FACIAL EXPRESSION IDENTIFICATION USING FOUR-BIT CO-OCCURRENCE MATRIXFEATURES AND K-NN CLASSIFIER

Bonagiri C S K Sunil Kumar[1], V Bala Shankar[2], Pullela S V V S R Kumar[3]

[1,2,3] Department of Computer Science & Engineering, Aditya College of Engineering, Surampalem, East Godavari District, Andhra Pradesh, India

Abstract

The present paper proposes a novel approach for facial expression identification based on the statistical features extracted from the 4-bit co-occurrence matrix. In the present, first color image is converted into grey level image using 7-bit quantization technique. To reduce the complexity of the Grey Level Co-occurrence matrix the present paper generates the co-occurrence matrix on 4 bit grey image which is generated by quantization technique. From The 4-bit CM extract 4 features; contrast, homogeneity, energy and correlation and generate the feature vector. By using the K-NN Classification technique classify the test image and extract the four statistical features and identify the type of expression of the test facial image. The present method got better comparative results when it is tested on Japanese Female Facial Expression (JAFFE) Database.

Key Words: *Facial Expression identification, Classification, k-NN classifier, Quantization, and GLCM*

---***---

1. INTRODUCTION

One of the rapidly growing fields of research is facial expression recognition due to continually growing interest in applications for automatic human behavior psychoanalysis and new technologies for human-machine announcement and multimedia retrieval. Mostly systems for Facial Expression Recognition and its Analysis proposed in the literature focused on detecting the occurrence of expressions, often using basic emotions or the Facial Action Coding System (FACS Action Units, AUs,[1]. In reality, expressions vary greatly in concentration, and concentration is often a strong cue for the explanation of the sense of expressions.

So many approaches are available in literature for the recognition of the facial expressions [2, 3]. The proposed method included the model based techniques for analyzing the face, which is considered as one global pattern without decomposing the face to different components. A feature vector, representing the expression information, is obtained by preprocessing the face image and applying different transformations for facial expression feature extraction, like Gabor wavelet [4], curvelets [5, 6], and local binary pattern [7, 8, 18, 19]. Principal component analysis (PCA) is mainly used for dimensionality reduction, and multilayer neural networks or support vector machines are widely used for image classification [9, 10]. The analytic or geometric feature based methods are used to divide the face into smaller components or subsection using which we can identify the expressions. Characteristic points are detected, and distances between Characteristic points are calculated to form the feature vectors or build a model of appearance [11, 12, 13] and support vector machines SVM [14].

The above approached methods have its own disadvantages and own demerits especially in the form of computational time and percentage of recognition. To overcome such disadvantages, the present paper derives a concept for the facial expression based on the statistical features derived from 16 gray values co-occurrence matrix. The paper is organized into 4 sections. Section 2 describe the proposed method and section 3 describes the results and discussions and conclusions are given in section 4.

2. METHODOLOGY: FACIAL EXPRESSION RECOGNITION SYSTEM

The proposed method mainly consists of 5 steps. In the first step, crop the given input image which covers the all facial skin of the image. In the second step, convert the cropped color image into 4-bit quantization technique. In the third step, generate the co-occurrence matrix which consists of 16 shades. Extract the 4 statistical features and generate the Feature Vector in the forth step. Based on the FV values and k-NN classifier recognize the type of expression in the last step. The block diagram of the facial expression recognition is shown in figure 1.

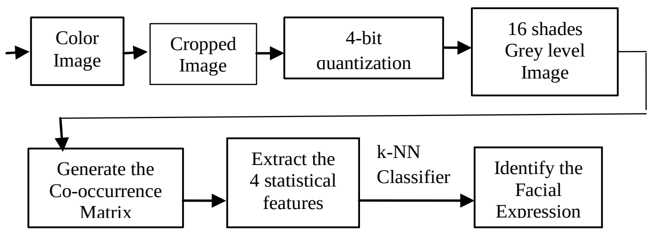

Fig -1: Block Diagram of the Facial expression Identification

Step 1 : Crop the given input image which covers the all facial skin of the image

Step 2: Crop the grey scale image: The gray facial image is cropped to cover whole skin area of the facial image. For efficient identification of the expression, cropping is necessary. The cropped image consists of forehead; two-eyes nose, mount, and chin area. All these appearance changed according the type of expression. Figure 2 shows an example of the original facial image and the cropped image.

(a) (b)

Fig -2: (a) original image (b) cropped image

Step 3: Convert the Color Image into 4-bit gray scale image using 4-bit quantization technique

The size of the Grey Level Concurrence Matrix (GLCM) depends on number of shades in the image. Generally, Gray Scale image has 256 shades and the size of the GLCM matrix is 256. So, in order to reduce the complexity of GLCM matrix, the present paper uses the 16 shades to generate the co occurrence matrix. 16 shades are represented by using 4 –bits. It can be accomplished by using quantization technique. The present paper uses 4-bit Binary Code quantization technique.

In 4-bit Binary Code quantization technique, the original images are quantized into 16shades of gray image is computed from the 256 gray shades images and then the statistical information of facial image is calculated to describe features of the image

To extract gray level features from color information, the present paper utilized the Gray shades which quantize the gray shades into 4-bins to obtain 16 gray levels. The index matrix of 16values gray image is denoted as GS(x, y). The Gray quantization process is done by using 4-bit binary code of 16 colors as follows:

GS(x,y)= 4*I(Red)+2*I(Green)+I(Blue) where

I(Red)= 0, 0≤Red≤16, I(Red)=k,

((4*k)+1) ≤ Red ≤ (4*(k+1)) k = [1, 2, 3, 4]

I(Green)= 0, 0≤Green≤16, I(Green)= k,

((4*k)+1) ≤ Green ≤ (4*(k+1)) k = [1, 2, 3, 4]

I(Blue)= 0, 0≤Blue≤16, I(Blur)= k,

((4*k)+1) ≤ Blue ≤ (4*(k+1)) k = [1, 2, 3, 4]

Therefore, each value of GS(x, y) is a 4 bit binary code ranging from 0 to 15. The process of 4-bit gray scale image generation is depicted in figure 3

139	128	131	134	132
142	140	127	133	138
142	124	129	145	142
141	129	128	131	133
137	134	134	137	137

(a)

9	8	8	8	8
9	9	8	8	9
9	8	8	9	9
9	8	8	8	8
9	8	8	9	9

(b)

Fig -3: 4-bit quantization procedure a) Sample Gray level Image b) Generated 4-bit 16 shade gray image

Step 4: generate the 4 bit grey scale concurrence matrix:
Grey level co-occurrence matrix (GLCM) is the one of the simplest technique for describing texture image[15]. The GLCM is gives complete and detailed information about the image. Generally the size of co-occurrence matrix of image number of gray level on the image. For Generating GLCM of the Gray level image, the size of the GLCM is 256×256. This I is the one of the drawback of GLCM. It takes more computational time for generating the co-occurrence matrix. To avoid such problem, the present paper generates the co-occurrence matrix on 16 shades image so that the size of the GLCM is reduced to 16×16 and its causes reduces the computational cost drastically. The generated matrix called Four-bit Co-occurrence Matrix (FCoM).
A set of statistical features defined by Haralick [15] are extracted on FCoM of the facial image. The features used in this method are energy, contrast, homogeneity, and correlation. The equations of the considered feature are shown in equations 1 to 4. The proposed FCoM combines the merits of both statistical computation cost for processing of the facial images. The GLCM gives the whole information of the facial expression image

$$\text{contrast} = \sum_{i,j=0}^{N-1} -\ln (P_{ij})^2 \qquad (1)$$

$$\text{Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \qquad (2)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (3)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln (P_{ij})^2 \qquad (4)$$

3. RESULTS AND DISCUSSIONS

To prove the functionality of the proposed scheme, it has established a database contains 213 facial expression images of females from Japanese Female Facial Expression (JAFFE) Database. The Database was collected by Kamachi and Gyoba at Kyushu University[16], Japan. Original images have been rescaled and cropped such that the eyes are roughly at the same position within a distance of 60 pixels in the final images (resolution: 256 × 256 pixels). The images include the seven categories of expressions (neutral, sadness, surprise, happiness, anger, disgust and fear) is roughly the same. A few of them are shown in Figure. 4.

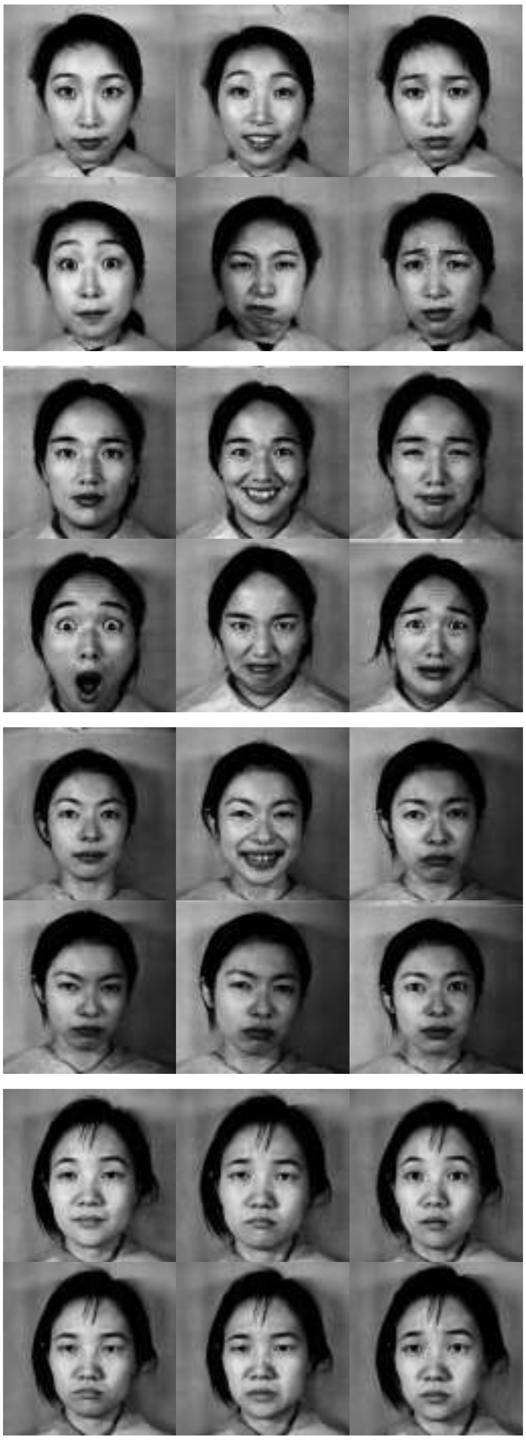

Fig -4: Facial expression database: Examples

In the proposed method the test images are grouped into seven categories based on expression (neutral, sadness, surprise, happiness, disgust, anger, and fear). The four statistical features are extracted from JAFFE database and generate the feature vector. FCoM of seven category results are stored in the feature vector. Feature vector directs to demonstration of features of the FAFFE images. The statistical features of seven groups of facial expressions are shown in tables1, 2, 3, 4, 5, 6, and 7 respectively. To prove the efficiency of the proposed method, took100 different facial expressions from JAFFE data base, Google database and scanned images and extracted the statistical features from those images and the results are stored in the test vector. Estimate the minimum distance between feature vector and test vector and stored the result in the library. Classify the test images into appropriate expression category using minimum distance K-nearest neighbor classifier. Some of the successful classification results of test data based on the proposed method are shown in table 8. The classification results of the proposed method are shown in table 9 and corresponding classification graph is shown in figure 5.

Table 1: Feature set values of Anger expression images

S. No	Image Name	Correla-tion	Contrast	Energy	Homogeneity
1	Img.104	-0.0358	32.33	0.028	0.2128
2	Img.105	-0.0317	31.39	0.028	0.2117
3	Img.106	-0.0683	31.67	0.033	0.2097
4	Img.125	0.0313	30.27	0.035	0.2404
5	Img.127	0.0499	30.75	0.032	0.2439
6	Img.146	0.0306	30.14	0.032	0.2407
7	Img.147	0.0387	29.93	0.027	0.2315
8	Img.148	0.0496	29.47	0.027	0.2280
9	Img.167	0.0013	33.94	0.037	0.2421
10	Img.168	0.0120	32.72	0.035	0.2350
11	Img.169	0.0117	32.61	0.032	0.2375
12	Img.17	0.0518	29.65	0.038	0.2616
13	Img.18	0.0568	30.45	0.036	0.2459
14	Img.19	0.0621	30.19	0.043	0.2627
15	Img.190	0.0595	29.75	0.033	0.2477
16	Img.191	0.0577	30.92	0.035	0.2479
17	Img.192	0.0484	30.58	0.034	0.2439
18	Img.211	0.0175	32.86	0.037	0.2344
19	Img.212	0.0560	31.45	0.037	0.2503
20	Img.213	0.0582	30.83	0.032	0.2492

Table 2: Feature set values of Disgust expression images

S No	Image Name	Correlation	Contrast	Homogeneity	Energy
1	Img 1.193	0.086	28.150	0.273	0.033
2	Img 86	-0.183	34.870	0.179	0.039
3	Img.107	-0.057	30.060	0.198	0.036
4	Img.128	0.032	29.390	0.235	0.037
5	Img.129	0.031	29.560	0.240	0.037
6	Img.130	0.047	30.800	0.244	0.038
7	Img.149	0.015	28.173	0.225	0.036
8	Img.150	0.096	26.264	0.242	0.041
9	Img.151	0.078	27.842	0.249	0.039
10	Img.170	0.015	31.270	0.245	0.038
11	Img.171	0.002	32.820	0.231	0.043
12	Img.172	-0.037	32.520	0.221	0.043
13	Img.173	0.032	32.030	0.244	0.040
14	Img.194	0.063	27.168	0.257	0.036
15	Img.195	0.018	29.784	0.238	0.040
16	Img.20	0.018	30.520	0.245	0.044
17	Img.215	0.067	30.150	0.240	0.040
18	Img.216	0.045	30.400	0.244	0.039
19	Img.22	0.082	27.590	0.255	0.044
20	Img.42	0.038	29.449	0.245	0.036

Table 3: Feature set values of Disgust expression images

Sno	Image Name	Correlation	Contrast	Homogeneity	Energy
1	img 117	-0.219	29.82	0.216	0.033
2	img 118	-0.247	30.83	0.216	0.034
3	img 137	-0.154	28.36	0.242	0.034
4	img 138	-0.124	28.09	0.247	0.036
5	img 139	-0.192	29.73	0.236	0.032
6	img 202	-0.202	31.43	0.236	0.035
7	img 203	-0.23	30.89	0.23	0.034
8	img 204	-0.28	29.6	0.201	0.031
9	img132	-0.167	31.17	0.245	0.038
10	img152	-0.089	27.78	0.277	0.042
11	img153	-0.138	29.84	0.251	0.041
12	img159	-0.21	31.87	0.234	0.038
13	img160	-0.21	31.79	0.23	0.035
14	img180	-0.197	30.51	0.24	0.035
15	img181	-0.211	30.67	0.226	0.031
16	img182	-0.149	29.69	0.259	0.036
17	img21	-0.219	31.14	0.211	0.031
18	img30	-0.203	30.71	0.218	0.034
19	img31	-0.222	31.19	0.217	0.031

Table 4: Feature set values of Netural expression images

Sno	Image Name	Correlation	Contrast	Homogeneity	Energy
1	img 1	0.0514	30.76	0.254	0.044
2	img 113	-0.0336	30.78	0.219	0.039
3	img 114	0.0034	30.24	0.222	0.037
4	img 115	-0.0436	30.68	0.212	0.035
5	img 134	0.0884	27.55	0.264	0.045
6	img 135	0.1134	27.34	0.272	0.046
7	img 136	0.1104	26.24	0.266	0.047
8	img 155	0.0114	30.7	0.248	0.045
9	img 156	0.0344	31.71	0.24	0.042
10	img 157	-0.0036	30.4	0.224	0.033
11	img 199	-0.0636	29.86	0.202	0.033
12	img 2	0.0784	29.39	0.25	0.04
13	img 200	-0.0216	31.22	0.222	0.035
14	img 201	-0.0126	28.78	0.212	0.032
15	img 26	0.0464	30.56	0.236	0.037
16	img 27	-0.0146	31.78	0.222	0.037
17	img 28	-0.0366	31.83	0.214	0.038
18	img 3	0.1184	28.13	0.268	0.047
19	img 49	0.1374	28.26	0.288	0.054
20	img 50	0.1354	27.34	0.295	0.057

Table 5: feature set values of Sadness expression images

Sno	Image Name	Contrast	Correlation	Energy	Homogeneity
1	img 10	29.14	0.0585	0.046	0.259
2	img 100	30.6	-0.0445	0.033	0.203
3	img 11	27.9	0.0075	0.035	0.224
4	img 119	30.38	0.0155	0.041	0.228
5	img 12	28.76	0.0035	0.039	0.236
6	img 120	29.8	-0.0605	0.036	0.212
7	img 121	30.54	-0.0005	0.039	0.224
8	img 140	27.19	0.0975	0.036	0.248
9	img 141	28.01	0.0585	0.033	0.232
10	img 142	28.67	0.0395	0.039	0.237
11	img 161	31.21	0.0295	0.043	0.248
12	img 162	31.34	0.0335	0.043	0.245
13	img 163	29.55	0.0615	0.041	0.251
14	img 184	28.99	-0.0195	0.036	0.232
15	img 185	29.86	0.0505	0.04	0.248
16	img 186	29.74	0.0605	0.041	0.255
17	img 205	30.02	0.0365	0.038	0.236
18	img 206	29.53	0.0705	0.037	0.251
19	img 207	30.82	-0.0185	0.034	0.218
20	img 33	31.12	-0.0195	0.037	0.23

Table 6: Feature set values of fear expression images

Sno	Image Name	Correlation	Contrast	Homogeneity	Energy
1	img 174	-0.003	31.78	0.242	0.042
2	img 175	0.056	30.38	0.247	0.044
3	img 176	-0.023	32.2	0.242	0.044
4	img110	-0.057	30.91	0.213	0.036
5	img111	-0.07	30.81	0.205	0.033
6	img112	-0.079	31.92	0.207	0.038
7	img131	0.067	29.54	0.243	0.041
8	img132	0.02	30.49	0.231	0.038
9	img133	0.022	31.52	0.244	0.044
10	img152	0.044	28.75	0.253	0.041
11	img153	0.088	28.32	0.253	0.039
12	img154	0.089	27.65	0.255	0.041
13	img196	0.1	29.03	0.262	0.041
14	img197	0.121	28.37	0.272	0.045
15	img198	0.058	30.41	0.263	0.047
16	img217	-0.025	32.01	0.223	0.038
17	img218	0.006	31.04	0.23	0.037
18	img219	0.03	29.77	0.244	0.036
19	img23	0.064	30.6	0.262	0.046
20	img24	0.013	28.32	0.227	0.038

Table 7: Feature set values of Surprise expression images

Sno	Image Name	Correlation	Contrast	Homogeneity	Energy
1	img101	-0.074	31.7	0.2	0.034
2	img102	-0.083	31.63	0.194	0.032
3	img103	-0.044	30.65	0.206	0.034
4	img122	-0.049	30.96	0.21	0.036
5	img123	0.01	30.69	0.229	0.038
6	img124	-0.031	30.49	0.222	0.036
7	img14	0.048	30.51	0.246	0.043
8	img143	0.055	29.27	0.243	0.038
9	img144	0.058	28.02	0.246	0.04
10	img145	0.039	29.07	0.234	0.035
11	img15	0.037	30.39	0.253	0.045
12	img16	0.063	29.42	0.253	0.042
13	img164	0.037	30.03	0.239	0.038
14	img165	0.019	31.08	0.232	0.04
15	img166	0.047	31.01	0.236	0.041
16	img187	0.032	29.05	0.244	0.039
17	img188	0.046	28.84	0.249	0.04
18	img189	0.041	29.58	0.239	0.039
19	img208	-0.03	32.08	0.22	0.038
20	img209	0.045	30.14	0.236	0.037

Table 8: Feature values of Test database images

Sno	Image Name	Correlation	Contrast	Homogeneity	Energy	Group	Result
1	ing190	-0.11366	34.4	0.198	0.033	Anger	correct
2	img144	-0.03	32.08	0.22	0.038	Surprise	correct
3	img156	-0.0126	28.78	0.212	0.032	Neutral	correct
4	gog_im1	-0.074	31.7	0.2	0.034	Surprise	correct
5	gog_im2	0.0395	28.67	0.237	0.039	Neutral	correct
6	gog_im3	-0.0195	28.99	0.232	0.036	Sadness	correct
7	gog_im4	0.063164	29.32	0.248	0.036	Disgust	correct
8	gog_im5	-0.179	28.82	0.221	0.028	Happiness	correct
9	si-08	-0.003	31.78	0.242	0.042	Fear	correct
10	si-09	0.066517	29.99	0.24	0.04	Disgust	correct
11	si-10	-0.21	31.79	0.23	0.035	Happiness	correct
12	si-11	-0.023	32.2	0.242	0.044	Fear	correct
13	img140	0.0035	28.76	0.236	0.039	Sadness	correct
14	img65	0.001981	32.28	0.23	0.043	Anger	correct
15	img204	-0.247	30.83	0.216	0.034	Happiness	correct
16	img131	0.06	28.65	0.261	0.045	Fear	correct
17	gog_im11	0.045202	30.042	0.244	0.039	Disgust	correct
18	gog_im12	-0.209	30.19	0.215	0.032	Happiness	correct
19	si-01	0.0784	29.39	0.25	0.04	Neutral	correct
20	gog_im6	-0.003	31.78	0.242	0.042	Fear	correct
21	gog_im7	-0.0486	30.59	0.209	0.035	Neutral	correct
22	gog_im8	-0.03165	31.93	0.211	0.028	Anger	correct
23	gog_im9	0.037	30.03	0.239	0.038	Surprise	correct
24	gog_im10	0.0344	31.71	0.24	0.042	Neutral	correct
25	si-02	0.049949	30.57	0.243	0.032	Anger	correct

Table 9: Classification Results of the test database

Data Base Name	No of Images	Correctly Classified	Not correctly classified	% recognition
JAFFE	60	59	1	98.33
Google	20	19	1	95.00
Scanned	20	19	1	95.00

3. CONCLUSIONS

The present paper proposed a new scheme for generating the gray scale image with 16 shades. The novelty of the present approach is that its take less time to generate the co-occurrence matrix because of the image has only 16 gray levels. The proposed method has got the %recognition is about 96.11 when applied on 3 different databases.

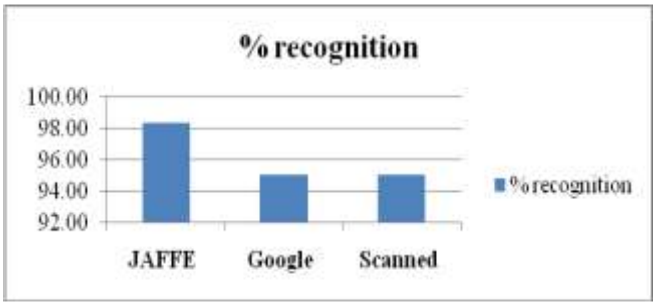

Fig -5: Classification graph of the proposed method

REFERENCES

[1] M. Bartlett, G. Littlewort, M. Frank, C. Lainscsek, I. Fasel, and J. Movellan. Automatic recognition of facial actions in spontaneous expressions. Journal of Multimedia, 1(6):22–35, 2006.

[2] B. Fasel and J. Luettin. Automatic facial expression analysis: a survey.Pattern Recognition, 36(1):259–275, 2003.

[3] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang. A survey of affectrecognition methods: audio, visual, and spontaneous expressions.IEEE Trans. Pattern Analysis nd Machine Intelligence, 31(1):39–58,2009

[4] Juliano J. Bazzo Marcus V. Lamar, “Recognizing Facial Actions Using Gabor Wavelets with Neutral Face Average Difference,” Sixth IEEE International Conference on Automatic Face and Gesture Recognition (FGR’04), 2004.

[5] Xianxing Wu and Jieyu Zhao, "Curvelet Feature Extraction for Face Recognition and Facial Expression Recognition", Sixth International

[6] Conference on Natural Computation, pp.1212-1216, 2010

[7] E. Candés, L. Demanet, D. Donoho and L. Ying, “Fast Discrete Curvelet Transforms,”Applied and Computational Mathematics, Caltech, Pasadena, 2006.

[8] S. Singh and R. Maurya, A. Mittal,"Application of Complete Local Binary Pattern Method for Facial Expression Recognition",IEEE Proceedings of 4th International Conference on Intelligent Human Computer Interaction, Kharagpur, India, December 27-29, 2012.

[9] R.Hablani,N. Chaudhari andS.Tanwani "Recognition of Facial Expressions using Local Binary Patternsof Important Facial Parts," International Journal of Image Processing (IJIP), vol. 7 (2), 2013.

[10] M.Pantic and L.J.M. Rothkrantz, “Expert System For Automatic Analysis Of Facial Expressions,” Image And Vision Computing,vol.18, pp. 881-905,2000.

[11] D. Arumugan, S. Purushothaman.”Emotion Classification Using Facial Expression,” International Journal of advanced Computer Science and Application, vol. 2, no 7,2011.

[12] T. F. Cootes, G. J. Edwards and C. J. Taylor. “Active Appearance Models,” IEEE Transaction on Pattern Analysis and Machine Intelligence , vol. 23, n° 6, 2001.

[13] M. S. Bartlett, J. C. Hager, P. Ekman, and T. J. Sejnowski.“Measuring facial expressions by computer image analysis,” Psychophysiology, Cambridge University, USA, vol. 36, pp. 253–263, 1999.

[14] Zheng You. “Feature-Based Facial Expression Recognition: Sensitivity Analysis and Experiments with a Multi-Layer Perceptron,” International Journal of pattern Recognition and artificial Intelligence vol. 13(6), pp. 893-911, 1999.

[15] M. S. Bartlett, J. C. Hager, P. Ekman, and T. J. Sejnowski.“Measuring facial expressions by computer image analysis, ”Psychophysiology, Cambridge University, USA, vol. 36, pp. 253–263, 1999.

[16] Robert M. Haralick, K Shanmugam and Its’Hak Dinstein(1979). “Textural Features for Image Classification.” IEEE Transactions on Systems, Man, and Cybernetics pp. 610-621.

[17] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba. Coding facial expressions with gabor wavelets. In *Proceedings of the Third IEEE International Conference on Automatic Face and Gesture Recognition*, Nara, Japan, Apr. 1998

[18] SVVSR Kumar, Pullela., V.Vijaya Kumar, and Rampay. Venkatarao. "Age Classification Based On Integrated Approach", International Journal of Image Graphics and Signal Processing, 2014

[19] Satyanarayana Murty, Gorti, J Sasi Kiran, and V.Vijaya Kumar. "Facial Expression Recognition Based on Features Derived From the Distinct LBP and GLCM", International Journal of Image Graphics and Signal Processing, 2014.

[20] Pullela S V V S R Kumar et.al., Classification of Facial Expressions based on Transitions Derived from Third Order Neighborhood LBP, Global Journal of Computer Science and Technology, Graphics & Vision, Vol. 14 no. 1, pp. 1-12, 2014.

BIOGRAPHIES

Bonagiri C S K Sunil Kumar is pursuing his masters degree from Aditya College of Engineering, Surampalem. His research interests include Data Mining and Image processing.

V Bala Shankar is working as Senior Assistant Professor in the Department of Computer Science & Engineering, Aditya College of Engineering, Surampalem. His research interests include Image Processing, Cloud Computing.

Dr. Pullela S V V S R Kumar is working as Professor in CSE at Aditya College of Engineering, Surampalem. He received his Ph.D degree from Acharya Nagarjuna University. He is having more than 15 years of experience and published 13 research papers in various International Journals and Conferences. He acted as a reviewer and PC Member for various international conferences. His research interests include Data Mining, Pattern Recognition and Image Processing.