# FACE RECOGNITION USING FISHERFACE ALGORITHM AND ELASTIC GRAPH MATCHING

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## ABSTRACT

*This paper proposes a face recognition technique that effectively combines elastic graph matching (EGM) and Fisherface algorithm. EGM as one of dynamic link architecture uses not only face-shape but also the gray information of image, and Fisherface algorithm as a class specific method is robust about variations such as lighting direction and facial expression. In the proposed face recognition adopting the above two methods, the linear projection per node of an image graph reduces dimensionality of labeled graph vector and provides a feature space to be used effectively for the classification. In comparison with a conventional method, the proposed approach could obtain satisfactory results in the perspectives of recognition rates and speeds. Especially, we could get maximum recognition rate of 99.3% by leaving-one-out method for the experiments with the Yale Face Databases.*

## 1. INTRODUCTION

As Information Age develops, the security of information is becoming more and more important and access to a reliable personal identification is becoming increasingly essential. Because conventional methods of identification based on possession of ID card or exclusive knowledge like a social security number or a password are not altogether reliable, biometrics that make out one's identity and authentication can be used. Especially, in the perspective of ease of use and accuracy, face recognition has an advantage compared with other biometrics [1].

In general face recognition procedure, the most important thing is which feature vector is used. In early 1990s, face recognition by using Karhunen-Loeve (K-L) projection was proposed [2]. And several methods such as Fisherface and elastic graph matching (EGM) were researched [3][4][5]. Principal component analysis (PCA) and Fisherface using K-L projection are used to reduce the dimensionality of the feature vector and classify the feature space. But these methods have a defect that recognition rate decreases rapidly as the transition of a face region happens. In the case of EGM, that problem can be solved by Global Move and its recognition rate is higher than the above methods also. But compared with methods using K-L projection, its recognition speed is so slow that the recognition procedure is impossible at real time.

We propose algorithms that effectively combine the face recognition methods such as EGM, PCA and Fisherface. In face, in our proposed face recognition adopting the above methods, linear projection per node of an image graph reduces dimensionality of labeled graph vector and provides a feature space to be used effectively for the classification. In comparison with a conventional method, the proposed approach could obtain satisfactory results in the perspectives of recognition rates and speeds.

## 2. FACE RECOGNITION USING KARHUNEN-LOEVE PROJECTION

We use the theories of optimal linear projection to recognize face. There are two projections: a K-L projection or PCA to produce a set of Most Expressive Features (MEFs), and a subsequent discriminant analysis projection or Fisherface to produce a set of Most Discriminating Features (MDFs) [6].

### 2.1. Principal Component Analysis (PCA) method

PCA is based on statistical properties of vector representations. This is one of the linear transformations that can be represented as following;

$$y = A^T x \qquad (1)$$

Above an equation shows that feature vector $y$ can be represented by projecting original vector $x$ onto domain $A$. PCA uses eigenvectors of covariance matrix of $x$ as the basis of $A$. Because generated feature vectors are uncorrelated each other, we can classify simply with Euclidean distance to recognize face without designing the classifier for these models.

### 2.2. Fisehrface method

Fisherface algorithm considers the ratio between the variation of one person and that of another person. That is to say, it maximizes the determinant of between-class scatter matrix simultaneously, minimizing the determinant of within-class scatter matrix.

Fisehrface procedure is as the following. Let there be total $N$ images and total $c$ persons. Suppose the number of images from one person is $K$. From PCA, we can get $N-1$ eigenfaces. To minimize the determinant of within-class scatter matrix and maximize that of between-class scatter matrix, we constitute the $S_w^{-1}S_b$ matrix and get Fisherfaces. The definition of $S_w$ and $S_b$ is as following;

$$S_w = \sum_{i=1}^{c}\sum_{j=1}^{K}(y_j - M_i)(y_j - M_i)^T \qquad (2)$$

$$S_b = \sum_{i=1}^{c}(M_i - M)(M_i - M)^T \qquad (3)$$

Where $M_i$ is the mean vector of $i$th class and $M$ is the mean vector of all classes. The $c$-$l$ dimensional feature vectors are obtained by projecting feature vectors of PCA onto the Fisherface matrix. And then, we recognize face by using predetermined feature vectors [6].

## 3. FACE RECOGNITION USING ELASTIC GRAPH MATCHING (EGM)

EGM is a simplified implementation as one of dynamic link architecture methods that base on neural network and geometrical measure [4]. Usually this method consists of at least two phases such as training phase and recall phase. In training phase, a graph of an image consists of a set of nodes and a set of edges. Each node is labeled with a set of features and the edges are used to code the topography. In recall phase, the graph matching algorithm tries to find a position or an overall costs for each node of the graph which maximizes the feature similarity and minimizes the topography costs at the same time. Finally, the overall cost function is used to recognize face.

### 3.1. Gabor wavelet

In computer vision, Daugman pioneered the use of Gabor wavelet in the 1980s. Recently Gabor features have been used in several image analysis applications including texture classification, texture segmentation, image recognition, image registration, and motion tracking. Gabor filter is designed from a simple model for the responses of simple cells in the primary visual cortex and represented by a complex-valued 2D plane wave restricted by a Gaussian envelope [7][8].

### 3.2. Elastic graph matching (EGM)

EGM is the method that compares a graph of a new image with that of a reference model. The relation between two graphs can be represented by overall cost function such as

$$d(G,R) = \sum_{i=1}^{N_n} d_n(G_{n_i}, R_{n_i}) + \lambda \sum_{j=1}^{N_e} d_n(G_{e_j}, R_{e_j}) \qquad (4)$$

where $G_{n_i}$ is $i$th node of a grid $G$ for a new image and $R_{e_j}$ is $j$th edge of a grid $R$ for a reference model. And $N_n$ and $N_e$ are each the total number of nodes and edges. $\lambda$ is a weighting factor that chatacterizes the stiffness of a graph. The matching algorithm is composed of Global Move and Local Move. In Global Move, we try to approximate the best matching position by not allowing distortion of the graph. This means whenever we move the graph on the image, we must move all nodes uniformly. In Local Move, we allow each node to move individually.

## 4. PROPOSED ALGORITHM

Proposed face recognition method is divided into 3 steps. As shown in Fig. 1, in the first step, the graph of a face image is constructed from the response of 2D Gabor wavelet. In Step 2, we apply PCA and Fisherface algorithm for labeled graph vector. And the last in Step3, the matching algorithm for feature vectors is executed.

In this paper, we propose two methods that one is combining fixed graph matching (FGM) with PCA/Fisherface that the other is combining EGM with PCA/Fisherface. Here, we define FGM as the EGM without Local Move consideration.

### 4.1. Algorithm combining fixed graph matching with PCA/Fisherface

This method is linear projection in FGM for all nodes of an image. First, after image graph is composed of feature vector extracted from 2D Gabor response, we obtain labeled graph vector $J(x_l)$ for each node $x_l$. The mean vector is $E\{J(x_l)\} = \frac{1}{M}\sum_{m=1}^{M} J_m(x_l)$. Let $\Psi(x_l) = J(x_l) - E\{J(x_l)\}$ be the normalized feature vector at node $x_l$, where $J(x) = (J(x_l), \ldots, J(x_{12\times N}))^T$ is the labeded graph vector if scale and orientaion is 3 and 4, respectively. $N$ represents the total number of nodes for an image. Let $M$ denotes the total number of face images extracted from a database for all persons. Let also $C(x)$ be the covariance matrix of the feature vectors $\Psi(x)$ at all nodes. In PCA we compute the eigenvectors that correspond to the $p$ largest eigenvalues of $\Psi(x)$, say $U_1(x), \ldots, U_p(x)$. The PCA projected feature vector is given by;

$$\Omega(x) = [U_1^T(x),...,U_p^T(x)]\Psi(x) = P(x)\Psi(x) \quad (5)$$

Where $T$ denotes the transposition operator. $\Omega(x_l)$ is of dimensions $p\times 1$, $p \le 12\times N$. Next, Fisherface is applied to feature vectors produced by PCA. Using equations, (2) and (3), we get the final feature vectors such as

$$Z = [W_1^T P(x)(J(x) - E\{j(x)\}),...W_M^T P(x)(J(x) - E\{J(x)\})]^T \quad (6)$$

Where $W_j$ is a basis vector extracted from $S_w^{-1}S_b$ matrix.

To recognize face, if test image enters, we obtain labeled graph vector $F_{in}$ that extracted from 2D Gabor response. And then, after we compute $\Psi_{in} = F_{in} - E\{F\}$ and $\Omega_{in}$, we can get $W_j^T\Omega_{in}$ for all $j=1, 2,..., M-1$. Finally, using the Euclidean distance between $Z_{in} = [W_1^T\Omega_{in} W_2^T\Omega_{in},...W_{M-1}^T\Omega_{in}]^T$ and Z of $\Psi(x)$, we recognize face.

### 4.2. Algorithm combining elastic graph matching with PCA/Fisherface

This method is linear projection in EGM per node of images. The first step is like the above method. And then if scale and orientation is 3 and 4, we obtain labeled graph vector, $J(x_l) = [J_1(x_l),...,J_{12}(x_l)]^T$ for each node $x_l$ and feature vector, $\Omega(x_l)$ computed by PCA. $\Omega(x_l)$ is of dimensions $p\times 1$, $p \le 12$. And as applying Fisherface like the above method, we obtain feature vectors from equation (6).

To do recognize procedure, the similarity function for node, $d_n(G_{n_i}, R_{n_i})$ in equation (4) is defined as;

$$d_n(G_{n_i}, R_{n_i}) = \left\| Z(x_l)^G - Z(x_l)^R \right\| \quad (7)$$

Finally, we recognize face by carrying out the computations explained in equations, (4) and (7).

## 5. EXPERIMENTAL RESULTS

All the image processing were performed in PC that is composed of Pentium processor III 450 MHz and 128 MB memory, with software written in C. We have used a database at Yale that includes variations in both facial expression and lighting. The Yale database contains 150 frontal face images covering 15 individuals taken under 10 different conditions as shown in Fig. 2. In this paper, we experimented with images $128\times 128$ size changed from those of original $320\times 243$ size for total 7 face recognition methods.

### 5.1. Experiment results by leaving-one-out method

The experimental results of recognition rates and speeds by leaving-one-out method for 7 different face recognition experiments are shown in Table 1. In PCA, we chose the number of eigenvectors that the sum of these unused eigenvalues is less than 5 percent of the sum of the entire set. In Fisherface method, 14 feature vectors were used. And in experiments on EGM and FGM, Global Move used to segment face region was omitted as the location of face region was specified. A graph of an image was composed of 7 width and 10 length nodes. To cover the whole face region, the spacing between vertices was set to 11 pixels and $\lambda$ charaterizing the stiffness of a graph was 0.003. To extract feature vectors, Gabor filter that had 3 scales and 4 orientations was used.

As shown in Table 1, in the perspectives of recognition rates Fisherface, EGM, and an algorithm combining FGM with Fisherface had the best performance. Especially, we could get maximum recognition rate of 99.3% and recognition speed of 6 sec. in an algorithm combining FGM with Fisherface. If there is transition of face region, in the case of methods by using K-L projection, the recognition rate decreases rapidly, but in FGM and EGM methods, this problem can be solved by Global Move.

### 5.2. Experiment results by hold-out method

Table 2 shows experimental results of recognition rates and speeds by hold-out method. After training with three images per person, we experimented with the others. In Table 2, 1, 2, 3rd images are chosen in a clockwise direction from the upper left hand of Yale database in Fig. 2.

As shown in Table 2, recognition rate of EGM and an algorithm combining FGM with Fisherface is 92.6%, 90.9%, respectively. The recognition rates of proposed algorithms were higher than conventional methods by K-L projection. Recognition speed of an algorithm combining FGM with Fisherface is 5 sec.. As the dimension of feature vectors reduced, the performance of recognition speed was improved. In the case of EGM, recognition rate is excellent but it takes too much time for training and recognition that they are constructing image graph and executing Local Move. Especially, the more resolution for spatial frequency and orientation of Gabor filter is used, the more recognition speed can be improved relatively.

## 6. CONCLUSIONS AND FUTURE WORKS

In this paper, we effectively combined the face recognition methods such as EGM, PCA, and Fisherface algorithm and could obtain the satisfactory results in the perspectives of recognition rates and speeds. Because of the dimensional reduction of labeled graph vector in applying PCA/Fisherface algorithm, the recognition speed of proposed methods was improved in comparison with EGM.

Especially, in matching procedure of proposed method, if the efficiency of Local Move is improved, recognition rate can be enhanced though Fisherface is not necessarily good enough for discriminating among classes defined by a set of feature vectors. In the future, we need more study for efficient construction of training model and how the transition of face region influences on recognition rate.

## 7. REFERENCES


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This work is being supported by the 2000 year University Basic Research program of the telecommunication Department of ROK.


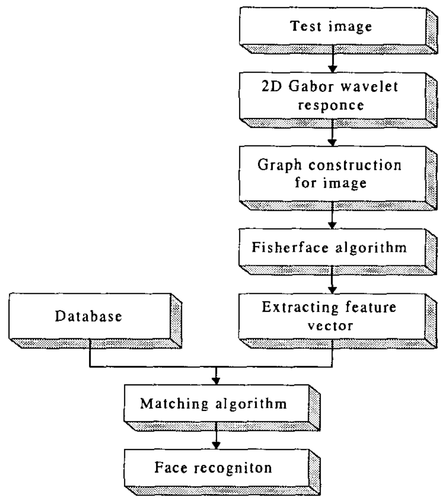


Fig. 1. Proposed algorithm for face recognition

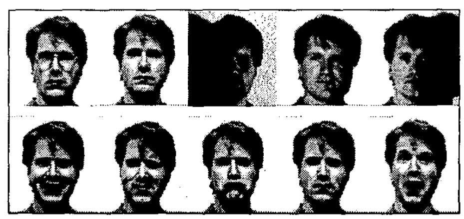

Fig. 2. Example of Yale database

Table 1. The experimental results by leaving-one-out method

| Recognition method | Recognition rate | Recognition speed |
|---|---|---|
| PCA | 79.3% | Within 0.5 sec. |
| Fisherface | 99.3% | Within 0.5 sec. |
| EGM | 99.3% | Approx. 2624 sec. |
| FGM + PCA | 88.7% | Within 6 sec. |
| FGM + Fisherface | 99.3% | Within 6 sec. |
| EGM + PCA | 88.0% | Within 892 sec. |
| EGM + Fisherface | 90.0% | Within 1118 sec. |

Table 2. The experimental results by hold-out method

| Images used in training | PCA | Fisherface | EGM | FGM + PCA | FGM + Fisherface | EGM + PCA | EGM + Fisherface |
|---|---|---|---|---|---|---|---|
| 1, 2, $3^{rd}$ images | 81.9% | 93.3% | 91.4% | 89.5% | 94.3% | 87.6% | 93.9% |
| 3, 4, $5^{th}$ images | 75.2% | 85.7% | 94.3% | 85.7% | 94.3% | 88.6% | 88.6% |
| 5, 6, $7^{th}$ images | 82.9% | 87.6% | 93.3% | 86.7% | 93.3% | 87.6% | 90.5% |
| 7, 8, $9^{th}$ images | 72.4% | 77.1% | 93.3% | 81.0% | 87.6% | 85.7% | 83.8% |
| 1, 9, $10^{th}$ images | 70.5% | 72.4% | 90.5% | 75.2% | 84.8% | 78.1% | 80.0% |
| Recognition rate (Ave.) | 76.6% | 83.2% | 92.6% | 83.6% | 90.9% | 85.5% | 87.2% |
| Recognition speed | Within 0.25 sec. | Within 0.25 sec. | Approx. 359 sec. | Within 5 sec. | Within 5 sec. | Within 235 sec. | Within 270 sec. |