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Bio-Metric Identification Utilizing Principal Component Analysis And Piece Coordinate Based Classifiers With Divided Approach

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Abstract: *A new approach of segmented face recognition which improves identification through better L2 Norm based distance classifier is proposed on this paper. The enrolled images are segmented into face blocks and face recognition algorithm is performed based on the blocks. By segmenting the image in to blocks we can identify and eliminate the problems of local occlusion and distortion in face images. The improved distance classifier which is able to select the best matched blocks and eliminates the affected blocks by providing appropriate weight for classifying each block depending upon the knowledge based on images simulated in particular condition*

Keywords: *Face recognition, PCA, Eigen face, Segmented PCA block.*

I. Introduction

Principal component analysis (PCA) was introduced to the field of face recognition in the early 1990's and became the most popular method since then, which is also known as eigen face method in face recognition [1,2].Under relatively ideal imaging condition, i.e., strictly controlled pose, illumination and expression variations, the conventional PCA can usually achieve very high recognition ratio. However, as an image or appearance based method, the conventional PCA takes a whole face image as an image vector and all the training and recognition procedures are based on such image vectors. That results in the following shortcomings. First, computation between huge vectors and matrixes is unavoidable. Second, mainly global features in face images are taken into account, but local features cannot be processed individually. Last, this approach is sensitive to variations in pose, illumination, occlusion and expression. In order to process face images locally and still make use of the basic principle of PCA at the same time, propose a segmented PCA block approach in this paper. It is shown by theoretical analysis and experiment that the proposed approach can not only both overcome the problem of computation between huge vectors and matrixes and lead to parallel algorithms, but can also achieve higher recognition accuracy under partial occlusions in face images.

II. The Segmented PCA block Approach

A. Basic approach

Given N facial image samples denoted by $h \times w$ matrixes $\{\mathbf{I}_1, \mathbf{I}_2, \cdots, \mathbf{I}_N\}$ belonging to C classes $\{\omega_1, \omega_2, \cdots, \omega_c\}$ conventional PCA converts all the N matrixes to n-D vectors $\{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$ in a lexicographic form first and then finds a linear transform to map the original n-D image vector space into a smaller m-D feature space. The transform is given by

$$\mathbf{y}_k = \mathbf{W}^t(\mathbf{x}_k - \boldsymbol{\mu}) \quad k = 1,2,\cdots,N \qquad (1)$$

where m $\mathbf{y}_k \in \mathbb{R}^m$ is a centralized

feature vector and $\boldsymbol{\mu} \in \mathbb{R}^n$ is the mean vector of all the sample vectors, while $\mathbf{W} \in \mathbb{R}^{n \times m}$ is a transform matrix with orthonormal column vectors. Specifically, $\mathbf{W} = (\mathbf{u}_1 \mathbf{u}_2 \cdots \mathbf{u}_m)$ □ is formed by

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$$\mathbf{C}_x \mathbf{u}_k = \lambda_k \mathbf{u}_k \qquad k = 1,2,\cdots,m \tag{2}$$

$$\mathbf{C}_x = \sum_{k=1}^{N} (\mathbf{x}_k - \boldsymbol{\mu})(\mathbf{x}_k - \boldsymbol{\mu})^t \tag{3}$$

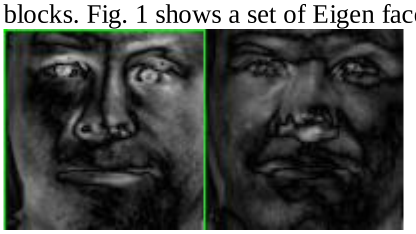
Generally, the dimension of the image vectors is huge. For instance, for 100×100 images, the image vectors will be 10000 dimensional and the covariance matrix will be of 10000×10000.Therefore, multiplication between high dimensional vectors and matrixes and finding the eigenvalues and eigenvectors of large sized matrixes are indispensable in the training and recognition stages of the conventional PCA. Therefore, the computation involved is usually time consuming [3]. In fact, as is known to all, the correlation existed in an image is relatively strong between nearby pixels and week between far apart pixels. To emphasize this point and make the transform and feature extraction more efficient, present the following block PCA approach. First, partition each image matrix into un overlapped $h_b \times w_b$ blocks. This is given by

$$\mathbf{I}_k = \bigcup_l \mathbf{B}_{kl} \qquad k = 1,2,\cdots,N \tag{4}$$

where the subscript *k* denotes the sequence of the training sample images and *l* that of the blocks in an image. If the original size of the images does not match that of the blocks, image re sampling, cropping, or zero padding can be performed first. Second, convert each block *kl* **B** into a block vector *kl* **x** and estimate the block covariance *xl* **C** from all the corresponding block vectors of all the sample images as shown in Eq. (5).

$$\mathbf{C}_{xl} = \sum_{k=1}^{N} (\mathbf{x}_{kl} - \boldsymbol{\mu}_l)(\mathbf{x}_{kl} - \boldsymbol{\mu}_l)^t \tag{5}$$

where $\boldsymbol{\mu}_l$ is the mean vector of the l^{th} image blocks. Third, for each block set denoted by different values of ***l***, find the eigenvalues and eigenvectors of its covariance $\mathbf{C}_{xl}$ according to Eq. (2) and form the block transform matrix $\mathbf{W}_l = (\mathbf{u}_{l1}\mathbf{u}_{l2}\cdots\mathbf{u}_{lm})$ where $m < h_b w_b$. Here, we call an eigenvector $\mathbf{u}_{lj}$ of a block covariance matrix *xl* **C** an segmented PCA block. Thus, an image block can be decomposed into the weighted sum of a number of segmented PCA blocks. Fig. 1 shows a set of Eigen faces consisted of 16×16 segmented PCA blocks from Yale face database.



(a)**Eigen faces of database images without segmentation**

(b)**Block eigen faces of data base images projected to eigen space(16 blocks - 25x25 sub image per block)**

(c **Block eigen faces of data base images projected to eigen space(100 blocks-10x10 sub image per block)**

Figure 1. The first 2 eigen faces consisted of segmented PCA blocks from Yale face database

Fourth, perform K-L transform on the basis of image blocks in the same way as in Eq. (1), that is

$$\mathbf{y}_{kl} = \mathbf{W}_l^t(\mathbf{x}_{kl} - \boldsymbol{\mu}_l) \qquad k = 1,2,\cdots,N \qquad (6)$$

Last, carry out classification in segmented PCA block space. To use a minimum distance classifier, the squared Euclidean distance between the object to be classified and each trained class center is to be finding by summing up all the block distances between the object blocks and the trained block means in the segmented PCA block space.

B. Some properties

1) Higher algorithm speed

Although the total number of pixels remains the same when an image is partitioned into blocks, the algorithms for training and recognition can usually both be speeded up. In linear transforms, main computation is multiplication between a vector and a matrix and this computation can be further decomposed into simple multiplication and addition between numbers. It is easy to show in theory that smaller number of such simple computations is required in segmented PCA block approach than in PCA because of the reduction of vector and matrix sizes despite the increase of block numbers. Experimental results in section 4 also validate the correctness of this analysis.

2) Possibility of parallel algorithms

Except for the block distance summing up stage, all the other stages for the training and recognition algorithms are exactly the same for every block. Moreover, there are only linear operations in the algorithms. So it is straightforward to realize the algorithms in a parallel hardware structure. In that case, the speed will be remarkably increased to as high as that of only one block's.

3) Local processing of face image features in transformed domain In segmented PCA block space, each block can be processed differently according to its specific statistics, which is not possible in conventional PCA. That is very helpful when there is local occlusion, distortion or uneven illumination. So give some experimental results on the case of local occlusion in section

4)It has been noticed that in the literature of face recognition, a technique called modular PCA was once put forward [4]. The key difference of the approach from that lies in what follows. On one hand, modular PCA takes all the sub-images of an image as the elements of a single set of sub-images so that all the sub-images are to be transformed into PCA space by the same transform matrix, but in segmented PCA block, each block has its own corresponding transform matrix. On the other hand, the main objective of modular PCA is to improve the accuracy of face recognition subjected to varying facial expression, illumination and head pose as was stated. However, the main consideration here is in the computation aspects.

III. Block Match Based Classifier

As is known, in image or appearance-based approaches such as conventional PCA, if there is severe local distortion such as partial occlusion in the object image, which is not usually existed in the training images, the performance of the classifier will drop down rapidly. However, in segmented PCA block approach, that can be improved by designing some block-based rules. Here, we propose the following modified minimum distance classifier to deal with the problem of local occlusion. Assume that the distances between the blocks of a test face image and the corresponding trained block centers of the *j*th class in the segmented PCA block space are denoted by $\{d_{j1}, d_{j2}, \cdots, d_{jM}\}$ for j=1, 2, … , C, we sort these values in an ascending order and only keep the first L items, which represent the L distances between the L best matched blocks of the test face image and the *j*th class. Then for each class, sum up all the L block distances obtained in the way just mentioned as the final distance metric.

Finally, perform classification by a general minimum distance classifier. In this way, it is possible to avoid those blocks affected by local occlusion or distortion.

IV. Experimental Results

A. Databases used in the experiments

Widely used face database Yale face database is adopted in our experiments. For the Yale database [5], The images were all cropped and normalized to 100×100 gray ones. Fig. 2 shows 3 images from of 4 person,. For the Yale database (http://www.yale.univ.edu), used the 18 images from 6 individuals and normalize the images to 100×100 for ease of image partition. When image of 100 x 100 is segmented to 25 x 25 sub image we got 16 blocks so that we created 16 threads to parallel compute which increased the speed of computation substantially .

Figure 2. Yale database samples used in the experiment

The performance of discriminating capability improves when the images are segmented to blocks in our experiment with images sized up to 100 x 100 we segmented blocks with sizes from 8 to 100 and result showed that optimum segmentation with best discrepancy achieved by L1 Norm classifier is around 20. Fig 4 shows the result discriminating capability for various sizes of segmented face blocks

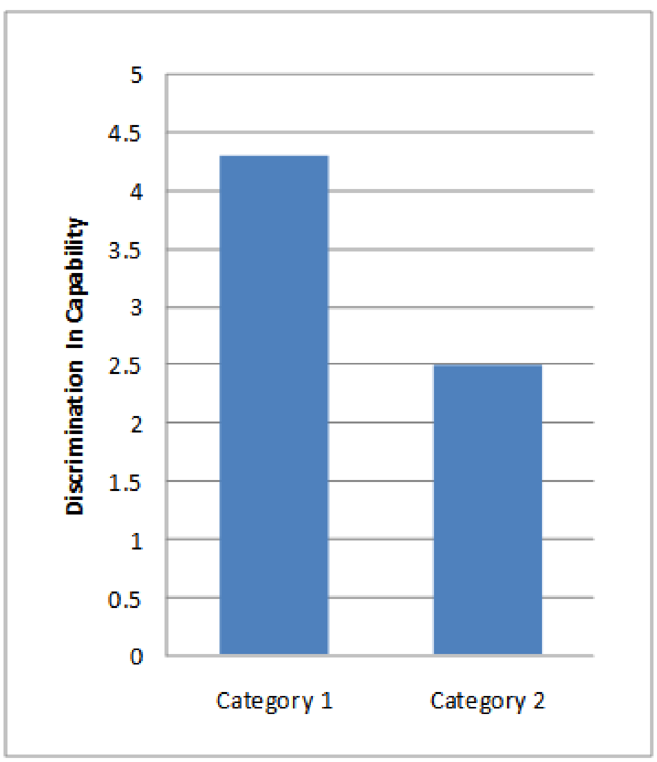


Figure 3 Result of discriminating Capabilities of Classifier

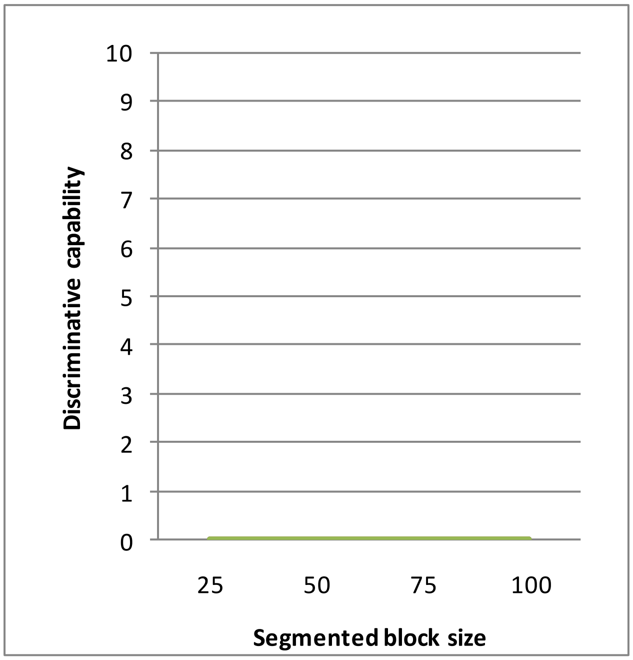


Figure 4 Result of performance of discriminating capability for various sizes of segmented face blocks

V. Conclusion

A block based PCA approach is proposed for face recognition in this paper. To deal with the problem of occlusion existed in face images, a block match based classifier is also proposed. Compared to the conventional PCA approach, the proposed segmented PCA block approach has several advantages, such as higher speed, parallel processing and local processing of face images. Further investigation on segmented PCA block approach is necessary in the future work. Because of the flexibility existed in this approach, it seems that segmented PCA block approach may further find its use in solving the problem of face recognition under variations in translation, pose, illumination and expression.

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