Nonlinear Fusion of Colors to Face Authentication Using EFM Method

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***Abstract*-The authentication systems of face generally used the grayscale face image as input, but in this paper we studied the contribution of the color to the authentication system of face. For the extraction of face characteristics for the data base, we tested different spaces colors on the Enhanced Fisher linear discriminant Model (EFM) which is presented as an alternative features extraction algorithm to Principal Component Analysis (PCA) widely used in automatic face recognition. And once the characteristic vector is extracted, the next stage consists of comparing it with the vector characteristic of face which is authenticated, and with the use of each component color alone at the input of this system, we calculated the error rates in the two sets of validation and test for the data base XM2VTS according to the protocol of Lausanne. Finally, the results obtained in different spaces or components colorimetric are combined by the use of a nonlinear fusion with a simple neuron network MLP (Multi layer perceptron), the results obtained confirm the efficient of color to improve the performance of an authentication system of face.**

Keywords: principal components Analysis PCA,, Enhanced Fisher linear discriminant Model (EFM), face authentication, Fisher linear discriminant (FLD), color spaces, MLP.

I. INTRODUCTION

The purpose of an authentication system is to check the identity of an individual which already identified. Thus is not about a system of identification which is responsible of discovering the unknown identity of an individual. In this context, we have developed an algorithm offering an expertise in a particular biometric field: face authentication.

The face is not rigid, it can undergo a large variety of changes due to the expression (joy, sorrow…), to the age, hair… etc, and research in this field is rather recent, and the interest of the researchers for this last is significant.

In 1991, the publication of the article entitled " *eigenfaces for recognition"* of Pentland and Turk [1][2], of MIT (Massachusetts Institute of Technology) was revolving regards to theoretical research in face recognition.

The *"eigenfaces"*, which are based on the principal component analysis PCA, it used the first clean vectors of the covariance matrix of the training data.

The method is simple; the face image is collected by a camera. The subject can arise in front of this one and according to the technique used; the system extracts the characteristics from the face to make the comparison with the characteristics of the claimed person which are preserved in a data base.

Generally, face recognition systems used the grayscale images as input, but in this paper we introduced the color information and answer the question: is color improving the performance of the authentication system of face or not?

This paper is organized as follows: section 2 explains the algorithm of the PCA and EFM used for the extraction of characteristics, in section 3 we present a comparison between the experimental results obtained, and finally we give the conclusion.

A system of authentication must check the identity which is already known for more safety, if it is really the client or an impostor.

The principal of this system is the extraction of a characteristic vector X of an individual, in order to compare it with a vector Y_i which contain the characteristics of this same individual extracted starting from his images which are stored in a data base ($1 \le i \le p$, where p is the number of images of face of this person in the whole of training).

II. 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 standalone performance, one needs to combine further this optimal representation criterion with classifica-tion somediscrimination 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)[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. 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][13][4].

II.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], [2], 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 $\chi \in \mathbb{R}^{nxn}$ define the covariance matrix of the data martix A :

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

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

$$\chi = \Phi\Lambda\Phi^T \quad \text{with} \quad \Phi = [\phi_1\phi_2 ... \phi_i ... \phi_n],$$

$$\Lambda = diag\left\{\lambda_1, \lambda_2, ...\lambda_n\right\} \tag{2}$$

where $\Phi \in \mathbb{R}^{nxn}$ is an orthogonal eigenvector matrix and

$\Lambda \in \mathbb{R}^{nxn}$ 2 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 $W \in \mathbb{R}^{nxm}$.

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)[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:

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

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

where P(C_i) is a priori probability, $S_W, S_B \in \mathbb{R}^{mxm}$, 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 $\Psi, \Delta \in \mathbb{R}^{mxm}$ 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 [8].

II.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. 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:

$$S_W \mathrm{E} = \mathrm{E}\Upsilon \quad and \quad \mathrm{E}^T\mathrm{E} = I \tag{7}$$

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

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

Now one has to simultaneously optimize the behavior 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 *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:

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

Diagonalize now the new between-class scatter matrix K_B:

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

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:

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

II.3. Similarity Measures and Classification

The Fisher Classifier (FC) applies the EFM method on the (lower dimensional) augmented feature vector Y_i derived by Eq. 3. 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. 3. 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. 11. The new feature vector, U_i, of the image is defined as follows:

$$U_i = Q^T Y_i \tag{12}$$

where $Q \in \mathbb{R}^{mxd}$, is a matrix formed by d first vectors columns of the matrix D derived by Eq. 11.

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

$$\delta_{L_1}(x, y) = \sum_i |x_i - y_i| \tag{13}$$

$$\delta_{\cos}(x, y) = -\frac{x^T y}{||x|| \ ||y||} \tag{14}$$

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).

III. EXPERIMENTAL RESULTS

III.1. Data base XM2VTS

Our experiments were carried out on frontal face images of the data base XM2VTS. The principal choice of this data base is its big size, with 295 people and 2360 images in total and its popularity, since it became a standard in the audio and visual biometric community of multimodel checking of identity [9].

For each person eight catches were carried out in four sessions distributed for five months.

The protocol related to XM2VTS divides the base into two categories 200 clients and 95 impostors; the people are of the two sexes and various ages. The photographs are color of high quality and size (256x256).

The protocol of Lausanne shares the data base in three sets [10]:

1) The set of **training** (training): it contains information concerning the known people of the system (only customers)
2) The set of **evaluation** (validation): allows to fix the parameters of the face authentication system.
3) The set of **test** : allows to test the system by presenting images of people to him being completely unknown to him.

For the class of impostors, 95 impostors are divided in two sets: 25 for the set of evaluation and 75 for the set of test.

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

TABLE 1. DISTRIBUTION OF THE PHOTOGRAPHS IN THE VARIOUS SETS

Set	Clients	Impostors
training	600 (3by subject)	0
Evaluation	600 (3by subject)	200 (8 by subject)
Test	400 (2 subject)	560 (8 by subject)

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 (it can be a client-specific threshold or global threshold).

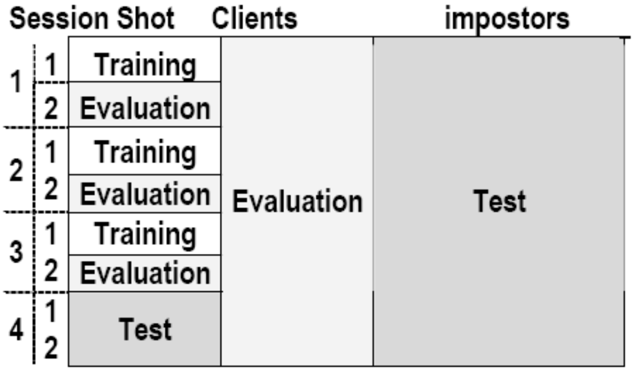

Figure 1. XM2VTS database with Lausanne protocol configuration I.

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. FAR and FRR are given by:

$$FAR=EI/I * 100\% \quad FRR = EC/C * 100\% \qquad (15)$$

where EI is the number of impostor acceptances, I is the number of impostor claims, EC the number of client rejections, and C 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 evaluation set to obtain certain false acceptance on the evaluation 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.

In our experiments we chose the distribution of the images in the various sets according to the configuration described by the figure 1. Figure 2 represents some examples of faces images in the data base XM2VTS.

III.2. Pretreatment

Indeed, all information which is not used for nothing, but inflates the size of the data unnecessarily, for example: the hair, background, ears… etc. Require a reduction of image from which the operation is to extract only the essential parameters for the identifier and who more stable with time.

The decimation consists in taking a pixel on two. In our work we used a filter passes low uniform (2x2) in order to carry out a decimation of factor 2. That reduces by a factor 4 the size of the cut image.

Figure 2. Examples of photographs in the data base XM2VTS .

Then we make the photonormalisation with the images it means: 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.

The photonormalisation for a double purpose: on the one hand it removes for any vector a possible shift compared to the origin, and then any effect of amplification.

Finally we applied the standardization which 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).

(a) (b) (c)

Figure 3. a) image of input , b) image after cutting and c) image after decimation.

III.4. Comparison

a. *Component color alone*

The goal of our system is a binary decision with the rate minimum of equal error, in an authentication system we want to answer by yes if it is a client or not if it is an impostor.

To do a comparison of results, we presented the latter with the PCA then EFM method, which have parameters:

- Pretreatment with photonormalisation
- Coefficients: following coefficients of sorted projection decreasing eigenvalues m=100 for PCA method.
- Measurement of score (similarity): Angle.
- Thresholding: Total.

The figure 4 shows the best success rate of these components colors.

From figure 3 we found that the EFM method achieves the best equal error rate on face authentication using only 50 to 60 features applied the angle distance on the test set and the success rate between 95% and 96%.

The component color Y of the color space YCrCb gives the best success rate 96.16%.

And the component color Z of the color space XYZ gives 96.12%.

In table 2 we shows some results obtained of EFM and the number of vectors d equal to 55.

The equal error rate (FAR+FRR)/2 obtained on the validation set in face authentication of this EFM method applied the angle distance measure in different colors spaces is shown in figure 6, and in figure 7 we can see the success rate in test set in different colors spaces.

From table II we observe that the color improve the performance of the authentication system of face, and for more improvement of the performance of this system, we have to apply a nonlinear fusion of this results.

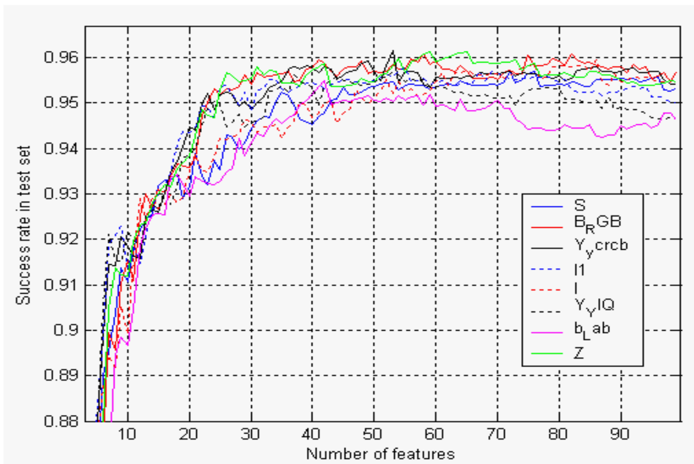

Figure 4. The best success rate of the components colors.

TABLE 2. ERROR RATE WITH EFM AND COLOR

D=55	evaluation set FRR	FAA	EER	Test set FRR	FAR	TS
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	0.0284	95.66%
Y	0.0267	0.0257	2.62%	0.0175	0.0255	95.70%
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%
L	0.0333	0.0328	3.31%	0.0150	0.0346	95.04%
a	0.0217	0.0221	2.19%	0.0325	0.0234	94.41%
b	0.0317	0.0323	3.20%	0.0175	0.0319	95.06%
grey	0.0333	0.0324	3.29%	0.0200	0.0332	94.68

b. Nonlinear fusion with MLP

For the improvement of the performance of this system, we have to apply a nonlinear fusion for classification with networks of neurons simple of MLP type (Multi layer perceptron)[11][12].

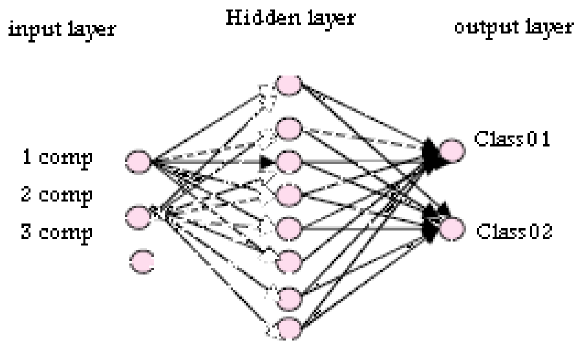

Figure 5. MLP network with a hidden layer

This network consists of three layers: input layer, hidden layer and output layer.

Each layer contains a finished number of the units which one calls the neurons which receive the signals of activation of the other neurons, by treating them then transmitted the output signal to all the units of the following layer. Each neuron of the layer (i-1) is connected to all neuron of layer (i). There is not any connection between the units of the same layer .

Figure 5 shows the synoptic diagram of MLP network with one hidden layer. In our work we used MLP network like a binary classifier (client or impostor).

We involved the MLP with pair's elements (distances intra from clients, distances extra from impostors) we use the set of evaluation to fix the parameters of MLP network. Then we calculate the success rates of this classifier in the set of test.

The parameters chosen for our MLP are:

- A hidden layer with nine neurons.
- Three neurons in the input layer .
- Two neurons in the output layer .

The parameters of the input of MLP network are:

- The distance by using the first component color of EFM.
- The distance by using the second component color of EFM.
- The distance by using the third component color of EFM.

The different success and error rates in the test set by using MLP classifier are shown in the table III using only 60 features.

It is observed that the nonlinear fusion of the results of the three components of colors of color space YCrCb gives the best rate of success TS about **97.68%**. That wants to say an improvement about **1.98%** to the use of only one colorimetric component like input Characteristic to the authentication system of face.

Also we observe that the TFR>>TFA this means that the system does not accept an impostor easily so we can employ this kind of a strict system if high security is required.

TABLE 3. ERROR RATES BY NONLINEAR FUSION

Color	Error rate in test set TFR	TFA	TS
YCrCb	**0,0175**	**0,0057**	**97,68%**
RGB	0,0575	0,0069	93.56%
YIQ	0,0300	0,0071	96.29%
YUV	0,0100	0,0189	97.11%
HSV	0,0225	0,0093	96,82%
I1I2I3	0,0200	0,0062	97,38%
XYZ	0,0175	0,0217	96,08%
Lab	0.0200	0.0127	96.73%

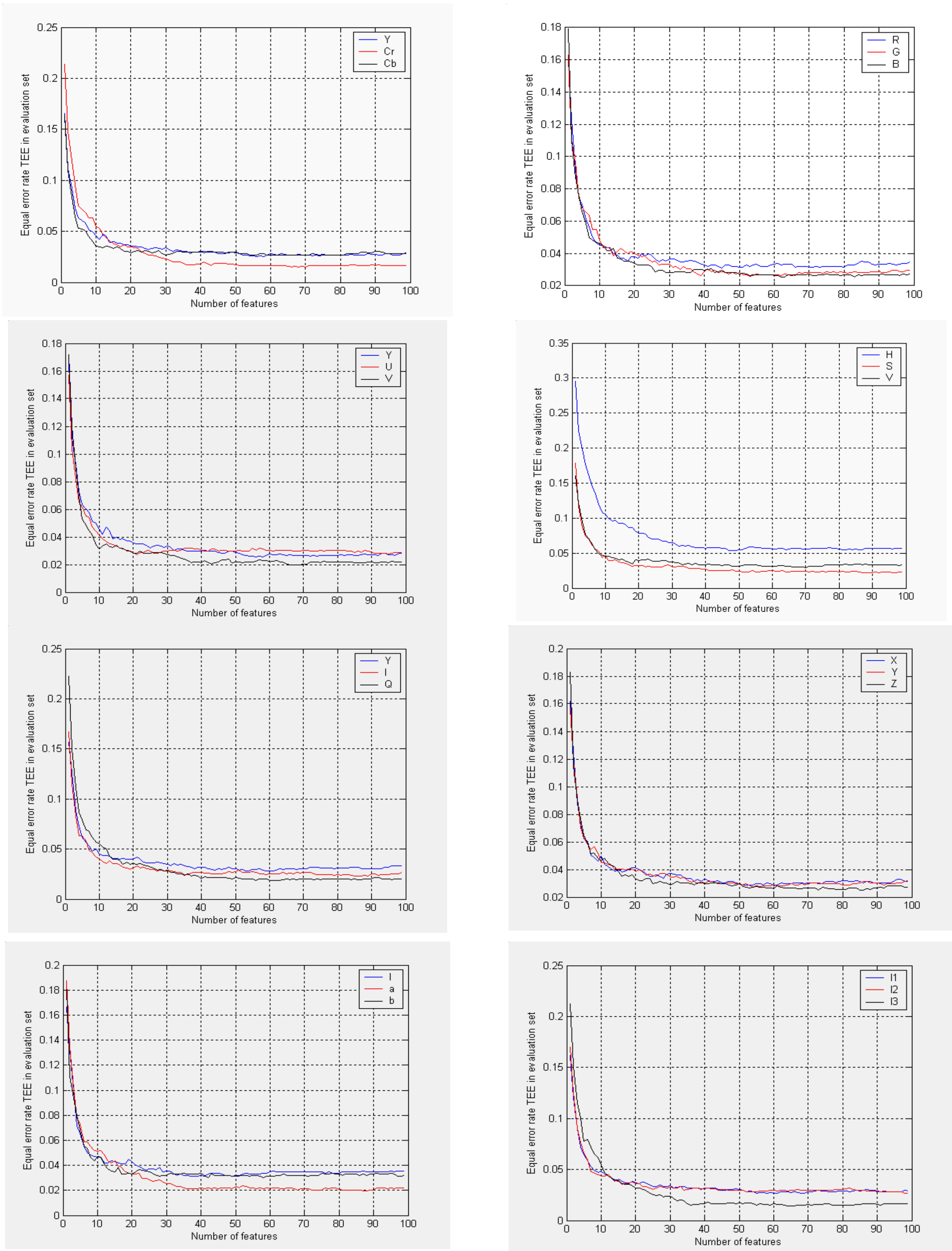

Figure 6. Equal error rate of EFM method using a different colors spaces with angle measure

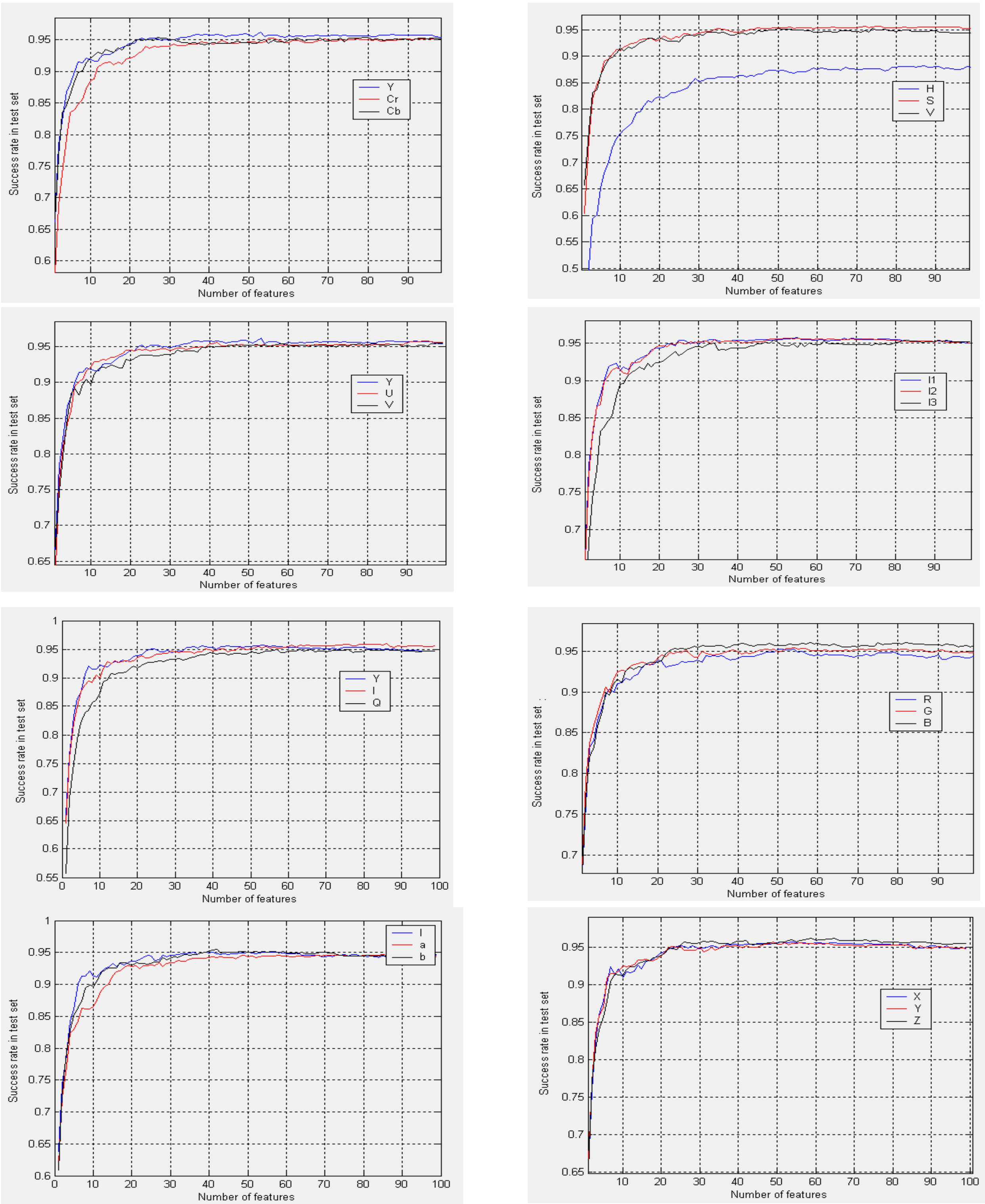

Figure 7. Success rate in test set of EFM method using different colors

CONCLUSION

Our principal goal is the improvement of the performances of our authentication system by introducing the color information of many color spaces.

The EFM method for face authentication is affected by variations in illumination and facial expression of face images. In particular, EFM method achieves 96.16% success rate on face authentication using only 53 features applying the angle distance and only one component color.

And We found that the use of nonlinear fusion by MLP network as classifier on colorimetric components improves the performance of the authentication system of face especially with the color space YCrCb which gives the best rate of success TS about **97.68 %**.

In fact, if we compare these results with that obtained in grayscale we find an improvement in the rate of success about **03 % ,** so the color information improve the performance of the authentication system of face.

In further works, we propose the fusion of the results of various spaces with different methods.

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