certain subbands. Wavelet-based methods prune away these variable subbands, and focus on the subbands that contain the most relevant information to better represent the data [11]

In signal processing, we often use Discrete Wavelet Transform (DWT) to represent a signal $f(t)$. Two Dimensional Discrete Wavelet Transform (2D-DWT) for a $\mathrm{m} \times \mathrm{n}$ image is defined as follows:

$$\mathrm{DWT}(\mathrm{i},\mathrm{j},\mathrm{k},\mathrm{h}) = \frac{1}{\sqrt{2^{\mathrm{i}}}}\sum_{\mathrm{x}=0}^{\mathrm{m}-1} \mathrm{f}(\mathrm{x})\emptyset\left(\frac{\mathrm{x}}{2}-\mathrm{k}\right) + \frac{1}{\sqrt{2^{\mathrm{j}}}}\sum_{\mathrm{y}=0}^{\mathrm{n}-1} \mathrm{f}(\mathrm{y})\varphi\left(\frac{\mathrm{y}}{2}-\mathrm{h}\right) \quad (1)$$

Where *i* and *j* are the power of binary scaling, *k* and *h* are constant of the filters.

Similar to one-dimensional wavelet transform of signal, in image processing, the approximation of images at various resolutions with orthogonal projections can also be computed by multiresolution which characterized by the two-channel filter bank that governs the loss of information across resolutions. The one-dimensional wavelet decomposition is first applied along the rows of the images, and then their results are further decomposed along the columns. This results in four decomposed sub images L_1, H_1, V_1, D_1. These sub images represent different frequency localizations of the original image which refer to Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH), corresponding to approximate, horizontal, vertical and diagonal features respectively (see Figure1). The subband denoted by LL is approximately at half the original image. While the subbands HL and LH contain the changes of images or edges along vertical and horizontal directions, respectively. The subband HH contains the detail in the high frequency of the image.



(c) (d)

Figure 1. Two level and three level 2D DWT. (a) 2-level 2D DWT, (b) 3 level 2D DWT, (c) 2 level 2D DWT on a face image, (d) 3 level 2D DWT on a face image

Earlier studies concluded that information in low spatial frequency bands play a dominant role in face recognition. Nastar *et al.* has investigated the relationship between variations in facial appearance and their deformation spectrums [12]. They found that facial expressions and small occlusions affect the intensity manifold locally. Under frequency-based representation, only high-frequency spectrum is affected, called high-frequency phenomenon. Moreover, changes in pose or scale of a face affect the intensity manifold globally, in which only their low-frequency spectrum is affected, called low-frequency phenomenon. Only a change in face will affect all frequency components. So, through watching experiments like Figure 1, some characteristics can be demonstrated that:

(1) The effect of different facial expressions can be attenuated by removing the high-frequency components.

(2) The low-frequency components are still sufficient for recognition.

So in the following, we will mainly use low-frequency subband coefficients for recognition to attenuate natural difference in the images of the same person. By processing of 2D-DWT, the processed images kept the main characteristic of the original image and reduce the dimensions of data for extraction. In this study, 112×92 images from ORL database with the gray scale of 256 are processed by 1 level 2D-DWT processing, the resolution of low-frequency component are 63×53.

3. Feature Extraction using 2D PCA Algorithm

By applying 2D-DWT on an image, we can gain three advantages: Dimensionality reduction, which will lead to less computational complexity; multi-resolution data approximation and insensitive feature extraction. It is so significant for feature extraction that reducing computational complexity when using 2D PCA.

In the PCA-based face-recognition technique, the 2D face-image matrices must be previously transformed into 1D image vectors. The resulting image vectors usually lead to a high-dimensional image vector space in which it's difficult to evaluate the covariance matrix accurately due to its large size and relatively few training samples. Fortunately, we can calculate the eigen-vectors (eigenfaces) efficiently using single value decomposition (SVD) techniques, which avoid the process of generating the covariance matrix. Unlike conventional PCA, 2DPCA is based on 2D matrices rather than 1D vector. That is, the image matrix doesn't need to be previously transformed into a vector. Instead, an image covariance matrix can be constructed directly using the original image matrices. In contrast to PCA's covariance matrix, the image covariance matrix's size using 2DPCA is much smaller. As a result, 2DPCA has two important advantages over PCA. First, it's easier to evaluate the covariance matrix accurately. Second, less time is required to determine the corresponding eigenvectors.

Consider an m by n random image matrix A, Let $X \in R^{n\times d}$ be a matrix with orthonormal columns, n⩾d. Projecting A onto X yields an m by d matrix Y=AX. In 2D PCA, the total scatter of the projected samples was used to determine a good projection matrix X. That is, the following criterion is adopted:

$$\begin{aligned} J(X) &= \mathrm{trace}\{E[(Y - EY)(Y - EY)^T]\} \\ &= \mathrm{trace}\{E\big[\big(AX - E(AX)\big)\big(AX - E(AX)\big)^T\big]\} \\ &= \mathrm{trace}\{X^T E[(A - EA)^T (A - EA)]X\} \end{aligned} \quad (2)$$

Where the last term in Eq. (4) results from the fact that trace (AB) = trace (BA), for any two matrices. Define the image covariance matrix $G = E[(A - EA)^T(A - EA)]$, which is an n by n nonnegative definite matrix. Suppose that there is M training face image s, denoted by m by n matrices $A_k (k = 1,2, \dots, M)$, and denote the average image as $\overline{A}$ =1/M$\sum_k A_k$. Then G can be evaluated by

$$G = {}^{1}\!/_{M} \sum_{K=1}^{M} (A_k - \overline{A})^T (A_k - \overline{A}) \quad (3)$$

It has been proven that the optimal value for the projection matrix X_{opt} is composed by the orthonormal eigenvectors $X_1, \dots, X_d$ of G corresponding to the d largest eigenvalues. $X_{opt} = [X_1, \dots, X_d]$. Because the size of G is only n by n, computing its eigenvectors is very efficient. Also, like in PCA the value of d can be controlled by setting a threshold as follows

$$\sum_{i=1}^{d} \lambda_i \Big/ \sum_{i=1}^{n} \lambda_i \geq \theta \quad (4)$$

where $\lambda_1, \lambda_2, \dots, \lambda_d$ is the d biggest eigenvalues of G and θ is a pre-set threshold, θ is set as $\theta \geq 0.9$ usually.

The optimal projection vectors of 2D PCA $[X_1, \dots, X_d]$ are used for feature extraction. For a given image sample A, let

$$Y_k = AX_k, k = 1,2, \dots, d \tag{5}$$

Then, we obtain a family of projected feature vectors, $Y_1, Y_2, \dots, Y_d$, which are called the principal component (vectors) of the sample image A. It should be noted that each principal component of 2D PCA is a vector, whereas the principal component of PCA is a scalar. The principal component vectors obtained are used to form an $m \times d$ matrix $B = [Y_1, Y_2, \dots, Y_d]$, which is called the feature matrix or feature image of the image sample A, and called as eigenfaces for face recognition field. The eigenfaces of the ORL face database after applying algorithm above are shown as Figure 2.

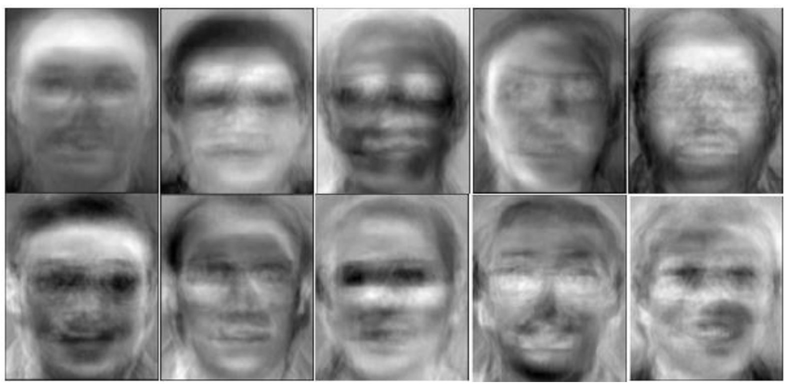


Figure 2. First 10 eigenfaces with highest eigenvalues

In our study, for a given set of training face images, feature vectors of faces are extracted through 2-D wavelet at appropriate LL subband. The reduced image data is then set to the 2D-PCA process for finding the principal component and reducing the dimensional space of the image which is stored into the library. For a given testing face image, feature vector is extracted through appropriate 2-D wavelet decomposition. The features are extracted using 2D-PCA and faces can be classified by measuring the Euclidian distance between mean values of training images in each class and the testing image.

4. Faces classifier using SVM approach

4.1. Support Vector Machines algorithm

Support Vector Machines (SVM) is a two-class classification method that finds the optimal decision hyper-plane based on the concept of structural risk minimization. The theory of SVM can be briefly summarized as follows.

Let us consider first the simple case of linearly separable data. We are searching an optimal separating hyperplane

$$\langle w, x \rangle + b = 0 \tag{6}$$

which minimizes the VC confidence term while providing the best generalization. The decision function is

$$f(x) = \mathrm{sgn}(\langle w,x \rangle + b) \quad (7)$$

Geometrically, the problem to be solved is to find the hyperplane that maximizes the sum of distances to the closet positive and negative training examples. The distance is called margin and the optimal plane is obtained by maximizing $2/\|w\|$ or, equivalently, by minimizing $\|w\|^2$ subject to $y_i(\langle w,x \rangle + b) \geq 1$. Suppose now that the two classes overlap in feature space. One way to find the optimal plane is to relax the above constraints by introducing the slack variables ξ_i and solving the following problem (using 2-norm for the slack variables):

$$\min_{\xi,w,b} \|w\|^2 + C\sum_{i=1}^{l} \xi_i{}^2 \quad (8)$$

$$\text{Subject to } y_i(\langle w,x \rangle + b) \geq 1 - \xi_i \text{ },\forall i = 1, \ldots, l \quad (9)$$

Where C controls the weight of the classification errors (C=∞ in the separable case). By introducing the lagrange multipliers, we obtain the primal and the dual Lagrangian form

$$L_p = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} \alpha_i [y_i(\langle w,x \rangle) - 1 - \xi_i] \quad 10)$$

$$L_D = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j \langle x_i, x_j \rangle - \frac{1}{C}\sum_{i=1}^{l} \alpha_i \quad (11)$$

where $\alpha_i \geq 0$. The solution of the primal problem is linked to the solution of the dual by $w = \sum_i y_i \alpha_i x_i$.

We can express now the decision function as a function of α:

$$f(x) = \mathrm{sgn}(\textstyle\sum_{i \in S} y_i \alpha_i \langle x, x_i \rangle + b) \quad (12)$$

where $S = \{i|\alpha_i > 0\}$. The vector x_i, $i \in S$ are called support vectors and are the only examples from the training set that affect the shape of the separating boundary.

In practice however, a linear separating plane is seldom sufficient. To generalize the linear case one can project the input space into a higher-dimensional space in the hope of a better training-class separation. In the case of SVM this is achieved by using the so-called "kernel trick". In essence, it replaces the inner product $\langle x_i, x_j \rangle$ in (13) and (14) with a kernel function $K(x_i, x_j)$. As the data vectors are involved only in this inner products, the optimization process can be carried out in the feature space directly. Some on the most used kernel functions are:

$$\text{the polynomial kernel} \qquad K(x,z) = (\langle x,z \rangle + 1)^d \quad (13)$$

$$\text{the RBF kernel} \qquad K(x,z) = exp(-\gamma\|x - z\|^2) \quad (14)$$

To apply SVM in face recognition, we use One-Against-All decomposition to transform multi-class problem to a set of two-class problems, namely, for each class of samples, n SVM classifiers should be trained. In this paper, we choose RBF kernel function for SVM classifier.

4.2. SVM face classifier combining with Wavelets and 2DPCA

Through the 2D DWT processing, the input images are decomposed into low frequency images by applying wavelet transform and ignored the high-frequency components, the processed images kept the main characteristic of the original image and reduce the dimensions of data for extraction.

Unlike conventional PCA, 2DPCA is based on 2D matrices rather than 1D vector. That is, the image matrix doesn't need to be previously transformed into a vector. Instead, an image covariance matrix can be constructed directly using the original image matrices. In contrast to PCA's covariance matrix, the image covariance matrix's size using 2DPCA is much smaller; it reduces the calculation and accelerates the speed of feature extraction. But 2D PCA algorithm only considers second-order statistics information of image data, the high order statistics information cannot be used and it ignores the nonlinearity of the multiple pixels. Although 2D PCA can recognize face with timeliness, the accuracy rate is limited.

Support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. As the dimensions of face image data is very large, although the satisfactory recognition rate can be obtained, but the processing time need so long as the large dimensions.

Based on the analysis above, we proposed a integrated method which is combined with 2D DWT, 2D PCA and SVM approach for face recognition. At first stage, the original images are decomposed into low frequency images by applying wavelets transform, the high-frequency components were ignored, while the low-frequency components which contains the primary information can be obtained. And then 2D PCA algorithm is used to deal with feature extraction. After generating feature vector, distance classifier and SVM are used for classification stage. We used "one-against-all" SVM multi-classification for recognizing face, and n SVM classifiers should be trained. The model of face recognition is shown as below.

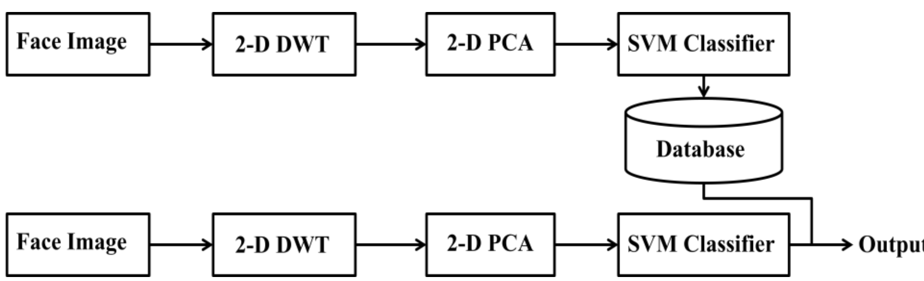


Figure 3. The flowchart of our face recognition method

5. Experimental Results

The experiment is performed using ORL face database and Yale face database; ORL database consists of 400 face images taken from 40 people, 10 images per person. All the images are against a dark homogeneous background with the subjects in an up-right, frontal position. There are variations in images of different persons like persons have beard, person have glasses, person have moustaches etc. The images are grayscale with a resolution of 92×112 pixels in bitmap file format. After processing of 2D DWT, the resolutions of low-frequency component are 63×53 pixels.

The Yale Face Database contains 165 grayscale images in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink. The images are 256 grayscales with a resolution of

243×340 pixels. After processing of 2D DWT, the resolutions of low-frequency component are 72×91 pixels.

In this study, an integrated algorithm for face recognition is proposed based on the respective advantages of 2D-DWT, 2D-PCA and SVM. Firstly, we used 2D-DWT for extracting the low frequency component and reducing the dimension of original image; secondly, 2D-PCA is used for extracting face features from low frequency component and to realize further dimension reduction; and then in recognition stage, One-Against-All decomposition SVM algorithm based on RBF is used for classifying faces feature.

Before using 2D DWT for decomposing the images, two crucial problems should be ensured, that are wavelet basis and decomposition level. By experiments research, db4 wavelets is selected for decomposing original images, and we do 1 level 2D DWT on ORL face database and 2 levels on Yale face database, these processing can reduce the dimensions of image and save the important information of face efficiently. For SVM classifier, we choose RBF kernel function and Kernel parameter γ is written as 0.015 for better performance. The results are shown as Table 1 and Table 2.

From Table 1, we can find that on ORL face database, when the number of training samples is 5, the recognition rate is 97.1%, it is better than SVM and 2DPCA as 0.7% and 7.4% respectively; when the number of training samples is 7, the face recognition rate is 98.3%, and it is similar to SVM algorithm, but it is much better than 2DPCA. From Table 2 that experiments on Yale face database, the recognition rate using our method is also better than other two approaches and the processing time is satisfactory.

Through the results tables below, we can find that it will take a short time by using 2D PCA for face recognition, but the recognition rate is not well. Using SVM could get an effect recognition rate but it will take a long time. The results show that the algorithm we proposed has a more sufficient accuracy rate and reduce training and testing time.

Table 1. Experimental results on ORL database

Algorithm	Training images	Testing images	Training Time (s)	Testing Time (s)	Recognition rate (%)
2D PCA	5	5	10.23	25.42	89.7
SVM	5	5	4017.52	2825.13	96.4
Proposed method	5	5	1056.2	591.45	97.1
2D PCA	7	3	14.20	19.44	93.3
SVM	7	3	4918.21	2236.12	98.1
Proposed method	7	3	1221.25	452.17	98.3

Table 2. Experimental results on Yale database

Algorithm	Training images	Testing images	Training Time (s)	Testing Time (s)	Recognition rate (%)
2D PCA	7	4	1.48	2.21	88.6
SVM	7	4	57.25	40.54	93.2
Proposed method	7	4	10.24	9.25	94.3
2D PCA	9	2	1.93	1.210	93.5
SVM	9	2	70.23	22.576	98.1
Proposed method	9	2	13.48	5.21	98.9

6. Conclusion

In this paper, an integrated algorithm for face recognition is proposed based on the respective advantages of wavelets transform (WT), 2D Principle Component Analysis (PCA) and Support Vector Machines (SVM). 2D DWT is used as a preprocessing tool which improves the recognition performance significantly. This improvement includes a substantial reduction in error rate and processing time of obtaining 2D PCA orthonormal basis representation. The extracted features are combined with SVM classifier for recognition. The results from our methods outperformed significantly.

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