Face Verification using SVM: Influence of illumination.

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Abstract: Influence of illumination conditions in face verification using support vector machines (SVM) and k-nearest neighbours is analysed using an experimental set up in which images are acquired in controlled or uncontrolled illumination conditions. Principal components analysis (PCA) has been considered to perform dimensional reduction. SVM techniques offers better results even if linear kernels are considered.
Keywords: Human face verification, Principal Components Analysis, K-Nearest Neighbours, Support Vector Machine, Image Processing.

Introduction

The experiment presented in this paper was focused to test performance of a face verification system under real control access conditions. In control access environments it is possible to obtain an initial set of images of the subjects in good illumination conditions, the face is located in this images and the system is trained. But in normal operation mode, the face verification system has to work with images in which illumination conditions may have changed. This cause errors in final verification process because of the differences with the initial face estimation. In this paper influence of illumination conditions in face verification using SVM and k-nearest neighbours is analysed using an experimental set up in which images are acquired in controlled (Experiment one) or uncontrolled (Experiment two) illumination conditions.

Experimental set-up.

A set-up was built to measure only illumination errors, so subject pose, gesture and distance camera–subject were maintained unchanged. Two diffuse lights offered controlled illumination conditions in Experiment one, two diffuse lights plus some ceiling fluorescent lamps were illumination conditions in Experiment two. CCD was placed firmly in front of the subject. Subjects were forced to change its pose between acquisition of two consecutive images. Figure 1 shows the 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 database is formed by 30 subjects (15 male and 15 female) with 12 images per subject. 8 images were used for train and 4 for test. The train images are captured with controlled illumination in both experiments. Test images are captured in controlled illumination conditions in case of Experiment one and in uncontrolled illumination conditions in case of Experiment two. Image size is 320 x 240 pixels with face covering great part of the image. 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 for illustration purposes.

Fig. 1. Diffuse lights and CCD camera

Fig. 2. One subject in front of the camera

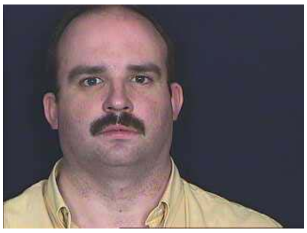

Fig. 3. Controlled illumination

Fig. 4. Uncontrolled illumination

State of the art.

Human face verification or recognition is a wide field of research. Automatically recognizing faces may help in a wide variety of forensic and security applications.

Several approaches have been taken: geometrical features with manual input, 3D images with laser measurements or 2D images with global or local extraction of features. 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.

In the design of a face verification system two different problems has to be solved: one is to built an on-line algorithm that has to work with high accuracy but in real time conditions (or at least with small response times) to perform verification tasks, second one is to find in a off-line procedure the values of all the parameters (i.e., to train the system). Off-line training algorithms has no time restrictions in industrial environments, computation time could be high without any critical impact on the system. But on-line verification algorithms has to be designed to be fast (response times bigger than few seconds are not allowed in any practical application) but with high accuracy (system is supposed to work correctly in the first attempt, a system in which the subject has to typed his code two times is allowed only if this is a very abnormal situation).

Our system has been split in three parts:

- Face extraction:

Our face location system cropped the face to a window of 130x140 pixels (as shown in figures 5 and 6). This process is made by selecting a region of the image in which the face is present. Using background subtraction and measuring the maximum correlation with a face template, faces are located and dimension is reduced to 130x140 pixels. As well image is converted to a grey level scale and equalized. Figures 5 and 6 show results of face location algorithm applied to Figure 3 and 4. To speed up this process convolution is done with a template representing only half face (so template size is 65x140 pixels). Using this template and considering face symmetry, convolution time is earned without any loss of information.

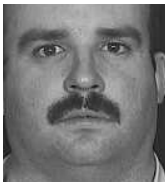

Fig. 5. Face location for figure 3

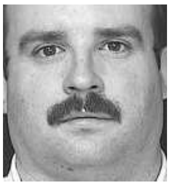

Fig. 6. Face location for figure 4

- Dimensional Reduction using PCA.

Principal Components Analysis has been used in face verification literature as a standard technique 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, PCA projection is done using first 150 eigenvalues, which are enough to represent almost all database variance (as shown in figure 7). PCA matrix computation can be done off-line and PCA projection is a fast method performed in on-line operation.

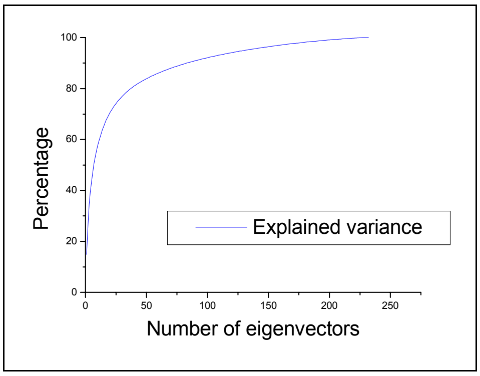

Fig. 7. Percentage of explained variance versus number of eigenvectors, 96.44% of variance is explained with 150 eigenvectors.

- 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. SVM offers excellent results in 2-class problems. This classifier could be easily used in verification problems (recognizing one subject against rest). In our experiment, linear kernel has been considered. Both algorithms has to be trained in off-line operation and applied to PCA coefficients of the image in normal verification operation.

Experimental Results.

SVM results are reported as a receiver operator characteristic (ROC). The ROC curve was computed by averaging the ROC curve for each of the individuals in the Database. For person p_i the probe set consisted of one test image of person p_i and 29 faces of different people.

To calculate the ROC curve a threshold magnitude is needed. The function decision value is selected as threshold magnitude for SVM. If the output value of this function 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 maximizes the correct rate.

KNN results are reported as a correct rate versus threshold parameter curve. The magnitude used as threshold is the Euclidean distance. 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. We have not analysed Positive False and Negative False for KNN classifier because this classifier is used just as a really simple comparative method, but the purpose of this paper is not to make a study of this classifier. KNN is a simple but powerful method to obtain an initial estimation of the faces distribution in PCA (reduced) space.

Figures 8 and 9 show experimental results of KNN classifier (with K=1), Figure 10 shows experimental results of SVM classifier.

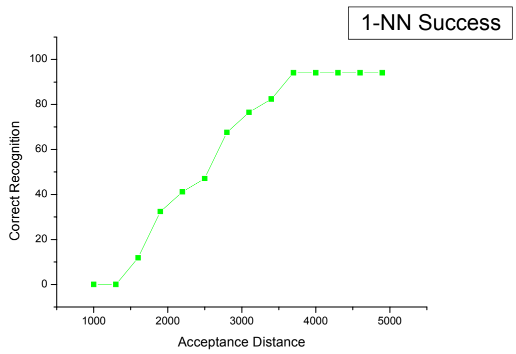

Fig. 8. Results for 1-NN, train and test with controlled illumination, test images acquired one day later.

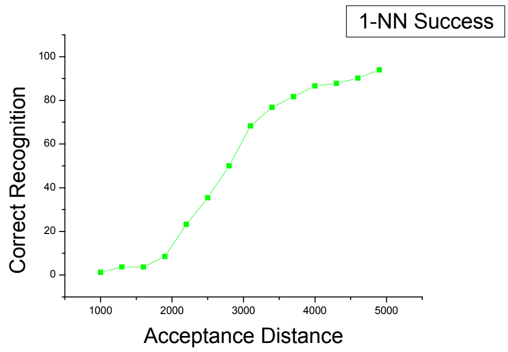

Fig. 9. Results for 1-NN, train and test sets with uncontrolled illumination conditions.

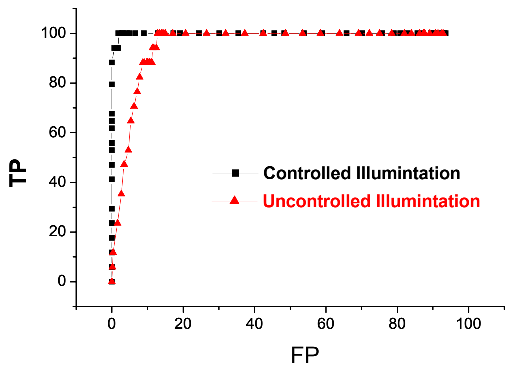

Fig. 10. Results for SVM for experiments one (controlled illumination) and two (uncontrolled illumination).

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. Figures 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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References.

[1] E. Cabello, A. Sánchez and L. Pastor. *Some experiments on Face Recognition with Neural Networks*. Face Recognition: From theory to applications. Springer-Verlag. Eds: H. Weeechsler et al. Pp: 589-599. 1998.

[2] R. Chellappa, C. L. Wilson and S. Sirohey. Human and Machine Recognition of Faces: A Survey. Proceedings of the IEEE. Vol. 83. Nº 5. pp 705-740 .May 1995.

[3] H. D. Ellis, M. A. Jeeves, F. Newcombe ,and A. Young Eds., Aspects of Face Processing, Martinus Nijhoff Publishers, Dordrecht, Netherlands, 1985.

[4] T. Joachims*, Making large-Scale SVM Learning Practical*. Advances in Kernel Methods Support Vector Learning, B. Schölkopf and C. Burges and A. Smola (ed.), MIT-Press, 1999.

[5] P. Jonathon Phillips. *Support Vector Machines Applied to Face Recognition.* Advances in Neural Information Processing Systems 11, eds. M.J. Kearns, S. A. Solla, and D.A. Cohn, MIT Press, 1999.

[6] M. Turk and A. Pentland. Face Recognition Using Eigenfaces. Proceedings Computer Vision and Pattern Recognition. pp 586-591. 1991.

[7] V.Vapnik. *The nature of statistical learning theory.* Springer, New york, 1995.

[8] H. Wechsler, P. Phillips, V. Bruce, F. Soulie and T. Huang, Eds. Face Recognition: From Theory to Applications, Springer-Verlag, 1998.

[9] J. Weng and D. L. Swets, "Face recognition," in Biometrics: Personal Identification in Networked Society, A. K. Jain, R. Bolle, and S. Pankanti, Eds., pp. 67–86, Kluwer Academic, Boston, MA, 1999.

[10] W. Zhao, R. Chellappa, A. Rosenfeld and P. J. Phillips, "Face recognition: A literature survey," CVL Technical Report, Center for Automation Research, University of Maryland at College Park, Oct. 2000, ftp://ftp.cfar.umd.edu/TRs/CVL-Reports-2000/TR4167-zhao.ps.gz.