On approaching heuristic weight mask to enhance LBP-based profile face recognition system

Article *in* Indian Journal of Science and Technology · May 2016

DOI: 10.17485/ijst/2016/v9i17/92314

Thai Hoang Le
VNU-HCM University of Science

Indian Journal of Science and Technology Vol 9(17), 10.17485/ijst/2016/v9i17/92314, May 2016

ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

On Approaching Heuristic Weight Mask to Enhance LBP-based Profile Face Recognition System

Thai Hoang Le*

Computer Science Department, University of Science, VNU - HCM, Vietnam; lhthai@fit.hcmus.edu.vn

Abstract

In this paper, a LBP-based profile face recognizer for identifying a query face image is proposed. A robust heuristic approach is proposed to improve the weight set of LBP face recognizers. Our method can be combined with other variants of LBP feature extraction to improve their accuracy, because it can help to avoid the local maxima. We also propose a method to predict the pose range of face image. Based on this method, we choose the proper gallery set of face images. This gallery set will help to reduce time matching between input image and database images, and error propagation when pose prediction returns false results. Experimental results on the FERET database show the effectiveness of these methods.

Keywords: Concatenated Local Binary Pattern, Heuristic Weight Search, Local Binary Pattern, Pose Range, Profile Face

1. Introduction

Face recognition has received much attention of researchers in biometric authentication because of potential commercial application. During the last decades, numerous face recognition methods have been developed. Many surveys[1–3] have been carried out to evaluate the advantages and disadvantages of face recognition methods that have been proposed. In general, face recognition methods can be classified into two categories: holistic based methods and local features-based methods[3]. Holistic methods consider whole image as a target for extracting feature. This approach is being used in face recognition methods such as Principal Component Analysis (PCA)[4], Linear Discrimination Analysis[5], and Support Vector Machine[6]. On the other hand, local feature based methods use features such as nose, eye corners, and mouth for describing a face. Holistic approaches require lower cost in computing than the local feature based ones. However, local feature based methods have higher accuracy rate than holistic approaches, because of exploiting discrimination of local features on the face. However, with the revolution of computer technology (computer is becoming cheaper and faster), the limitation of computation cost of local feature based approach can be overcome in future.

Local Binary Patterns (LBP) is a proposed method for face recognition problems. Not only to be used in face recognition, LBP has also been used in many other applications[7] due to their effective in image presentation. Some example applications that can be pointed out are: granite texture classification[8], facial expression recognition[9] and gender recognition[10].

The robustness of LBP for multi-view facial expression recognition was reported by researchers[11], which promises the applications of LBP for profile face recognition.

For pose variation, this paper proposes a novel method using LBP to recognize profile faces. First step, this method chooses a proper image gallery (Chosen gallery in Figure 1.) by estimating pose range of face. It does not predict exactly pose of input image, but it estimate the pose range of input image. In proposed framework, a novel algorithm for searching efficient weight set which can boost the LBP based face recognition rate is proposed. Face image should be split into many regions, proposed algorithm computes the weights set by measuring the contribution of every region and use this information for

*Author for correspondence

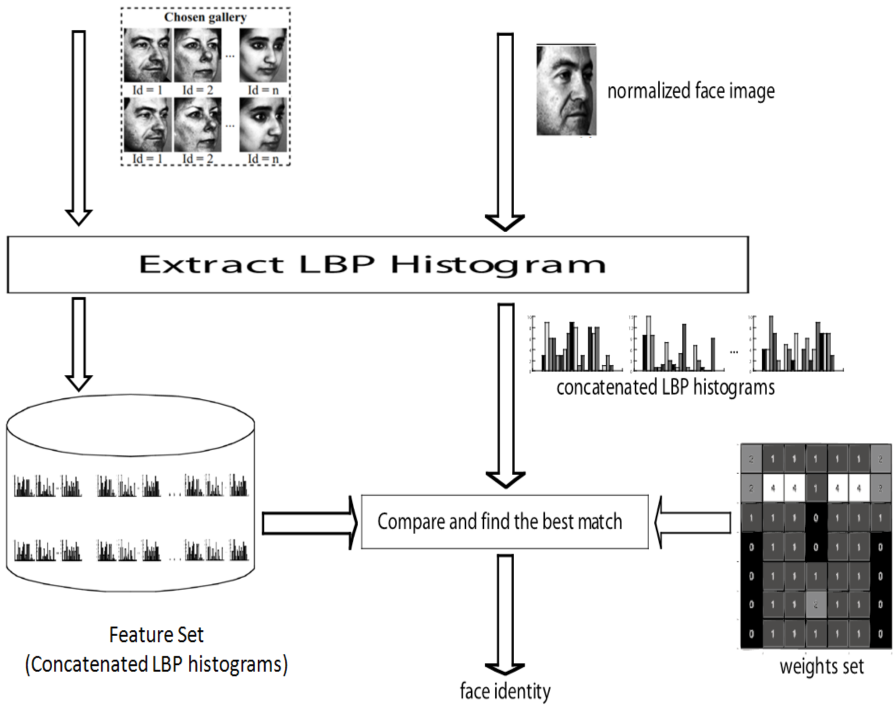

Figure 1. Structure of a LBP- based profile face recognition system.

establishing rules in weight set heuristic search, called Heuristic Weight Search.

Figure 1 shows the processing pipeline of a LBP- based profile face recognizer for identifying a query face image. The performance of our method was evaluated with the public database FERET.

The paper is structured as follows: section 2 presents the method of Heuristic Weight Search (HWS) which computes different contributions of patches for face recognition. Section 3 presents the framework to identify images across pose. The experimental results are presented in section 4. Finally, section 5 concludes the paper.

2. Heuristic Weight Search (HWS) to Compute Different Contributions of Patches for Face Recognition

2.1 Local Binary Pattern and Its Histogram

The original LBP operator was first introduced as a complementary measure for local image contrast[12] by thresholding the 3 x 3 neighborhood of each pixel with the center pixel. It is defined as a sequence binary string. Then, the operator was extended to have 2 arguments: R and N. R is distance between the pixel and its neighbors. N is the number of neighbor pixels around the centric pixel. Given a location (x, y) in an image, the gray values of neighbor pixels are compared with a threshold, which is the gray value of the pixel (x, y). If the gray value of the neighbor pixel is higher than the threshold, the output will be 1; otherwise the output will be 0. These binary outputs of these neighbor pixels are concatenated to form a binary code, so called Local Binary Pattern (LBP) of the location (x, y). Figure 2 shows how to apply $LBP_{8,2}$ operator on face image.

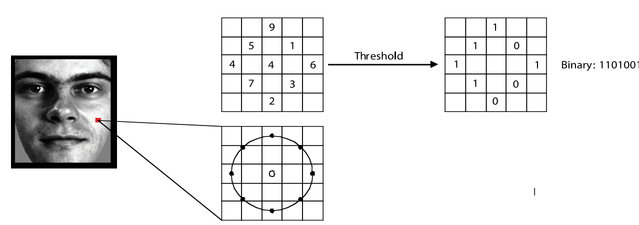

Figure 2. Apply $LBP_{8,2}$ operator at location (x, y) on an image.

Distribution of LBP patterns on the face image can be used as a feature to describe a face. Ahonen et al use LBP histogram to represent this distribution[13]. Figure 3 shows the image presentation of LBPs and LBP histogram.

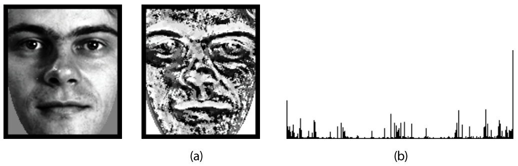

Figure 3. (a) Image presentation of LBPs and (b) LBP histogram.

The distance between two face images is the distance between their histograms[13]. There are many methods for measuring distance between two histograms. Chi square formula is widely used for this purpose. Below is its formula:

$$\chi^2(S,M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i} \tag{1}$$

Where S and M are two LBP histograms of the two compared images respectively and are frequencies of appearance of pattern i in S and M respectively. In order to reserve the spatial information like size, shape and position of face local features, Ahonen has recommended that the face image should be split into grid of cells and then obtain LBP histogram for each cell[13]. Based on their experiments on FERET database, Ahonen et al stated that the chosen of a 7x7 grid is a good balance between computation cost and accuracy rate of the face recognition as they has made comparison between other grid sizes. Figure 4 shows the concatenated LBP histograms of a face image.

By linking all LBP histograms of cells together, we obtain concatenated LBP histograms, called CLBP histogram, as a feature vector of the face image. According to[13], some cells are more significant than the others in describing the face. As this reason, each cell is assigned a weight value, which is used in computing the distance between two feature vectors. The Chi squared distance between two face images becomes[13]:

$$\chi_w^2(S,M) = \sum_{i,j} w_j . \frac{\left(S_{i,j} - M_{i,j}\right)^2}{S_{i,j} + M_{i,j}} \tag{2}$$

Where S and M are two CLBP histograms; $S_{i,j}$ and $M_{i,j}$ are frequencies of appearance of pattern *i* in cell *j* of S and M respectively; W_j is weight for cell *j*.

2.2 Heuristic Approach for Computing Optimal Weight Set

In this study, we propose a novel method to compute optimal weight set for LBP based-face recognizer. The ideal behind this method is: if we can evaluate the contribution level of every weight cells (i.e. their individually contribution in face discrimination), we can used that information to confine domain of searching; so that searching for optimal weight set can converge faster. The searching method that we used is derived from hill climbing technique with the heuristic is based on the proportion of weight values between weight cell. Our approach includes 2 steps: the first step estimates the contribution level of each cell in face discrimination. The second step consists of prioritizing the cells and searching the efficient weight value for each cell in the priority order.

2.2.1 Weight Set Fitness Function (Ws Fitness)

For LBP based-face recognizer, weight-set is an important factor that affects the accuracy of the recognizer. Measurement goodness of weight set is a key in most part of our algorithm. This measurement is for evaluating if a weight set is better or worse than other weight sets. In this section, we introduce Ws Fitness function, which is used for this purpose.

Ws Fitness function accepts input as a weight set, and output a floating point value, which represents goodness

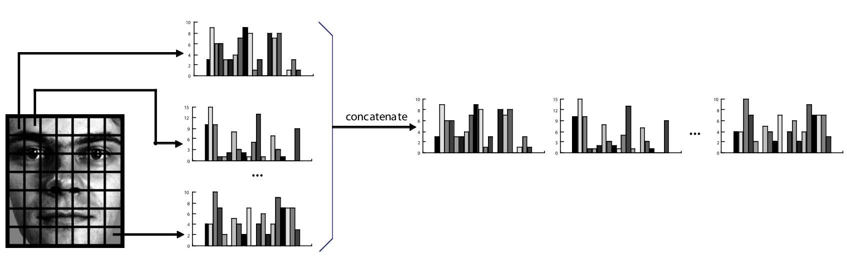

Figure 4. Face division and concatenated LBP histograms.

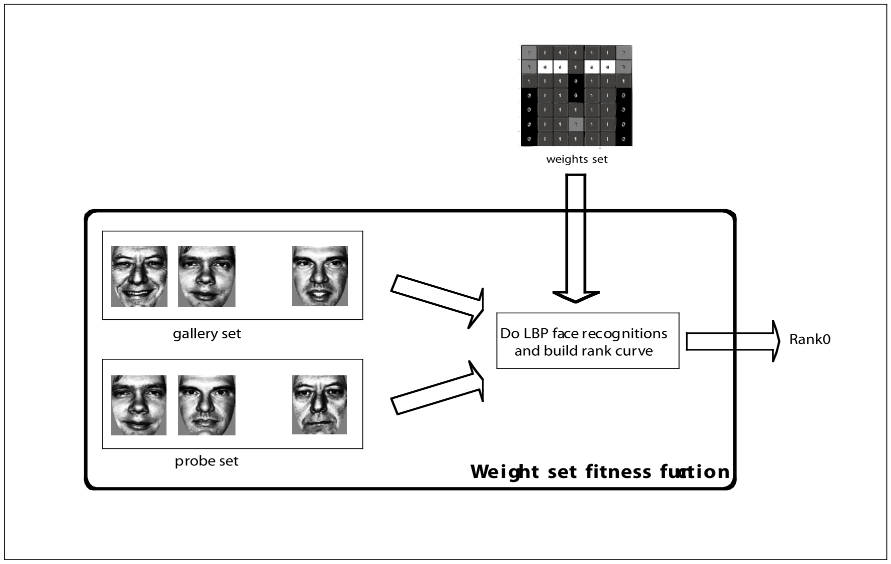

Figure 5. Ws Fitness function for evaluating goodness of a weight set.

of the weight set. The higher output value is, the better weight set is. Figure 5 presents the evaluating goodness of a weight set using Ws Fitness function.

In this paper, the Ws Fitness function is genuine accept rate of LPB based-face recognizer when it's false accept rate is zero, in which the weight set is used. To calculate the genuine accept rate and false accept rate, we use three image sets: 1. Gallery set is used as template dataset. It is feret_gallery.srt from the FERET database; 2. Genius probe set is used for calculating genuine accept rate. It contains face images of some people from the gallery set. The images were taken in a different condition from the images in the gallery set (e.g. different in time, light); 3. False probe set is used for calculating false accept rate. It contains face images of individual that not exist in the gallery set.

Fitness of a weight set is calculated as follow:

$$WsFitness(W) = \frac{\left|\left\{ q_i \;\middle|\; \begin{array}{l} q_i \in S_1,\ similarity(q_i, t_k, W) < \theta,\ label(t_k) = label(q_i), \\ t_k = \arg\min_{t_j \in S_3}\left(similarity(q_i, t_j, W)\right) \end{array} \right\}\right|}{|S_1|},$$

$$\theta = Min\left(\left\{ similarity(q_i, t_j, W) \mid q_i \in S_2,\ t_j \in S_3 \right\}\right), \tag{3}$$

$$similarity(q, t, W) = \sum_{i,j} w_{j} \cdot \frac{\left(h(q)_{i,j} - h(t)_{i,j}\right)^2}{h(q)_{i,j} + h(t)_{i,j}}$$

Where: $WsFitness(W)$ is fitness of the weight set W; S_1 is genuine probe set; S_2 is false probe set; S_3 is gallery set; $similarity(q,t,W)$ is Chi Square distance between CLBP histogram of image q and CLBP histogram of image t with the weight set W; $label(x)$ is class of the image x. Two face images belong to the same class if they belong to the same individual.

2.2.2 Prioritize Cells by their Contribution in Face Distinction

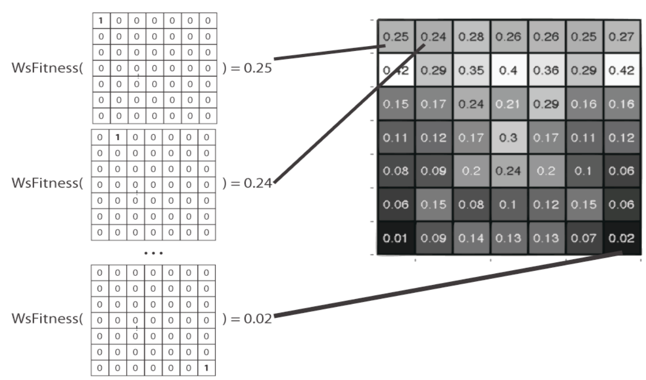

Figure 6. Contribution matrix of cells over fafb dataset of FERET.

To calculate the contribution level of a cell in face distinction, we create a single entry weights matrix corresponding to the cell and calculate its Ws Fitness. A single entry matrix has all of its elements is zero except the element of the cell. If we apply the matrix in face recognition, only the nonzero cell is participated in the recognition. It means the Ws Fitness of the matrix is the contribution level of the cell in face recognition.

The process is demonstrated in figure 6. In which, a single entry matrix is built for each cell. The nonzero entry takes value 1, while the other entries take value 0. Then, Ws Fitness function is used for calculating the goodness of each cell. Gathering those goodness values, we have a matrix, which is called the contribution matrix. This matrix presents the contribution of each cell in face distinction. In the second step, which is described in the next section, those goodness values will be used for determining the priority of the cells in discovering optimal weight.

2.2.3 Finding Optimal Weight Set by Heuristic Search

After having the contribution level of every cell, a heuristic search is applied for searching the optimized weights. We take the scale [0..1] for the weight values. At initial, we assign the highest weight value (value 1) for most important cell; the other cells are assigned weight value of 0. Then we start searching optimal weight value for the second important cell by let its weight value run from 1 to 0. The weight value, which maximizes the Ws Fitness of the whole weights matrix, is the optimal weight value of the second important cell. We do the same for the third important cell, fourth important cell, and so on, until optimal weight value for all cells has been calculated. Figure 7 shows the steps of algorithm for finding optimal weight set with Heuristic search.

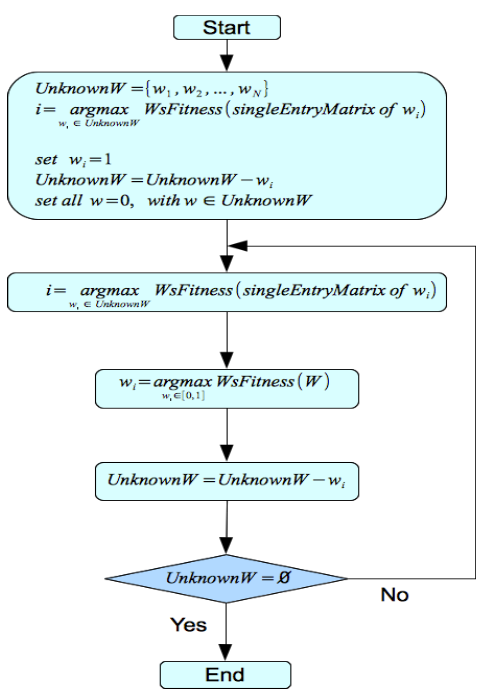

Figure 7. Algorithm for finding optimal weight set with Heuristic search.

In which: $i = \underset{w_i \in UnknownW}{\text{argmax}}\ WsFitness(singleEntryMatrix\ of\ w_i)$: Means to retrieve index of the most important cell in the UnknownW. UnknownW is set of cells that their optimal weights haven't been found yet. $w_i = \underset{w \in [0,1]}{\text{argmax}}\ WsFitness(W)$: Means to search the value for W_i so that maximizing the goodness of the whole weight set W. Here, $W = \{w_1, w_2, \dots, w_N\}$ is the weight-set, and N is the number of cells of the weight set.

3. Applying Local Binary Patterns and Heuristic Weight Search (HWS) for Profile Face Recognition

A gallery set[3] in classical methods is often frontal images or random poses images. The performance of these approaches is quite low in the case of processing images with large yaw angles. In our work, the pose of image is predicted before identification[14].

3.1 Predicting Pose Range of Input Face Image

Almost previous researches, the rotation angle of a face image must have detected exactly. However, the face recognition system does not need to return value of rotation angle of an input image. It only returns the suitable label of an input image. Therefore, we propose a method for predicting pose range of input image. Figure 8 shows the process of estimating the pose range of a face image.

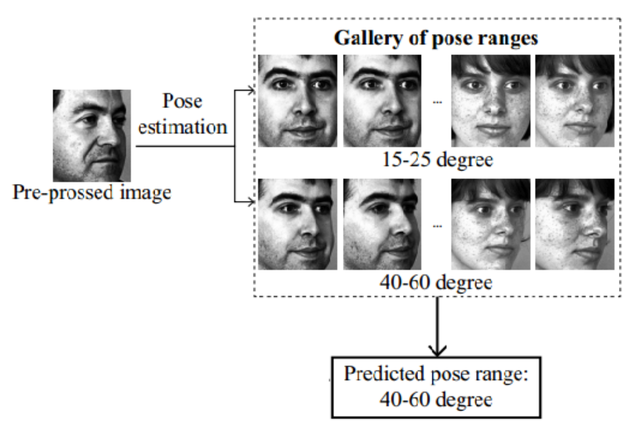

Figure 8. An example of estimating the pose range of a face image.

3.2 Profile Face Recognition using Predicted Pose Range Method

Input of profile face recognition using predicted pose range method is a face image and output of this method is a predicted label of this image. It includes two steps:

Step 1: Choosing a proper gallery set from a database image based on the input image using pose range estimation (In section 3.1). Figure 9 illustrates the first step.

Step 2: Identifying the image by matching the input image with the images in the chosen gallery to take a suitable image.

In detail, LBP-based method in section 2.1 extract feature vectors of input image and all images in chosen gallery (by linking all LBP histograms of cells together, called Concatenated LBP histogram (CLBP), as a feature vector of the face image).

The association of Optimal Weight Set and Chi-square measurement is used to match input feature vector with other feature vectors to get its label. Section 2.2 presents proposed Heuristic approach for computing Optimal Weight Set. Figure 1 in section 1 illustrates the second step.

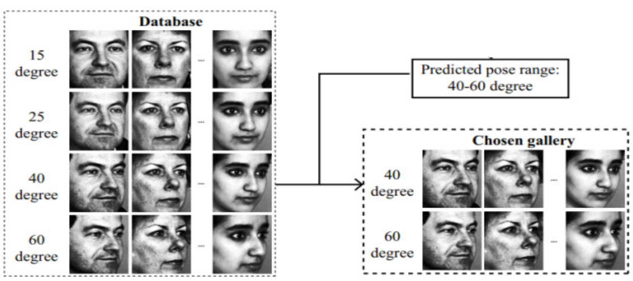

Figure 9. An example of choosing a suitable gallery set.

4. Experiment Results

Database: The frontal and profile images from FERET database[15] are used for our experiment. It includes 14051 face images (many subsets based on their conditions).

4.1 Accuracy of HWS Algorithms

According to FERET Tests in September 1996, some frontal images subset was generated, all changes of non-Gallery (we can name it Probe) images is compared to those one in the Gallery set: (the Gallery includes 1196 single images of all subjects; FAFB includes 1195 images with changes in face expression; FAFC includes 194 images captured in difference illumination; DUP1 includes 722 images taken between 0 to 1031 days later and DUP2 includes 234 images captured at least 18 months later (subset of DUP1)). For experiments, Gallery set of FERET database is used as Gallery set S_G of HWS algorithm. Training set S_{Tr} and testing set S_{Ts} is generated by cross-validation k-fold method with k = 2 for each FERET's Probe set. The final result of a certain Probe set is an average of experiments on that image set.

Table 1. Boosting performance ability of HWS algorithm in comparison with original approaches

Methods	FAFB	FAFC	DUP1	DUP2
LBP16	93.0	51.0	61.0	
LBP + Ahonen16	97.0	79.0	66.0	50.0
LBP + HWS	98.33	84.07	67.88	71.90

Result: We made some experiments using HWS algorithm to find an optimal weight set for the LBP descriptor. Performances of the same descriptor use the same parameters (Table 1 shows the feasibility of the HWS and LBP combination).

4.2 Experiments of Local Binary Patterns and HWS for Profile Face Recognition

160 images of 20 subjects from FRVT 2000 Tests May 2000 are chosen to make a gallery set for pose estimation. We divide the other images into the gallery and testing set.

Table 2. The results in predicting the exact value of rotation angle

		Predicted Rotation Angle			
		15	**25**	**40**	**60**
True Angle	15	1.0	0	0	0
	25	0.2	0.8	0	0
	40	0	0.25	0.75	0
	60	0	0	0.15	0.85

Result: (i) Pose Prediction: Table 2 shows the results in predicting poses of profile images using LBP + HWS.

(ii) Profile Face Recognition: We compare our method with other methods in Table 3. The results in this table show that our method having performance better than others.

Table 3. Performance of pose estimation in profile face recognition

Method	Number of Subjects	Poses	Performance
Eigenfaces[3]	100	9 poses within 40 degree in yaw	39.40
KPDA[3]	200	7 poses: 0, 15, 25 and 45 degree in yaw	44.32
Proposed framework	**180**	**2 poses ranges: 15-25 and 40-60 degree**	**87.22**

5 Conclusions

In this paper, we propose a LBP-based profile face recognizer for identifying a query face image. To create this profile face recognizer, two methods are proposed: 1. A robust heuristic approach for improving the weight set of LBP face recognizers is proposed. The method uses hill climbing technique with our proposed heuristic so that the local maxima can be avoided. It is potential that our method can be combined with other variants of LBP feature extraction to improve their accuracy; 2. A method for recognize a profile face image is proposed. The pose range of input image was predicted to choose the proper gallery set. This gallery set will help to reduce time matching between input image and database images, and error propagation when pose prediction returns false results. The performance of our methods was evaluated with the public database FERET. The experimental results showed the feasibility of our proposed models.

6. References

1. Tana X, Chena S, Zhou Z, Zhang F. Face recognition from a single image per person: A survey. Pattern Recognition. 2006; 39:1725–45.
2. Zhao W, Chellappa R, Phillips PJ, Rosenfeld A. Face Recognition: A Literature Survey. Association for Computing Machinery Computing Surveys. 2003; 35:399–458.
3. Zhang X, Gao Y. Face recognition across pose: A review. Pattern Recognition. 2009; 42(11):2876–96.
4. Belhumeur PN, Hespanha JP, Kriegman DJ. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1997; 19:711–20.
5. Jelsovka D, Hudec R, Breznan M. Face recognition on FERET face database using LDA and CCA methods. Telecommunications and Signal Processing. 2011; 34:570–4.
6. Guo G, Li SZ, Chan K. Face recognition by support vector machines. Fourth IEEE International Conference; 2000. p. 196–201.
7. Pietikainen M, Hadid A, Zhao G, Ahonen T. LBP in Different Applications. Computational Imaging and Vision. 2011; 40:193–204.
8. Fernandez A, Ghita O, Gonzalez E, Bianconi F, Whelan PF. Evaluation of ro-bustness against rotation of Local Binary Pattern, Coordinated Clusters Representation and Improved Local Binary Pattern features in granite texture classification. Machine Vision and Applications. 2011; 22:913–26.
9. Shan C, Gong S, McOwan PW. Facial expression recognition based on Local Binary Patterns: A comprehensive study. Image and Vision Computing. 2009; 27:803–16.
10. Shan C. Learning local binary patterns for gender classification on real-world face images. Pattern Recognition Letters. 2012; 33:431–7.
11. Moore S, Bowden R. Local binary patterns for multi-view facial expression recognition. Computer Vision and Image Understanding. 2011; 115(4):541–58.
12. Ojala T, Pietikainen M, Harwood D. A comparative study of texture measures with classification based on featured distributions. Pattern Recognition. 1996; 29:51–9.
13. Ahonen T, Hadid A, Pietikainen M. Face description with local binary patterns: Application to face recognition. Pattern Analysis and Machine Intelligence. 2004; 28:2037–41.
14. Nguyen NH, Le TH. Pose estimation using Local Binary Patterns for face recognition. Proceedings of CSOC 2015; Spinger; 2015. p. 39–50.
15. Phillips PJ, Moon H, Rizvi SA, Rauss PJ. The feret evaluation methodology for face-recognition algorithms. IEEE Transactions of Pattern Analysis and Machine Intelligence. 2000; 22(10):1090–104.
16. Ahonen T, Hadid A, Pietikainen M. Face description with local binary patterns: Application to face recognition. IEEE Transactions of Pattern Analysis and Machine Intelligence. 2006; 28(12):2037–41.