Face Verification using SVM: Influence of illumination.

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Abstract: *Influence of Illumination conditions in face verification using SVM and k-nearest neighborhoods is analyzed using an experimental set up in which images are acquired in controlled or uncontrolled illumination conditions.*

Keywords: *Human face verification, Principal Components Analysis, K-Nearest Neighborhood, Support Vector Machine, image processing.*

Introduction

Support Vector Machines (SVM) [7] is a technique that suits very well to solve human face verification problem. Several papers have addressed face verification problem in recent years using SVM, neural networks or other techniques. Most part of this research has been done using public domain databases or databases in which variations of subject appearance have been well controlled or even eliminated. In this paper influence of illumination conditions in face verification using SVM and k-nearest neighbourhoods is analysed using an experimental set up in which images are acquired in controlled (Experiment one) or uncontrolled (Experiment two) illumination conditions.

Experimental setup.

Experimental setup was built to test several parameters that affect face verification. In this paper light conditions were changed. Two diffuse lights offered controlled illumination conditions in Experiment one, two diffuse lights plus some ceiling fluorescent lamps were illumination conditions in Experiment two. Figure 1 shows acquisition set up, with diffuse lights and the CCD camera in front of the subject. Figure 2 represents one typical acquisition session in which the subject was placed in front of the camera, the subject is forced to change its pose between the acquisition of two consecutive images. Figure 3 shows one image of the subject in experiment one and Figure 4 shows the same subject in Experiment two, both images have been reduced (their initial size was 320x240 pixels)

Figure 1: Diffuse lights and CCD camera

Figure 2: One subject in front of the camera

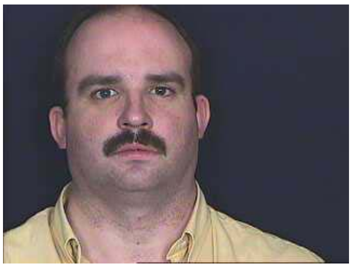

Figure 3: Image with controlled illumination

Figure 4: Image with uncontrolled illumination.

State of the art.

Human face verification or recognition is a wide field of research. Its interest is not only academic but also economic. Automatically recognizing faces can help in a wide variety of forensic and security applications. Several approaches have been taken: geometrical characteristics with manual input, 3D images with laser measurements or 2D images with global or local extraction of characteristics. Extensive reviews of approaches to face recognition were published in 1995 [2], 1999 [9], and in 2000 [10]. A workshop on face processing in 1985 [3] presented studies of face recognition. In 1998, lectures on face recognition using 2D face patterns were presented from theory to applications [8].

Global characteristics using principal components analysis has become an standard in face processing and is widely used in research and commercial systems. Turk and Pentland [6] developed a face recognition system that recognize the person by projecting face images into a feature space where only significant characteristics are represented. The significant features are known eigenfaces because they are eigenvectors of a set of images. This allows a great reduction of the information to process. Results of the experiments show a 96% of correct classification. P. Jonathon Phillips [5] compared rate of correct verification using SVM (77-78%) with a principal component analysis (PCA) (54%).

Our group has [1] presented several results of face recognition with neural networks. Two algorithms were tested: learning vector quantization (LVQ) and multilayer perceptron (MLP). Experimental results show higher recognition rates for LVQ tan for MLP (96.7% versus 83.3%)

Algorithm Description.

Preprocessing and processing algorithms have been split in three parts:

1.- Face extraction:

This process selects a region of the image in which the image is present. Using background subtraction and a convolution with a face template, faces are located in image and dimension is reduced to 130x140 pìxels. Also, image is converted to a gray level scale. Figures 5 and 6 show results of face location algorithm applied to Figure 3 and 4.

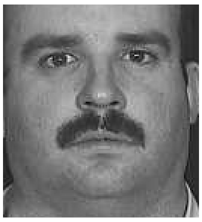

Figure 5.- Face location for figure3

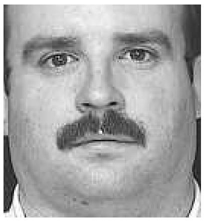

Figure 6.- Face location for figure 4.

2.- Dimensional Reduction using PCA.

Principal Components Analysis has been used in face verification to reduce image dimensionality loosing as little information as possible. This approach has been considered in our work. The reduction depends on the train set variability, and also on the variance that we want to conserve in the reduced space. In our experiments, the 100% of the initial variance may be conserved in a reduced space of 100 dimensions (from the initial 130 x 140 pixels = 18,200 dimensions).

3.- Verification using SVM and Knn.

As classificators, an implementation of SVM by T. Joachims [10] with linear kernels were used. To test our results, a classical KNN was also considered.

Experimental Results.

These methods of dimensional reduction and classification were applied to an illumination controlled or uncontrolled data set. As experimental set we consider a database with 29 individuals. Train set consists of 9 images per person and test set consists of 6 images per person with a controlled illumination and 6 images per person with an uncontrolled illumination. Experimental results are shown in figures 7 and 8.

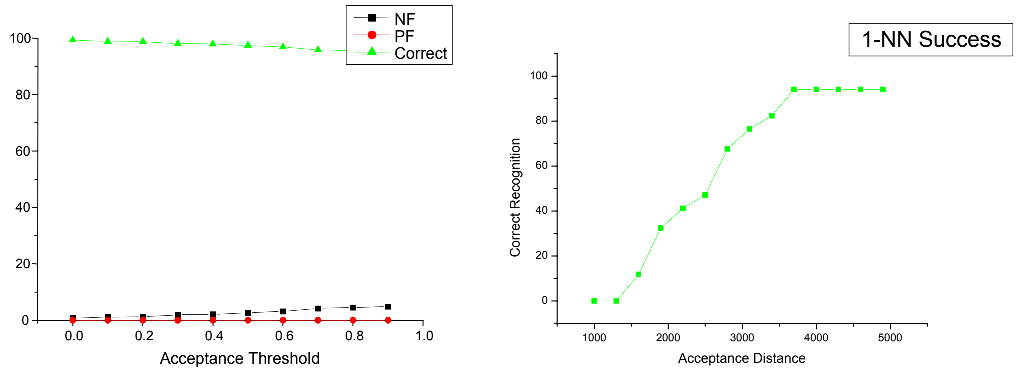

Figure 7: Results for SVM and 1-NN, train and test with controlled illumination, test images acquired one day later.

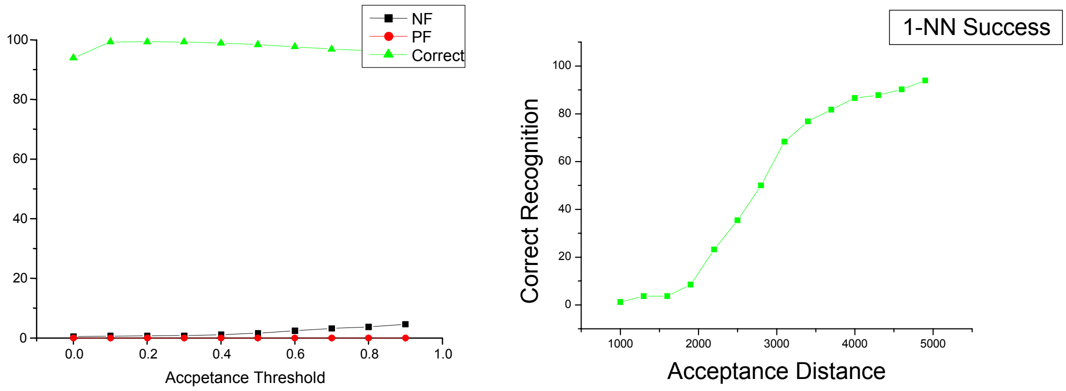

Figure 8.- Results for SVM and 1-NN, train and test sets with uncontrolled illumination conditions.

Conclusions.

In our experiments, SVM achieves better recognition rates than kNN. Results show that SVM offers better results in both conditions (controlled-uncontrolled lights), kNN is more sensitive to this parameter.

The parameter we considered in SVM was the result of the decision function. Figure 7 and 8 show that acceptable working conditions are tuning the parameter with a value higher than zero. Knn parameter is euclidean distance. SVM parameter is independent on light conditions but distance parameter is more sensitive to light conditions . In figure 7 and 8 for a correct recognition of 90% parameter is about 3500 with controlled light and 5000 with uncontrolled lights.

An important conclusion is also that achieving appropriate success rates needs the careful design of the image acquisition and preprocessing stages. Being faces 3D entities, differences in pose or position may affect projected shadows on the face to be analysed. Since it is unfeasible to limit pose and positions variations, it is advisable to use diffuse lighting to minimise this problem. In general, false positives are strongly increased when the amount of projected shadows is also increased.

Acknowledgements

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