

Local Binary Pattern based Facial Expression Recognition

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ABSTRACT

Automated analysis of facial expression recognition is complex one. The representation of facial features is very crucial for robust recognition as it consists of discriminating information of expressions. Local Binary Pattern (LBP) is used for analysis of facial expressions. To accomplish the high performance, the Uniform LBP is also used. Neural Network Systems are employed for classification of the expressions. The JAFFE database is used for evaluation.

Keywords: *Local binary patterns (LBP), facial expression recognition, Neural Network*

I. INTRODUCTION

The Human Facial Expression Recognition (FER) has begun to attract the attention of the researchers in the domain of Image Processing, Computer Vision and Machine Learning since 1990. It is most among dynamic research areas in the arena of Medical applications, Smart environments, Human Computer Interaction (HCI), automated access control and artificial intelligent based robotics. Facial expressions are basic way of conveying human emotions. Facial expression, paralinguistic features of speech, body language, physiological signals such as Functional Magnetic Resonance Imaging (FMRI), Electrocardiogram (ECG), Electrooculogram (EOG), Electromyogram (EMG), Electroencephalography (EEG), and so forth are utilized for recognition. Facial Expression Recognition is a difficult task. Ekman and Friesen [1] represent six basic facial emotions such as Happy, Surprise, Disgust, Sad, Angry, Fear and also Neutral, as shown in figure 1. According to Mehrabian [2], powerful communication comprises of 7 % of spoken words, 30% of paralinguistic – normal or sarcastic words and 55% by facial expressions. Hence facial expressions play a vital in human communication.

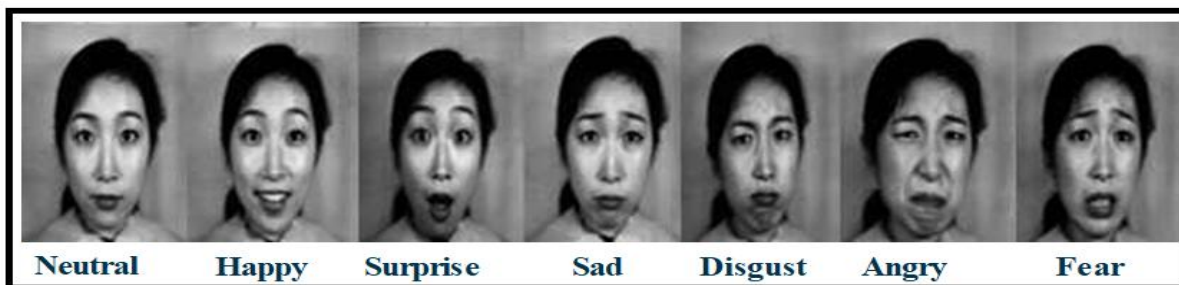


Fig1: Basic Facial Emotions (from JAFFE database)

The Automated FER system comprises of three phase – face acquisition, extraction of features and classification of facial expression, as shown in figure 2. Firstly face acquisition is for detecting features like nose, mouth, eyes and eyebrows in any FR system. Extraction of feature is the second step. There are various techniques utilized for extraction of feature. But many of the existing techniques are depends on appearance and geometric based features. Finally classification of expression is accomplished in the learned subspace. Various scientists express that accurate facial feature extraction can be accomplished by separating the face into few components. However, this methodology fails with improper occlusions and face alignment. Discriminating the expression is mostly decided by the facial regions, contributed by the features from the certain facial regions, depending on training data. Also, the sizes and locations of the facial spots are varying in this class of methodologies, accomplishing it hard to consider a general system. Facial expression recognition is a mechanism done by humans or a computer consisting of finding the faces in the scene, extracting facial features, analyzing the motion of facial feature. The extracted sets of features from the face are used to describe the facial expression in classification stage. The classification of facial expression is performed with the help of Action Units, suggested in Facial Action Coding System (FACS) [1] and using six universal emotions: fear, happy, anger, disgust, sad and surprise defined by Ekman [3]. Automated recognition of Facial Expression and Facial Action Units (AU) have drawn much consideration in the latest years because of its promising applications.

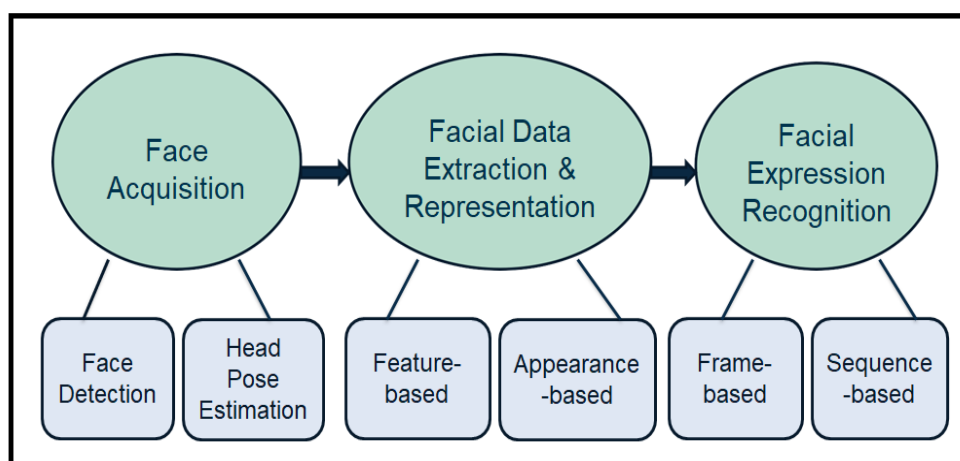


Fig2: Basic Structure of Facial Expression

II. TECHNIQUES AND METHODS

Geometric feature-based methods use the locations and size of facial components such as mouth, nose, eye and eyebrows. The facial components are extracted to construct a feature vector that depicts the face geometry.

Based on analogous position of these facial features, the expressions are classified. The facial actions are estimated by the geometrical relocation of facial feature focuses between the initial and the current frames in image sequences. In practical circumstances, it is hard to accomplish the tracking of facial historic points and for that these strategies usually need very reliable and accurate detection. The distance between facial historic points is distinctive in various individuals, thereby developing expression recognition system less reliable on the person independent.

To overcome this, **appearance-based methods** apply image filters like Local Binary Pattern (LBP), Gabor wavelets, and so on. They are used to either the whole face or specific part in face image to extract a feature vector. Because of their better achievement, the majority of the appearance-based techniques have concentrated on using Gabor-wavelets. However, the calculation of Gabor-wavelets is both memory and time intensive. Various techniques have been advanced for feature extraction from facial images are Active Appearance Model (AAM), Line Edge Mapping (LEM), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), Gabor Filter/Energy, Neural Network and Local Binary Pattern (LBP), Support Vector Machine and using SIFT descriptor [4-9].

Facial Action Coding System (FACS) was proposed by Paul Ekman and Wallace Friesen in 1976, a system for recognizing facial expression. Facial actions are the contractions of muscles, marked as an Action Unit (AU). Action Units (AU) characterizes the basic muscular actions of face. Action Units are alterations in the face activated by one muscle or a mix of muscles. The expression analysis with FACS depends on breaking down the noticed expression into the set of Action Units. There are 46 AUs which indicate the changes in facial expression and 12 AUs associated with head orientation and eye gaze direction. Action Units are extremely expressive in terms of facial actions, yet, they do not contribute any data about the message they represent. AUs are labeled with the narration of the action.

Local Binary Patterns (LBP), an appearance-based methodology for recognizing the facial expression is proposed. Earlier LBP was utilized for texture analysis and Ahonen et al. [14] discussed LBP for detection and recognition of faces and now it is enhancing further to acknowledge facial expressions person independent. My motivation is that face images can be seen as a composition of smaller patterns on that LBP can be applied.

Input face image is split into a group of smaller regions from that LBP histograms are drawn and fashioned into a one feature histogram. While for classification several classifier styles are available like neural network (NN), SVM, Self-Organizing Map (SOM) etc. Neural Network is adopted by me. In depth experiments are done to point out through empirical observation that the features of LBP are economical for recognition of facial expressions.

This work suggests the representation of faces using Local Binary Pattern (LBP) for recognizing facial expression. LBP were developed actually for analysis of texture and by latest, it has been made for facial images analysis. The significance of LBP features are their resistance against illumination variations and their computational simplicity. To perform facial expression recognition using LBP features, various machine learning methods, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and the linear programming technique including template matching, are examined. Contrasting Gabor wavelets, the features of LBP can be

separated rapidly in a simple sweep from the original image and presents in low-dimensional feature space, yet have discriminating facial data in a compact manner.

III. PREVIOUS WORK

The facial expression analysis has been an effective analysis topic for behavioural scientists since the work of **Darwin** in 1872 [10]. **Suwa et al.** [11] presented an early effort to definitely analyze facial expressions. After that, a lot of progress has been done. The automated facial expression recognition consists of 2 important forms: facial illustration and classification style. Facial illustration is to acquire a group of characteristics from original facial images to completely represent the faces. The choice of these characteristics should be minimal within-class variations of expressions whereas maximal between class differences. If inappropriate features are involved, even the best classifier might fail to achieve correct recognition. **Ekman and Friesen** [1] represent six basic face emotions: Happy, Surprise, Disgust, Sad, Angry, and Fear. According to **Mehrabian** [2], 55% of communication signals are determined by facial expression and hence facial expressions recognition evolved into powerful.

A. Colmenarez et al. [12] presented that facial images give hint as a group of regions containing sub-groups of facial characteristics. It is believed that the facial features can be precisely located with the help of model. The looks of each facial component is given by the image sub-window set around its position and thus the position of feature is standardized with reference to the outer eye corners.

X. Feng et al. [13] proposed a total unique approach to acknowledge facial expressions from static pictures. Firstly, LBP are used for the facial images, needs linear programming methodology to choose the categorization of 7 facial expressions such as neutral, happy, sad, fear, anger, disgust, surprise. 21 classifiers are made upheld by linear programming technique and classification is enforced with a binary tree tournament theme.

T. Ahonen et al. [14] used template matching to execute facial expression recognition to make use of the LBP for representing faces. For every category of facial images a template is made and then for matching the input image, a nearest-neighborhood classifier is applied. Recently Local Binary Patterns are utilized for facial analysis [21] as effectual appearance features. Completely distinct techniques have been proposed to classify facial expressions, related to Support Vector Machine (SVM), Neural Network and rule-based classifiers.

Caifeng Shan et al. [15] contributed an exhaustive study and they judge LBP for recognizing facial expression. **Donato et al.** [16] investigated particularly distinct technique to represent facial images that incorporate Local Feature Analysis (LFA), LDA, ICA, Gabor-wavelet representation and PCA. Utilizing Gabor-wavelet representation and ICA, higher rate of execution was obtained. **Ojala et al.** [17] represent the basic binary patterns as uniform patterns. It is confirmed that uniform pattern with (8, 1) neighborhood has accuracy rate of 90% for all patterns and 70% within the neighborhood of (16, 2) in texture images [17].

For recognizing action units and their combination, rule-based reasoning is employed by **Pantic and Rothkrantz** [18] and the temporal behaviours of facial expressions are utilized. **Tian et al.** [19] suggested a Neural Network based approach to acknowledge facial action units in image sequences. **Cohen et al.** [20] suggested a multi-level HMM classifier that allows not alone to perform classification of expressions on a video phase, consequently to automatically phase a protracted video sequence to the various expressions segments

while not resorting to heuristic methods of segmentation. However HMMs cannot handle dependencies in observation

III. LOCAL BINARY PATTERN

The Local Binary Pattern (LBP) operator is a powerful technique for texture description. The LBP operator manages eight neighborhood pixels. The operator describes the image by thresholding the pixels of 3x3 encompassing neighborhood of each pixel with the center pixel and denoting the result as a binary. If neighbor pixel has a greater or equal gray value to the center pixel value, then pixel value is "1" otherwise, "0" [22]. The LBP number for the central pixel is computed by the weighted sum of 8-bit binary number, depicted below (figure 3)

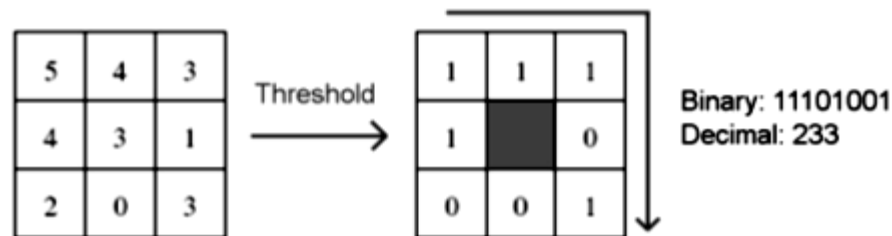


Fig 3: The basic LBP operator.

By creating extra-interpolated neighborhoods, the computation of more exact LBP codes can be enhanced and for this, a circle having R as radius from the center pixel is assumed. On the outskirts of this circle, P points are calculated. Hence, the process of an interpolation is important to create additional point from its pixels neighborhood. The neighborhood for distinct values of P and R [23, 24] is shown in the figure 4.

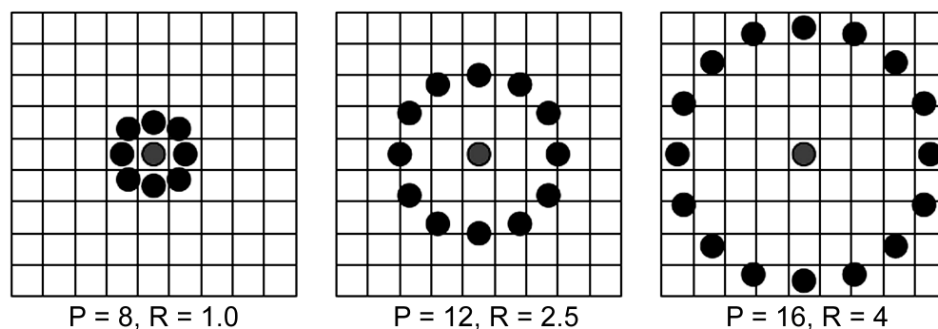


Fig4: The Circular neighborhood for distinct values of P and R.

A Local Binary Pattern is said to be uniform if it consists of at most two bitwise transitions from 0 to 1 or vice versa. It means that a uniform pattern has no transitions or only two transitions [25]. Since the binary requires being circular, only one transition is not possible. There are $P(P-1)$ possible combinations for patterns with two transitions. Using uniform patterns, it has two important benefits [26]. Firstly it utilizes less memory. For the standard LBP, the number of possible patterns is 256 and for uniform pattern 56. Secondly, the uniform pattern identifies only the significant local textures such as edges, spots, corners and line ends shown in the figure 5. The basic concept of using the texture descriptor is to build different local descriptions of the face and fusing them to describe the face globally [27].

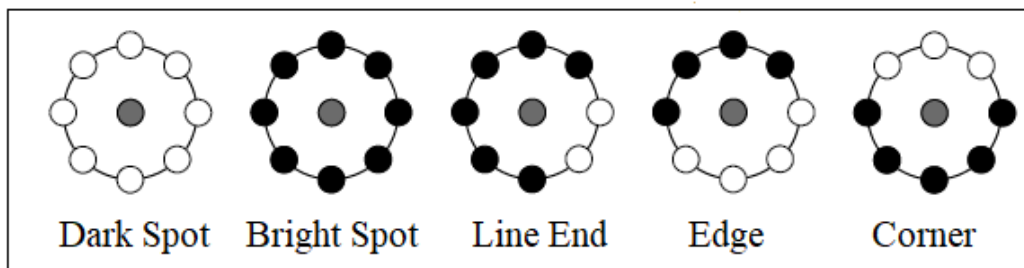


Fig5: Samples of textures acknowledged by LBP (1 for white circle and 0 for black circles)

The LBP for each pixel is computed and extract the description of texture facial image is divided into 5 x 5 local sub- blocks and the histograms of every sub-block are separately extracted. Then, these histograms are fused together to construct an overall histogram of the face, which represents the feature vector, and hence, the texture of the image is represented. The distance between the histograms [11] can be calculated by measuring the similarity between the image histograms. Figure 6 shows the image subdivision. Figure 7 shows the LBP histogram concatenation.



Fig 6: Example for image with division

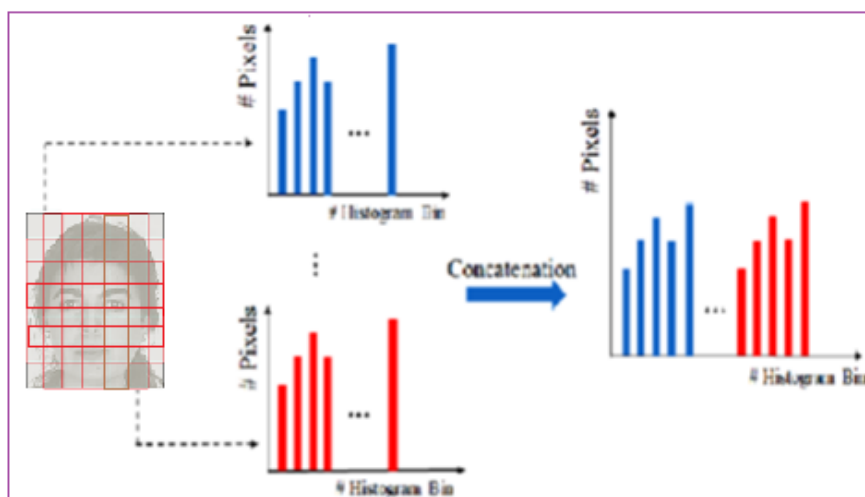


Fig 7: Formation of feature vectors (concatenation of histograms)

IV. IMAGE DATABASE

We have considered the 7-class expression recognition by adding the neutral expression. The images are taken from JAFFE (Japanese Female Facial Expression) database which is an open face image database. It consists of 10 women's expressions. Everyone has given 7 different expressions as Neutral, Anger, Disgust, Fear, Happy,

Sadness and Surprise. Every expression has 3 or 4 samples and therefore the total is 213. Every image has been rated by 60 subjects on scale of 6 and each has resolution of 256 x 256. The purpose of the database is mainly accustomed for facial expression recognition. The following figure shows the sample images from JAFFE data base.

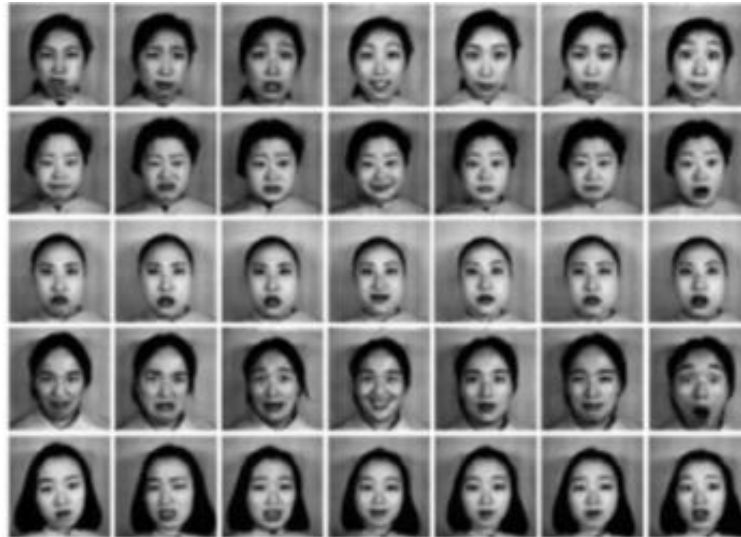


Fig 8: Some images for JAFFE data base

V. EXPRESSIONS RECOGNITION

The input image is partitioned into 16 equal non-overlapping regions with each region's size is 64 x 64. Then (8, 1) neighbourhood LBP is on each region and corresponding LBP features are integrated to get 944 dimension feature vector. After the dimensionality reduction of feature vector, it is fed as input to neural network of size 20 x 7. The output classes are seven distinct categories Happy, Sad, Surprise, Anger, Disgust, Fear and Neutral and the specified output is set to be binary. That is if the specified output is happy expression, then it is set {1, 0, 0, 0, 0, 0, 0}. 1 denotes true and 0 denotes the false. The classification step is followed after the extraction. For the classification two-layer feed-forward network using sigmoid function each in the hidden layer and the output layer, is utilized to distinguish feature vectors. Hence a neural network is used to classify inputs into a group of target classes.

A network is created after feeding extracted classification information. The network consists of 7 output neurons, since 7 classes are connected with each input vector and each output neuron denotes a class. Once an input vector of the corresponding class is fed to the network, the analogous neuron gives output as 1 and the other neurons should give output as 0. Therefore created network is trained to classify the inputs by arbitrarily keeping with targets, dividing the input vectors and target vectors into three sets-training, testing and validation. The training is given throughout the network and hence the network is adjusted in keeping with its error. The testing no impact on training and hence it gives an independent measure throughout the performance of the network. The validations are used for generalizing the network and to stop training once generalization is stopped.

VI. EXPERIMENTAL RESULTS

Among the data taken, 70% of the data is taken for training, 15% for validation and 15% testing. The dimension of the extracted LBP features is 944. PCA is used to eliminate the redundant or unnecessary information and utilized for training the neural network. Table I depicts the confusion matrix for all the seven basic expressions like Sad, Surprise, Disgust, Happy, Angry, Fear, and Neutral. It is noticed that the average recognition accuracy obtained is 87.7%. Overall, Neural Network based technique performs with highest recognition accuracy 94.4% and average accuracy 87.7% for seven basic expressions.

TABLE 1: Confusion matrix using LBP

	Anger	Disgust	Fear	Happy	Sadness	Surprise	Neutral	Accuracy
Anger	27	0	0	0	0	0	0	100
Disgust	0	25	1	0	2	0	0	89.3
Fear	0	0	29	0	0	0	0	100
Happy	0	2	0	29	1	1	0	87.9
Sadness	1	0	1	0	27	0	0	93.1
Surprise	0	0	0	0	0	27	0	100
Neutral	1	0	1	1	0	0	29	90.6
	93.1	92.6	90.6	96.7	90.0	96.4	100	94.4

VII. CONCLUSIONS

The proposed Neural Network system for recognizing the facial expression uses only 59 uniform patterns of facial image. The advantages of using uniform LBP are its computational simplicity and usage of less memory space. The micro features of the facial images which are robust to variations of illumination are extracted using LBP. The dimensionality is reduced by PCA. The NN is used to classify the expressions and it gives efficient 94.4% recognition accuracy rate and 87.7% on the average.

REFERENCES

- [1] P. Ekman and W. V. Friesen, Facial Action Coding System: A technique for the measurement of facial movement, *Consulting Psychologists Press*, 1978.
- [2]. Mehrabian, Communication without words, *Psychology today*, 2, 1968, pp. 53-56.
- [3] Paul Ekman, Wallace V. Friesen and Joseph C. Hager, *The Facial Action Coding System*, 2nd ed. London: Weidenfeld and Nicolson, 2002.
- [4] Hong-Bo Deng, Lian-Wen Jin, Li-Xin Zhen and Jian-Cheng Huang, A New Facial Expression Recognition Method Based on Local Gabor Filter Bank and PCA plus LDA, *International Journal of Information Technology*, 11(11), 2005.
- [5] Praseeda Lekshmi V., Dr.M.Sasikumar and Naveen S, Analysis of Facial Expressions from Video Images using PCA, WCE 2008, London, U.K, 2008, July 2 - 4.

- [6] Yongsheng Gao, Maylor K. H. Leung, Siu Cheung Hui, and Mario W. Tananda, Facial Expression Recognition from Line-Based Caricatures, *IEEE-PART A: Systems And Humans*, 33(3), MAY 2003.
- [7] Caifeng Shan, Shaogang Gong and Peter W. McOwan, Robust Facial Expression Recognition Using Local Binary Patterns, *IEEE*.2005.
- [8] BouchraAbboud, Franck Davoine and Mo Dang, Facial expression recognition and synthesis based on an appearance model,Elsevier ,3 May 2004.
- [9] Stefano Berretti, Boulbaba Ben Amor, Mohamed Daoudi and Alberto del. Bimbo, 3D facial expression recognition using SIFT descriptors of automatically detected keypoints,Vis Comput,27,Springer-Verlag 2011,1021–1036.
- [10] Darwin, The Expression of the Emotions in Man and Animals, John Murray, London,1872.
- [11] M. Suwa, N. Sugie and K. Fujimora, A preliminary note on pattern recognition of human emotional expression, *International Joint Conference on Pattern Recognition*, 1978, pp. 408–410.
- [12] Colmenarez, B. Frey and T.S. Huang, A Probabilistic Framework for Embedded Face and Facial Expression Recognition ,*IEEE*, 1999.
- [13] X. Feng, M. Pietikäinen and A. Hadid, Facial Expression Recognition with Local Binary Patterns and Linear Programming,*Pattern Recognition and Image Analysis*,15(2), 2005, pp. 546–548.
- [14] T. Ahonen, A. Hadid and M. Pietikäinen, Face recognition with local binary patterns, European Conference on Computer Vision (ECCV), 2004.
- [15] Caifeng Shan, ShaogangGong and Peter W. McOwan, Facial expression recognition based on Local Binary Patterns: A comprehensive study,*Elsevier - Image and Vision Computing*, 27,2009,pp. 803–816.
- [16] G. Donato, M.S. Bartlett, J.C. Hager, P. Ekman and T.J. Sejnowski, Classifying Facial Actions, *IEEE Transactions Pattern Analysis and Machine Intelligence*, 21(10), 1999,pp. 974-989.
- [17] T. Ojala, M. Pietikäinen and T. Mäenpää, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24 (7), 2002, pp. 971–987.
- [18]. M. Pantic and L.J.M. Rothkrantz, Facial action recognition for facial expression analysis from static face images, *IEEE Transactions on Systems, Man, and Cybernetics*, 34 (3), 2004, pp.1449–1461.
- [19]. Y-L. Tian, T. Kanade and J.F. Cohn, Recognizing Action Units for Facial Expression Analysis, *IEEE Transactions Pattern Analysis and Machine Intelligence*, 23(2),2001,pp. 97-115.
- [20] I. Cohen, N. Sebe, A. Garg, L. Chen and T.S. Huang, Facial expression recognition from video sequences: temporal and static modeling”, *Computer Vision and Image Understanding*,91,2003, pp. 160–187,2003.
- [21] H. Hong, H. Neven and C. von der Malsburg, Online Facial Expression Recognition Based on Personalized Galleries, International Conference Automatic Face and Gesture Recognition, 1998,pp. 354-359.
- [22] Timo Ojala, Matti Pietikäinen and TopiMäenpää, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,*IEEE Transactions on Pattern Analysis and Machine Intelligence* 24(7),971-987.

- [23] T. Ojala, M. Pietikinen, and D. Harwood, A Comparative Study of Texture Measures with Classification Based on Featured Distributions, *Pattern Recognition*, 29(1),1996, pp. 51-59.
- [24] Matti Pietikäinen, Abdenour Hadid, Guoying Zhao and Timo Ahonen, *Computer Vision Using Local Binary Patterns*, Springer-Verlag London Limited, 2011.
- [25] Laura Sánchez López, *Local Binary Patterns applied to Face Detection and Recognition*, Signal Theory and Communication Department, Universitat Politècnica de Catalunya, Spain, 2010.
- [26] T. Ahonen, A. Hadid, and M. Pietikainen, Face recognition with local binary patterns, In "European Conference on Computer Vision (ECCV),2004, pp. 469–481.
- [27] Y. Rodriguez and S. Marcel, Face authentication using adapted local binary pattern histograms, in Proc. 9th European Conference on Computer Vision, ser. Lecture Notes in Computer Science, 3954. Springer, 2006, pp. IV: 321–332.