# Influence of Location over Several Classifiers in 2D and 3D Face Verification

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**Abstract.** In this paper two methods for human face recognition and the influence of location mistakes are shown. First one, Principal Components Analysis (PCA), has been one of the most applied methods to perform face verification in 2D. In our experiments three classifiers have been considered to test influence of location errors in face verification using PCA. An initial set of "correct located faces" has been used for PCA matrix computation and to train all classifiers. An initial test set was built considering a "correct located faces" set (based on different images than training ones) and then a new test set was obtained by applying a small displacement in both axis (20 pixels) to the initial set. Second method is based on geometrical characteristics constructed with facial and cranial points that come from a 3D representation. Data are acquired by a calibrated stereo system. Classifiers considered for both methods are k-nearest neighbours (KNN), artificial neural networks: radial basis function (RBF) and Support Vector Machine (SVM). Given our data set, results show that SVM is capable to classify correctly in the presence of small location errors. RBF has an acceptable correct rate but the number of false positives is always higher than in the SVM case.

## 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] Methods based on PCA consider only global information for the face. Using PCA, a dimensional reduction is performed in order to obtain a compact representation of the face.

Elastic Bunch Graph Matching (EBGM) [3] uses wavelet transformation to obtain local description of the face and a graph to obtain the global face description

Local Feature Analysis (LFA) [6], 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.

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Research is also developed considering 3D information [5][6][7]. Laser scanners to obtain 3D data are very expensive, so a stereo pair was used to acquire the 3D data.

In our experiment, two methods of representing a face are considered: PCA in 2D representation and geometrical characteristics in 3D representation.

Principal Components Analysis offers a compact representation of the face, well suited for its transmission. in a distributed environment. On the other hand, PCA is quite sensitive to small displacements in face location. To observe the sensitivity of classifiers to these location errors, small displacements were introduced.

The 3D description is obtained by the calibration of a stereo pair of cameras for head navigation. The algorithm has been tested in the 3D reconstruction of real faces.

Experiments presented in this paper compare results obtained with three classifiers. K-Nearest Neighbours (KNN), artificial neural networks: Radial Basis Functions (RBF) and Support Vector Machine (SVM) [8].

## 2 Experimental Set Up Description

Two set ups were built: one for 2D image capture and one for 3D characteristics acquisition.

2D set-up was built to measure only location errors, so illumination and distance camera–subject were maintained unchanged. Two diffuse lights offered controlled illumination conditions. CCD was placed firmly in front of the subject. Subjects were forced to change its pose between acquisitions of two consecutive images.

The 2D 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.

3D set-up was built by a stereo pair of CCD cameras. Figure 1 shows the considered architecture.

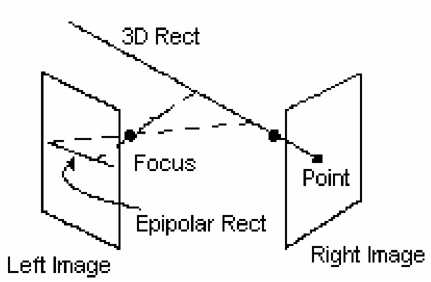


**Figure 1.** A diagram of the stereo geometry considered.

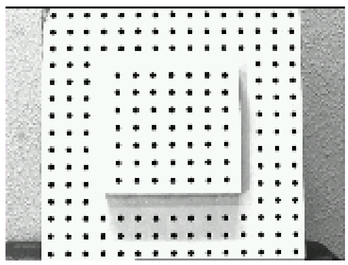

**Figure 2.** Calibration plate.

Camera calibration is a crucial phase in most vision systems and a first step in 3D reconstruction. Using a plate calibration is possible to obtain a set of 3D data. Figure 2 shows the calibration plate used. It has 193 points distributed over two planes. The 3D database is formed by 20 subjects (10 male and 10 female) with 8 images per subject (than belong to 4 stereo pairs). Four images were used for train and four for test.

# 3 Algorithm Description

## 3.1 2D System

Face verification process is split in three parts: Face location, PCA computation and classification.

### 3.1.1 Face Location

In this step, background is eliminated. Then a convolution with a face template is done. When the convolution reaches the maximum over the images, a window containing the face is extracted. 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. To test location errors, three different test set were built. An initial test set was built in a similar way as explained before, considering the maximum of convolution ("correct located images"). To obtain two test sets, small displacements were applied in both axes (0 and 20 pixels). This gives us two sets of images, each set corresponds to images displaced the same value. Final dimension was 130 x 140 pixels. In this step all images were also converted from colour to grey scale (Figure 3 and 4).

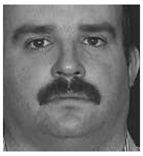


**Figure 3 and 4.** A correct located face and the same face, but displaced 20 pixels in both axes

### 3.1.2 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 to compute PCA matrix. Our tests show that 150 eigenvalues are needed to explain the 99,9% of the variance.

## 3.2 3D System

The geometrical characteristics are constructed with facial and cranial points similar to those used by forensic doctors and legal police. Initially thirty points were considered, but only the fourteen most robust were selected. These points had to be manually introduced in the images captured by the stereo pair and after that the characteristics in the 3D space were calculated. To minimize the error of the manual location of these points, the epipolar rectification (see Figure 3) was considered.

### 3.3 Classification

Three classifiers has been considered: K-nearest neighbours (KNN), Artificial Neural Networks: Radial Basis Function (RBF) and Support Vector Machine (SVM).

KNN is a simple and linear classifier but it result can be considered as an initial clue of the spatial configuration of face clusters. K=1 and k=3 has been considered. RBF has been used as an artificial neural network classifier for face verification. In our experiment, Gaussian functions considered are symmetric and centred in the middle of each face subject cluster. SVM could be easily used in verification problems (recognizing one subject against rest). In our experiment, linear kernel has been considered.

## 4 Experimental Results

### 4.1 2D Results

Results are represented in a ROC (Receiver Operator Characteristic) curve, one curve per classifier and location condition There are four possible experimental outcomes: true positive, true negative, false positive and false negative.

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 results, so positive verification has been considered when the output value is larger than acceptance threshold. The magnitudes used as threshold for each classifier are KNN Euclidean distance, RBF output neuron value and SVM function decision value. Graphical results are obtained in a cross validation procedure.

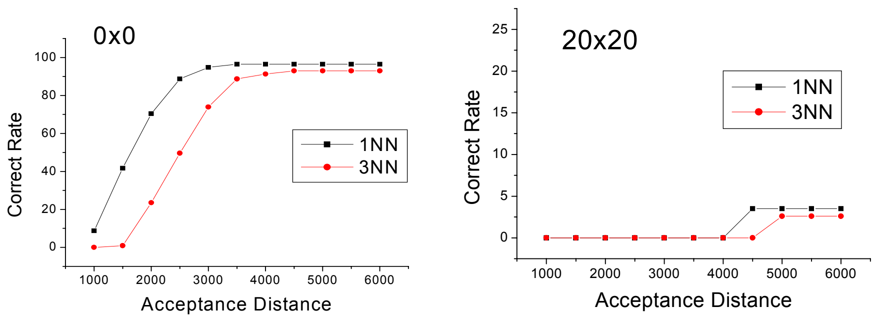


**Figure 5.** KNN results for each face location

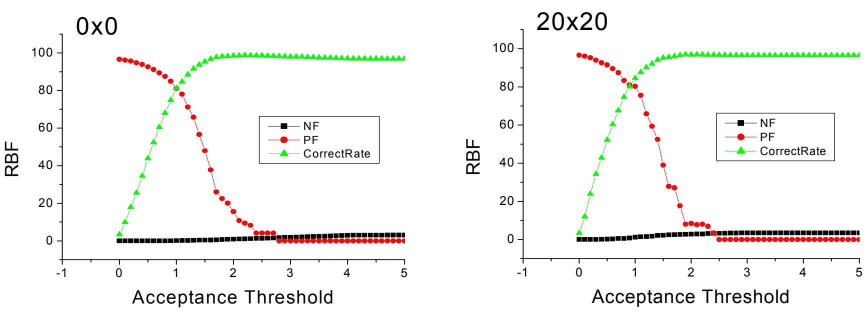


**Figure 6.** RBF results for each face location

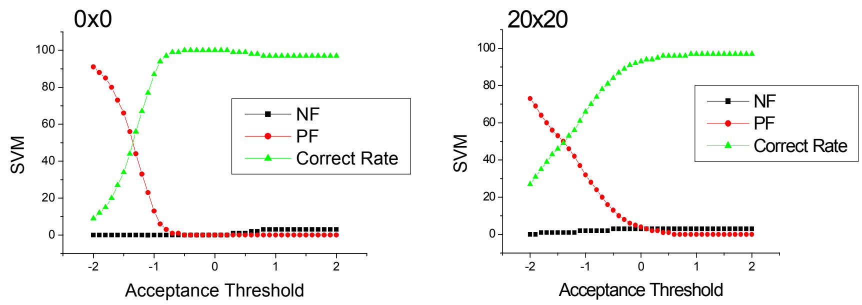


**Figure 7.** SVM results for each face location

## 4.2 3D Results

Classification conditions are the same as 2D. Figures 8, 9 and 10 show the results.

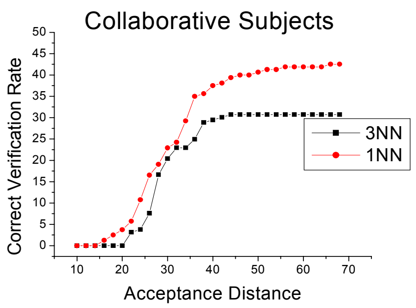


**Figure 8.** KNN results. 3D Data.

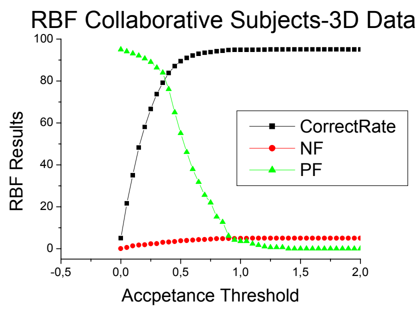


**Figure 9.** RBF results. 3D Data.

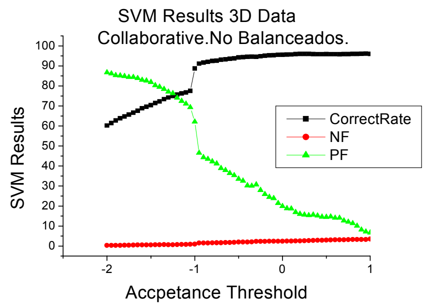


**Figure 10.** SVM results. 3D Data

## 5 Conclusions

Given our 2D dataset, worst results have been achieved with KNN. SVM reduces False Positive and False Negative percentages in all the location cases. RBF is more sensitive to location errors (Figures 5, 6 and 7).

Results obtained by the system applied to the 3D data, have been worst due to the important error location introduced in the manual point selection stage. KNN results are really poor, but with a better classifier like SVM, correct rate increases it value significantly (Figures 8, 9 and 10).

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