

Face Recognition Using Gradient Derivative Local Binary Patterns

D. Sharadamani and C. NagaRaju

Research Scholar, Dept of CSE, JNTUA, AP, India.

Associate Professor, Dept of CSE, YV University, AP, India.

Abstract

The emerging notion of the smart city has paying attention in the research field of urban development. One of the challenges of the smart city is how to understand the data collected by the sensor and make a decision. The face detection plays a key role in our social communication in turning over the identity and emotions. The human ability to recognize faces is notable but the face is a complex multidimensional visual model and for developing a computational model for face recognition is difficult. In this paper a new unique real time face recognition system is proposed by combining local orientation gradient XOR patterns and Local gradient XOR patterns. This new technique consists of three steps 1) local gradient XOR patterns are calculated 2) Local Oriented Gradient XOR patterns are calculated and 3) feature vector is constructed by concatenating the histograms of LGXORP and LOGXORP. This method tested on Standard databases and found that the recognized rate is very fruitful and accurate compared to Local Binary Pattern technique and its variants.

Keywords: RLBP, WSN, ICT, PCA, LOGXORP and LGXORP

INTRODUCTION

The emerging notion of the smart city has paying attention in the urban development policy field. It proposes that smart cities are defined by their novelty and their ability to resolve problems and the use of Information Communication Technologies (ICTs) to progress this capacity [1]. A smart city can be considered as a city-scale example of an Internet of Things (IoT) applications. Wireless Sensor Networks (WSNs) and a variety of sensors are the essential elements of the IoT. One of the challenges of the smart city is how to discriminate the data collected by the sensor network to make a robust decision. This is an application level topic mainly concerning pattern recognition based on the sensor based systems like smart surveillance, face recognition; behavioral analysis and pedestrian detection are exploited. This paper mainly focused on the face recognition issues, which is extensively used in the smart video surveillance [2] and general identity verification like electoral registration, banking, and electronic commerce [3] as for 2D face recognition, various features are proposed. Typical applications of Face Recognition System are Human-Robot-interaction, Smart cards, Human-Computer-interaction,, National ID, Driver's license, , Passports, Security system, Voter registration Personal device logon, Criminal identification, Desktop logon, Database security, Information

security, Intranet security and access, Video surveillance, CCTV control and Suspect tracking, Medical records and investigation[4]. We can recognize thousands of faces learned throughout our life span and identify well-known faces at a momentary look even after years of separation. The classification of face recognition techniques are divided into global and local classes according to their features. The universal feature descriptor is also called holistic system. These methods treat the face as a whole, and extract a descriptor from it in such a way. The ability is fairly robust notwithstanding huge changes in the visual stimulus due to viewing conditions, expressions, aging, and interruption such as changes in hairstyle or glasses. But developing a computational model of face recognition and classification is quite complicated, because faces are complex, multidimensional, and subject to change over time [5]. The LBP is a simple yet very efficient operator which labels the image pixels by thresholding the neighborhood pixels and considers the resultant pixel as a binary digit [6]. The LBP is a non-parametric descriptor which competently summarizes the local structures of images [7]. The unique version of the LBP operator works in a mask of 3X3 pixels of an image. The reward of LBP is tolerance against gray level illumination changes and their computational simplicity. The limitations of the basic LBP operator are that its small 3X3 mask neighborhood cannot capture dominant feature with in large scale structures. The recently proposed LBP features which was originally designed for feature extraction shown to be effective local features for face analysis. LBP shows robustness against expression variations and pose. It is also insensitive to gray-level differences caused by illumination discrepancies. due to the sturdiness of LBP, various LBP-based face techniques have been established and demonstrated the successful in improving face recognition performance [8]. The guidelines of the maximum discrimination are not the same as the guidelines of extreme variance as it is not essential to pay the class information such as the within class distribute and between class disseminate. The PCA is unsupervised technique [9]. Face recognition and analysis has been examined intensively throughout the recent decades as a research emphasis of computer vision due to its extensive range of applications. A lot of outstanding achievements are made including Fisher face [10], Gabor feature [11], Scale-Invariant Feature Transform (SIFT) features [12], the Principal Component Analysis (PCA) method [13], the Sparse Depicted-based Classification algorithm [14], Nearest Features Line-based Subspace Analysis [15], Neural Networks [16], Wavelets [17], Fast Independent Component Analysis (ICA) [18] and kernel methods [19]. Also, deferent frequency features, e.g., dominant frequency features [20] and polar frequency features

[21], are also analyzed for holistic face recognition. The performance of face recognition techniques have increased severely. However, the robustness of face recognition quiet needs enhancement. The results of most techniques are influenced by environmental changes, such as illumination deviations, expression disparity and pose variations. It is tough to find a technique that can deal with these variations. Usual way of communication between man and machine can be gained by detecting and classifying of facial expressions for Creation face recognition more reliable under unrestrained lighting conditions is one of the important challenges for real-world facial emotional credit systems [22]. This problem tackle by combining the strengths of robust illumination local texture based face representations, normalization, multiple feature fusion and distance transform based matching. The LBP with entropy and variety of approaches proposed in the literature to symbolize and to recognize faces but it has many limitations like, not apt for shadow images and low contrasted images [23]. To overcome those tribulations 2D-PCA was presented for the facial feature extraction of an image [24]. This technique does not retain significant and important features of Image. The decision making technique is one of the burning problems and also human emotions play vital role in decision-making. While human being is in high emotion he cannot construct correct decision. To overwhelm this weakness extended fuzzy LTP is proposed in [25].

EXISTING METHOD

This method defines the controlling speed and the fidelity function to depend on which denotes the number of similar pixels in a neighborhood, and is significantly dissimilar for pixels of edge noisy pixels and interior pixels. According to their controlling function, the dispersal and fidelity procedure at pixels of edge noisy pixels and inner pixels can be selectively accepted. Further a class of improved second-order, edge-

preserving is proposed based on the controlling function in order to handle with random-valued impulse noise consistently.

Algorithm

Step1: Find the absolute changes between significant pixel p and its neighbourhood pixel q. $B(p,q)=|A(p)-A(q)|$

Step 2: The gray level values which are obtained from step1 are made into two groups such that greater than T is one group and less than T is another group, Where T is central pixel of original window.

Step3: Find entire no of foreground pixels where I(q) is equal to 1 by using the formula $Z = \sum_{i=0}^{n-1} I(q)$

Step4: The Rotation invariant value is calculated by controlling speed and reliability function $M = \frac{1}{4} - \frac{1}{4} \cos(\frac{\pi Z}{N})$ Where N is the no of pixels in A and Z is no of object pixels.

Step5: The edge-preserving pixel value is calculated by

$$W_x = (A(i,j) - A(i,j-1)) / 2;$$

$$W_{xx} = (A(i,j+1) + A(i,j-1)) - 2 * A(i,j);$$

$$W_y = (A(i+1,j) - A(i,j)) / 2;$$

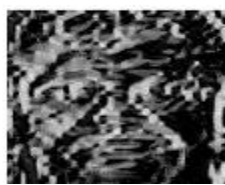
$$W_{yy} = (A(i+1,j) + A(i-1,j)) - 2 * A(i,j);$$

$$R1 = A(i,j) + (W_y^2 * W_{xx} - (2 * W_x * W_y) + W_x^2 * W_{yy}) / (W_x + W_y);$$

Where W_{xx}, W_{yy} are the gradients of second order along with X and Y directions and W_x, W_y are the first order gradients along with X and Y directions. The R1 value preserves the edges in noisy images. This method demonstrates the performance of standard images for test and corrupted by random valued impulse noise with a mixture of noise levels.



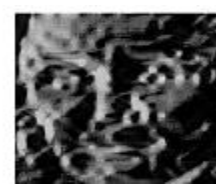
Fig1 a) 1-face



b) 2-face



c) 3-face



d) 4-face

PROPOSED METHOD

Preprocessing:

It improves the quality of the image by normalizing and removing the noise in the Image. Morphology is one of image processing operations that enhances the images based on shapes. Morphological operations smear a structuring element of input image to create an output image of the same size. The dilation adds pixels to the boundaries of foreground of an image, while erosion removes pixels on image boundaries. The number of pixels added or removed from the image depends on the outline and magnitude of the structuring element used to

process the image. In the dilation and erosion operations the value of any given pixel of output image is resolved by applying a rule to the matching pixel and its neighbors of input image. The rule used to process the pixels defines by the operation as an erosion and a dilation as follows.

The erosion on the binary image A and the structuring element B is defined by: $A \ominus B = \{ z \in E | B_z \subseteq A \}$, $A \oplus B = \{ z \in E | B_z \subseteq A \}$, where B_z is the translation of B by the vector z, i.e., $B_z = \{ b + z | b \in B \}$, $\forall z \in E$ When the structuring element B is a disk and this center is positioned on the origin of E then the erosion of A by B can be.

The dilation on the binary image A and the structuring element B is defined by: $A \oplus B = \{ z \in E \mid (Bs)_z \cap A \neq \emptyset \}$, where B^s denotes the symmetric of B , that is, $B^s = \{ x \in E \mid -x \in B \}$. Morphological openings γ_λ and/or closings ϕ_λ are used to remove the amount of image details with cumulative size λ . The volumes of the opened or closed images are plotted against λ , or more usually with discrete derivative $\text{Vol}(\gamma_\lambda - \gamma_{\lambda+1})$, i.e., *pattern spectrum*. Closing is a morphological operator which can be expressed in terms of geodesic erosions. Geodesic erosion $\varepsilon_g^{(1)}(f)$ and dually geodesic dilation $\delta_g^{(1)}(f)$ are operations that are applied to a marker image f and a mask g , where the first is processed conditionally to the second

$$\varepsilon_g^{(1)}(f) = \varepsilon(f) \vee g \quad (1)$$

Where ε and δ are the dilation and erosion of the neighborhood origin. Both the operators can be further applied consecutively as follows:

$$\psi_g^{(n+1)}(f) = \psi_g^{(1)}(\psi_g^{(n)}(f)) \quad (2)$$

Hence, by repeating them until stability (i times, $\psi_g^{(i)}(f) = \psi_g^{(i+1)}(f)$) one can realize correspondingly reconstructed by erosion and by dilation $R_g^\varepsilon(f) = \varepsilon_g^{(\infty)}(f)$; $R_g^\delta(f) = \delta_g^{(\infty)}(f)$ which reaches stability after a finite number of steps Accordingly one can be defined closing by reconstructing with a structuring element (SE) $B_{\phi_{R,B}}(f) = R_g^\delta[\delta_B(f)]$ Opening and closing can be done along SE of various sizes. Fig1 shows that in the fig1b) second Image face is not recognized because of low contrast and wearing glasses, fig2 c) shows that after preprocessing it has been recognized.



Fig2. a) original image b) before preprocess c) after preprocess

Face Detection :

The face recognition process used to notice the location of face in the image because of variability in the orientation, scale and location. Face detection from a single image is challenging task. Face recognition is system that determines the location and size of human face in digital images. It discovers face and it ignores anything else, such as roads, trees, buildings and bodies. Face recognition can be observed as a more universal case of face localization the task that finds the location and size of a known face. In face recognition face is handled and matched bitwise with the core face image in the database. In

this paper face is detected using Viola-Jones Algorithm which is more commanding to extract face even in low contrast. fig2b) shows that all the four faces in the image are recognized and placed red box around faces.

Cropping :

Image cropping separates the detected faces from the image and significant information is carried by them. in fig3.a),b),c) and d) face images are cropped images and used as input images for face detection algorithm.



Fig4. cropping faces a) 1-face b) 2-face c) 3-face d) 4-face

RLBP operator :

Rule Based LBP can be generally described as dynamic technique completely defined by the set of rules in a neighborhood. The value of technique is represented in regular mask on which the rules are applied to harvest a new value. An interesting property of rule based local binary pattern is that very simple rule that can be resulted in very complex behavior. Now consider sample window $S_{3 \times 3}$ and compare each pixel with

centers of the sample window of size 3×3 . All neighboring pixels which otherwise greater than the center replace them with value 1 replace them with 0 such that gray image is converted to binary image. On the binary image the following rules have been applied to remove the uncertainty of texture classification.

1) The column wise counts (CS_i) are calculated on sample space S_{3x3}

$$C_i = \sum_{i=1}^3 S(CS_i, n); \text{ where } n=1, 2, 3$$

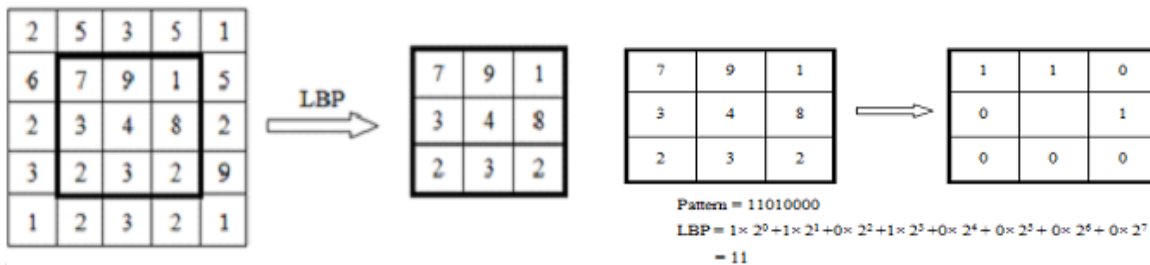
$$C_i = \begin{cases} 1 & C_i \geq 2 \\ 0 & C_i < 2 \end{cases}$$

2) The row wise counts (RS_i) are calculated on sample space S_{3x3}

$$R_i = \sum_{i=1}^3 S(RS_i, m) \text{ where } m=1, 2, 3$$

$$C_i = \begin{cases} 1 & R_i \geq 2 \\ 0 & R_i < 2 \end{cases}$$

5) work out the LBP operator on new sample space and replace the center pixel.



6) Iteration step1 to step5 on whole images and form the new unambiguous image.

The outcome of this method can be conveniently presented as a two-dimensional pattern used in image processing, especially with parallel computing. RLBP of 8-bit, segments the Image in better way even for Noisy Images and comparatively better than conventional methods.in the fig5a), b), c) and d) images are output of RLBP.

Local Gradient Patterns :

In the proposed LGP for face detection a center pixel in an image the LGP value is computed by comparing its gray scale value with its neighbors based on equations (3) and (4).

$$LGP_{pr} = \sum_{i=1}^p (2)^{(i-1)} * f1(|g_i - g_c|) - Th \tag{3}$$

$$Th = 1/p \sum_{i=1}^p (|g_i - g_c|) \tag{4}$$

The proposed LGP is virtual homogeneous to the consummated LBP magnitude (CLBP_M).The only distinction between these two features is that, the LGP calculates the threshold (Th) from the mean /average of the entire image LDO.

3) The counts for left diagonal D1 and right diagonal D2 are computed on sample space S_{3x3}

4) From the new sample counts the matrix like is giving blow.

R1	D1	C1
R2		C2
R3	D2	C3

Local Orientation Gradient XOR Patterns :

The conception of RLBP, LGP, and LGXP has been adapted to define the LOGXORP. Given a center pixel in an image, the gradients (p=8) are calculated as,

$$I_{gc}^G = g_1 - g_9 \tag{5}$$

$$I_{gc}^V = g_3 - g_7 \tag{6}$$

where {g₁,g₂,g₃,g₄,g₅,g₆,g₇,g₈}|p=8 are the gray values of neighbors for a given center pixel g_c.

The orientation and gradient values are calculated as

$$I_{gc}^G = \sqrt{((I_{gc}^h)^2 + (I_{gc}^v)^2)} \div 2 \tag{7}$$

$$\theta_{gc} = \tan^{-1} \left(\frac{I_{gc}^v}{I_{gc}^h} \right) \tag{8}$$

$$(I_{g0}^G) = \begin{cases} 0^\circ + \theta_{gc} & I_{gc}^h \geq 0 \text{ and } I_{gc}^v \geq 0 \\ 180 - \theta_{gc} & I_{gc}^h < 0 \text{ and } I_{gc}^v \geq 0 \\ 180^\circ + \theta_{gc} & I_{gc}^h < 0 \text{ and } I_{gc}^v < 0 \\ 360^\circ - \theta_{gc} & I_{gc}^h \geq 0 \text{ and } I_{gc}^v < 0 \end{cases} \tag{9}$$

The local gradient XOR patterns (LGXORP) local oriented XOR patterns (LOXORP) are calculated as:

$$LGXORP = \begin{bmatrix} \{Q(I_{g1}^G) \otimes (I_{gc}^G)\}, \\ \{Q(I_{g2}^G) \otimes (I_{gc}^G)\}, \\ \vdots \\ \{Q(I_{gp}^G) \otimes (I_{gc}^G)\} \end{bmatrix} \quad (10)$$

$$LOXORP = \begin{bmatrix} \{Q(I_{gc}^O) \otimes (I_{gc}^G)\}, \\ \{Q(I_{gc}^O) \otimes (I_{gc}^G)\}, \\ \vdots \\ \{Q(I_{gc}^O) \otimes (I_{gc}^G)\} \end{bmatrix} \quad (11)$$

Where $Q(x)$ denotes the quantized value of x and represents the exclusive or(xor) operation. Similarly, orientation and gradient patterns are calculated utilizing diagonal directions additionally. For the local pattern with p neighborhoods, $2p$ coalescence of RLBP is possible resulting in a feature vector length $(2p)$. The feature Vector computational cost is very high. The uniform patterns are used to reduce the computational cost. The uniform patterns refer to the uniform appearance pattern that has inhibited discontinuities in the circular binary representation. Fig1, shows the output of ENI method, Fig5 is LGXORP output Fig6 is LOXORP and Fig7 is the final output of the proposed method. By the comparison we found that proposed method has formed better result than ENI feature extraction method

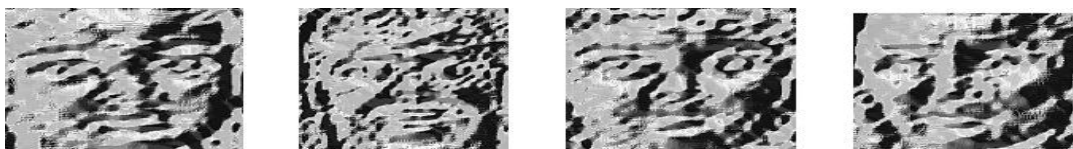


Fig5.LGXORP a)1-face b) 2-face c) 3-face d)4-face



Fig6.LOXORP a) 1-face b) 2-face c) 3-face d)4-face

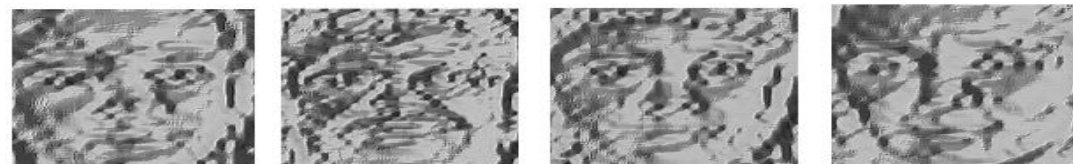


Fig7.LOGXORP a)1-face b) 2-face c) 3-face d)4-face

CLASSIFICATION PARAMETERS

Standard Deviation :

The standard deviation is calculated on gray level image as follows

$$Std(\sigma) = \sqrt{\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n (f(x, y) - \mu)^2} \quad (12)$$

Where $f(x, y)$ the gray level is value of the image m, n are the number of rows and number of columns of the resulting image and μ is the mean of the image.

Mean :

The mean of the gray level image is calculated as

$$Mean = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n f(x, y) \quad (13)$$

Where $f(x, y)$ is the gray level image and m and n are number of rows and number of columns of resulting image.

Jaccard Index :

The similarity measures with the Jaccard Index known as similarity coefficient of Jaccard very popular and often used as similarity indices of binary Image data. The area of overlap A_j is calculated between the binary image B_j and its corresponding gold standard image G_i as shown in equation

$$Jaccard\ Index\ (A_i) = \frac{|B_i \cap G_i|}{|B_i \cup G_i|} \times 100 \quad (14)$$

If the threshold object and corresponding gold standard image G_i (associated ground truth image) are exactly similar then indexed value is 100 and indexed value 0 represents that are totally dissimilar, however the higher the values of indicates are more similarity.

Peak Signal Noise Ratio / MSE :

PSNR looks at how many pixels in the digital image fluctuates from the original image values and by how much value. This metric is on the image difference and is calculated by

$$PSNR(x, y) = 20 * \log_{10} \left(\frac{255}{\sqrt{MSE(x,y)}} \right) \quad (15)$$

Where the Mean Square Error (MSE) is calculated from

$$MSE(x, y) = \frac{\sum_{x=1}^M \sum_{y=1}^N (I_1(x,y) - I_2(x,y))^2}{M * N} \quad (16)$$

A higher PSNR indicates a better match.

EXPERIMENTAL RESULTS

This method tested on Standard face databases like Sterling face databases, ORL face database and my own databases which are developed for my DST projects and quality parameters like mean, standard deviation, Jaccard index and PSNR are applied on specified databases and results have been produced in the form of tables and graphs. We kept only my own database Images, graphs and tables in the results. In the graphs and tables from P1 to P10 images values are pruthvi data base from SP1 to SP10 images are from sivapriya database and R1 to R10 are images Rakesh database. The proposed method gives better results than existing ENI method because mean, Jaccard index and PSNR values are higher than ENI method and standard deviation is very nearer to both methods.

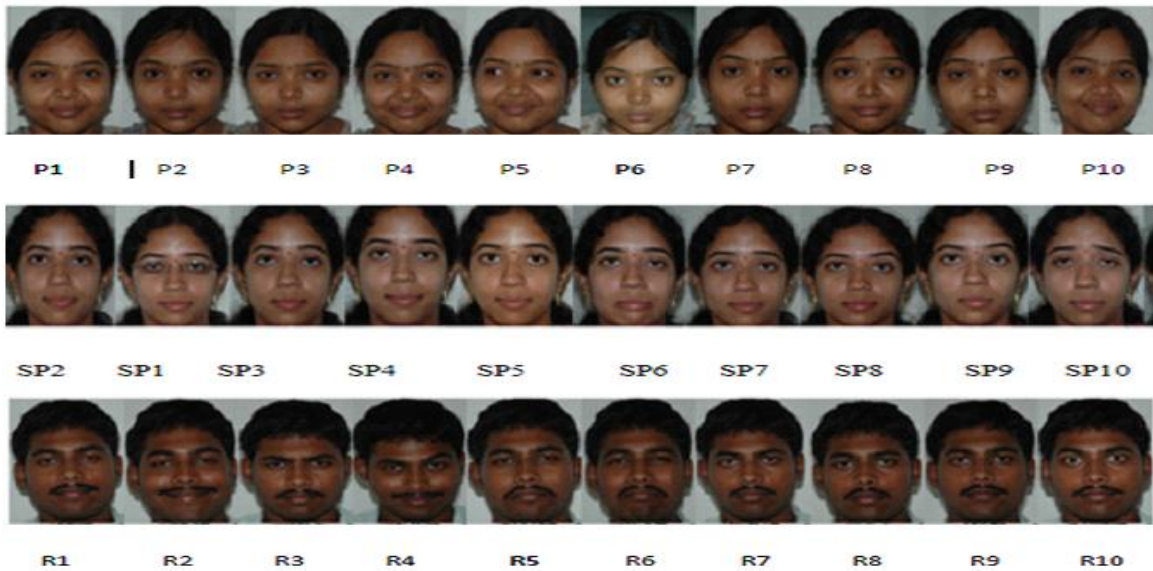


Figure 8: Data Base Images

Table1. Mean Table2. Standard Deviation Table3. Jaccard Index Table4. PSNR

ENI	GDLBP	ENI	GDLBP	ENI	GDLBP	ENI	GDLBP
2.7355	1.7326	0.042	0.102	0.9172	0.8641	0.0758	0.0106
2.9314	1.7406	0.0443	0.1023	0.9219	0.8667	0.0739	0.0106
2.8733	1.3106	0.0428	0.0875	0.9167	0.8409	0.0767	0.0106
2.5846	1.3317	0.0395	0.0879	0.9208	0.8331	0.0764	0.0098
2.7059	1.3317	0.0417	0.0879	0.9212	0.8331	0.0758	0.0098
3.1037	1.5559	0.0472	0.0954	0.907	0.8351	0.0755	0.0106
3.0857	1.3811	0.0477	0.0895	0.909	0.8247	0.075	0.0106
3.2588	1.5724	0.0496	0.096	0.9116	0.8325	0.0698	0.0106
2.7347	1.4574	0.0421	0.0925	0.9184	0.8528	0.0698	0.0106
4.8033	1.4616	0.0726	0.0927	0.9053	0.8059	0.078	0.0099
4.2874	1.5866	0.0658	0.0962	0.9973	0.9582	0.0602	0.0111
4.9686	1.5422	0.0736	0.0955	0.907	0.8586	0.0899	0.0067
4.5448	1.7289	0.0691	0.1017	0.903	0.8755	0.0698	0.0106
5.0971	1.5068	0.0765	0.0941	0.9092	0.8085	0.0698	0.0106
4.2014	1.3326	0.0636	0.0877	0.9199	0.8378	0.0648	0.0115
5.0139	1.5491	0.0763	0.0961	0.8959	0.8269	0.057	0.01
5.1245	1.4952	0.0774	0.0948	0.8945	0.6726	0.0588	0.0107
4.5232	1.6735	0.0685	0.1003	0.9142	0.8624	0.0595	0.0115
4.9154	1.4282	0.0748	0.0915	0.9073	0.763	0.069	0.0106
2.2365	1.3186	0.0372	0.0865	0.911	0.7481	0.0551	0.0115
3.0731	1.4679	0.0473	0.0925	0.9222	0.836	0.0815	0.0106
2.0124	0.149	0.0012	0.0736	0.9128	0.8059	0.0822	0.0104
2.2365	1.3186	0.0372	0.0865	0.911	0.7481	0.0793	0.0106
2.1714	1.3612	0.0365	0.0878	0.9103	0.8158	0.0815	0.0106
3.2569	1.3458	0.0491	0.0874	0.9077	0.7985	0.0803	0.0107
2.1949	1.5222	0.0363	0.0939	0.914	0.8603	0.084	0.0106
2.814	1.3866	0.0444	0.0888	0.9125	0.801	0.0789	0.0106
2.7377	1.8043	0.0423	0.105	0.9152	0.8788	0.0811	0.0106
2.8812	1.8424	0.0445	0.1058	0.9094	0.8725	0.0786	0.0106
3.0148	1.876	0.0463	0.0912	0.9094	0.9124	0.0776	0.011
						0.0812	0.0126



Graph1. Mean Graph2. Standard Deviation Graph3. Jaccard Index Graph4. PSNR

CONCLUSIONS

In this paper new face recognition technique has been proposed to classify the different face databases. The new method encodes the images database based on the basis of the XOR operation between the central pixel and its neighbors of quantized orientation and gradient operations. The performance of the proposed has been compared with existing method on gray Images. Due to the efficiency of the proposed method it can be additionally opportune for other pattern applications such as Bio security and other IoT applications.

REFERENCES

- [1]. Caragliu, A.; Del Bo, C.; Nijkamp, P. Smart cities in Europe. *J. Urban Technol.* 2011, 18, 65–82.
- [2]. Tian, Y.-L.; Brown, L.; Hampapur, A.; Lu, M.; Senior, A.; Shu, C.-F. IBM smart surveillance system (S3): Event based video surveillance system with an open and extensible framework. *Mach. Vision Appl.* 2008, 19, 315–327. *Sensors* 2014, 14 19579
- [3]. Jafri, R.; Arabnia, H.R. A Survey of Face Recognition Techniques. *JIPS* 2009, 5, 41–68.
- [4]. C. NagaRaju, SharadMani, Vijay kumar, Shoba Bindu C. Emotional Face Recognition System For Decision Making Based On Statistical Features Of Q-Matrix published in *i-manager's Journal on Image Processing* 2014 vol.2 issue no.1 34-41
- [5]. Rajesh Kumar Gupta, Umesh Kumar Sahu, "Real Time Face Recognition under Different Conditions", *International Journal of Advanced Research in Computer Science and Software Engineering* Volume 3, Issue 1, January 2013, 86-89.
- [6]. C. Nagaraju, B. Srinu, E. Srinivasa Rao— An efficient Facial Features extraction Technique for Face Recognition system Using Local Binary Patterns *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* ISSN: 2278 -3075, Volume-2, Issue-6, May 2013.
- [7]. Di Huang, Caifeng Shan, Mohsen Ardabilian, Yunhong Wang and Liming Chen—Local Binary Patterns and Its Application to Facial Image Analysis: A Survey—*IEEE Transactions On Systems, man, and cybernetics—part c: applications and reviews*, vol. 41, no. 6, november 2011
- [8]. Huang, D.; Shan, C.; Ardabilian, M.; Wang, Y.; Chen, L. Local binary patterns and its application to facial image analysis: A survey. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 2011, 41, 765–781. 13
- [9]. Zhao, W.; Chellappa, R.; Phillips, P.J.; Rosenfeld, A. Face recognition: A literature survey. *ACM Comput. Surv.* 2003, 35, 399–458.
- [10]. Belhumeur, P.N.; Hespanha, J.P.; Kriegman, D. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Trans. Pattern Anal. Mach. Intell.* 1997, 19, 711–720.
- [11]. Liu, C.; Wechsler, H. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE Trans. Image Process.* 2002, 11, 467–476.
- [12]. Lowe, D.G. Distinctive image features from scale-invariant key points. *Int. J. Comput. Vision* 2004, 60, 91–110.
- [13]. Zhang, J.; Yan, Y.; Lades, M. Face recognition: Eigen face, elastic matching, and neural nets. *Proc. IEEE* 1997, 85, 1423–1435.
- [14]. Wright, J.; Yang, A.Y.; Ganesh, A.; Sastry, S.S.; Ma, Y. Robust face recognition via sparse representation. *IEEE Trans. Pattern Anal. Mach. Intell.* 2009, 31, 210–227.
- [15]. Y. Pang, Y. Yuan and X. Li, Iterative subspace analysis based on feature line distance, *Image Processing, IEEE Transactions on*, vol.18, pp.903-907, 2009.
- [16]. S. Lawrence, C. Giles, A. C. Tsoi and A. Back, Face recognition: A convolutional neural-network approach, *Neural Networks, IEEE Transactions on*, vol.8, pp.98-113, 1997.
- [17]. S. Yan, H. Wang, X. Tang and T. Huang, Exploring feature descriptors for face recognition, *Acoustics, Speech and Signal Processing, IEEE International Conference on*, vol.1, pp.629-632, 2007.
- [18]. Q. Z. C. Zhou, X. Wei and B. Xiao, Image reconstruction for face recognition based on fast ica, *International Journal of Innovative Computing, Information and Control*, vol.4, no.7, pp.1723-1732, 2008.

- [19] J. Yang, A. Frangi, J.-Y. Yang, D. Zhang and Z. Jin, Kpca plus lda: A complete kernel fisher discriminant framework for feature extraction and recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.27, pp.230-244, 2005.
- [20] I G. P. S. Wijaya, K. Uchimura and Z. Hu, Face recognition based on dominant frequency features and multiresolution metric, International Journal of Innovative Computing, Information and Control, vol.5, no.3, pp.641-651, 2009.
- [21] Y. Zana and R. M. Cesar Jr., Face recognition based on polar frequency features, ACM Trans. on Applied Perception, vol.3, no.1, pp.62-82, 2006.
- [22] C. Naga Raju, SivaPriya. T, prudvi.ch “A novel method for recognizing face to indicate the state of emotion in order to avoid consistent effect on decisions making” has been published in International Journal of Advancements in Computer Science & Information Technology (IJACSIT) September 2011Edition.pp.10-17.
- [23] C.NagaRaju, B.Srinu, B.Srinivasa Rao “An efficient Facial Features extraction Technique for Face Recognition system Using Local Binary Patterns” has been published in International Journal of Innovative Technology and Exploring Engineering (IJITEE).pp.76-78.
- [24] C.NagaRaju,P.PrathapNaidu,R.PradeepKumarReddy and G.SravanaKumari “Robust multi gradient entropy method for face recognition system for low contrast noisy images” has been published in International Journal of Emerging Trends & Technology in Computer Science (IJETTCS) Volume 2, Issue 4, May - June, 2013 .pp.19-197
- [25] C. NagaRaju et al, Evaluation of LBP-Based Facial Emotions Recognition Techniques to Make Consistent Decisions published in international journal of pattern recognition and artificial intelligence. World Scientific Publishing Company Vol. 29, No. 6 (2015) 1556008 (15 pages)