Face authentication using logic fusion of Color with EFM Feature Extraction

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Abstract In this paper, we investigate the use of colour information to face authentication systems. In order to improve the performance of these systems many colour components have been used. The results in different colorimetric components are combined by using a logic fusion for classification with different operators. For the extraction of feature vectors we have applied the Enhanced Fisher linear discriminant Model (EFM) which is presented as an alternative features extraction algorithm to Principal Component Analysis (PCA) which is widely used in automatic face recognition. We calculate the error rates in the two sets of data validation and data test according to the Lausane protocol (XM2VTS). The results obtained show that the use of colour improves the performance of authentication by (3%) compared to greyscale system. This system can be employed in high security.
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Keywords: Biometric, Face recognition, Color spaces,EFM , Fusion decisions, security.

1. Introduction

Actually, face recognition is an important issue in many applications such as security systems, credit card verification and criminal identification. For example the ability to model a particular face and to distinguish it from a large number of different faces. This would make possible to vastly improve criminal identification. Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by the human brain. Human face recognition has been studied for more than twenty years [1,24]. Unfortunately developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimulation [2]. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. The goal of an automatic identity verification system is to either accept or reject the identity claim made by a given person.

In fact, recent studies demonstrate that colour information makes contribution and enhance robustness in face recognition. Until 2001 the common belief was the contrary [13]. In the literature, only few works with colour information has been used in face recognition applications. Now day, this subject becomes very attractive and more researchers are working intensively colour information to face authentication systems [14-23][26-28].

In this paper, we investigate the use of colour information as features with a logic fusion decision of the three components colour of each colour space in face authentication system using Enhanced Fisher linear discriminant Model (EFM).

The main idea of face authentication system is the extraction of a vector X describing the personal features and to compare it with a vector Y_i that contains the approached features from different pictures of the same person that are stocked in a database. To estimate the difference between two pictures, it is necessary to introduce a measure of similarity. Several metrics can be used as the L1 distances and L2 (Euclidian), the interrelationship, the distance of Mahalanobis etc. 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 authenticated and wrongly rejected. The validation and test sets must be independent 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, we use the global threshold leading to FRR = FAR in the remaining of this paper.

2. Feature Extraction

Applying PCA technique to face recognition, Turk and Pentland 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 [1,24,25] standalone performance, one needs to combine further this optimal representation criterion with classification 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)[11], 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. 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 Fisherfaces method due to Belhumeur et al. [4]. Subsequent FLD transformation is used then to build the most features (MDF) space for classification [7,4,11].

2.1 Dimensionality Reduction and Discriminant Analysis

Let A=(X_1 X_2 X_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 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. Psychophysical findings indicate, however, that "perceptual tasks such as similarity judgment tend to be performed on a low-dimensional representation of the sensory data. Low dimensionality is especially important for learning, as the number of examples required for attaining a given level of performance grows exponentially with the dimensionality of the underlying representation space". Low-dimensional representations are also important when one considers the intrinsic computational aspect. Principal component analysis, or PCA [1,24,25] 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. PCA is a standard decorrelation technique and following its application one derives an orthogonal projection basis that directly leads to dimensionality reduction, and possibly to feature selection. Let $\chi \in \Re^{n \times n}$ define the covariance matrix of the data martix A:

$$\chi = \sum_{i=1}^{N} \varepsilon\left\{(X_i - \varepsilon(X_i))(X_i - \varepsilon(X_i))^T\right\} \quad (1)$$

Where $\varepsilon(.)$ is the expectation operator. The PCA of a data matrix A factorizes its covariance matrix χ into the following form:

$$\chi = \Phi\Lambda\Phi^T \text{ with } \Phi = [\phi_1\phi_2...\phi_i...\phi_n],\ \Lambda = diag\left\{\lambda_1\lambda_2...\lambda_n\right\} \quad (2)$$

Where $\Phi \in \Re^{n\times n}$ is an orthogonal eigenvector matrix and $\Lambda \in \Re^{n\times n}$ a diagonal eigenvalue matrix with diagonal elements in decreasing order $(\lambda_1 > \lambda_2 > ... > \lambda_n)$.

An important property of PCA is its optimal signal reconstruction in the sense of minimum mean square error when only a subset of principal components is used to represent the original signal. Following this property, an immediate application of PCA is dimensionality reduction:

$$Y_i = W^T X_i \tag{3}$$

Where $W = [\phi_1 \phi_2 ... \phi_i ... \phi_m], m < n$ and $W \in \Re^{n\times m}$. The lower dimensional vector $Y_i \in \Re^m$ 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)[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 [7] and the Fisherfaces method [4].

FLD is a popular discriminant criterion that measures the between class scatter normalized by the within class scatter [6]. 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:

$$S_W = \sum_{i=1}^{L} \sum_{Y_k \in Y_i} P(C_i) \varepsilon \left\{ (Y_k - M_i)(Y_k - M_i)^T \right\} \tag{4}$$

$$S_B = \sum_{i=1}^{L} P(C_i)(M_i - M)(M_i - M)^T \tag{5}$$

where $P(C_i)$ is a priori probability, $S_W, S_B \in \Re^{m\times m}$ $S_W, S_B \in$ □ ^{mxm}, and L denote the number of classes.

FLD derives a projection matrix Ψ that maximizes the ratio $\left|\Psi^T S_B \Psi\right| / \left|\Psi^T S_W \Psi\right|$ [4].This ratio is maximized when Ψ consists of the eigenvectors of the matrix $S_W^{-1} S_B$ [7].

$$S_W^{-1} S_B \Psi = \Psi \Delta \tag{6}$$

Where $\Psi, \Delta \in \Re^{m\times m}$ are the eigenvector and eigenvalue matrices of $S_W^{-1} S_B$.

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 [8].

2.2 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 [8]. The simultaneous diagonalization is stepwisely equivalent to two operations as pointed out by Fukunaga [6]: whitening the within class scatter matrix and applying PCA on the between-class scatter matrix using the transformed data. The stepwise operation shows that during whitening the eigenvalues of the within class scatter matrix appear in the denominator. As the small (trailing) eigenvalues tend to capture noise [6][8], they cause the whitening step to fit for misleading variations and thus generalize poorly when exposed to new data. To achieve enhanced performance EFM preserves a proper balance between the need that the selected eigenvalues (corresponding to the principal components for the original image space) account for most of the energy of the raw data, i.e., representational adequacy, and the requirement that the eigenvalues of the within-class scatter matrix (in the reduced PCA space) are not too small, i.e., better generalization.

The choice of the range of principal components (m) for dimensionality reduction (see Eq. 3) takes into account the energy requirement [3]. The eigenvalue of the covariance matrix (see Eq. 2) provides a good indicator for meeting the energy criterion; one needs then to derive the eigenvalue of the within-class scatter matrix in the reduced PCA space to facilitate the choice of the range of principal components so that the magnitude requirement is met. Towards that end, one carries out the stepwise FLD process described earlier. 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:

$$S_w E = E\gamma \quad \text{and} \quad E^T E = I \tag{7}$$

$$\gamma^{-1/2} E^T S_W E \gamma^{-1/2} = I \tag{8}$$

Where $E, \gamma \in \Re^{m \times m}$ are the eigenvector and the diagonal eigenvalue matrices of S_W respectively.

No one has to simultaneously optimize the behaviour of the trailing eigenvalues in the reduced PCA space (Eq. 7) with the energy criteria for the original image space (Eq. 2).

After the feature vector Y_i (Eq. 3) is derived, EFM first diagonalizes the within class scatter matrix S_W using Eq.7 and 8. Note that now E, γ 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:

$$\gamma^{-1/2} E^T S_B E \gamma^{-1/2} = K_B \tag{9}$$

Diagonalizable now the new between-class scatter matrix K_B:

$$K_B H = H\Theta \quad \text{and} \quad H^T H = I \tag{10}$$

Where $H, \Theta \in \Re^{m \times m}$ are the eigenvector and the diagonal eigenvalue matrices of K_B, respectively. The overall transformation matrix of EFM is now defined as follows:

$$D = E\gamma^{-1/2}H \tag{11}$$

2.3 Similarity Measures and Classification

The similarity measures used in our experiments to evaluate the efficiency of different representation and authentication method are correlation similarity measure, which are defined as follows:

$$Corr(A,B) = \sum_{i=1}^{N} \frac{(A_i - \mu_A)(B_i - \mu_B)}{\sigma_A \sigma_B} \tag{12}$$

The threshold is fixed to have FAR= FRR on evaluation set; 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).

3. Experimental results

3.1 Database

Our experiments were performed on frontal face images from the XM2VTS database [9][10]. The XM2VTS database is a multimodal database consisting of face images, video sequences and speech recordings taken of 295 subjects at one month intervals. The database is primarily intended for research and development of personal identity verification systems. 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.

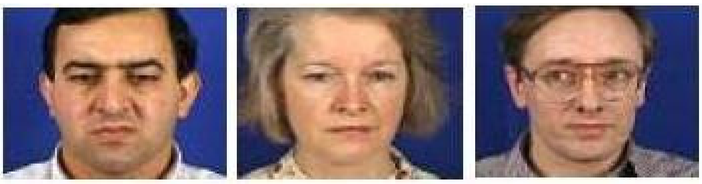


Fig. 1. Sample images from XM2VTS database [9].

The subjects were volunteers, mainly employees and PhD students at the University of Surrey of both sexes and many ethnical origins. The XM2VTS database contains 4 sessions[9].
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 evaluation impostors and 70 test impostors. Eight images from 4 sessions are used.

From these sets consisting of face images, training set, evaluation set and test set is built. There exist two configurations that differ by a selection of particular shots of people into the training, evaluation and test set. The training set is used to construct client models. The evaluation set is selected to produce client and impostor access scores, which are used to find a threshold that determines if a person is accepted or not .According to the Lausanne protocol the threshold is set to satisfy certain performance levels (error rates) on the evaluation set. Finally the test set is selected to simulate realistic authentication tests where impostor's identity is unknown to the system.

The performance measures of a verification system are the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). False acceptance is the case where an impostor, claiming the identity of a client, is accepted. False rejection is the case where a client, claiming his true identity, is rejected.

In our experiments we chose the distribution of the images in the various sets according to the configuration described by the figure 2 .

Fig. 2. XM2VTS database with Lausanne protocol configuration I [10].

The sizes of the various sets are included in table 1.

Table 1. Photos distribution in the various sets[9].

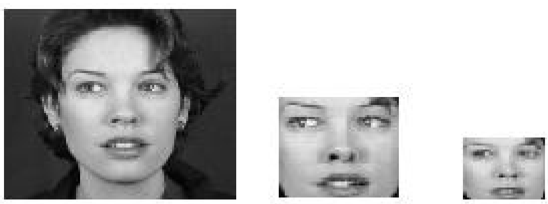
Set	Clients	Impostor
Training	600(3 by subject)	0
Evaluation	600(3 by subject)	200(8 by subject)
Test	400(2 by subject)	400(8 by subject)

3.2 Pre-treatment

Each picture is composed by several information as : the hair, the collars of shirt etc. Indeed, all these information don't serve to anything, but inflates the size of the data uselessly. Therefore a reduction of picture is necessary whose operation is to extract the essential parameters only for the identifier and that change very little with time.

It is for that, one cuts the picture by an oblong window centred around the steadiest features bound to the eyes, to the eyebrows, to the nose and to the mouth of size 132x120. Then one filters the pictures by a filter passes low uniform (2x2) in order to do a decimation of factor 2. Then we make the photo normalisation to the pictures, it means that for every picture, we subtract to every pixel the middle value of these on the picture, and that we divide these by their standard deviation.

The photo normalisation has a double effect: on the one hand it suppresses for all vectors a possible shift in relation to the origin, and then all effect of amplification. Finally one applies the normalization and that acts on a group of pictures (for every component, one withdraws the average of this component for all pictures and one divides by the standard deviation). After all this operation of pre-treatment on the pictures, the next step is the extraction of the features by the based EFM method.



(a) (b) (c)

Fig. 3. Picture of input (a) picture after cutting (b) and after decimation (c).

3.3 Colour Results

We use different colour spaces: Gray, RGB, HSV, XYZ, I1I2I3, YUV, YIQ and YCbCr spaces [12,15,16,17]. To make a comparison of results, we presented them with the based EFM method, which has the parameters:

- Coefficients: 50 to 60 coefficients projection sorted following values decreasing.
- Measure similarity: correlation.
- Threshold: Global.

In table 2 we shows the best results obtained of EFM of each component colour.

Table 2. Error rate with EFM method of each component colour.

Color	Evaluation set			Test set		
	FRR	FAR	EER (%)	FRR	FAR	SR (%)
X	0.0300	0.0296	2.98	0.0150	0.0297	95.53
Y	0.0283	0.0276	2.80	0.0175	0.0277	95.48
Z	0.0283	0.0274	2.79	0.0150	0.0238	96.12
Y	0.0267	0.0257	2.62	0.0175	0.0209	**96.16**
Cr	0.0167	0.0166	1.67	0.0325	0.0156	95.19
Cb	0.0267	0.0272	2.70	0.0325	0.0228	94.47
R	0.0333	0.0332	3.33	0.0175	0.0340	94.85
G	0.0267	0.0275	2.71	0.0200	0.0276	95.24
B	0.0267	0.0271	2.69	0.0150	0.0275	95.75
Y	0.0300	0.0296	2.98	0.0150	0.0302	95.48
I	0.0283	0.0269	2.76	0.0250	0.0227	95.23
Q	0.0200	0.0207	2.04	0.0325	0.0213	94.62
Y	0.0267	0.0257	2.62	0.0175	0.0255	95.70
U	0.0317	0.0323	3.20	0.0200	0.0299	95.01
V	0.0217	0.0221	2.19	0.0300	0.0186	95.14
H	0.0583	0.0580	5.82	0.0625	0.0672	87.03
S	0.0233	0.0233	2.33	0.0225	0.0235	95.40
V	0.0333	0.0326	3.30	0.0175	0.0330	94.95
I1	0.0267	0.0268	2.68	0.0150	0.0272	95.78
I2	0.0283	0.0284	2.84	0.0150	0.0283	95.67
I3	0.0150	0.0144	1.47	0.0425	0.0127	94.48
Greyscale	0.0333	0.0324	3.29	0.0200	0.0332	94.68

From table 2, we observe that the colour improve the performance of the authentication system of face. We found that the use of a single component colour with the EFM method achieves **96.16%** success rate on face authentication using only 53 features applying the Correlation distance and only one component colour and for more improvement of the performance of this system, we have to apply a logic fusion of this results.

3.4 Logic Fusion of Colour decisions

We applied a logic fusion of decisions of the three component colour of each colour space in order to improve the performance of this system. Table 3 explains the idea clearly. If the system with the first component colour answers that the person is a client and the second component colour answers that it is an imposter and the third component colour answer that it is a client, so the decision with the OR operator will be a Client but with the AND operator the decision will be an impostor, and with the operator (2 AND) we make a vote of three decisions for the three component colour of each colour space, so the decision will be a client.

Table 3. logic fusion of colour decisions

Color component	Results of each component Color	Logic fusion		
		OR	2 AND	AND
Component 01	Client	Client	Client	Impostor
Component 02	Impostor			
Component 03	Client			

With the logic fusion OR we obtain the results in table 4.

Table 4. error rate with the Logic fusion OR of EFM.

Color	test set		
	FAR	FRR	SR (%)
I1I2I3	0.0444	0.0125	94.31
HSV	0.1046	0.0075	88.79
RGB	0.0493	0.0125	93.82
XYZ	0.0395	0.015	**94.55**
YCrCb	0.057	0.0100	93.30
YIQ	0.0613	0.0075	93.12
YUV	0.056	0.0100	93.40

With a logic fusion OR the system can be used in a low security because the FRR<<FAR with rate of success SR about **94.55** % with the XYZ colour space.

With a logic fusion AND the system can be used in a high security because the FAR<<FRR. The system rejects customers easily so it is a very strict system, the rate of success SR about **96.20**% with a colour space RGB.

With the logic fusion AND we obtain the results in table 5.

Table 5. Error rate with the Logic fusion AND of EFM.

Color	Test set		
	FAR	FRR	SR (%)
I1I2I3	0.0032	0.0475	94.93
HSV	0.0023	0.0750	92.27
RGB	0.0155	0.0225	**96.20**
XYZ	0.0202	0.0225	95.73
YCrCb	0.0014	0.045	95.36
YIQ	0.0018	0.0525	94.57
YUV	0.0034	0.0400	95.66

With the logic fusion 2AND we obtain stable results in table 6.

Table 6. Error rate with the Logic fusion 2AND

Colour	2AND in test set			
	FAR	FRR	EER	SR (%)
I1I2I3	0.0269	0.0200	0.0234	95.31
HSV	0.0150	0.025	0.0200	96.00
RGB	0.0267	0.0255	0.0261	95.08
XYZ	0.0302	0.0175	0.0238	95.23
YCrCb	**0.0097**	**0.0150**	**0.0123**	**97.53**
YIQ	0.0112	0.0150	0.0131	97.38
YUV	**0.0136**	**0.0100**	**0.0118**	**97.64**

We observe that only a logic fusion 2AND gives a stable system because the FRR2AND ≈ FAR2AND in each colour space. Also we observed that the use of the logic fusion 2AND improve the performance of the face authentication system with stability, the best rate of success SR about **97.64 %** with the colour space YUV. With the YCrCb colour space the system can be used in a high security because FAR<<FRR. The system rejects customers easily so it is a very strict system, with a high rate of success SR about **97.53**%.

Conclusion

The results show that the colour information improves the performance of face authentication system. We find that the use of a single component colour with the EFM method achieves 96.16% success rate on face authentication using only 53 features applying the correlation distance and only one component colour.
With the use of a logic fusion 2AND, we improve the performance of the face authentication system with stability, the best rate of success SR is about **97.64** % with the colour space YUV. If we apply the YCrCb colour space the system can be used in a high security and with a high rate of success SR about **97.53**%.
In fact, if we compare these results with that obtained in grayscale we find that the improvement of the rate of success is about **03 %,** so the colour information improves the performance of the authentication system of faces.

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