A SVM-BASED METHOD FOR FACE RECOGNITION USING A WAVELET-PCA REPRESENTATION OF FACES

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ABSTRACT

This paper proposes a new method of face representation which is used for face recognition by SVM. For face representation we have used a two-step method, first two-dimensional Discrete Wavelet Transform (DWT) is used to transform the faces to a more discriminated space and then Principal Component Analysis (PCA) is applied. The proposed method produced a significant improvement which includes a substantial reduction in error rate and in time of processing during the obtaining PCA orthonormal basis.

1. INTRODUCTION

Several features (height, iris, fingerprint, voice, face) have been used for human identification. Face recognition is a natural, user friendly and non-contact way for human identification/authentication. Face recognizers are used in the recent years for identity authentication, access control, surveillance, human-computer interface and smart environments [1].

Current Face recognizers can be categorized into two groups, component-based face recognizers and image-based face recognizers [2]. Component-based systems use only a few features that are extracted from image. These features are the important and mostly invariable parts of face (e.g. eyes, nose, mouth and chin). However, this method has limited applications because of its difficult implementation and its unreliability in some cases. Image-based systems use a pixel intensity matrix that yields a high dimensional feature space. The image-based method is more desirable for researchers due to its ease of implementation and robustness. In order to build an accurate and fast face recognizer, a lower dimension representation from the raw image must be obtained. Principal Components Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) have been used for this purpose. Turk successfully used the PCA to represent faces and introduced the Eigenface method for face recognition [4]. PCA delivers a low dimensional representation of an image and extracts a compact global structure from it. On the other hand, LDA extracts discriminatory features so that the classes can be differentiated in an optimum way. These two linear methods can be changed to some nonlinear methods by means of Kernel functions (i.e. KPCA and KDA, [7]). Applying PCA on wavelet diagonal detail coefficients of images was examined by Yuela [9]. After representing faces in a lower dimension space, a classifier such as nearest distance classifier, k-nearest neighborhood, neural network or support vector machine (SVM) [3], [8]) can be applied to perform the recognition process. Recently, interests on using SVM have been increased because of its promising speed and accuracy.

In this work SVM is used as a face classifier with RBF and polynomial kernel function. We also utilized DWT as a preprocessing tool for face representation. The new proposed method decreases the error rate by more than 2.5% comparing to the PCA. The proposed method also reduces processing time for determining Eigenfaces significantly.

In the next section we will introduce our face representation system and proposed face recognition method. In section 3 the simulation results are reported and comparisons to Eigenface method are made. Finally conclusions are given in section 4.

2. METHODOLOGY

The first step of every pattern recognition system is feature extraction. The extracted features must be low in dimension and optimum in the discriminatory power simultaneously in order to decrease the time and error of recognition. To achieve these goals a two-stage approach was used for extracting face features. First the mean image is subtracted from all the training images in order to normalize them. A subband representation of normalized data was obtained by means of DWT. By applying PCA

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on the subband images Eigenfaces are obtained (Fig. 1). PCA orthonormal bases in order to project images into a lower dimension space for recognition. These projected vectors are sent to SVM system to train with database vectors or recognize the received image identity.

In our work the various forms of wavelet function are used in an attempt to find the optimum one. The two-dimensional intensity matrix of the input image works as the input of DWT system and the output is made by saving the approximation coefficients and discarding the three sets of detail coefficients. The approximation coefficients are the input of the PCA system to determine eigenfaces (Fig. 1) in the learning phase or to project images to coordinates that are defined by eigenfaces in the recognition phase (Fig. 2).

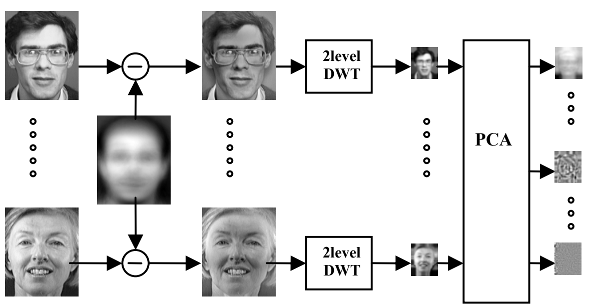

Fig 1 Block diagram for obtaining Eigenfaces by DWT-PCA process.

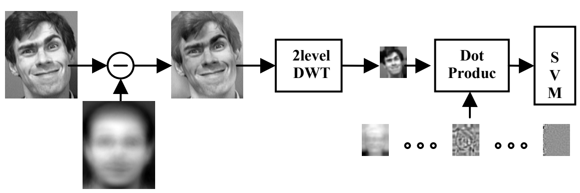

Fig 2 Block diagram of projecting images into eigenfaces space.

3. EXPERIMENTAL RESULTS

For evaluating our new method, we have used the ORL[1] database. The ORL face database (developed at the Olivetti Research Laboratory, Cambridge, U.K.) is composed of 400 images with ten different images for each of the 40 distinct subjects. The variations of the images are across pose, size, time, and facial expression. All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position, with tolerance for some tilting and rotation of up to about 20°. There is some variation in scale of up to about 10%. The spatial and grey-level resolutions of the images are 92 112 and 256, respectively. Five images from each individual are selected randomly for training and the five rest images are used for testing.

3.1. DWT-PCA

Two-dimensional wavelet transform is used in this method. The recognition rate is dependent to the selected wavelet function and the level of decomposition. In order to obtain the best result, these parameters were examined by experiments. Fig. 3 shows error rate for different levels of decomposition in the training phase. The best results are obtained when two level of decomposition is used. In Fig. 3 and Fig. 5, DWT-PCA and PCA methods are compared with different orders of polynomial SVM and RBF SVM respectively.

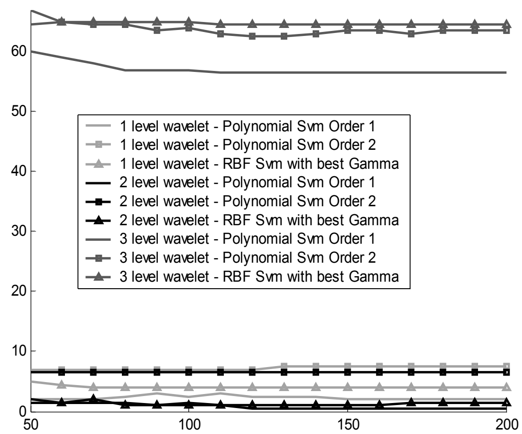

Fig 3 Error rate vs. number of Eigenfaces for one (light gray lines), two (black lines), and three (dark gray lines) levels of DWT decomposition.

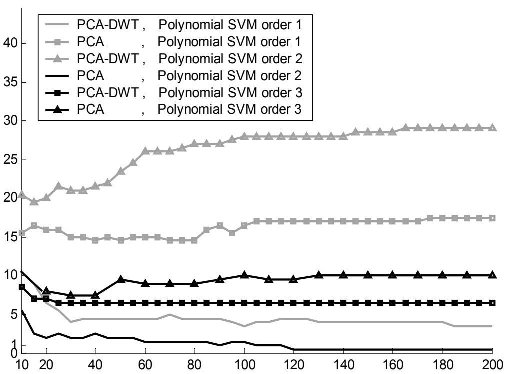

Fig 4 Error rate vs. different number of Eigenfaces for PCA method (gray lines) and DWT-PCA method (black lines) using polynomial SVM classifiers with different orders.

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[1] Olivetti Research Laboratory

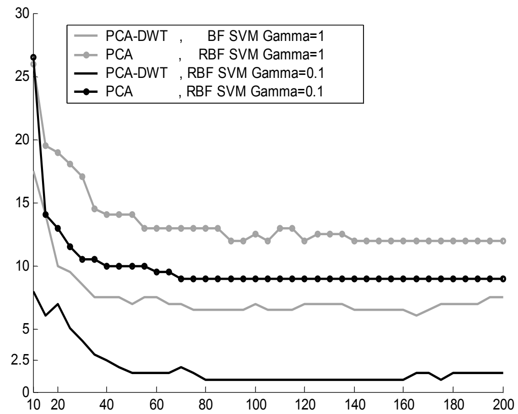

Fig 5 - Error rate vs. different number of Eigenfaces for PCA (gray lines) and the DWT-PCA methods (black lines) using RBF SVM classifier with two different values of Gamma.

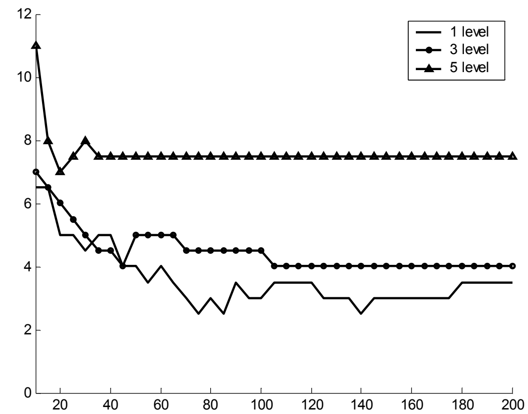

Fig 6 - Error rate vs. different number of Eigenfaces for one, three and 5 levels of DWT decomposition (one dimensional wavelet).

With respect to these figures, it is concluded that the new method decreases the error rate by more than 3% relative to the PCA method and maintains the property of having the same or better discriminatory power with less features. A great advantage is that the time of processing for determining Eigenfaces decreased significantly. This is due to the fact that wavelet transform reduces the size of images which must be processed to obtain eigenfaces. This effect significantly overcomes the effect of extra time-consuming processing which is done by wavelet transform.

The improvement of new DWT-PCA method (by two-dimensional wavelet transform) inspired us to examine some related methods to discover their effects.

3.2. DWT-PCA Using One-Dimensional Wavelet Transform

In this experiment one-dimensional wavelet transform is used instead of two-dimensional one. The results show that using one-level of decomposition makes no significant changes compared to PCA method. One can see by increasing levels of decomposition discriminatory power and efficiency reduces extremely (Fig. 6).

This result can be interpreted in this way, the correlation between each pixel and its' neighbors in the same row is neglected. In fact this transform supposes that the image space is a one-dimensional space which reduces between pixels information and consequently the efficiency.

3.3. DWT without PCA

In this experiment, the DWT approximation coefficients are reordered by zigzag scanning and the SVM input vectors are constructed directly from the rearranged approximation coefficients. Here face recognition was carried done without using PCA.

In Fig. 7 error rate for three levels of wavelet decomposition for different number of preserved approximation coefficient is shown. One can obtain similar error rate when using a large number of coefficients and dimension reduction ability doesn't exist. In the case of four level of wavelet decomposition, the number of coefficients can be reduced significantly but error rate is more than the PCA method (Fig. 8).

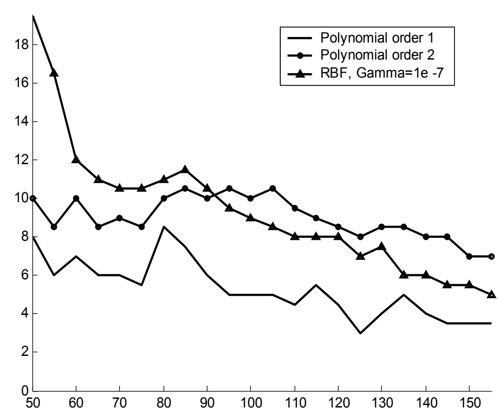

Fig 7 Error rate vs. different number of coefficients for three level of DWT decomposition.

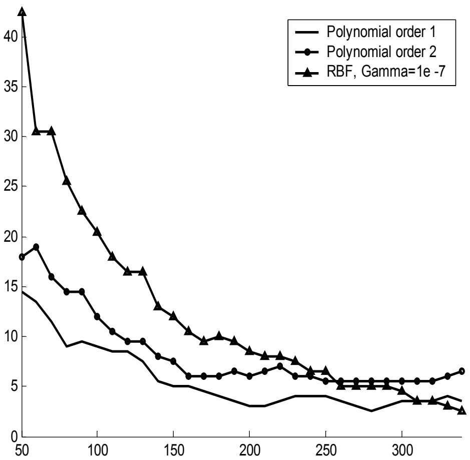

Fig 8 Error rate vs. different number of coefficients for four level of DWT decomposition.

3.4. DCT-PCA

Discrete Cosine Transform (DCT) is used instead of DWT in the first stage. The results are similar to PCA and it seems that the DCT has no effect on images. The representation vectors in two methods (PCA and DCT-PCA) are also similar in most of coefficients and the few differences are neglected by SVM.

4. CONCOLUSIONS

In this paper a new method for face representation and recognition using DWT and SVM classifier is proposed. 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 PCA orthonormal basis representation. These improvements lead an enhancement in efficiency or, in other words, security of system and moving toward real-time face recognizer. It is noteworthy that these improvements didn't affect other suitable properties of PCA method adversely.

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