International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 04 Issue: 06 | June -2017 www.irjet.net p-ISSN: 2395-0072

Local Descriptor based Face Recognition System

Rashmi P[1], Shifana Begaum[2], B R Kishore[3]

[1] *Post Graduate student, Dept of CSE, Srinivas School of Engineering, Mukka, Mangalore, Karnataka, India*
[2] *Assistant Professor, Dept of CSE, Srinivas School of Engineering, Mukka, Mangalore, Karnataka, India*
[3] *HOD, Dept of CSE, Srinivas School of Engineering, Mukka, Mangalore, Karnataka, India*

---***---

Abstract – *The human face conveys a lot of information about emotion and identity of an individual. Recognizing facial expression automatically is an impressive and demanding problem, which affects necessary applications in various fields such as authentication for banking and security system access, personal identification among others to name a few. From the existing Local Binary Pattern (LBP) operator and its types, it is difficult to handle all the properties like scale, robustness, the length of feature histogram and discriminative ability. This paper proposes a method called Asymmetric Region Local Binary Pattern (AR-LBP) operator along with Principal Component Analysis (PCA) technique for facial expression recognition. The AR-LBP operator includes the properties of LBP, Extended LBP(ELBP) and Multi-scale Block LBP(MB-LBP) and reduces the disadvantages of these three operators in terms of scale, the length of feature histograms and discriminative ability of the operator. In the experiments, a face image is first divided into small regions from which AR-LBP histograms are extracted and then concatenated into a single feature vector. The proposed operator was evaluated on ORL, JAFFE and INDIAN FACE benchmark face recognition datasets and accuracy of 96.43%, 97.14% and 86.67% respectively were achieved. The results are evaluated using several similarity metrics viz: Mahalanobis Cosine distance, Euclidean distance and City Block distance to verify the robustness of the system and observed that Mahalanobis Cosine distance performs better compared to other two datasets. Experiments were carried out by varying grids size and operator sizes.*

***Key Words*: Asymmetric Region Local Binary Pattern, Principal Component Analysis, Feature extraction, Face Classification, Facial expression Recognition;**

1. INTRODUCTION

Facial expression plays an important role in individual's conversation as a natural, powerful and effective medium of face to face interaction. Facial expression recognition by a computer system is an useful and powerful application of image analysis. Biometric-based methods are employed today in many applications like Human Computer Interaction (HCI), Human-Robot Interaction (HRI), prevent unauthorized access to ATM's, criminal identification, security systems and animation. A biometric system operates in two modes, such as identification mode (1:N matching) or verification mode(1:1 matching).

The aim of face recognition system outputs satisfying performance under controlled environment and it will reduce gradually with real world scenarios. The real world scenarios have challenges such as large dimensionality, illumination variations, facial expressions, pose variations, occlusions, facial accessories and aging effects. It is also recommended to consider intra class variance and inter class variance of individual face images for better recognition rate. This paper proposes a facial expression recognition using AR-LBP operator.

Local Binary Pattern (LBP) is a parametric independent visual descriptor used for texture classification. LBP and its various types are implemented for still images and video sequences in the case of facial expression analysis. Many studies will consider visual face data for facial expression analysis and classify the given input expressions in seven states viz. fear, anger, surprise, happy, disgust, sad and neutral. Girish et al. [1] conducted experiment using MBLBP with PCA feature extraction technique and obtained recognition rate of 91.79% on ORL dataset for 3 X 3 operator scale. They again conducted the same experiment on INDIAN FACE dataset with 9 X 9 operator scale and achieved recognition rate of 85.71%. Shirinivas et al. [2] conducted experiment using AR-LBP with SVN feature extraction technique and obtained recognition rate of 84.29% on JAFFE dataset for 3 X 3 operator scale. They again conducted the same experiment on FGNET dataset with 3 X 3 and 15 X 9 operator scale and achieved recognition rate of 71.6% and 79.46% respectively. PCA is the most successfully used technique for image analysis and it is considered as baseline method for face recognition. PCA is less sensitive to different datasets compared to other holistic methods [4], hence it is widely used technique in the area of face recognition. Turk et al. [5] conducted an experiment on PCA using datasets of 2500 images of 16 subjects along with 3 different head scales, 3 different head orientations and 3 lighting conditions and achieved 96%, 85% and 64% recognition rates for lighting, head orientation and head scale variation. Ahonen et al. [6] conducted an experiment on PCA feature extraction with Mahalanobis Cosine distance similarity metric and reported 65%, 85%, 44%, 22% on fc, fb, dup-I, dup-II FERET datasets.

This paper describes Asymmetric Region Local Binary Pattern (AR-LBP) method together with Principal Component Analysis (PCA) feature extraction technique to yield better recognition rate. AR-LBP is scalable and can capture dominant features such as micro and macro images at larger scale. Experiments were conducted on the datasets having pose variation, facial expression and variation images and evaluate the result using different similarity metrics such as Mahalanobis Cosine distance, Euclidean distance and City Block distance.

2. SYSTEM DESIGN

Automatic detection and identification of human face is carried out by computer based security systems called as Face recognition systems. The general components of automatic face recognition system are face detection, face localization/ normalization, feature extraction and classification (verification or identification) as shown in the Fig - 2.1. There is no particular and strict order in each component. Depending upon the application need, these components may overlap. For example, face localization may overlap with face detection or feature extraction component.

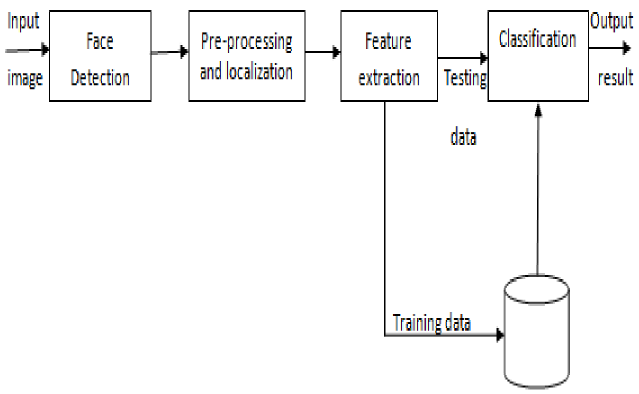

Fig- 2.1: General components of Face recognition system

For non automatic face recognition system, face detection and face normalization components could be ignored and in such case face normalization could be manually done using tools for creating training and test data.

In Face detection, system will find all the face images regardless of their pose, scale, position, illumination, occlusions and facial expression. Face can be detected in color, single image or video sequence, here single image per frame is taken. Face detection can also be defined as determining presence of one or more face images which are unknown prior. Facial feature detection is to detect the presence and exact location of facial features like eyes, nose, mouth, eyebrows, nostrils, ears and lips in the face image.

Face localization is preprocessing process of face image alignment, illumination normalization and pose correction, etc. These variations gradually decrease the performance of face recognition system and it would increase the intra class variations than inter class variations. One way of solving this task is face localization or normalization.

Feature extraction is similar to reduction of image dimensionality. Whenever the input face image is too large to practice in the algorithm, and it is identified as unnecessary then it can be transferred and reduced into a set of features. The reduced set of features should contain all the necessary information from the input data so that the expected task can be performed by considering reduced features instead of the complete initial data. The redundant data in the input might affect the classification. Hence feature extraction technique plays an important role in face recognition.

Classification process is categorized into two modes of actions such as Verification and Identification. In the case of identification mode, subjects face images are obtained during the registration process and these face images are trained by the system. A face template is learned for each subject and stored in trained data. Matching task is done between a probe image and each face template in the trained data. The result may be a score or a distance telling the comparability between the person probe image and the person label. The system will assign label to the probed image which is identical to the face template of the trained data. In the case of verification mode of identity, similarity matching is conducted between the templates of the claimed label and the probe image. The person's individual template is used to compare and verify the claim.

3. IMPLEMENTATION

There are various feature extraction techniques used with LBP method for face recognition. This paper describes AR-LBP operator with PCA feature extraction techniques for facial expression recognition. PCA is an example for global descriptors or Holistic method where as AR-LBP is an example for local descriptors.

3.1 Principal Component Analysis

PCA method is used for searching data patterns which is having higher dimensionality and it is also used for trimming the number of variables in facial expression recognition. Karl Pearson invented PCA in the year 1901. Using PCA method, the original data with higher dimensionality is transformed into new coordinate system with lesser dimensionality.

This can be achieved by finding the values of eigenvalues and eigenvectors of covariance matrix of the original data. The covariance matrix indicates the change in dimensions from the mean with respect to each other. The eigenvectors having largest eigenvalues are the principal component of analysis and they consist of most information. Original data set is multiplied with the few eigenvectors to produce new data set with less dimensions.

Various applications of PCA are data reduction, object recognition, object prediction, feature extraction and data compression to name a few. In PCA method, new image in the eigenface subspace is recognized and then the subject is classified based on the location in eigenface subspace and known individual. The PCA approach is preferred because of its speed and simplicity.

3.2 Asymmetric Region Local Binary Pattern (AR-LBP) operator

LBP operator is used to describe the shape and texture of gray scale image. LBP is binary code of image pixel which tells something about the local surrounding area of that image pixel. However, the LBP operator takes more time for computation with respect to operator size and grid size. LBP operator and its various types are unable to describing face images independently with respect to operator size, robustness, discriminative ability and length of feature histogram.

The main drawback of original LBP operator is it cannot capture dominant features and hence it is not recommended for larger dimension facial analysis. An Elongated LBP (ELBP) operator was proposed to solve this problem. Its oblique surrounding is stated by two terms say P and R. Where P represents the number of pixels that are to be considered for evaluation in the circle of radius R around the center pixel. The length of feature histogram is directly proportional to the value of P. Whereas MB-LBP operator deal with average intensity values of surrounding regions. MBLBP method is scalable and produces constant histogram bins as it is independent of operator size. The average grey values are calculated using either summed area table or integral image.

The recommended AR-LBP operator solves all the problems related to scalability, discriminative ability and the length of feature histogram. Rounded average intensity values of different sized sub regions around a pixel to be labeled are considered by AR-LBP. The AR-LBP operator can capture both micro and macro features of image at larger scale and the length of the feature histogram bins is directly proportional to the number of sub regions. As compared to ELBP, the number of histogram bins derived from the sub regions is constant in AR-LBP. AR-LBP supports neighboring regions of different sizes and hence scale down the loss of feature information. As compared to MBLBP, the discriminative ability of the operator is increased by calculating the average pixel intensities for different sized sub regions.

The following Fig - 3.1 (a) depicts AR-LBP operator with nine regions in which eight regions viz. R1 to R8 are labeled and the center region is not labeled. The regions R1, R3, R5 and R7 are non colored and their sizes vary in both vertical and horizontal directions. The size of regions with color such as R2 and R6 vary in vertical direction and R4 and R8 in horizontal directions. The center region size remains constant to the modifications in neighboring regions. The operator size varies with size of regions.

An AR-LBP operator with size (2n+1) x (2m+1) contains 4 n x m, 2 1 x m, 2 n x 1 and one 1x1 rectangular sized regions where n represents width and m represents the height of the region. The AR-LBP operator size variations are not identical to that of MBLBP which yields asymmetry and hence, the name Asymmetric Region Local Pattern. When both m and n are equal to 1, AR-LBP operator is same as basic LBP operator.

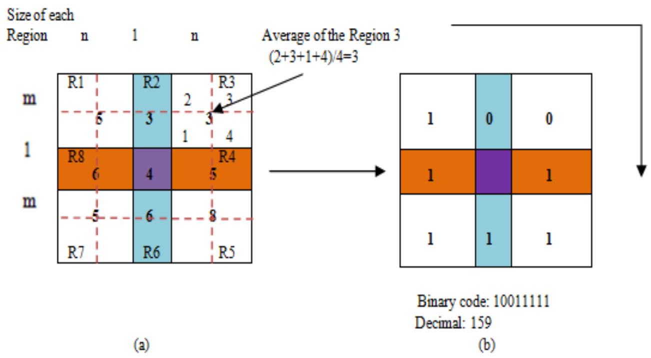

Fig - 3.1 (a): 5 x 5 size AR- LBP operator along with average of that region at the center of each regions. (b) Threshold AR-LBP code for the center pixel 3 in (a).

Given a pixel at location (xc, yc) of the face image. The AR-LBP code can be represented in decimal form as follows:

$$\text{AR-LBP}(x_c, y_c) = \sum_{i=1}^{8} s(a_i - a_c)2^{i-1} \quad (1)$$

Where, a_i represents the average grey values of surrounding region Ri, (i takes values 1,2,3,4,5,6,7,8) and ac represents the center region. The function s(x) for AR-LBP is described as:

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (2)$$

A face image with AR-LBP label describes both micro and macro features. The histogram obtained on the entire face represents only micro and macro information but the spatial information is not represented. The face image is break down into sub regions and concatenated to form feature histogram of face image. The derived feature histogram depicts both local and global shape of face image as shown in Fig – 3.2.

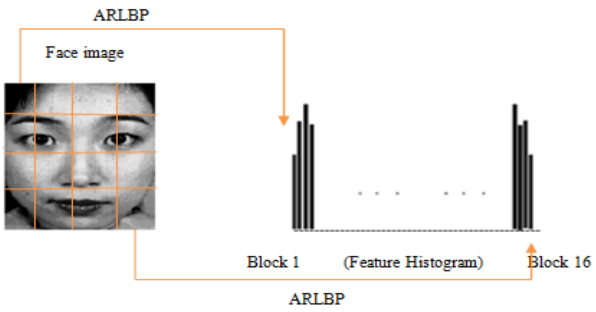

Fig - 3.2: A feature histogram for AR-LBP

4. EXPERIMENTS AND RESULTS

The proposed AR-LBP feature extraction for face recognition was tested and trained by considering three different datasets namely, ORL, JAFFE and INDIAN FACE. No particular selection procedure is considered for choosing the images of individual faces. The training and testing images of datasets are dependent on person and there exist an similarity between the train and test images of subject and facial expression.

The face image is cropped to the size of 64 x 64-pixel and is divided into 16 sub regions of size 16 x 16 pixels. Each sub-region produces 256 bin length histogram and combined histogram of length 16 * 256 was produced as the facial expression image. The AR-LBP operator size is independent of sub regions size and the cropped image size. The feature histogram will always be of length 4096.

PCA feature extraction technique is preferred for reduction of dimensionality of face image of individual person. Experiments were evaluated using several similarity measures like Euclidean distance (Euc), Mahalanobis Cosine distance (MahCos) and City Block distance (CTB) during the verification phase of FRS.

4.1 Olivetti Research Laboratory (ORL) Dataset:

The ORL dataset consists of 40 different subjects and each subject contains 10 different face images. Experiments are conducted by using grayscale images of 92 x 112 pixels which are pre normalized. The following Fig - 4.1 depicts the sample face images from ORL dataset.

Fig - 4.1: Set of face images from ORL dataset

40 subjects with 10 images are considered for experiment. The results of PCA on ORL dataset with different similarity metrics is shown in below Fig - 4.2. From the figure it can be observed that recognition rate on MahCos is better than other metrics. The highest recognition rate achieved on ORL dataset with PCA and MahCos metric is 96.43% for 16 grids per image.

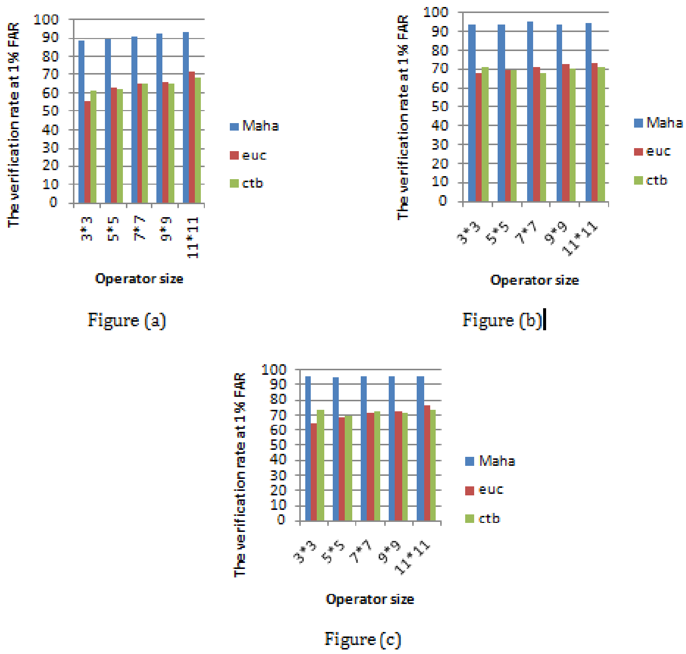

Fig - 4.2: Verification rate at 1% FAR of AR-LBP on ORL dataset with different similarity metrics and operator size. a) 4 grids per image b) 9 grids per image c) 16 grids per image

4.2 Japanese Female Facial Expression (JAFFE) Dataset:

The JAFFE dataset contains 213 face images of 10 Japanese female models. The example images contain 7 different facial expressions (like 6 basic facial expressions and 1 neutral). The following Fig - 4.3 depicts the sample face images from JAFFE dataset.

Fig - 4.3: Set of face images from JAFFE dataset

Experiment is conducted for 10 subjects with 10 images. The results of PCA on JAFFE dataset with different similarity metrics is shown in below Fig - 4.4, from the figure it can be observed that recognition rate on MahCos is better than other metrics. The highest recognition rate achieved on ORL dataset with PCA and MahCos metric is 97.17% for 16 grids per image.

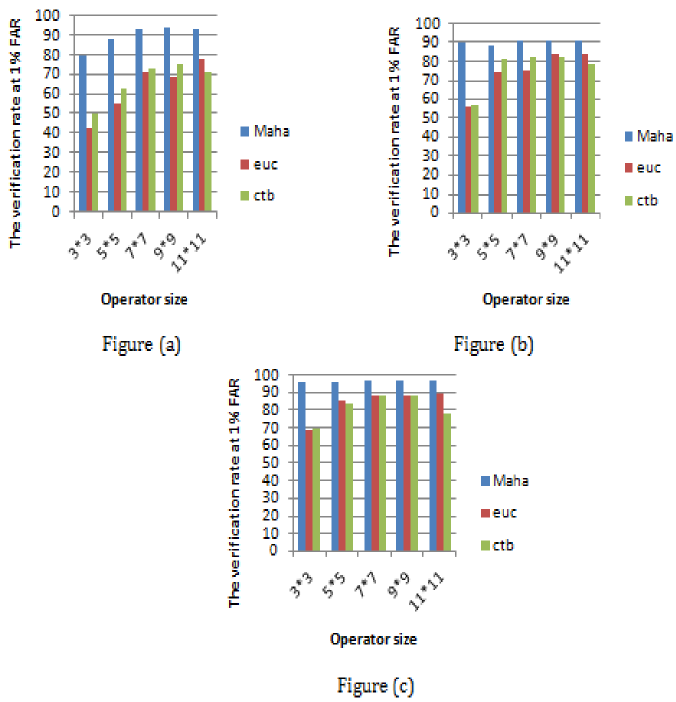

Fig - 4.4: Verification rate at 1% FAR of AR-LBP on JAFFE dataset with different similarity metrics and operator size. a) 4 grids per image b) 9 grids per image c) 16 grids per image

4.3 INDIAN Face dataset:

The INDIAN face dataset contains 10 different face images of 40 different subjects with 11 different pose variations. For each subject the following different poses are considered like looking left, looking front, looking right, looking up towards right, looking up towards left, looking down, in addition to the pose variation, following facial emotions are considered for experiment that is smile, neutral, sad/disgust and laughter. The following Fig - 4.5 depicts the set of facial images from INDIAN face dataset.

Fig - 4.5: Set of face images from INDIAN FACE dataset

40 subjects with 10 images are considered for experiment. The results of PCA on INDIAN FACE dataset with different similarity metrics is shown in below Fig - 4.6, From the figure it can be observed that recognition rate on MahCos is better than other metrics. The highest recognition rate achieved on ORL dataset with PCA and MahCos metric is 86.67% for 16 grids per image.

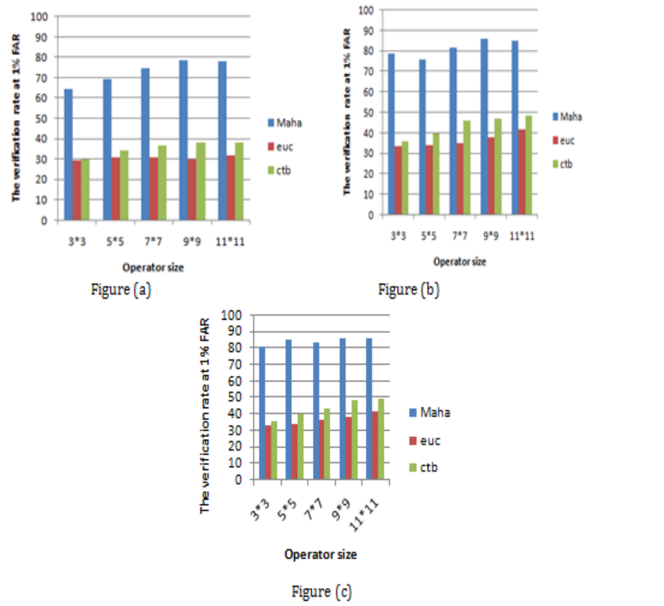

Fig - 4.6: Verification rate at 1% FAR of AR-LBP on INDIAN FACE dataset with different similarity metrics and operator size. a) 4 grids per image b) 9 grids per image c) 16 grids per image.

5. CONCLUSION

In this paper Facial expression recognition is done using an AR-LBP operator with PCA feature extraction technique. This method is preferred to differentiate both foreground and background images and achieve better recognition rate. The demerit of basic LBP method of recognizing micro and macro images are reduced by using AR-LBP method. Results show that the proposed method achieve better recognition rate than the one observed from previous survey. The proposed method explained here yields accuracy of 97.14% as compared to 95.71% reported on the JAFFE dataset [2]. The proposed method reduces the loss of feature information and also reduces the time required for computation. Here, the operator size is not depending upon the image size and sub region size. From the results it is observed that the recognition rate is directly proportional to the operator size and grid size. By using AR-LBP method we can achieve scalability, increase the discriminative ability of the operator and get constant histogram bins.

REFERENCES

[1] Girish G N, Shrinivasa Naika C. L. and P. K. Das, "Face recognition using MB-LBP and PCA: A comparative study," 2014 International Conference on Computer Communication and Informatics, Coimbatore, 2014, pp. 1-6.

[2] C. L. Shrinivasa Naika, P. K. Das and S. B. Nair, "Asymmetric region Local Binary Pattern operator for person-dependent facial expression recognition," 2012 International Conference on Computing, Communication and Applications, Dindigul, Tamilnadu, 2012, pp. 1-5.

[3] Julsing, B. K. "Face recognition with local binary patterns." Research No. SAS008-07, University of Twente, Department of Electrical Engineering, Mathematics & Computer Science (EEMCS) (2007).

[4] R. Jafri and H.R.Arabnia, "A survey of face recognition techniques." JIPS, vol.5,no.2,pp.41-68, 2009.

[5] M. Turk and A.Pentland, "Eigen faces for recognition," J. Cognitive Neuroscience, vol.3,no.1,pp. 71-86, January1991.

[6] T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in European Conference on Computer Vision-ECCV 2004. Springer, 2004, pp.469-481.

[7] C. H. Chan, J. Kittler, and K. Messer, "Multi-scale local binary pattern histograms for face recognition," in Proceedings of the international conference on Advances in Biometrics, ser.ICB'07.Berlin, Heidelberg:Springer-Verlag,2007,pp.809-818.

[8] T. Ahonen, A. Hadid and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp. 2037-2041, Dec. 2006

[9] T. MÄENPÄÄ, "The local binary pattern approach to texture analysis-extensions and applications." Oulun Yliopisto, Oulun, 2003

[10] G. Zhang, X. Huang, S. Li, Y. Wang and X. Wu, "Boosting Local Binary Pattern Based Face Recognition," Peking University, Center of Information Science, China, 2004.

[11] W. S. Yambor, B. A. Draper, J. Ross Beveridge, "Analyzing PCA-based face recognition algorithms: Eigenvector selection and distance measures," Computer Science Department, Colorado State University, 2000.

[12] S. Balakrishnama and A. Ganapathiraju. "Linear discriminant analysis - a brief tutorial," Institute for Signal and Information Processing, Department of Electrical and Computer Engineering, Mississippi University, Mississippi, 1998.

[13] O. Lahdenoja, M. Laiho and A. Paasio. "Reducing the feature vector length in local binary pattern based face recognition," University of Turku, Department of Information Technology, Finland, 2005.

[14] L.I. Smith, "A tutorial on Principal Component Analysis," Cornell University, USA, 2002.

[15] D. Huang, C. Shan, M.Ardabilian, Y. Wang and L. Chen, "Local binary patterns and its application to facial image analysis: A survey," IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews(TSMC-C), vol.41,no.6,pp.765-781,2011.