A new approach based in mean and standard deviation for authentication system of face

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Abstract – Face authentication is a significant problem in pattern recognition. The face is not rigid it can undergo a large variety of changes in illumination, facial expression and aging. Principal Component Analysis (PCA) is a typical and successful face based technique which considers face as global feature. In this paper, we developed a new simple method to extract the global feature vector based in the Mean and the Standard deviation (MS) of the image of face. Once the feature vector is extracted, the next stage consists of comparing it with the feature vector of face which is authenticated, and then we calculated the error rates in the two sets of evauation and test for the data base XM2VTS according to the protocol of Lausanne. The experimental results indicated that the extraction of image features is more efficient and faster using MS method than PCA. *Copyright* © 2010 Praise Worthy Prize S.r.l. - All rights reserved.

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I. Introduction

The face authentication systems are used for the verification of a user's identity on the Net, when using a bank automaton, when entering a secured building, etc. Face authentication system knows a priori the identity of the user (for example through its pin code), and has to verify this identity; in other words, the system has to decide whether the a priori user is an impostor or not; it is a binary decision. In most image processing problems, features are extracted from the images before processing. Working with rough images is not efficient: in face authentication, several images of a single person may be dramatically different, because of changes in viewpoint, and illumination, or simply because the person's face looks different from day to day. One of the methods often used to extract features in face authentication is PCA (Principal Component Analysis) by the publication of the paper entitled " eigenfaces for recognition" of Pentland and Turk [1][2], of MIT (Massachusetts Institute of Technology) which was revolving regards to theoretical research in face recognition. The PCA method used the first clean vectors of the covariance matrix of the training data.

In this paper, we show how the method proposed improves the success rate compared to an equivalent system using PCA. 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. This paper is organized as follows. Section II presents the problem of face authentication. Section III shows how to extract features from images with PCA, and presents the procedure based on MS. Section IV shows the experimental results, finally we give the conclusions.

II. 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 $(1 \le i \le p$, 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. 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 respectively being wrongly classified, 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.

III. Feature extraction

III.1. Principal component analysis

The principal component analysis (PCA) is a linear mathematical method to data analysis, the rules 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].

In the case of face recognition we regard the set of the faces images of training as a set of a random vectors (matrix of faces vectors), where each vector face is consisted the sequence of the lines or the columns of a face image. The PCA is applied to this matrix of the faces vectors. It primarily consists in carrying out a reduction of dimensionnality by coding the faces in a new base formed by the first clean vectors (EigenFaces) coming from the calculation of the PCA.

The method of EigenFaces proceeds as follows:

Let $A = (x_1 x_2 \dots x_i \dots x_N)$ represent the $(n \times N)$ 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.

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

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

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

$$\chi = \Phi \Lambda \Phi^T \tag{2}$$

With $\Phi = [\phi_1 \phi_2 \dots \phi_n], \Lambda = diag\{\lambda_1, \lambda_2, \dots, \lambda_n\}$ 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 element in decreasing order $(\lambda_1 > \lambda_2 > \dots > \lambda_n)$.

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:

$$Y_i = \boldsymbol{W}^T \boldsymbol{x}_i \tag{3}$$

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

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

III.2. Proposed approach MS

When a large collection of numbers is assembled, we are usually interested not in the individual numbers, but rather in certain descriptive quantities such as the average or the median. In general, the same is true for the image of face. So we shall discuss two such descriptive quantities the mean and Standard Deviation [5][6][7][8][9].

a. Mean

the most common and familiar is the arithmetic mean, defined by :

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \tag{4}$$

b. Standard Deviation

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

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

If we consider the image as a matrix where every row and column will be a numerically valued random variable, the feature vector Y_i is the combination between mean and standard deviation of each rows and columns of image. So we have reduced the size of image from $(n \times n)$ to $(2 \times n)$.

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





Fig.3 The feature vector of the MS method.

The figure 3 show the feature vector which is combined by mean and standard deviation for one image.

The principal of this system is the extraction of a feature vector of an individual, in order to compare it with a vector Yi which contain the feature of this same individual extracted starting from his images which are stored in a data base.

Also we can use the standard deviation for detecting the components of human face like eyes, mouth and nose which are located at the maxima of the standard deviation and the figure 4 explain this idea clearly.



Fig.4 (a) image of face (b) Vertical Standard deviation (c) Horizontal Standard deviation . Detection of eyes, mouth and nose of a human face by the standard deviation of each rows and columns of the image.

We observe that this method is very interesting and easy and faster for searching the position of different parts of the face image.

IV. Experimental results

IV.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 [3]. 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 [4]:

1. The set of **training** (training): it contains information concerning the known people of the system (only clients)

- 2. The set of **evaluation** (validation): allows fixing 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 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, the people are of the two sexes and various ages.



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

IV.2. Pretreatment

By looking at the images we clearly note the appearance of characteristics not desired on the level of the neck, like the collars of shirt, the sports shirts, etc. In addition, the hair is also a characteristic changing during the time (change of cut, colour, baldness...). The background appears on the images; it is used for nothing, and inflates the size of the data unnecessarily. Finally the ears cause also a problem. Indeed, 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 cantered on the face. This window is automatically extracted from the frontal image by a technique based on projections of gradients.



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).

IV.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:

$$Corr(A, B) = \sum_{i=1}^{N} \frac{(A_i - \mu_A)(B_i - \mu_B)}{\sigma_A \sigma_B}$$
(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. Comparison between PCA and MS

In an authentication system of face the goal is a binary decision client or impostor with the rate minimum of equal error in test.

In table II we observe that the use of the mean alone or the standard deviation with photonormalisation and correlation distance gives a rate of success about 85.66% and 84.06% respectively which are similar with the use of PCA without photonormalisation and with correlation distance. But if we combined the mean and the standard deviation we found that the rate of success with MS method is higher than PCA if we applied a photonormalisation and Correlation distance for classification. Where The MS method gives the best rate of success about **89.48**% and The PCA gives 88.70%.

In general, the MS method is more efficient than PCA; the rate of success of MS method is better than PCA, and the MS method is faster because PCA involves calculating the eigenvectors of a big covariance matrix. Also we don't need any memory with MS method than PCA who need a memory to preserve the space of projection. the next figure represent different distances intra for clients and extra for impostors in the two sets of evaluation and test



Fig.7 Different distances by PCA and MS method.

The table II shows the different errors rate of the PCA and MS method.

Type of distance 'Correlation'	Validation Set	Test Set				Dimension of	
	FAR= FRR	FAR	FRR	(FAR+ FRR)/ 2	Photonormalisation	feature vector	
PCA	7.55	7.66	7.75	7.70	NO	520	
MS	8.67	10.02	9.25	9.63	NO	520	
PCA	4.67	6.54	4.75	5.65	YES	520	
Mean	6.99	7.59	6.75	7.17	YES	260	
Std	7.04	8.94	7.00	7.97	YES	260	
MS	5.47	5.77	4.75	5.26	YES	520	

 TABLE 2

 Different errors rate of the PCA and MS method.

V. Conclusion

In this paper, new technique for image feature extraction and representation was developed. The MS method has many advantages over conventional PCA. In the first place, since MS method based in mean and standard deviation of the image, it is simpler and faster than PCA which involves calculating the eigenvectors of a big covariance matrix. Second, it is better to use for authentication systems of face in terms of success rate. Third, MS method didn't need memory than PCA which need a memory for the matrix of projection. But the difficulty caused by illumination variation, facial expression and aging are still exists for the MS method like PCA.

In further works, we propose the use of color to improve the performance of this system.

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