# Facial Expression Recognition Using Local Positive Directional Pattern (LPDP)

**Naga Raju Katta, M. Babu Reddy**

***Abstract: This paper proposes an efficient facial expression system (FES) that can be adapted for many real time applications. Many researchers are concentrated on real time facial expression system, but there are still various issues to be solved like noise due to various reasons. The pixels in real time images are distributed based on the distances with respect to camera. This is also one of the reasons for noise. The performance of FER system is mostly dependent on robust feature extraction. From the literature survey, it is observed that most of the local descriptors are defined and derived on 3x3 neighborhoods and here central pixel is characterized with 9 pixels and these descriptors shown good performance in different applications. This paper proposes new descriptor named as local positive directional pattern (LPDP) which is derived on 5x5 neighborhood which consisting of 25 pixels. Here central pixel is characterized with 25 pixels so that the proposed descriptor has more discriminative power than exiting local descriptors. This descriptor captured more discriminative features from the facial image by using positives directional responses. For achieving better results, the LPDP code histograms is considered as features that are further processed by generalized discriminant analysis (GDA). This GDA is more helpful for distinguishing the expressions as much as possible that in a non-linear space. Extensive experiments on three kinds of datasets (namely JAFFE, CK+ and CASME-II) prove that the proposed method can improve the accuracy. The proposed approach has shown its superiority by achieving mean recognition rate of 95.23 where other state-art-methods could make 90.21 at the best.***

***Keywords: FER, positive direction, GDA, noise, expression***

## 1. INTRODUCTION

In Human communication, expression is realistic and mighty concept. Person emotions and intentions are indicated mostly by facial expressions [1, 2]. Hence, automatic facial expression recognition (FER) system has great role in human computer interaction (HCI) interaction and data driven animation using speech signal [3]. Some of the video processing applications also need effective facial expression recognition. Recently usage of mobiles is too high and users are very fascinated to wards to change their expression and feel happy. Most of the users, addicted for selfie of their different expressions and posting in social media. In this area much of the work has already been done [4, 5] with high accuracy. Consequently, a robust facial expression recognition system is very much needed to support these applications. The success of the facial expression system is mostly depends on efficient facial feature representation [6]. For efficient feature extraction, need to consider some criteria like low dimensionality, easy to calculate and which minimizes the within-class variations of expressions [7, 8].

Many muscles are attached to the facial skin which can make movements called as facial expressions. Obviously human face exhibit different facial expressions such as angry, sadness, happy, fear, disgust, neutral , surprise by human beings [9]. Latest FER systems are popularly used in various fields, for example laptop games, detection of mental disorder, driver, driver exhaustion detection, e-learning and their emerging applications [10]. In broad discussion, the facial expression recognition has three stages: As first stage, area or region of face used for recognition, second step is facial feature extraction, and here appearances based and geometric are used. The third one is the expression recognition and it classifies the expression. The common approach for facial feature description is divided into two groups: the first group is getting the features from entire face image which is termed as holistic manner and second one is local manner i.e. getting features from parts of facial image like mouth, eyes and chin etc. [11, 12].

In literature, many researchers proposed many novel methods for efficient facial feature extraction. One of the novel approaches called local directional position pattern (LDPP) which is proposed by [13]. The common content of the facial image is shape, appearance and texture. Based on these features Sajjad et al. [14] proposed mixture of histogram oriented gradients (HOG) and uniform local ternay operator (U-LTP) for efficient facial extraction on entire face image. All features are combined into the single feature vector and classify using multi scale SVM classifier.

The geometric features are extracted using active appearance model (AAM). And then classification is performed using hidden markov model (HMM) [15] Mistry et al. proposed FER system through the emotion recognition having three stages like feature extraction, feature optimization and emotion recognition. After feature extraction , these features are optimized through the particle swarm optimization (PSO) and classification is performed by diverse classifiers. Baddar et al. [16] suggests new approach for minimizing features using convolution neural network (CNN) using optimal objectives.

Nazir et al. [17] advocates the FER using HOG based transformed features. These features are extracted from image and catch high variance features using discrete cosine transform (DCT). Abdul and Holambe [18] proposed the approach which is combination of LBP and directional wavelet transform (DWT) for efficient face expression classification. The FER system generates 16-bit code using multi-stage binary pattern (MSBP) based on holistic and zone based feature extraction which is proposed by Arshid et al. [19].

**Revised Manuscript Received on March 10, 2019**.

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In this paper a novel descriptor known as local positive directional pattern (LPDP) is proposed which exploits the existing descriptors. The features optimization which is derived on LPDP is done effectively using GDA. Then facial expression recognition is performed using machine learning classifiers. One of the best contributions of this paper is effective classification even in noisy condition.

In conclusion, the contributions of our work are three-fold.

1. This paper proposes a LPDP descriptor for facial expression recognition, which is derived on 5x5 masks. We considered histogram of LPDP on different sizes of image patches. To the best of our knowledge, this is the first descriptor which is derived on 5x5 masks.
2. Since LPDP features are processed with GDA, achieves better classification results than the state-of-the-art methods.
3. The proposed descriptor applied on micro regions and features are optimized using GDA for more accuracy.
4. The proposed descriptor considered only positive edge directions hence there is chance of obtaining efficient features which are having high discriminative power. This is the strong asset of our proposed descriptor.

The rest of the paper is structured as follows. Section 2 gives the working of the proposed methodology. Section 3 illustrates the experimental results and discussion of the proposed method. Section 4 explains the conclusion of the proposed method.

### A. Local binary pattern

The local binary pattern (LBP), is proposed by Ojala et al. [20], for texture image classification. As per his investigation, it is more popular descriptor and easy to compute. The LBP is computed as follows: the given 3x3 neighborhood is justified with single code, where central pixel is compared with 8-neighbors and placed binary response using Eqn. 1 and weights are assigned with base 2 and evaluated a LBP code as shown in Fig.1. This LBP is more sensitive to noise.

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(g_p - g_c)2^P, s(x) = fx=0, \&x<01, \&x\geq 0 \qquad (1)$$

Where P is no of neighbors, R is radius, gp is neighboring pixels intensity and gc is central pixel intensity.

| | | |
|---|---|---|
| $I_3$ | $I_2$ | $I_1$ |
| $I_4$ | $I_c$ | $I_0$ |
| $I_5$ | $I_6$ | $I_7$ |

Spatial arrangement of a 3x3 gray scale image patch

| | | |
|---|---|---|
| 51 | 48 | 52 |
| 51 | 62 | 39 |
| 81 | 84 | 65 |

3x3 Sample Image

| | | |
|---|---|---|
| | | |
| | 7 | |
| | | |

LBP Code: 00000 111

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | | 0 |
| 1 | 1 | 1 |

ζ (Ip- Ic)

**Fig.1: The LBP Transformation**

### B. Local directional pattern

The local directional pattern (LDP) is proposed by Jabid et al. [21] for face recognition. The LDP code evaluation on the 3x3 neighborhood which consists of 8 neighbors processed with Kirsch operator (Fig.2) and finds 8 significant edge responses. By using k value the LDP code is derived using following Eqn.

$$LDP = \sum_{P=0}^{7} 2^P \, \zeta\left|\left|ER_P\right| - \left|ER_k\right|\right| \qquad (2)$$

Where $ER_k$ is the k-th most significant directional response and $ER_P$ is the p-th directional response.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}$$

(KM0) (KM1)

$$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

($KM_2$) ($KM_3$)

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$$

KM4 (KM5)

$$\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

($KM_6$) ($KM_7$)

**Fig. 2: Kirsch edge response masks in eight directions**

## 2. PROPOSED METHOD

The proposed approach adapted unique strategy called LPDP with GDA for robust FER. Fist input image is divided into n micro regions r0, r1, r2…rn. For each micro region, features are extracted using LPDP descriptor. Finally, each micro region features are concatenated and optimized with GDA. The frame work of proposed method is given in Fig.3

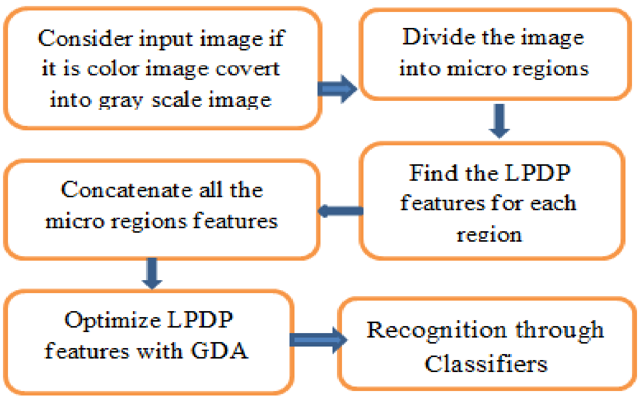


**Fig.3: Frame work of proposed method.**



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Due to binary coding of local binary pattern the great amount of texture image information is lost. The basic strategy of LBP, local ternary pattern (LTP) and many other LBP like texture descriptors, using 3x3 mask i.e. 8 neighboring pixels to define characteristics of central pixel. Because of this, it ignores most significant information of the neighborhood. To overcome this issue, this paper considered 25 neighboring pixels to define characteristics of central pixel.

On the other side, the local directional pattern (LDP) treats all directions equally, but it is characterized by k value. The LDP code is evaluated using this k. This k value is decided by human. This human interaction is most un-appropriate issue in LDP. The individual calculation of LDP overlooks the prominent information and poured into the code. [22]. To avoid this weakness, we investigate new descriptor which inherits local directional features in all directions with respect to 5x5 masks. The proposed descriptor referred as LPDP which uses only kirch operator. This paper avoids this human interaction and defined precise local information of the neighborhood. Thus, the proposed LPDP operator encodes the texture image by computing edge responses in all directions for every 5x5 window in overlapped manner. Initially, the image texture is divided into micro regions and then encoded into desired coded image. The resultant LPDP features describes local primitives in a more stable way and also extracts more information since edge responses are less sensitive to illumination and noise than intensities.

***Algorithm:***

***Input:*** Color image

***Output:*** Optimized feature vector

{

***Step 1:*** Divide the image into n number of micro regions r1,r2..rn for every micro region apply step 2 to step 5.

***Step 2:*** Consider 5x5 windows in overlapping manner. Each 5x5 window, we get eight directional 3x3 neighborhood masks. NH1, NH2...NH8 as shown in Fig. 5

***Step 3:*** Apply the compass Kirsch masks = Kc, for eight directional masks, these operations produces the edge responses = ERp, where p=1..8.

***Step 4:*** Find the number of positive and negative responses, Signum (R) in ERp.

***Step 5:*** Evaluate binary response using Eqn. 3

5.1 if the positive responses are more than one 5 place 1 otherwise place 0.

***Step 6:*** For every 3x3 neighborhood (NH1. NH2,..NH8) central pixel is characterized with single binary pattern i.e. 0 or 1 using step 5.1, in overall every 5x5 window is characterize with binary pattern code which is called as LPDP code (LPDP).

***Step 7:*** The micro region of the image is defined with LPDP. Now histogram of LPDP code is consider as features of micro regions.

***Step 8:*** Concatenate all micro region features and optimize LPDP features with GDA.

***Step 9:*** Apply machine learning classifiers for expression recognition.

}

The Fig.4 demonstrates the division of micro regions of original image.

(a) (b)

**Fig. 4: (a) Facial expression (b) Division of image into 7x6 micro regions.**

Each micro region is considered as individual image and apply the proposed procedure. As shown in Fig. 5, consider 5x5 windows and try to characterize the central pixel. This 5x5 window, interpreted as eight 3x3 masks.

| | | |
|---|---|---|
| 12 | 53 | 26 |
| 52 | 62 | 34 |
| 14 | 85 | 67 |

$NH_1$

| | | |
|---|---|---|
| 53 | 26 | 54 |
| 62 | 34 | 58 |
| 85 | 67 | 48 |

$NH_2$

| | | |
|---|---|---|
| 26 | 54 | 52 |
| 34 | 58 | 36 |
| 67 | 48 | 51 |

$NH_3$

| | | |
|---|---|---|
| 52 | 62 | 34 |
| 14 | 85 | 67 |
| 52 | 36 | 41 |

$NH_4$

| | | | | |
|---|---|---|---|---|
| 12 | 53 | 26 | 54 | 52 |
| 52 | 62 | 34 | 58 | 36 |
| 14 | 85 | 67 | 48 | 51 |
| 52 | 36 | 41 | 85 | 85 |
| 48 | 96 | 32 | 15 | 69 |

$NH_5$

| | | |
|---|---|---|
| 34 | 58 | 36 |
| 67 | 48 | 51 |
| 41 | 85 | 85 |

$NH_6$

| | | |
|---|---|---|
| 14 | 85 | 67 |
| 52 | 36 | 41 |
| 48 | 96 | 32 |

$NH_7$

| | | |
|---|---|---|
| 85 | 67 | 48 |
| 36 | 41 | 85 |
| 96 | 32 | 15 |

$NH_8$

| | | |
|---|---|---|
| 67 | 48 | 51 |
| 41 | 85 | 85 |
| 32 | 15 | 69 |

$NH_9$

**Fig.5: Consideration of 3x3 neighborhoods of 5x5 window**

For each 3x3 window, edge directional responses (ERi) are calculated using kirch masks as shown in Fig.6. The Kirsch operator is given in Fig.2.


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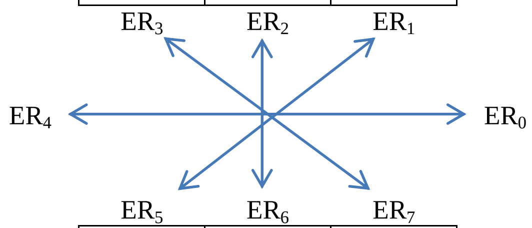
| | | |
|---|---|---|
| 12*5 | 53*5 | 26*-3 |
| 52*5 | 62*0 | 34*-3 |
| 14*-3 | 85*-3 | 67*-3 |

| | | |
|---|---|---|
| 53*5 | 26*5 | 54*5 |
| 62*-3 | 34*0 | 58*-3 |
| 85*-3 | 67*-3 | 48*-3 |

| | | |
|---|---|---|
| 26*-3 | 54*5 | 52*5 |
| 34*-3 | 58*0 | 36*5 |
| 67*-3 | 48*-3 | 51*-3 |

| | | |
|---|---|---|
| 52*5 | 62*-3 | 34*-3 |
| 14*5 | 85*0 | 67*-3 |
| 52*5 | 36*-3 | 41*-3 |




| | | |
|---|---|---|
| 34*-3 | 58*-3 | 36*5 |
| 67*-3 | 48*0 | 51*5 |
| 41*-3 | 85*-3 | 85*5 |

| | | |
|---|---|---|
| 14*-3 | 85*-3 | 67*-3 |
| 52*5 | 36*0 | 41*-3 |
| 48*5 | 96*5 | 32*-3 |

| | | |
|---|---|---|
| 85*-3 | 67*-3 | 48*-3 |
| 36*-3 | 41*0 | 85*-3 |
| 96*5 | 32*-5 | 15*5 |

| | | |
|---|---|---|
| 67*-3 | 48*-3 | 51*-3 |
| 41*-3 | 85*0 | 85*5 |
| 32*-3 | 15*5 | 69*5 |

**Fig. 6: Edge directional responses in eight directions**

.

The binary edge response (BERi) is calculated by using following eqn. 3.

$$BER_i = \begin{cases} 1 \; if \; No. of \; positvies \; (ER_i) \geq 4 \\ 0 \qquad\qquad\qquad\qquad Otherwise \end{cases} \qquad (3)$$

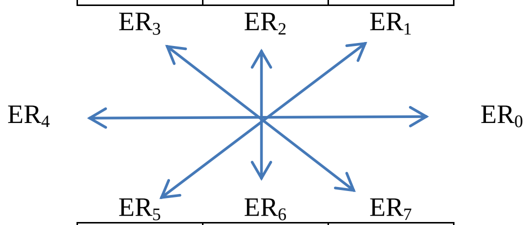
Where BERi, i=1,2..8 is individual binary response of 3x3 masks and ERi is direct edge responses. Here 4, indicates maximum positive responses of in ER0… ER7. This positive ness indicates strong responses which has more discriminative power.

| | | |
|---|---|---|
| -13 | -125 | -301 |
| -93 | | -405 |
| 179 | 299 | 459 |

| | | |
|---|---|---|
| -79 | -255 | -295 |
| -231 | | 241 |
| 353 | 241 | 25 |

| | | |
|---|---|---|
| 8 | 32 | -48 |
| -192 | | -88 |
| 88 | 224 | -24 |

| | | |
|---|---|---|
| 62 | 230 | 110 |
| -50 | | -130 |
| -258 | -42 | 78 |




| | | |
|---|---|---|
| 5 | -211 | -347 |
| -99 | | -235 |
| 173 | 317 | 397 |

| | | |
|---|---|---|
| -185 | 239 | 23 |
| -97 | | -393 |
| 263 | 103 | 47 |

| | | |
|---|---|---|
| -208 | 208 | 208 |
| 112 | | 344 |
| -80 | -248 | -336 |

| | | |
|---|---|---|
| 416 | 248 | 104 |
| 24 | | -104 |
| -520 | -296 | 128 |

**Fig.7 : Direct edge responses of 5x5 window**

The Fig.7 gives the responses of Kirch operator in 8 directions i.e. ER0, ER1.. ER7. These directive responses are represented as a binary using Eqn.3 as shown in Fig. 8.

| | | | | |
|---|---|---|---|---|
| 0 | | 1 | | 1 |
| BER$_3$ | | BER$_2$ | | BER$_1$ |
| 1 | | | | 1 |
| BER$_4$ | | | | BER$_0$ |
| 1 | | 1 | | 1 |
| BER$_5$ | | BER$_6$ | | BER$_7$ |

(a) Binary edge response

1111 0111

(b) Binary response

247

(c ) LPDP code

**Fig. 8: LPDP code derivation**

By applying above procedure on 5x5 windows in overlapping manner, we get LPDP coded image of micro region (r1,…rn). The histogram of LPDP coded image region ri is represented as rfi then final feature vector (FFV) is dfined using Eqn.4

$$FFV = [rf_1, rf_2, \dots \dots rf_n\,] \qquad (4)$$

The FFV is optimized using GDA. This GDA can separate features non-linearly with help of kernel. The key objective of GDA is maximizing the scatterings of samples between classes while minimizing the scatterings of samples within classes. GDA can be defined as

$$G_{GDA} = {|G^T S_B G|}/{|G^T S_T G|} \qquad (5)$$

Where S_B and S_T two matrices between-class and total classes using kernel function. LPDP features are projected on the features space of GGDA.

$$F = G_{GDA}^T A \qquad (6)$$

LPDP-GDA features from each image in a facial expression are augmented to represent the features for the individual expression. For a feature length r , the LPDP-GDA feature vector Q can be obtained as

$$Q = F^1 , F^2 , \dots , F^r . \qquad (7)$$



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Once LPDP-GDA features are gained from all the facial expression the next step is to use classifiers for expression recognition.

### C. Optimal selections of micro regions

In this paper experimental purpose, four image divisions are considered on input image i.e. 3×3, 5×5, 7×6, and 9×8. The Table 1, gives expression classification rate for these blocks.

**Table 1: Classification rate (%) Micro regions corresponding classification rate (%) and feature length.**

| No. of micro regions | Classification rate (%) |
|---|---|
| 3x3 | 86.22 |
| 5x5 | 88.15 |
| 7x6 | 90.25 |
| 9x8 | 89.21 |

The Table 1, show the effect of no. of regions on recognition rate(%). Dividing into small no. of regions gives low recognition rate (%). While increasing no. of regions, the recognition rate will be start to increase as more local and spatial relationships information is seized. However, after certain point, more no. of regions allows to capture unnecessary information into features, as a result the performance is decreased. In our work, 7x6 giving highest recognition rate for considered database.

## 3. RESULTS AND DISCUSSION

Seven different facial expressions were considered and used for training and testing in this work. The expressions are Anger, disgust, fear, happy, neutral, sad, surprise. For each expression, some images are training and some images are used for testing. Then, a two-fold cross validation was done on expressions for logistic regression, k-nearest neighborhood, support vector machine and random forest classifiers. The proposed method is compared with state-art-of descriptors like LBP, LBP hidden markov model (LBP-HMM), LDP, LDP-HMM.

**Experiment #1:**

One of the most popular bench mark database for facial expression recognition is JAFFE [23]. To study the performance of proposed method, JAFFE is used to derive feature vector. In JAFFE dataset, there are 213 images of 10 categories with 7 expressions viz. viz. ³anger´, ³disgust´, ³fear´, ³happy´, ³neutral´, ³sad´ and ³surprise´. The number of images for one expression of a subject varies from 3 to 4. The sample images of JAFFE are given Fig.9.

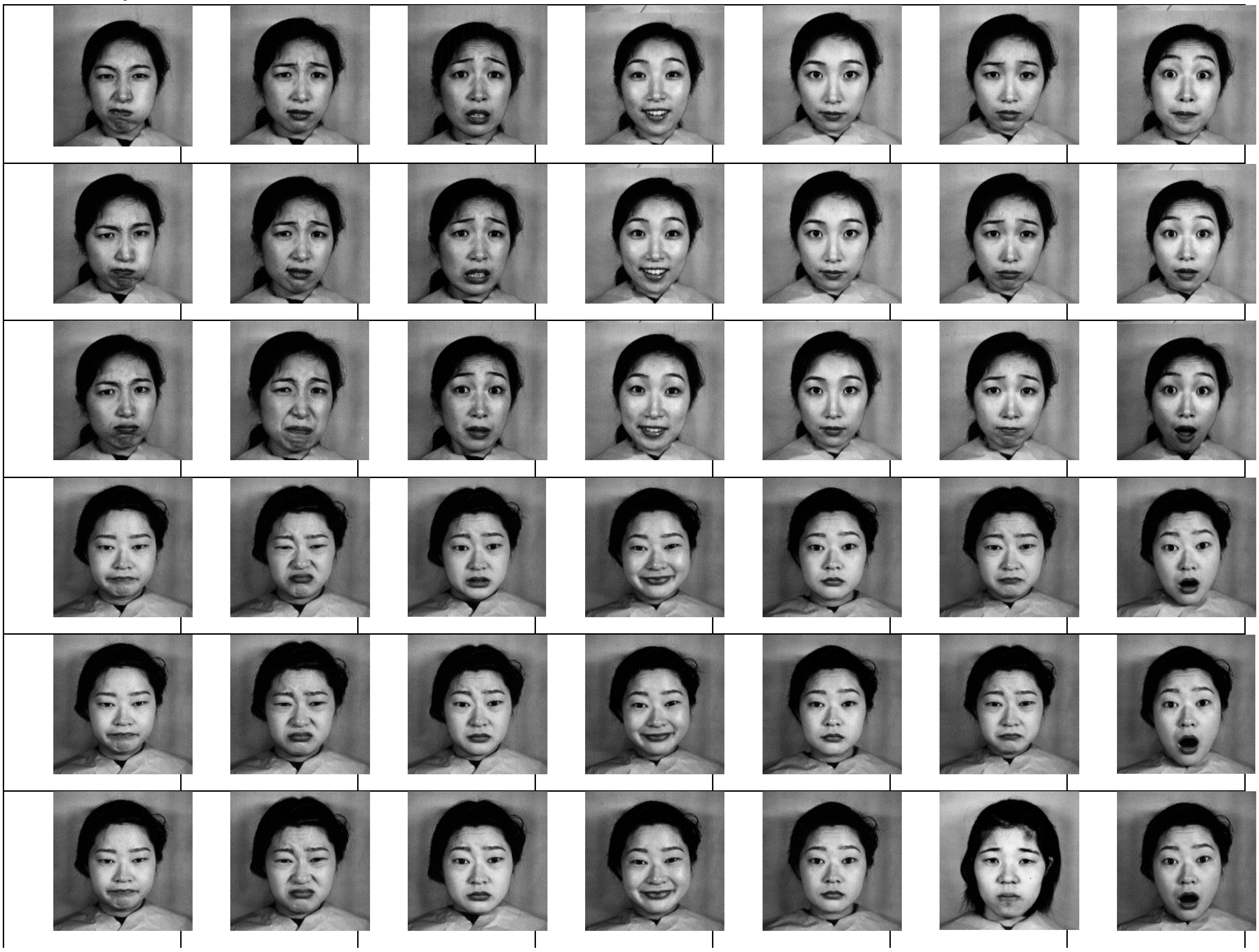

**Fig.9: Sample images of JAFFE database**

**Table 2: Expression recognition rate(%) on JAFFE database**

| Methods | Expression | Logistic Regression | K-Nearest neighbor | Support Vector Machine | Random Forest |
|---|---|---|---|---|---|
| LBP | Anger | 85.12 | 86.2 | 86.63 | 87.62 |
| | Disgust | 85.21 | 86.21 | 86.65 | 87.72 |
| | Fear | 85.15 | 86.52 | 86.85 | 87.21 |
| | Happy | 82.5 | 85.86 | 85.95 | 86.63 |
| | Neutral | 85.23 | 85.62 | 86.36 | 87.96 |
| | Sad | 85.24 | 85.96 | 86.99 | 88.21 |
| | Surprise | 85.23 | 86.21 | 86.65 | 87.62 |
| LBP+HMM | Anger | 86.33 | 87.44 | 87.95 | 88.65 |
| | Disgust | 86.42 | 87.45 | 87.97 | 88.75 |
| | Fear | 86.36 | 87.76 | 88.17 | 88.24 |
| | Happy | 83.71 | 87.1 | 87.27 | 87.66 |
| | Neutral | 86.44 | 86.86 | 87.68 | 88.99 |
| | Sad | 86.45 | 87.2 | 88.31 | 89.24 |
| | Surprise | 86.44 | 87.45 | 87.97 | 88.65 |
| LDP | Anger | 85.10 | 86.26 | 86.73 | 87.89 |
| | Disgust | 87.5 | 87.81 | 87.95 | 88.1 |
| | Fear | 85.11 | 87.52 | 87.85 | 87.99 |
| | Happy | 84.5 | 87.86 | 87.95 | 87.99 |
| | Neutral | 85.1 | 86.62 | 87.36 | 87.99 |
| | Sad | 87.52 | 88.96 | 89.97 | 89.96 |
| | Surprise | 89.62 | 89.81 | 89.88 | 89.92 |
| LDP+HMM | Anger | 86.82 | 87.5 | 87.94 | 89 |
| | Disgust | 88.52 | 89.05 | 89.16 | 89.21 |
| | Fear | 86.02 | 88.76 | 89.06 | 89.1 |
| | Happy | 85.52 | 89.1 | 89.16 | 89.1 |
| | Neutral | 86.12 | 87.86 | 88.57 | 89.1 |
| | Sad | 88.54 | 90.2 | 91.18 | 91.07 |
| | Surprise | 90.64 | 91.05 | 91.09 | 91.03 |
| Proposed LPDP | Anger | 86.98 | 87.86 | 88.63 | 89.2 |
| | Disgust | 88.87 | 89.81 | 89.15 | 89.92 |
| | Fear | 86.89 | 87.82 | 88.85 | 90.12 |
| | Happy | 85.65 | 88.96 | 89.95 | 90.56 |
| | Neutral | 86.19 | 88.82 | 89.86 | 90.62 |
| | Sad | 88.52 | 89.16 | 90.12 | 91.2 |
| | Surprise | 91.12 | 90.81 | 91.2 | 91.53 |

**Experiment #2:**

Cohn-Kanade (CK+) database [24] : This database consists of 719 subjects and for each subject there 123 folders. Totally 10558 images are considered for experimental setup. The sample images of CK+ database are given in Fig. 10;

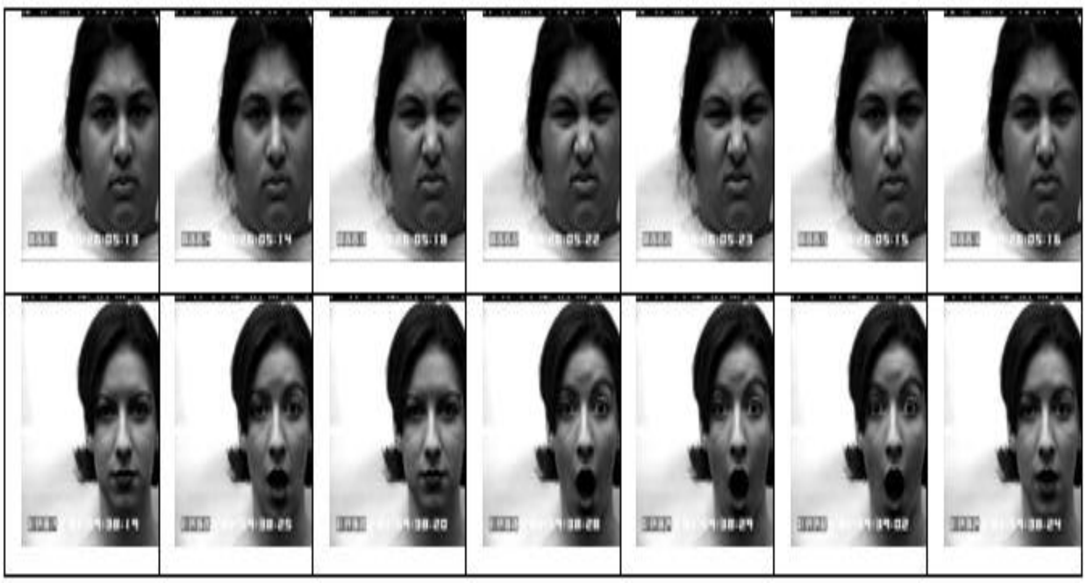

**Fig.10: Sample images of CK+ database images**



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**Table 3: Expression recognition rate (%) on CK+ database.**

| Methods | Expression | Logistic Regression | K-Nearest neighbor | Support Vector Machine | Random Forest |
|---|---|---|---|---|---|
| LBP | Anger | 84.1 | 85.18 | 86.51 | 86.51 |
| | Disgust | 84.19 | 85.19 | 86.53 | 86.61 |
| | Fear | 84.13 | 85.5 | 86.73 | 86.1 |
| | Happy | 81.48 | 84.84 | 85.83 | 85.52 |
| | Neutral | 84.21 | 84.6 | 86.24 | 86.85 |
| | Sad | 84.22 | 84.94 | 86.87 | 87.1 |
| | Surprise | 84.21 | 85.19 | 86.53 | 86.51 |
| LBP+HMM | Anger | 85.31 | 86.42 | 87.83 | 87.54 |
| | Disgust | 85.4 | 86.43 | 87.85 | 87.64 |
| | Fear | 85.34 | 86.74 | 88.05 | 87.13 |
| | Happy | 82.69 | 86.08 | 87.15 | 86.55 |
| | Neutral | 85.42 | 85.84 | 87.56 | 87.88 |
| | Sad | 85.43 | 86.18 | 88.19 | 88.13 |
| | Surprise | 85.42 | 86.43 | 87.85 | 87.54 |
| LDP | Anger | 83.98 | 85.24 | 86.61 | 86.78 |
| | Disgust | 86.48 | 86.79 | 87.83 | 86.99 |
| | Fear | 83.98 | 86.5 | 87.73 | 86.88 |
| | Happy | 83.48 | 86.84 | 87.83 | 86.88 |
| | Neutral | 84.08 | 85.60 | 87.24 | 86.88 |
| | Sad | 86.5 | 87.94 | 89.85 | 88.85 |
| | Surprise | 88.6 | 88.79 | 89.76 | 88.81 |
| LDP+HMM | Anger | 85.8 | 86.48 | 87.82 | 87.89 |
| | Disgust | 87.5 | 88.03 | 89.04 | 88.1 |
| | Fear | 85 | 87.74 | 88.94 | 87.99 |
| | Happy | 84.5 | 88.08 | 89.04 | 87.99 |
| | Neutral | 85.1 | 86.84 | 88.45 | 87.99 |
| | Sad | 87.52 | 89.18 | 91.06 | 89.96 |
| | Surprise | 89.62 | 90.03 | 90.97 | 89.92 |
| Proposed LPDP | Anger | 85.96 | 86.84 | 88.51 | 88.09 |
| | Disgust | 87.85 | 88.79 | 89.03 | 88.81 |
| | Fear | 85.87 | 86.8 | 88.73 | 89.01 |
| | Happy | 84.63 | 87.94 | 89.83 | 89.45 |
| | Neutral | 85.17 | 87.81 | 89.74 | 89.51 |
| | Sad | 87.5 | 88.14 | 90.10 | 90.09 |
| | Surprise | 90.1 | 89.79 | 91.08 | 90.42 |

**Experimental #3:**

CASME II dataset [25] contains 246 spontaneous micro-expression sequences by 26 subjects. The Chinese Academy of Sciences Micro-expression (CASME) database contains 195 micro-expressions filmed under 60fps. They were selected from more than 1500 elicited facial movements. These samples were coded with the onset, apex and offset frames1, with action units (AUs) marked and emotions labeled. This database having 2 classes i.e. Class A and Class B. The samples in Class A were recorded by BenQ M31 camera with 60fps, with the resolution set to 1280 × 720 pixels. The participants were recorded in natural light. The sample images are shown in Fig.11.

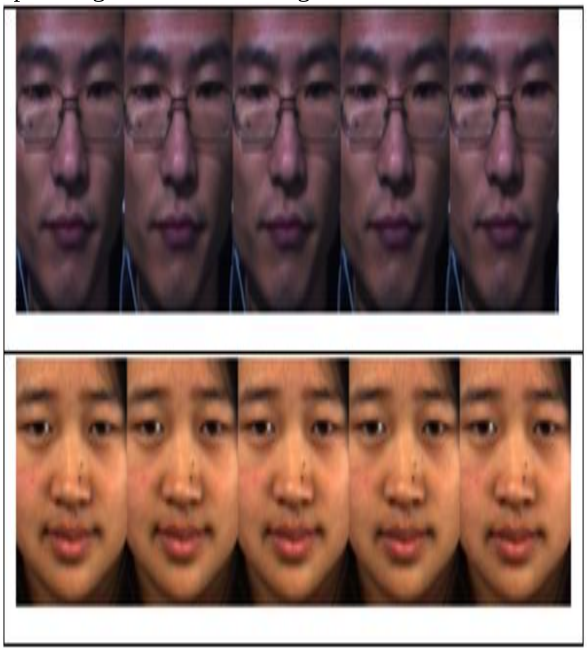

**Fig.11; Sample images of CASME II dataset**

**Table 4: Expression recognition rate (%) on CASME-II database**

| Methods | Expression | Logistic Regression | K-Nearest neighbor | Support Vector Machine | Random Forest |
|---|---|---|---|---|---|
| LBP | Anger | 82.88 | 83.95 | 85.27 | 85.28 |
| | Disgust | 82.97 | 83.96 | 85.29 | 85.38 |
| | Fear | 82.91 | 84.27 | 85.49 | 84.87 |
| | Happy | 80.26 | 83.61 | 84.59 | 84.29 |
| | Neutral | 82.99 | 83.37 | 85.21 | 85.62 |
| | Sad | 83.10 | 83.71 | 85.63 | 85.87 |
| | Surprise | 82.99 | 83.96 | 85.29 | 85.28 |


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| | | | | | |
|---|---|---|---|---|---|
| LBP+HMM | Anger | 84.09 | 85.19 | 86.59 | 86.31 |
| | Disgust | 84.18 | 85.2 | 86.61 | 86.41 |
| | Fear | 84.12 | 85.51 | 86.81 | 85.9 |
| | Happy | 81.47 | 84.85 | 85.91 | 85.32 |
| | Neutral | 84.2 | 84.61 | 86.32 | 86.65 |
| | Sad | 84.21 | 84.95 | 86.95 | 86.9 |
| | Surprise | 84.2 | 85.2 | 86.61 | 86.31 |
| LDP | Anger | 82.76 | 84.01 | 85.37 | 85.55 |
| | Disgust | 85.26 | 85.56 | 86.59 | 85.76 |
| | Fear | 82.76 | 85.27 | 86.49 | 85.65 |
| | Happy | 82.26 | 85.61 | 86.59 | 85.65 |
| | Neutral | 82.86 | 84.37 | 86.22 | 85.65 |
| | Sad | 85.28 | 86.71 | 88.61 | 87.62 |
| | Surprise | 87.38 | 87.56 | 88.52 | 87.58 |
| LDP+HMM | Anger | 84.58 | 85.25 | 86.58 | 86.66 |
| | Disgust | 86.28 | 86.8 | 87.8 | 86.87 |
| | Fear | 83.78 | 86.51 | 87.7 | 86.76 |
| | Happy | 83.28 | 86.85 | 87.8 | 86.76 |
| | Neutral | 83.88 | 85.61 | 87.21 | 86.76 |
| | Sad | 86.3 | 87.95 | 89.82 | 88.73 |
| | Surprise | 88.4 | 88.8 | 89.73 | 88.69 |
| Proposed LPDP | Anger | 84.74 | 85.61 | 87.27 | 86.86 |
| | Disgust | 86.63 | 87.56 | 87.79 | 87.58 |
| | Fear | 84.65 | 85.57 | 87.49 | 87.78 |
| | Happy | 83.41 | 86.71 | 88.59 | 88.22 |
| | Neutral | 83.95 | 86.57 | 88.5 | 88.28 |
| | Sad | 86.28 | 86.91 | 88.76 | 88.86 |
| | Surprise | 88.88 | 88.56 | 89.84 | 89.19 |

Table 5 gives average expression classification rate of proposed and existing methods with respect to considered facial expressions.

**Table 5: Average classification of proposed and existing methods.**

| Methods | Expression | JAFFE | CK+ | CASME II |
|---|---|---|---|---|
| LBP | Anger | 86.39 | 85.58 | 84.35 |
| | Disgust | 86.45 | 85.63 | 84.40 |
| | Fear | 86.43 | 85.62 | 84.39 |
| | Happy | 85.24 | 84.42 | 83.19 |
| | Neutral | 86.29 | 85.48 | 84.25 |
| | Sad | 86.60 | 85.78 | 84.55 |
| | Surprise | 86.43 | 85.61 | 84.38 |
| LBP+HMM | Anger | 87.59 | 86.78 | 85.55 |
| | Disgust | 87.65 | 86.83 | 85.60 |
| | Fear | 87.63 | 86.82 | 85.59 |
| | Happy | 86.44 | 85.62 | 84.39 |
| | Neutral | 87.49 | 86.68 | 85.45 |
| | Sad | 87.80 | 86.98 | 85.75 |
| | Surprise | 87.63 | 86.81 | 85.58 |
| LDP | Anger | 86.47 | 85.65 | 84.42 |
| | Disgust | 87.84 | 87.02 | 85.79 |
| | Fear | 87.09 | 86.27 | 85.04 |
| | Happy | 87.08 | 86.26 | 85.03 |
| | Neutral | 86.77 | 85.95 | 84.72 |
| | Sad | 89.10 | 88.29 | 87.06 |
| | Surprise | 89.81 | 88.99 | 87.76 |
| LDP+HMM | Anger | 87.82 | 87.00 | 85.77 |
| | Disgust | 88.99 | 88.17 | 86.94 |
| | Fear | 88.24 | 87.42 | 86.19 |
| | Happy | 88.22 | 87.40 | 86.17 |
| | Neutral | 87.91 | 87.10 | 85.87 |
| | Sad | 90.25 | 89.43 | 88.20 |
| | Surprise | 90.95 | 90.14 | 88.91 |
| Proposed LPDP | Anger | 88.17 | 87.35 | 86.12 |
| | Disgust | 89.44 | 88.62 | 87.39 |
| | Fear | 88.42 | 87.60 | 86.37 |
| | Happy | 88.78 | 87.96 | 86.73 |
| | Neutral | 88.87 | 88.06 | 86.83 |
| | Sad | 89.75 | 88.93 | 87.70 |
| | Surprise | 91.17 | 90.35 | 89.12 |

The Fig.12 shows the comparison of proposed method with state-of-art methods in terms of classification. By analyzing Fig.12, we can conclude that

1. The proposed descriptor is derived on 5x5 neighborhood, hence we are considered 25 pixels for justifying the central pixel. Consideration of more number of pixels obviously gives more discriminative power.
2. The proposed descriptor is shown high classification rate (%) on JAFFE database than CK+ and CASME-II database. The reason is, JAFFE database images having clear expressions than CK+ and CASME-II database images.



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3. The proposed descriptor shown different behavior for different considered expressions (anger, disgust, fear, happy, Neutral, sad and surprise).
4. By combining HMM with LBP and LDP these operators shown good classification rate. The proposed LPDP descriptors shown high classification than existing methods without combining any other concepts.

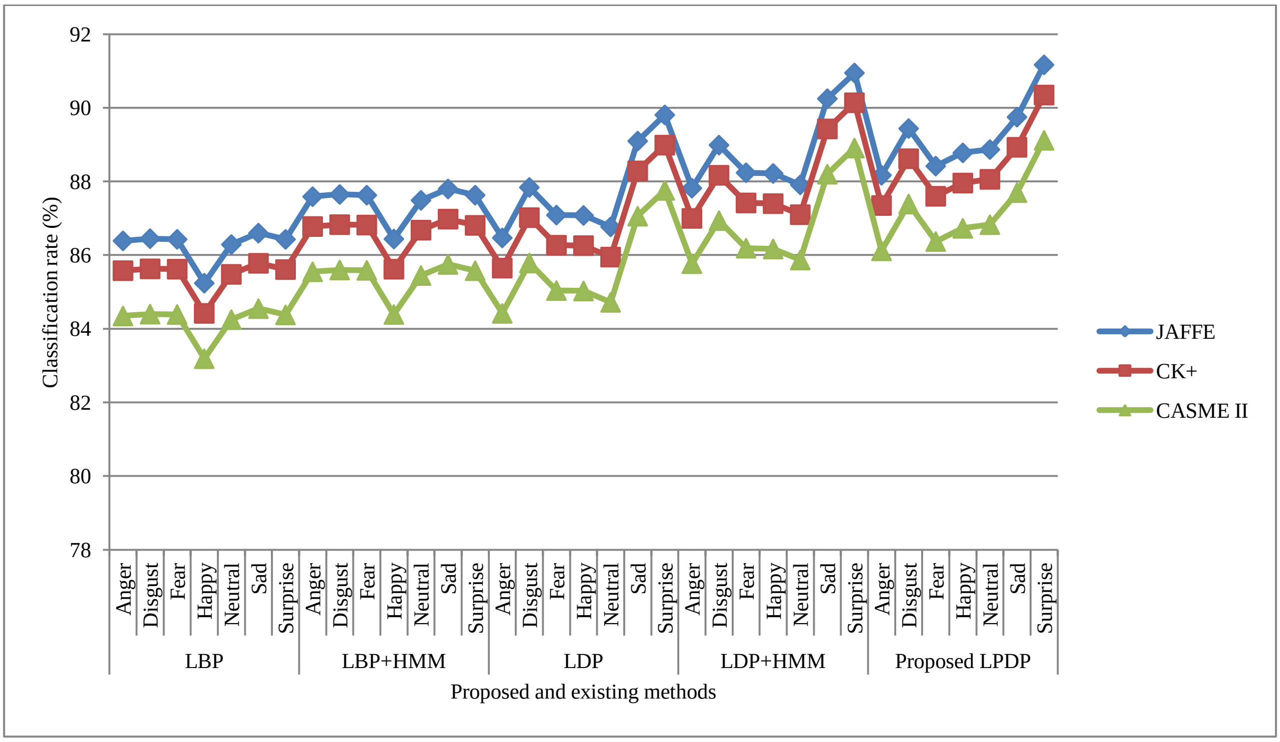


**Fig.12: Comparison of proposed and existing methods on considered databases**

## 4. CONCLUSIONS

This paper describes a new local positive directional pattern descriptor based on LDP codes for facial expression recognition. The LPDP code contains local information and spatial information encoding the texture, and the descriptor contains the global information. Extensive experiments reveal that the LPDP features are effective and efficient for expression recognition. This proposed descriptor having complete strength of LDP without influence of k value. The discriminative power of the LPDP descriptor mainly lies in the strong positive edge responses of the local edge response pattern. Further, the LPDP features also maintain a high recognition rate with lower computational cost. By the help of GDA, the features are optimized so that LPDP shown its superiority than other state-of-art methods

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