International Journal of Information Sciences and Application (IJISA). ISSN 0974-2255, Vol.11, No.1, 2019, (Special Issue)

Robust face recognition system using HOG features and SVM classifier

Amrendra Pratap Singh, Ankit Kumar

Abstract

Face Recognition Systems has been applied in a wide range of applications. However, their efficiency drastically diminishes when they are applied under un-controlled environments such as illumination change conditions, face position and expressions changes. Because of that, it is necessary to evaluate the performance of different feature extraction techniques robust to this kind of transformations for its further integration to a Face Recognition System. In this paper, we study and evaluate the pertinence of using the Histogram Oriented Gradients (HOG) method as a feature extraction technique to deal with the transformations already mentioned. The experimental results show that using HOG combined with SVM classifier provides better results than those achieved with the well-known Eigenfaces technique.

Keywords: Facial recognition, histogram of oriented gradients, multi-class classification.

1 Introduction

During the last decades we notice a wealth of scientific research in computer vision for the problem of facial landmark points localization using visual deformable models. The main reason behind this are the countless applications that the problem has in human-computer interaction and facial expression recognition.

Amrendra Pratap Singh

Student, Computer Science and Engineering Department1,

ABES Engineering College, Ghaziabad, India.

e-mail: amrendra.15bcs1183@abes.ac.in

Ankit Kumar

Assistant Professor, Computer Science and Engineering Department,

ABES Engineering College, Ghaziabad, India.

e-mail: anketvit@gmail.com

The intelligent interaction between human and computers is one of the primary goals of contemporary artificial intelligence technologies. Many facial expression recognition techniques have been proposed in the past few years which has been summarized in [1][2]. Researchers tend to use more complex feature extraction and classification techniques to improve the accuracy of facial expression systems. However, the real-time implementation of such systems has always been a challenging task.

The texture descriptors such as Gabor descriptor [3], local binary patterns [4], local Gabor binary patterns [5], histogram of oriented gradients [6] etc. Encodes the local texture of facial regions. The movement of facial components produces wrinkles or skin folds which are effectively presented by the appearance features.

However, based on the computational cost of feature computation, LBP and HOG are preferable for real-time applications. HOG features are used in this work. In 1991, Alex Pentland and Matthew Turk [7] [8] applied Principal Component Analysis (PCA) which was invented in 1901 to face classification. This has become the standard known as the Eigenfaces method and is today an inspiration or all face recognition algorithms evolved [9]. Navneet Dalal et. al. [10] made a paradigm shift by introducing Histogram of Oriented Gradient (HOG) features instead of Eigen faces which are in the standard PCA algorithms [11] [12]. HOG features being dense overlapping grid gives very good results for person detection. HOG features have the advantage of fine orientation binning, fine scale gradient, relatively course spatial binning and high quality local contrast normalization which are important for good performance. This is an automatic face recognition which localizes the facial features. The author considered 68 fiducial points. Descriptors based on Histogram of Oriented Gradient (HOG), which are invariant to illumination and rotation, has been applied in object recognition and pedestrian recognition. Recently, HOG descriptors have been applied to face recognition. This paper is focused on the robustness of the HOG descriptor as a feature extraction technique to deal with face recognition problems under illumination and expression changes. The paper is organized as follows. Section II describes the methodology adopted in this paper. Section III explains the results obtained. Section IV concludes

the paper.

2 SYSTEM ARCHITECHURE

2.1 HOG Descriptor

The main idea behind this descriptor is that local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions. Basically, the HOG descriptor divides the image into many cells where a histogram counts the occurrences of pixels' orientations given by their gradients. Finally, the HOG descriptor is built with combination of these histograms.

Based on this process, four major steps can be delighted: image derivative computing, magnitude and gradient orientation computing, partial histograms building, and normalization of partial histograms. Each pixel has to vote for some orientation in the histogram channels, this could be done based on the orientation of the gradient and the votes are added for the channels and for the cells. The cells could be radial o rectangular. The orientations could be separated between 0 and 180 or 0 and 360, depending on the use of the sign. Interpolation could be done over neighbors.

The vote is a function of the magnitude of the gradient of the pixel, could be the magnitude itself, the square of the magnitude or the magnitude squared.

2.2 Support Vector Machine Classification

SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes by finding a decision surface that has maximum distance to the closest points in the training set which are termed support vectors. Assuming linearly separable data 1, the goal of maximum margin classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. There are two basic strategies for solving n -class problems with SVMs: i) In the one-vs-all approach n SVMs are trained. Each of the SVMs separates a single class from all remaining classes. ii) In the pairwise approach n(n-1)/2 machines are trained. Each SVM separates a pair of classes. The pairwise classifiers are arranged in trees, where each tree node represents an SVM. A bottom-up tree similar to the elimination tree used in tennis tournaments

3 Corpus Description

In this work, we used 500 images of 10 persons of age ranging from 20-30 years. Images were captured in different lighting conditions. for training, 50 images of every person was collected and testing was performed on 2 different images of each person.

Table 1 Self-created dataset description

Dataset	Total No. of Persons	Total No. of Images
Train	10	500
Test	10	20

4 Experimental Results

To train the face recognizer we first ran the component- based detector over each image in the training set and extracted the components. To generate the input to our face recognition classifier we normalized each of the components in size and combined their gray values into a single feature vector 5. As for the first global system we used a one-vs-all approach with a linear SVM for every person in the database.

The training data for the face recognition system were recorded with a mobile camera at a frame rate of about 5 Hz. The training set consisted of 500 gray face images of ten subjects. The test set was recorded with the same camera but on a separate day and under different illumination and with different background. The test set included 20 images of all ten subjects in our database.

Table 2 Performance Measure of system

Dataset	**Features**	**No. of points**	**Classifier**	**Accuracy%**
Test	HOG	68	SVM	92%

5 Conclusion

Linear SVMs trained on HOG features have pervaded many visual perception tasks. This is motivated by similar findings within the human visual system. With these simple assumptions combined with large amounts of training data, it is possible to learn a classifier that performs well.

References

1. E. Sariyanidi, H. Gunes, and A. Cavallaro, Automatic analysis of facial affect: A survey of registration, representation, and recognition, IEEE transactions on pattern analysis and machine intelligence, vol. 37, no. 6, pp. 11131133, 2015.

2. A. K. Jain and S. Z. Li, Handbook of face recognition. Springer, 2011.

3. W. Gu, C. Xiang, Y. Venkatesh, D. Huang, and H. Lin, Facial expression recognition using radial encoding of local gabor features and classifier synthesis, Pattern Recognition, vol. 45, no. 1, pp. 8091, 2012.

4. C. Shan, S. Gong, and P. W. McOwan, Facial expression recognition based on local binary patterns: A comprehensive study, Image and Vision Computing, vol. 27, no. 6, pp. 803816, 2009.

5. T. R. Almaev and M. F. Valstar, Local gabor binary patterns from three orthogonal planes for automatic facial expression recognition, in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 356361.

6. T. Gritti, C. Shan, V. Jeanne, and R. Braspenning, Local features based facial expression recognition with face registration errors, in Automatic Face Gesture Recognition, 2008. FG08. 8th IEEE International Conference on. IEEE, 2008, pp. 18.

7. M. Turk and A. Pentland (Jun. 1991). Face Recognition Using Eigenfaces. Proceedings of CVPR IEEE Computer Society. [Online]. pp. 586-591. Available: https://www.cs.ucsb.edu/mturk/Papers/mturk-CVPR91.pdf.

8. Georghiades A.S., Belhumeur P.N., and Kriegman D.J., From Few To Many: Illumination Cone Models For Face Recognition Under Variable Lighting and Pose, IEEE Trans. Pattern Anal. Mach. Intelligence, vol. 23, no. 6 pp. 646-660 Jun 2001.

9. Hailing Zhou, Ajmal Mian, Lei Wei, Doug Creighton, Mo Hossny, and Saeid Nahavandi (December 2014). Recent Advances on Single Modal and Multimodal Face Recognition: A Survey. IEEE Transactions on Human-Machine Systems. [Online]. 44(6) pp.701-716. Available: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=arnumber=6876188.

10. Navneet Dalal and Bill Triggs (Jun. 2005). Histograms of Oriented Gradients for Human Detection. IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). [Online]. 1, pp. 886-893 Available: https:// lear .inrialpes. Fr/ people/triggs/pubs/Dalal-cvpr05.pdf.

11. Harihara Santosh Dadi and P G Krishna Mohan, Performance Evaluation of Eigen faces and Fisher faces with different pre- processed Data sets, International Journal of Advanced Research in Computer Engineering Technology (IJARCET), vol. 4, no. 5, pp. 2110 2116. May 2015.

12. Harihara Santosh Dadi and P G Krishna Mohan, Enhancement of Face Recognition Rate by Data Base Pre-processing, International Journal of Computer Science and Information Technologies, IJCSIT, vol. 6, no. 3, pp. 2978-2984. Jun. 2015