Illumination Invariant Face Recognition Using Principal Component Analysis – An Overview

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Abstract. Illumination variation is a challenge problem at face recognition since a face image varies as illumination changes. In this paper, it is reviewed the illumination variation methods in the state-of-the-art such as the single scale retinex algorithm, the multi scale retinex algorithm, the gradientfaces based normalization method, the Tan and Triggs normalization method and the single scale weberfaces normalization method. The face recognition is performed by using Principal Component Analysis (PCA) in MATLAB environment. AR face database is used for evaluating the face recognition algorithm using PCA. The distance classifier called as Squared Euclidean is used. Experimental results are comparatively demonstrated.

Keywords: Face recognition, Principal Component Analysis, Illumination variation, MATLAB.

1 Introduction

Face is our attention point which comes into prominence in our social life relationship and it has an important role to identity and transfer of emotions [1-4]. Understanding intelligence or character from facial appearance as well as suspicious but talent of face recognition of person is extraordinary. We can recognize thousands of face which we learnt during all our life and we can distinguish a familiar face even we are far away from each other for years. This recognition talent is pretty strong despite of big alterations at visually stimulating because of distractions such as viewing conditions, expression, aging and glasses, beard or hair style changes.

Face recognition has become a rapidly growing applications area in recent years. Recently this topic is quite remarkable wide range of applications such as security systems, credit card verification, and criminal identification [5]. At this point, it is important to generate successful face recognition algorithm is important. Face recognition is a system with capable of learning. This means that the system provides the determined outputs for the determined inputs after being trained. Performance of system depends on the transformation implemented to the input of system and the system capability to able the properties of input [6]. Face recognition process is done by searching the best matching over face pairs in the database to the face to be recognize. The information of face image to be recognized is firstly normalized and then compared to other faces in system [1, 4, 7]. Karhunen-Loeve transformation called as

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Principal Component Analysis which has wide range of application in pattern recognition area is a subspace projection method. The most appearance based face recognition algorithms depends on the dimension reduction method. That is why it generates the solution model to the new methods requiring complex calculation algorithms and also that the understanding of mathematical elements such as vector, matrix, eigenvalue, eigenvector is easy [8]. PCA is a multi-variable statistical method which explains the variance-covariance structure of a dataset consisting of by linear combination of the variables and provides, dimension reduction and interpretation between the variables [9]. PCA in a face recognition applications aims to obtain the principal components of face images, and to modeling the face images approximately by using linear combination of these principal components which are called as eigenface.

PCA is a vector-based approach. The purpose of this method is that the vectors which are large dimension and correlated with each other are transformed into small and uncorrelated ones. In PCA, a digital image data is represented in a form of vector.

PCA has a high sensitivity against to illumination. Variations in lighting conditions are the one of challenging problems in face recognition. In this paper, the combinations of PCA and illumination normalization methods are proposed as a solution to the problem. In the literature, many face illumination normalization methods developed [10-14]. Especially, Gradientfaces [15] was recently proposed as an outstanding illumination insensitive face representation method. In Gradientfaces, the ratio between y- and x-gradient of an image is accepted nearly an illumination insensitive measure. The arc tan of such ratio is defined as Gradientfaces. The illumination normalization methods are then used to update the reference image, which is reconstructed from the restored image by means of PCA in order to obtain a visually better restored image.

The rest of this paper is organized as follows. In Section 2, the phases of a typical face recognition algorithm are shortly introduced. Some illumination normalization methods are reviewed in Section 3. In Section 4, the PCA is in detailed. The Section 5 gives the comparative experimental results. In Section 6, the paper is concluded.

2 Phases of a Typical Face Recognition

Face recognition is an image recognition duty realized specifically on a face. This work can be expressed that a face is classified as "known" or "unknown" after comparing with a registered face images in store.

Face recognition is a difficult problem. One of the reasons of this difficulty is that the representation of an available face information lie on a best way in order to distinguish a special face from the other faces. In addition, all face images look like the other face images since all components such as eyes, nose, and mouth are arranged more or less in the same way and have same features.

The follow diagram of a face recognition algorithm is shown as in Fig. 1.

Generally face recognition process consists of three main phases:

1. Image pre-processing phase: Face detection, illumination normalization
2. Training phase: Feature extraction,
3. Feature comparison and classification phase.

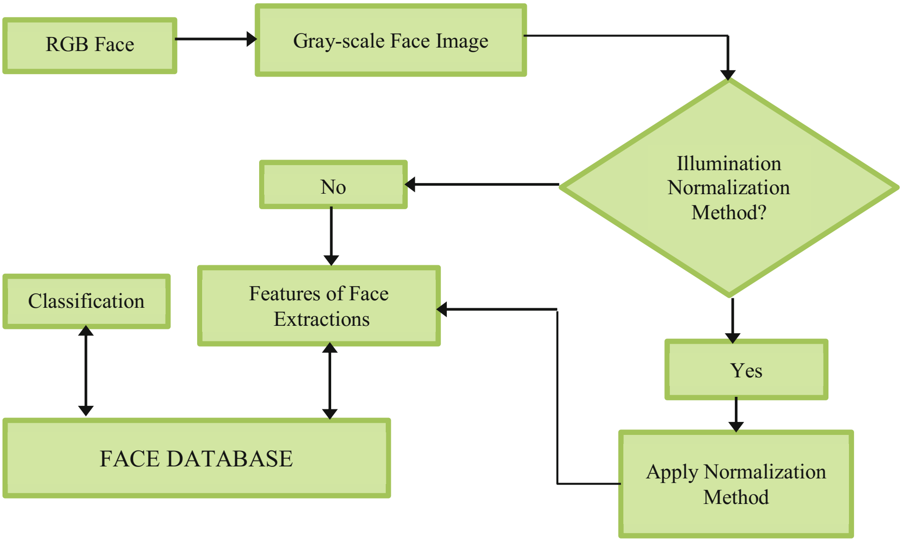

Fig. 1. Flow diagram of face recognition process

3 Illumination Normalization Methods for Face Recognition

This section explains some conventional illumination normalization methods used in this paper.

3.1 The Single Scale Retinex Method

The single scale retinex was proposed by Jobson. Like the majority of photometric normalization methods it is based on the retinex theory which is explained in [16] in more detail.

The output of algorithm is expressed by (1) and (2)

$$R_i(x,y) = \log I_i(x,y) - \log[F(x,y) \times I_i(x,y)] , \qquad (1)$$

$$R_i(x,y) = \log \frac{I_i(x,y)}{F(x,y) \times I_i(x,y)} = \log \frac{I_i(x,y)}{\bar{I}_i(x,y)} \quad . \qquad (2)$$

where $I_i(x,y)$ is the image distribution in the ith spectral band and $R_i(x,y)$ is retinex output.

Note here that the luminance function is returned only for visualization purposes, as it is usually only of little value from the perspective of illumination invariant face recognition.

3.2 The Multi Scale Retinex Method

The multi scale retinex algorithm is an extension of the single scale retinex algorithm again proposed by Jobson. The output of algorithm is calculated by (3)

$$\sum_{n=1}^{N} \omega_n \{\log I_i(x,y) - \log[F_n(x,y) \times I_i(x,y)]\} . \tag{3}$$

where F_n is a Gaussian function and ω_n is a weight associated with the nth scale.

The method is better than single scale retinex in balance of dynamic compression and color rendition.

3.3 The Gradientfaces Normalization Method

The Gradientfaces based normalization method represents a normalization method first proposed in [15]. By this method, the orientation of the image gradients in each pixel of the face images is computed and is used the computed face representation as an illumination invariant version of the input image.

3.4 The Tan and Triggs Normalization Method

The Tan and Triggs normalization method is a normalization method proposed by Tan and Triggs in [17]. The method normalizes the input image through the use of a processing chain that the first applies gamma correction to the input image, then subjects the corrected image to the Difference of Gaussian (DoG) filtering and finally employs a robust post-processor to produce the final result.

3.5 The Single Scale Weberfaces Normalization Method

The single scale Weberfaces normalization method represents a normalization method first proposed in [18]. By this method, the relative gradient in the form of a modified Weber contrast is computed and is used the computed face representation as an illumination invariant version of the input image.

3.6 The Multi Scale Weberfaces Normalization Method

The multi scale Weberfaces normalization method is a straight forward extension of the single scale Weberfaces approach proposed in [18]. By this method, the relative gradient in the form of a modified Weber contrast for different neighborhood sizes is computed and is used a linear combination of the computed face representations as an illumination invariant version of the input image.

4 Face Recognition by Using Principal Component Analysis

First of all let's look at what is PCA; Karl Pearson has started PCA works in 1901, it has improved by Hotelling in 1933. PCA is transformation method which is provided dimension reduction and is protected alteration in data as much as possible has many variables which have a relationship each other in data set extents. This analysis is aimed to determine the best transformation that is all the available data represent with fewer variables. All the available data after transformation are called as principal components of first variables.

First principal component has the biggest value of variance and the other principle components are arranged with respect to the value of variance from the most to least.

These are some advantages of PCA method:

1. Low sensitivity to noise,
2. Reduce requirements of memory and capacity,
3. Enable to more active index in less dimensional space.

The most known and affective application of face recognition in PCA method is eigenface which is improved by Turk and Pentland [19]. In PCA method, the variance of images in training set is chosen the max extent value and these images are projected in these extents. These every extents are called as eigenface. Be projected means that face is expressed that total weighted of these eigenfaces. Recognition is done finding the closest template in database after this transformation.

In the training stage of PCA method, the face images in database are transformed from a x b dimensionality to one extent row vector. If we think that a x b=N; we have M times a face vector of N. That is shown in (4) and (5)

$$X = \left[x^1 \middle| \; x^2 \; \middle| \; \dots \; \middle| \; x^M \right] \qquad (\mathrm{N} \times \mathrm{M}), \tag{4}$$

$$X = \begin{bmatrix} x_1^1 & x_1^2 & . & x_1^M \\ x_2^1 & x_2^2 & . & x_2^M \\ . & . & . & . \\ x_N^1 & x_N^2 & . & x_N^M \end{bmatrix}. \tag{5}$$

In multi-variable analysis, the measure units of variables are mostly different from each other. However in some cases if data is same in of measure unit it gives better results. For this reason, firstly the values of variable centralize to convert same unit. This standardization is made from decreasing data average to 0. Training vectors average, m is calculated as in (6)

$$m = \frac{1}{M} \sum_{i=1}^{M} x^i = \begin{bmatrix} m_1 \\ m_2 \\ . \\ m_N \end{bmatrix}. \tag{6}$$

Calculated average vector is subtracted from every observation vector; all the variables become zero average. If observation vectors that are subtracted from average are shown as data matrix that is subtracted from average in (7), also the observation matrix with zero average is determined as in (8) and (9)

$$\tilde{x}^{i} = x^{i} - m \ , \ \ \forall \ \mathrm{i} \ , \tag{7}$$

$$\tilde{X} = \left[\ \tilde{x}^{1} \ \middle| \ \tilde{x}^{2} \ \middle| \ \ldots \ \middle| \ \tilde{x}^{M} \ \right] \qquad (\mathrm{N} \times \mathrm{M}) \ , \tag{8}$$

$$\tilde{X} = \begin{bmatrix} x_1^1 - m_1 & x_1^2 - m_1 & . & x_1^M - m_1 \\ x_2^1 - m_2 & x_2^2 - m_2 & . & x_2^M - m_2 \\ . & . & . & . \\ x_N^1 - m_N & x_N^2 - m_N & . & x_N^M - m_N \end{bmatrix} . \tag{9}$$

In the next step covariance matrix of zero average observation data is obtained from (11)

$$C = (\tilde{X} \times \tilde{X}^{T}) \qquad (\mathrm{N} \times \mathrm{N}) \ , \tag{10}$$

$$C = \begin{bmatrix} (X_1^1 - m_1)^2 & (X_1^2 - m_1)(X_2^1 - m_2) & . & (X_M^1 - m_1)(X_N^1 - m_N) \\ (X_2^1 - m_2)(X_1^2 - m_1) & (X_2^2 - m_2)^2 & . & (X_M^2 - m_2)(X_N^2 - m_N) \\ . & . & . & . \\ (X_N^1 - m_N)(X_1^M - m_1) & (X_N^2 - m_N)(X_2^M - m_2) & . & (X_N^M - m_N)^2 \end{bmatrix} \cdot \tag{11}$$

The dimensions of obtained covariance matrix C will be NxN. In this step, the eigenface method can be applied found eigenvectors of matrix C. However, if we consider in this case we need to apply pre-treatment on matrix C. The dimension of matrix C is NxN and M images are used for creating C matrix. In fact, the dimension of C matrix is NxM. N eigenvectors of matrix C have 0 eigenvalue except for only M one and the matrix $\tilde{X}$ that is used for generating matrix C is NxM dimensional and the rank of $\tilde{X}$ matrix is M, for this reason it has only M eigenvectors.

In this case, if the eigenvector matrix in (12) is used instead of matrix in (10), an eigenvector of non-zero eigenvalues M appears.

$$C = (\tilde{X}^{T} \times \tilde{X}) \qquad (\mathrm{M} \times \mathrm{M}) \tag{12}$$

In this equation, the coefficients on the diagonal are called as variance as the other ones are called as covariance. Variance gives information about the distribution around average value of data at only one dimension independently of the others. As for covariance, it gives information about how one variable show a variation together with the others and is always calculated between two variables. While the value of one of the variables increase at the same time the other one is also increase or while the value of one variable decrease at the same time the other one also decrease the covariance value is positive. While the value of one of the variables increase at the same time the other one is decrease or while the value of one variable decrease at the same time the other one is increase the covariance value is negative. If there is no a determined relationship between variables, the covariance value is zero.

Eigenvalue-eigenvector separation of covariance matrix is implemented by using (13). Given that C is NxN dimensionality matrix, λ is any scalar and v is a column vector that is different from zero; λ achieving (13) is eigenvalue of C and v is eigenvector having correlation with λ.

$$(\tilde{X}^T \times \tilde{X}) \times x_i = \lambda_i \times x_i \tag{13}$$

The following equation is obtained by multiplying both sides;

$$\tilde{X} \times \tilde{X}^T \times \tilde{X} \times x_i = \tilde{X} \times \lambda_i \times x_i \tag{14}$$

$\tilde{X} \times x_i$ is correspond to eigenvector of matrix C

$$C \times v = v \times \lambda . \tag{15}$$

The eigenvector of C can be used for showing the feature groups in face images. If the obtained eigenvectors are considered as a new transformed matrix in new coordinate system and it is applied to the data set, the data set is transformed to the required coordinate system. This is shown by (16)

$$v = \tilde{X} \times v . \tag{16}$$

When the eigenvalues are arranged from biggest to smallest the first p of eigenvalues having higher variance are used order to create the projection matrix W in (17)

$$W = \begin{bmatrix} w_1 & w_2 & . & w_p \end{bmatrix} . \tag{17}$$

Training phase is completed after determining the eigenfaces (W). The next step is classification phase.

In the classification phase of PCA method, a test image that is not used in training set is assigned to one of the classes at training phase by using the features obtained at the training phase.

Once the eigenfaces is obtained, every image in database is projected to low-dimensional subspace, i.e. eigenface space as in (18)

$$y^i = W^T \times x_i \quad , \quad i = 1, 2, \dots, M. \tag{18}$$

Assignment operation is carried out by calculating the distance between the features of test images and features of training images. If the distance gives the smallest value for which class is used at the training phase and the determined distance is not bigger than the determined threshold value, the test image belongs to that class. Artificial neural networks, support vector machines, fuzzy systems and extreme learning machines can be used the classifying the data [20-24].

Several methods are used in order to calculate the distance in the literature. In this paper, Squared Euclidean distance classifier is used due to its simple application steps.

5 Experimental Results

All of the phases of face recognition algorithm including illumination normalization methods and PCA were applied on the AR database [25]. The database covers wide range of facial variability and moderately controlled capturing conditions: facial expression and illumination changes. Fig. 2 shows the some image samples relating to persons in the AR database used in our experiments. All of the phases of face recognition process are done by MATLAB software and the recognition is automatically carried out.

Fig. 2. The example images of people in the AR database

For PCA method firstly the images which belong to completely face are needed to find. The images in AR database are RGB images of 165x120 resolutions. RGB images in database are firstly transformed to gray scale images. This conversion is shown in Fig. 3.

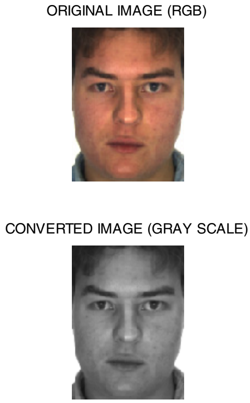

Fig. 3. Conversion from RGB to gray scale

Six images are taken from the images in AR database for every class. 3 of these images are used for training and the others of images are used for testing. 3 test images have the variations in illumination in from right, left and front. For this reason, the recognition rate will be low with PCA. Because PCA method exhibits the low success in applications including illuminated images in test set. Therefore, the illumination normalizations methods are used in order to provide a similarity between training and test images. The results relating to the methods are given in Figs. 4-9. In the figures, the first of the first row shows the training image, the other images show test images in first row.

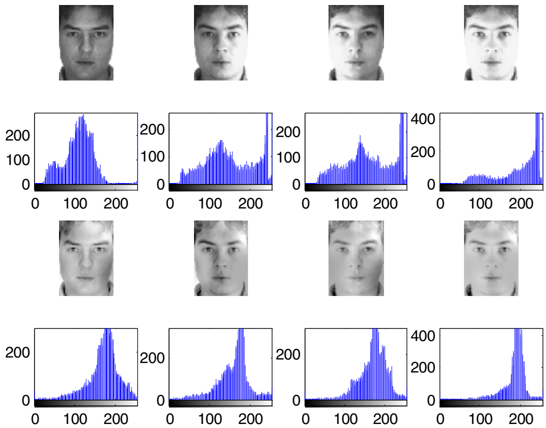

Fig. 4. Sample images (first row), SSR processed images (third row)

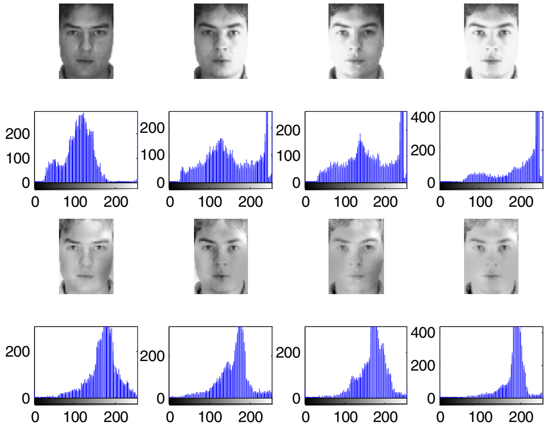

Fig. 5. Sample images (first row), MSR processed images (third row)

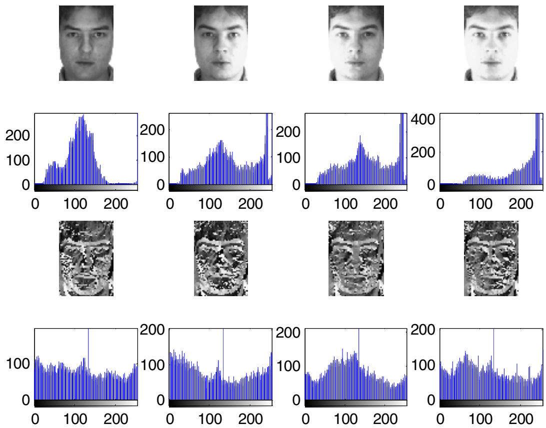

Fig. 6. Sample images (first row), GFR processed images (third row)

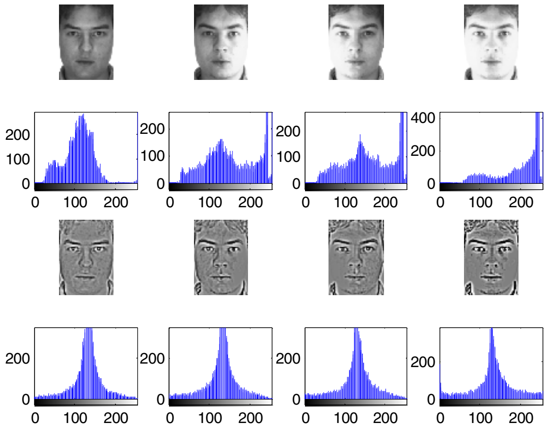

Fig. 7. Sample images (first row), SSR processed images (third row)

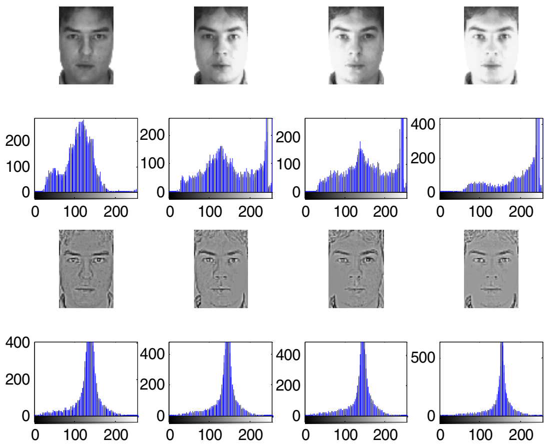

Fig. 8. Sample images (first row), WEB processed images (third row)

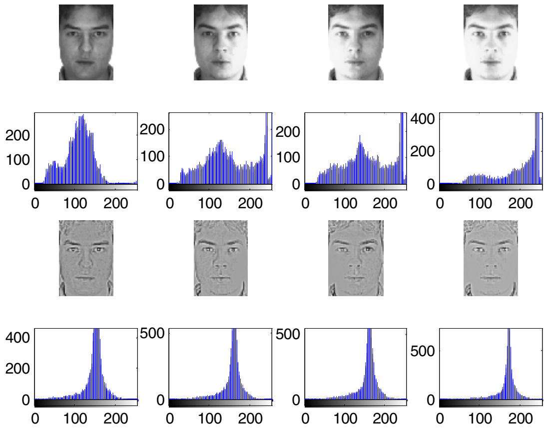

Fig. 9. Sample images (first row), MSW processed images (third row)

If it is used only PCA method without any illumination normalization method, average image of the training images is shown in Fig. 10.

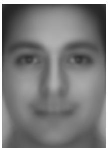

Fig. 10. Average image of training images

In our works, good results were taken using 80 percent of 300 eigenfaces. The overall architecture of the operating stages is shown in Fig. 11 and eigenface examples of training images are shown in Fig. 12.

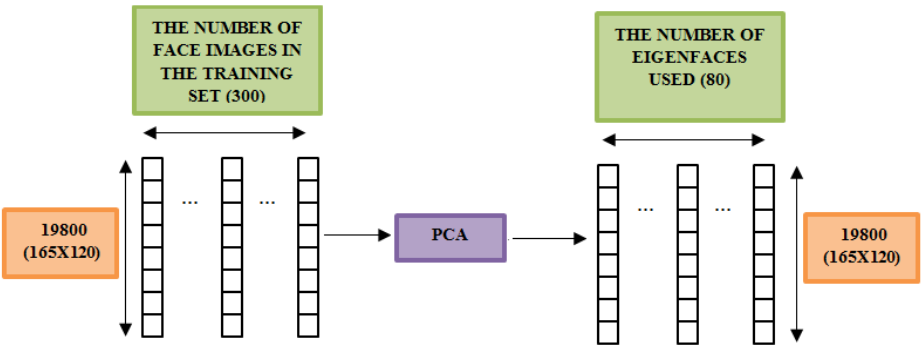

Fig. 11. The overall architecture of the operating stages

Fig. 12. Eigenface examples of training images

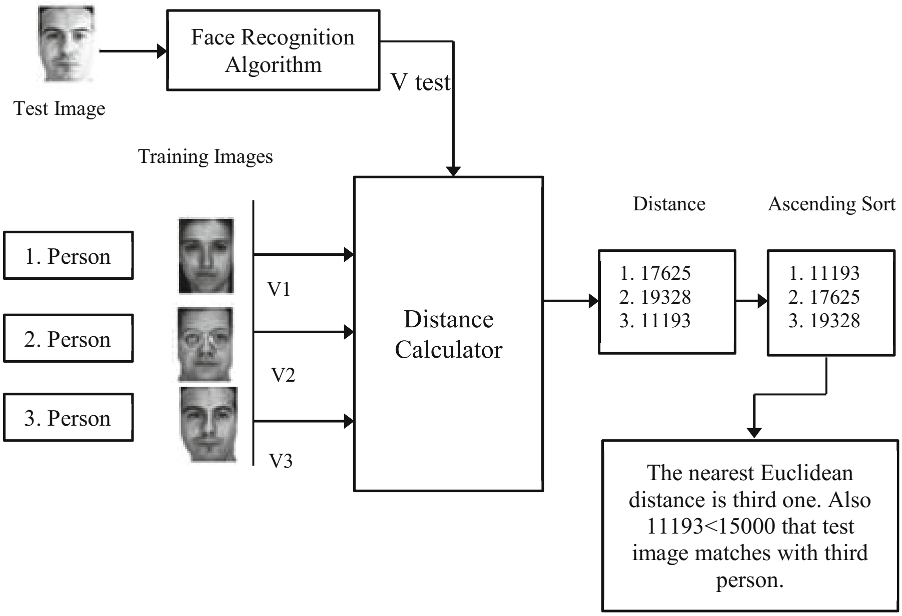

Fig. 13. Diagram showing how the face recognition stages are realized for some persons in AR database

Diagram in Fig. 13 shows how to make classification process. On this diagram, threshold value of Squared Euclidean distance is accepted as 15000.

As for threshold value which is accepted is shown a change according to method that is used and the method of distance classifier.

Examples of output of the program are given in Figs. 14, 15 and 16. In addition, the names that match can be seen in the output of the program. The training images are saved by using person's name.

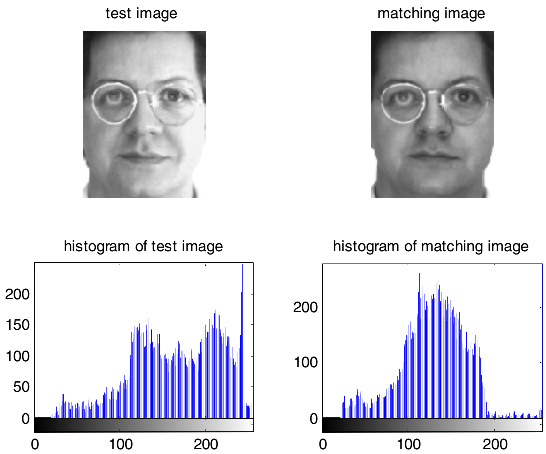

Fig. 14. Example figure window from the output of the program (only PCA)

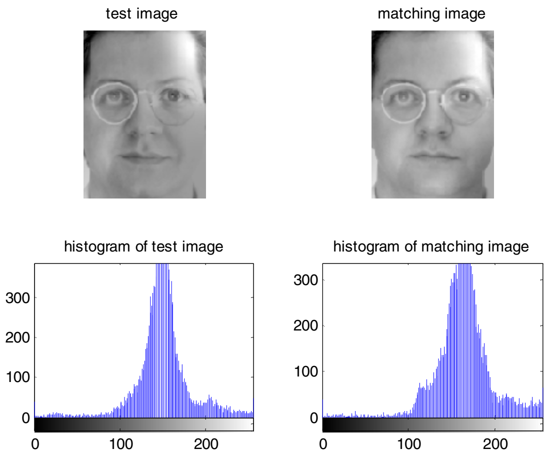

Fig. 15. Example figure window from the output of the program (PCA+SSR)

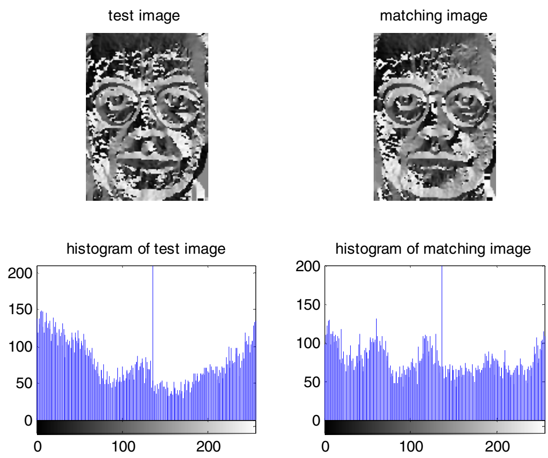

Fig. 16. Example figure window from the output of the program (PCA+Gradientfaces)

Recognition rates of algorithm for test images from 300 out of 100 people are given in Table 1. When PCA is only used, the recognition rate is 41.67 %.

Table 1. Correct recognized person numbers and recognition rates for six different illumination normalization methods

Illumination Normalization Method	Correct Recognized Person Number	Recognition Rate (%)
Single Scale Retinex	129	43
Multi Scale Retinex	130	43.33
Gradientfaces	184	61.33
Tan and Triggs	162	54
Single Scale Weberfaces	134	44.67
Multi Scale Weberfaces	136	45.33

6 Conclusions

In this paper, it is carried out a review of the illumination invariant face recognition algorithms by using the PCA and some illumination invariant methods. For this purpose, the training set is created using the face images in AR database. Features are calculated for each image in training set by means of the PCA. After completing the training phase, the performance of algorithm is evaluated on test images from the AR database AR. In the classification phase, the matching process with the closest class is made to calculate the distance between vectors. Squared Euclidean distance classifier is used to calculate distances. In addition, the illumination normalization methods are applied to the training and test images from the AR database for the same processing steps. Experimental results show that using only PCA exhibits a low recognition rate on the illuminated test images and the combination of PCA and illumination normalization methods significantly increase the recognition rate. It is illustrated that Gradientfaces method is best one for illuminated applications.

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