Face Recognition Based on Robust Third Order Symmetric Texture Matrix

B Vamsee Mohan[1], V. Vijaya Kumar[2]
[1]*Rayalaseema University (Research Scholar –CSE-0076C),Associate Professer, PBR Visvodaya Technology and Science ,Kavali, Andhra Pradesh, India,*
[2]*Professo & Dean , Aurag Group of Instititopms, Hyderabad, Telangana, India*

Abstract -The local binary pattern (LBP) played a vital role in many image processing applications and it is basically derived on a 3x3 neighborhood (Radius R=1 and sampling points P=8), which is a second order neighborhood. The LBP derives local attributes of on image more precisely and that why they are more popular. Researchers later extended the basic LBP with R=1 and P=16; R=2 and P=8, however much research is not progressed in this direction, since it derives a wide and wide histograms or LBP codes and this has become the basic disadvantage of any LBP frame work. The Center Symmetric-LBP (CS-LBP)with R=1 and P=8, derived in the literature quantifies the LBP code from 2P to 2P/2. This paper found one of the major disadvantages of CS-LBP is, it completely eliminates the role of center pixel in deriving CS-LBP code. Further, so far no one has derived CS-LBP on third order neighborhood. This paper addresses these issues by deriving center symmetric LBP on a third order neighborhood by computing center symmetric relationship using center pixel of the Third order neighborhood. The proposed Robust Third-order Symmetric Texture Matrix (RTSTM) initially transforms the facial image into Robust Third-order CenterSymmetric LBP (RT-CS-LBP) coded image. The RT-CS-LBP reduces the third order LBP code from 212 to 26. The gray level co-occurrence (GLCM) features derived on RTSTM on facial images exhibits high recognition rate on popular facial datasets when compared to the other local based methods.
Keywords: Histogram, third order neighborhood, robust, symmetric.

I. INTRODUCTION

The face recognition (FR) methods over the several past decades are mainly used to provide a biometric authentication [1-2]. The other biometric systems like finger prints etc. requires physical touch/ contact between the authentication devices and bio-metric object like finger etc…. The FR does not require this and facial images can be captured easily through powerful cameras even when humans are located at a far distance from the authentication point. And by the time they reach authentication point the FR can be carried out. This is very beneficial and also major requirement for many applications. Further the user will be known an authentication process is being carried out on him through other biometric systems, whereas by using FR the user may not know an authentication has been processing on him. For example by using surveillance cameras the facial images can be captured at a distance, for example before passing through the entrance and recognition process can be carried out automatically. The FR is also applied as an authentication in E-commerce applications like debit/credit card transaction [8], also in house/locking / opening systems [9, 10]. In the literature various face recognition methods are developed [11 - 17]. Though lot of research has been carried out in the field of FR, however recognition of a human face in various situations has become one of the challenging problems. The crucial task of any image recognition classification, identification or retrieval is mainly dependent on extraction of discriminative characteristic features from the object or image surface.

The feature extraction on human face can be carried out globally, region wise and locally. The local based feature extraction methods are more popular in the literature due to their high discriminative capabilities. The local binary pattern (LBP) is one of the well-known and popularly used approaches to extract local features [18]. Many variants are proposed on LBP like local gradient pattern (LGP) [19], local phase quantization (LPD) [20], local ternary pattern (LTP) [21], uniform LBP [22], local directional number pattern (LDN [23], Eigen directional bit-plain (EDBP) [24]. Recently a random-projection based LBP method is developed for feature extraction on human faces and it improved the recognition performance using random sampling method [25]. To reduce dimensionality the subspace methods are introduce in the literature, the popular subspace methods are principal component analysis (PCA), LDA[26], ICA[27], and these methods project the facial image in high dimensional image space into a low dimensional image space.

This paper is organized as follows: the section one describes the introduction. The section two elaborates the proposed method. The section three presents results and discussions with major contribution of the paper. The conclusions are presented in section four.

II. PROPOSED WORK

LBP was introduced by Ojala et al.[18] for texture classification initially and later due to its powerful extraction process of local features more significantly, the concept of LBP is extended to almost all domains of image processing including medical imaging [28, 29], face recognition [30, 31] age classification [32, 33], and content based image retrieval (CBIR) [34, 35]. In the literature local based features are more preferred than global or region based methods. The LBP derives local features more precisely and efficiently. The LBP derives local features in two steps: in the initial step, it derives local binary patterns i.e. replaces the gray level values with binary values {0,1} by comparing the gray level value of each of the neighboring pixel with the center pixel as given in equation. The LBP value of a neighborhood is derived based on equation 1 and 2.

$$LBP_v = \sum_{y=0}^{7} f\left(P_y - P_c\right) * 2^y \qquad (1)$$

$$f(x) = \begin{cases} 1 \text{ if } P_y \geq P_c \\ 0 \quad \text{otherwise} \end{cases} \qquad (2)$$

Where P_y and P_c are gray level values of the neighboring pixel P_y and center pixel P_c. Fig.1 shows the derivation of LBP values from a 3x3 neighborhood.

Spatial arrangement of a 3x3 gray scale image patch

I3	I2	I1
I4	Ic	I0
I5	I6	I7

3x3 Sample Image

85	32	26
53	50	10
60	38	48

LBP Code
00011100

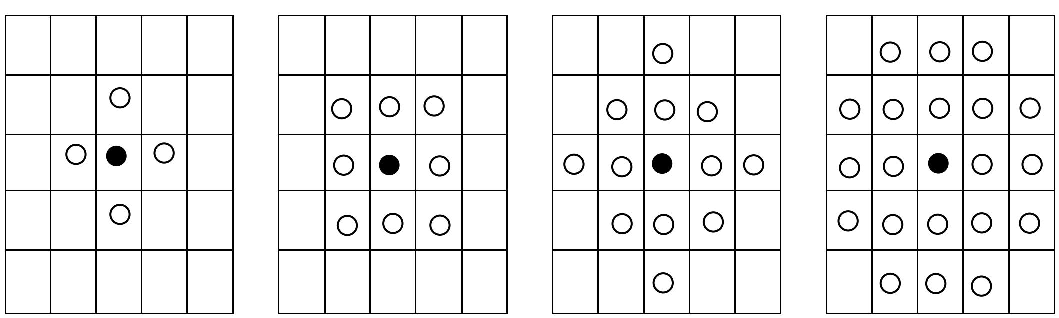
	28	

ζ (Ip- Ic)

1	0	0
1		0
1	0	0

Fig.1: The LBP Transformation.

The disadvantage of LBP is,it derives huge number codes i.e the code ranges from 0 to 2P-1, where P is the number of sampling points. LBP is basically derived on a second order neighborhood as shown in Fig.1.
The Fig. 2 illustrates different orders of neighborhoods. Researchers attempted to derive LBP on third order neighborhoods (TN). The LBP on TN have not become popular due to more number of sampling points i.e. 12, and it derives a wide range of histogram bins i.e. 0 to 212-1.



(a) (b) (c) (d)

Fig. 2: Neighborhood for a central pixel: (a) First Order (b) Second Order (c) Third Order (d) Fourth Order.

In the literature to address this wide range of LBP codes center symmetric LBP (CS-LBP) is proposed on the second order neighborhood. The advantage of CS-LBP is it is more robust in the sense; it quantizes the LBP code from 0 to 2P-1 to 0 to 2P/2-1. The CS-LBP derives the relationship between center symmetric neighbors around the center pixel. The frame work of CS-LBP is shown in the following Fig.3.

P1	P2	P3
P4s	Pc	P4
P3S	P2S	P1S

Fig.3: Frame work of CS-LBP on a second order neighborhood.

In the above Fig.3, the neighboring pixels of the center pixel Pc are denoted as P1,P2,P3,P4,P1s,P2s,P3s,P4s. The center symmetric pixels of P1, P2, P3 and P4 are denoted as P1s, P2s, P3s and P4s respectively. The CS-LBP finds the binary relationship between P1 vs.P1s; P2 vs.P2s; P3 vs. P3s; P4 vs. P4s, as given in equation 3 and 4.

$$CS-LBP = \sum_{i=1}^{4} 2^{i-1} * f(I(P_i) - I(P_{is})) \quad (3)$$

Where $f(x) = f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases}$ (4)

The advantage of CS-LBP is it reduces the overall dimensionality of LBP and makes it more suitable to integrate with the second order statistical features. This paper identified one major disadvantage of CS-LBP frame work is, it does not consider into account the center pixel in deriving CS-LBP code. Further, no one attempted in the literature the derivation of CS-LBP on third order neighborhood. The Fig.4 represents the third order neighborhood with 12 sampling points.

		P5		
	P1	P2	P3	
P12	P10	PC	P4	P6
	P9	P8	P7	
		P11		

Fig.4: Representation of third order neighborhood.

This paper derived a robust LBP on a third order neighborhood by using a new concept of center symmetric by considering the center pixel. This frame work initially derives a Robust third-order Center Symmetric LBP (RT-CS-LBP) coded image. The RT-CS-LBP derives a center symmetric LBP code on the third order neighborhood by considering the center pixels grey level value as given in equation 5 and 6.

$$RT-CS-LBP = \sum_{i=1}^{6} 2^{i-1} * f((I(P_i) + I(P_{i+6})) - 2 * P_c) \quad (5)$$

Where $f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases}$ (6)

The RT-CS-LBPderives a code of 0 to 63 i.e. 0 to 2P/2 -1. This paper initially transformed the raw facial image into a RT-CS-LBPcoded image with a step length of one i.e. replacing the center pixel value with the RT-CS-LBPcode. Thus the RT-CS-LBPframework transforms the facial image into a RT-CS-LBPcoded image with code value ranging from 0 to 63. This paper derived a co-occurrence matrix on RT-CS-LBPcoded facial image and this derives a Robust Third order Symmetric Texture Matrix (RTSTM).

This paper derives four GLCM feature namely: i) Homogeneity or Angular Second Moment (ASM) ii) Energy iii) Contrast iv) Correlation on RTSTM as given in equations from 7 to 10. This paper computed four RTSTM with varying distances'd' rages from 1,2, 3 and 4. On each distance value this paper computed RTSTM with four different angles 00,450,900 and 1350. The four GLCM features are derived on each angle of rotation. This paper computed the average feature value on each distance value and this is considered as feature value of the di. The process of derivation of GLCM with gray level range 0 to 3 for 00,450,900 and 1350 are shown in Fig.5.

0	2	3	1	2
0	2	1	3	1
2	3	3	2	1

00	0	1	2	3
0	0	1	2	0
1	1	0	2	1
2	0	2	0	2

450	0	1	2	3
0	0	0	2	0
1	0	2	0	1
2	0	1	1	1

3	1	0	1	2
900	0	1	2	3
0	1	0	0	0
1	0	1	2	2
2	1	1	1	1
3	0	2	2	0

3	0	3	1	1
1350	0	1	2	3
0	0	0	0	1
1	0	1	2	2
2	1	1	1	0
3	1	0	1	1

3	0	1	1	2

Fig. 5: Derivation of Co-occurrence matrix in four directions (00,450,900 and 1350).

The GLCM features evaluated using following equations
Homogeneity or Angular Second Moment (ASM):

$$ASM= \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \quad (7)$$

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

Energy :

$$Energy = \sum_{i,j} P(i,j)^2 \quad (8)$$

Contrast :

$$Contrast = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\right\}, |i-j| = n \quad (9)$$

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.
Correlation:

$$Correlation = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{iXj\}XP(i,j)-\{\mu_x X\mu_y\}}{\sigma_x X\sigma_y} \quad (10)$$

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

III. CONTRIBUTION OF THE PAPER

- Derivation of a new framework of CS-LBP that accounts the gray level value of center pixel.
- Derivation of center symmetric relationships on third order neighborhood.
- Quantization of local features from 212 to 26 on third order neighborhood with 12 sampling points, without losing any significant features.

The novel way of integration of Third order center symmetric-LBP with Co-occurrence matrix and derivation of Robust Third-order-Symmetric Texture Matrix (RTSTM) with GLCM features for effective face recognition.

IV. RESULTS AND DISCUSSIONS

To test the efficacy of the proposed RTSTMmethod, this paper selected the four popular facial databases namely ORL[36], Yale B[37], FERET[38] , CMU Multi-PIE [39] and CAS-PEAL [40], the sample images of these databases are shown in Fig.6, 7, 8, 9 and 10 respectively. The brief descriptions about these four databases are given below. The performance of the proposed RTSTMdescriptor is computed on these facial data bases and compared with seven state-of-the-art face image descriptors, i.e., LBP [18], Local Ternary Patterns (LTP) [21], MsDLBP[41], MCM[42], CS-LBP[43]. This research used SVM classifier for FR purpose.
The ORL data set [36] contains images from 40 subjects and each subject contains ten face images. This results a total of 400 (40 x 10) face images in ORL data base. For most of the subjects, the images are captured at different times with varying facial details i.e., with glasses and without glasses; with varying lighting conditions; with varying facial expressions like open/closed eyes, smiling/not smiling, etc. The first 2–6 face images of each subject were

used as training samples and the remaining face images were used as test samples. Fig. 6 shows Sample Facial Images of ORL database.

The extended Yale B facial database consists of facial images of 38 different people [37]. Further there are more than 64 facial images per each individual and this lead to a minimum total of 2432 facial images (38*64) under this dataset. This paper randomly selected 20 facial images of each person p for training propose and this leads to a total 38*20 =760 images. The remaining facial images are used for testing purpose and sample images of this data set are shown in Fig. 7.

There are two sub categories of facial images under FERET database [38], namely frontal and non-frontal FERET image sets (Fig. 8). This paper considered only frontal dataset facial images for experimental sake. The frontal FERET dataset consists of various facial image sets known as Fa, Fb, Fc, duplicate I (DUP I) and duplicate II (DUP II). This paper used Fa set facial images of frontal FERET data set for training purpose and the remaining sets are used for testing purpose.

The CMU multi PIE face data set consists of facial images of 337 persons and these images are captured under varying conditions [39] (Fig. 9). This paper considered facial images of 300 persons and seven different samples of each person captured fewer than 7 different smiling expressions. Further there are 20 different images of each person captured with different illumination conditions. This leads to a total of 27 images of each person. This leads to a total of 300x27 = 7100 facial images. This paper selected two facial image from smiling expressions and 5 facial images with different illuminations conditions for training purpose. This leads to a total of 300x7=2100 facial images and remaining images are used for testing purpose.

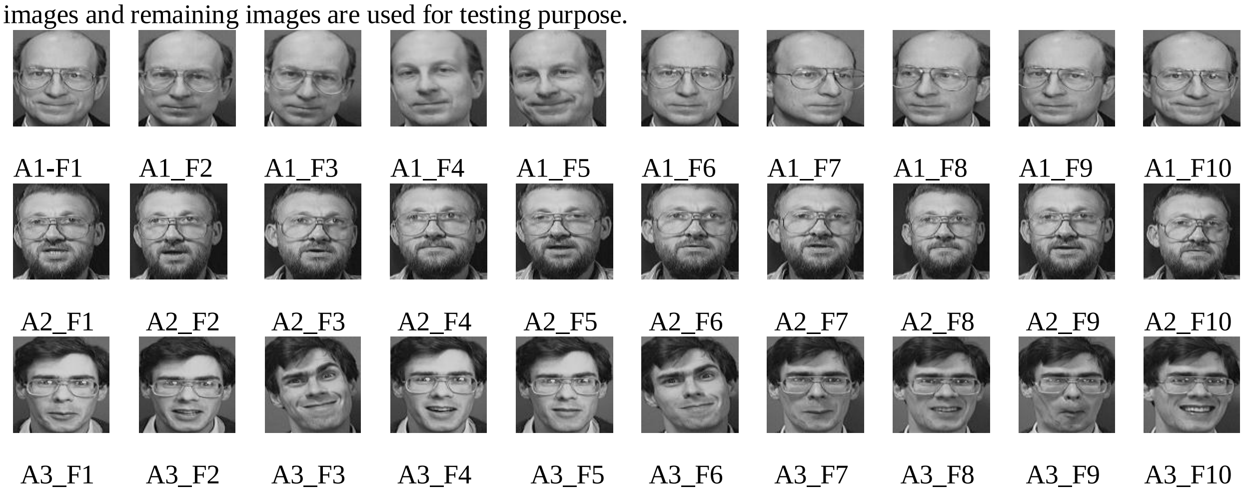


Fig. 6: Sample facial images of AT&T ORL database.

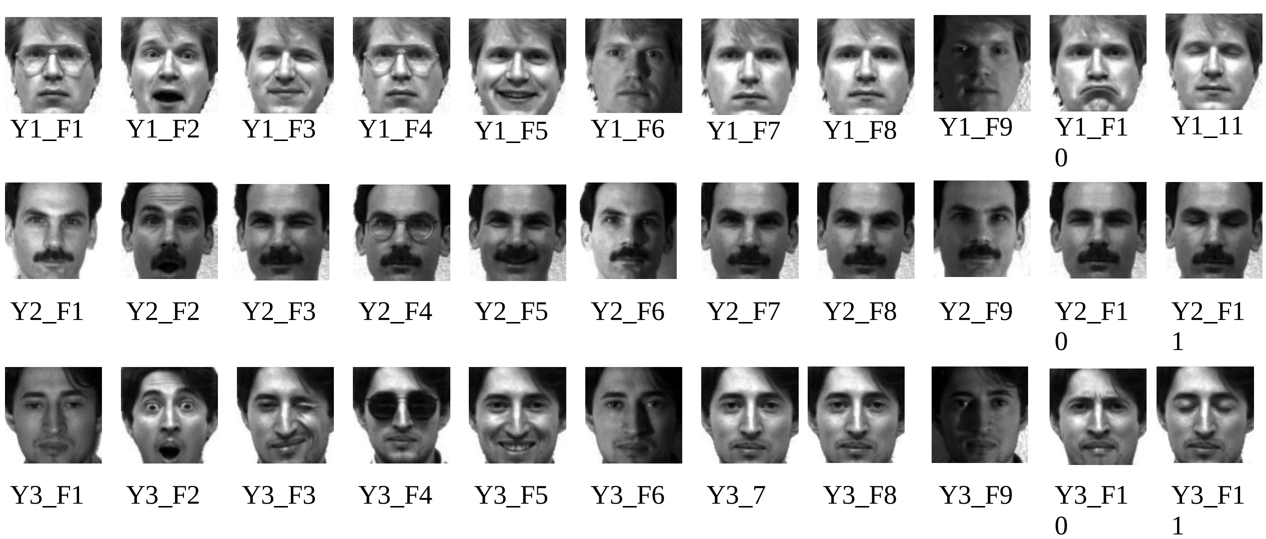


Fig. 7: Sample facial images of Yale database.

4 5 6 7 8 32 33

34 35 36 37 38 20 21

Fig.8: Sample facial images of FERET database.

Fig. 9: sample facial images from CMU-PIE database.

To consider facial images with different races and continents the CAS-PEAL facial dataset is used in the recent literature. The CAS-PEAL facial data set consists of chines face dataset with different orientations like pose, expressions, accessories and lighting (PEAL) conditions. This datasets consists of 1040 individual facial images which 595 are male and rest are female. Totally this database consists of 99,594 facial images with different PEAL of each individual. The publically available CAS-PEAL face dataset is referred as CAS-PEAL R1 facial dataset and it consists of 30,900 facial images of 1040 persons. This data set consists of one training set and six probe sets. The six probe/test facial datasets are denoted as PE, PA, Pl, PT, PB and PS corresponds to variations in expression, accessories, lighting, time, back ground and distance respectively. The sample images of this data are shown in Fig. 10.

CAP1 GLASS1 BLUE RED YELLOW CLOSEEYES SUPRISE

SMILE OPENMOUTH LIGHT1 LIGHT2 LIGHT3 FM_000046 FY_000007

Fig. 10: Sample facial images of CAS-PEAL database.

The proposed RTSTM experimented with different d values of GLCM. The best results are obtained for d=2 on the proposed RTSTM. This paper used RTSTM with d=2 in the remainder of this paper. The face recognition rates of the proposed and existing methods on the five different databases are given in Table 1 and plotted in Fig.11.

Table 1: Face Recognition rate of proposed RTSTM on considered databases.

	AT&T ORL [36]	Yale B [37]	FERET [38]	CMU Multi PIE [39]	CAS-PEAL [40]
LBP [18]	84.26	77.41	64.63	90.11	82.86
LTP[21]	85.63	79.84	72.65	92.10	83.09
MsDLBP [41]	83.12	74.69	63.67	91.32	80.88
MCM [42]	85.95	72.91	66.98	92.32	83.11
CS-LBP [43]	83.26	78.24	65.02	88.02	80.45
Proposed RTSTM	86.22	80.94	73.86	92.10	83.89
Average	86.48	77.03	70.58	93.33	83.46

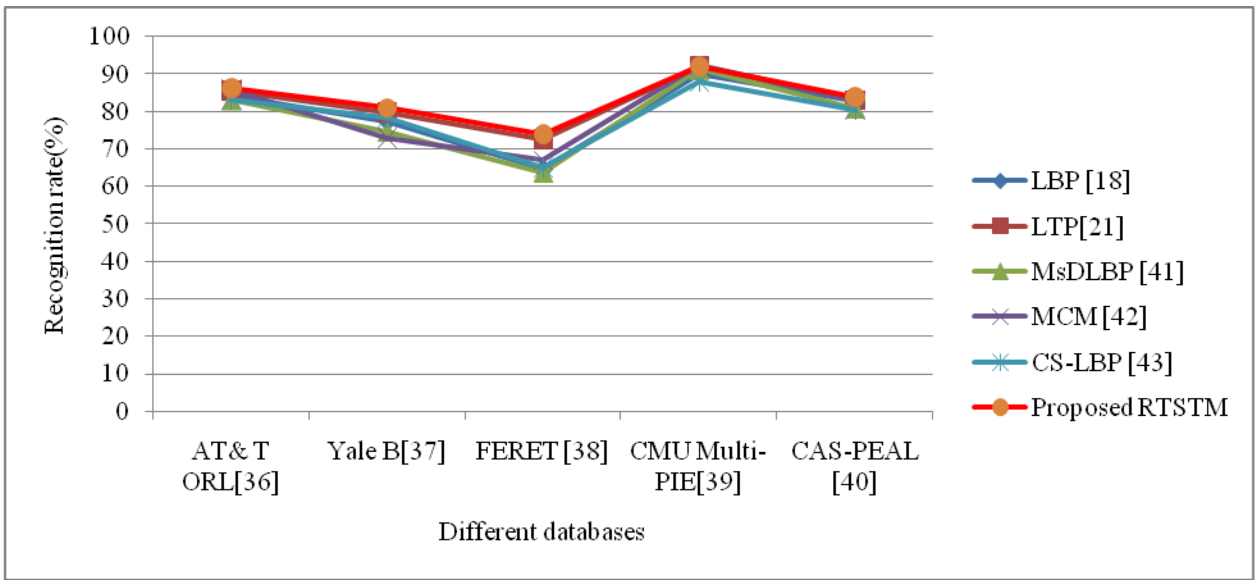


Fig. 11: Comparison of proposed and existing methods in terms of recognition rate (%).

From the experimental investigations it is noted that the proposed RTSTM exhibited high face recognition than its popular counter parts of other local based models. The proposed RTSTM derived high face recognition rate on all considered databases when compared to all other popular local models. The CMU Multi PIE and ORL exhibited a high FR when compared to other four databases. Out of the LBP based descriptors, the LTP followed by MsDLBP and LBP achieved a good FRR. The existing LBP and its variants i.e., LTP, MsDLBP, CS-LBP and the other popular local based pattern approach of 2 x 2 grid i.e. MCM and the proposed RTSTMexhibited high performance on relatively small-scale data sets (e.g., the ORL data set) and the data sets with slight pose or expression variations (e.g., the CMU-Multi-PIE data set). The existing methods exhibited moderate Face Recognition Rate on Facial data bases with high variations and high-scale data i.e., Yale and FERET, However the proposed RTSTM exhibited high face recognition rate on the above and thus the proposed RTSTMobtains better FRR than other LBP based methods. It indicates that our method is more robust to various variations (illuminations, facial expressions, and poses) of human face images.

V. CONCLUSIONS

This paper attempted to derive LBP code on a third order neighborhood using center symmetric relationship. This paper derived a novel way of quantizing the local features from 212 to 26 on third order neighborhood. This advantage of the proposed TN-CS-LBP is, it has taken in to account of center pixels gray level value in estimating the relationship between symmetric sampling points/pixels of the third order neighborhood. Thisprocess has made to integrate the proposed TN-CS-LBP facial coded image with Co-occurrence matrix. The GLCM features derived on RTSTM exhibited high facial recognition rate than existing local based methods on well-known popular facial databases with large variations. The proposed RTSTM is easy to understand, compute and reduced the overall dimensionality while preserving the significant facial features.

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Author’s Profile

Mr. B Vamsee Mohan is working as Associate Professor, at PBRVisvodaya Technology and Science ,Kavali, and after obtaining B.E (Electronics and Communication Engineering) passed from St Peters Engineering College affiliated to Madras University 1999 and M.Tech. from JNTU , Kakinada in 2007 . At present he is pursing Ph.D. from Rayalaseema University under the guidance of Dr.V.Vijaya Kumar, Dean- of CSE & IT and Director for Advanced Computational Research (CACR) Labs of AGI, Hyderabad. He has published 6 research papers.

Dr. V. Vijaya Kumar is working as Professor & Dean Department of Computer Science & Engineering and Information Technology in Anurag Group of Institutions (Autonomous) Hyderabad and Director- Center for Advanced Computational Research (CACR). He received integrated M.S.Engg, in CSE from USSR in 1989. He received his Ph.D. from Jawaharlal Nehru Technological University (JNTU), Hyderabad, India in 1998 in CSE and guided 33 research scholars for Ph.D. He acted as principle investigator for various R&D projects. He has served JNT University for 13 years as Assistant Professor, Associate Professor and Professor. He has received Distinguished Professor award from Computer Science of India (CSI), Mumbai, best researcher and best teacher award from JNT University, Kakinada, India, Leading Scientist of the WORLD -2009 and Top 100 Scientists award in 2010 from International Biographical Centre, Cambridge, England. His research interests include Big data and image analytics, image retrieval, texture analysis, author attribution, digital water marking. At present he is also acting as BoS member for various universities and institutions. He is the life member of CSI, ISCA, ISTE, IE (I), IETE, ACCS, CRSI, IRS and REDCROSS. He published more than 120 research publications till now in various national, international journals and conferences. He has delivered key note addresses at various international conferences.