Linear Discriminant Analysis LDA and logic fusion of Color decisions to face authentication

M.Fedias[1], D.Saigaa[2]

Automatic Department, University Mohamed khider
B.P 145 RP Biskra (07000), Algeria,
Tél/Fax : +213-33-74-31-21
Email : [1]meriem_fedias@yahoo.fr, [2]saigaa_dj@yahoo.fr

Abstract
In this paper , we investigate the use of color information to face authentication in order to improve the performance of this system, Many color components have been used. The results in different colorimetric components are combined by using a logic fusion for classification with different operators like: and, or, 2 and. We have applied the method of linear discriminant analysis: LDA for the extraction of feature vectors. The proposed feature set is tested on benchmark database, namely XM2VTS according to its associated Protocol (Protocol of Lausanne).

Index Terms—**Linear discriminant analysis (LDA), face authentication, colorspaces, fusion.**

1. Introduction

Face recognition has become 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 distinguish it from a large number of stored face models would make it 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. Unfortunately developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. 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 this paper, we investigate the use of color information as features in order to train face authentication systems using Fischer linear discriminant analysis: FLD or LDA .

The organization of this paper is as follows: The section 2 present the problem of face authentication , the section 3 explains the LDA for the extraction of characteristic, in the section 4 we present the experimental results finally gotten and perspectives.

2. Face authentication

The principle of system of authentication of face of an individual is the extraction of a vector X of the features of this last, in order to compare it with a vector Y_i that contains the features of this same individual extracts from its pictures 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 authentified 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.

3. Linear discriminant analysis (LDA)

the steps to follow to extract the discriminants for a set of images are[1][2][3][4] :

a) Calculate the within class scatter matrix

For the *ith* class, a scatter matrix (S_i) is calculated as the sum of the covariance matrices of the centered images in that class.

$$S_i = \sum_{x \in x_i} (x - m_i)(x - m_i)^T \quad (01)$$

m_i is the mean of the images in the class. The within class scatter matrix (S_W) is the sum of all the scatter matrices.

$$S_w = \sum_{i=1}^{c} S_i \quad (02)$$

C is the number of classes.

b) Calculate the between class scatter matrix

The between class scatter matrix (S_B) measures the amount of scatter between classes.

$$S_B = \sum_{i=1}^{c} n_i (m_i - m)(m_i - m)^T \quad (03)$$

n_i is the number of images in the class, m is the mean of all the images.

3. Solve the generalized eigenvalue problem

Solve for the generalized eigenvectors (V) and eigenvalues (Λ) of the within class and between class scatter matrices.

$$S_B V = \Lambda S_W . V \quad (04)$$

c) Keep first C-l eigenvectors

Sort the eigenvectors by their associated eigenvalues from high to low and keep the first $C - 1$ eigenvectors. These eigenvectors form the Fisher basis vectors.

d) Project images onto basis vectors

Project all the original images onto basis vectors by calculating the dot product of the image with each of the basis vectors.

4. **Experimental results**

4.1 Database

Our experiments were performed on frontal face images from the XM2VTS database[5][6]. 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.

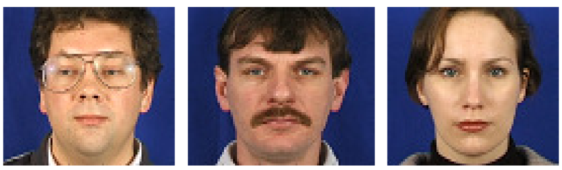


Fig 1. Sample images from XM2VTS database[5]

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. 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 .

Session	Shot	Clients	impostors	
1	1	Training	Evaluation	Test
	2	Evaluation		
2	1	Training		
	2	Evaluation		
3	1	Training		
	2	Evaluation		
4	1	Test		
	2			

Fig 2 XM2VTS database with Lausanne protocol configuration I [6].

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

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)

Table 1 Photos distribution in the various sets

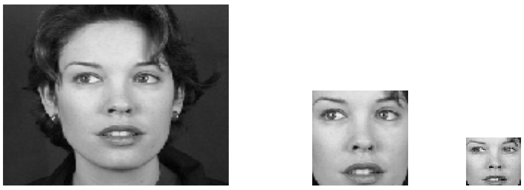
4.2 Pre-treatment

Every picture is constituted of several information as: the hair, the collars of shirt, ...

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 changes very little with time.

It is for that, one cuts the picture by an oblong window centered 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 photonormalisation 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 photonormalisation to a double effect: on the one hand she/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) .



(a) (b) (c)

Fig. 3. Picture of entry (a) picture after carving (b) and picture after decimation (c)

After all this operation of pre-treatment on the pictures, one can use it for the stage of the extraction of the features by the based LDA method.

4.3 Color Results

To answer the question: what color component choose?. We made our experiments on several colors [9][10][11] . To make a comparison of results, we presented them with the based LDA method, which has the parameters:

- ✓ Pre-treatment with photonormalisation
- ✓ Coefficients: coefficients projection sorted following values decreasing.
- ✓ Measure similarity: cos.
- ✓ Threshold: Global.
- ✓ Number of features 100.

We have already found a rate of succeed TS 93.03% Using images to greyscale as characteristic to the entry face authentication system with LDA method.

in table 02 we observed that the LDA method achieves **1.65%** equal error rate on face authentication system with the use of the component color Cr of the color space YCrCb as characteristic of the entry system and gives the best rate of succeed TS= **96.10 %**.

comp	Evaluation set			Test set		
	FRR	FAR	EER (%)	FRR	FAR	TS (%)
X	0,030	0,030	3,01%	0,030	0,031	93,91%
Y	0,032	0,033	3,22%	0,025	0,035	93,97%
Z	0,027	0,027	2,69%	0,018	0,030	95,23%
Y	0,030	0,030	2,99%	0,033	0,031	93,62%
Cr	**0,017**	**0,016**	**1,65%**	**0,023**	**0,017**	**96,10%**
Cb	0,032	0,032	3,20%	0,025	0,029	94,62%
R	0,037	0,036	3,65%	0,048	0,033	91,94%
G	0,030	0,031	3,04%	0,023	0,032	94,56%
B	0,027	0,026	2,65%	0,015	0,030	95,53%
Y	0,032	0,033	3,22%	0,030	0,032	93,78%
I	0,028	0,028	2,83%	0,028	0,022	95,03%
Q	0,020	0,020	1,99%	0,030	0,020	94,99%
Y	0,032	0,033	3,22%	0,030	0,032	93,78%
U	0,030	0,031	3,05%	0,020	0,027	95,33%
V	0,022	0,021	2,13%	0,025	0,022	95,27%
H	0,067	0,066	6,65%	0,055	0,083	86,22%
S	0,023	0,024	2,38%	0,030	0,026	94,38%
V	0,033	0,034	3,35%	0,040	0,031	92,89%
I1	0,030	0,031	3,03%	0,030	0,033	93,73%
I2	0,033	0,032	3,21%	0,038	0,032	93,06%
I3	0,017	0,017	1,67%	0,030	0,015	95,50%

Table 02 error rate with LDA method.

This means that the use of color information by LDA method of the component Cr of color space YCrCb, as characteristic of entry in face authentication system, represents an improvement in the rate of succeed about 3.07% compared to the use of images represented in greyscale .

In table 03 we compared this results with the use of the method PCA(Principal component Analysis) to face authentication system , with greyscale and the component color Cr of color space YCrCb.

	TS (%)	
Method	Grayscale	Color (Cr)
PCA	89,16	91.90
LDA	93,03	96,10
Comparison	**03.87**	**04.20**

Table 03 comparison between LDA and PCA.

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4.4 Logic Fusion of Color decisions

We have an idea to using a logic fusion in order to improve the performance of this system. Table 04 explains the logic fusion of decisions with the three component colors in each color space:

Color component	Résults Of each component	Logic fusion		
		OR	2 AND	AND
Component 01	Client	Client	Client	Impostor
Component 02	Impostor			
Component 03	Client			

Table 04 logic fusion of colors decisions

The figure 04 show the error rate with a logic fusion of color decisions in LDA method with different color space in test set.

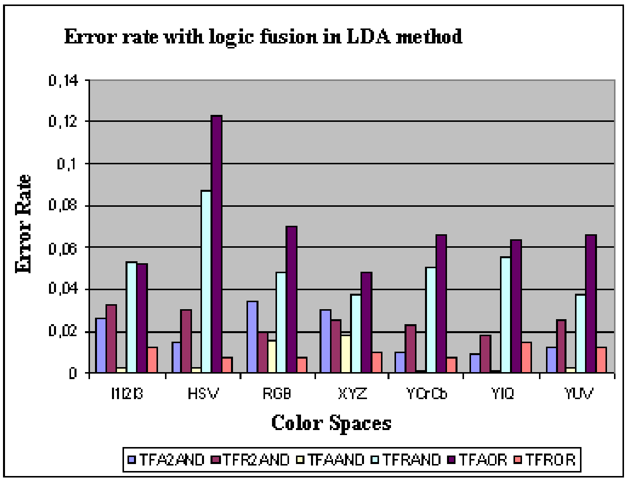

Fig .4 error rate with a logic fusion of color decisions in LDA method.

We observed that only a logic fusion 2AND gives a stable system because the TFR2AND ≈ TFA2AND in each color space.

With the logic fusion OR we obtain the results in table 05.

	OR in teste set		
	FAR	FRR	**TS (%)**
I1I2I3	0,0517	0,0125	93,58%
HSV	0,1231	0,0075	86,94%
RGB	0,0701	0,0075	92,24%
XYZ	0,04829	0,01	**94,17%**
YCrCb	0,0662	0,0075	92,63%
YIQ	0,0642	0,015	92,08%
YUV	0,0664	0,0125	92,11%

Table 05 error rate with the Logic fusion OR

With the logic fusion AND we obtain the results in table 06.

	AND in teste set		
	FAR	FRR	**TS (%)**
I1I2I3	0,00245	0,0525	94,51%
HSV	0,00207	0,0875	91,04%
RGB	0,01527	0,0475	93,72%
XYZ	0,0179	0,0375	94,46%
YCrCb	0,001	0,05	94,90%
YIQ	0,0011	0,055	94,39%
YUV	0,00236	0,0375	**96,01%**

Table 06 error rate with the Logic fusion AND

With the logic fusion 2AND we obtain stable results in table 07.

	2AND in teste set			
	FAR	FRR	EER	**TS (%)**
I1I2I3	0,026	0,033	0,029	94,16%
HSV	0,015	0,030	0,022	95,51%
RGB	0,034	0,020	0,027	94,59%
XYZ	0,030	0,025	0,028	94,49%
YCrCb	0,009	0,023	0,016	**96,81%**
YIQ	0,009	0,018	0,013	**97,34%**
YUV	0,012	0,025	0,019	96,26%

Table 07 error rate with the Logic fusion 2AND

With a logic fusion OR the system can be used in a low security because the FRR<<FAR with rate of succeed TS about **94.17** %.

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 succeed TS about **96.01**% with a color space YUV.

We observed that the use of the logic fusion 2AND improve the performance of the face authentication system with stability, the best rate of succeed TS about **97.34 %** with the color space YIQ.

Conclusion

The results show that The color information improves the performance of face authentication system .
We found that the use of a single component color with the linear descriminant analysis LDA achieves **1.65%** equal error rate so **96.10**% rate of succeed using only 100 features apply the color component of color space YCrCb and cos distance on the test set.

And with the use of a logic fusion of colors decisions in LDA method achieves **1.30%** equal error rate and **97.34**% rate of succeed using 100 features apply the color space YIQ and cos distance on the test set.

This means that the use of color information with a logic fusion of colors decisions in LDA method of color space YIQ, as characteristic of entry in a face authentication system, represents an improvement in the rate of succeed about **4.31**% compared to the use of images represented in greyscale .

In future work we propose the fusion of different methods with different components of colors.

REFERENCES

[1] Wendy S. Yambor, Analysis of PCA-based and fisher discriminantbased image recognition algorithms, Technical Report CS-00-103, july 2000.

[2] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. IEEE Trans. on Pattern Recognition and Machine Intelligence, 19(7):711– 720, 1997.

[3] W. Zhao, R. Chellappa, and A. Krishnaswamy. Discriminant analysis of principal components for face recognition. In Proc. of Int. Conf. on Automatic Face and Gesture Recognition, pages 336– 341, 1998.

[4] C. Liu and H. Wechsler. Enhanced fisher linear discriminant models for face recognition. In Proceeding of the International Conference on Pattern Recognition (ICPR), 1998.

[5] K. Messer, J. Matas, J. Kittler, J. Luettin, and G. Maitre. XM2VTSDB: the extended M2VTS database. In Proc. of Int. Conf. on Audio- and Video-based Person Authentication, pages 72– 77, March 1999.

[6] J. Luettin and G. Maitre. "Evaluation protocol for the extended M2VTS database". IDIAP, availableat http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/face-avbpa2001/protocol.ps, 1998.

[7] D. Saigaa, N. Benoudjit, K. Bemahammed and S. Lelandaius "Face Authentication using Enhanced Fisher linear discriminant Model (EFM)", WSEAS International. Conference on Computational Intelligence, Man-Machine Systems and Cybernetics (CIMMACS'05), in Miami Florida (USA), Nov. 17-19, 2005, pp. 155-160.

[8] D. Saigaa, N. Benoudjit, K. Bemahammed and S. Lelandais "Using Enhanced Fisher linear discriminant Model (EFM) for Frontal Face Authentication", WSEAS Transactions on Computers, ISSN 1109-2750, Vol. 4, Issue 12, December 2005, pp. 1748-1753.

[9] Alain Tremeau, « Représentation numérique des images couleur », *Ecole de Printemps – Images Couleur*, Pau, France, Mars 2001.

[10] M. Fedias, D. Saigaa "l'apport de la couleur à l'authentification de visage", *Proc. Conf. JIG'2007*, 3éme journée Internationale sur l'informatique Graphique, Constantine, Algérie, Oct. 2007.

[11] M. Fedias, D. Saigaa " Fusion de la couleur à l'authentification de visage", *Proc. Conf. STA'2007*, the eighth international conference on sciences and techniques of automatic control, Sousse, Tunisia, Nov. 2007.