Logic Fusion of Color based on new Fast Feature extraction for face authentication

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Abstract
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. Principal Component Analysis (PCA) is a typical face based method which considers face as global feature. In this paper, we propose a new face based authentication approach based on the use of face image mean and standard deviation (MSD) as feature vector. Once the feature vector is extracted, the next stage consists in comparing it with the feature vector of the claimed client face. To demonstrate the efficiency of the MSD approach many experiments have been done using XM2VTS database according to the protocol of Lausanne. The obtained results show that the proposed method is more efficient and faster than PCA.

Keywords: PCA, face authentication, statistical pattern recognition, feature extraction, Color.

1. Introduction

Research in face recognition is currently one of the most important computer vision applications, including matching, surveillance, access control, personal identification, forensic and law enforcement applications. Face authentication system knows a priori the identity of the user (for example through its pin code), and has to verify this identity; the system has to decide whether the a priori user is an impostor or not; it is a binary decision.
PCA (Principal Component Analysis) [1][2], is one of the often used methods for feature extraction in face authentication. Eigenfaces approach is based on Principal Components Analysis (PCA) dimensionality. The basic idea is to treat each image as a vector in a high dimensional space. Then, PCA is applied to the set of images to produce a new reduced subspace that captures most of the variability between the input images. The Principal Component Vectors (eigenvectors of the sample covariance matrix) are called the Eigenfaces. Every input image can be represented as a linear combination of these eigenfaces by projecting the image onto the new eigenfaces space.
Recently, Mohan and al. [16] proposed a new method of face recognition based on a second order statistical texture features. The texture features are derived from co-occurrence parameters with different orientations. In this paper we propose a new approach using only first order statistical features. The proposed approach is based on the use of face image mean and standard deviation (MSD) as features. To demonstrate its efficiency the new approach is compared with the well established algorithm of Eigenfaces.
The main characteristic of the proposed approach is its simplicity. In the proposed face authentication system, 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 database.
The rest of the paper is organized as follows. Section II formulates the problem of face authentication. Section III shows how to extract features from images with PCA, and presents feature extraction procedure based on MSD approach. Experimental results and the analysis of these results are presented in Section IV. Finally, a conclusion and a brief discussion on future research directions are outlined in Section V.

2. Face Authentication

Face authentication systems often 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 ($1\leq i \leq p$, 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. 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 (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. We use the global threshold leading to FRR = FAR in the remaining of this paper.

3. Feature extraction

3.1 *Principal component analysis*

The principal component analysis (PCA) is a linear mathematical method to data analysis, the rule is to seek the directions of axes which maximizes the variance of the data and minimizes the variation squared compared to the axes [1][2][5][13][15][10].

In face recognition, the training set of face images is expressed as a set of random vectors where the rows of pixels in each image are placed one after the other to form a one-dimensional image. The PCA is applied to the matrix of image vectors. It consists in carrying out a reduction of dimensionality by coding the faces in a new base formed by the first clean vectors (EigenFaces) coming from the calculation of the PCA.

The EigenFaces method proceeds as follows:

Let $A = (x_1 x_2 ... x_i ... x_N)$ represents the $(n \times N)$ data matrix, where $\boldsymbol{x_i, i = 1,..., N}$ is the ith n dimension face vector. Here n represents the total number of pixels in the face image and N is the number the training set face images. The vector x_i belongs to a high dimensionality space.

Let $\chi \in \Re^{n \times n}$ be the data matrix A covariance:

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

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

$$\chi = \Phi \Lambda \Phi^T \quad (2)$$

With $\Phi = [\phi_1 \phi_2 ... \phi_i ... \phi_n]$, $\Lambda = diag\{\lambda_1, \lambda_2, ... \lambda_n\}$

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

The most important PCA property 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, dimensionality reduction is an immediate application of PCA.

$$Y_i = W^T x_i \quad (3)$$

Where $W = [\phi_1 \phi_2 ... \phi_i ... \phi_m]$, $m < n$ and $W \in \Re^{n \times n}$.

The lower dimensional vector $Y_i \in \Re^m$ captures the most expressive features of the original data x_i.

3.2 *Proposed approach MS*

When a large collection of numbers is assembled, certain descriptive quantities such as the average or the median are usually more significant than the values of the individual numbers. In this paper, the face image feature extraction uses two descriptive quantities; the mean(M) and standard deviation (SD) [6]-[9].

a. Mean

The mean of a collection of pixels is their arithmetic intensity value average, computed by adding them and dividing the result by their their total number and is defined by:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \quad (4)$$

b. Standard Deviation

The standard deviation (SD) is *extremely* important**.** It is defined as the square root of the variance:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n}} \quad (5)$$

If we consider the image as a matrix where every row and column is a numerically valued random variable, the feature vector Y_i is the concatenation of the horizontal and vertical profile. Vertical profile and horizontal profile are the combination between mean and standard deviation of each row and column respectively. So the size of the feature is reduced to $(2 \times (n + m))$, where m is the number of columns and n is the number of rows .

The figure 1 and 2 represent an example of the mean and the standard deviation for one image.

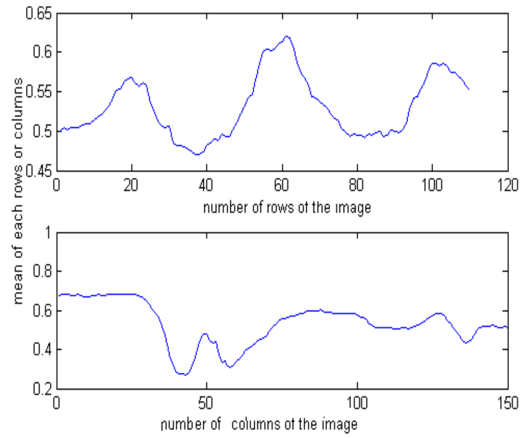

Fig.1 Mean of an image.

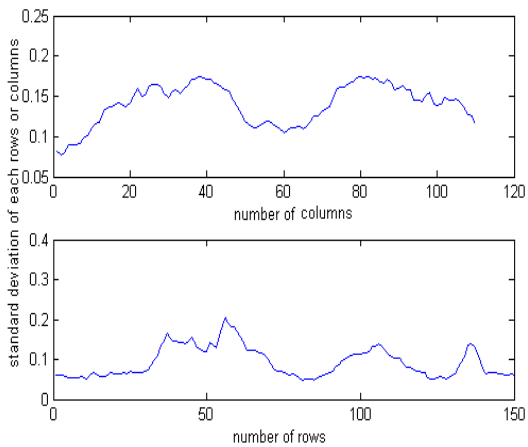

Fig2. Standard deviation of an image.

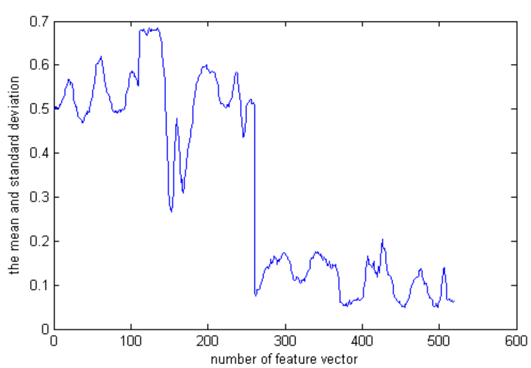

Fig.3 Feature vector of the MSD method.

Figure 3 shows the feature vector which is the combination of the image rows and columns mean and standard deviation.

The principal of the proposed face authentication system is based on the extraction and the comparison of the MSD feature vector with the MSD feature vector of the claimed individual obtained from his database images.

Furthermore, horizontal and vertical standard deviation can be used to detect the position of human face parts like eyes; mouth and nose which are located at the maxima of the standard deviation and the figure 4 explain clearly this idea.

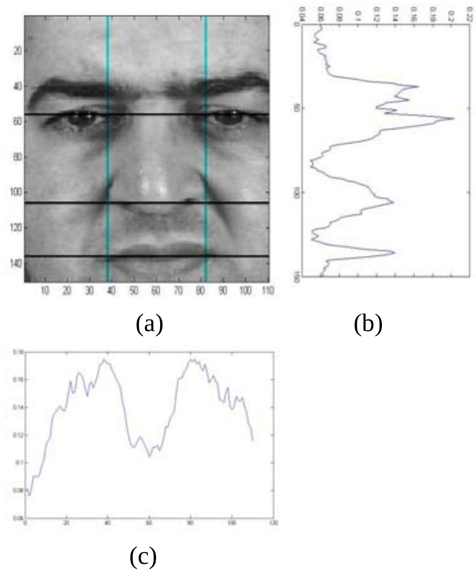

Fig.4 Detection of eyes, mouth and nose of a human face by vertical and horizontal standard deviation. (a) Image of the face, (b) Vertical standard deviation, (c) Horizontal standard deviation.

4. EXPERIMENTAL RESULTS

4.1 Data base XM2VTS

The experiments were carried out on the frontal face images of the XM2VTS data base. The choice of this database is motivated by its big size, 295 people and 2360 images in total and its popularity since it became a standard in the audio and visual biometric community of multimodal checking of identity [3]. The XM2VTS database is a multi-modal database containing 295 identities, among which 200 are used as true clients (the remainders are considered as impostors). Recordings were acquired during four sessions over a period of five months under controlled conditions (blue background, uniform illumination). Each session contains two pictures of each individual.
The protocol related to XM2VTS divides the database into two categories 200 clients and 95 impostors; the subjects are of the two sexes and various ages. The photographs are color of high quality and size (256x256).
The data base is divided into three sets [4]:

1. The **training** set: contains information concerning the known people of the system (clients)
2. The **evaluation** set: used to establish client-specific verification thresholds of the face authentication system.
3. The **test** set**:** used to obtain estimates of the true verification rate on independent data.

For the class of impostors, 95 impostors are divided into 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 I.

Table. I
Photos distribution in the various sets

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

The next figure represents some examples of faces in the data base XM2VTS.

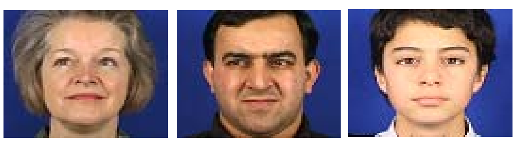

Fig.5 represents some examples of faces images in the data base XM2VTS.

The experiments were performed following *the Lausanne Protocol Configuration I.*

4.2 Preprocessing

In order to reduce the computational complexity and memory consumption we resize the face database from 256x256 to 150x110. By looking at the images we note the appearance of non desired characteristics on the level of the neck, like the collars of shirt. In addition, the hair is a changing characteristic during time (change of cut, colour, baldness...). The background inflates the size of the data unnecessarily. Finally the ears cause a problem. If the person presents herself slightly differently in front of the camera (rotation), we can see only one ear. This is why we decided to cut the image vertically and horizontally and to keep only one window of size 150x110 centred on the face. This window is automatically extracted from the frontal image by a gradient projection based technique.

(a) (b)

Fig. 6 The image before (a) and after (b) Cutting.

Afterwards, we apply a photonormalization. That wants quite simply 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).

4.3 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:

$$Corr(A,B) = \sum_{i=1}^{N} \frac{(A_i - \mu_A)(B_i - \mu_B)}{\sigma_A \sigma_B} \qquad (6)$$

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).

IV.4.1 Comparison between PCA and MS

In order to assess the efficiency of the proposed method we compared it with the PCA approach.

In table II we observe that the use of the mean or the standard deviation alone with photo-normalization and correlation distance achieves a rate of success about 85.66% and 84.06% respectively which are similar with the result of the PCA approach without photo-normalization. But if we combined the mean and the standard deviation we found that the rate of success with MSD method is higher than PCA approach if we applied photo-normalization and correlation distance for classification. The best rate of success is **89.48** % for the MSD method and 88.70% for the PCA approach for the grey scale space.

In general, the MSD method is more efficient than the PCA approach. The rate of success of MSD method is higher than PCA, and the MSD method is faster because PCA involves the eigenvector computation of high-dimensional matrix. Furthermore, MSD method doesn't need an additional memory to store face features while the PCA approach needs a memory space to preserve the projection space. Also, the addition of new client to the authentication system using MSD approach is straightforward and doesn't need any additional computations. However, for the other methods like PCA, LDA [15] and EFM [17], the addition of a new client needs the redoing of all computations to extract a novel projection matrix.

From this table, we can see that the best results are obtained with the S component color of the HSV color space followed by those of the component Y of color space XYZ, and the G component color of the color space RGB then by the luminance component of I1I2I3, YUV, YIQ, YCbCr color spaces.
In particular, the proposed MSD method achieves 90.44 % success rate on face authentication using the component S of the HSV color space with photo-normalization and correlation distance for classification. We can observe that the error rates in validation and test sets are equal in the MSD method with all color spaces, which demonstrates the stability of the proposed approach
In order to reduce the feature vector dimensionality we have applied a wavelet 9/7 filter to each gray image. Figure 5 shows the three stage transform of the wavelet 9/7, and the success rate are shown in figure 6. When the feature vector dimension was reduced to 62 with the 3-stage wavelet 9/7 transform the success rate for the MSD method is 85.80% witch is still acceptable compared to the size of the original feature vector equal to 520.

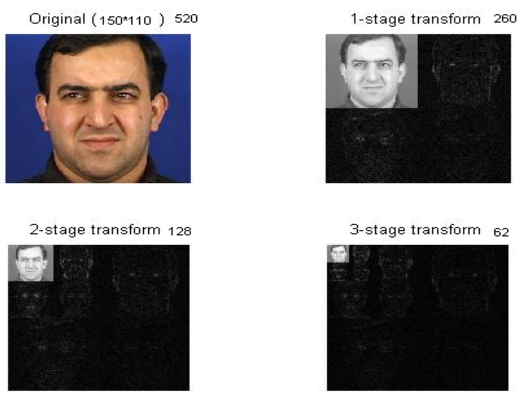

Fig. 5 the three stages transform of the wavelet9/7 of the face image

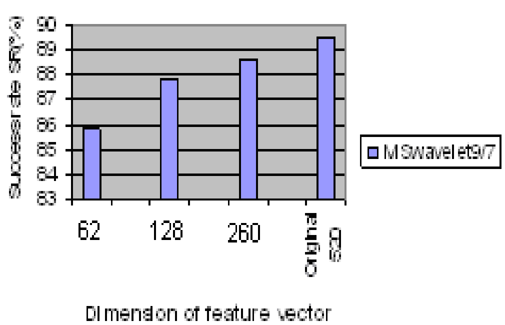

Fig. 6 results of the MS method applying the wavelet9/7

The following figure represents different distances intra for clients and extra for impostors for the two sets of evaluation and test.

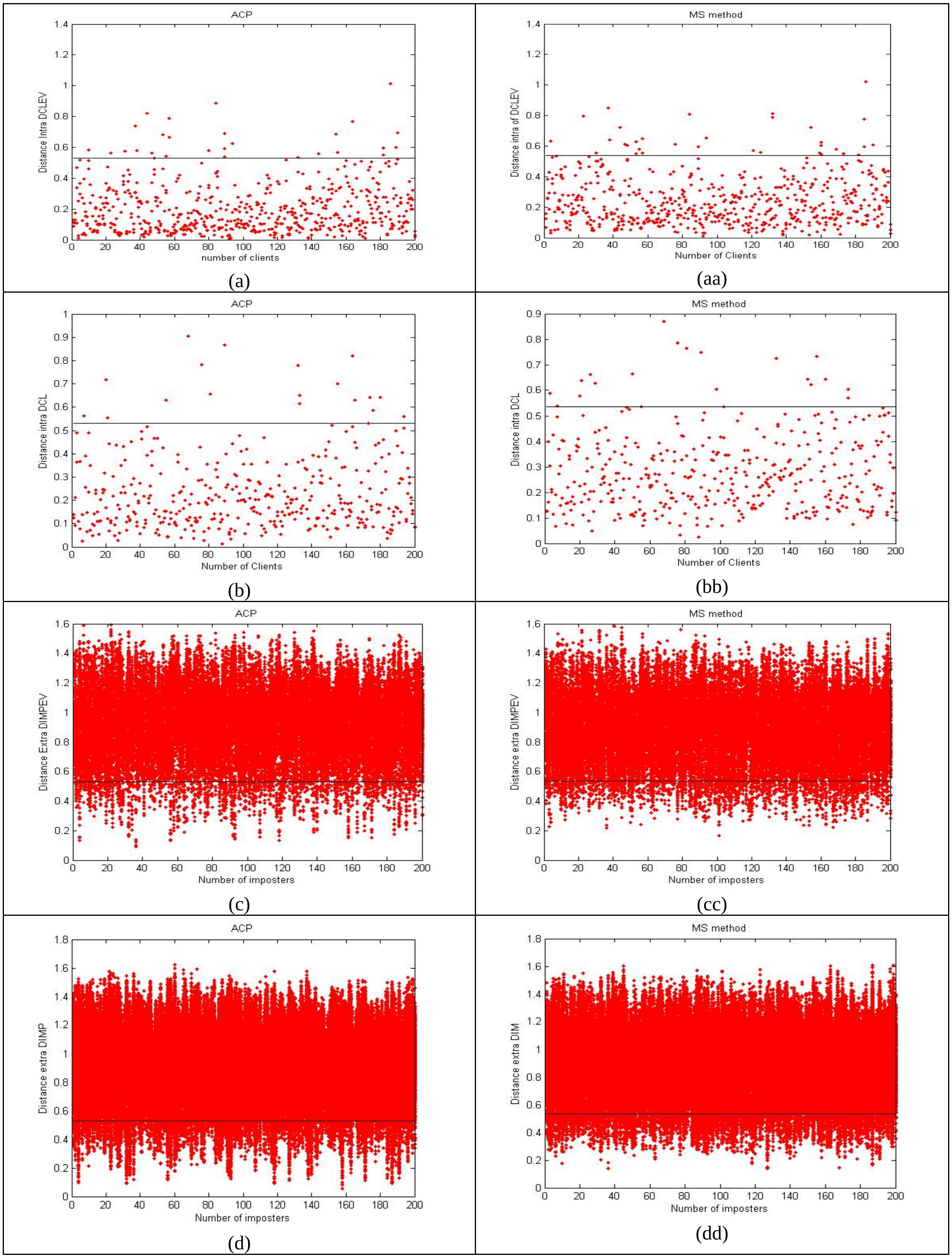

Fig.7 Different distances by PCA and MS method for grey scale.

The table II shows error rates of the PCA and MSD method for different color spaces.

TABLE II DIFFERENT ERRORS RATE OF THE PCA AND MSD METHOD FOR DIFFERENT COLOR SPACES.

Type of distance 'Correlation'	Validation Set	Test Set			Photo-normalisation	Dimension of feature vector	Color Space or Component color
	FAR= FRR	FAR	FRR	SR (%)			
PCA	7.55	7.66	7.75	84.60	NO	520	Grey
MSD	8.67	10.02	9.25	80.74	NO	520	Grey
PCA	**4.67**	**6.54**	**4.75**	**88.70**	YES	520	**Grey**
Mean	6.99	7.59	6.75	85.66	YES	260	Grey
Std	7.04	8.94	7.00	84.06	YES	260	Grey
MSD	**5.47**	**5.77**	**4.75**	**89.48**	YES	520	**Grey**
	6.13	6.41	6.50	87.09	YES	520	R
MSD RGB	**5.13**	**5.42**	**5.00**	**89.58**	YES	520	**G**
	4.35	4.44	6.75	88.81	YES	520	B
	28.16	29.45	29.25	41.30	YES	520	H
MSD HSV	**4.13**	**4.81**	**4.75**	**90.44**	YES	520	**S**
	5.80	6.12	6.75	87.13	YES	520	V
	5.64	5.93	5.75	88.32	YES	520	X
MSD XYZ	**5.51**	**5.78**	**4.50**	**89.72**	YES	520	**Y**
	4.46	4.54	6.75	88.71	YES	520	Z
	5.49	**5.76**	**4.75**	**89.49**	YES	520	**I1**
MSD I1I2I3	5.54	5.77	6.25	87.98	YES	520	I2
	8.81	8.06	9.75	82.19	YES	520	I3
	5.47	**5.76**	**4.75**	**89.49**	YES	520	**Y**
MSD YUV	5.03	4.96	6.50	88.54	YES	520	U
	5.16	5.07	6.00	88.93	YES	520	V
	5.47	**5.76**	**4.75**	**89.49**	YES	520	**Y**
MSD YIQ	5.47	5.27	5.50	89.23	YES	520	I
	13.46	14.55	19.50	65.95	YES	520	Q
	5.47	**5.76**	**4.75**	**89.49**	YES	520	**Y**
MSD YCbCr	5.04	4.97	6.50	88.53	YES	520	Cb
	5.14	5.04	6.00	88.96	YES	520	Cr

IV.4.2 Logic Fusion of Color decisions for MSD method

In this section, we investigate the use of a logic fusion decision of the three component colors of each color space in order to improve the performance of the face authentication system [14].
Table III explains the logic fusion of decisions with the three component colors in each color space.

Table III logic fusion of colors decisions

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

With the logic fusion OR we obtain the results shown in table IV.

Table IV error rate with the Logic fusion OR

	OR in test set		
	FAR	FRR	**SR (%)**
I1I2I3	13.23	1.50	85.27
HSV	35.47	1.00	63.53
RGB	8.07	4.25	87.68
XYZ	6.74	4.25	89.01
YCbCr	11.84	1.50	86.66
YIQ	22.16	1.25	76.59
YUV	11.85	1.50	86.65

With the logic fusion AND we obtain the results shown in table V.

Table V error rate with the Logic fusion AND

	AND in test set		
	FAR	FRR	**SR (%)**
I1I2I3	0.81	14.50	84.69
HSV	0.65	35.75	63.60
RGB	3.13	8.75	88.12
XYZ	3.88	8.00	88.12
YCbCr	0.73	11.50	87.77
YIQ	0.35	23.25	76.40
YUV	0.73	11.50	87.77

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

Table VI error rate with the Logic fusion 2AND

	FAR	FRR	**SR (%)**
I1I2I3	5.54	4.75	89.71
HSV	4.27	4.00	91.73
RGB	5.07	5.25	89.68
XYZ	5.64	4.75	89.61
YCbCr	**3.21**	**4.25**	**92.54**
YIQ	3.07	5.25	91.68
YUV	**3.21**	**4.25**	**92.54**

With OR logic fusion the system can be used in low security because the FRR<<FAR with rate of success about **89.01** % using XYZ color space.
With a logic fusion AND the system can be used in a high security because the FAR<<FRR. The system rejects clients easily so it is a very strict system, the rate of success SR about **88.12** % with a XYZ or RGB color space.
We observed that the use of the logic fusion 2AND improve the performance of the face authentication system, the best rate of success SR is **92.54 %** with the color space YUV and YCbCr.
Finally, we can conclude that the color decision logic fusion improves the performance of the face authentication system especially with the use of the YUV or YCbCr color space and correlation distance measure for classification. Also, it represents an improvement in the rate of success about **03%** compared to the use of images represented in grey level.

5. CONCLUSION

In this paper, an MSD face authentication approach is proposed. The MSD method has many advantages over conventional PCA approach. In the first place, since MSD method is based on the use of image mean and standard deviation as image features, it is simpler and faster than PCA which involves calculating the eigenvectors of a big covariance matrix. Secondly, it has a high success rate which made it better to use for authentication systems. Third, MSD method needs a lower memory size than PCA which need more memory size for projection matrix storage. Furthermore, new client addition to the MSD based authentication system is not a problem; we can add a new client directly to the training data. However, this can be difficult with other methods like PCA, LDA or EFM which need to redo all the computations to extract a novel projection matrix. But the difficulty caused by facial expression and aging still exists for the MSD method like PCA.

MSD approach achieves 90.44% as face authentication success rate using correlation distance and component color S of the HSV color space. With the use of a color decision logic fusion, MSD method achieves 92.54% as success rate using color space YUV or YCbCr and correlation distance. This means that the use of color information with a color decisions logic fusion in the proposed MSD method using color space YUV or YCbCr represents an improvement of **03**% in the rate of success compared to the use of grey scale images.

As future work we propose the use of nonlinear fusion of different components of colors to improve MSD approach efficiency.

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