1DLBP and PCA for Face Recognition

Amir Benzaoui
Laboratory of Inverses Problems, Modeling, Information and Systems (PI:MIS)
Department of Electronics and Telecommunications
University of 08 Mai 1945- Guelma -, Algeria
benzaoui.amir@univ-guelma.dz

Abdelhani Boukrouche
Laboratory of Inverses Problems, Modeling, Information and Systems (PI:MIS)
Department of Electronics and Telecommunications
University of 08 Mai 1945- Guelma -, Algeria
boukrouche.abdelhani@univ-guelma.dz

***Abstract*—A new algorithm for face recognition is proposed in this work, this algorithm is mainly based on LBP texture analysis in one dimensional space *1DLBP* and Principal Component Analysis *PCA* as a technique for dimensionalities reduction. The extraction of the face's features is inspired from the principal that the human visual system combines between local and global features to differentiate between people. Starting from this assumption, the facial image is decomposed into several blocks with different resolution, and each decomposed block is projected in one dimensional space. Next, the proposed descriptor *1DLBP* is applied for each projected block. Then, the resulting vectors will be concatenated in one global vector. Finley, Principal Component Analysis is used to reduce the dimensionalities of the global vectors and to keep only the pertinent information for each person. The experimental results applied on AR database have showed that the proposed descriptor *1DLBP* combined with *PCA* have given a very significant improvement at the recognition rate and the false alarm rate compared with other methods of face recognition, and a good effectiveness against to deferent external factors as: illumination, rotations and noise.**

Keywords— face recognition; local binary pattern (LBP); local binary pattern in one dimensional space (1DLBP); texture description; dimesionalities reduction, Principal Compenent Analysis (PCA).

I. INTRODUCTION

The automatic analysis of the human face has become recently an active research area in the artificial vision and patterns recognition domains, due to its important use in several applications such as: electronic election, biometrics and video surveillance. Face analysis includes: face detection and tracking, face recognition, age and gender recognition, emotion recognition…Human face is dynamic entity which changes under the influence of several factors as: pose, size, occlusion, background complexity, lighting and the presence of some components such as mustaches, beard and glasses. So, the essential key for any face analysis problem is: How to find an efficient descriptor to represent and to model the face in a real context??

The crucial step in any problem of face analysis is the phase of features extraction. In this phase, there are two major approaches: local and global approaches. Global approaches are based on pixel information; all pixels of the facial image are treated as a single vector, the vector size is the total number of the image pixels [1]. Most methods of this approach use another space of representation (subspace) to reduce the number of pixels and to eliminate the redundancies. Principal Component Analysis (PCA) [2] and Linear Discernment Analysis (LDA) [3] are the most popular methods used to reduce the dimensions and to select the useful information. However, these approaches are not effective in the unconstrained cases i.e. situation where occlusion, lighting, pose and size of the face are uncontrolled.

Recently, the scientists concentrate on local approaches, which are considered as a robust approaches in the unconstrained cases compared with global approaches; in this case, the face analysis is given by the individual description of its parts and their relationships, this model corresponds to the manner of perception by the visual human system. The methods of this approach are based on the extraction of features from the facial image and the definition of an adequate model to represent the face [4]. Several methods and strategies have been proposed to model and classify faces essentially based on the texture, normalized distances, angles and relations between eyes, mouth, nose and edge of the face. Local Binary Pattern (LBP) [5], Local Gabor Binary Pattern (LGBP) [6] and Oriented Edge Magnitudes (POEM) [7] are the recent methods in this approach.

Psychological and neuroscience studies have showed that the human visual system combines between local and global features to differentiate between people [8]. LBP is the best descriptor for capturing the local features, but it is not performed in the description of the global features [5]. From these assumptions, we have proposed in this work a new feature extraction method based on a descriptor proposed in [9,10,11]. Called: 1DLBP (*Local Binary Pattern in One Dimensional Space*), inspired from classical LBP. The proposed method, which is applied on face recognition, is characterized by the combination of the local and global features for modeling faces. The algorithm of extraction is decomposed into five principal stages; first, the input image is decomposed into several blocks with different resolutions. A vertical projection in one dimensional space is applied for each decomposed block. Next, the proposed descriptor 1DLBP is applied on each projected block. Then, the resulting vectors from each block are concatenated in one global vector.

978-1-4799-1153-0/13/$26.00 ©2013 IEEE

Finally, Principal Component Analysis (PCA) is needed to regroup the global vectors, to reduce the dimensionalities and to keep only the useful information for each individual.

This paper is organized as follows: in the next section, we describe the classical LBP and histogram feature. In the section 3, the proposed algorithm of feature extraction for face recognition is presented. For this purpose, *Hamming distance* is required to measure similarities between face templates. In the section 4, we present our experimental results by applying the proposed algorithm on AR database. Finally, a conclusion related to this work is given in section 5.

II. LOCAL BINARY PATTERN (LBP)

The original LBP operator introduced by *Ojala et al* [12], which has been used for texture discrimination, has shown a powerful and effective results against to the variations in rotation and illumination. The operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the center value and considering the result as a binary code [13, 14]. Next, the histogram of the labels can be used as a texture descriptor (see fig.1).

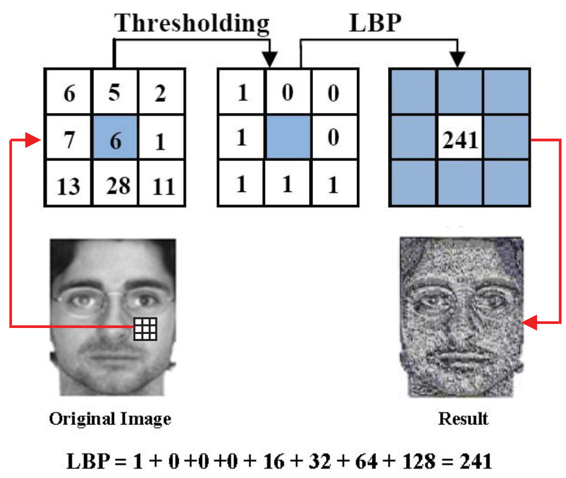

Figure 1. LBP calculation performed into 3×3 neighborhood.

When given a pixel $g_c(x_c,y_c)$ from gray image, its texture LBP is calculated by comparing g_c with its neighbors pixels P on a circle of radius R (see fig.2 for more details on circular neighborhood). The value of LBP(g_c) is obtained as [13,14]:

$$LBP^{P,R}(x_c, y_c) = \sum_{i=1}^{P} S(g_i^{P,R} - g_c)\, 2^{i-1} \qquad (01)$$

$$S(x) \text{ is defined as: } S(x) = \begin{cases} 1 & if\ x \geq 0; \\ 0 & otherwise; \end{cases} \qquad (02)$$

The major disadvantage of the original LBP operator resides in the size of the descriptor, a mask of 3×3 pixels can't capture the structures of large scale which can considered as a dominants structures in the image. Recently, the size of the operator has been extended by using a mask with different large sizes. Figures fig.2. (a), (b), (c) show three examples of the extended LBP.

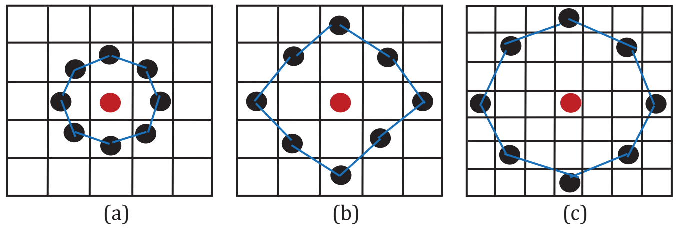

Figure 2. Neighborhood set for different (P,R). (a) The basic LBP operator (P,R) = (8,1) (b) LBP with circular neighborhood (8,2). (c) LBP with circular neighborhood (8,3).

Another type of the extended operators of LBP called: **Elliptical Local Binary Patterns (ELBP)** [15]. In ELBP, at each pixel $g_c(x_c,y_c)$, we consider its surrounding pixels that lie on an ellipse (see fig.3) with (x_c,y_c) is the center. ELBP of (x_c, y_c) with P neighboring pixels at (R1, R2) distances is computed as:

$$ELBP^{P,R1,R2}(x_c, y_c) = \sum_{i=1}^{P} S(g_i^{P,R1,R2} - g_c)\, 2^{i-1} \qquad (03)$$

S(x) function is defined as (2).

In details, the coordinates of the i th neighboring pixel of (x_c,y_c) is calculated using the formulas:

$$angle\text{-}step = 2 * \pi / P \qquad (04)$$

$$x_i = x_c + R1 * \cos((i-1) * angle\text{-}step) \qquad (05)$$

$$y_i = y_c + R2 * \sin((i-1) * angle\text{-}step) \qquad (06)$$

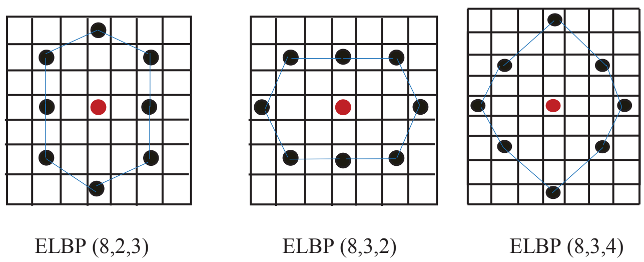

Figure 3. ELBP samples with different extention [15].

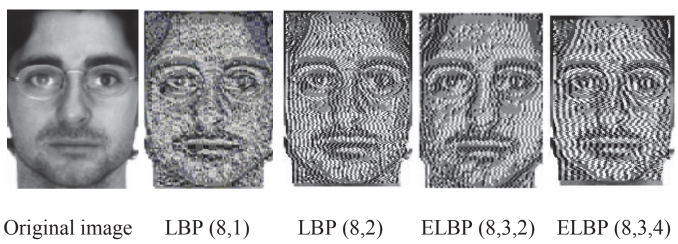

Figure 4. Results of LBPs application with differentd masks .

However, the extend versions of LBP operators and the Elliptical LBPs present a good results by capturing the local and global patterns but they are not performed for capturing the micro characteristics (fine details) of the human face. Figure fig.4 shows the rsults of LBP and ELBP applications using different masks.

III. Proposed Approach

The proposed algorithm used to extract information for face recognition is described in the following recapitulation; next we present each step in details. The process of features extraction is composed into six principal stages for each person:

- Preprocessing of the N training images.
- Decomposition of each image N_i into several blocks with different resolution.
- Projection of each block decomposed in 1D space.
- Application of the proposed descriptor 1DLBP for each projected block.
- Concatenation of the resulting vectors of an image N_i in one global vector V_i.
- Dimensionalities reduction of the grouped vectors using PCA.

A. Preprocessing

The objective of the preprocessing is the modification of the source's image representation to facilitate the task of the following steps and to improve the rate of recognition. First, the facial image is converted into grayscale image. Next, every grayscale image is filtered by median filter to suppress noise. Lastly, the noise suppression image is then adjusted to improve the contrast of the image [16].

B. Image decomposition

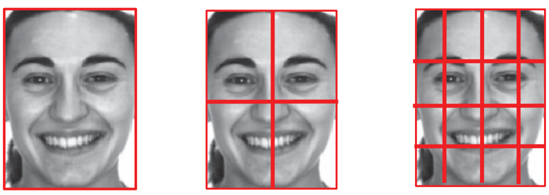

Figure 5. The decomposition of the image into differents blocks.

Most LBP operators characterize the face texture distribution of each pixel with its neighborhood only. But, the differences between two faces can be demonstrated not only by the texture distribution of each pixel with its neighborhood, but also by the relative connection with other pixels (correlation between pixels). With this intention, we have decomposed the original image into several sub-images with different size like presented in fig.5, to characterize better the details and the relationships between all the image's pixels. Next, the extracted histograms will be concatenated in one global vector in the next stages. With this technique, we can obtain the fine details and the relative connections between all pixels.

C. 1D vertical projection

The 1D projection of rows or columns of each level provides an effective mean to describe better the local and global patterns. Figure fig.6 presents an example of vertical projection. The objective of the projection is to validate the descriptor LBP in one dimensional space to find another mean for describing and analyzing better the human face's texture.

D. 1DLBP application

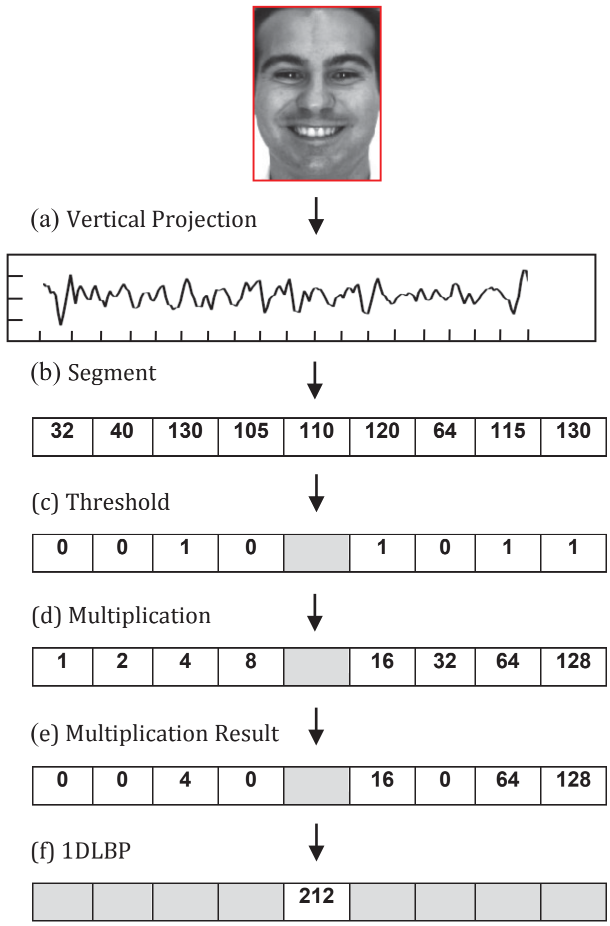

Figure 6. Example of vertical projection in 1D space + 1DLBP application.

The concept of the 1DLBP method consists in a binary code describing the local agitation of a segment in 1D signal. It is calculated by thresholding of the neighborhood values with the central value. All neighbors get the value **1** if they are greater or equal to the current element and **0** otherwise. Then, each element of the resulting vector is multiplied by a weight according to its position (see fig.6.e). Finally, the current element is replaced by the sum of the resulting vector. This can be recapitulated as follows:

$$1DLBP = \sum_{n=0}^{N-1} S(g_n - g_0).2^n \qquad (07)$$

S(x) function is defined as (2).

g_0 and g_n are respectively the values of the central element and its 1D neighbors. The index ***n*** increases from the left to the right in the 1D string as shown in fig.6 (e). The 1DLBP descriptor is defined by the histogram of the 1D pattern.

E. Concatenation of the resulting vectors

The proposed descriptor 1DLBP is applied on all blocks of the decomposed image with the different resolution presented in fig.5. The extracted histograms from each block are concatenated in one global histogram (vector) representing one face image V_i. A problem of information redundancies is appeared due to the important size of each global vector. To resolve this problem, we have used the Principal Component Analysis (PCA) as a technique of dimensionalities reduction, to regroup all the training vectors of the same person in one global matrix and to select the useful information needed to modeling each person.

F. Dimensionalities reduction with PCA

The principal idea of PCA is to represent a group of images (vectors) of a same person X in another space of lower dimension; this space is constructed from a set of training images. PCA begins with a set of 1D training vectors of the same class; each vector Γ_i represents a training image I_i (I = 1...N), and construct $O_i = \Gamma_i - \acute{\Gamma}$ where $\acute{\Gamma}$ represents the mean vector of all Γ_i vectors. Then, determinate the eigenvectors μ_i of the covariance matrix $C = \sum_i O_i \times O_i^T$. The first K "Principal axis" corresponds to the K largest eigen values (the value of K is chosen in the same that the sum of the first axis K provides a large proportion of the total eigen values sum).

Now, given a new image ξ considered as a test example. First, we built its 1D representation using the extraction method proposed in this work (stages: 1-5), and we subtract the average face as follows: $\theta = \xi_{1D} - \acute{\Gamma}$. Next, we project the image in the principal axis elaborated as: $\theta_p = \sum_{i=1,K} \mu_i^T.\theta.\mu_i$. Finlay, we calculate the Hamming Distance (HD) to classify the image ξ in the nearest class corresponding to a degree of similarities that exceeds a fixed threshold. Hamming Distance formula is given as:

$$HD\,(X, Y) = \frac{1}{M} \sum_{i=0}^{M} Xi(XOR)Yi \qquad (08)$$

IV. EXPERIMENTAL RESULTS

To evaluate the effectiveness of our facial representation for unconstrained settings, we conducted extensive experiments following the guidelines of the AR database and we have compared the obtained results (identification and false alarm rates) with other methods based on classical LBP. The AR database was collected at the Computer Vision Center in Barcelona, Spain in 1998 [17]. It contains images of 116 individuals (63 men and 53 women). The imaging and recording conditions (camera parameters, illumination setting, and camera distance) were carefully controlled and constantly recalibrated to ensure that settings are identical across subjects. The resulting RGB color images are 768×576 pixels in size. The subjects were recorded twice at a 2–week interval [17]. During each session 13 conditions with varying facial expressions, illumination and occlusion were captured (fig.7).

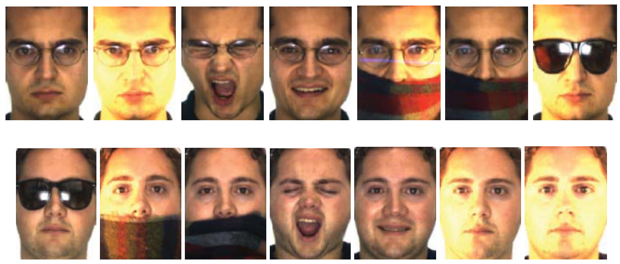

Figure 7. Some images from AR database [17].

A half of samples (200 images, 13 for each person) are selected to create the training set and the remaining samples as the testing set. The proposed approach have been evaluated with all possible probabilities and the mean rate of the possible selection have taken in consideration. The results of different algorithms primary based on LBP operator, applied on AR database, are presented in figures fig.8 and fig.9.

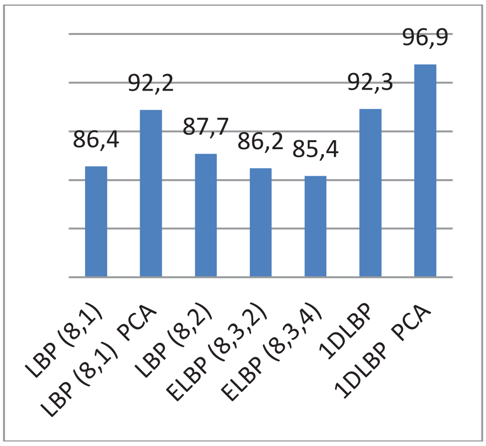

Figure 8. Rates of Recognition applied on AR database %.

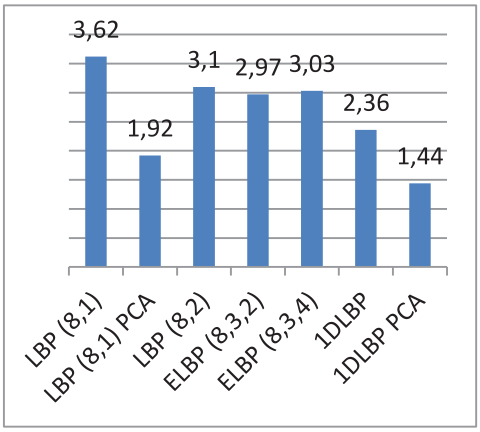

Figure 9. Falses Alarm Rates applied on AR database %.

The proposed descriptor 1DLBP combined with PCA have given a very good improvement and a significant results in recognition rate, false alarm rate and an important effectiveness against to the variations in different factors like as: occlusion, lighting, rotation and noise. Fig.8 and fig.9 indicate that we have obtained a maximum mean accuracy of identification rate around 96,9 and a minimun mean of false alarm rate around 1,44.

V. Conclusion

Facial image can be considered as a composition of local and global features. Starting from this assumption, we have successfully developed a new algorithm for texture face discrimination, this algorithm is primary based on Local Binary Patterns but projected in one dimensional space; it combines between local and global features, capable of recognizing faces in different situations. Each facial image is decomposed on multi blocks with different resolution and each decomposed block will be vertically projected in one dimensional space. Next, the proposed descriptor *1DLBP* is applied on each projected block. Then, the extracted vectors from each block will be concatenated in one global vector. Finally, Principal Component Analysis (PCA) is applied on the regrouped vectors to reduce the dimensionalities of the concatenated vectors and to extract the useful information. The experimental results applied on AR database have showed that the feature extraction method based on 1DLBP and PCA have given a very significant improvement at the recognition rate, false alarm rate and a good effectiveness against to deferent external factors as: occlusion, illumination, rotations and noise.

Acknowledgment

This work has been supported by the PI:MIS Laboratory, 08 MAI 1945 University, Guelma, Algeria, which is gratefully acknowledged. The authors would like to thank the reviewers for helpful comments.

References

[1] R.S. Kathavarayan and M. Karuppasamy, “Identification of Untrained Facial Image in Combined Global and Local Preserving Feature Space,” International Journal of Biometrics and Bioinformatics (IJBB), Vol.04, No.01, pp.1-12, March 2010.

[2] Matthew Turk and Alex Pentland, “Eigenfaces for recognition,” Journal of Cognitive Neuroscience, Vol.03, No.01, pp.71-86, 1991.

[3] P.N. Belhumeur, J.P Hespanha and D.J. Kriegman, “Eigenfaces vs Fisherfaces: Recognition using class specific linear projection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No.07, pp.711-720, July 1997.

[4] T. Ahonen, A. Hadid and M. Pietikainen, “Face Description with Local Binary Pattern: Application to Face Recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.28, No.12, pp.2037-2041, 2006.

[5] T. Ahonen, A. Hadid and M. Pietikainen. “Face Recognition with Local Binary Pattern,” Springer: Proceeding of the 8th European Conference on Computer Vision (ECCV), Vol.3021, No.01, pp.469-481, Prague, Czech Republic, May 11-14, 2004.

[6] Hieu V. Nguyen, Li Bai and Linlin Shen. “Local Gabor Binary Pattern whitened PCA: A novel approach for face recognition from single image per person,” Springer: Proceeding of the 3rd IAPR/IEEE International Conference on Biometrics (ICB), Vol.5558, pp.269-278, Alghero, Italy, June 2-5, 2009.

[7] N.S Vu and A. Caplier. “Face recognition with patterns of oriented edge magnitudes,” Springer: Proceeding of the 11th European Conference on Computer Vision (ECCV), Vol.6311, No.01, pp.313-326, Heraklion Crete, Greece, September 5-11, 2010.

[8] Alice J. O'Toole, Dana A. Roark and Hervé Abdi. “Recognizing moving faces: A psychological and neural synthesis,” Trends in Cognitive Science, Vol.06, No.06, pp.261-266, June 2002.

[9] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche and E. Lespessailes. “Trabecular Bone Anisotropy Characterisation Using 1D Local Binary Patterns,” Springer: Proceeding of the 12th Conference on Advanced Concepts for Intelligent Vision Systems (ACIVS), Vol.6474, No.01, pp.105-113, Sydney, Australia, December 13-16, 2010.

[10] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche and E. Lespessailes. “Trabecular Bone Texture Classification Using 1DLBP and Wavelets Coefficients in High-pass Bands,” Proceeding of the International Conference on Signal, Image, Vision and their Application (SIVA), pp.116-121, Guelma, Algeria, November 21-24, 2011.

[11] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche and E. Lespessailes. “Texture characterization using Local Binary Pattern and Wavelets. Application to Bone Radiograph,” Proceeding of the 3rd IEEE International Conference on Image Processing, Theory, Tools and Applications (IPTA), pp.371-367, Istanbul, Turkey, October 15-18, 2012.

[12] T. Ojala, M. Pietikainen and D. Harwood. “A comparative study of texture measures with classification based on featured distribution,” Elsevier: Pattern Recognition, Vol.29, No.01, pp.51-59, January 1996.

[13] Juha Ylioinas, Abdenour Hadid and Matti Pietikainen. “Age Classification in Unconstrained Conditions Using LBP Variants,” Proceeding of the 21st IEEE International Conference on Pattern Recognition (ICPR), pp.1257-1260, Tsukuba, Japan, November 11-15, 2012.

[14] Jukka Maatta, Abdenour Hadid and Matti Pietikainen. “Face Spoofing Detection from Single Images Using Micro-Texture Analysis,” Proceeding of the IEEE International Joint Conference on Biometrics (IJCB), pp.01-07, Washington, USA, October 11-13, 2012.

[15] H.T. Nguyen, N.S. Vu, A. Caplier. “How far we can improve micro features based face recognition systems?,” Proceeding of the 3rd IEEE International Conference on Image Processing, Theory, Tools and Applications (IPTA), pp.350-353, Istanbul, Turkey, October 15-18, 2012.

[16] Amir Benzaoui and Hayet Farida Merouani. “Hybrid System for Automatic Faces Detection,” Journal of Electronic Science and Technology (JEST), Vol.10, No.02, pp.167-172, June 2012.

[17] A.M. Martinez and R. Benavente. “The AR face database”, CVC Technical Report, 24, 1998.