Face Recognition of Enhanced Contrast Limited Adaptive Histogram Equalization using Feature Extraction Method

Thamizharasi A, Jayasudha J.S

Abstract— ***Face recognition is most widely useful for social networks and surveillance applications. Face recognition is complex if there are variations in light. The proposed work is to develop an illumination invariant face recognition system by enhancing Contrast Limited Adaptive Histogram Equalization (CLAHE). The face recognition of Enhanced CLAHE is done using feature extraction method. The features extracted are DWT statistical features, moments, texture, regional features, shape ratios, Fourier descriptors and facial features from Enhanced CLAHE images. These features are combined to create a feature vector. The feature vector is classified using Support Vector Machine (SVM) classifier and Multilayer Perceptron (MLP) neural network. The efficiency of feature vector is tested with three public face databases AR, Yale and ORL. The testing result proves that feature vector has high recognition accuracy rate.***

Index Terms— ***face recognition, CLAHE, Enhanced CLAHE, feature vector, illumination invariant, SVM and MLP classifier.***

I. INTRODUCTION

In recent years face recognition has received substantial attention from researchers in biometrics, pattern recognition, and computer vision communities [1]. Researchers have proved that for a face image, the variability caused by illumination changes even exceeds the variability caused by identity changes [2]. The illumination normalization technique is applied on input images to remove the variations of lighting. The illumination normalization techniques are grouped into gray-level transformations, gradient-based methods, reflectance field methods, illumination models, wavelet based methods, Discrete Cosine Transform based methods and feature descriptors.

In machine learning, pattern recognition and image processing, feature extraction is a way of dimensionality reduction. Feature extraction is measurement of data from image. A feature vector is created from the measured features. The set of all possible feature vectors constitutes a feature space. The feature vector is a form of pattern. It is classified using supervised or unsupervised classification techniques.

Illumination invariant face recognition by enhanced contrast limited adaptive histogram equalization is developed [3]. The enhanced contrast limited adaptive histogram equalization is a hybrid method which uses gray-level transformations and wavelet based methods. The proposed work is to do face recognition using the features extracted from enhanced CLAHE images. The geometric features, shape features, moments, statistical features and texture features are the various features extracted from images.

II. RELATED WORKS

The gray-level transformations [4] like Logarithm Transform, Gamma Intensity Correction and Histogram Equalization are used for image enhancement, but could not remove the uneven illuminations in face images. The gradient-based method like gradientfaces is an illumination insensitive method which uses gradient domain, but it is more complex [5]. The reflectance field estimations methods are Self Quotient Image [6], Multiscale Quotient Image [7], Single Scale Retinex [8], Mutliscale Retinex [9], logarithmic total variation [10] and Tan and Triggs method [11]. The illumination models construct a model using the training images. They are more complex [12]. Wavelet based methods like Discrete Wavelet Transform are simple, fast and efficient and it is a multi-resolution method which extracts both coarse and fine facial features [13]. Discrete Cosine Transform based methods uses local approach for face recognition [14]. The two representative feature based methods are Gabor Wavelet and Local Binary Pattern [15]. There is lot of variants of LBP methods. The Gabor based LBP methods also exist. The feature based methods extracts local features for face recognition. Some of the recent approaches are cost sensitive learning [16], ensemble string matching [17], Joint feature learning [18] etc.

The feature extraction method is a pattern recognition approach for face recognition. This work is based on the pattern recognition approach.

III. METHODOLOGY

The feature extraction of enhanced CLAHE method has the following steps:

- The illumination of the input image is normalized using Enhanced CLAHE algorithm [3].

Manuscript published on 30 October 2016.
* Correspondence Author (s)
Thamizharasi A M.E., M.B.A., Research Scholar, Manonmaniam Sundaranar University, Abhishekapatti, Tirunelveli -627012, Tamilnadu, India.
Dr Jayasudha J.S., Professor, Department of Computer Science & Engineering, SCT College of Engineering, Pappanamcode, Trivandrum, Kerala, India.

- The feature extraction is done using Enhanced CLAHE image, mask images and elliptical gray images. These features are concatenated to create a feature vector.
- The feature vector is tested for face recognition using SVM classifier and Multilayer Perceptron (MLP) Neural Network.

A. Feature Extraction

The seven types of features are extracted from Enhanced CLAHE image, mask image and elliptical gray-scale image.

1) Discrete Wavelet Transform statistical features

The Discrete Wavelet Transform is applied on elliptical gray-scale image 'E' at level one using haar wavelet. The mean, variance, standard deviation and normalized energy of the four sub images L1, H1, V1 and D1 are stored as features. Thus 16 features are extracted.

2) Moment and Texture features

Moments are the most useful features to identify the shape because they provide global information about the random variable [19]. The first order moment mean, second order moment variance and normalized fourth order moment, Kurtosis [20] of four sub images L1, H1, V1 and D1 are used as features.

The contrast, energy, correlation and homogeneity [21] are the four statistical texture features extracted from four sub images L1, H1, V1 and D1. Thus 12 moment features and 16 texture features are extracted.

3) The region based properties

The elliptical binary mask image 'BM' is measured that represents face shape features. The nine regional features are area, major axis length, minor axis length, eccentricity, extent, solidity, Equivalent diameter, orientation and Euler number of region [4]. The seven shape ratio's like thinness ratio, area to perimeter ratio, circularity, irregularity ratio, roundness, aspect ratio, compactness, are calculated from the elliptical face image [19]. The above ratios are given in equations 1 to 7.

$$\text{Thinness ratio} = 4 * \pi * \left(\frac{\text{area of region}}{(\text{perimeter of region})^2}\right) \quad (1)$$

$$\text{Area to perimeter ratio} = \frac{\text{area of region}}{\text{perimeter of region}} \quad (2)$$

$$\text{Circularity} = \frac{(\text{perimeter of region})^2}{\text{area of region}} \quad (3)$$

$$\text{Irregularity ratio} = \frac{1}{\text{thinness ratio}} \quad (4)$$

$$\text{Roundness} = 4 * \frac{\text{area of region}}{(\pi * (\text{major axis length}^2))} \quad (5)$$

$$\text{Aspect ratio} = \frac{\text{major axis length}}{\text{minor axis length}} \quad (6)$$

$$\text{Compactness} = \frac{\sqrt{\left(\frac{4}{\pi}\right) * \text{area of region}}}{\text{major axis length}} \quad (7)$$

4) Shape distance measures

The distance measures [19] like Euclidean distance of the shape boundary points set; centroid distance between the shape boundary points and the centroid X0 and Y0, the root mean square distance, the mean size of the shape and centroid size are measured from the elliptical shape. The equations 8 to 12 are given below. X1 and Y1 are the vectors of boundary points of the elliptical shape curve and X0 and Y0 are the centroids. Thus five features are measured from this category.

$$\text{Euclidean distance} = \sqrt{\text{sum}(x1^2) + \text{sum}(y1^2)} \quad (8)$$

$$\text{Centroid distance} = \sqrt{\text{sum}((x1 - x0)^2) + \text{sum}((y1 - y0)^2)} \quad 9)$$

$$\text{Root Mean Square distance} = \frac{\text{centroid distance}}{2 * \text{length}(x1)} \quad (10)$$

$$\text{Mean Size} = \text{sum}(\sqrt{(x1 - x0)^2 + (y1 - y0)^2}) \quad (11)$$

$$\text{Centroid size} = \frac{\sqrt{\text{sum}((x1 - x0)^2) + \text{sum}((y1 - y0)^2)}}{\text{length}(x1)} \quad (12)$$

5) Fourier Descriptors

The Fourier Descriptors are translation invariant, rotation invariant and scale invariant [22]. The boundary points of the elliptical face shape is represented as Z=X+ i Y where X and Y are the vectors showing 'x' set of points and 'y' set of points on the boundary curve respectively.

The Fourier transform is applied on this 1 D signal and Fourier descriptors are obtained. The first term in Fourier Descriptor is DC component depends only on the position of the shape, it is not useful in describing shape thus it is discarded. Scale invariance is then obtained by dividing the magnitude values of the first half of Fourier Descriptor's by the DC component. Rotation invariants of the Fourier Descriptors are achieved by ignoring the phase information and by taking only the magnitude values of the Fourier Descriptors [22]. Here instead of using half of the Fourier Descriptors, only first eight terms (after ignoring FD0 term) are used for feature vector creation. Thus eight features are measured.

6) Thinning feature

The morphological operation thinning [4] is applied on mask image to create thinned image. The thinned image gives the structure of the face shape. The count of white pixels in the thinned image, branch points and end points are the three features.

7) Facial features

The eight facial features extracted from Enhanced CLAHE are face length ratio, face width ratio, forehead width ratio, forehead length ratio, chin width ratio, chin height ratio, triangle to area ratio and face area ratio. The face features forehead width, forehead length, face length, face width, chin width, chin height and face triangle are shown in fig. 1.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

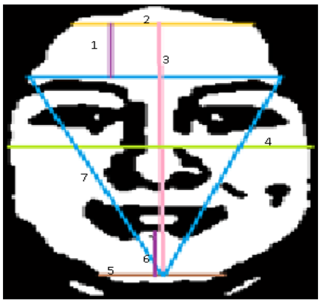

Fig.1. Facial features of Enhanced CLAHE

The facial features extractions are given in equations 13 to 20.

$$\text{Face length ratio} = \left(\frac{\text{face length}}{\text{number of rows in image}}\right) * 100 \quad \textbf{(13)}$$

$$\text{Face width ratio} = \left(\frac{\text{face width}}{\text{number of columns in image}}\right) * 100 \quad \textbf{(14)}$$

$$\text{Forehead width ratio} = \left(\frac{\text{forehead width}}{\text{number of columns in image}}\right) * 100 \quad \textbf{(15)}$$

$$\text{Forehead length ratio} = \left(\frac{\text{forehead length}}{\text{number of rows in image}}\right) * 100 \quad \textbf{(16)}$$

$$\text{Chin width ratio} = \left(\frac{\text{chin width}}{\text{number of columns in image}}\right) * 100 \quad \textbf{(17)}$$

$$\text{Chin height ratio} = \left(\frac{\text{chin height}}{\text{number of rows in image}}\right) * 100 \quad \textbf{(18)}$$

$$\text{Triangle area ratio} = \left(\frac{\text{face triange area}}{\text{face area}}\right) * 100 \quad \textbf{(19)}$$

$$\text{Face area ratio} = \left(\frac{\text{face area}}{\text{number of rows} * \text{number of columns}}\right) * 100 \quad \textbf{(20)}$$

B. Features Classification

The feature vector thus created consists of 84 different features representing the face features. The feature vector is classified using the supervised machine learning technique SVM classifier [23]. The class label has to be added at the end of the feature vector for supervised learning. Thus the feature vector length is 85.

SVMs are set of related supervised learning methods used for classification and regression [24]. SVM simultaneously minimize the empirical classification error and maximize the geometric margin. So SVM is called Maximum Margin Classifiers. SVM map input vector to a higher dimensional space where a maximal separating hyper plane is constructed. Here Polynomial Kernel SVM is used for face classification. Multilayer Perceptron's (MLP) are the most popular type of neural networks. They belong to a general class of structures called feed forward neural networks [25].

C. Description of Databases

The face recognition accuracy rate of feature vector extracted is tested using three public face databases AR, ORL and Yale.

The AR database (Martinez and Benavente) [26] contains images of 100 persons taken in two different sessions. Neutral, expressions (anger, scream, and smile), illumination in (right, left and both sides) and occluded images are present. A subset is created with 1400 images for testing purpose. It contains 100 persons, 14 images of each person of different illuminations, expressions and neutral conditions.

The Olivetti and Oracle Research Laboratory (ORL) Face Database [27] contains 10 different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying lighting, facial expressions (open / closed eyes, smiling / not smiling), facial details (glasses / no glasses) and head pose (tilting and rotation up to 20 degrees).

The Yale Face Database contains 165 gray scale images of 15 individuals in GIF format. There are 11 images per individual, one per different facial expression or configuration; centre-light, w/o glasses, happy, left-light/no glasses, normal, right-light, sad and sleepy, surprised and wink [28] in database.

D. Experimental results of Enhanced CLAHE using feature extraction

The proposed method is implemented in MATLAB 2013 [29]. Fig. 2a-c shows the outputs of pre-processing of sample AR face image. Fig. 3a shows the elliptical color image and figure 3b shows the Enhanced CLAHE image.

Fig. 2 a) Original color image b) Average filter c) CLAHE

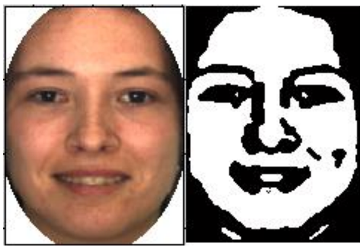

Fig. 3 a) Elliptical color image b) Enhanced CLAHE image

The feature extraction is done using Enhanced CLAHE images, mask images and elliptical gray-scale images. Fig. 4a-b shows the mask image and masked-gray-scale image.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

The masked-gray-scale image is obtained by adding the mask image of Enhanced CLAHE with original gray-scale image. The Discrete Wavelet Transform is applied on this gray-scale image and four sub images L1, H1, V1 and D1 are obtained as shown in figure 4c. The statistical features are extracted using fig. 4c. The facial features are extracted from Enhanced CLAHE as shown in fig. 1. Thus the size of feature vector for a single image is 85 x 1.

a)Mask image of Enhanced CLAHE image   b) Gray-scale image using mask   c)DWT's four sub images L1, H1, V1 and D1

Fig. 4. Sample Images used for feature extraction

The face recognition accuracy rate is tested on AR, ORL and Yale databases. The feature vectors size of AR, ORL and Yale databases are 1400 x 85, 400 x 85 and 165 x 85 respectively. These feature vectors are classified using Polynomial Kernel SVM classifier and Multilayer Perceptron Neural Network with learning rate=0.3, number of iterations N=500 using Weka software [30].

The feature vector of each face database subset is tested with cross-validation. In Cross-validation test is repeated for all samples and each sample becomes the test data once. Cross-validation fold of 10, standard value for testing [30] is used for testing the feature vector. The feature vector extracted contains 84 features and one class label, thus 85 dimensions are used for face recognition.

Out of these 85 features, six features such as standard deviation, Kurtosis, Contrast, Energy, Homogeneity and Correlation of L1 Sub image for all persons are not different values and they are not significant for classification purpose. Thus the same face recognition rates are produced by using 85 dimensions or 79 dimensions.

The face recognition rate is computed by removing the features that are insignificant for face recognition. The first order moment mean and second order moment of four sub images L1, H1, V1 and D1 constitutes 8 features. Out of these 8 features, the first order moment of L1 alone is significant for classification. The other 7 moment features are eliminated from feature vector. Thus, the dimension of feature vector is reduced to 72. The area of mask and face area ratio are eliminated from feature vector and the dimension of feature vector is reduced to 70. The Euler and orientation features are eliminated from feature vector and the dimension of feature vector is reduced to 68.

E. Performance of Enhanced CLAHE using feature extraction

The performance of Enhanced CLAHE using feature extraction on AR, ORL and Yale databases is shown in Table 1. In **Error! Reference source not found.**1, the face recognition results on three face database using Polynomial Kernel SVM and MLP classifiers are shown. It contains 79, 72, 70 and 68 dimensions. Using 72 dimensions, MLP with learning rate 0.3 and 500 iterations shows recognition accuracy rate of 88.63% in AR database. Using 68 dimensions, ORL database has recognition accuracy rate of 94% with MLP and using 70 dimensions, Yale database has recognition accuracy rate of 84.81% with MLP. Using 70 dimensions, SVM shows recognition accuracy rate of 86.11% in Yale database.

Classifier	Database	Total number of test images	Recognition Accuracy %			
			Number of Dimensions			
			79	72	70	68
Polynomial Kernel SVM	AR	1400	85.71	86.13	86.06	85.63
	ORL	400	90.25	91.25	91.25	92.00
	Yale	165	84.81	86.11	**86.11**	86.03
Multilayer Perceptron Neural Network	AR	1400	86.42	**88.64**	87.781	87.925
	ORL	400	91.00	92.75	92.50	**94.00**
	Yale	165	83.44	84.33	84.815	84.735

F. Performance Comparison

Amany et al. [31] shows that Wavelet Packet Decomposition using block difference of inverse probabilities with variable block size shows highest recognition accuracy rate of 95.2% using 185 dimensions in ORL database.

In this method, the feature vector is classified using Support Vector Machine Classifier with Radial Basis Function (RBF) kernel using Euclidean distance. The performance of Enhanced CLAHE using feature extraction is compared with Wavelet Packet Decomposition method. Using 68 dimensions, the proposed method has face recognition accuracy rate of 94% with MLP NN classifier. Thus the Enhanced CLAHE using feature extraction method is better than the above method. Table 2 shows the performance comparison of Feature extraction using Enhanced CLAHE method on ORL database. From the table it is found that feature extraction method using Enhanced CLAHE outperforms the seventeen methods on ORL database. Table 3 shows the performance comparison of Feature extraction using Enhanced CLAHE method on Yale database. From the table it is found that feature extraction method using Enhanced CLAHE outperforms the six methods on Yale database.

Table 2 Performance Comparison of Feature extraction using Enhanced CLAHE on ORL database

Serial No.	Method	Recognition Accuracy Rate %
1	LDA [32]	82.00
2	U-LDA [32]	85.00
3	PCA [32]	88.50
4	R-LDA [32]	88.50
5	D-LDA [32]	89.50

6	KPCA [33]	90.50
7	HE+DWT [35]	90.66
8	INUM+DWT [35]	90.75
9	N-LDA [32]	91.00
10	O-LDA [32]	91.00
11	Complete 2DPCA [32]	91.50
12	KPCA [34]	91.75
13	HE+INUM+DWT [35]	92.16
14	2DLDA [32]	92.50
15	DWT 1D [35]	92.66
16	PCA+LDA [32]	93.00
17	ASDCT [36]	93.40
18	**Proposed Method**	**94.00**

Table 3 Performance Comparison of Feature extraction using Enhanced CLAHE on Yale database

Serial No.	Method	Recognition Accuracy Rate %
1	KPCA [36]	68.82
2	Kernel Eigenfaces [37]	75.76
3	KFA [36]	76.88
4	2DLDA(6:5) [32]	78.67
5	PCA (6:5) [32]	81.00
6	PCA [36]	83.99
7	**Proposed method**	**86.11**

IV. CONCLUSION

The illumination invariant face image is created using Enhanced CLAHE method. The Enhanced CLAHE images extract facial details like eyes, eye brows, nose and mouth. This method can be employed to extract the facial parts individually. The robust features are extracted from the Enhanced image and a feature vector of length 85 is created. This feature vector created is tested using cross-validation. The classifiers used are Poly kernel SVM classifier and Multilayer Perceptron (MLP) Neural Network classifier. In AR and ORL databases, Enhanced CLAHE using feature extraction method with MLP NN classifier has recognition accuracy of 88.63% and 94% using 72 dimensions and 68 dimensions respectively. The results in Yale database shows that Enhanced CLAHE using feature extraction method with Polynomial Kernel SVM classifier has recognition accuracy of 86.11% using 70 dimensions. The face recognition of Enhanced CLAHE using feature extraction method outperforms the results of LDA and PCA based methods on ORL and Yale databases.

REFERENCES

1. R. Chellappa, C.L. Wilson, and S. Sirohey, “Human and machine recognition of faces: A survey,” Proceedings of. IEEE, vol. 83, pp. 705–740, 1995.
2. Franco Scarselli and Ah Chung Tsoi, “Universal Approximation Using Feed forward Neural Networks: A Survey of Some Existing Methods, and Some New Results”, Neural Networks, Vol 11, No 1, pp15-37, 1998
3. A. Thamizharasi and J.S. Jayasudha, “An Illumination invariant face recognition by enhanced contrast limited adaptive histogram equalization”, ICTACT Journal on Image and Video Processing, May 2016, Vol. 06, Issue: 04, ISSN: 0976-9102
4. Rafael C.Gonzalez and Richard E.Woods, "Digital Image Processing", Addison-Weseky, 1993.
5. Taiping Zhang, Yuan Yan Tang, Bin Fang and Xiaoyu Liu, "Face Recognition Under Varying Illumination using Gradientfaces," IEEE Transactions on Image Processing, Vol. 18, No. 11, pp. 2599-2606, 2009.
6. H.Wang, S.Z.Li and Y.Wang, "Face Recognition under varying lighting conditions using self-quotient image," in Proceedings of IEEE International Conferencec on Automatic Face and Gesture Recognition, pp. 819-824, 2004
7. Zhang Y., Tian J., He X. and Yang X., "MQI Based Face Recognition under Uneven Illumination," Advances in Biometircs, Vol. 4642, pp. 290-298, 2007
8. D.J.Jobson, Z.Rahman and G.A.Woodell , "A multiscale retinex for bridging the gap between color images and the human observation of scenes," IEEE Transactions on Image Processing, Vol. 6, pp. 965-976, 1997
9. D.J.Jobson, Z.Rahman and G.A.Woodell , "Properties and Performance of a Center/Surround Retinex," IEEE Transactions on Image Processing, Vol. 6, No. 3, pp. 451-462, 1997.
10. T.Chen, W.Yin, X.S.Zhou, D.Comaniciu and T.S.Huang, "Total Variation Models for variable lighting face recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 28, pp. 1519-1524, 2006.
11. X.Tan and B.Triggs , "Enhanced local texture feature sets for face recognition under difficult lighting conditions," IEEE Transactions on Image Processing, Vol. 19, pp. 1635-1650, 2010
12. A.S.Georghiades , P.N.Belhumeur and D.J.Kriegman , "From few to many: Illumination cone models for face recognition under variable lighting and pose," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No. 6, pp. 643-660, 2001
13. Dao Qing Dai and Hong Yan, Wavelets and Face Recognition.: ISBN 978-3-902613-03-5, I-Tech, Austria, pp. 558, 2007
14. X.Xie, W.Zheng, J.Lai, P.C.Yuen and C.Suen , "Normalization of face illumination based on large and small-scale features," IEEE Transactions on Image Processing, Vol. 20, pp. 1807-1821, 2011.
15. Zhenhua Chai, Heydi Mendez Vazquez, Ran He and Tieniu Tan, "Gabor Ordinal Measures for Face Recognition," IEEE Transactions on Information Forensics and Security, Vol. 9, No. 1, 2014.
16. Jiwen Lu and Yap-Peng Tan, "Cost-Sensitive Subspace Analysis and Extensions for Face Recognition," IEEE Transactions on Information Forensics and Security, Vol. 8, No. 3, pp. 510-519, 2013
17. Weiping Chen and Yongsheng Gao, "Face Recognition using Ensemble String Matching," IEEE Transactions on Image Processing, Vol. 22, No. 12, pp. 4798-4808, 2013.
18. Jiwen Lu, Venice Erin Liong, Gang Wang and Pierre Moulin, "Joint Feature Learning for Face Recognition," IEEE Transactions on Information Forensics and Security, Vol. 10, No. 7, pp. 1371-1383, 2015
19. Luciano da Fontoura Costa and Roberto Marcondes Cesar Jr., "Shape Classification and Analysis:Theory and Practice", 2nd Edition, Pages. 674, 2009
20. Christican Walck , "Hand-book on Statistical Distributions for experimentalists", Internal Report, University of Stockholm, Pages.190, 1996
21. Shailendrakumar M.Mukane , Dattatraya S.Bormane , and Sachine R.Gengaje , "Wavelet and Co-occurence Matrix based Rotation Invariant Features for Texture Image Retrieval Using Fuzzy Logic," International Journal of Computer Applications, ISSN 0975-8887, Vol. 24, No. 7, 2011

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

22. Dengsheng Zhang and Guojun Lu , "A Comparative Study on Shape Retrieval Using Fourier Descriptors with Different Shape Signatures," Journal of Visual Communication and Image Representation, Vol.14, No. 1, pp. 39-57, 2003
23. Mark Nixon and Alberto Aguado, "Feature Extraction and Image Processing for Computer Vision", Third Edition, Academic Press, Pages. 350, 2012
24. V.Vapnik , "The Nature of Statistical Learning Theory", Springer-Verlag, Newyork, Pages.39, 1995
25. Franco Scarselli and Ah Chung Tsoi , "Universal Approximation Using Feed Forward Neural Networks: A Survey of Some Existing Methods and Some New Results," Neural Networks, Vol. 11, No. 1, pp. 15-37, 1998
26. A.M.Martinez and R.Benavente, "The AR Face Database," 24, CVC Technical Report, 1998.
27. (Checked on 10th September 2016) ORL Face database. [Online]. http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html
28. P.N.Belhumeur, J.P.Hespanha and D.J Kriegman, "Eigenfaces vs Fisherfaces: Recognition using class specific linear projection," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No. 7, 1997.
29. Rafael C.Gonzalez , Richard E.Woods and Steven L.Eddins, "Digital Image processing with MATLAB", 2nd Edition, 2009
30. (Checked on 10th September, 2016) Weka Software. [Online]. http://www.cs.waikato.ac.nz/ml/weka/
31. Amany Farag and Randa Atta , "Illumination Invariant Face Recognition Using the Statistical Features of BDIP and Wavelet Transform," International Journal of Machine Learning and Computing, Vol. 2, No. 1, 2012
32. Kai Li, Zhen Liu and Peng Tang , "On Linear Discriminant Analysis and its Variants in Face Recognition," International Journal of Artificial Intelligence and Mechatronics, Vol. 4, No. 1, 2015.
33. Jamal Husain Shah , Muhammad Sharif, Mudassar Raza and Aisha Azeem, "A Survey: Linear and Nonlinear PCA Based Face Recognition Techniques," The International Arab Journal of Information Technology, Vol. 10, No. 6, 2013.
34. Liu N., Wang H. and Yau W., "Face Recognition with Weighted Kernel Principal Component Analysis," in Proceedings of the nineth International Conference on Control, Automation, Roboticcs and Vision, pp. 1-5, 2006.
35. Gautham Sitaram Yajia, Sankhadeep Sarkara, K Manikantana and S Ramachandran, "DWT feature extraction based face recognition using intensity mapped unsharp masking and laplacian of Gaussian filtering with scalar multiplier," in Second International Conference on Communication, Computing and Security (ICCCS-2012), Procedia Technology, Vol.6, pp. 475-484, 2012
36. Zahraddeen Sufyanu, Fatma S.Mohamad, Abdulganiyu A.Yusuf and Mustafa B.Mamat, "Enhanced Face Recognition Using Discrete Cosine Transform," Engineering Letters, Vol. 24, No. 1, pp. 52-61, 2016
37. M.H Yang, "Kernel Eigenfaces vs Kernel Fisherfaces: Face Recognition using Kernel Methods," in Proceedings of fifth IEEE International Conference on Automatic Face and Gesture Recognition (RGR'02), pp. 215-220, 2002

A. Thamizharasi M.E., M.B.A is working Assistant Professor in Department of Computer Science and Engineering, Mohandas College of Engineering and Technology, Trivandrum. She has 12 years of teaching experience. She has organized many workshops and conferences. She is a research scholar in Manonmaniam Sundaranar University, Tirunelveli. Her research interest is image processing and pattern recognition. She had published several papers in National, International Conferences and Journals.

Dr. Jayasudha J. S. is working as Professor in the department of computer Science & Engineering, Sree Chitra Thirunal College of Engineering, Thiruvananthapuram. She has 20 years of teaching experience. She has organized many community development programmes, short term courses and conferences. She did her B. E. degree from Madurai Kamaraj University and M. E. degree from National Institute of Technology, Trichy and doctorate degree from University of Kerala. Her Ph.D. thesis title is "Web caching and Pre-fetching techniques for Web traffic/Latency reduction". She is recognized as approved research guide in the Ph. D. programme in Kerala University, Manonmaniam Sundaranar University and Noorul Islam University. She is also doing research in Computer Networks and Image Processing. She has published her research works in many national and international conferences and journals.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)