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Improving the eigenphase method for face recognition

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Abstract: This paper proposes an improvement to the Eigenphases method, in which the image is normalized to reduce the illumination and facial expression effects and the Principal Components Analysis (PCA) is used for feature extraction, while the Gaussian Mixture Model (GMM) is used to improve the performance of classification stage. An important advantage of GMM is that this system is trained without supervisor and constructs an independent model for each user. The proposed method is evaluated using the "AR Face Database", which includes the face images of 120 subjects (65 males and 55 females). Evaluation results show that the proposed method provides better performance than the original eigenphases method.

Keywords: eigenphases, GMM, face recognition and verification, phase spectrum

Classification: Science and engineering for electronics

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1 Introduction

The biometric-based security systems have been a topic of active research during the last three decades, because they are suitable alternatives to increase the security in offices, banks, airports, etc. To this end several biometric systems have been developed using finger printing, iris and retina patterns, voice characteristics, face features, etc. Among them, the face recognition systems appear to be an attractive alternative because the data acquisition is easy and non-invasive; and it can be done to relatively long distance, etc. Because of that several face recognition methods have been proposed [1], which achieve recognition rates higher than 90% [1] under desirable conditions. However they still present limitations under different illumination conditions or facial expression, etc. To improve the recognition rate, under above mentioned conditions, of currently available face recognition algorithms; several schemes have been proposed. Among them, the eigenphases method [2] was proposed to reduce the illumination effects by using only the phase extracted from the Fourier transform, together with the Principal Component Analysis (PCA) for feature extraction and the Euclidean distance for recognition. This algorithm performs fairly well although the global features can be easily influenced by illumination and facial expression [3]. This paper proposes an improvement to the Eigenphases method [2], in which the Fourier transform is also used for phase extraction from the image, emphasizing the local features of a face image, as mentioned below, instead of only the global ones as in [2], before extracting the phase spectrum. Additionally the Euclidian distance is replaced by the GMM, which provides a more accurate identification. The proposed and conventional methods are evaluated under the same conditions, using "the AR Face Database" [4] which includes face images with different illumination and facial expressions variations. Evaluation results show that the proposed modification outperforms the conventional eigenphase method [2].

2 Proposed system

Oppenheim et al. [5] show that phase information retains the most part of the intelligibility of an image, because the phase spectrum contains most of the image information. Based on this result the Eigenphases method was proposed [2], in which firstly the image phase is estimated. Next the PCA algorithm is applied for obtaining the features which are then used together with the Euclidean distance to carry out the face recognition. This method performs well although the recognition performance can be influenced in the presence of variation of illumination and facial expression. To improve the

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performance of the eigenphases method, this paper proposes some modifications such as: a) Introduction of a global normalization of the image, to obtain the phase spectrum of the complete image (Global norm). b) Perform a local normalization of the image under analysis using windows of size 3×3, estimating the phase spectrum of the complete image (Local 3). c) Perform a local normalization of the image under analysis using windows of size 6×6, estimating the phase spectrum of the complete image (Local 6). d) Perform a normalization of the image under analysis and estimate the phase spectrum locally using windows of size 3×3 of each image (Local Fourier 3). e) Perform a normalization of the image under analysis and estimate the phase spectrum locally using windows of size 6×6 of each image (Local Fourier 6). Finally, in all cases non overlapping windows are used and the Euclidean distance used in the original algorithm is replaced by a GMM, which provides a better recognition performance.

The proposed algorithm assumes that the gray level of picture background is constant. Firstly the image is decimated to reduce the data size and then the algorithm estimates the phase information using any of the variants mentioned before in each image (Fig. 1b), where local normalized image is given by

$$I_k(x) = \frac{I_k(x_{i,j})}{\|I_k(x)\|} \tag{1}$$

where I_k^n denotes the normalized image block, k is the number of the local block, x_{ij} denotes $(i,j)-th$ pixel of the $k-th$ local region and $\|I(x)\|$ is the norm of the local region. Once the normalized image and phase spectrum have been estimated, the image is converted into a column vector, repeating this process with all training images to obtain a matrix (Fig. 1c). Next, the PCA algorithm [6] is applied to reduce the information size; subsequently the new matrix is multiplied by each column vector to obtain the features vectors (Fig. 1c). Then the features vectors of training images, of a given person, are applied to a Gaussian Mixture Model (GMM) [7] to obtain his model, which is then used in the classification stage. It is well known that, one of the advantages of GMM is that it only needs the information of the person under analysis to construct his model. However because the GMM system is unsupervised, it requires much more information than a supervised training system. Once the model of each person in the database is obtained, these are used for recognition or verification task, where, the input of each GMM is the feature vector obtained in the same manner as during the training stage, and the output is a conditional probability value. Here if the task is the recognition of a person among a given set, the class to which belongs is obtained by selecting maximum likelihood of the system output, while in a verification task, the output is compared with a given threshold. The threshold is selected between 0.9 and 0.99, such that the system achieves a correctly verification between 90% to 99%.

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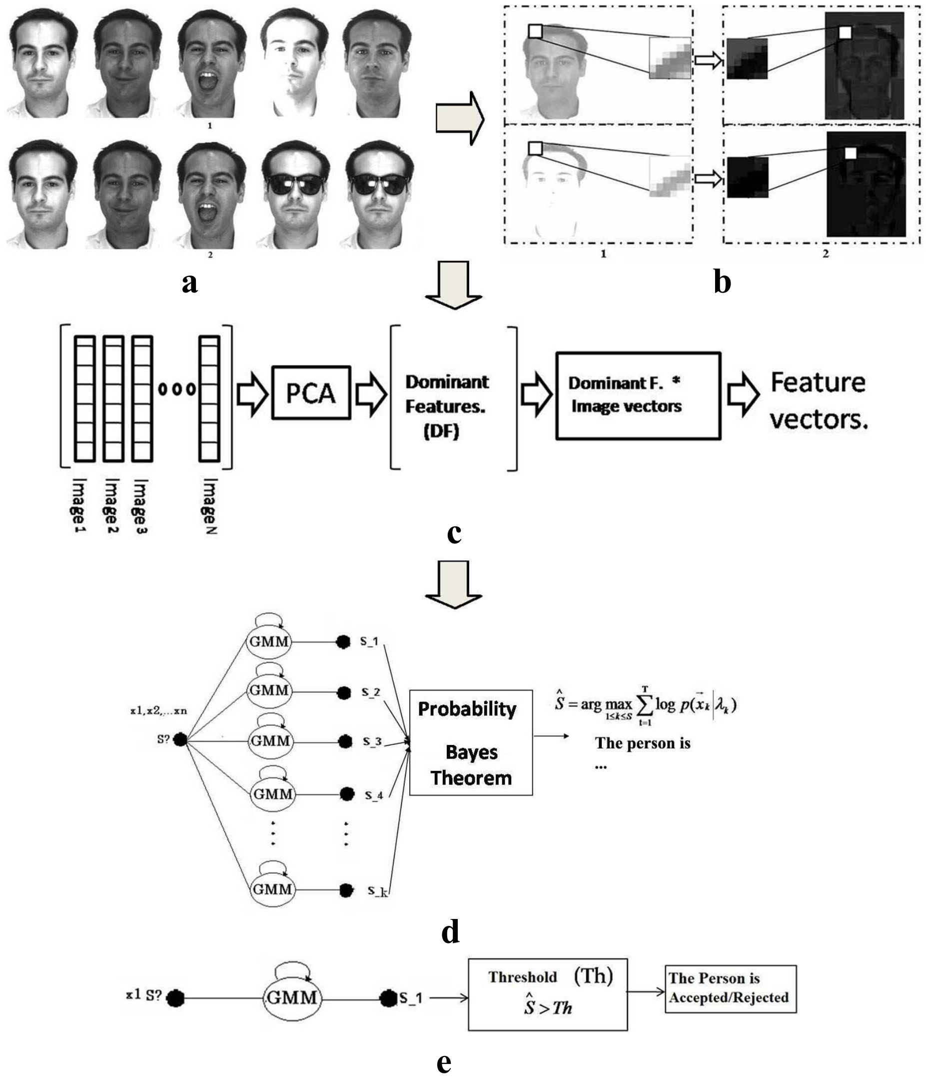

Fig. 1. a) Training set 1 and 2. b) Example of 2nd variation of the Eigen-phase. c) Extraction of features vectors. d) Recognition stage. e) Verification stage

3 Results

The evaluation of the proposed system was carried out by computer simulations using images of size 288 × 384 pixels, which are decimated to obtain images of 48×30 pixels to reduce the processing time. Two different training set are used. The first one consists of 26 images without occlusion, in which only illumination and expressions variations are included. On the other hand the second image set consists of 30 images with illumination and expressions variations, as well as sunglasses, as occlusions. These images sets and the remaining images of the AR face database are used for testing.

Table I shows that, when the training set 1 is used, the proposed face recognition algorithms present better performance than the original eigenphases algorithm [2], except when a global normalization is used. The recognition rate increases significantly, when the GMM is trained using the train-

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ing set 2, giving results up to 97%. Again the proposed algorithms perform better than the eigenphases except when a global normalization and Local Fourier 3 are used. In both training set, the proposed Local 3 outperforms the original as well as the other four proposed modifications.

Table I. Accuracy on face recognition

Performance of face recognition algorithm

	Global. Norm.	Local 3	Local 6	Local fourier 3	Local fourier 6	Eigen-phases [2]
Training set 1	73.32	79.94	76.42	74.03	78.03	73.86
Training set 2	92.86	97.04	94.88	93.18	95.63	93.47

Table II. Accuracy on face verification

		% average of	
		False Accept	False Reject
Training set 1	Global Norm	31.75	17.99
	Local 3	19.36	18.24
	Local 6	28.13	16.22
	Local fourier 3	39.83	17.08
	Local fourier 6	30.19	16.26
	Eigenphases	31.17	18.80
Training set 2	Global Norm	11.09	16.10
	Local 3	7.20	13.39
	Local 6	13.50	12.65
	Local fourier 3	31.83	11.01
	Local fourier 6	19.62	10.53
	Eigenphases	11.16	16.80

In the identity verification process, shown in Table II, the most important issue is to minimize the false acceptance rate. That is the system must not accept as true the identity of a person that is not him/her claims to be. To minimize this error rate is very important because it represents the robustness of the system. On the other hand there is the false rejection error which consists in that the system rejects a person that should be accepted, although it is desirable to keep it as low as possible, it is much more important to keep the false acceptance rate much lower.

Regarding the GMM it was trained using the tool called "stprtool" with 16 mixtures with a diagonal covariance matrix. The GMM system is initialized using the K-means method to obtain the initial value of the mean vector and the covariance matrix of each Gaussian function.

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4 Conclusion

This paper proposed an improvement of the face recognition algorithm based on the eigenphases method [2], in which several image normalization approaches are used before PCA to improve the feature extraction procedures and the GMM is used to perform the recognition and verification task instead of the Euclidean distance used in [2]. Evaluation results show that the proposed system performs better, in general, than the conventional one. Although when global and "Local Fourier 3" normalization schemes are used, the improvement is not significant. Additionally if we increase the number of images for training including images with partial occlusion, the system performance is expected to become better, because the GMM is an unsupervised algorithm, and therefore it needs more training information. The proposed method outperforms the conventional eigenphase method [2], obtaining higher accuracy in the recognition and verification tasks, especially when the "Local 3" normalization scheme is used. This is because the "Local 3" normalization removes, more efficiently, locally lighting changes improving the phase features extraction.

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