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A Study on Detection and Recognition of Facial Area Using Linear Discriminant Analysis

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Abstract

We propose a more stable robust recognition algorithm which detects faces reliably even in cases where there are changes in lighting and angle of view, as well it satisfies efficiency in calculation and detection performance. We propose detects the face area alone after normalization through pre-processing and obtains a feature vector using (PCA). The feature vector is applied to LDA and using Euclidean distance of intra-class variance and inter class variance in the 2nd dimension, the final analysis and matching is performed. Experimental results show that the proposed method has a wider distribution when the input image is rotated 45 ° left / right. We can improve the recognition rate by applying this feature value to a single algorithm and complex algorithm, and it is possible to recognize in real time because it does not require much calculation amount due to dimensional reduction.

Keywords: *LDA, PCA, Face Recognition, Face Detection*

1. Introduction

Although there are a great number of studies which analyse[1,2] each characteristic of human behavior in diverse ways, it is not going too far to say that biometrics recognition is their main focus. In particular, facial recognition can be classified into four approaches as follows: template matching, statistical classification, contextual approach and neural network[3]. The main approaches for statistical classification are: facial recognition by Principal Component Analysis(PCA)[4,5], facial recognition by Support Vector Machine(SVM)[4][6][10], facial recognition by Linear Discriminant Analysis(LDA)[5][7], facial recognition by Independent Component Analysis(ICA)[8] and facial recognition by neural network[9].

We propose a more stable facial recognition algorithm which detects faces and is robust to changes in lighting and viewing angle, and satisfies efficiency of calculation and detection performance. The system proposed normalized the images through pre-processing.

First, in order to accurately detect face candidates alone from normalized images, the background was

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removed from two light and dark images through a difference operation. Second, PAC was applied to the candidates detected to decrease the dimensions in high-dimensional data and to obtain low-dimensional feature vectors. Third, to obtain stable recognition rates, LDA was applied and the Euclidean distances between within-class scatter and between-class scatter were compared in a final check. For the directions of each face image input to improve face recognition rates, images with information on left and right 45° angles were obtained and a database was created to obtain representative values, and with PAC applied, the values were projected into eigenspace to calculate a feature value for each face.

This process improved the stability and accuracy of the recognition rate with regard to the input orientations. Also as a lot of calculation was not required due to the decreased dimension, the algorithm could be applied in a real-time recognition system.

2. Composition of the Whole System

We propose a stable face recognition algorithm and the whole system composition is presented in Figure1.

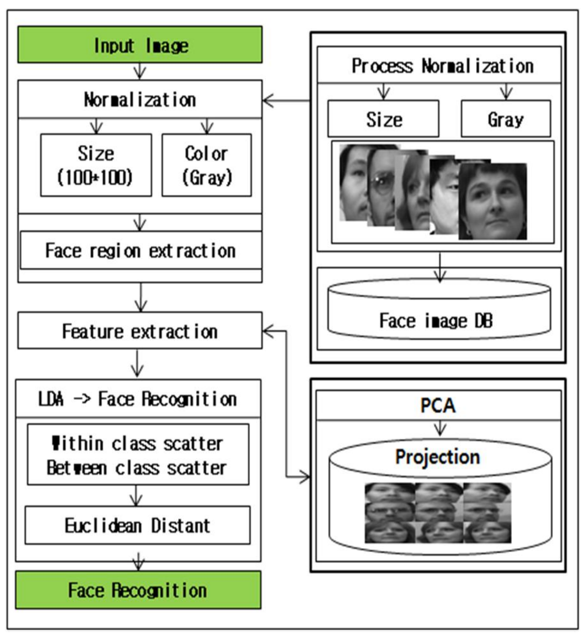

Figure 1. Algorithm of the Whole System

3. Elimination of the Background

This study measured changes in the brightness of the background due to changes in lighting and obtained I_t as a background image for T_i, after a certain period in consideration of time(t), and then, each pixel (x) within the R, image area was analysed to obtain $P_{max}(x)$, a value for the brightest area and $P_{min}(x)$ a value for the darkest area. The difference between the two values D(x) was a critical value of brightness according to changes in lighting. With the three elements used, a background model was made. To put this in equations, Equations (1-4) are presented.

$$BM = \{P_{max}(x), P_{min}(x), D(x)\}_{x \in R} \tag{1}$$

$$P_{max}(x) = \mathrm{Max} I_t, (1 \le t \le T_i) \tag{2}$$

$$P_{min}(x) = \mathrm{Min} I_t, (1 \le t \le T_i) \tag{3}$$
$$D(x) = P_{max}(x) - P_{min}(x) \tag{4}$$
$$B(x) = \begin{cases} 255 \text{ if} |P_{max}(x)| \text{or} |P_{min}(x)| > D(x) \\ 0 \quad \text{other wise} \end{cases} \tag{5}$$

Equation(5) presents a criterion which only divides the areas with different movements in faces ignoring changes in brightness and through morphology, noise was eliminated.

4. Face Detection for Principal Component Analysis(PCA)

We propose an approach to solve the problem of the directionality of faces by creating a parametric space using PCA)[4,5]. To make the change rate of input images larger, a data base was created for images with faces turned 45° left and right and the system can recognize images even though the facial images are distorted. Figure2 presents some images obtained with 5° distortion in facial images in consideration of the directionality of the faces which are freely input(each face is divided into 19 images).

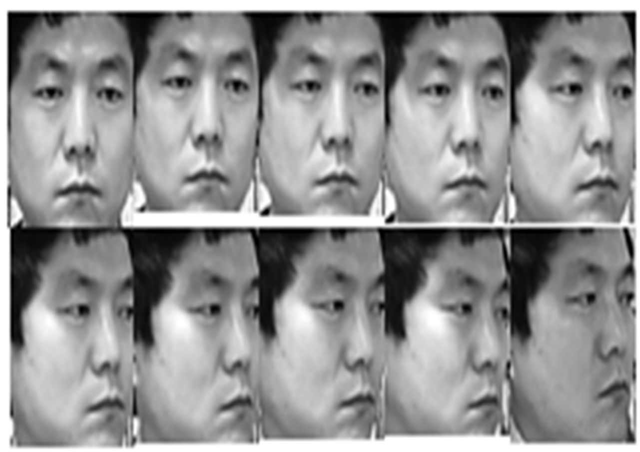

Figure 2. Facial images in consideration of the directionality

4.1 Composition of Eigenspace by PCA

To calculate eigenvectors, mean data from each image was obtained and then differences in data for each image was obtained. □, mean data and X, a set of new image data, are presented in Equation(6) and (7).

$$C = (1 / N) \sum_{i=1}^{N} x_i \tag{6}$$
$$X \triangleq \{x_{1,1}^{(1)} - c, x_{2,1}^{(1)} - c, \ldots x_{R,1}^{(1)} - c, \ldots x_{R,L}^{(P)} - c\} \tag{7}$$

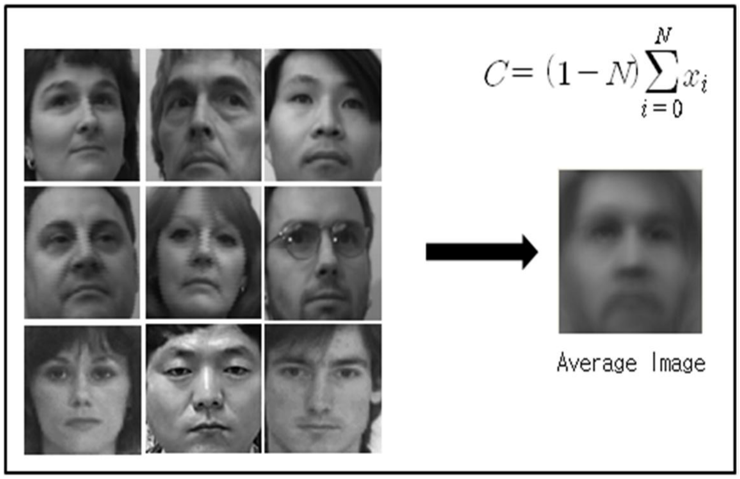

Figure 3. Average image of face

To obtain eigenspaces, X, an image set with size $M * N$ was calculated as in Equation(8) and an eigenvector which satisfied Equation(9) was obtained. That is, λ (eigen value) and e (eigenvector) in Q, a covariance matrix was then obtained.

$$Q \triangleq XX^{T} \tag{8}$$

$$\lambda_i e_t = Q_{ei} \tag{9}$$

Here, M is the data for one image(100x100) and N is an integral number indicating the entire number of images.

This study obtained eigenspaces using Singular Value Decomposition to gain eigenvectors in a covariance matrix of X, an image set.

The matrix could be decomposed as in Equation(10) and the original equation could be presented as in Equation(11).

$$X = \sum_{i=1}^{r} \sigma_i V_i \upsilon_i^{T} \tag{10}$$

$$X = V \sum U^{T} \tag{11}$$

As V and U matrices lie at right angles, they are expressed as in Equation(12).

$$[V^{T}] \cdot [V] = [U^{T}] \cdot [U] = [I] \tag{12}$$

As the size of each eigenvector implies the importance of each eigenvector, an important eigenvector defining the eigenspace was selected with the use of Equation(13). Therefore, all eigenvectors with main composition which represent many images without using all the eigenvectors for composition of an eigenspace could be used and they were expressed as eigenspaces for facial images.

$$\frac{\sum_{i=1}^{k}\lambda_i}{\sum_{i=1}^{N}\lambda_i} = T_1 \tag{13}$$

4.2 Correlations and Distance in Eigenspace

In the eigenspaces of facial images obtained in the previous section, X, a set of images removed from C, average images in the eigenspace were projected with the use of Equation(14).

$$f_j = [e_1, e_2, e_3, \ldots\ldots, e_k]^T (x_n - c) \tag{14}$$

The face images obtained, f_j were expressed as dots in eigenspace and the dots consisted of input feature symbols as they contained information from each face's features. The results of the projection were expressed as scattered dots, and each dot indicates a facial input. Vectors with similar feature values were projected closely in eigenspace. That is, the closer the dots were projected in eigenspace, the higher the correlation each image had. The distribution of each facial image in the eigenspace is shown in Figure 4.

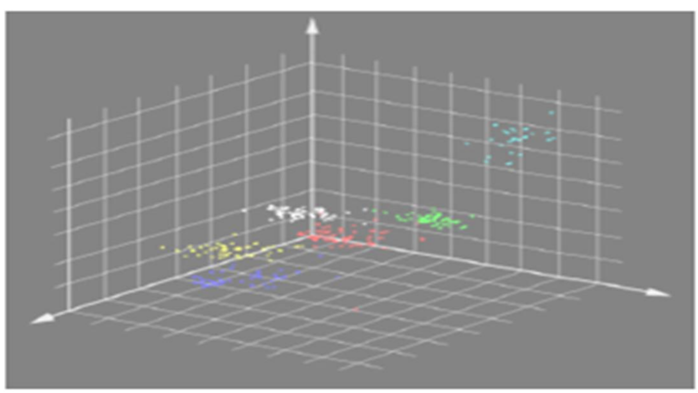

Figure 4. Face distribution of eigenspace

5. The Optimal Separation of LDA for Facial Recognition

Feature values tested through PCA[4,5] were applied in LDA)[5][7] and euclidean distances were compared through within-class scatter and between-class scatter in the 2nd dimension space for a final face determination.

5.1 Linear Discriminant Analysis

LDA is a system that reduces the dimension of feature vectors in a way of minimizing the rates of between-class scatter and within-class scatter[11,12]. In LDA, scatter between images which belong to different classes after transformation was maximized while scatter between images from the same class was minimized. To express the enormous amount of data which is input in real-time, it is important to convert high-dimensional data into low-dimensional data, but it is more important to separate faces with different features into groups of face images. LDA can differentiate faces with different features [12]. Therefore, it has a superior recognition rate than that of Eigenface which analyses the eigenvalue in scatter of the facial image vectors.

LDA maximizes the class separation in the feature space to decrease the dimension to a linear subspace. Expression of within-class scatter and between-class scatter in the two dimensional space is presented in Figure5 and if the dimension is decreased into LDA, features are rearranged after the reduction of dimension as in Figure6.

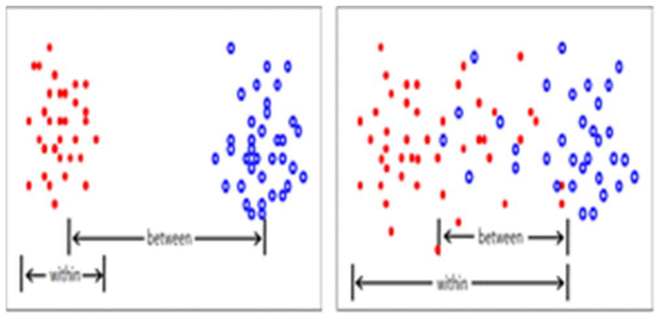

Figure 5. Within-class and between class scatter

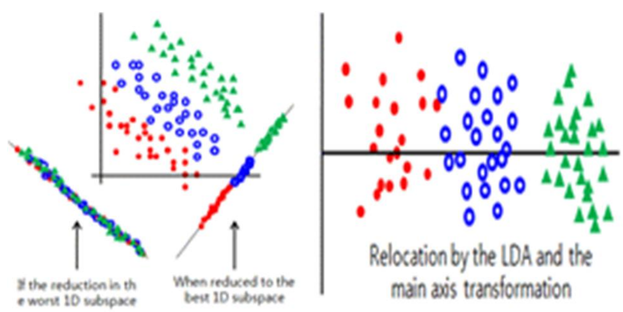

Figure 6. Dimensionality reduction

The purpose of LDA is to decrease the dimension while maintaining the determining information between the classes as in Equation(15), which means that the problem of selecting one axis which maximizes the degree of scatter of a one-dimensional scalar is solved with LDA.

$$y = W^T x \tag{15}$$

W is a $D * 1$ matrix, and is $D * 1$ dimension data.

To obtain an optimal projection vector with maximum of separation, the projection vectors are used to obtain average vectors. Because class separation is easier as mean points in classes were farther apart. μ_y, the average vector in the sample of the original data and $\bar{\mu}_y$, a mean vector of y, the projected sample, are presented as in Equation(16).

$$\mu_i = \frac{1}{N}\sum_{X\in\omega_i} x,\ \tilde{\mu}_i = \frac{1}{N}\sum_{y\in\omega_i} y = \frac{1}{N}\sum_{y\in\omega_i} W^T x = W^T \mu_i \tag{16}$$

When average vectors of samples x and y are $\mu_{1,}\mu_2$, the distance between the centers of the projected data were selected as an objective function as in Equation(17).

$$J(W) = |\tilde{\mu}_1 - \tilde{\mu}_2| = \left|W^T(\mu_1 - \mu_2)\right| \tag{17}$$

The objective function is not a good measure as the distance between the center of the projected vectors does not consider standard deviation. To overcome this problem, Fisher normalized the difference between standards using within-class scatter for expression of a function, and Equation(18) is presented to maximize the objective function.

$$\tilde{S}_i^2 = \sum_{y \in \omega_i} (y - \tilde{\mu}_i)^2 \tag{18}$$

$(\tilde{S}_1^2 + \tilde{S}_2^2)$ is the within-class scatter of a projected sample and samples of the same classes had an adjacent projection made. At the same time, between-class projection finds as far as possible. Fisher's objective function is briefly defined as and as in Equation(19).

$$J(W) = \frac{W^T S_B W}{W^T S_W W} \tag{19}$$

(19)To find W with a maximum objective function using Equation(19), optimalization is helpful. If maximization and generalized eigenvalues are used as solutions, optimalized W is presented in Equation(20).

$$W^* = \operatorname{argmax}\left\{\frac{W^T S_B W}{W^T S_W W}\right\} = S_W^{-1}(\mu_1 - \mu_2) \tag{20}$$

The Equation(20) is Fisher's Linear Discriminant.

5.2 Optimal Separation of Faces using Feature Values

The feature vectors obtained above were used for LDA to measure the within-class scatter and between-class scatter in the two dimensional space and then Euclidean distance was used for effective separation of different feature values and the recognition rate was greatly improved.

6. Result and Discussion

For facial recognition, first, images input from a camera were normalized at 100*100 and were transformed into Gray scale for speed. Second, for less sensitivity to changes in lighting, critical values were applied for differences between two images with different brightness values to improve accessibility to the target area and detection capacity. Third, after measuring within-class scatter and between-class scatter in the two dimensional space with the use of LDA, Euclidean distance values were compared for the final determination. To evaluate the performance of the facial recognition system proposed in this study, it was compared with different existing algorithms. Table 1 shows a comparison of its performance with those of existing algorithms.

Table 1. Recognition compared to the existing algorithms(%)

Algorithm	Success Ratio	Fail Ratio	Time (sec)
Single-PCA	82.1	17.9	0.82
Single-LDA	84.7	15.3	0.95
Single-SVM	85.5	14.5	1.12
PCA+SVM	90.4	9.6	1.58
PCA+LDA	92.7	7.3	1.23

As seen in Table 1, when it was used alone, SVM had the highest recognition rate in this test followed by SVM, PCA. There was a 1% difference in recognition rate between LDA and SVM. When a combined algorithm was used, the recognition rate was improved by about 2%. Both had high recognition rates. However, in considering overall recognition rate, the system proposed in this study had the highest recognition rate of 92.7%, which indicates that more stable facial recognition is available in comparison with existing systems. However, the four algorithms showed insignificant differences in recognition time while the system proposed in this study fell a little behind the other algorithms in response time though this was insignificant.

Table 2 compares the recognition rates in the case the images input from the camera had a simple background included with them and the case when images from the camera had a complex background. Table 3 compares images taken in bright lighting with those taken in poor lighting and the detection rates of faces by the algorithm proposed in this study.

Table 2. Comparison of recognition in the background change(%)

Background	Success Ratio	Fail Ratio	Time (sec)
The input image from a simple background	98.6	1.4	0.93
The input image in complex background	92.7	7.3	1.23

To examine the recognition rate in Table 2, the recognition rate of images input with a simple background was 98.6%, or very high.

Table 3 shows a test to confirm facial detection rates with respect to changing lighting. The algorithm proposed in this study had a 92.8% facial detection rate which was higher than those of the other algorithms. Through this test, it was demonstrated that changes in lighting for facial detection is a very sensitive element.

Table 3. Face detection by comparison to lighting changes(%)

Lighting changes	Success Ratio	Fail Ratio	Time (sec)
The input image in bright light	84.5	15.5	0.61
Using the difference image	92.8	7.2	0.57
The input image in low light	81.6	18.4	0.71

7. Conclusion

We propose a stable face detection algorithm which is robust to changes in lighting and turning and satisfies efficient calculation and detection performance parameters. If facial images are input through a web camera, they are normalized through pre-processing and in order to precisely detect faces alone from the normalized images, through a difference operation of the two images with different brightness values, accessibility of the target area and detection capacity were improved. The principal component analysis (PCA) is applied to the detected candidate region, and the feature vector is obtained. Finally, feature vectors was treated with LDA to compare Euclidean distance and the final faces were determined.

Also, in considering the viewing angle of facial images input, a database for facial images turned 45° left and right was created, and PCA was applied to reduce recognition errors in the directionality of input images.

It is suggested that further studies on the development of new algorithms are sought just beyond the application of existing algorithms.

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