LOPHOSCOPIC PCA: A NOVEL METHOD FOR FACE RECOGNITION[1]

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ABSTRACT

In this paper, a new technique called Lophoscopic PCA is developed for recognition of partially occluded faces and faces with strong facial expression variations. As opposed to the PCA or the Eigenfeatures approaches, this method does not try to solve the face recognition problem neither from a holistic, nor a feature perspective; in fact it studies the problem from a near or pseudo-holistic perspective. The main idea is to "eliminate" some features which may cause a reduction of the recognition accuracy under special conditions (facial expression variations or appearance of disguises). To test and evaluate the performance of the new technique, a series of experiments are carried out on the UPC face database. The experimental results have shown that using Lophoscopic PCA the recognition accuracy can increase in comparison with the classical PCA method and be more robust against exaggerated changes in the facial expression or the appearance of objects like sun glasses.

1. INTRODUCTION

One of the most important challenges in face recognition is the problem of the appearance of new objects like sun glasses, scarves, masks, beards or moustaches which may partially occlude the face. Moreover the recognition task is a difficult challenge when the facial expression varies e.g. when the person sticks the tongue out or opens the mouth considerably. In such cases conventional methods such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) may fail or present low recognition rates.

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]. For example, the *Eigenfeature* approach [2], proposed to divide the face and extended the *Eigenfaces* method [3] by creating different *Eigenfeature* spaces (eigeneyes, eigennose or eigenmouth spaces) where the extracted local features were projected and compared separately. The authors reported better results than in [3] for face images with approximately 20% of face partially occluded or not-well illuminated images as well as with use of disguise, scarf, sun glasses or masks. 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 most 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. Another similar *near-holistic* approach called Local Feature Analysis (LFA) [4] combines PCA and the analysis of local information around some critical points of the face. The authors of this method reported good results for face reconstruction when large datasets are available for learning. The main problem can be summarized in one question: "*is face recognition the result of holistic or feature analysis?*" The authors of this document think that both holistic and feature information are crucial for the recognition task. So, a new technique based on PCA is presented.

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 and with LFA. This section contains also 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 TECHNIQUE

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 that provide the best performance [5]. 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

[1] The work presented was developed within VISNET, a European Network of Excellence (http://www.visnet-noe.org), funded under the European Commission IST FP6 programme.

(*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 different face images of different persons similar to the unknown images which are to be recognized.

The new Lophoscopic PCA (LPCA) technique is from the mathematic point of view similar to the *Eigenfaces* approach but with the main difference that for each face image in the database, six different images were created: one with the whole face (original image), one with the left eye covered, one with the right eye covered, another with both eyes covered, other with the nose covered and finally one with the mouth covered as illustrated in Fig 1. Now 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. Fig 2 shows an example of the *Eigenface* subspace corresponding to the subset of images with the two eyes covered.

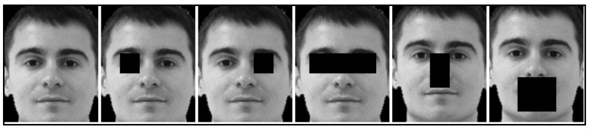

Fig 1 Training images for Lophoscopic PCA

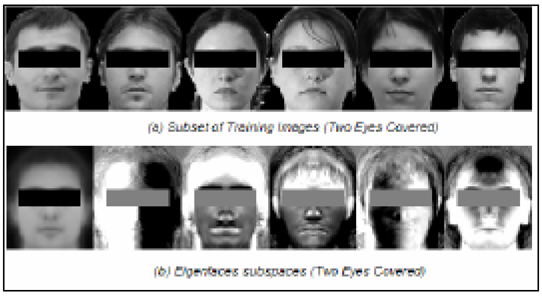

Fig 2 TwoEyes Eigenface subspace

The objective of the black rectangles is that the part of the face covered with it, has 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, LPCA can be considered as the complementary of the *Eigenfeatures* approach, because the entire face image except the region of a local feature is used to create the projection space, instead of using only the region of the local feature. The diagram shown in Fig 3 summarizes the steps of LPCA.

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).

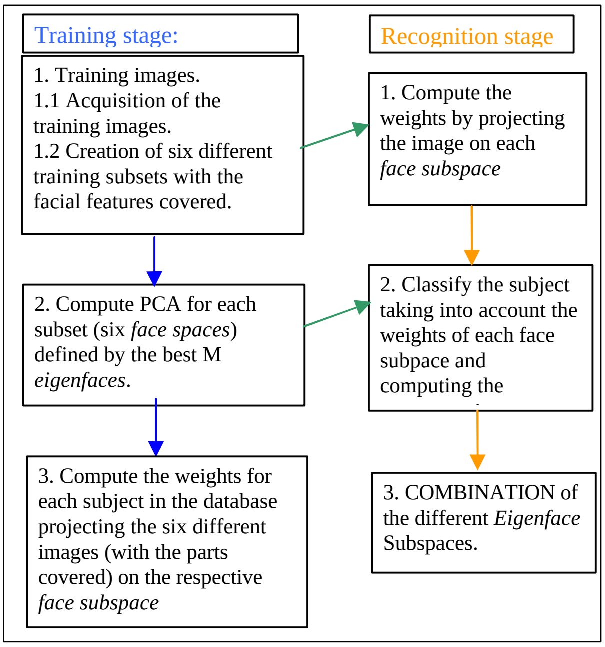

Fig 3 Scheme of Lophoscopic PCA technique

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 at least 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 face occlusions as shown in Fig 4. The original colour images of 1000x1500 pixels were manually cropped and resized by 122x100 pixels and converted to grey level images.

Finally, all the images (training and test samples) are warped using an affine transform (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 inter-eye distance of 40 pixels for all individuals. Automatic detection of the iris centre is currently being considered using the algorithm described in [6]. Once the images have been normalized, each mask is positioned at the same fixed coordinates and covering area.

4. EXPERIMENTS DESCRIPTION AND RESULTS

4.1. Experiments description

A total of 480 face images were created by mirroring the 240 frontal face images. 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. 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.

Four different experiments have been carried out to evaluate and test the performance of the LPCA technique. First, PCA and the new five subspaces of LPCA have been tested separately. For every test image a subset of five images have been created by masking one part of the face; this five different masked images are projected to their respective LPCA face subspaces. The second experiment addresses the problem of how to combine the different subspaces in order to build up the LPCA approach. The third experiment compares the technique with two of the most representative methods in face recognition: conventional PCA [3] and Local Feature Analysis [4]. And finally, the last experiment tries to model how well LPCA solves the feature localization problem.

4.2. Performance of each face subspace independently

Face PCA	Left Eye	Right Eye	Two Eyes	Nose	Mouth
86.29	86.57	86.85	84.57	70.57	64.86

Table 1 Recognition rates for each Eigenface subspace

The results for the first experiment show that in general the Face Subspaces corresponding to the eyes (*RightEye*, and *LeftEye*) presented a slightly higher recognition rate than conventional PCA, 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.

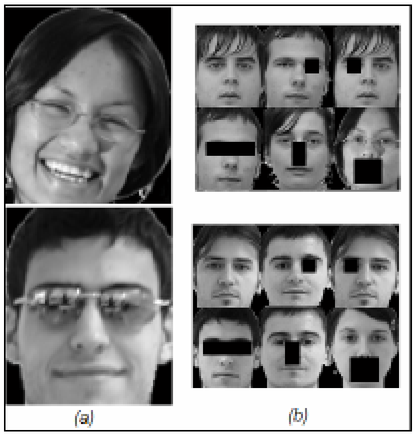

Fig 4 (a) Test image, (b) Recognized IDs in all face Subspaces

4.2. Combination of all subspaces: PCA Lophoscopic

The above preliminary experiment 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 (MRE) 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 will be the one with the minimum error. As shown in Table 2 Lophoscopic PCA using these two combination strategies presents better results than the PCA approach by itself.

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

Table 2 Recognition Rate for Lophoscopic PCA

4.4. Comparison with Local Feature Analysis (LFA)

Since the Local Feature Analysis approach proposed by Penev and Atick [4] can also be described as a *near-*

holistic approach, some results will be presented in this subsection. It is not the intention of the authors of this paper to compare directly LFA with Lophoscopic PCA, since both techniques may be complementary and can be used together in a face recognition system.

Penev and Atick tried to overcome the main limitation of the PCA representation by developing LFA, a method for deriving a dense set of *local topographic feedforward* receptive fields, defined at each point of the input grid (face image), different from each other and optimally matched to a second-order statistics of the input ensemble. Since the authors of LFA do not present any results of the approach for face recognition, the first part of the LFA algorithm (without using residual correlations for dimensionality reduction) has been implemented and tested with the UPC face database. The obtained results are similar to conventional PCA with a recognition accuracy of 87.5%. But after analyzing the LFA approach, it should be concluded that LFA can distinguish between the local points that are statistically more different from the training ensemble. So LFA can be used to detect the points of the face image which should be eliminated or covered by the Lophoscopic PCA technique.

4.5. Simulation of Feature Error Localizations

The Lophoscopic PCA technique requires an eye detection and localization stage. Although, the eye centres have been labelled manually in this work, an experiment for simulating the performance of the algorithm under the presence of error in the detection of the eye centres have been conducted. 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%.

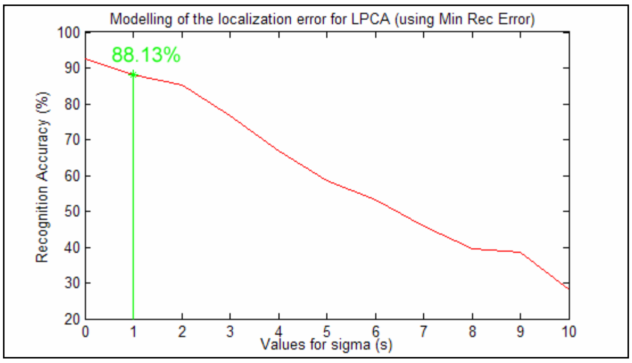

Fig.5. Recognition rate towards localization errors

5. CONCLUSIONS AND FUTURE WORK

This paper has presented a new face recognition technique based on PCA which try to cope with the problem of partially occluded faces or strong facial expression variations. The results have 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 a problem of strong illumination variations; thus, an equivalent *Lophoscopic LDA* technique is currently being implemented to make the whole approach more robust against different illumination conditions. Moreover, when comparing the technique with the LFA approach, some new research possibilities appeared. Since LFA is able to detect the local points of the face image which deviate considerably from the expectation of a face image computed during the training stage, it can be used as a pre-processing stage to determine which points of the test face image should be eliminated or covered. Moreover, a *Lophoscopic LFA* algorithm can be developed by covering the output grid (after applying LFA) and not the face image directly.

6. REFERENCES

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