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Color Space for Face Authentication Using Enhanced Fisher linear discriminant Model (EFM)

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Abstract: The performance of face authentication systems has steadily improved over the last few years, mainly focusing on models rather than on feature processing. State-of-the-art methods often use the grayscale face image as input. In this paper, we propose to use the color information as a feature for face image. The proposed feature set is tested on a benchmark database, namely XM2VTS, using Enhanced Fisher linear discriminant Model (EFM). Results show that the color information improves the performance and that the proposed model achieves robust state-of-the-art results.

Keywords: Eigenfaces, Fisherfaces, Enhanced Fisher linear discriminant Model (EFM), Face authentication, Fisher Linear Discriminant (FLD), Principal Component Analysis (PCA), Color space.

1 Introduction

Identity verification is a general task that has many real-life applications such as access control, transaction authentication (in telephone banking or remote credit card purchases for instance), voice mail, or secure teleworking [1; 2; 3].

The goal of an *automatic identity verification system* is to either accept or reject the identity claim made by a given person. Biometric identity verification systems are based on the characteristics of a person, such as its face, fingerprint or signature. A good introduction to identity verification can be found in [4]. Identity verification using face information is a challenging research area that was very active recently, mainly because of its natural and non intrusive interaction with the authentication system.

In this paper, we investigate the use of color information as features in order to train face authentication systems using Enhanced Fisher Linear Discriminant Model (EFM)[5; 6; 7].

In the following of this paper, firstly, we introduce the reader to the problem of identity verification, based on face image (face authentication). Secondly, we present the new proposed approach. Thirdly, we then compare this proposed model of features on the well-known benchmark database XM2VTS using its associated Lausanne protocol. Finally, we analyze the results and conclude.

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 a validation set being wrongly classified, respectively wrongly authentified and wrongly rejected [1; 7; 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 Proposed Approach

In face authentication, we are interested in particular objects, namely faces. The representation used to code input images in most state-of-the-art methods are often based on gray-scale face image. In this section, we propose to use the three components of the color space as a feature for the face image.

3.1 Color Spaces Used

The traditional RGB color space is a space which lends itself very badly to mathematical calculation in the Euclidean direction: primarily for distance notion. That means that two mathematically points very close can be subjectively very distant. Conversely, two points appearing subjectively rather close can be in fact very distant within the meaning of their Euclidean distance. For this reason, certain color spaces were created, such as CIE_XYZ, HSI, CIE_L*u*v* and CIE_L*a*b* spaces. For a complete definition of various color spaces, we return the reader to [10].

3.2 Dimensionality Reduction and Discriminant Analysis

Let $A=(X_1X_2X_3...X_i...X_N)$ represent 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 color face image and ***N*** is the number of face images in the training set.
The Vector X_i is formed by connecting the lines (or the columns) of the three colorimetric components of the suitable color space. For example an image in the HSI color space, is transformed into vector X_i by connecting the lines (or the columns) of the three colorimetric components H, S and I respectively in this same vector. The vector X_i resides in a space of high dimensionality.
Principal Component Analysis (or PCA) [1; 11; 12; 13;14] , 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:

$$Y_i = W^T X_i \tag{1}$$

where W is an orthogonal eigenvector and $W \in \mathbb{R}^{mxn},\ m < n$. But 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. One solution that has been proposed to solve this new problem is to use the Fisher linear discriminant (FLD) [6] 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 [15] and the Fisherfaces method [16].FLD is a popular discriminant criterion that measures the between class scatter normalized by the within class scatter [6]. Let $C_1, C_2, \ldots, C_L$ and $\omega_1, \omega_2, \ldots, \omega_L$ 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:

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

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

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

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FLD derives a projection matrix Ψ that maximizes the ratio $\left|\Psi^T S_B \Psi\right| / \left|\Psi^T S_W \Psi\right|$ [16]. This ratio is maximized when Ψ consists of the eigenvectors of the matrix $S_W^{-1} S_B$ [15]

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

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 [6; 17].

3.3 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; 15; 17]. 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. 1) 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 $H, \Theta \in \mathbb{R}^{mxm}$ are the eigenvector and the diagonal eigenvalue matrices of K_B, respectively. The overall transformation matrix of EFM is now defined as follows:

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

3.4 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 augmented 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. 9.

The similarity measures used in our experiments to evaluate the efficiency of different representation and authentication methods include ***L2*** distance measure, δ_{L_2} and cosine similarity measure $\delta_{\cos}$, which are defined as follows:

$$\delta_{L_2}(x, y) = \sqrt{\sum_i (x_i - y_i)^2} \tag{11}$$

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

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 [18]. The XM2VTS database is a multimodal database consisting of face images, video sequences and speech recordings taken of 295 subjects, four taken over a period of four months. The database is primarily intended for research and development of personal identity verification systems where it is reasonable to assume that the client will be cooperative. Since the data acquisition was distributed over a long period of time, significant variability of appearance of clients, e.g. changes of hair style, facial hair, shape and presence or absence of glasses, is present in the recordings (see figure 1).

Fig. 1 Sample images from XM2VTS database.

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. The client group contains 200 subjects; the impostor group is divided into 25 validation impostors and 70 test impostors. Eight images from 4 sessions are used.

The performance measures of a verification system are the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). FAR and FRR are given by:

$$FAR = EI / Im * 100\% \quad FRR = EC / Cl * 100\% \qquad (13)$$

where EI is the number of impostor acceptances, Im is the number of impostor claims, EC the number of client rejections and Cl the number of client claims. Both FAR and an FRR are influenced by an acceptance threshold. To simulate real application the threshold is set on the data from validation set to obtain certain false acceptance on the validation set (FAR) and false rejection error (FRR). The same threshold is afterwards applied to the test data and FAR and FRR on the test set are computed. The sizes of the various sets are given in table 1.

Table 1 Photos distribution in the various sets

Set	Clients	Impostor
Training	600(3 by subject)	0
Evaluation	600(3 by subject)	200(8 by subject)
Test	400(2 by subject)	400(8 by subject)

We decided to cut the image vertically and horizontally and to keep only one window of size 132x120 centered on the face.

This window is automatically extracted from the frontal image by a technique based on projections of gradients, similar to that proposed by [20]. Then we pass the images by a 2x2 uniform filter to be able to carry out a decimation of factor 2. The face image will pass thus from a dimension 256x256=65536 to a dimension 66x60. Afterwards, we apply a photonormalization. That is to say that for each image, we withdraw from each pixel the average value of those on the image, and that we divide those by their standard deviation. Finally we make standardization. The photonormalization acts on an image whereas standardization acts on a group of images (for each component, one withdraws the average of this component for all the images and one divides by the standard deviation).

Fig.2: Example XM2VTS images used in our experiments (cropped to the size of 132x120)

For comparison purpose, we first implemented the EFM method and tested their performance using the face images as illustrated in Fig. 2.

Note that the images are acquired during different photo ***sessions;*** they display both different lighting conditions and facial expressions. Three images are chosen from the eight images available for each subject for training, and three images are chosen for validation, while the remaining images (unseen during training and validation) is used for testing. In particular, the above figure shows in the top two rows the examples of training and validation respectively images used in our ***experiments*** and in the bottom row the examples of test images. The equal error rate FAR=FRR obtained on the validation set in face authentication performance of our approach applying the ***L2*** distance measure is shown in figure 3.

From this figure, we can see that the results obtained with the La^*b^* color space are the best followed by those of XYZ color space, then by those of RGB color space and lastly the results obtained by the HSI

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color space. The Good results of La^*b^* color space are obtained with the help of the no-coherence between the colorimetric components of this space.

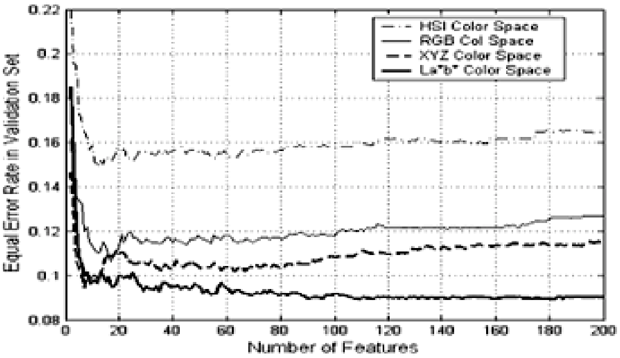

Fig.3: Comparative face authentication performance of the EFM using different color spaces and L2 distance measure

It has been found experimentally that using cos distance between feature vectors instead of the Euclidean distance further improves the results (see figure 4), therefore the measurement of similarity by ***cos*** distance is adapted to data in great dimension.

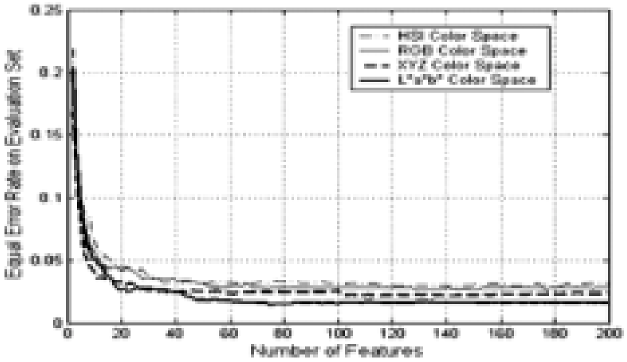

Fig.4: Comparative face authentication performance of the EFM using different color spaces and cos distance measure

In particular, EFM method achieves 1.50% equal error rate on face authentication using only 94 features apply La*b* color space and ***cos*** distance on the test set (see figure 5).
Table 2 shows some results obtained, of EFM using a different color spaces and a different sizes of feature vector.
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 validation set.

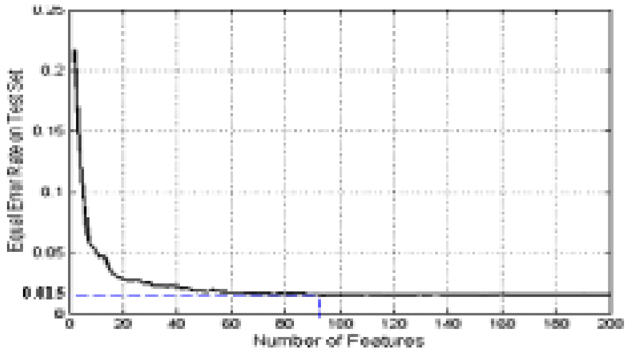

*Fig.5: Face authentication performance of EFM method using La*b* color space and cos distance measure*

In this table, we presented the results with ***cos*** as distance from measurement because it is most adapted to the data on large scale. The best results are obtained in the case of La*b* color space (see last line). It is also noticed that the error rates in validation and test sets are equal by using La*b* color space, that signified then that the proposed system for face authentication is more stable in this space than in the others.

5 Conclusion

We introduced in this paper our approach for face authentication. This approach consists to use the three colorimetric components of the face image and the EFM method. Our approach is robust to variations in illumination and facial expression of face images. The feasibility of our approach 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, our approach achieves 1.50% equal error rate on face authentication using only 94 features apply the cos distance measure in La*b* color space.
Further work may consist in replacing the simple decision system to authentify faces through simple distance comparisons between feature vectors, by a multi-dimensional classifier (artificial neural network) on the components of these vectors. We can also propose the fusion of the various color spaces results.

*Table 2: Comparative face authentication results using EFM method for color images in HSI, RGB, XYZ, La*b* color spaces*

Color Space	Validation Set	Test Set			Dimension **"d"** after EFM	Dimension **"m"** after PCA
	FAR= FRR %	FAR %	FRR %	(FAR+FRR)/ 2 %		
HSI	2.99	2.94	2.25	2.60	137	200
RGB	2.73	2.08	2.75	2.41	141	200
XYZ	2.67	2.61	1.75	2.18	137	200
La*b*	1.51	1.49	1.50	1.50	94	200

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