4th WSEAS Int. Conf. on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS Miami, Florida, USA, November 17-19, 2005 (pp155-160)

Face Authentication Using Enhanced Fisher linear discriminant Model (EFM)

DJAMEL SAIGAA[1], N. BENOUDJIT[2], K. BENMAHAMED[3], S LELANDAIS[4]
[1]Automatics Department, University Mohamed khider
B.P 145 RP Biskra (07000), ALGERIA,

[2]Electronics Department, University of Batna (05000), ALGERIA

[3]Electronics Department, University of Setif (19000), ALGERIA,
[4]Complex Systems Laboratory (LSC),
University of Evry Val Essonne, FRENCH

Abstract: - In this paper, Enhanced Fisher linear discriminant Model (EFM) is presented as an alternative feature extraction algorithm to Principal Component Analysis (PCA) widely used in automatic face recognition/authentication tasks. We show that the promising EFM algorithm extracts from faces features that are relevant and efficient for authentication. This leads to improved success rates and a reduced client model size over a PCA based feature extraction. The feasibility of the EFM method has been successfully tested on face authentication using 2360 XM2VTS frontal face images corresponding to 295 subjects, which were acquired under variable illumination and facial expressions. By the EFM method we obtain an equal error rate of 1.96% on face authentication using only 56 features.

Key-Words: - Eigenfaces, Enhanced Fisher linear discriminant Model (EFM), Face authentication, Fisher Linear Discriminant (FLD), Principal Component Analysis (PCA).

1 Introduction

Automatic personal identity verification based on facial images is important for many security applications [1] [2] [3]. In face authentication, as in most image processing problems, features are extracted from the images before processing. Working with rough images is not efficient: in face authentication, several images of a single person may be dramatically different, because of changes in viewpoint, in colour and illumination, or simply because the person's face looks different from day to day. Therefore extracting relevant features, or discriminant ones, is a must. Nevertheless, one hardly knows in advance which possible features will be discriminant or not. For this reason, one of the methods often used to extract features in face authentication is PCA (Principal Component Analysis) [4]. Another family of methods is the local features based methods such as [5], or those based on FLD (Fisher Linear Discriminant) as in [6]. In this paper, we show how the promising EFM (Enhanced Fisher linear discriminant Model) technique extracts features that are more closely related to our intuition of discriminant information, and that improve the success rate compared to an equivalent system using PCA or FLD. EFM also belongs to the family of subspace methods [7]. The remaining of this paper is organised as follows. Section 2 presents the problem of face authentication. Section 3 shows how to extract features from rough images, and presents the procedure based on EFM. Section 4 shows the experimental results. Section 5 concludes the paper.

2 Face authentication

Face authentication systems typically compare a feature vector X extracted from the face image to verify with a client template, consisting in similar feature vectors Y_i extracted from images of the claimed person stored in a database ($1 \le i \le p$, where p is the number of images of this person in the learning set). The matching may be made in different ways, one being to take the Euclidean distance between vectors (this method will be taken as an example here). If the distance between X and Y_i is lower than a threshold, the face from which X is extracted will be deemed to correspond with the face from which Y_i is extracted. Choosing the best threshold is an important part of the problem: a too small threshold will lead to a high False Rejection Rate (FRR), while a too high one will lead to a high False Acceptance Rate (FAR); FRR and FAR are defined as the proportion of feature vectors extracted from images in the evaluation set being wrongly classified, respectively wrongly authentified and wrongly rejected [1] [8] [9]. The validation and test sets must be independent (though with faces of the same people) from the learning set, in order to get objective results. One way of setting the threshold is to choose the one leading to equal FRR and FAR. If the a priori probabilities of having false acceptances (impostors) and false rejections are equal, this corresponds to the minimization of the number of wrong decisions, as a result of Bayes' law. Other criteria could be considered, such as using individual thresholds for each person in the database; again, as our goal is to measure the advantages of EFM with respect to PCA feature extraction, we will not investigate other ways of fixing thresholds, and use the global threshold leading to FRR = FAR in the remaining of this paper.

3 Feature extraction

Face recognition/authentication depends heavily on the particular choice of features used by the classifier [10] [7]. One usually starts with a given set of features and then attempts to derive an optimal subset (under some criteria) of features leading to high classification performance with the expectation that similar performance can also be displayed on future trials using novel (unseen) test data. Principal component analysis (PCA) is a popular technique used to derive a starting set of features for both face representation and recognition. Kirby and Sirovich [11] showed that any particular face can be: (i) economically represented along the eigenpictures coordinate space, and (ii) approximately reconstructed using just a small collection of eigenpictures and their corresponding projections (‘coefficients’). Applying PCA technique to face recognition, Turk and Pentland [4] developed a well- known Eigenfaces method. The Eigenfaces method, however, does not consider the classification aspect, as it is based on the optimal representation criterion (PCA) in the sense of mean square error. To improve the PCA standalone performance, one needs to combine further this optimal representation criterion with classification of some discrimination criterion. One widely used discrimination criterion in the face recognition / authentication community is the Fisher linear discriminant (FLD, a. k. a. linear discriminant analysis, or LDA) [12] [13], which defines a projection that makes the within-class scatter small and the between-class scatter large. As a result, FLD derives compact and well-separated clusters. FLD is behind several face recognition methods [12] [6] [14] [7]. As the original image space is high dimensional, most of these methods apply PCA first for dimensionality reduction, as it is the case with the Fisher faces method due to Belhumeur et al. [6]. Subsequent FLD transformation is used then to build the most features (MDF) space for classification [12] [14] [15] [6].

3.1. Dimensionality Reduction and Discriminant Analysis

Let $A = (X_1 X_2 X_3 ... X_i ... X_N)$ represents the (***nxN***) data matrix, where each X_i is a face vector of dimension ***n***. Here ***n*** represents the total number of pixels in the face image and ***N*** is the number of face images in the training set. The vector X_i resides in a space of high dimensionality. Principal component analysis, or PCA [1] [4] [16] [17], whose primary goal is to project the high dimensional visual stimuli (face images) into a lower dimensional space, is the optimal method for dimensionality reduction in the sense of mean-square error. Following this property, an immediate application of PCA is dimensionality reduction [4] [18]:

$$Y_i = W^T X_i \qquad (1)$$

where W is an orthogonal eigenvector and $W \in \mathbb{R}^{nxm}$, $m < n$. The lower dimensional vector $Y_i \in \mathbb{R}^m$ captures the most expressive features of the original data X_i. However, one should be aware that the PCA driven coding schemes are optimal and useful only with respect to data compression and decorrelation of low (second) order statistics. PCA does not take into account the recognition (discrimination) aspect and one should thus not expect optimal performance for tasks such as face authentication when using such PCA-like encoding schemes. To address this obvious shortcoming, one has to reformulate the original problem as one where the search is still for low-dimensional patterns but is now also subject to seeking a high discrimination index, characteristic of separable low-dimensional patterns. One solution that has been proposed to solve this new problem is to use the Fisher linear discriminant (FLD) [19] for the very purpose of achieving high separability between the different patterns in whose classification one is interested. Characteristic of this approach are recent schemes such as the most discriminating features (MDF) method [12] and the Fisherfaces method [6].FLD is a popular discriminant criterion that measures the between class scatter normalized by the within class scatter [19]. Let $c_1, c_2, ..., c_L$ and $\omega_1, \omega_2, ..., \omega_L$ denote the classes and the number of images within each class, respectively. Let $M_1, M_2, ..., M_L$ *and* M be the means of the classes and the grand mean. The within class and between class scatter matrices, S_W *and* S_B, are defined as follows:

$$S_W = \sum_{i=1}^{L} \sum_{Y_k \in Y_i} P(C_i) \mathcal{E}\{(Y_k - M_i)(Y_k - M_i)^T\} \tag{2}$$

$$S_B = \sum_{i=1}^{L} P(C_i)(M_i - M)(M_i - M)^T \tag{3}$$

where $p(C_i)$ is a priori probability, $S_W, S_B \in \mathbb{R}^{mxm}$, and $\boldsymbol{L}$ denote the number of classes.

FLD derives a projection matrix Ψ that maximizes the ratio $|\Psi^T S_B \Psi| / |\Psi^T S_W \Psi|$ [6]. This ratio is maximized when Ψ consists of the eigenvectors of the matrix $S_W^{-1} S_B$ [12],

$$S_W^{-1} S_B \Psi = \Psi \Delta \tag{4}$$

where $\Psi, \Delta \in \mathbb{R}^{mxm}$ are the eigenvector and eigenvalue matrices of $S_W^{-1} S_B$, respectively.

One drawback of FLD is that it requires large training sample size for good generalization. When such requirement is not met, FLD overfits to the training data and thus generalizes poorly to the novel testing data [7] [19].

3.2. The Enhanced Fisher Linear Discriminant Model

The Enhanced Fisher linear discriminant Model (EFM) improves the generalization capability of FLD by decomposing the FLD procedure into a simultaneous diagonalization of the two within class and between class scatter matrices [7]. In particular, the stepwise FLD procedure derives the eigenvalues and eigenvectors of $S_W^{-1} S_B$ as the result of the simultaneous diagonalization of S_W *and* S_B. First whiten the within-class scatter matrix:

$$S_W \mathrm{E} = \mathrm{E}\Upsilon \quad and \quad \mathrm{E}^T \mathrm{E} = I \tag{5}$$

$$\Upsilon^{-1/2} \mathrm{E}^T S_W \mathrm{E} \Upsilon^{-1/2} = I \tag{6}$$

where $\mathrm{E}, \Upsilon \in \mathbb{R}^{mxm}$ are the eigenvector and the diagonal eigenvalue matrices of S_W respectively.

After the feature vector Y_i (Eq. 3) is derived, EFM first diagonalizes the within class scatter matrix S_W using Eq.5 and 6. Note that now E *and* Υ are the eigenvector and the eigenvalue matrices corresponding to the feature vector Y_i. EFM proceeds then to compute the between class scatter matrix as follows:

$$\Upsilon^{-1/2} \mathrm{E}^T S_B \mathrm{E} \Upsilon^{-1/2} = K_B \tag{7}$$

Diagonalize now the new between-class scatter matrix K_B:

$$K_B \mathrm{H} = \mathrm{H}\Theta \quad and \quad \mathrm{H}^T \mathrm{H} = I \tag{8}$$

where $\mathrm{H}, \Theta \in \mathbb{R}^{mxm}$ are the eigenvector and the diagonal eigenvalue matrices of K_B, respectively. The overall transformation matrix of EFM is now defined as follows:

$$D = \mathrm{E}\Upsilon^{-1/2}\mathrm{H} \tag{9}$$

3.3 Similarity Measures and Classification Rule for EFM Feature

The Fisher Classifier (FC) applies the EFM method on the (lower dimensional) augmented feature vector Y_i derived by Eq. 1. When an image is presented to the FC classifier, the high dimensionality feature vector X_i of the image is first formed, and the lower dimensional feature, Y_i, is derived using Eq. 1. The dimensionality of the lower dimensional feature space is determined by the EFM method, which derives further the overall transformation matrix, D, as defined by Eq. 9. The new feature vector, U_i, of the image is defined as follows:

$$U_i = Q^T Y_i \tag{10}$$

where $Q \in \mathbb{R}^{mxd}$, is a matrix formed by d first vectors columns of the matrix D derived by Eq. 10.

The similarity measures used in our experiments to evaluate the efficiency of different representation and authentication methods include ***L1*** distance measure, δ_{L_1}, and cosine similarity measure, $\delta_{\cos}$, which are defined as follows:

$$\delta_{L_1}(x, y) = \sum_i |x_i - y_i| \tag{11}$$

$$\delta_{\cos}(x,y) = -\frac{x^T y}{||x|| \ ||y||} \tag{12}$$

where $||\bullet||$ denotes the norm operator.

Three parameters must be determined in the method: ***m***, ***d***, and the threshold used for the authentication procedure. For each value of ***m*** and ***d***, the threshold is fixed to have FAR= FRR; *m* and *d* are chosen to minimize this error rate. Finally, the performances of the method (including the threshold value) are measured on an independent test set (on this set, FAR will not be necessarily equal to FRR).

4. Experimental results and discussion

Our experiments were performed on frontal face images from the XM2VTS database [20]. This database is available at the cost of distribution from the University of Surrey (see [21] for details). For the task of personal verification, a standard protocol for performance assessment has been defined. The so called Lausanne protocol splits randomly all subjects into a client and impostor groups [22]. The performance measures of a verification system are the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). The significant part of the face is automatically extracted from the frontal image by a technique based on projections of gradients, similar to that proposed by [23].

For comparison purpose, we first implemented the Eigenfaces method [4], the Fisherfaces method [6], and the EFM method and tested their performance using the face images as illustated in Fig. 1.

Fig. 1 *Example XM2VTS images used in our experiments (cropped to the size of 132 x 120 to extract the facial region and filtred for downsampled by two).*

The equal error rate FAR=FRR obtained on the evaluation set in face authentication performance of these three methods apply the δ_{L_1} distance measure shown in Fig. 2, and one can see from the figure that the EFM method performs better than the Fisherfaces method followed by the Eigenfaces method by using a small number of features.

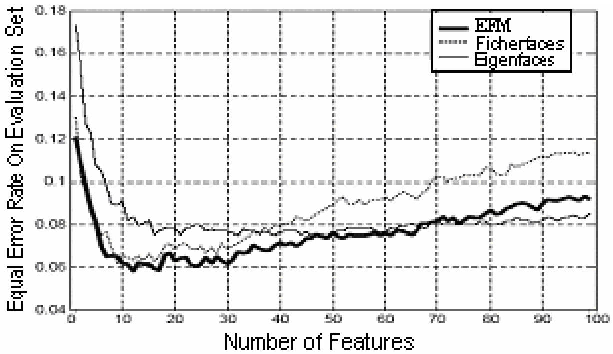

Fig. *2 Face Authentication performance of the Eigenfaces method, the Fisherfaces method, and the EFM method using* δ_{L_1}.

It has been found experimentally that using cos distance between feature vectors instead of the Euclidean distance further improves the results (see Fig. 3), therefore the measurement of similarity by cos distance is adapted better than the Euclidian norm to data in great dimension.

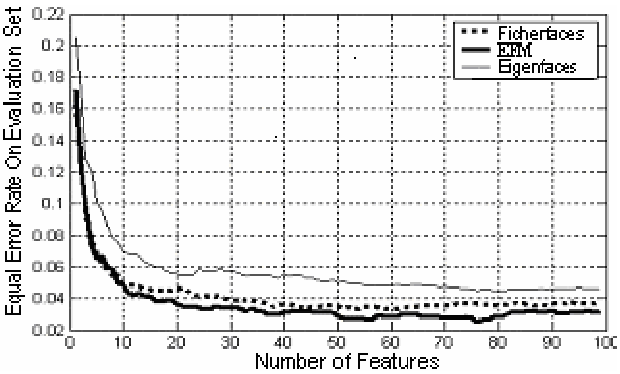

Fig. 3 *Comparative face Authentication performance of the Eigenfaces, the Fisherfaces, and the EFM using* $\delta_{\cos}$.

In particular, EFM method achieves 1.97% equal error rate on face authentication using only 56 features apply the cos distance on the test set(see Fig.4).

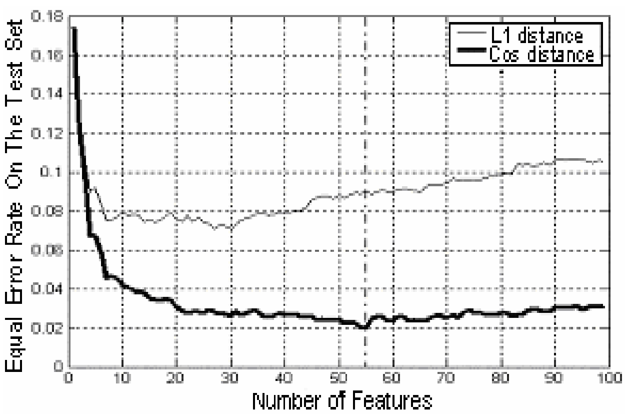

Fig. 4 *Face Authentication performance of the EFM using* δ_{L_1} *and* $\delta_{\cos}$

Table 1 shows some results obtained, of EFM on different sizes of feature vector. Two matching distances are presented: Euclidean and cosine (also called normalized correlation). The two last columns show the number of EFM vectors used, and the dimensionality of the intermediate PCA subspace. The values shown for dimensions ***m*** and ***d*** are those found after the optimization of equal error rate in evaluation set.

Type of distance	Evaluation Set	Test Set			Dimension d after EFM	Dimension m after PCA
	FAR= FRR	FAR	FRR	(FAR+ FRR)/ 2		
δ_{L_1}	5.84	7.66	8.00	7.73	13	100
δ_{L_1}	5.52	5.77	6.75	6.26	17	40
$\delta_{\cos}$	2.88	3.19	2.75	2.87	37	60
$\delta_{\cos}$	3.21	3.44	3.00	3.22	19	40
$\delta_{\cos}$	2.67	2.69	1.25	1.97	56	100

Table 1: FEM results for XM2VTS database with Lausanne protocol configuration I.

5 Conclusion

We have introduced in this paper the EFM method for face authentication. The EFM method, which is robust to variations in illumination and facial expression of face images. The feasibility of the EFM method has been successfully tested on face authentication using a data set from the XM2VTS database, which is a standard test bed for face authentication technologies. Specifically we used 2360 frontal face images corresponding to 295 subjects, which were acquired under variable illumination and facial expressions. In particular, EFM method achieves 1.97% equal error rate on face authentication using only 56 features we apply the $\delta_{\cos}$ distance.

Further work may focus on consist in replacing the simple decision system authentifying the faces through simple distance comparisons between feature vectors, by a multi- dimensional classifier (artificial neural network) on the components of these vectors.

References:

[1] C. Havran, L. Hupet, J. Czyz, J. Lee, L. Vandendorpe, M. Verleysen "Independent Component Analysis for face authentication" KES'2002 proceedings –Knowledge- Based Intelligent Information and Engineering Systems, Crema (Italy),16- 18 September 2002.

[2] J.Kittler and K. Messer "Fusion of Multiple Experts In Multimodal Biometric Personal Identity Verification systems," IEEE Workshop

[3] Norman Poh Hoon Thian, Skbastien Marcel and Samy Bengio " Improving Face Authentication Using Virtual Samples ", IEEE Conf. Acoustics, Speech, and Signal Processing, Vol. 3, 2003, pp. 233-236.

[4] M. Turk and A. Pentland,"Eigenfaces for recognition," Journal of Cognitive Neuroscience, vol. 3, no. 1,1991, pp. 71–86.

[5] L.Wiskott, J.-M. Fellous, N.Kruger and C.von der Malsburg "Face recognition by elastic bunch graph matching" Trans. on Pattern Analysis and Machine Intelligence, Vol.19, 1997, pp.775-779.

[6] P.N. Belhumeur, J.P. Hespanha, and D.J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, 1997, pp. 711–720.

[7] C. Liu and H.Wechsler, "Robust coding schemes for indexing and retrieval from large face databases," IEEE Trans. on Image Processing, vol. 9, no. 1, 2000, pp. 132–137.

[8] A. Tefas, C. Kotropoulos and I. Pitas, Using Support Vector Machines to Enhance the Performance of Elastic Graph Matching for Frontal Face Authentication, IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 23, No. 7, 2001, pp. 735-746.

[9] C. L. Kotropoulos, A. Tefas and I. Pitas, Frontal Face Authentication Using Discriminating Grids with

Morphological Feature Vectors, IEEE Transactions on Multimedia, Vol. 2, No 1, 2000, pp. 14-26.

[10] C. Liu and H. Wechsler " Evolutionary pursuit and its application to face recognition ", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 6, 2000, pp. 570– 582.

[11] M. Kirby and L. Sirovich, "Application of the Karhunen-Loeve procedure for the human faces", IEEE Trans. Pattern Analysis and Machine Intelligence, characterization, vol. 12, no. 1, 1990, pp. 103– 108.

[12] D. L. Swets and J. Weng, "Using discriminant eigenfeatures for image retrieval," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 18, no. 8, 1996, pp. 831– 836.

[13] S. Cruz et al., "A Comparative Evaluation of Global Representation-Based Schemes for Face Verification" IEEE Conf. Image Processing, vol. III.2, 2003, pp. 905-908.

[14] K. Etemad and R. Chellappa, "Discriminant analysis for recognition of human face images", *J. Opt. Soc. Am.* A, vol. 14, 1997, pp. 1724–1733.

[15] W. Zhao and R. Chellappa, "Discriminant analysis of principal components for face recognition, " *IEEE Conf. Automatic Face and Gesture Recognition* , 1998, pp. 336 –341.

[16] Wendy S. Yambor "analysis of PCA and Ficher discriminant-based imag recognition algorithms", Technical repport, Colorado State University July 2000.

[17] J. Short, J. Kittler and K. Messer, "A Comparison of Photometric Normalisation Algorithms for Face Verification", IEEE Conf. Automatic Face and Gesture Recognition, 2004, pp. 254 – 259.

[18] S. Edelman " Representation and Recognition in Vision ", MIT Press, 1999.

[19] Chengjun Liu and Harry Wechsler " Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition ", IEEE Trans. Image Processing, vol. 11, no. 4, 2000, pp. 467- 476.

[20] K.Messer, J.Matas, J. Kittler, J. Luettin, G. Maître "XM2VTSBD: The Extended M2VTS database", Int'l Conf. on Audio- & Video-based Biometric Authentication (AVBPA-99), Washington, 1999, pp. 72-77.

[21] http://xm2vtsdb.ee.surrey.ac.uk/.

[22] J.Luettin and G.Maître, Evaluation Protocol for the extended M2VTS database (XM2VTSDB) IDIAP tech. report, Martigny, July 98.

[23] Roberto Brunelli and Tomaso Poggio "Face Recognition: Futures Versus Templates", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no.10, 1993, pp. 1042–1052.