ELLIPTICAL LOCAL BINARY PATTERN FOR FACIAL EXPRESSION RECOGNITION

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Abstract: In real time, Facial expression recognition has always been a difficult task in the field Computer Vision and Image Analysis. Expressions are generated from very bendable features and differ in sexes, ages and cultures among people. Furthermore, varying illuminations, complicate surroundings and complex backgrounds makes the recognition more complex. The Local Binary Pattern (LBP) which acquires the local area characteristics from the images are widely for facial expression recognition. But still LBP are able to solve the few issues of the local regions such as occlusions, varying lighting conditions and so on. This study presents the local feature descriptor, Elliptical Local Binary Pattern (ELBP) for facial expression recognition. In ELBP, horizontal and vertical ellipse patterns are used to acquire micro facial features in both horizontal and vertical directions. For comparing the ELBP histograms, a template matching strategy called Chi-Square distance is suggested. The efficiency of the proposed method is evaluated on bench-marking datasets JAFFE.

Index terms: **Local Binary Pattern, Elliptical Local Binary Pattern, Chi Square, Support Vector Machine**

I INTRODUCTION

Facial Expression Recognition (FER) is a classical problem of Pattern Recognition and Machine Learning. It plays a significant role in social communication and in conveying emotions [1]. In the earlier development stage, the scope of FER was limited to psychological studies only, but nowadays it covers a broad range of applications including human-computer interfaces (HCI), industrial automation, surveillance systems, sentiment identification, etc. Precise recognition of facial expressions can become a driving force for the future automation interfaces like car driving, robotics, driver alert systems, etc.

In Facial Expression Recognition System, the image is processed to extract the information for recognizing six universal expressions for example, fear, happy, sad, angry, disgust and surprise. This processing is carried out in several phases including image acquisition, features extraction and finally expressions classification using different techniques. Nowadays, a study on the combination of face representation and classification is crucial in facial expression recognition. Besides, the best classifier could fail to get accurate recognition if inadequate features are used. Numerous studies have been done on recognizing facial expression with a high accuracy yet remains difficult due to subtlety, complexity, and variability of facial expressions.

Furthermore, low-resolution images in real-world environments make real-life expression recognition much more difficult [1]. It is necessary to extract important facial features for classifying facial expressions into variance categories which contribute in identifying proper and expression. Facial basic expressions, for example, are sad, happy, disgust, fear, surprise, angry and neutral. Those particular facial expressions of emotions are termed as universal emotion by Ekman [2] hence over a decade; other researchers have used a similar method in their research [3], [4], [5]. Figure shows a neutral face and six expressions posed by a subject of the popular Japanese Female Facial Expression (JAFFE) database.

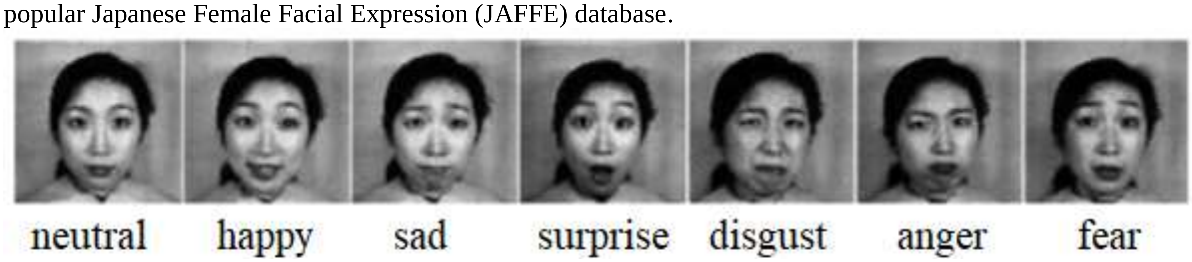

Fig. 1 Universal Expressions posed by subject from JAFFE

Recognition of facial expressions is done to perceive the distinction among emotions like sadness (disappointment), happiness, disgust, surprise, fear and anger. These expressions will vary in each individual. Mehrabian [6] indicated that spoken words (7%), voice (38%) and facial expressions (55%) are accustomed to convey messages by humans. Extraction of facial expression is the basic step of derivation of expression recognition. Facial expressions recognition technique consists of three steps, face acquisition, facial feature extraction and facial feature classification. The basic structure of facial expression analysis shown in the figure 2. There are two types of facial feature extraction methods – Geometric-based and Appearance-based approaches.

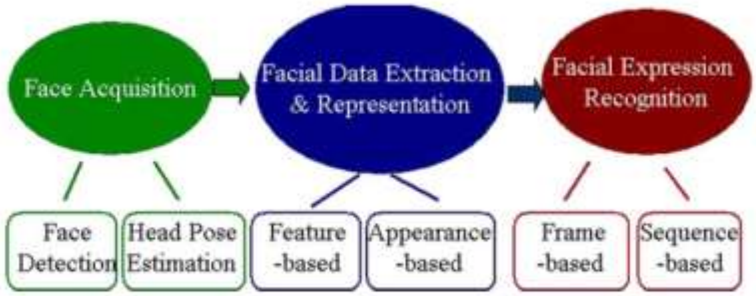

Fig .2 Basic structure of Facial Expression Analysis

Geometric–based method utilizes location, angle, distance and other relations between the facial components. Appearance –based method utilizes texture or color combinations from the whole or part of the facial image. Both the approaches are equally familiar in this field of research. In Geometric-based approaches, it is necessary to determine the position of the facial components [7][1]. Most of the existing works on geometric-based approaches were based on Facial Action Coding System (FACS) in which facial expressions were coded using one more Action units [8]. AUs were based on one or more facial muscle actions. The authors[9] manually made some of the Candide grid nodes to the facial landmarks to form facial wire frame model for facial expressions and utilized a Support Vector Machine (SVM) for classification. The authors [10][11] utilized some fiducial points on the face to create geometric features and stated that "geometric approaches are better in feature extraction than appearance-based approaches". The authors [12] suggested IR illumination camera for facial feature detection and tracking. Dynamic Bayesian Networks (DBNs) are used to recognize the facial expressions. They identified facial expressions by detecting 26 facial features around the areas of nose, mouth and eyes. Apart from the geometric–based approaches using AUs, few local appearance based feature representations were also suggested. These local features are easier for feature extraction than those of AUs.

II FACIAL ACTION CODING SYSTEM (FACS)

The most common descriptors used in facial expression analysis are specified by the Facial Action Coding System (FACS). The FACS is taxonomy of human facial expressions. It was originally developed by [13], and revised in [14]. The revision specifies 32 atomic facial muscle actions, called Action Units (AUs), and 14 additional Action Descriptors (ADs) which account for head pose, gaze direction, and miscellaneous actions such as jaw thrust, blow and bite. In this survey, we will limit our discussion to AUs, because it is they that describe the muscle-based atomic facial actions. The FACS are shown in the table 1.

Table 1 Facial Action Units (AUs)

Upper Face Action Units					
AU 1	AU 2	AU 4	AU 5	AU 6	AU 7
Inner Brow Raiser	Outer Brow Raiser	Brow Lowerer	Upper Lid Raiser	Cheek Raiser	Lid Tightener
*AU 41	*AU 42	*AU 43	AU 44	AU 45	AU 46
Lid Droop	Slit	Eyes Closed	Squint	Blink	Wink
Lower Face Action Units					
AU 9	AU 10	AU 11	AU 12	AU 13	AU 14
Nose Wrinkler	Upper Lip Raiser	Nasolabial Deepener	Lip Corner Puller	Cheek Puffer	Dimpler
AU 15	AU 16	AU 17	AU 18	AU 20	AU 22
Lip Corner Depressor	Lower Lip Depressor	Chin Raiser	Lip Puckerer	Lip Stretcher	Lip Funneler
AU 23	AU 24	*AU 25	*AU 26	*AU 27	AU 28
Lip Tightener	Lip Pressor	Lips Part	Jaw Drop	Mouth Stretch	Lip Suck

III LOCAL BINARY PATTERN

Ojala et al. [19] introduced the original version of LBP operator for discrimination of textures and has shown that it robust to the illumination and rotation variations. The two integral measures such the gray scale contrast and the local spatial patterns are the two integral measures are basic concepts for developing the LBP operator. Due to its computational simplicity and power of discrimination, it became famous in variety of applications. One of the best essential properties of the LBP is its potentiality to variations in monotonic gray-scale like illumination variations in real-time applications. Its computational simplicity is another important property which helps to analyze images in demanding real-time environments.

The LBP operator works in 3 x 3 pixel block of an image and these image pixels are thresholded by its center pixel value. If the intensity of pixel values is greater than the center pixel value, the neighboring pixels are thresholded to 1 and 0 otherwise. These thresholded values are multiplied with weights corresponding to the pixels and then summed to get an LBP binary code. These steps of computation are shown in the figure.

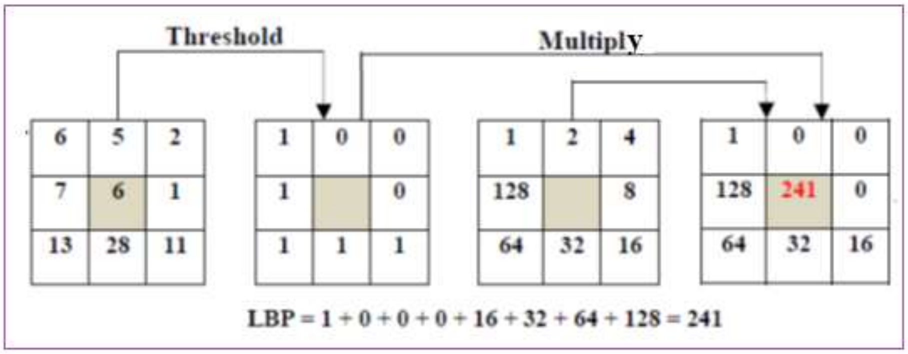

Fig. 3 Computation of LBP

The histogram of ($2^8 = 256$) distinct labels can be used to describe the texture. For a given a pixel $g_c(x_c,y_c)$ from grayscale image, its LBP texture is computed by comparing neighbors pixels P of radius R on a circle . The LBP code can be obtained using the equation

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

where s(x) is defined by

$$s(x) = \begin{cases} 1 \text{ if } x \geq 0; \\ 0 \text{ if } x < 0. \end{cases}$$

The original LBP operator's size of 3x3 pixels is its major disadvantage since it cannot capture the large scale structures which are dominant in the image. Recently, the neighborhood size of the LBP was extended to different larger sizes. The variables P and R denoting the number of neighbourhood pixels and the radius respectively. The multiresolution analysis [20] can be achieved by differing the values of P and R. The following figure shows the distinct values for (P, R).

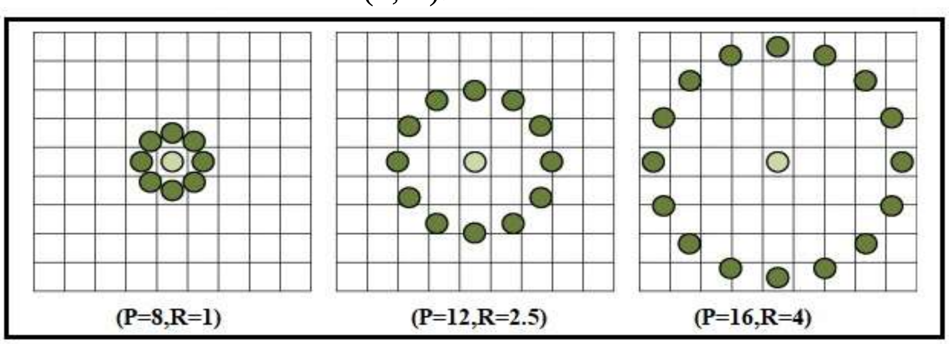

Fig. 4 Neighborhood of different values for (P, R)

Uniform patterns are another extended version of the conventional LBP. It is used to reduce feature vector's length. This idea is motivated by the fact that in texture images, some of the binary patterns occur more commonly. An LBP is said to be uniform if in the binary pattern there exists no more than transitions from 1 to 0 or vice versa. It is evident that there are P+1 of uniform patterns. The following are the examples for uniform and non-uniform patterns:

$$\left.\begin{array}{l} 00000000 \text{ - } 0 \text{ transitions} \\ 01110000 \text{ - } 2 \text{ transitions} \\ 11001111 \text{ - } 2 \text{ transitions} \end{array}\right\} \text{Uniform patterns}$$

$$\left.\begin{array}{l} 11001001 \text{ - } 4 \text{ transitions} \\ 01010010 \text{ - } 6 \text{ transitions} \end{array}\right\} \text{Non-uniform patterns}$$

While computing the LBP labels, the separate bin is used for every uniform pattern. A single bin is assigned for the all remaining non-uniform patterns. In (8, R) neighborhood, there are 58 uniform patterns out of total 256 patterns, gives 59 distinct labels. The extracted final feature vector consists of the existence of each type of uniform pattern in an input image. In the notation $LBP_{P,R}^{u2}$ superscript u2 is used to represent only the uniform patterns

IV ELLIPTICAL LOCAL BINARY PATTERN

Elliptical Local Binary Patterns (ELBP) is a new version of the extended operators of LBP used for face recognition. There is a significant enhancement in encoding the micro features that is fine details of the face image comparing to LBP. The micro features of the facial images are captured in both the directions of vertical and horizontal using vertical and horizontal patterns. The aim of feature extraction is to acquire the most discriminant and significant features of facial images for representing the faces in an effective manner. These representations should be very powerful to represent the many possible facial recognition challenges. For that, between the different identical facial images should have maximized extra-class variations and minimized intra-class variations. The mouth and the eyes of the human face are the most important facial components and their shapes are elliptic in nature [22, 24, 25, 26]. In addition the face image consists of more horizontal information, plays vital role in face recognition, than vertical. Hence, the elliptical patterns in horizontal are more powerful and suitable than circular patterns. When the information along the horizontal direction is combined with vertical information, the recognition performance is improved [16]. The recognition performance can be improved by combining the horizontal information with vertical information [16].The Elliptical patterns [17] in Elongated LBP to describe the anisotropic information of the facial image. The authors used four distinct elliptical patterns for directions and the weighted factor for six regions are used by them.

The Elliptical Local Binary Pattern (ELBP) uses vertical and horizontal ellipse patterns to represent the features of the face So, to enhance the discriminative face representation, instead of using single horizontal ELBP only, it can be fused with its vertical counterpart. Only one vertical ellipse and one horizontal ellipse patterns are used to acquire the micro facial images in ELBP and to produce the histogram sequence of ELBP images the non-weighted factors are used.

The circularly symmetric neighborhood definition is used by the conventional LBP. The intention of isotropic definition of neighbouring pixels is to address the problem of rotation invariant in the texture classification by eliminating the anisotropic structure information. But, the problem of rotation invariant does not exist in face recognition. Since many anisotropic structures such as eyes, mouth etc., exist in the face, anisotropic structure information is a significant feature for face recognition. The Elliptical LBPs and the variants of LBP operators are capable of obtaining the local patterns as well as the micro features of the face image.

Elliptical Local Binary Patterns (ELBP) has significant enhancement to encrypt the micro- features of the facial image In ELBP, for each pixel $g_c(x_c,y_c)$, with (x_c, y_c) as center and its nearby or adjacent pixels constitutes an ellipse (as shown in figure). The distance between the ELBP of (x_c, y_c) at (R1, R2) with P neighbouring pixels can be defined as

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

where s(x) is

$$s(x) = \begin{cases} 1 \text{ if } x \geq 0; \\ 0 \text{ if } x < 0. \end{cases}$$

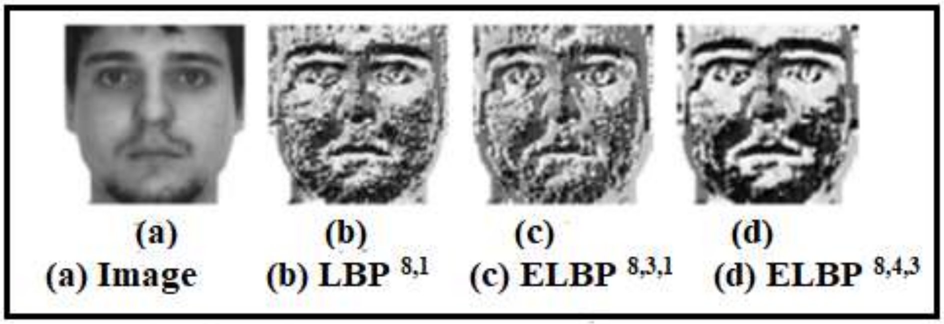

Fig.5 (a) Image and its (b) $LBP^{8,1}$ (c) $ELBP^{8,3,1}$ (d) $ELBP^{8,4,3}$

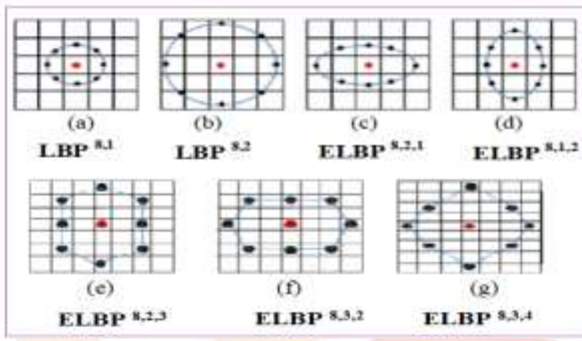

Fig 6 ELBP with different extensions

The i^{th} neighboring pixel coordinate of (x_c, y_c) is calculated using the formula:

$$angle\_step = 2 * \pi / P$$

$$x_i = x_c + R1 * cos((i-1) * angle\_step))$$

$$y_i = y_c - R2 * sin((i-1) * angle\_step))$$

For a single pixel, calculation of ELBP is illustrated below

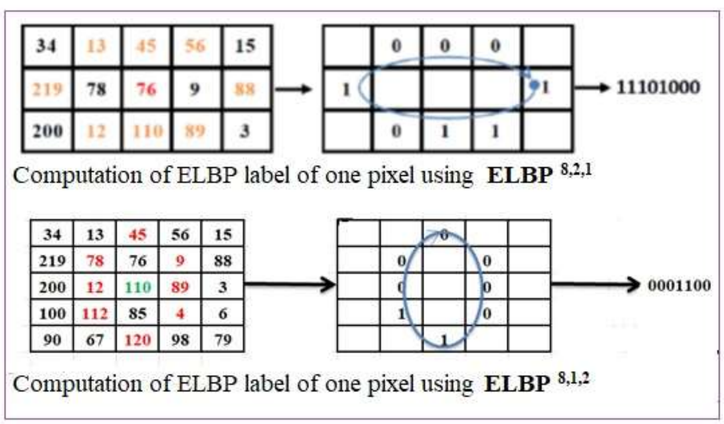

Fig. 7 Computation of ELBP

In facial recognition, mouth and eyes are the most significant facial features [21]. Naturally, human mouth and eyes are elliptic in nature. So, ELBP in horizontal is more powerful and suitable than LBP in the extraction of facial features. The ELBP image is generated by ELBP operator which is constructed by the feature vector of ELBP. In ELBP, the sampling of pixels distribution forms an elliptic shape and mostly looks like the eyes and mouth of human

If R1= R2, then ELBP becomes LBP
If R1< R2, then ELBP represents Vertical ELBP
If R1>R2, then ELBP represents Horizontal ELBP

If the coordinate of pixel $p_i(x_i,y_i)$ on ellipse does not belong the center pixel, then bilinear interpolation is applied to nearest four pixels to get gray value g_i . This is shown in figure. Let a, b, c, d be the four nearest pixels of p_i, and their gray values are g_a, g_b, g_c, g_d respectively. The distance between these pixels and center is single pixel. Let d_x be the distance between the centers of (a, c) and p_i horizontally and let d_y be the distance between the centers of (b, d) and p_i vertically. Then p_i , the gray-scale value is computed as:

$$g_i = g_a(1-d_x)(1-d_y) + g_b(d_x)(1-d_y) + g_c(1-d_x)(d_y) + g_d(d_x)(d_y),$$

where d_x and d_y can be calculated as

$$\begin{aligned} d_x &= 1-(x_i - floor(x_i)) \\ d_y &= 1-(y_i - floor(y_i)) \end{aligned}$$

Floor() gives the greatest previous integer.

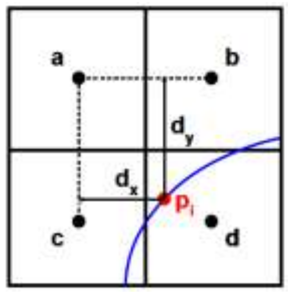

Fig. 8 ELBP bilinear interpolation scheme

The study in face perception [16, 23] confirms that information available horizontally play vital role in the face identification of humans. Thus, horizontal elliptic pattern is used for ELBP thresholding. Further, both vertical and horizontal ELBP are used to capture the micro features in both directions since the fusion of vertical and horizontal information provides at most excellent recognition accomplishment [16].

The ELBP image is firstly generated only when ELBP in horizontal is used and then the ELBP is split into local regions. The histogram of each region are computed independently and concatenated to construct the feature vector of ELBP. Also, uniform patterns [15] are used to reduce the dimension of the feature vector. While using both vertical and horizontal ELBP, two equivalent ELBP operators ELBP $^{P, R1, R2}$ and ELBP $^{P, R2, R1}$ are applied to generate two ELBP images simultaneously. Then feature vector for each ELBP is computed. After that, for the given facial image, to construct the entire vertical and horizontal ELBP feature vector, the two feature vectors are concatenated. These steps of computation are illustrated in the figure 9.

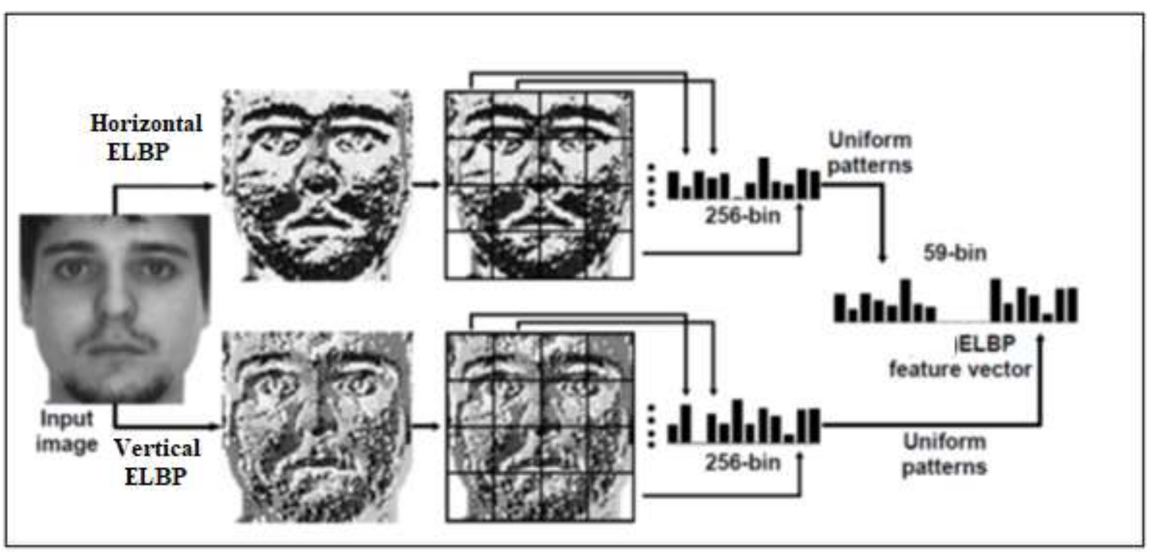

Fig. 9 Steps of Computation for ELBP vector

The code for the traditional LBP, Horizontal ELBP and Vertical ELBP ranges from 0 to 255. The histograms of horizontal and vertical ELBP's are concatenated to get the complete anisotropic structural information and the dimension of these histograms ranges from 0 to 511, but it does not capture the isotropic information. The complete isotropic information can be obtained by LBP with a histogram range of 0 to 255. Hence, both horizontal and vertical ELBP's and LBP should be integrated to get both isotropic and anisotropic information. But, in this case, the dimensionality of histogram bins increased, which ranges from 0 to 767.

To construct feature vector, the ELBP image is splitted into W×H sub regions. Generally, for the horizontal ELBP feature vector with neighborhood patterns (8, R1, R2), the length is W xHx256 and both vertical and horizontal feature vector (entire ELBP) length is 2xWxHx256. An ELBP [4] value is said to be uniform if it has no more than two transitions from 0 to 1 and vice versa. Each uniform ELBP value is assigned with separate bin whereas all non-uniform patterns are assigned with only one bin. For ELBP feature vectors, there are 59-bin sequence of histogram out of which 58 are for uniform ELBP. Thus, the length of ELBP feature vector is reduced to almost 4 times that is from W x H x 256 to W x H x 59 and from 2 x W x H x 256 to 2 x W x H x 59. Hence, uniform patterns are used to enhance the speed of the computations of ELBP and to have enough memory space for storing ELBP feature vectors.

For ELBP template matching and classification, Chi Square non-weighted distance function is used. It can be defined between vectors $X = [x_1\ x_2 ::: x_M]$ and $Y = [y_1\ y_2 ::: y_M]$ as :

$$dist_{chi}(X,Y) = \sum_{i=0}^{M} \frac{(x_i - y_i)^2}{x_i + y_i}$$

V FACIAL EXPRESSION RECOGNITION WITH ELBP

For dimensionality reduction, WPCA and for classification negative cosine distance function and template matching methods are used for ELBP based face recognition. In template matching scheme, LBP, ELBP_h (Horizontal ELBP) , ELBP_h (Vertical ELBP) and ELBP_h_v (vertical and horizontal ELBP) are used as notations to represent the related feature extraction methods and for WPCA based methods, the word "WPCA" is added as suffix.

VI RESULTS AND DISCUSSION

Generally, the seven type of facial expressions are used to evaluate the FER system. The efficiency of the suggested local descriptor was evaluated on the bench-marking JAFFE dataset. It consists of 213 images of 7 facial expressions posed by 10 Japanese female models. The image was divided into 9 x 9 blocks and each consists of 11 x 11 pixels. Polynomial SVM was used to classify the testing images. The 90% of the images form each expression were used for training and the remaining 10% of the images were used for testing. The suggested system accomplished better accuracy using polynomial kernel and the accuracy is 94.41%.

The confusion matrix of 7-class expression recognition is shown in Table 2. It is clear from the table that the expressions sad and fear are the most confusing while comparing with other expressions. The results are compared with those of early works on JAFFE dataset, as shown in the table 3.

Table 2 Confusion Matrix for facial expression recognition system using suggested feature extraction technique ELBP

	Anger (%)	**Disgust (%)**	**Fear (%)**	**Happy (%)**	**Sadness (%)**	**Surprise (%)**	**Neutral (%)**
Anger	**100**	0	0	0	0	0	0
Disgust	0	**99.1**	6.9	0	0	0	0
Fear	0	3.1	**84.4**	0	6.3	3.1	3.1
Happy	0	0	0	**96.8**	3.2	0	0
Sadness	3.2	0	6.5	3.2	**87.1**	0	0
Surprise	0	0	0	3.3	0	**96.7**	0
Neutral	0	0	0	0	0	0	**100**
94.41							

Table 3 Comparison of facial expression recognition accuracy of the suggested system and by some other recent works on JAFFE dataset

Author	**Technique**	**Classifier**	**Accuracy**
Suggested	Elliptical Local Binary Pattern	Multi class SVM (Poly)	94.41
Islam and Auwatanamongkol [28]	Gradient Direction Pattern	Multi class SVM (Poly)	92.11
Subramanian et al. [29]	Local Binary Pattern	SVM	88.09
Lyons et al. [30]	Gabor Filter	LDA -based classification	92
Zhang et al.[31]	Gabor Filter	NN	90.1
Guo and Dyer [32]	Gabor Filter	Linear programming	91

VII CONCLUSION

The feature representation for facial expression recognition is suggested in this study. Facial pattern at a pixel is extracted from pixels gray color intensity values of its neighbouring pixels in 5 x 5 pixels region. The features are chosen on their variance values to reduce the dimensionality of the feature vector. The experiments carried out on JAFFE data set illustrates that the suggested approach outperforms the several other approaches. The suggested approach successfully classifies nearly 95% of facial expressions accurately. The experimental results illustrate that the suggested approach is more efficient and utilizes less extraction time for facial expression recognition comparing with others. Future works may be working motion images.

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