International Journal of Engineering & Technology, 7(4.16) (2018) 290-292

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Face Recognition Based on Features of Triple Descriptors

Bashier Elkarami[1], Majid Ahmadi[2]

[12] Department of electrical and Computer Engineering, University of Windsor, Windsor, Canada
**Corresponding author E-mail: Elkaram@uwindsor.ca*

Abstract

Recently, texture descriptors and object detection descriptors have been used widely in face recognition due to their discriminative ability and fast implementation. In this paper, we investigate the efficiency of face recognition based on image blocking and a combination of triple descriptors, LBP, LTP, and HOG. The method is applied to Color Feret dataset and AT&T along with four classifiers to measure the accuracy rate. The experimental results show a better recognition rate on AT&T and stable performance on both datasets.

***Keywords**: Classification; face recognition; Histogram of the Oriented Gradient; Local Binary Pattern; Local Ternary Pattern*

1. Introduction

Texture descriptors have gained a lot of popularity in face recognition domain due to their desired characteristics such as low computational complexity; strong distinguishability power, and robustness to illumination variations. These descriptors have been used as standalone feature extractor like LBP in [4] and LTP in [11], or can be used in combination with different descriptors as in [5, 8, 12]. In this paper, we investigate a face recognition system based on the combination of Local Binary Pattern (LBP), Local Ternary Pattern (LTP), and Histogram of oriented gradient (HOG) as a facial feature extractor due to their insensitivity to illumination and pose variations. Both LBP and LTP divide the image into small regions and threshold the pixels with respect to the center pixel, but they use different coding techniques. HOG divides the images into small cells and compute gradient directions, then utilize overlapping blocks to form the histogram. To capture more of the local feature, each image will be divided into non overlapping blocks and apply the three descriptors to each block. The rest of the paper is organized as follows. In section 2, we present the descriptors LBP, LTP, and HOG. In 3, the proposed methods in detail steps are presented. In 4, we present our results with discussion and analysis.

2. Feature extraction.

2.1. Local Binary Pattern

Originally, LBP descriptor was formulated as a texture description, and now is considered as one of best feature extraction techniques used for face recognition due to its robustness toward illumination, scaling, and rotation variation [1,2]. The original LBP performs on 3x3 neighbourhood pixels where each pixel is coded a value of 1 if its intensity value higher or equal to the intensity value of the canter pixel otherwise it is coded value of 0. The produced binary number is transferred to a decimal number and assigned to the canter pixel,

and then utilized to construct the image histogram. Circular LBP is an extension of the original LBP where the intensity value of P neighbourhood pixels distributed on a circle of radius R and compared with the intensity value of the pixel at the canter of the circle. Fig.1 illustrates the original and circular LBP. Further improvement was achieved by utilizing a uniform binary pattern which encompasses no greater than two bitwise transitions from 1 to 0 or 1 to 0 such as 11111111 (0 transitions), and 01000000 (2 transitions) are uniform whereas 01010111 (5 transitions), and 0011101 (3 transitions) are considered to be non - uniform. Uniform LBP produces histogram of $(P-1)+2$ bins and non- uniform LBP produces histogram of $(P-1)+3$ bins.

2.2. Local Ternary Pattern

LTP is another texture descriptor similar to LBP and regarded as an extension of LBP. LTP operates on 3x3 neighbourhood pixels and each pixel is coded a value of -1, 0, or 1 according to a user - defined threshold t [6] as follows:

$$S(P_i, P_c, t) = \begin{cases} 1, & P_i \geq P_c + t \\ 0, & P_i < P_c + t \\ -1, & P_i \leq P_c - t \end{cases} \quad (1)$$

To overcome the negative values, the LTP codes are divided into two codes of LBP codes, upper pattern (positive) of LTP and lower pattern (negative) of LPT as illustrated in figure 2. Finally, the two histograms produced by the two LBP codes are combined to form the histogram of the LTP. from 1 to 0 or 1 to 0 such as 11111111 (0 transitions), and 01000000 (2 transitions) are uniform whereas 01010111 (5 transitions), and 0011101 (3 transitions) are considered to be non - uniform. Uniform LBP produces histogram of $(P-1)+2$ bins and non- uniform LBP produces histogram of $(P-1)+3$ bins.

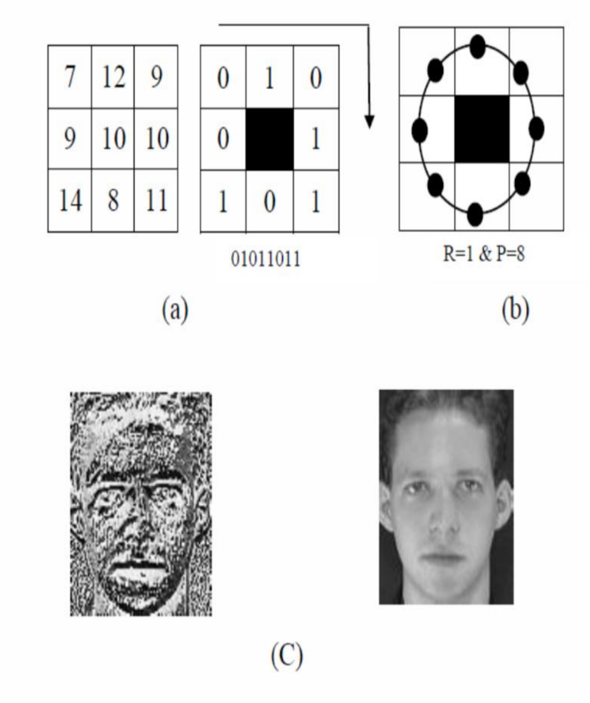

Fig. 1: LBP Descriptor: (a) Basic LBP. (b) Circular LBP. (C)LBP image

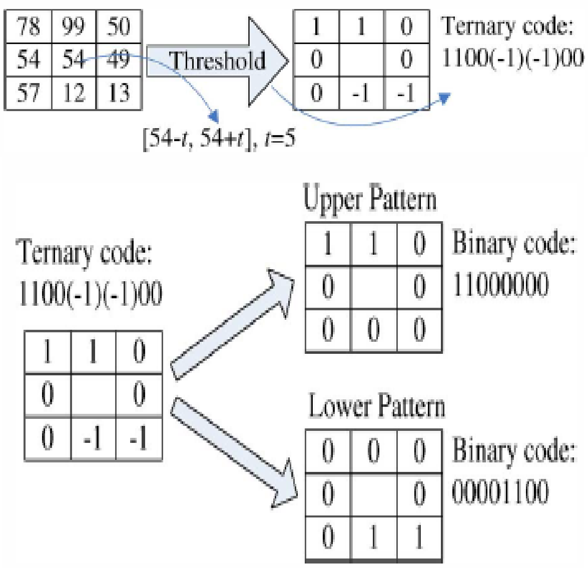

Fig. 2: Procedure of the LTP [6]

2.3. Histogram of the Oriented Gradient (HOG)

HOG descriptor has been widely used in object detection [7]. HOG features are extracted based on the distribution of the local intensity gradients or edge directions leading to better distinguishability of the local shape and appearance of local object. The first step in extracting HOG features is computing the Horizontal and vertical gradients of the image. Then, the image is divided into non overlapping small regions called cells of size N x N (originally was 8 x 8). Each cell yields a P-bins histogram of gradient orientation based on the weight of each pixel in the cell. The bins spread equally over 0-180° when 'unsigned' gradient is considered, or 0-360° if 'signed' is considered. To smooth the effects of illumination and contrast, typically overlapping blocks are used to group the cells and concatenate the normalized cell histograms. Furthermore, the overlapping blocks allow cells to participate in constructing the final HOG feature more than once. Fig.3 illustrates the HOG descriptor.

Fig. 3: HOG Descriptor

3. The proposed method

The proposed block diagram of the proposed method is illustrated in fig. 4 which is executed in four steps. (1) Each face image is portioned into M- equal and non-overlapping blocks [3, 4]. (2) LBP, LTP, and HOG are applied to each block to extract local features of the sub image. (3) The produced three histograms of each block are concatenated in one histogram. (4) The M-histograms resulting from the M- blocks are concatenated into one histogram to represent the image. (5) Normalize the feature histogram. (6) The feature histograms of all images are fed into the classifier.

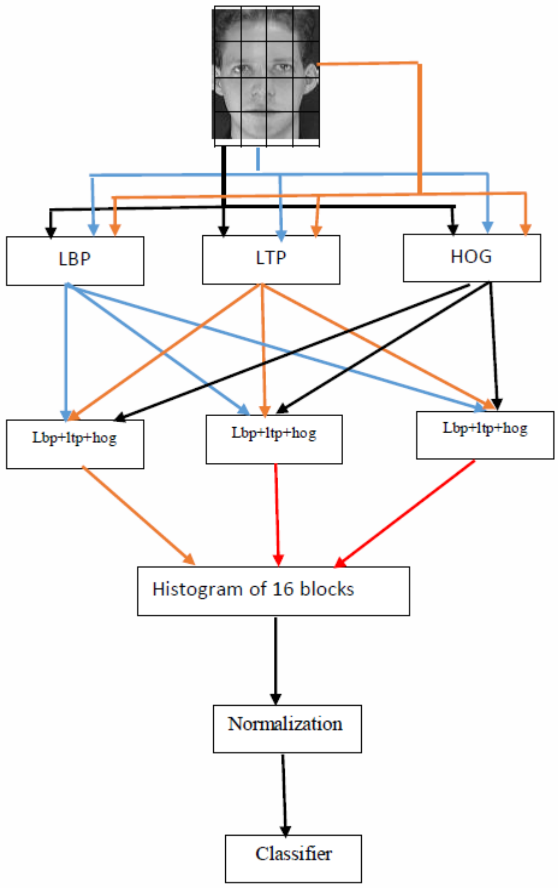

Fig. 4: Illustrate the steps of proposed method

4. Experimental Results

The efficiency of the proposed method was investigated by applying the method on two datasets (AT&T and Color Feret) with four different classifiers (Support Vector Machine, KNN, Random Forest, and Chi-Square based local nearest neighbour classifiers) to compare the accuracy of the method. Furthermore, different number of blocks is selected to study the performance of the method with different size of blocks. All experiments were conducted under the same parameters' value as following: uniform

LBP and LTP with R=3, P=8, and R=2, P=8 respectively, and threshold t of LTP is set to10. Cell size of 8x8 pixels, and block size 0f 2x2 for HOG descriptor with 9 bins. A number of 300 trees are used for Random Forest classifier. No preprocessing operation of any kind was applied to the datasets.

4.1. AT&T database

There are 400 images in AT&T of size 112 × 92, belonged to 40 people, which means 10 images for each person with different lighting conditions, scales, rotation, and facial expression. The dataset is divided equally into train and test sets of 200 per set with 5 images per person. [10]. Table (1) and Fig. 5 shows the recognition rate of the proposed method with AT&T dataset with different number of blocks and different classifiers. The results show the steady performance and high accuracy rate of the classifiers despite the different number of blocks and lack of any preprocessing operations. The only exception is the Random forest classifier which shows some fluctuations in its performance

Table 1: The recognition rate of the proposed method for AT&T

Classifier	Number of Blocks			
	16 Blocks	8 Blocks	4 Blocks	2 Blocks
SVM(RBF)	99	99.00	99.50	99.50
Chi-square	99	98.50	97.00	98.50
KNN	98	98.00	97.00	97.00
Random forest	97	93.00	95.00	93.00

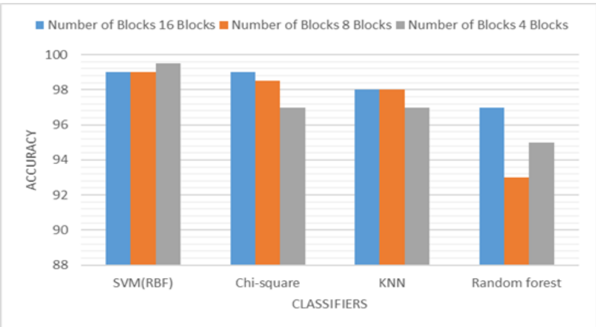

Fig. 5: The recognition rate of the proposed method for AT&T

4.2. The Color Feret Dataset

This database was created between 1993 and 1996, and has 11338 images of size 512 x 768 with 994 individuals. It has 13 different orientation poses such as frontal, head right or left. Some subjects are wearing glasses or different hair style [9]. Two sets of Color Feret are used, Fa for training set, and Fb as test set. Fa has the frontal image of each person and Fb contains the alternative frontal images. Fa consists of 994 images whereas Fb has 992 images and there is only one image for each subject. Before applying the proposed method, the images were converted to grayscale images and resized to 112 x 92. Table (2) and fig. 6 show the recognition rate of The proposed method with Color Feret dataset with different number of blocks and different classifiers. The recognition rate of all classifiers is lower than the AT&T rate due to having only one training sample of each subject in the dataset. However, the results still show the steady performance despite having limited training samples and different number and size of blocks.

Table 2: The recognition rate of the proposed method for Color Feret

Classifier	Number of Blocks			
	16 Blocks	8 Blocks	4 Blocks	2 Blocks
SVM(RBF)	90.82	91.42	89.92	92.92
Chi-square	89.82	90.83	92.80	93.23
KNN	89.50	90.6	91.12	93.00
Random forest	80	77.78	77.76	77.46

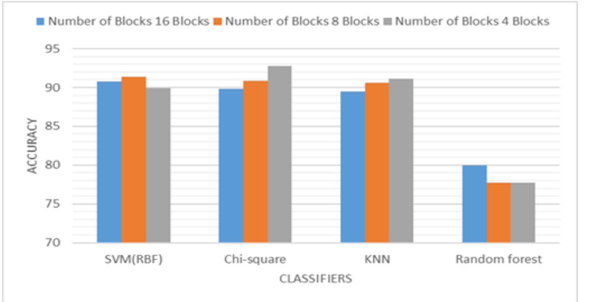

Fig. 6: The recognition rate of the proposed method for Color Feret

5. Conclusions

In this paper, three powerful feature extraction descriptors, local Binary Pattern (LBP), Local Ternary Pattern (LTP), and Histogram of the Oriented Gradient (HOG) were combined to extract better features of the face image. Since different areas of a face convey different details, image blocking was employed to strengthen extracted features with more local facial features. To validate the strength of the method, two datasets were used in our experiments with different blocking number. Support Vector Machine, Chi- square distance, k nearest neighbour, and Random forest were utilized to measure the accuracy of our method. The outcome was promising despite the recognition rate was around 90% in Color Feret which due to having only one training sample per subject. Moreover, improvement can be made by applying preprocessing operation to reduce noise and brightness.

References

[1] T. Ojala, M. Pietika¨inen, and T. Ma¨enpa¨a¨, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, July 2002.

[2] Ojala, T., M. Pietikäinen, and D. Harwood, "A Comparative Study of Texture Measures with Classification Based on Feature Distributions," Pattern Recognition 29, 1996, pp.51-59.

[3] T. Ahonen, A. Hadid, and M. Pietikainen. Face recognition with local binary patterns. ECCV, 469–481, 2004.

[4] S. Nikan, M. Ahmadi, "Human face recognition under occlusion using LBP and entropy weighted voting," in International Conf. on Pattern Recognition (ICPR12), Tsukuba, November 2012, pp. 1699-1702.

[5] Soodeh Nikan, Majid Ahmadi, "Local gradient-based illumination invariant face recognition using local phase quantisation and multi-resolution local binary pattern fusion", The Institution of Engineering and Technology (IET), vol. 9, Issue no.1, pp. 12–21, 2014.

[6] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," IEEE Transactions on Image Processing, vol. 19, pp. 1635-1650, June 2010.

[7] N. Dalal, B. Triggs, Histograms of oriented gradients for human detection, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2005, pp. 886–893.

[8] Kang Wang , Zhenxue Chen, Q.M. Jonathan Wu, Chengyun Liu, "Illumination and pose variable face recognition via adaptively weighted ULBP_MHOG and WSRC" Signal Processing: Image Communication 58 (2017) 175–186

[9] P.J. Phillips, H. Moon, P.J. Rauss, S. Rizvi, "The FERET evaluation methodology for face recognition algorithms," IEEE Trans. Pattern Anal. Mach. Intell., 22, pp. 1090–1104, October 2000.

[10] ORL and Yale face databases. [Online]. Available: http://www.face-rec.org/databases/

[11] Zhang H and Xu S (2016), "The Face Recognition Algorithms Based on Weighted LTP" in Journal of Image and Graphics, Vol. 4, No. 1.

[12] O. Rama Devi, L.S.S.Reddy, E.V.Prasad, " Face Recognition Using Fused Spatial Patterns", International Journal of Advanced Trends in Computer Science and Engineering, Vol. 4, No. 2, pp. 15-21, Mar 2015.