

# **Facial Expression Recognition using Curvelet based RLBP Features**

Rajashri M. Ladhe<sup>1</sup>, Prof. Pankaj A. Salunkhe<sup>2</sup>

P.G. Student, Dept. of EXTC, SES GOI FOE, Mumbai University, Bhivpuri Road, Karjat, India<sup>1</sup>

Assistant Professor, Dept. of EXTC, YTIET, Mumbai University, Bhivpuri Road, Karjat, India<sup>2</sup>

**ABSTRACT:** Facial expression recognition has wide variety of application such as, man-machine communication, behavioral science, clinical studies, psychological treatment, video- conferencing, border security system, robotics and computer games and many more. Hence facial expression analysis is an interesting and challenging problem. This paper proposed a technique for facial expression recognition based on extraction of Robust Local binary Pattern (RLBP) features in curvelet domain. The curvelet transform preserves the edges and other variations occurred in the face during expression and the RLBP extracts noise and illumination invariant features from the face images. The Euclidean distance classifier classifies the facial expressions as angry, disgust, fear, happy, neutral, sad and surprise.

**KEYWORDS:** Preprocessing, Feature extraction, Curvelet transform, Facial expression, Classification.

## **I. INTRODUCTION**

Facial expression is the most powerful, natural and immediate mean for human beings to communicate their emotions. Facial expression provides a non-verbal form of communication that facilitates the recognition of human emotions and intentions. It provides information about human personality, thoughts and emotions. Facial expression provides sensitive cues about emotional response and plays important role in human interactions and non-verbal communication. The verbal part of human communication contributes only 7%, the vocal part contributes 38% and facial movement and expression yields 55% to the meaning of the communication [1]. This means that facial part does the major contribution in human communication as well as man-machine interaction. Different peoples have different appearance for different expressions. But still human can recognize a wide range of different expressions. If we are not familiar with someone's face we can recognize the person's facial expressions due to the universality of expression. However it is a challenging task for a compute vision system to recognize an individual across different expressions or to classify the basic facial expression across different persons. Facial expression recognition has wide variety of application, such as, man-machine communication, behavioral science, clinical studies, psychological treatment, video- conferencing, image retrieval, face animation, border security system, robotics and computer games and many more.

Facial expression recognition involves two vital aspects: facial feature extraction and facial expression recognition. Facial feature extraction is to derive a set of features from original face images. There are two main types of approaches to extract facial features: geometric feature-based methods [2] [3] and appearance-based methods [4]. In the geometric feature extraction system, the shape and location of various face components are considered. The geometry-based methods require accurate and reliable facial feature detection, which is difficult to achieve in practical applications. In contrast, the appearance-based methods, image filters are applied to either the whole face image known as global feature or some specific region of the face image known as local feature to extract the appearance change in the face image. The appearance features generally refer to the skin texture changes on the face, such as wrinkles and furrows.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

## II. RELATED WORK

Hazar Maliki et al. [5] proposed a new feature based approach for recognition of facial expression. In this paper the author provides the solution to identify human expressions, expressions variation and intensity problem automatically. Here the active contour is applied to segment the detected facial features like eyes, eyebrows and mouth. The distance between facial features is computed and used the set of prediction rules generated via data mining process for classification of facial expressions. This paper defines the seven facial feature classes as joy, smile, surprise, disgust, anger, sadness and fear and the performance evaluated by computing the global error rate, priori error rate and posteriori error rate. R. Verma et al. [6] proposed a facial expression recognition algorithm based on Local Binary Patterns (LBP). Local binary pattern (LBP) is a gray-scale invariant texture description operator which labels the pixels of an image by thresholding the neighborhood of each pixel with the center value and considering the result as a binary pattern. Here various machine learning approaches including Support Vector Machine (SVM) and Adaptive Boosting (AdaBoost) have also been examined for facial expression recognition. This system recognizes expressions accurately at the rate of 4.8 frames per second. C. Shan et al. [7], describes the facial expression recognition using Local Binary patterns. This paper shows that effectiveness of LBP-based algorithm on different image resolutions and robustness of LBP features for low-resolution face images. Template matching with weighted Chi square statistic and Support Vector Machine are adopted to classify facial expressions.

A. Saha and Q. Jonathan [8], proposed a combination of curvelet transform and local binary patterns for recognition of facial expressions. Expression recognition performed by using nearest neighbor classifier with Chi-square as the dissimilarity metric. This method demonstrates the efficiency of curvelet based LBP as a good feature extractor. S. Nagaraja et al. [9], proposed a technique for facial expression recognition based on combination of curvelet transform and complete Local binary Pattern (CLBP). Rotation invariant uniform binary patterns extracted from the approximate sub-band using CLBP method to represent facial expressions. Tingfan Wu et al. [10] used biologically inspired spatiotemporal Gabor Motion Energy filters (GME) for low level integration of spatiotemporal information in facial expression recognition tasks. This proves GME filters are particularly effective for representing low intensity facial expressions. Here Support Vector Machine (SVM) used for classification. Irene Kotsia et al. [11] described the facial expression recognition using geometric deformation features. Author presents the candidate grid node information extraction and grid node information classification. The grid node information extraction is performed by a tracking system, while the grid node information classification is performed by a SVM system.

## III. PROPOSED SYSTEM

This paper proposed a technique for facial expressions recognition based on combination of curvelet transform and Robust Local Binary Pattern (RLBP). In this work, first the input image is preprocessed to filter the noise. The Viola and Jones face detection algorithm is used which extracts the face from the input image. After detecting the face from image the curvelet transform decomposed the normalized image into approximate sub-band and detailed sub-bands. To extract the features from the image, we used the Robust Local Binary Pattern (RLBP) which is invariant to illumination and insensitive to noise. Facial expression recognition from the texture features perform by using Euclidean distance classifier.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

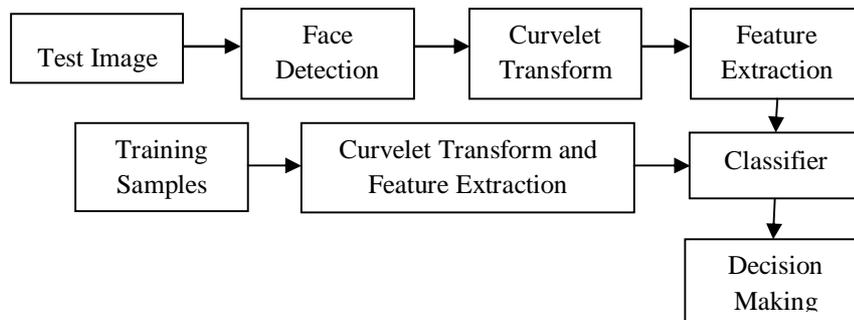


Fig 1. Facial Expression Recognition System

## A. Preprocessing and Face Detection:

After entering the data into facial expression recognition system next step is pre-processing. Several factors of collected may affect the accuracy and robustness of facial expression analysis system, such as contrast, illumination, size of image, too much redundant information etc. Therefore it is most vital to pre-process the taken image before starting the facial expression analysis. Pre-processing includes removal of noise and unwanted information from input image. In this step images are cropped and resized into same dimension. Pre-processing is applied to images in training database and test database. Pre-processing involves the stages such as the image resizing, RGB to gray scale conversion and noise removal using median filter. For the facial expression recognition first need to crop the face area correctly. Viola Jones algorithm is used to detect the face.

## B. Curvelet Transform:

The curvelet transform was proposed by Candes and Donoho. Curvelet transform is used to overcome these problems of the wavelet and Gabor filters. It can obtain the complete spectral information of the image and handle with the different orientations of the image edges. The curvelet transform has better ability to represent the edges and improved directional capability as compared to wavelet transform. Curvelet transform have two generations, first generation curvelet (1999) used complex series of steps involving ridgelet analysis of the radon transform of an image, the performance is exceedingly slows. Later the same authors proposed a considerably simpler second-generation curvelet transform based on a frequency partition technique. The second generation curvelet transform called as Fast Discrete Curvelet Transform (FDCT) is not only simpler, but it is faster and less redundant compared to its first generation version.

There are two separate algorithms of fast discrete curvelet transform. The first algorithm is the unequally spaced Fast Fourier Transform (USFFT), where the curvelet coefficients are found by irregularly sampling the Fourier coefficients of an image. The second algorithm is the Wrapping transform, using a series of translations and a wraparound technique. Curvelets via wrapping has been used in this work as this is the fastest and simplest curvelet transform currently available. The new implementation of curvelet transform, based on wrapping of Fourier samples, takes a 2D image as input in the form of a Cartesian array and the output will be a collection of curvelet coefficients.

Main steps of wrapping are as follows:

1. The 2D Fast Fourier transform (FFT) of  $f[t_1, t_2] \rightarrow \hat{f}[n_1, n_2]$  is calculated.
2.  $\hat{f}[n_1, n_2]$  is separated into dyadic subbands using a scale window  $W_j$ ,  $j$  representing  $j^{th}$  scale.
3. Each subband is separated into angular wedges using angular windows  $W_{j,l}$  with  $l$  representing  $l^{th}$  scale.
4. The product  $\tilde{U}_{j,l}[n_1, n_2] \hat{f}[n_1, n_2]$  is computed, where  $\tilde{U}_{j,l}[n_1, n_2]$  is the discrete localizing window.

## International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

5. The product is wrapped inside a rectangle  $W$  of size  $L_{1,j} \times L_{2,j}$  (in east-west) or  $L_{2,j} \times L_{1,j}$  (in north-south) around the origin to obtain  $\tilde{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}\hat{f})[n_1, n_2]$ ; where the range for  $n_1$  and  $n_2$  is now  $0 \leq n_1 < L_{1,j}$  and  $0 \leq n_2 < L_{2,j}$ ;  $L_{1,j} \sim 2^j$  and  $L_{2,j} \sim 2^{j/2}$  are constants.
6. The 2D inverse FFT of each  $\tilde{f}_{j,l}$  is calculated to obtain curvelet coefficients at scale  $j$  and orientation  $l$ .

### C. Local Binary Pattern (LBP)

Local binary pattern (LBP) is a gray-scale and rotation invariant texture description operator which labels the pixels of an image by thresholding the neighborhood of each pixel with the center value and considering the result as a binary pattern. Then the histogram of the labels can be used as a texture descriptor. It is low cost image descriptor. LBP features were originally proposed for texture analysis. LBP is a nonparametric method which means that no underlying assumptions are needed for its computation. The LBP operator is an excellent measure of the spatial structure around a pixel. Various circular neighborhoods can be obtained using bilinear interpolation of the pixel values thereby allowing any radius and number of pixels in the neighborhood of a center pixel. LBP recently used in face recognition and facial expression recognition because of its low computation and high discrimination capability. The LBP approach efficiently encodes the texture features of micro-pattern information in the face image; it considers the uniform patterns. It is powerful extraction technique for effectively characterizing different facial expression patterns. The LBP operator labels the pixel of an image. Every pixel is compared with its eight neighbors in  $3 \times 3$  neighborhood by subtracting the centre pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top left neighbor.

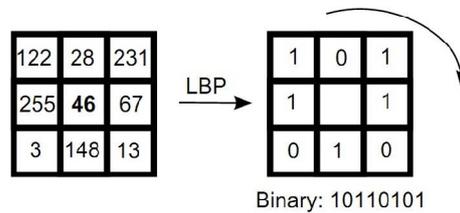


Fig 2. An example of the basic LBP operator

Consider texture  $T$  in a local neighborhood with gray levels of  $P$  ( $P > 1$ ) image pixels.

$$T \approx t(s(g_0 - g_c), s(g_1 - g_c), \dots, s(g_{P-1} - g_c))$$

Where  $g_p$  ( $p = 0, \dots, P - 1$ ) gray values,  $g_c$  is the center gray value and,

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

The above is transformed into a unique P-pattern code by assigning binomial coefficient  $2^p$  to each sign  $S(g_{p-1} - g_c)$ .

$$LBP = \sum_{p=0}^{P-1} S(g_{p-1} - g_c) 2^p$$

The number of labels clearly depends on the number of neighbors used in the LBP operator. For  $N$  neighbors, number of labels will be maximum  $2^N$ . The operator was modified to use neighborhoods of different sizes. In the modified operator, the neighborhood of any pixel was defined as a circular region of radius  $R$ . Using bi-linear interpolation, a number of  $P$  (depending on  $R$ ) pixels can be sampled on the circumference of the circular region using the center pixel as threshold. The LBP is therefore represented by  $LBP(P, R)$ .

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

## D. Robust Local Binary Pattern (RLBP):

LBP operator increases the intra-class variance which is undesirable for face recognition. Intra class variance increases due to discrimination of bright face against dark background vice-versa. Since the gray value of the threshold isn't suitable, LBP is sensitive to noise and illumination variants, especially in the near-uniform image areas. As demonstrated in Fig. 3, we can observe that a little change of the central pixel greatly affects the LBP code.

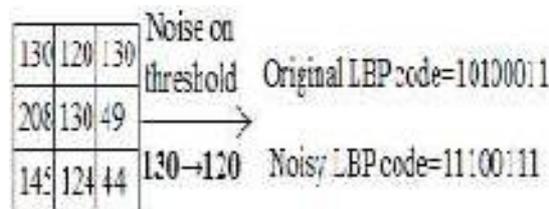


Fig 3. An instance that LBP is susceptible to noise.

To overcome this problem, we're looking for a suitable threshold. This work attempts to overcome this basic problem by using RLBP. The RLBP produces code, which is invariant to monotonic gray scale transformation and insensitive to noise. The gray value of centre pixel in 3x3 local area is replaced by its average local gray value of the neighbourhood pixel values instead of the gray value of centre pixel value, in which the RLBP is calculated.

In order to find a threshold which isn't sensitive to noise and stable to monotonic gray scale transformation, we apply the Average Local Gray Level (ALG) as follows:

$$ALG = \frac{\sum_{i=1}^8 g_i + g}{9}$$

Where  $g$  is the gray value of the centre pixel and  $g_i (i = 0, 1, \dots, 8)$  denotes the gray value of the neighbor pixel. ALG represents the average gray level of local area, which is obviously more robust to noise than the gray value of the central pixel. Then the LBP process is applied by using ALG as the threshold instead of the gray value of the central pixel, named Robust Local Binary Pattern (RLBP). As a result, we can define RLBP as follows:

$$RLBP_{P,R} = \sum_{p=0}^{P-1} S(g_p - ALG_c) 2^p = \sum_{p=0}^{P-1} S\left(g_p - \frac{\sum_{i=1}^8 g_{ci} + g_c}{9}\right) 2^p$$

Where  $g_c$  represents the gray value of the center pixel and  $g_p (p = 0, 1, \dots, P - 1)$  denotes the gray value of the neighbor pixel on a circle of radius R, P is the total number of the neighbors and  $g_{ci} (i = 0, 1, \dots, 8)$  is the gray values of the neighbor pixel of  $g_c$ . Here average local gray level of pixel is used as threshold, hence It is obviously that RLBP is insensitive to noise. Besides, two different patterns with the same LBP code may have different RLBP code because that the neighbors of each neighbor pixel are also considered. Thus RLBP can overcome the aforementioned two demerits of original LBP.

## E. Euclidean Distance Classifier:

Here the Euclidean distance classifier is used to classify the different facial expressions. It is a minimum distance classifier. The minimum distance classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Euclidean distance based classifier is used which is obtained by calculating of distance between image to test and available images that are taken as training images. Using the given set of values minimum distance can be found. In testing, for every expression computation of

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Euclidean distance (ED) is done between new image (testing) Eigenvector and Eigen subspaces, to find the input image expression classification based on minimum Euclidean distance is done. The formula for the Euclidean distance is given by

$$ED = \sqrt{\sum (x_2 - x_1)^2}$$

## IV. EXPERIMENTAL RESULTS AND DISCUSSION

The algorithm was developed in MATLAB and applied on the collected database. It consist of 224 images of 7 expressions namely angry, disgust, fear, happy, sad and surprise with neutral from which 168 images used for training and remaining used for testing.

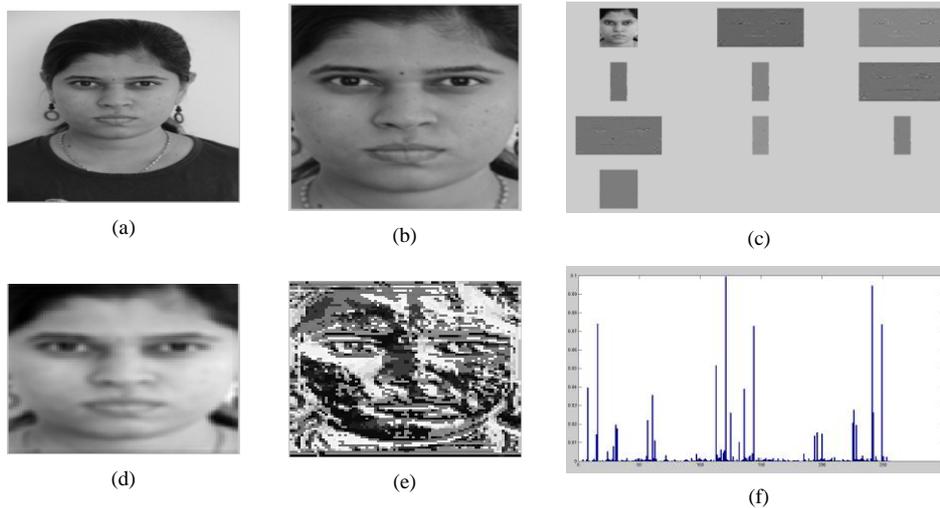
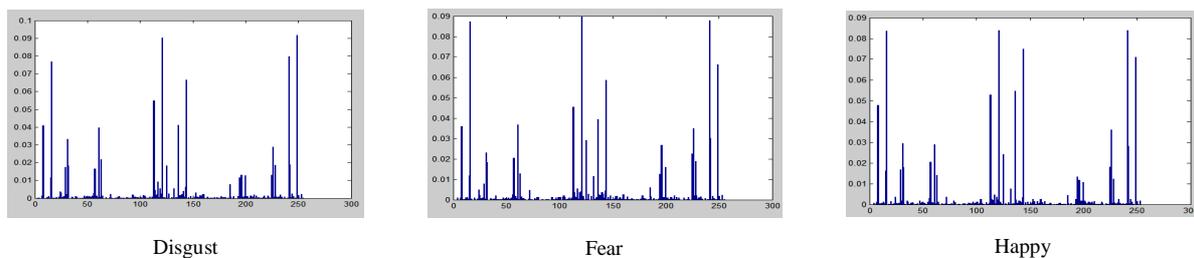


Fig 4. Results for Angry expression (a) Test image (b) Face detection (c) Curvelet transform subband (d) Average local gray value (e) RLBP image (f) RLBP histogram

The above fig. 4 shows the results of one expression, in which the face is detected from test image. After that the curvelet transform decomposes the image into approximate sub-band and detailed sub-bands. Finally we extract robust and noise invariant features from approximate sub-band obtained from curvelet transform using RLBP. Then the RLBP histogram is calculated based on the class labels of the face images.



# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

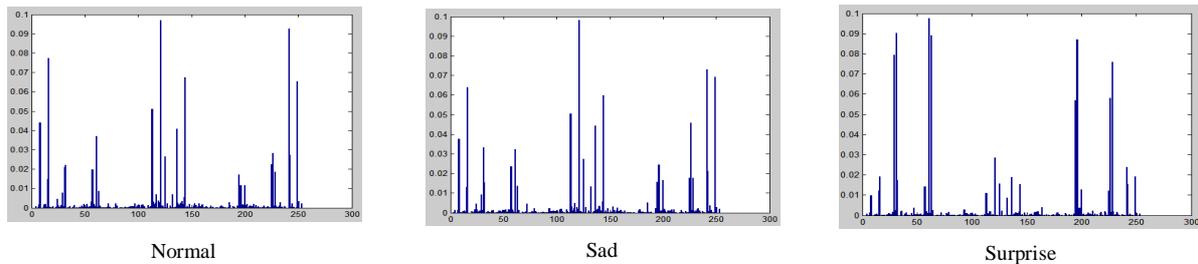


Fig 5. RLBP Histograms of Different Expressions

The RLBP histogram is calculated based on the class labels of the face images. The above fig. 5 shows the different histograms of expressions as disgust, fear, happy, normal, sad and surprise. Each expression has the different RLBP histogram. According to the histogram the different expressions are recognized.

Target Recognition Rate	Angry (8)	Disgust (8)	Fear (8)	Happy (8)	Neutral (8)	Sad (8)	Surprise (8)
Angry	8	0	0	0	0	0	0
Disgust	0	8	0	0	0	0	0
Fear	0	0	4	0	0	1	0
Happy	0	0	0	8	0	1	0
Neutral	0	0	0	0	8	1	0
Sad	0	0	4	0	0	5	0
Surprise	0	0	0	0	0	0	8

Table I. System Performance Results

Table I demonstrate the system results for 56 testing images using curvelet based RLBP method. There are 8 images of each expression used for testing. The expressions angry, disgust, happy, neutral, surprise are recognized more correctly as compared to the fear and sad. In that fear expression confused with the sad and sad expression confused with fear, happy and neutral.

Facial Expressions	Recognition Rates (%)
Angry	100
Disgust	100
Fear	50
Happy	100
Neutral	100
Sad	62.5
Surprise	100

Table II. Recognition Rates of Various Facial Expressions

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Table II reveals the comparison of recognition rate for every expression with curvelet based RLBP method with test set of 56 images. The recognition rate of angry, disgust, happy, neutral and surprise is higher than the sad and fear for 56 test samples.

Algorithm	Recognition Rates (for 56 images)
Proposed method	87.50%

Table III. Recognition Rate of Facial Expression System

Above Table III shows the overall recognition rate of facial expression recognition system for the proposed system is 87.50%. Curvelet based RLBP method gives the more recognition rate than other methods.

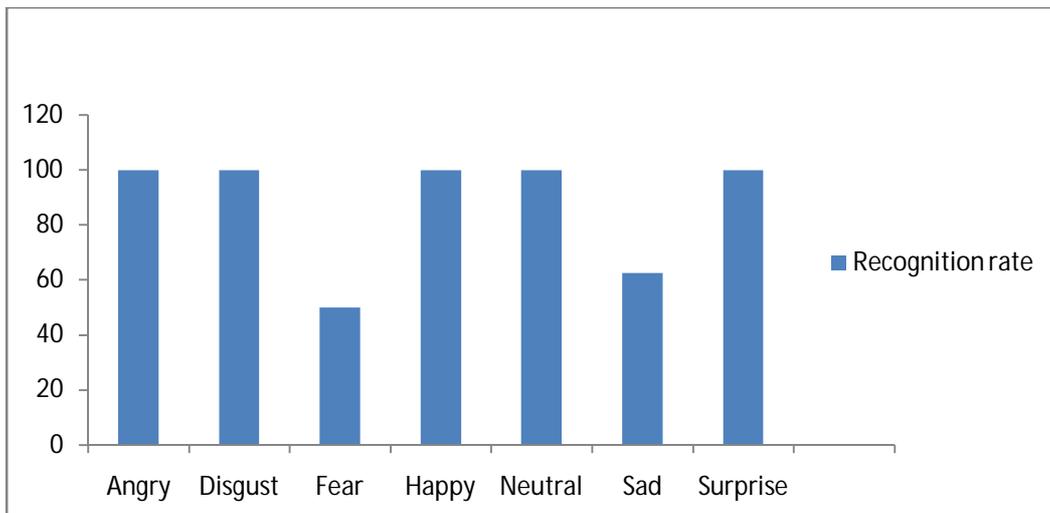


Fig 6. Bar Graphs showing Recognition Rates of various Facial Expressions

The above table shows the system performance results, recognition rates of various facial expressions and recognition rate of facial expression system. This system has greater accuracy even with the small number of training images.

## V. CONCLUSION

We have implemented a new technique for facial expression recognition, the combination of curvelet transform and RLBP. This approach has been studied using image database. The features are extracted from the still images using curvelet based RLBP. Euclidean distance classifier is used for classification of facial expressions. The proposed method has the greater accuracy with consistency. There recognition rate was greater even with the small number of training images which demonstrated that it is fast, relatively simple and works well in a constrained environment. Future work may include extensive experiments of the proposed method on motion pictures or real-time videos and images having different viewpoints.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

## REFERENCES

- [1] Mehrabian, "Communication without Words," Psychology Today, vol. 2, no. 4, pp. 53-56, 1968.
- [2] M. Valstar and M. Pantic, "Fully Automatic Facial Action Unit Detection and Temporal Analysis", Conference on Computer Vision and Pattern Recognition Workshop, CVPRW'06, pp.149-156, 2006.
- [3] L. Gang, L. Xiao-hua, Z. Ji-Liu, G. Xiao-gang, "Geometric feature based facial expression recognition using multiclass support vector machines", IEEE International conference on Granular Computing, pp. 318-321, 2009.
- [4] G. Zhao and M. Pietikainen, "Experiments with Facial Expression Recognition using Spatiotemporal Local Binary Patterns", IEEE International Conference on Multimedia and Expo, pp. 1091-1094, 2007.
- [5] H. Mliki, N. Fourati, S. Smaoui and M. Hammami, "Automatic Facial Expression Recognition System," International Conference on Computer Systems and Applications, pp.1-4, 2013.
- [6] R. Verma, M.-Y. Dabbagh, "Fast Facial Expression Recognition Based on Local Binary Patterns," IEEE Conference on Electrical and Computer Engineering, pp.1-4, 2013.
- [7] C. Shan, S. Gong, P.W. McOwan, "Robust Facial Expression Recognition using Local Binary Patterns," IEEE International Conference on Image Processing, pp. II-370-373, 2005.
- [8] A. Saha and Q.M. Jonathan Wu, "Facial Expression Recognition using Curvelet based Local Binary Pattern," IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 2470-2473, 2010.
- [9] Nagaraja S., Prabhakar C.J. and Praveen Kumar P.U., "Complete Local Binary Pattern for Representation of Facial Expression based on Curvelet Transform," International Conference on Multimedia Processing, Communication and Information Technology (MPCIT), pp.48-56, 2013.
- [10] Wu. Tingfan, M.S. Bartlett and R. Javier, "Facial Expression Recognition Using Gabor Motion Energy Filters," IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, pp.42-47, 2010.
- [11] I. Kotsia, I. Pitas, "Facial Expression Recognition in Image Sequences Using Geometric Deformation Features and Support Vector Machines," IEEE Transactions on Image Processing, vol.16, no.1, pp.172-187, 2007.