Extraction of Curvelet based RLBP Features for Representation of Facial Expression

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Abstract—**In this paper, we proposed a technique for representation of facial expression based on extraction of Robust Local Binary Pattern (RLBP) features in curvelet domain. The curvelet transform exhibit improved directional capability, better ability to represent edges and other singularities along curves as compared to traditional multiscale transform such as wavelet transform. Hence, we transform original face images to frequency domain at a specific scale and orientation using curvelet transform. Noise and illumination invariant features are extracted from approximate sub-band using robust local binary pattern, which forms the feature vector of facial expression. The proposed method is evaluated based on facial expression recognition carried out using a benchmark database such as JAFFE. The facial expression recognition is performed using a chi-square distance measure with a nearest neighbor classifier. Experimental results show that our approach outperforms other popular LBP based approaches.**

Keywords—facial expression; curvelet transform; robust local binary pattern; texture features

I. INTRODUCTION

Facial expression is one of the most important communications for human beings to express their emotions and intentions. Facial expression recognition is very interesting and challenging topic in Digital Image Processing and Computer Vision. It is the task of identifying mental activity, facial motion and facial feature deformation from still images, image sequences of video and classifying them into abstract classes based on the visual information only, this is possible because human facial gestures are similar. Facial expression recognition form static images is more challenging than from image sequences due to less information obtained from expression actions [1].

There are mainly two methods are used to extract facial features, one is geometry-based methods [2] [3] and appearance-based methods [4] [5]. The geometric based features are present in shape and locations of facial components such as mouth, eyes, nose and eyebrows. The facial feature points are extracted to form a feature vector that represents the face geometry. The geometry based techniques require reliable and accurate facial features, which is difficult to find in real time applications. In appearance based methods, the facial features are extracted from whole face image known as global features or some specific region of the face image known as local feature. Recently many researchers have proposed appearance based methods to extract facial features. Most promising appearance based methods are based on Local Binary Pattern (LBP) features, because the important properties of LBP features are tolerance against illumination changes and computational simplicity.

X. Feng et al [1] divide the face area of the face image into small regions, from which the LBP histograms are extracted and concatenated into a single feature histogram that represents facial expression descriptor. In [4] region based local descriptors are used to recognize facial expressions in image sequences using spatiotemporal LBP. C. Shan et al. [6] extract most discriminant LBP features from Boosted-LBP and achieve good recognition rate using support vector machine classifier. S. Zhang et al. [7] proposed a method for facial expression recognition based on LBP and local fisher discriminant analysis. Initially, LBP features are extracted from the original images and reduced the feature dimension of LBP features using local fisher discriminant analysis. Support vector machines classifier is used for recognition of facial expression. In [8] LBP is applied to face image and then LBP image is divided into 3x5 non overlapping blocks, calculate the LBP histogram of each block and concatenating it. Laplacian Eigenmaps is used for feature dimensionality reduction and support vector machine classifier is used for classification.

A new multiresolution analysis tool curvelet transform [9] [10] has been proved to be a powerful tool for analysis of face images. Wavelets do work in one-dimension, but they fail to represent higher dimensional singularities especially curved singularities. Curvelet can provide a sparse representation of the objects that exhibit 'Curve punctuated smoothness' [11] i.e. objects those are smooth except along a curve with bounded curvature. X. Wu et al. [12] used to curvelet transform to extract features of face images for face and facial expression recognition. Recently many researchers proposed curvelet based facial expression recognition [13] [14]. The literature survey reveals that, the combination of curvelet transform with LBP yields good feature descriptor than using curvelet transform alone. The curvelet based LBP texture operator is a good feature extractor. A. saha et al. [15] proposed the combination of curvelet transform and LBP for recognizing the facial expression from still images. In [16] our previous work, we presented facial expression recognition based on curvelet transform with complete local binary pattern. The original LBP texture operator has two demerits, i.e., sometimes it produces same binary code for different structural patterns and sensitive to noise. In order to overcome these two drawbacks of LBP, Completed Robust Local Binary Pattern (CRLBP) was introduced by Y.Zhao et al. [17] for texture classification. In CRLBP, the image local differences are decomposed into three components i.e., signs, magnitudes and central information, in which the gray value of centre pixel in a 3x3 local area is replaced by its average local gray value.

In this paper, we proposed a method for facial expression recognition based on combination of curvelet transform and RLBP. Initially, we decomposed the face image using curvelet transform which yields various sub-bands of curvelet and then apply the uniform RLBP on the approximate sub-band to extract the noise and illumination invariant features of facial expression that forms the feature vector. Experiments shows that these texture features are useful for facial expression recognition is performed by using nearest neighbor classifier and obtained the good recognition rate compared to other methods. The rest of the paper is organized as follows; Section II describes the curvelet transform, Section III and IV introduces LBP and RLBP. Section V and VI present a proposed method and experimental results respectively. Finally, Section VII conclude the paper.

II. CURVELET TRANSFORM

The curvelet transform was introduced by Candes and Donoho [9] in 1999. The transform has better ability to represent edges and improved directional capability as compared to wavelet transform. Later the authors construct second generation curvelet transform [10] called as Fast Discrete Curvelet Transform (FDCT) is not only simpler, but it is faster and less redundant compared to earlier implementation of curvelet transform. Curvelet transform is multiscale and multidirectional and exhibit highly anisotropic behavior as it has both variable length and width. In order to implement the curvelet transform, initially 2D Fast Fourier Transform (FFT) of the image is taken. Then 2D Fourier frequency plane is divided into parabolic wedges. Finally, inverse FFT of each wedge is taken to find the curvelet coefficients at each scale *j* and *l*. The Fast Discrete Curvelet Transform has two digital implementation.

a. Curvelets via Unequally Spaced Fast Fourier Transform (USFFT).

b. Curvelets via Wrapping.

The two digital implementations use the same digital coronization but differ in the choice of spatial grid to translate curvelets at each scale and angle. Curvelets via Wrapping has been used in this work as this is the fastest and simplest curvelet transform currently available. If $f[t_1, t_2]$, $0 \leq t_1, t_2 < n$ is taken to be a cartesian array and $\hat{f}[n_1, n_2]$ to denote its 2D Discrete Fourier Transform, then the architecture of curvelet via wrapping is as follows.

1. 2D FFT (Fast Fourier Transform) is applied to obtain Fourier samples $\hat{f}[n_1, n_2]$.

2. For each scale j and angle l, the product $\tilde{U}_{j,l}[n_1, n_2]\,\hat{f}[n_1, n_2]$ is formed, where $\tilde{U}_{j,l}[n_1, n_2]$ is the discrete localizing window.

3. This product is wrapped 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.

4. Inverse 2D FFT is applied to each $\tilde{f}_{j,l}$, hence creating the discrete curvelet coefficients.

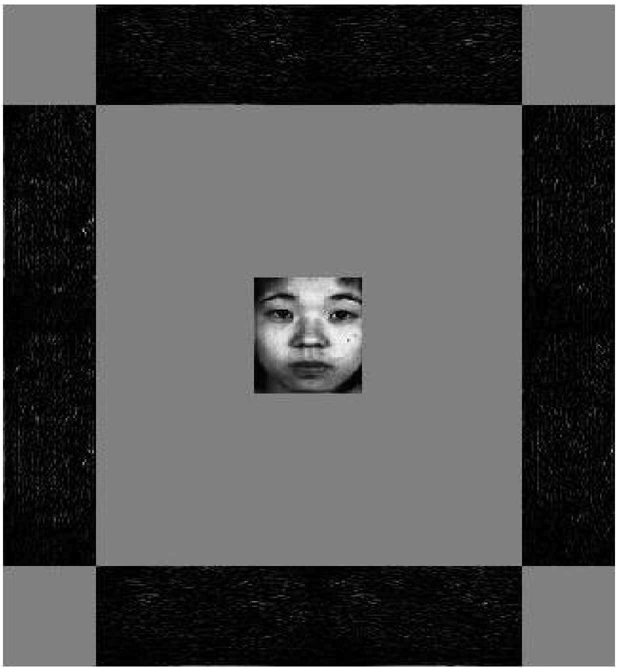

Figure 1: Curvelet coefficients (scale 3 and orientation 8) for one of the facial expressions

III. LOCAL BINARY PATTERN (LBP)

The LBP operator was first developed by Ojala et al. (1996) [19] for texture classification. LBPs by the definition are invariant with respect to any monotonic transformation of the gray scale. This is achieved by considering only the signs of differences instead of the exact values of the gray scale. Consider texture T,

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

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

Where $g_P(p = 0, \ldots, P-1)$ gray values, g_c being the centre gray value and

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}, \quad (2)$$

the sign is 1 if positive and 0 if negative. The above is transformed into a unique P-bit pattern code by assigning binomial coefficient 2^P to each sign $S(g_{p-1} - g_c)$.

$$LBP = \sum_{p=0}^{P-1} S(g_{p-1} - g_c)2^P. \quad (3)$$

Later the operator was extended to use neighborhoods of different sizes [20]. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods, we use the notation (*P, R*) which means *P* sampling points on a circle of radius of *R*.

IV. ROBUST LOCAL BINARY PATTERN (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. The Average Local Gray value (ALG) is defined as

$$ALG = \frac{\sum_{i=1}^{8} g_i + g}{9}, \quad (4)$$

where g is the gray value of the centre pixel and g_i (i=0,1,…8) represents the gray value of the neighbor pixels. ALG is the average gray level of local area, which is obviously more robust to noise than the gray value of the centre pixel. The LBP process is applied by using ALG as the threshold instead of the gray value of central pixel, named as Robust Local Binary pattern (RLBP). This can be defined as

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - ALG_c)2^p$$
$$= \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right)2^p, \quad (5)$$

where g_c is the gray value of central pixel and g_p*(p=0,1,…P-1)* represents the gray value of the neighbor pixel on 3x3 local area of radius R, P is the number of neighbors and g_{ci}(i=0,1,…8) is the gray values of the neighbor pixel of g_c. Average local gray level of pixel is used as threshold, therefore RLBP is insensitive to noise and also two different patterns with same LBP code may have different RLBP code, because that neighbors of each neighbor pixel are considered. The RLBP can overcome mentioned demerits of LBP.

Sometimes specific information of the central pixel is needed, but ALG ignores the specific information of individual pixel. In order to define Weighted Local Gray Value (WLG) to balance between anti-noise and information of individual pixel. The WLG is defined as follows

$$WLG = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8+\alpha}, \quad (6)$$

where g and g_i are defined in Eq. (4), α is a parameter set by user. If α is set to 1, WLG is equivalent to ALG. The RLBP is calculated as follows

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - WLG_c)2^p$$
$$= \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8+\alpha}\right)2^p, \quad (7)$$

where g_p, g_c and g_{ci} are defined Eq. (5), α is a parameter of WLG. A LBP is called uniform, if it contains at most two bitwise transitions from 0 to 1 or 1 to 0, when binary string is considered as circular. For example 10000000, 11100011 and 11110000 are uniform patterns. We extend the RLBP to uniform, rotation invariant and rotation invariant uniform RLBP. The uniform notation is used for RLBP is $RLBP_{P,R}^{u2}$ or $U(RLBP_{P,R})$ is defined below

$$U(RLBP_{P,R}) = |s(g_{p-1} - WLG_c) - s(g_0 - WLG_c)| + \sum_{p=1}^{P-1} |s(g_p - WLG_c) - s(g_{p-1} - WLG_c)|. \quad (8)$$

The subscript denotes using the operator in a (P, R) neighborhood. Superscript *u2* represents only uniform patterns and remaining patterns are label with single label.

The $RLBP_{P,R}$ operator produces 2^pdifferent output values, corresponding to the 2^pdifferent binary patterns that can be formed by the *P* pixels in the neighbor set. When the image is rotated, the gray values $g_p$will correspondingly move along the perimeter of the circle around g_0. Since $g_0$is always assigned to be the gray value of element (0, R) to the right of $g_c$rotating a particular binary pattern naturally results in a different $RLBP_{P,R}$ value. This does not apply to patterns comprising on only 0s (or 1s) which remain constant at all rotation, i.e., to assign a unique identifier to each rotation invariant robust local binary pattern. The rotation invariant RLBP is defined as

$$RLBP_{P,R}^{ri} = min\{\, ROR(RLBP_{P,R}, i) \;\mid i = 0,1, \dots P-1\}, \quad (9)$$

where $ROR(x, i)$ performs a circular bit-wise right shift on the *P*-bit number *x*, *i* times. In terms of pixels, simply corresponds to rotating the neighbor set clockwise so many times that a maximal number of the most significant bits, starting from g_{p-1} is 0. $RLBP_{P,R}^{ri}$ quantifies the occurrence statistics of individual rotation invariant patterns corresponding to certain micro features in the image.

The local rotation invariant uniform pattern could be defined as

$$RLBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - WLG_c) & if\ U(RLBP_{P,R}) \le 2 \\ P+1 & otherwise. \end{cases} \quad (10)$$

Superscript *riu2* reflects the use of rotation invariant uniform patterns.

V. FACIAL EXPRESSION RECOGNTION

The images are initially cropped to extract face of the image. Before extracting the features of face image, normalization is done using histogram equalization to increase the contrast of the image, because curvelet transform is not independent of illumination changes. After that curvelet transform is applied to the normalized image at a selected scale and orientation.

The curvelet transform decomposes the normalized image into approximate sub-band and detailed sub-bands shown in Fig. 1. It is observed that the approximate sub-band (Fig. 2(d)) as more energy than detailed sub-bands. Therefore, we apply uniform RLBP on the approximate sub-band by varying the value of weighing parameter α in the range of 1 to 8. Finally, we extract robust and noise invariant features from approximate sub-band obtained from curvelet transform using RLBP (Fig. 2(e)), which represents the expression of the face. The RLBP histogram of 255 labels is calculated based on the class labels of the face images. Feature vectors of the same class labels are grouped to form the training template Z^c for a particular class of facial expression. Thus,

$$Z^c = \{z_1^c, z_2^c, z_3^c, \dots, z_n^c\}, \quad (11)$$

where n denotes number of training samples available for the corresponding class. The representative feature set of the class c is the cluster center of template Z^c and is calculated as

$$M^c = \frac{1}{n}\sum_{i=1}^{n} z_i^c. \quad (12)$$

Nearest neighbor classifier is used for classification with Chi-Square metric.

$$\chi^2(S, M^c) = \sum_{i=1}^{N} \frac{(S_i - M_i^c)^2}{S_i + M_i^c}, \quad (13)$$

where S is the feature vector of length N extracted from the test image.

VI. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness of our proposed technique, we carried out experiments on JAFFE [18] database (sample images are shown in Fig. 5) which includes 3 or 4 samples for each of the six basic facial expressions and a neutral face image for each subject or person. A total 213 images of 10 subjects and each image size is 256x256 pixels.

Initially all the images of JAFFE database are cropped with size 110x150 pixels to extract the face from the image. Then we normalization is done using histogram equalization to increase the contrast of the face image. Normalized face images are divided into ten sets to carry out 10-fold cross validation i.e. ten rounds of testing carried out and each time, a different combination of nine sets are used for training and the remaining one set is used for testing. Final recognition rates are average of the recognition rates of ten tests. We have conducted several experiments on JAFFE database to identify the optimal value of scale and orientation for curvelet transform and optimal parameters such as α , R and P for RLBP using Nearest Neighborhood (NN) classifier. In all tests the histogram is calculated, which is the facial feature vector of the face expressions. The experiments are conducted using RLBP and its extensions such as uniform RLBP ($RLBP_{P,R}^{u2}$), rotation invariant RLBP ($RLBP_{P,R}^{ri}$) and uniform rotation invariant RLBP ($RLBP_{P,R}^{riu2}$). The Curvelet (scale 3, orientation 8) and $RLBP_{8,1}^{u2}$ combination yields good results for 6-class expression compare to other combinations. Similarly same combination yields good results for 7-class facial expressions.

Also we conducted experiments on noisy images because RLBP is robust against noise and illumination. The test images were corrupted by additive Gaussian noise with mean 0 and variance 0 to 0.05 shown in Fig. 3. Curvelet + RLBP (α=8) still achieve higher recognition rate than Curvelet + CLBP, but Curvelet + RLBP (α=1) performs less recognition rate than Curvelet + CLBP on normal face images. Curvelet + RLBP (α=1) exhibit much better recognition rate on noisy conditions as shown in the Fig. 4.

The confusion matrices calculated using the combination of Curvelet(3,8) and $RLBP_{8,1}^{u2}$ for 6-class and 7-class facial expression. The confusion matrix shows the proportion in percentage, any expression shown in a row is falsely detected as another expression in the column. The confusion matrix of 6-class and 7-class expression recognition for the above said combination is shown in the Table III and Table IV respectively. It is observed that Happiness and Surprise expressions can be recognized with high accuracy, while Anger, Fear and Sad are easily confused with others in 6-class. For 7-class observe that, Surprise, Happy, Fear can be recognized with high accuracy, while the recognition rates for Anger, Disgust, Neutral and Sad are less accurate.

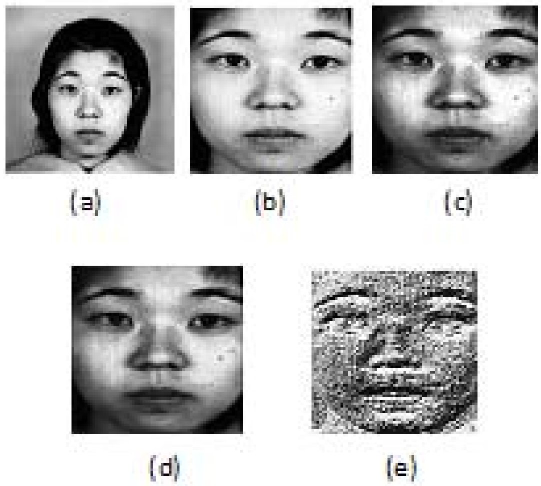

Figure 2: (a) Original Image (b) Cropped Image (c) Normalized Image (d) Curvelet Approximate Sub-band (e) RLBP Image

The proposed approach is compared with LBP based approach [19], curvelet with LBP approach [15] and curvelet with CLBP approach [16], the results are shown in the Table II. Chi-square based nearest neighbor classifier is used for all the experiments. Our approach yields 97.22% recognition rate, where as LBP method performs 85.57%, Curvelet based LBP approach yields 93.69% and curvelet with CLBP yields 95.56%. Therefore, our approach outperforms against LBP and curvelet based LBP and CLBP approach. This is due to fact that, the curvelet transform preserves the crucial edge information and other variations occurred in the face during expression. Further, the RLBP extracts noise and illumination invariant features from faces images.

TABLE I. RECOGNITION RATE OF OUR APPROACH FOR DIFFERENT COMBINATIONS

Curvelet and RLBP Combination	Recognition rate (%)	
	α=1	α=8
Curvelet(3,8) + $RLBP_{8,1}$	93.29	96.11
Curvelet(3,8) + $RLBP_{8,1}^{u2}$	**94.45**	**97.22**
Curvelet(3,8) + $RLBP_{8,1}^{ri}$	92.22	95.56
Curvelet(3,8) + $RLBP_{8,1}^{riu2}$	93.69	96.66
Curvelet(3,8) + $RLBP_{8,2}$	90.56	92.78
Curvelet(3,8) + $RLBP_{8,2}^{u2}$	92.37	94.45
Curvelet(3,8) + $RLBP_{8,2}^{ri}$	89.62	91.67
Curvelet(3,8) + $RLBP_{8,2}^{riu2}$	91.89	93.89
Curvelet(2,8) + $RLBP_{8,1}$	90.22	92.45
Curvelet(2,8) + $RLBP_{8,1}^{u2}$	91.89	93.47
Curvelet(2,8) + $RLBP_{8,1}^{ri}$	88.35	90.56
Curvelet(2,8) + $RLBP_{8,1}^{riu2}$	91.29	92.78
Curvelet(2,8) + $RLBP_{8,2}$	89.26	91.68
Curvelet(2,8) + $RLBP_{8,2}^{u2}$	90.37	92.45
Curvelet(2,8) + $RLBP_{8,2}^{ri}$	86.62	88.69
Curvelet(2,8) + $RLBP_{8,2}^{riu2}$	89.89	91.89

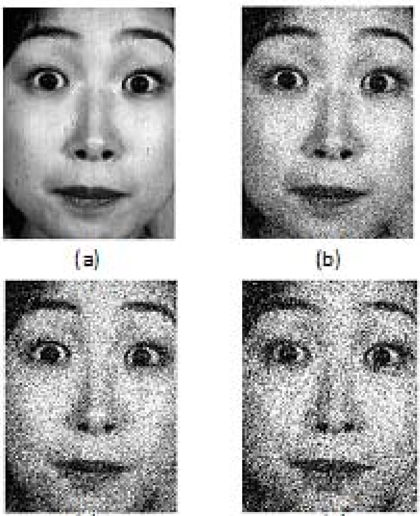

Figure 3: (a) Original Image (b) (c) and (d) images are corrupted by Gaussian noise with mean 0 and variance 0.01, 0.03 and 0.05 respectively

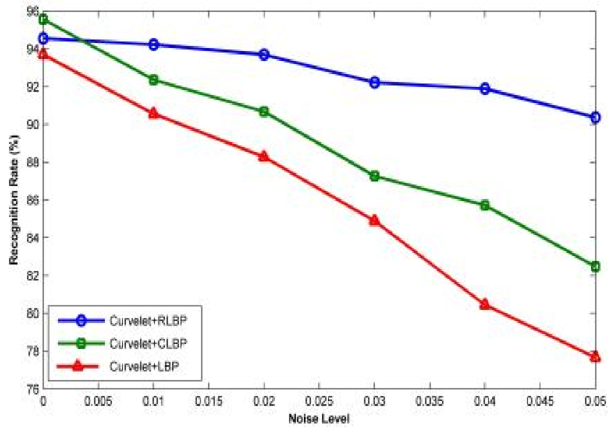

Figure 4: Recognition rate (%) of our approach for various noisy conditions

TABLE II. COMPARISON RESULTS OF OUR APPROACH FOR JAFFE DATABASE

Methods	Recognition Rate (%)
LBP [20]	85.57
Curvelet + LBP [15]	93.69
Curvelet + CLBP[16]	95.56
Our Approach	**97.22**

VII. CONCLUSION

In this paper, we proposed a new technique for facial expression recognition, the combination of curvelet transform and RLBP. The features are extracted from still images using curvelet based RLBP. It is evaluated on JAFFE database and experimental results shows that our methods yields a good recognition rate compared to LBP, curvelet based LBP and curvelet with CLBP methods. This is due to fact that, the curvelet transform preserves the edges and other variations occurred in the face during expression. Further, the RLBP extracts noise and illumination invariant features from faces images.

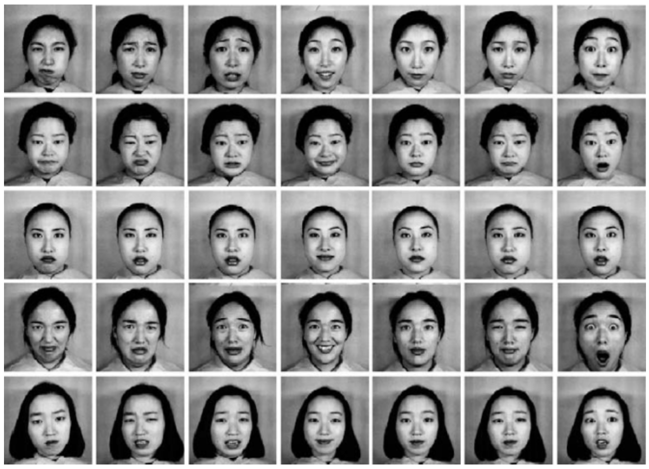

Figure 5: Sample facial expression images from the JAFFE database

REFERENCES

[1] X. Feng, M. Pietikainen and A. Hadid, "Facial Expression Recogntion based on Local Binary Patterns", Pattern Recogntion and Image Analysis, 2007, vol. 17, No. 4, pp. 592-598.

[2] M. Valstar and M. Pantic, "Fully Automatic Facial Action Unit Detection and Temporal Analysis", Conference on Computer Vision and Pattern Recogntion Workshop, CVPRW'06, 2006, pp.149.

[3] L. Gang, L. Xiao-hua, Z. Ji-Liu, G. Xiao-gang, "Geometric feature based facial expression recogntion using multiclass support vector machines", IEEE International conference on Granular Computing, GRC'09, 2009, pp. 318-321.

[4] G. Zhao and M. Pietikainen, "Experiments with Facial Expression Recognition using Spatiotemporal Local Binary Patterns", IEEE International Conference on Multimedia and Expo, 2007, pp. 1091-1094.

[5] C. Shan, S. Gong, P.W. McOwan, "Robust Facial Expression Recogntion using Local Binary Patterns", IEEE International Conference on Image Processing, ICIP2005, 2005, pp.II.

[6] C. Shan, S. Gong, P.W. McOwan, "Facial expression recogntion based on Local Binary Patterns: A comprehensive study", Image and Vision Computing, 27 (2009), pp. 803-816.

[7] S. Zhang, X. Zhao and B. Lei, "Facial Expression Recognition Based on Local Binary Patterns and Local Fisher Discriminant Analysis", WSEAS Transcation on Signal Processing, vol. 8, Issue 1, 2012, pp.21-31.

[8] Z. Ying, L. Cai, J. Gan and S. He, "Facial Expression Recogntion with Local Binary Pattern and Laplacian Eigenmaps", ICIC 2009, LNCS 5754, 2009, pp. 228-235.

[9] E.J. Candes and D.L. Donoho, "Curvelets – A Surprisingly Effective Nonadaptive Representation for Objects with Edges", Vanderbilt University Press, Nashville, TN, 2000.

[10] E.J. Candes, L. Demanet, D.L. Donoho and L.Ying, "Fast Discrete Curvelet Transform", SIAM Multiscale Model, Simul, 2006.

[11] E.J. Candes, "What is Curvelet", Notices of Americal Mathematical Society, vol. 50, 2003, pp. 1402-1403.

[12] X. Wu and J. Zhao, "Curvelet Feature Extraction for Face Recogntion and Facial Expression Recogntion", Sixth International Conference on Natural Computation, vol. 3, 2010, pp. 1212-1216.

[13] M. Tang and F. Chen, "Facial Expression Recognition and its Application based on Curvelet transform and PSO-SVM", Optik, 124(2013), pp. 5401-5406.

[14] T. Mandal, Q.M. Jonathan Wu and Y. Yuan, "Curvelet based Face Recognition via Dimension Reduction", Signal Processing, 89(2009), pp. 2345-2353.

[15] 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, 2010, pp. 2470-2473.

[16] 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), published in ACEEE, 2013, pp.48-56.

[17] Y. Zhao, W. Jia, R. Hu and H. Min, "Completed Robust Local Binary Pattern for texture classification", Neurocomputing, 106(2013), pp. 68-76.

[18] M.J. Lyons, M. Kamachi, and J. Gyoba, "Japanese Feamle Facial Expression (JAFFE)", Database of digital images, 1997.

[19] T. Ojala, M. Pietikaninen and D. Harwood, " A Comparative study of Texture Measures with Classification based on Feature Distribution", Pattern Recognition, vol. 29, 1996, pp.51-59.

[20] T. Ojala, M. Pietikaninen and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary pattern", IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, 2002, pp.971-987.

TABLE III. CONFUSION MATRIX OF 6-CLASS FACIAL EXPRESSION RECOGNITION USING OUR APPROACH ON JAFFE DATABASE.

Expressions	**Anger %**	**Disgust %**	**Fear %**	**Happy %**	**Sad %**	**Surprise %**
Anger	**96.67**	3.33	0	0	0	0
Disgust	3.33	**96.67**	0	0	0	0
Fear	3.33	0	**96.67**	0	0	0
Happy	0	0	0	**100**	0	0
Sad	3.33	0	3.33	0	**93.33**	0
Surprise	0	0	0	0	0	**100**

TABLE IV. CONFUSION MATRIX OF 7-CLASS FACIAL EXPRESSION RECOGNITION USING OUR APPROACH ON JAFFE DATABASE.

Expressions	**Anger %**	**Disgust %**	**Fear %**	**Happy %**	**Sad %**	**Surprise %**	**Neutral %**
Anger	**88.23**	2.94	2.94	0	2.94	0	2.94
Disgust	5.88	**88.23**	5.88	0	0	0	0
Fear	2.94	2.94	**91.17**	0	2.94	0	0
Happy	0	0	2.94	**91.17**	0	0	5.88
Sad	2.94	2.94	8.82	0	**85.29**	0	0
Surprise	0	0	0	2.94	0	**94.11**	2.94
Neutral	0	0	5.88	5.88	0	0	**88.23**