International Journal of Advanced Technology and Innovative Research

ISSN 2348–2370
Vol.07,Issue.03,
March-2015,
Pages:0310-0311

www.ijatir.org

An Efficient and Enhanced Face Recognition System using Matlab

GHANTA JEEVAN BABU[1], CHERUKURI NAGA LAKSHMI NARESH[2], THATI VANI[3], MYLA MANEESHA[4], LAKSHMI CHERUKURI[5]

[1]Gandhiji Institute Of Science And Technology, Jaggayyapet, AP, India, E-mail: ghantajeevanbabu416@gmail.com.
[2]Gandhiji Institute of Science and Technology, Jaggayyapet, AP, India, E-mail: nagan1464@gmail.com.
[3]Gandhiji Institute of Science and Technology, Jaggayyapet, AP, India, E-mail: thativani40@gmail.com.
[4]Gandhiji Institute of Science and Technology, Jaggayyapet, AP, India, E-mail: mylamaneesha429@gmail.com.
[5]Gandhiji Institute of Science and Technology, Jaggayyapet, AP, India, E-mail: cherukuri.lakshmi20@gmail.com.

Abstract: Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. We tackle this by combining the strengths of robust illumination normalization, local texture based face representations, and distance transform based matching, kernel-based feature extraction and multiple feature fusion. Specifically, we make three main contributions: (*i*) we present a simple and efficient preprocessing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; (*ii*) we introduce Local Ternary Patterns (LTP), a generalization of the Local Binary Pattern (LBP) local texture descriptor that is more discriminant and less sensitive to noise in uniform regions, and we show that replacing comparisons based on local spatial histograms with a distance transform based similarity metric further improves the performance of LBP/LTP based face recognition; and (*iii*) we further improve robustness by adding Kernel PCA feature extraction and incorporating rich local appearance cues from two complementary sources.

Keywords: LBP, LTP, PCA, Kernel.

I. INTRODUCTION

Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement, surveillance and more generally image understanding. Numerous approaches have been proposed, including (among many others) eigenfaces, fisherfaces and laplacian faces, nearest feature line-based subspace analysis, neural network, elastic bunch graph matching, wavelets, and kernel methods. Most of these methods were initially developed with face images collected under relatively well controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, ageing, partial occlusions, etc. This paper focuses mainly on the issue of robustness to lighting variations. For example, a face verification system for a portable device should be able to verify a client at any time (day or night) and in any place (indoors or outdoors). Unfortunately, facial appearance depends strongly on the ambient lighting and – as emphasized by the recent FRVT and FRGC trials – this remains one of the major challenges for current face recognition systems.

Traditional approaches for dealing with this issue can be broadly classified into three categories: appearance-based, normalization based, and feature-based methods. In direct appearance-based approaches, training examples are collected under different lighting conditions and directly (i.e. without undergoing any lighting preprocessing) used to learn a global model of the possible illumination variations, for example a linear subspace or manifold model, which then generalizes to the variations seen in new images. Direct learning of this kind makes few assumptions but it requires a large number of training images and an expressive feature set, otherwise it is essential to include a good preprocessor to reduce illumination variations.

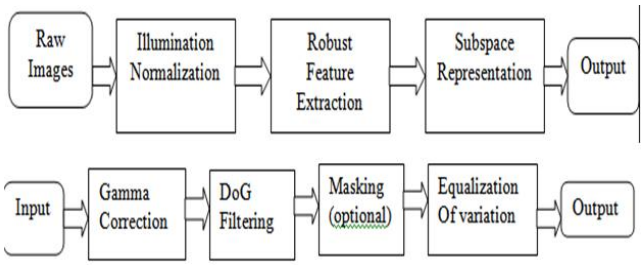

Fig1. the stages of Image Processing Pipeline, and (bottom) an Example of the effect of three stages –from left to right: input image, image after Gamma Correction, image after DoG filtering, image after robust contrast normalization.

The overall process can be viewed as a pipeline consisting of image normalization, feature extraction and subspace representation, as shown in Fig. 1. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The method centres on a rich set of robust visual features that is selected to capture as much as possible of the available information. A well-designed image preprocessing pipeline is prepended to further enhance robustness. The features are used to construct illumination-insensitive subspaces, thus

capturing the residual statistics of the data with relatively few training samples.

II. THE RELATIONSHIP BETWEEN IMAGE NORMALIZATION AND FEATURE SETS

Normalization is known to improve the performance of simple subspace methods (e.g. PCA) or classifiers (e.g. nearest neighbors) based on image pixel representations, but its influence on more sophisticated feature sets has not received the attention that it deserves. A given preprocessing method may or may not improve the performance of a given feature set on a given data set. For example, for Histogram of Oriented Gradient features combining normalization and robust features is useful, while histogram equalization has essentially no effect on LBP descriptors, and in some cases preprocessing actually hurts performance – presumably because it removes too much useful information. Here we propose a simple image preprocessing chain that appears to work well for a wide range visual feature sets, eliminating many of the effects of changing illumination while still preserving most of the appearance details needed for recognition.

III. ROBUST FEATURE SETS AND FEATURE COMPARISON STRATEGIES

Current feature sets offer quite good performance under illumination variations but there is still room for improvement. For example, LBP features are known to be sensitive to noise in near-uniform image regions such as cheeks and foreheads. We introduce a generalization of LBP called Local Ternary Patterns (LTP) that is more discriminant and less sensitive to noise in uniform regions. Moreover, in order to increase robustness to spatial deformations, LBP based representations typically subdivide the face into a regular grid and compare histograms of LBP codes within each region. This is somewhat arbitrary and it is likely to give rise to both aliasing and loss of spatial resolution. We show that replacing histogramming with a similarity metric based on local distance transforms further improves the performance of LBP/LTP based face recognition.

IV. FUSION OF MULTIPLE FEATURE SETS

Many current pattern recognition systems use only one type of feature. However in complex tasks such as face recognition, it is often the case that no single class of features is rich enough to capture all of the available information. Finding and combining complementary feature sets has thus become an active research topic, with successful applications in many challenging tasks including handwritten character recognition and face recognition. Here we show that combining two of the most successful local face representations, Gabor wavelets and Local Binary Patterns (LBP), gives considerably better performance than either alone. The two feature sets are complimentary in the sense that LBP captures small appearance details while Gabor wavelets encode facial shape over a broader range of scales.

V. CONCLUSION

Finally, this project have presented new methods for face recognition under uncontrolled lighting based on robust preprocessing and an extension of the Local Binary Pattern (LBP) local texture descriptor. There are following main contributions: (i) a simple, efficient image preprocessing chain whose practical recognition performance is comparable to or better than current (often much more complex) illumination normalization methods; (ii) a rich descriptor for local texture called Local Ternary Patterns (LTP) that generalizes LBP while fragmenting less under noise in uniform regions: (iii) a distance transform based similarity metric that captures the local structure and geometric variations of LBP/LTP face images better than the simple grids of histograms that are currently used; and (iv) a heterogeneous feature fusion-based recognition framework that combines two popular feature sets – Gabor wavelets and LBP – with robust illumination normalization and a kernelized discriminative feature extraction method. The combination of these enhancements gives the state of the art performance on three well-known large-scale face datasets that contain widely varying lighting conditions.

VI. REFERENCES

[1] Y. Adini, Y. Moses, and S. Ullman, “Face recognition: The problem of compensating for changes in illumination direction,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 19, no. 7, pp. 721–732, 1997.

[2] T. Ahonen, A. Hadid, and M. Pietikainen, “Face recognition with local binary patterns,” in European Conf. Computer Vision, Prague, 2005, pp. 469–481.

[3] “Face description with local binary patterns: Application to face recognition,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 28, no. 12, 2006.

[4] R. Basri and D. Jacobs, “Lambertian reflectance and linear subspaces,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 25, no. 2, pp. 218–233, February 2003.

[5] P. Belhumeur, J. Hespanha, and D. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 19, no. 7, pp. 711–720, 1997.

[6] P. Belhumeur and D. Kriegman, “What is the set of images of an object under all possible illumination conditions,” Int. J. Computer Vision, vol. 28, no. 3, pp. 245–260, 1998.

[7] G. Borgefors, “Distance transformations in digital images,” Computer Vision, Graphics & Image Processing, vol. 34, no. 3, pp. 344–371, 1986.

[8] R. Brunelli and T. Poggio, “Face recognition: Features versus Templates,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 15, no. 10, pp. 1042–1052, 1993.

[9] H. Chen, P. Belhumeur, and D. Jacobs, “In search of illumination invariants,” in CVPR, 2000, pp. I: 254–261.

[10] T. Chen, W. Yin, X. Zhou, D. Comaniciu, and T. Huang, “Total variation models for variable lighting face recognition,” IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 28, no. 9, pp. 1519–1524, 2006.