PCA vs Low Resolution Images in Face Verification

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Abstract

Principal Components Analysis (PCA) has been one of the most applied methods for face verification using only 2D information, in fact, PCA is practically the method of choice for applications of face verification in real-world. An alternative method to reduce the problem dimension is working with low resolution images. In our experiments three classifiers have been considered to compare the results achieved using PCA versus the results obtained using low resolution images. An initial set of located faces has been used for PCA matrix computation and for training all classifiers. The images belonging to the testing set were chosen to be different from the training ones.

Classifiers considered are k-nearest neighbours (KNN), artificial neural networks: radial basis function (RBF) and Support Vector Machine (SVM). Results show that SVM always achieves better results than the other classifiers. With SVM correct verification difference between PCA and low resolution processing is only a 0.13% (99.52% against 99.39%).

1. Introduction

In recent years three main approaches to face verification problem using only 2D information has appeared.

Principal Components Analysis (PCA) and related methods such as Fisherfaces [1] [2] [3] [4] Methods based on PCA consider only global information for the face. Using PCA, dimensional reduction is performed to obtain a small vector representing the face.

Elastic Bunch Graph Matching (EBGM) [5] uses wavelet transformation to obtain local description of the face and a graph to obtain global face description

Local Feature Analysis (LFA) [6] [7], similar to PCA, considers different kernel functions to obtain local features (eyes, mouth and nose). In this case, selection of facial features and kernels is an open issue.

Research is also developed considering 3D information [8][9][10]. But laser scanners to obtain 3D data are very expensive and stereo requires a more elaborate set-up, both situations are unpractical for most real applications.

In this project, objective was to develop a face verification system, which could be useful for applications related with access control in a distributed environment. In this case, each subject has a personal identification number (PIN). Subject types this PIN and an image is acquired. Image is used to verify if subject is PIN owner or not.

In our first experiment, Principal Components Analysis has been considered for high-level image processing. This method offers a compact representation of the face, well suited for its transmission in a distributed environment. In the other approaches, the set of numbers representing a face is bigger than in the case of PCA. On the other hand, PCA is quite sensitive to small displacements in face location.

In our second experiment, we reduced the size of our images to 17x18 pixels, and carried out the classification process. Object recognition based on pixel data has been widely considered mainly for it use with neural networks. A simpler approach to obtain a compact representation of the face, is working with a low resolution level. Some practical applications, such as surveillance systems, may

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require a fast image treatment and a whole face could appear in few pixels if resolution is reduced. [11]

Most of the experiments developed in face verification or recognition consider only one classifier. Experiments presented in this paper compare results obtained with PCA analysis and low resolution images, working in both cases with three classifiers. K-Nearest Neighbours (KNN), artificial neural networks: Radial Basis Functions (RBF) [12] and Support Vector Machine (SVM) [13].

2. Experimental Set Up Description

Figure 1 shows the image acquisition set-up, consisting on two diffuse light sources placed on both sides of the video camera. In Figure 2 a subject in front of the camera is shown. The effect of zenithal lighting (from overhead fluorescent tubes) creating projected shadows can be easily noticed: the subject's smile in figure 2 creates important shadows around the mouth and nose which can hamper the verification process.

Fig. 1. Experimental set up showing diffuse lighting and the CCD camera.

Fig. 2. A subject in front of the camera.

In order to minimise distortions originated by changes in the lens focal length and the camera-subject distance, it is advisable to fix both in any operation environment. These requirements are easily met in any exploitation site.

Even thought that there are several database used in research, our selection was to built a local database. A local database is preferred because several effects could be studied: number of subjects could be increased, number of training images could be bigger than in other database (Olivetti, Yale, etc), it is possible to obtain images with different face expression, light conditions, even ageing. Our database is formed by 29 subjects (22 male and 7 female) with 12 images per subject. 8 images were used for train and 4 for test. Image size is 320 x 240 pixels with face covering great part of the image. Subjects were forced to change its pose between acquisition of two consecutive images.

3. Algorithm description

Face verification process is split in three parts: Face location, dimension reduction (PCA vs low resolution images) and classification.

3.1. Face Location

In this step, the background is firstly removed. In our set-up a uniform background has been placed, so background subtraction is applied but in general cases, there are several methods in computer vision bibliography that can be considered with excellent results. Then, convolution with a face template is done. When the convolution reaches the maximum over the images, a window containing face is extracted. This window is considered the "correct located face" image.

Once the face is located, a set of "correct located faces" is built. These images were considered for computing PCA matrix and training all classifiers. Final dimension was now 130 x 140 pixels. In this step all images were also converted from colour to grey scale.

3.2 Dimension reduction

Two different approaches have been studied in order to accomplish an efficient dimension reduction.

The first one is PCA, in which a transformation matrix is computed and a dimensional reduction is obtained.

The second one is working with low resolution images.

3.2.1. PCA computation

PCA transformation matrix is computed using a number of eigenvectors that retains almost 100% of the initial variance. Only one PCA matrix is computed with the "correct located faces" set.

In our experiment eight images per subject are considered for compute PCA matrix, our tests show that 150 eigenvalues are needed.

3.2.2. Low resolution

A very simple way to reduce the size of data representing an image consists in using a low resolution representation.

In our case we reduced the image size from 130x140 to 17x18 pixels so finally a 306 dimension vector in considered to classification.

Figure 3 shows a reduced image and an amplified version in order to appreciate the image blurring.

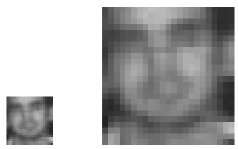

Fig. 3. Low resolution images. 17x18 pixels.

3.3 Classification

Three classifiers has been considered: K-nearest neighbours (KNN), Artificial Neural Networks: Radial Basis Function (RBF) and Support Vector Machine (SVM). In all cases, train is done with eight images of the correct located faces set (same ones used for PCA computation). Tests are done using four images per subject. Train and test sets do not overlap.

3.3.1. *K-nearest neighbours (KNN)*

KNN is a simple and linear classifier but its result can be considered as an initial clue of the spatial configuration of face clusters. In our experiments, k=1 and k=3 has been considered.

3.3.2. *Artificial Neural Networks: Radial Basis Function (RBF).*

RBF has been used as an artificial neural network classifier for face verification. For verification, initial information is subject image and personal identification number (PIN) code. PIN code indicates which output neuron is considered. In our experiment, Gaussian functions considered are symmetrics and centered in the middle of each face subject cluster.

3.3.3. *Support Vector Machine (SVM).*

SVM offers excellent results in 2-class problems. This classifier could be easily used in verification problems (recognizing one subject against rest). For recognition, in a N-class problem, we can consider N svm-models (each one defined for each subject in database). In our experiment, linear kernel has been considered.

3. Experimental results

Results are represented in a ROC (Receiver Operator Characteristic) curve, one curve per classifier and location condition.

As the system has two kind of data input (the subject's image and the PIN he introduces), there are four possible experiment outcomes: true positive, true negative, false positive and false negative. For each of the tests, the data presented in this section uses the following notation:

Percentage of correct verification: (TP+TN)/(TP+TN+FP+FN)

Percentage of false negatives: FN/(FN+TP)

Percentage of false positives: FP/(FP+TN)

Where TP, TN, FP and FN are the total numbers of true positives, true negatives, false positives and false negatives.

KNN classifier output is more reliable if distance is low, so a positive verification has been considered when output value is smaller than acceptance threshold. SVM and RBF provide opposite result, when output value is big this means that confidence is high. So positive verification has been considered when output value is bigger than acceptance threshold. This acceptance threshold has to be set to obtain the optimum value that minimizes positive false and negative false, and maximize the correct rate. Magnitude used as threshold is different for each classifier: KNN: Euclidean distance, RBF: output neuron value and SVM: function decision value.

Graphical results are obtained in a cross validation procedure. Ten sets of 4 subject images and 4 non-subject images are tested and after that the average of the results are made. This method provides us a collection of results that are independents of the non subject images selected. The alternative case is to compare 4 subject images against all non subject images but in this case a "total rejection" algorithm will lead to a confused high correct verification rate.

Figures 4 and 5 show experimental results of KNN classifier (with K=1 and K=3), Figure 4 shows experimental results of KNN classifier using PCA as dimension reduction method and Figure 5 shows experimental results of KNN classifier using low resolution as dimension reduction method.

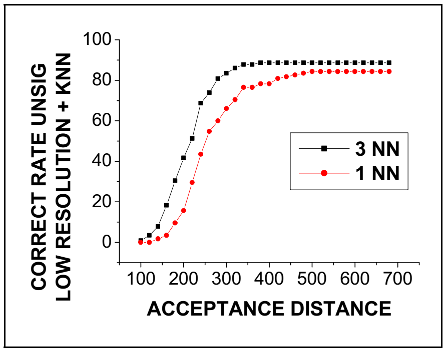

Fig. 4. KNN Results using Low Resolution

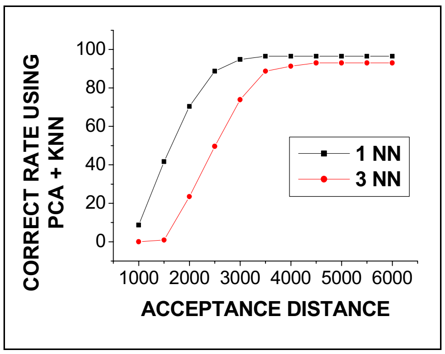

Fig. 5. KNN Results using PCA

Table 1 shows a comparative between PCA and Low Resolution for KNN classifier. It has to be noted that PCA reaches a greater correct rate in both cases (k=1 and k=3).

	1 NN	3 NN
PCA + KNN	96.5 %	93%
Low Resol. + KNN	84.34%	88.69%

Table 1. KNN Correct Rate

Figure 6 show experimental results of RBF classifier using both dimension reduction methods: PCA and Low Resolution.

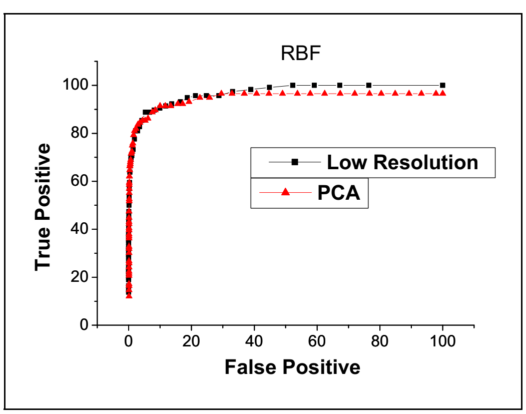

Fig. 6. RBF Results using Low Resolution and PCA

Table 2 shows a comparative between the maximum correct rate obtained using PCA or Low Resolution and RBF as classifier.

	Maximum Correct Rate
PCA + RBF	92.16%
Low Resol. + RBF	91.57%

Table 2. RBF Correct Rate

Obviously, better results have been achieved with RBF than with KNN.

Figure 7 show experimental results of SVM classifier using both dimension reduction methods mentioned before.

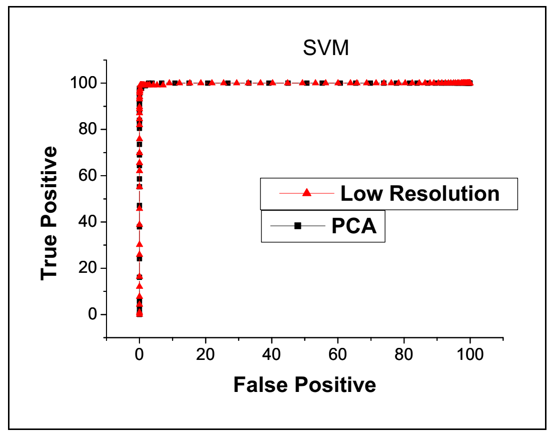

Fig. 7. SVM Results using Low Resolution and PCA

Table 3 shows a comparative between the maximum correct rate obtained using PCA or Low Resolution and SVM as classifier.

	Maximum Correct Rate
PCA + SVM	99.52%
Low Resol. + SVM	99.39%

Table 3. SVM Correct Rate

4. Conclusions

In our experiments, all subjects in data base are placed in front of the camera and they do not conceal its identity. In commercial applications of access control this is not a restriction, due to such systems are used in collaborative environments. Considering the three classifiers SVM achieves better correct verification rates than RBF. KNN is significantly worst than any of them.

SVM has an interval parameter in which correct verification rate is high with almost zero positive false and negative false. For RBF classifier, high correct verification rates are achieved but positive false and negative false are not negligible. SVM could be used in high security environments in which low FP percentage is crucial.

Using PCA processing better results are obtained than using low resolution processing, independently of the classifier. But the difference falls from 12% in KNN to 0.13% in SVM. With SVM process time for low resolution is significantly reduced than for PCA.

Both methods (PCA and low resolution) are built up a very precise face location algorithm. The final correct verification, FP and FN percentages depend on all the computer vision algorithms applied. A non precise face detection stage will achieved poor results.

We can conclude that a complete study of the final application may be done before the selection of the dimension reduction method. If a really high correct rate is needed PCA method is right and if obtain a fast result is the fundamental thing, low resolution is more adequate. Also, low resolution is really a solution if frontal images can be obtained because there is no a significant difference with PCA, if frontal images can not be guaranteed, PCA is a more powerful tool.

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