A Novel Method for Face Recognition under partial occlusion or facial expression Variations[1]

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Abstract - *This paper presents a new technique for face recognition that can cope with partial occlussion or strong variations in facial expression. The method tries to solve the face recognition problem from a near-holistic perspective. The main idea is to "eliminate" some features which may cause a reduction of the recognition accuracy under occlusion or expression changing. To test and evaluate the performance of the new technique, a series of experiments have been carried out which have shown improved performance and robustness when compared to the classical PCA.*

Keywords – *Face Recognition, Lophoscopic PCA, face occlusion, facial expression variations, Principal Component Analysis*

1. INTRODUCTION

Face recognition has been an active topic within the research community during the last three decades; however, it remains still an unsolved problem which presents only successful results under controlled scenarios where the acquisition conditions like illumination, pose, facial expressions and face occlusions don't vary significantly. This paper proposes a novel approach to deal with some of these difficulties; more specifically to deal with problems due to face occlusions and facial expression variations which are present in most of the real face recognition systems.

The problem of partially occluded faces has been analyzed by using local approaches which divided the face into different parts and, then, use a voting space to find the best match [1, 2]. The main difference between the technique presented in this paper and other local methods is that these try to solve the face recognition problem from a *feature* analysis, whereas in this paper a *near-holistic* perspective is used. In [1, 2] the authors try to find the best suitable (most discriminative) features and then combine them; whereas in this approach, the features are eliminated and the rest of the face is treated as the useful information.

The rest of the paper is organized as follows. In section 2 an overview of the proposed technique is given. Section 3 defines the face database that has been used for experimenting and describes the process for face normalization. Section 4 includes some of the more salient results which are compared with conventional PCA. It also contains an analysis of the effects of feature localization errors in the recognition accuracy. Finally, some conclusions and future work are presented in section 5.

2. LOPHOSCOPIC PCA: AN OVERVIEW

Among the best known approaches for face recognition, Principal Component Analysis (PCA) has been object of much interest [3] and is considered one of the techniques with better results [4]. In PCA, the recognition system is based on the representation of the face images using the so called *Eigenfaces*. The main idea of the PCA is to obtain a set of orthogonal vectors (*Eigenfaces*) that optimally represent the distribution of the data in the root mean square (rms) sense. In a usual *Eigenfaces*-based scheme for face recognition, such as identification for law enforcement or personal identification, the PCA is performed on a mixture of several face images of different persons similar to the unknown images which are to be recognized.

The technique proposed in this paper is a natural extension of the PCA approach where several subsets of images are created through masking. In each subset, the images used in the training and recognition stages are masked in those regions where significant modifications are expected to occur as a consequence of occlusion or expression change. Fig 1 shows the six subsets of images which correspond to the whole face (original image), and the masking of the left eye, the right eye, both eyes, nose and mouth respectively.

Therefore instead of having only one set of training images which will be used to create only one face space, six different training subsets are used to create also six different face projection spaces.

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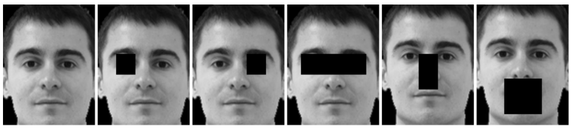

Fig. 1. Training images for Lophoscopic PCA

Fig. 2. TwoEyes Eigenface subspace

Fig 2 shows an example of the *Eigenface* subspace corresponding to the subset of images with the two eyes covered.

The objective of introducing the masks (black rectangles) is that the part of the face covered with them, will have no influence in the respective projection subspace. Thus, if the face image, used in the recognition task, presents one occluded part or parts that have changed drastically (e.g. moustaches and beards) the best match will take place when projecting to the face subspace with this part covered.

In some way, this technique can be considered as the complementary of the *Eigenfeatures* approach because the entire face image except the region of a local feature is used, instead of using only the region of the local feature. The method has been called Lophoscopic PCA because its ability to recognize faces under the absence of part of the relevant information. The diagram shown in Fig. 3 summarizes the main steps of this technique.

3. DATABASE DESCRIPTION

The proposed Lophoscopic PCA method was used for face recognition and tested on a database which has been created in the Universitat Politècnica de Catalunya (UPC). This database makes special emphasis in facial expression variations and in partially occluded faces due to the appearance of some objects like sun glasses. Up to now it is composed of 25 individuals with 40 images each including three different illuminating conditions and 9 angles of view. The database has been created in color and high resolution and is being used to test several face recognition and face reconstruction algorithms. This database will be soon publicly available at http://gps-tsc.upc.es\GTAV.

The subset of images used to train and test the Lophoscopic PCA are extracted from the previous database. It includes frontal views of 20 individuals with 12 pictures per individual under three different illuminations (environment or natural light, strong light source from an angle of 45º, and finally an almost frontal mid-strong light source. These frontal views make special emphasis in facial expression variations and the appearance of objects which occlude part of the face as shown in Fig. 4. The original colour images of 1000x1500 pixels were manually cropped and resized by 122x100 pixels and finally converted to grey level images.

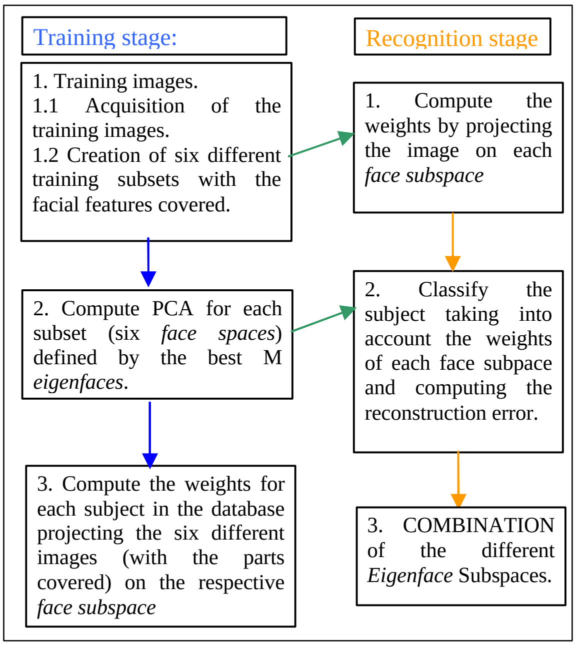

Fig. 3. Scheme of Lophoscopic PCA technique

Since three different illuminations are presented in the acquisition of the images, it is required to attenuate the effect of illumination in the face recognition process. For this reason, an illumination correction factor is applied for all the images before the recognition stage. This factor is computed as a ratio between the accumulative grey level of the nose region of the current image and the mean accumulative grey level of the same region in all the training images acquired with natural light:

$$ICF = \frac{\sum_{i=-N_b}^{N_t} \sum_{j=-M_b}^{M_t} I(i,j)}{\frac{1}{TN} \sum_{k=1}^{TN} \sum_{i=-N_b}^{N_t} \sum_{j=-M_b}^{M_t} I_k(i,j)} \qquad (1)$$

where N_b, N_t, M_b and M_t are the pixels which enclose the region of the nose, and TN is the number of training images under natural light conditions. Introducing this factor an increase of the 5% in the recognition accuracy is obtained.

Finally, all the images (training and test samples) are warped using an affine transformation (translation, rotation and scale) to guarantee that the eyes, nose and mouth are more or less in the same coordinates for all individuals. The parameters for computing the affine transform are extracted from the position of the eye centres, which were labelled manually. The scale factor is computed taking an eye distance of 40 pixels for all individuals. Automatic detection of the iris centre is currently being considered using the algorithm described in [6] before converting to grey level images. Once the images have been normalized, each mask is positioned at the same fixed coordinates and covering area.

4. EXPERIMENTS AND RESULTS

4.1. Experiments description

A total of 480 face images were created by mirroring the 240 frontal face images and only 120 of them, 6 for each person, were used in the training stage. These 6 training images correspond to the 3 different illuminations and their mirror images. All of the images in the training set were frontal, with neutral expression and without occlusions. For the test stage, the remaining 360 face images were used as a closed-set for testing the algorithm.

The number of *Eigenfaces* used for the creation of the face subspaces was set to 45 (from the 119 available), which is the value that produced highest recognition accuracy in PCA for the testing database.

Two different experiments have been carried out to evaluate the recognition accuracy of the Lophoscopic PCA technique. First, PCA and the new five subspaces of Lophoscopic PCA have been tested separately on both databases without modifying the original images (experiment 1), i.e. the test images were projected directly into the six different face subspaces. Second, the original database images have been modified and subsets of five images for every test image have been created masking one part of the face; i.e. the same masking procedure has been used in the recognition and the training stages so that from each test image, five different masked images are projected to their respective Lophoscopic PCA face spaces (experiment 2). The parts have been covered so that all the black rectangles of all *Eigenface* subspaces match perfectly.

4.2. Results on the UPC Face Database

Table 1 summarizes the results for all the *Eigenface* subspaces separately. In the first experiment the space corresponding to the entire face (equivalent to conventional PCA) presents a higher recognition rate towards the other subspaces. These big differences were predictable because in the first experiment a complete face image is projected to a face subspace with one part covered; thus, the reconstruction error may be large depending on the uniformity of the face image within the "assumed" covered part. This fact produces lots of false matches and reduces the recognition rates in the "covered" face subspaces.

Table 1. Recognition rates for the two experiments

	Face PCA	Left Eye	Right Eye	Two Eyes	Nose	Mo-uth
E1	86.29	78.57	77.14	78.57	71.28	69.71
E2	86.29	86.57	86.85	84.57	70.57	64.86

On the contrary, the results for the second experiment show that in general the Face Subspaces corresponding to the eyes (*RightEye*, *LeftEye* and *TwoEyes*) have improved between 6% and 10% in comparison with the other experiment. It can also be concluded that in this case the "covered· subspaces obtained a slightly higher recognition rate than conventional PCA, for the *Eyes* (*LeftEye* and *RightEye*) subspaces. The main reason for this improvement is that in these subspaces the changes due to the appearance of sunglasses or facial expression variations have an attenuated effect in the final recognition decision by eliminating these parts of the face. The "*TwoEyes*" and "*Nose*" subspace have a lower performance than the "*OneEye*" subspaces because the area of the eliminated part of the face is too big and has a negative influence in the final results. Similarly, the "*Mouth"* subspace has the lowest recognition rate because in has the biggest covered area and in normal cases (frontal views without strong variations in facial expressions) some discriminant information is lost. Nevertheless, if the positive matches are analyzed in detail, it can be concluded that these are uncorrelated with the positive matches of the other subspaces, so that the "*Mouth"* subspace may be of big importance when combining all the face subspaces.

Fig. 4 illustrates two examples in which the "*TwoEyes*" and the "*Mouth*" spaces recognize the individual correctly whereas the other subspaces fail.

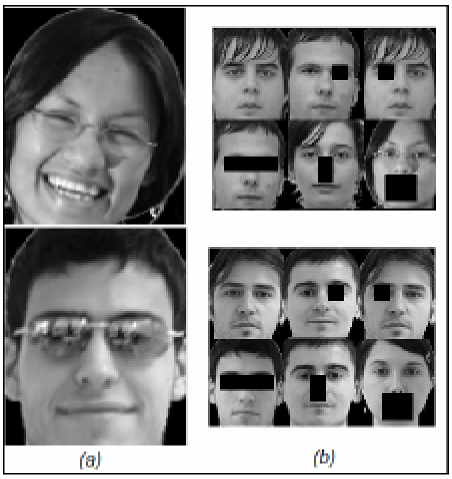

Fig.4. (a) Test images, (b) Recognized IDs in all face Subspaces

4.3. Combination of all subspaces: Lophoscopic PCA

The above preliminary experiments showed that the recognition rate of Lophoscopic PCA can outperform the conventional PCA by attenuating the effects of disguises which may partially occlude the face image and the effects of facial expression variations. The next step is how to combine the different eigenface subspaces of the Lophoscopic PCA approach in order to get one final decision that will present better recognition rates than each subspace separately. Two different combination strategies have been implemented: a minimum reconstruction error and a majority voting. For the first combination strategy the recognized ID is the one chosen by the *Eigenface* Subspace with the minimum reconstruction error; whereas in the majority voting strategy the final ID is the one which has been decided by the majority of the *Eigenface* subspaces; in the case of draw the ID which be the one with the minimum reconstruction error. As shown in Table 2 Lophoscopic PCA using these two simple combination strategies presents better results than the PCA approach by itself.

Table 2 Recognition Rate for Lophoscopic PCA using two different combination strategies

PCA	Min. Rec. Error	Majority Voting
86.29 %	92.42%	89.14%

4.4. Simulation of Feature Error Localizations

The Lophoscopic PCA technique requires an eye detection and localization stage. Although, the eye centers have been labeled manually in this work we have conducted an experiment for simulating the performance of the algorithm under the presence of error in the detection of the eye centers. Using the iris centre localization approach proposed by Rurainsky [6] as reference, the error in pixels can be modelled by a Gaussian probability function of μ=1 and s=1. The experiment presented here intends to show the degradation of the recognition accuracy for different values of s by adding a certain Gaussian noise to the manually marked feature points of the test image set. Fig 5 represents the recognition accuracy for Lophoscopic PCA (using a combination strategy of the Min. Rec. Error) when using different values of s. As depicted in Fig. 5, the localization error of the features degraded the recognition accuracy of the algorithm considerably as it has been expected. Nevertheless, the localization error at s=1 (green line) which corresponds to the results presented by Rurainsky [6], presents a small degradation of the 4.29%. In order to smooth the effect of these localization errors, the localization errors can be modeled and compensated by means of Mixtures of Gaussian [1].

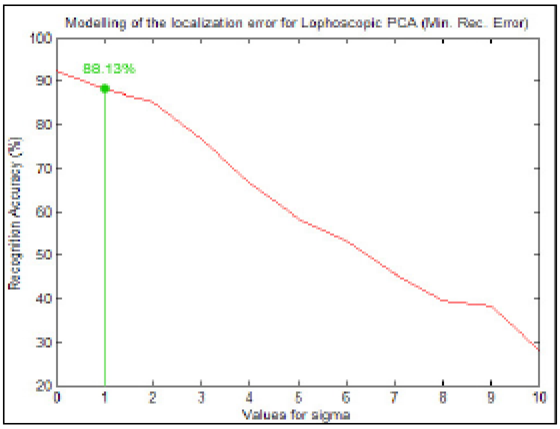

Fig.5. Evolution of the recognition rate of Lophoscopic PCA towards localization errors

5. CONCLUSIONS AND FUTURE WORK

This paper has presented a new face recognition technique based on PCA which tries to cope with the problem of partially occluded faces or strong facial expression variations. The results has shown that the performance of PCA can be increased using the new Lophoscopic PCA approach. The main drawback of the new algorithm is the computational cost which is 6 times higher than the *Eigenfaces* algorithm. After analyzing the results and the errors of the test images of the UPC database, it has been concluded that the main false recognition decisions were due to the strong illumination variations; thus, an equivalent *Lophoscopic LDA* technique is currently being implemented to make the whole approach more robust against different illumination conditions.

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