Facial Expression Recognition Using Diagonal Crisscross Local Binary Pattern

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Abstract: Facial expression analysis is a noteworthy and challenging problem in the field of Computer Vision, Human-Computer Interaction and Image Analysis. For accomplishing FER, it is very difficult to acquire an effective facial description of the original facial images. The Local Binary Pattern (LBP) which captures facial attributes locally from the images is broadly used for facial expression recognition. But conventional LBP has some limitations. To overcome the limitations, novel approach for Facial Expression Recognition based Diagonal Crisscross Local Binary Pattern (DCLBP). It is based on the idea that pixel variations in diagonal as well as vertical and horizontal (crisscross) should be taken as an image feature in the neighborhood different from the other conventional approaches.The Chi-square distance method is used to classify various expressions. To enhance the recognition rate and reduce the classification time, weighted mask is employed to label the particular components in the face like eyebrow, mouth and eye with larger weights than the other parts of the face. The results of comparison showed the performance of the suggested approach comparing to the other approaches and the experimental results on the databases JAFFE and CK exhibited the better recognition rate.

Keywords—*Facial Expression Recognition, Chi-square Distance, Local Binary Pattern, Diagonal Crisscross Local Binary Pattern (DCLBP)*

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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 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.

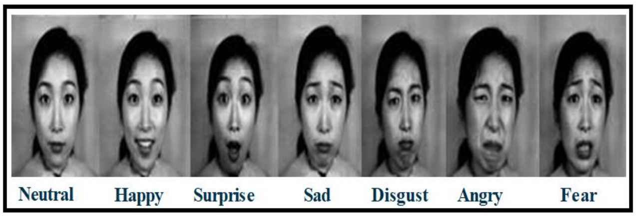

Figure 1. Basic Facial Emotions (from JAFFE database)

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.

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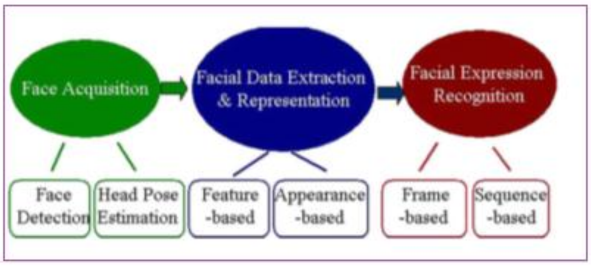

Figure 2. Basic Structure of Facial Expression

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, a**ppearance- 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].

Local Binary Patterns (LBP), an appearance-based methodology *f*or recognizing the facial expression is proposed. Earlier LBP was utilized for texture analysis and Ahonen et al.[10] 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 FACIAL ACTION CODING SYSTEM (FACS)

The widely used descriptors infacial expression analysis are represented by the Facial Action Coding System (FACS). The FACS is scientific classification of human facial expressions. It was initiallycreated by [1], and modified in [2]. The updation indicates 32 atomic facial muscle activities, called Action Units (AUs), and 14 extra Action Descriptors (ADs) which account for head pose, gaze direction, and miscellaneous actions such as bite, jaw thrust and blow. The FAUs are shown in the table 1.

TABLE I 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

IV. 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" [12]. The LBP number for the central pixel is computed by the weighted sum of 8-bit binary number, depicted below (figure 3)

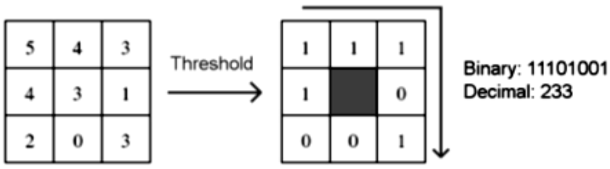

Figure 3.The basic LBP operator.

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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 outskirt 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 [13, 14] is shown in the figure 4.

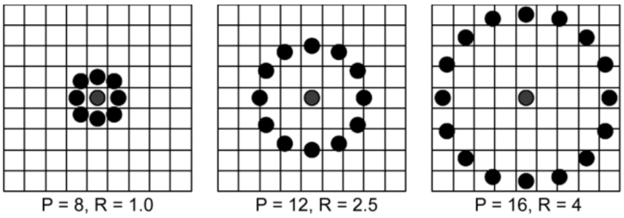

Figure 4.The Circular neighborhood for distinct values of P and R.

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 [15]. 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 [10]. 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 [16].

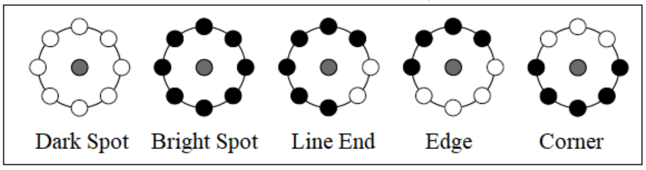

Figure 5. Samples of textures acknowledged by LBP (1 for white circle and 0 for black circles)

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.


Figure 6 Example for image with division

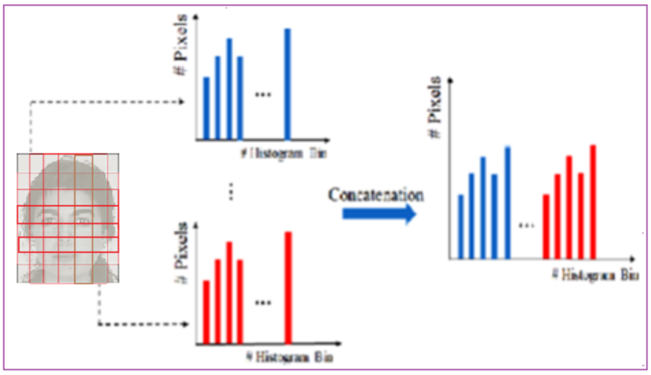

Figure7. Formation of feature vectors (concatenation of histograms)

VDIAGONAL-CRISSCROSS LOCAL BINARY PATTERN

Diagonal-Crisscross Local Binary Pattern(DCLBP) is new image or texture representation operator. It is established on the idea that pixel variations in diagonal as well as vertical and horizontal (crisscross) should be taken as an image feature in the neighborhood. The significance of center pixel values should be maintained to change the value with new pixel value. So, for analysis, each block's center value is included. The neighbourhood of center value is represented by the each block. Here, the differences between the mutual diagonal (front and back) pixels and also for vertical and horizontal directions called crisscross are taken into account.Within the square mask, thresholding computation of neighbourhood pixels differs from the basic LBP. The strategy for computation of new value is stated as follows: For 3 x 3 image patch,

- Begin from the pixel position N_0 from the topmost left corner

Then compute four difference values

- Obtain ($N_0 – N_4$), front-diagonal difference
- Obtain ($N_1 – N_5$), vertical direction difference
- Obtain ($N_2 – N_6$), back-diagonal direction difference and
- Obtain ($N_3 – N_7$), horizontal direction difference

To calculate new value, each difference should be multiplied with 2^1, 2^3, 2^5 and 2^7 sequentially and finally the average between estimated new valueand the center pixel is calculated.Also 2^0, 2^1, 2^2 and 2^3 is computed for one computation as well as, 2^4, 2^5, 2^6 and 2^7- to verify the chance of enhancement. Anyhow, in both the cases results are poor. Because it is evident that, for '2^0, 2^1, 2^2 and 2^3' combinations, the maximum value is '$2^0 + 2^1 + 2^2 + 2^3$' = 1+2+4+8 = 15. So for a gray-scale image range from 0-255 changes into 0-15 values. Thus, produces poor results for this combination. Then, for the combination of '2^4, 2^5, 2^6 and 2^7', the maximum value is '$2^4 + 2^5 + 2^6 + 2^7$' = 16+32+64+128 = 240. Hence, the new values range from 16 - 240, which is moderately less than gray-scale image ranges. The figure shows the computation of Diagonal Crisscross for a 3 x 3 mask.

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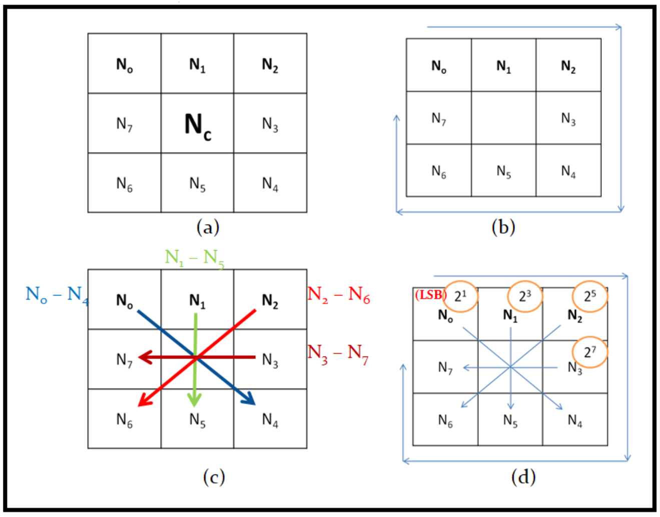

Figure 8. (a) 3x3 image patch (b) Starting pixel position - N_0 (c) ($N_0 – N_4$) - front-diagonal, ($N_1 – N_5$)-vertical direction, ($N_2 – N_6$) - back-diagonal direction and ($N_3 – N_7$) - horizontal direction (d) Sequential multiplication of each difference with 2^1, 2^3, 2^5 and 2^7 for computation of a new value

The reflection of central pixel in the new value is another important point. So far, the central pixel value (N_c) have not been computed or considered. The study shows that the central pixel value is not used in computation but only replaced through pixels of neighbourhood, which shows poor representations.Therefore, in this method, the combinations of four directions '2^1, 2^3, 2^5 and 2^7' and the center pixel value (N_c) are considered. The average between computed new value and the center pixel value is taken. The central pixel value (N_c) will be replaced by this mean value and in this similar fashion the final image will be found on the Diagonal-Crisscross Local Binary Pattern(DCLBP) technique. The following equation is used for computation.

$$\boxed{DCLBP_{p,r}(N_c) = \frac{\left[\left(\sum_{k=0}^{|P|-1} \vartheta\left(\delta_{k,|P|+k}\right) \times 2^{p_k \in P}\right) + N_c\right]}{2}}$$

$p_0 = 2^1 \quad p_1 = 2^3 \quad p_2 = 2^5 \quad p_3 = 2^7$

where ,

Neighboring point set is, $P = \{1, 3, 5, 7\}$

Number of elements in the set is, $|P| = 4$

δ , called difference parameter is $\delta_{k,|P|+k} = \left(N_k - N_{|P|+k}\right)$

The threshold function $\vartheta(\delta)$ is, $\vartheta(\delta) = \begin{cases} 0, & \delta < 0 \\ 1, & \delta \geq 0 \end{cases}$

The neighborhood radius r is 1 or more. For 3x3 image mask, the radius is 1. The intensity value is bilinearly interpolated for the coordinates which do not fall at integer positions. Incrementing the value of radius improves the redundant information and so that, increases the cost of computation. A multi-scaling can be considered by taking different combinations of radius and but performance analysis shows that, it does not contribute better discrimination of distinct textures. Here, $|P| = 4$ that explains that there exists 4 distinct probable values as '2^1, 2^3, 2^5 and 2^7'.

when $k = 0$, $\delta_{0,4+0} \times 2^1 = \delta_{0,4} \times 2^1$, involves the front-diagonal difference of $(N_0 - N_4)$.

Similarly,when $k = 1, \delta_{1,5} \times 2^3$ involves the vertical difference of $(N_1 - N_5)$;

when$k = 2, \delta_{2,6} \times 2^5$ involves the back-diagonal difference of $(N_2 - N_6)$;

when$k = 3, \delta_{3,7} \times 2^7$ involves the horizontal difference of $(N_3 - N_7)$.

Like this, the new central pixel value for each patch is calculated. The Computation of DCLBP is illustrated in the figure

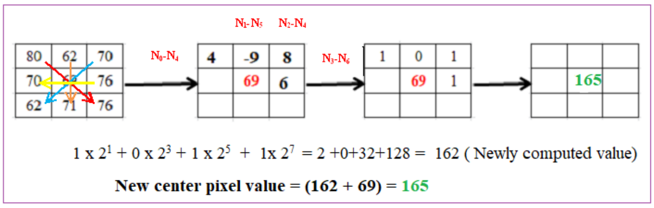

Figure9. Computation of DCLBP

VI. FACIAL RECOGNITION EXPRESSION WITH DCLBP

The following figure shows the steps of the proposed system.

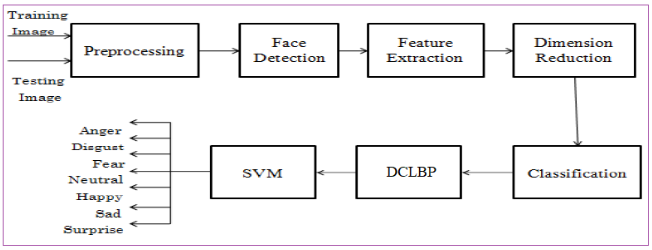

Fig .10 Steps for facial expression recognition

The image region is splitted into multiple squares for extracting features from "uniform" DCLBP and its DCLBP image is build by these sub-areas. After defining one image by DCLBP, the histogram of each square in $f_b(x, y)$ is defined as

$$H_i = \sum_{x,y} I\left(f_b(x,y) = i\right), \quad i = 0, \cdots, n-1$$

where$n$ denotes number of the patterns generated by "uniform"DCLBP operator, and I is described as

$$I(A) = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false.} \end{cases}$$

Then, the entire histogram of single image is computed as

$$H_{i,j} = \sum_{x,y} I\left(f_b(x,y) = i\right), \quad I\left(f_b(x,y) \in R_j\right)$$

where$j$= 0, $\cdot\cdot\cdot$, k, size of sub-regions which forms he feature vector. It is denoted by DCLBP histogramof size$k$ x (P^{P-1}+3), which comprises ofthe "uniform" patterns. For (P, R) = (8, 1), the "uniform" patterns are59, each with the dimension of 34×59 with34 squares, is much lesser than 34×2^8. The image is splitted into 64 squares. For the extraction based on

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AUs, each feature area is splitted into multiple squares according to their size to build the feature vector.

VIICLASSIFICATION BY USING *K*-NN

There are various measures available for calculating the dissimilarity between histograms, like log-likelyhood ratio, histogram intersection,and $\chi 2$ statistic[28]. In this work,$\chi 2$ statistic is utilized toevaluate the dissimilarity between the testing and the trainingimages. It computes the differences at each *i*-th bin, thehistogram estimation of "uniform" DCLBP, as prominent measurement.Chi squaremetric is defined by

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

where *S*and *M* are two DCLBP histograms. To recognize the expression, *K*-NN classifier is utilized. It labelsthe expression type for images of testing sample as well as to the training type of images seenamong most of the times at $\chi 2$ distance of the *K* smallest. The aim of *K*-NN is to determine*K* nearestneighbors between the known samples and one unknown sample at the distances between them [29] and here $\chi 2$ metric is used to calculate the distances.

For a given known N samples, there are N_1 samples from class w_1, N_2 samples from class w_2, ・・・, and $N_c$samples from class w_c. When the number of samples belonging to classes of w_1, w_2, ・・・, $w_c$are k_1, k_2, ・・・, k_c, the discriminating function is defined as

$$g_i(x) = k_i, \quad i = 1, 2, \cdots, c.$$

The basic determining rule is described as

$$g_j(x) = \max_i k_i.$$

Then, the class of *x* is treated as w_j. As per [30], features captured by DCLBP are in the histogram form of information, having lower dimensions. Hence, *K*-NN is used for its easiness and convenience. For efficiency, *K* is chosen to be 1.

VIII RESULTS AND DISCUSSION

The two databases namely Japanese female facial expression (JAFFE) and Cohn-Kanade, are used to demonstrate the proposed work, which are popular and benchmark databases for The JAFFE database consist of 213 images of ten female Japanese, whose six predefined facial expressions surprise, anger, fear, disgust, happiness and sadness. Each one gave poses 2 to 4 images with neutral and six expressions.. The Cohn-Kanade database contains 100 university students, in the age group of 18 to 30. 1752 images from 97 subjects are utilized for experimental analysis. Alsothere are also neutral and 6 expressions. The experimental results are shown in the table

TABLE II CONFUSION MATRIX OF JAFFE DATABASE

	Anger (%)	Disgust (%)	Fear (%)	Happy (%)	Neutral (%)	Sad (%)	Surprise (%)
Anger	**100**	**0**	**0**	**0**	**0**	**0**	**0**
Disgust	**3.33**	**93.34**	**0**	**0**	**0**	**0**	**0**
Fear	**0**	**3.33**	**90.31**	**0**	**3.33**	**0**	**3.03**
Happy	**0**	**0**	**0**	**100**	**0**	**0**	**0**
Neutral	**0**	**0**	**0**	**0**	**100**	**0**	**0**
Sad	**0**	**0**	**3.33**	**0**	**3.33**	**93.34**	**0**
Surprise	**0**	**0**	**0**	**3.33**	**0**	**0**	**96.67**
96.23							

TABLE III CONFUSION MATRIX OF CK

	Anger (%)	Disgust (%)	Fear (%)	Happy (%)	Neutral (%)	Sad (%)	Surprise (%)
Anger	**99.33**	0	0	0	0	0.67	0
Disgust	0	**99.51**	0	0	0.49	0	0
Fear	0	0	**100**	0	0	0	0
Happy	0	0	0	**100**	0	0	0

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Neutral	0	1.02	0	0	**98.98**	0	0
Sad	0	0	0	0	0	**100**	0
Surprise	0	0	0	0	0	0	**100**
99.69							

TABLE IV COMPARISON OF THE ACCURATE FACIAL EXPRESSION RECOGNITION RATES OF EXISTING APPROACHES AND SUGGESTED APPROACH ON JAFFE DATABASE

Author(s)	**Technique**	**Classifier**	**Accuracy (%)**
Suggested	DCLBP	K-NN	99.69
Xiaozhou Wei et al., 2008, [22]	Expressive Texture or Active Texture	Topographic Mask - (TM)	80.9
Miriam Schmidt et al., 2010, [17]	PCA, Orientation histograms, Optical flow	Hidden Markov Model (HMM)	86.1
Chen-Chiung Hsieh et al.,2011, [20]	Active shape model, Gabor filter and Laplacian of Gaussian	Support Vector Machine (SVM)	91.7
Daw-Tung Lina et al., 2009, [19]	2DPCA and LBP	Support Vector Machine (SVM)	81.46
X. Zhao et al., 2012, [18]	Discriminant Kernel Locally Linear Embedding (DKLLE)	Nearest neighbor (1-NN)	95.85

TABLE V COMPARISON OF THE ACCURATE FACIAL EXPRESSION RECOGNITION RATES OF EXISTING APPROACHES AND SUGGESTED APPROACH ON CK DATABASE

Author	**Technique**	**Classifier**	**Accuracy (%)**
Suggested	DCLBP	K-NN	99.69
Xiaozhou Wei et al., 2008, [22]	Expressive Texture or Active Texture	Topographic Mask - (TM)	80.9
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X. Zhao et al., 2012, [18]	Discriminant Kernel Locally Linear Embedding (DKLLE)	Nearest neighbor (1-NN)	95.85

IX CONLUSIONS

Afeature extraction technique for FERis suggested. Low computational complexity and easier implementation are the advantages ofthe suggested approach. FER is carriedout on facial areas to autmost level. Highly-prominent facial feature vectors are generated through "uniform" DCLBP for simplification. Forfacial expressionrecognition, the classifier*K*-NNis used.Experimental results demonstrate that the proposed approach can get significantly more accurate recognition rate in comparison with other approach. Besides, the suggested method based on DCLBP and K-NN is simple and fast. So, these advantages are great importance for applications in intelligent communication systems, particularly for real time applications.

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