FACE RECOGNITION USING COMMON MATRIX APPROACH

Ü.Çiğdem Turhal[1], M.Bilginer Gülmezoğlu[2] and Atalay Barkana[3]

[1]Bilecik Technical College , Anadolu University
Gülümbe, Bilecik, Turkey
phone: + (90) 228-2160061, email: ucturhal@anadolu.edu.tr

[2]Department of Electrical and Electronics Engineering, Osmangazi University
Batı-Meşelik, 26480, Eskişehir, Turkey
phone: + (90) 222-2393750, fax: + (90) 222-2200535, email: bgulmez@ogu.edu.tr

[3]Department of Electrical and Electronics Engineering, Anadolu University
Muttalip, Eskişehir, Turkey
phone: + (90) 222-3213550, email: atalaybarkan@anadolu.edu.tr

ABSTRACT

In this paper, a new approach which is called the common matrix approach is proposed for face recognition. The common matrix for each class can be calculated either using Gram-Schmidt orthogonalization method or using scatter matrix of each class. In both ways, orthonormal matrices in the indifference subspace represent the directions that contain important discriminative information. The proposed approach overcomes the small sample size problem and the dimensionality problem in face recognition. The applications on AR-Face database give satisfactory results.

1. INTRODUCTION

Face recognition (FR) has a wide range of applications, such as face-based video indexing and browsing engines, human-computer interaction, and multi-media monitoring/surveillance. Developing a computational model for face recognition is quite difficult, because faces are complex, multidimensional and have meaningful visual stimuli.

Liner Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are the basic face recognition techniques [1-4]. LDA and PCA have been successfully used as a dimensionality reduction technique to many classification problems, such as speech recognition, face recognition, handprint recognition and multimedia information retrieval. It is commonly believed that a direct LDA solution for such high-dimensional data is infeasible [1,3,5]. LDA-based methods often fail to deliver good performance when face patterns are subject to large variations in view-points, illumination or facial expression, which result in a highly nonlinear and complex distribution of face images.

Improvements on the LDA such as quadratic LDA [5], Fisher's LDA [6], and direct, exact LDA [3] were proposed. Jing et al. used PCA+LDA method for face recognition [7]. In their work, PCA is used to project images from the original image space into a face-subspace, where dimensionality is reduced, so that LDA can be applied without trouble. A potential problem is that the PCA criterion may not be compatible with the LDA criterion thus the PCA step may discard dimensions that contain important discriminative information [3]. To prevent this, LDA without a separate PCA step DLDA have been developed [5].

Linear feature extraction based methods have been widely used in face recognition. Fisherfaces and Eigenfaces are two most famous techniques among them. In Fisherface method [6], PCA is first used to reduce the dimensionality of the feature space. Then in the lower dimensional PCA subspace, the Fisher discrimination vectors are computed. However Fisherface method has a drawback that it cannot completely solve the small sample size problem, which occurs when the within-class scatter matrix, S_w, is singular. The Eigenface method is based on linearly projecting image space to a low dimensional feature space. However, the Eigenface method, which uses PCA for dimensionality reduction, yields projection directions that maximizes the total scatter across all classes, i.e., across all images of all faces [8]. In choosing the projection which maximizes total scatter, PCA retains unwanted variations due to lighting and facial expression [6].

Yang et al. combined PCA-transformed feature vectors and Kernel PCA transformed feature vectors via complex vectors [9]. Then, the combined feature vectors are applied to a feature fusion container called Complex Fisher Linear Discriminant Analysis (Complex LDA) for a second fetaure extraction. Çevikalp et al. proposed a new face recognition method called the Discriminative Common Vector method based on a variation of Fisher's LDA for the small sample size case [10]. In their work, two different algorithms are given to extract the discriminative common vectors representing each person in the training set of the face database.

New face recognition approaches are needed, because, although much progress has been made to identify face taken from different viewpoints, we still cannot robustly identify faces under different illumination conditions, or when the facial expression changes, or when a part of the face is occluded on account of glasses or parts of clothing. In all approaches used for image recognition, an image with the size of nxm pixels is generally represented by a vector in an (n.m) dimensional space. These (n.m) dimensional spaces are too large to allow robust and fast object recognition.

In this paper, a new approach is proposed to overcome the small sample size problem and dimensionality problem in face recognition. The proposed approach depends on calculation of common matrix for each class which can be calculated with two different methods. In one method, difference matrices with size of nxm of any class are directly orthonormalized instead of the orthonormalization of (n.m) dimensional vectors using the Gram-Schmidt orthogonalization method [11]. The orthonormal matrices constitute difference subspace for that class. The projection matrix for this subspace is 3-dimensional (size of nxmxp) and called a tensor [12,13]. When the projection of any pixel matrix in any class onto the difference subspace of that class is subtracted from itself, the common matrix for that class is obtained. Use of the common matrix in face recognition gives satisfactory results for the training and test sets.
In the second method of this approach, the scatter matrix with size of (n.m)x(n.m) is constructed using mxm submatrices instead of using (n.m) dimensional vectors.The eigenmatrices corresponding to nonzero eigenvalues constitute difference subspace and the eigenmatrices corresponding to zero eigenvalues constitute indifference subspace [14]. The projection of any pixel matrix in any class on the indifference subspace gives the common matrix for that class. This second method has the same dimensionality problem with the vectorization of the images since they both have the scatter matrix with the same dimensions.

Our aim is to develop a computational model of face recognition which is fast, reasonably simple, and accurate in constrained environments such as an office or a household. The proposed approaches have advantages over the other face recognition schemes in its speed and simplicity, learning capacity and relative insensitivity to small or gradual changes in the face image.

2. COMMON MATRIX APPROACH

In this proposed approach we extract the common properties of images in each individual class in the training set by eliminating the differences of images. A common matrix for each class is obtained and then used in face recognition. To find the common matrix for each individual class from the training set we use two methods. In the first one Gram-Schmidth orthogonalization method and in the second, within-class scatter matrix of each class are used.

2.1 Obtaining Common Matrix Using the Gram-Schmidt Orthogonalization Method

Let us denote images in each class with pixel matrices A_i^c:

$$A_i^c = \begin{bmatrix} a_{11}^c & a_{12}^c & . & . & a_{1m}^c \\ a_{21}^c & . & . & . & . \\ . & . & & & \\ . & & . & & \\ . & & & . & \\ a_{n1}^c & a_{n2}^c & . & . & a_{nm}^c \end{bmatrix}$$

where c is the class number (c=1,….,C) and i indicates the number of images (i=1,…,K). Taking any pixel matrix of any class in the training set as a reference we find difference matrices:

$$B_j^c = A_{j+1}^c - A_1^c$$

where A_1^c is the subtrahand matrix.

The orthonormal basis matrices $\beta_1^c,...,\beta_{K-1}^c$ are obtained by using the Gram-Schmidt orthogonalization method [11]. In the orthogonalization procedure, the matrices with size of (nxm) are used instead of (n.m) dimensional vectors. The difference subspace $\mathbf{B^c}$ of the class c is defined as $\mathbf{B^c} = span(\beta_1^c,...,\beta_{K-1}^c)$. Any pixel matrix from each class can now be projected onto the difference subspace of that class. Then by subtracting the result from that pixel matrix we can find the common matrix for that class:

$$A^c_{com} = A^c_i - \left\langle A^c_i, \beta^c_1 \right\rangle \beta^c_1 - \ldots - \left\langle A^c_i, \beta^c_{K-1} \right\rangle \beta^c_{K-1}.$$

The common matrix is independent from the subtrahand matrix (A^c_1) and reference matrix A^c_i. Therefore a unique common matrix is obtained for each class.
In the testing procedure we take the projections of any pixel matrix A^c_x from the test set onto difference subspace of each class. Then by subtracting the result from test pixel matrix we can find remaining matrix A^c_{remain} for each class :

$$A^c_{remain} = A^c_x - \left\langle A^c_x, \beta^c_1 \right\rangle \beta^c_1 - \ldots - \left\langle A^c_x, \beta^c_{K-1} \right\rangle \beta^c_{K-1}.$$

The decision criterion is defined as:

$$w = \arg\min_{1 \le c \le C} \left\{ \left\| A^c_{remain} - A^c_{common} \right\|^2 \right\}.$$

If the test image belongs to the class c, the distance between A^c_{remain} and A^c_{common} should be minimum.

2.2 Obtaining Common Matrix Using Subspace Methods

A common matrix for each individual class is also obtained using the within-class scatter matrix of that class. In this approach, the information in the direction of the eigenmatrices corresponding to nonzero eigenvalues of the scatter matrix is discarded. Therefore the projection of any pixel matrix in any class onto the eigenmatrices corresponding to zero eigenvalues gives the common matrix for that class.

The within class scatter matrix with size of (n.m)x(n.m) is constructed using mxm submatrices instead of using (n.m) dimensional vectors.
We define images in each class as:

$$A^c_i = \begin{bmatrix} \mathbf{y^c_1} \\ \cdot \\ \cdot \\ \mathbf{y^c_n} \end{bmatrix}$$

where $\mathbf{y}_i$'s are the m-dimensional row vectors of A^c_i.

If we find the average matrix in each class, μ^c and subtract it from all pixel matrices in that class we can find the pixel matrices ($\overline{A}^c_i$):

$$\overline{A}^c_i = \begin{bmatrix} \mathbf{y^c_1} \\ \cdot \\ \cdot \\ \mathbf{y^c_n} \end{bmatrix} - \mu^c = \begin{bmatrix} \overline{\mathbf{y}}^\mathbf{c}_\mathbf{1} \\ \cdot \\ \cdot \\ \overline{\mathbf{y}}^\mathbf{c}_\mathbf{n} \end{bmatrix}.$$

Then within-class scatter matrix S^c_W, can be obtained as follows:

$$S^c_W = \begin{bmatrix} \left[(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{1})'(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{1})\right]_{mxm} & \cdot & \left[(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{1})'(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{n})\right]_{mxm} \\ \cdot & & \cdot \\ \left[(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{n})'(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{1})\right]_{mxm} & \cdot & \left[(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{n})'(\overline{\mathbf{y}}^\mathbf{c}_\mathbf{n})\right]_{mxm} \end{bmatrix}$$

Then we find the eigenvalues and the eigenmatrices of the within class scatter matrix. To find the common matrix, we project any pixel matrix onto the subspace spanned by the eigenmatrices corresponding to the zero eigenvalues. Then it is observed that the common matrix for each individual class is the same with the common matrix obtained from Gram-Schmidt orthogonalization method.

In the testing procedure, first of all, the remaining matrix A^c_{remain} is calculated by taking the projections of any pixel matrix from the test set onto the subspace spanned by the eigenmatrices corresponding to the zero eigenvalues. Then the decision criterion given in the section 2.1 is used in the recognition process.

3. EXPERIMENTAL STUDY

The AR-Face database is used in the experimental study [15]. The database includes frontal view of faces with changes in illumination and facial expressions. Each face is represented by a 192x256 pixel matrix. We randomly selected 37 individuals (20 males and 17 females). The elements of pixel matrices are 8-bit gray levels whose values change between 0-255. The size of pixel matrices are reduced to 50x40. Two different works are made in the experimental study.

i) In the first part, only nonoccluded 63 images from the training set and 63 images from the test set were chosen for every subject (class). Randomly selected 100 images were used in the training process of algorithms and the remaining 26 images were used in the test process.

In the first method, we find 99 orthonormal basis matrices from 100 pixel matrices. When the projection of any matrix belonging to each class in the training set onto the orthonormal basis matrices is subtracted from itself, the common matrix for that class is obtained. If the test matrix is used in the above procedure, the resulting matrix will be the remaining matrix. According to the decision criterion given in sectin 2.1 we classify the test pixel matrices and recognition rate of %99.1 is obtained in average.

In the second method, we used the indifference subspace spanned by the eigenmatrices corresponding to the zero eigenvalues and project each test pixel matrix on to the this subspace. So the remaining matrix from each test pixel matrix is calculated. When the decision criterion is used in the recognition process, the same results with that of first method are obtained.

ii) In the second part of the experimental study, totally only nonoccluded 14 images (7 images from the training set and 7 images from the test set) were chosen for every class. The recognition rates were computed by the "leave one out" strategy since the training set size is relatively small. When the decision criterion given in section 2.1 is used, the recognition rate was obtained as %97.7 in average.

4.CONCLUSION

The small sample size problem and dimensionality problem are the most important problems in face recognition. The small sample size problem has been overcome with different techniques.

It is commonly believed that the solutions for high-dimensional data are still infeasible. Usually an image of size (nxm) pixel matrix is generally represented by a vector in an (n.m) dimensional space. Then PCA and LDA are used to reduce dimension of these vectors. In reduction process, some important information can be discarded. Since there is no dimensionality reduction in our proposed method, all important information is included in the common matrix.

Since our aim is to develop a computational model of face recognition which is fast, reasonably simple and accurate, the proposed approach satisfies these requirements. These results can change for large number of persons in the same database. The performance also depends on matching of training and test sets.

The comparison of the proposed approach with the other well-known methods is missing in this paper. In future work, this comparison will be made using the methods mentioned in the Introduction section.

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