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AN ILLUMINATION INVARIANT FACE RECOGNITION BY ENHANCED CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

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Abstract
Face recognition system is gaining more importance in social networks and surveillance. The face recognition task is complex due to the variations in illumination, expression, occlusion, aging and pose. The illumination variations in image are due to changes in lighting conditions, poor illumination, low contrast or increased brightness. The variations in illumination adversely affect the quality of image and recognition accuracy. The illumination variations in face image have to be pre-processed prior to face recognition. The Contrast Limited Adaptive Histogram Equalization (CLAHE) is an image enhancement technique popular in enhancing medical images. The proposed work is to create illumination invariant face recognition system by enhancing Contrast Limited Adaptive Histogram Equalization technique. This method is termed as "Enhanced CLAHE". The efficiency of Enhanced CLAHE is tested using Fuzzy K Nearest Neighbour classifier and fisher face subspace projection method. The face recognition accuracy percentage rate, Equal Error Rate and False Acceptance Rate at 1% are calculated. The performance of CLAHE and Enhanced CLAHE methods is compared. The efficiency of the Enhanced CLAHE method is tested with three public face databases AR, Yale and ORL. The Enhanced CLAHE has very high recognition accuracy percentage rate when compared to CLAHE.

Keywords:
Illumination Invariant, Face Recognition, Contrast Limited Adaptive Histogram Equalization (CLAHE), Enhanced CLAHE, Fisher Face

1. INTRODUCTION

The various biometric techniques used in security systems [28] are face, ear, voice, gait, iris, retina, finger print, palm print recognition etc. Among these, face recognition is the most suitable technique in surveillance applications, since it does not require the aid of the tester. The automatic facial recognition is started in early 1960's by Woody Bledsoe, Helen Chan Wolf, and Charles Bisson.

The face recognition approaches in the literature is broadly classified as geometric or feature based methods, statistical or appearance based methods, model based methods and neural network approaches. The recognition of faces is done by detecting individual features such as the eyes, nose, mouth and head outline, and defining a face model by the position, size and relationships among these features. This approach is called as geometric feature based methods. Kaya & Kobayashi, 1972 [29]; Kanade, 1973 [30]; Canon, Jones, Campbell, & Morgan, 1986 [31]; Craw, Ellis, & Lishman, 1987 [32]; Wong, Law, & Tsaug, 1989 [33] characterized a face by a set of geometric parameters and perform pattern recognition on the parameters measured. The geometric feature based methods also called as local approaches are insensitive to small variations in illumination and viewpoint. Yuille, Cohen, and Hallinan (1989) [34] used template matching for face recognition.

A lot of research work is carried out in face recognition for the last five decades. Face recognition is still an active research area due to its popularity and challenges. The variations caused by pose, expression, head orientations, aging, occlusion or illumination complicates the face detection process [5]. Moses, Adini and Ullman (1969) states that, "The variations between the images of the same face due to illumination and viewing direction are almost always larger than image variations due to change in face identity" [6].

The recognition of poor illumination face images would be difficult task. The uneven illumination in an image has to be normalized for recognizing the image. Thus, there is a need for illumination normalization for creating an illumination invariant or illumination insensitive face recognition system for increasing the recognition accuracy. The proposed work is to create an illumination invariant face recognition system by combining CLAHE and thresholding technique.

The organization of the paper is as follows. The previous works done in face recognition is discussed in section 2. The methodology is given in section 3. The section 3 includes the concepts of CLAHE, thresholding, proposed work, Enhanced CLAHE, the classifiers (FKNN classifier & Fisher face subspace method), face databases used for testing and experimental results of Enhanced CLAHE. The section 4 describes the results and discussion. Finally, Conclusion is given in section 5.

2. PREVIOUS WORK

The statistical or appearance based methods is a holistic approach and the pixel intensities of the entire image is used for recognition. In 1990's, Turk and Pentland used the statistical method involving Principal Component analysis (PCA) for face recognition. They proposed a scheme called "Eigen faces" or "face space" based on information theory approach for face recognition [36]. This method is insensitive to small or gradual changes in the face image. The Eigen face approach is not sensitive to head orientations (side way tilts). But, the performance of Eigen face approach degrades when there are changes in lighting conditions, non-upright view, size and position of face image.

The statistical methods are further classified as linear and non-linear sub space methods. The Linear sub space methods used for face recognition are PCA [36], LDA [42], ICA [42] [43] and SVD [38]. The non-linear sub space methods are the kernel based methods. The variants of PCA are Eigen face [37], KPCA [41], 2DPCA [44], Binary 2DPCA [48], Kernel 2DPCA [47] and Non Linear PCA (NLPCA). The variants of LDA are Direct LDA [45], PCA+LDA [19], fisher faces [19], Regularized LDA [49], Orthogonal LDA [53], Kernel LDA [46], 2D LDA [52] and Kernel 2DLDA. The above methods are used for feature extraction, dimensionality reduction and recognition in face recognition.

The model based methods for face recognition are EGBM [39], Reflectance models [11], Active Appearance Model [40] etc. These methods use graphs for representing the face model.

The neural network approach for face recognition is started in 1980's. Kohonen (1989) [35] described an associative network with a simple learning algorithm that can recognize (classify) face images. The face recognition work is done using Back Propagation, Hidden Markov Model [50] and Self-Organizing Map.

For many years, varying illuminations is one of the important issues in image processing and face recognition. So far, a lot of research is carried out in this area. The survey of various illumination normalization techniques in face recognition is discussed [1] [51]. The techniques presented [1] are log transformations, power law transformations, contrast stretching, Histogram equalization [3], Contrast Limited Adaptive histogram equalization (CLAHE) [4], Homomorphic filter [6], Single Scale Retinex [11], Multi scale Retinex [13], Difference of Gaussian [13], DCT Normalization [12], Gradient face [15], Self-Quotient [14], Multi scale Self Quotient [14], Discrete Cosine Transform [17], Discrete Wavelet Transform [16] etc. The texture based features used for illumination pre-processing are Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Tan and Triggs (TT) and Gabor methods [51].

The face recognition accuracy percentage rate is computed for all illumination normalization techniques through Fuzzy K Nearest Neighbour Classifier [1]. AR face image database is chosen for testing. The test results prove that the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique has highest face recognition accuracy rate [1]. This has motivated to use CLAHE for this work.

3. METHODOLOGY

The proposed method in this work is done using CLAHE and thresholding.

3.1 CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Histogram equalization (HE) [3] is one of the well-known image enhancement techniques. In Histogram Equalization, the intensity levels are changed such that the peaks of the histogram are stretched and the troughs are compressed. If a digital image has N pixels distributed in L discrete intensity levels and n_k is the number of pixels with intensity level i_k, the probability density function (PDF) and cumulative density function (CDF) is defined in Eq.(1) and Eq.(2).

$$f_i(i_k) = \frac{n_k}{N} \tag{1}$$

$$F_k(i_k) = \sum_{j=0}^{k} f_i(i_j) \tag{2}$$

A mapping function is used to replace the original pixel intensities using CDF. The image obtained is called as histogram equalized image. It increases the global contrast of the image. The drawbacks of histogram equalization are over enhancement, loss of detail, noise amplification etc. In histogram equalization, contrast enhancement is proportional to the height of the histogram at that intensity. The high peaks in the histogram are normally caused by nearly uniform regions.

Adaptive Histogram Equalization (AHE) [27] constructs several histograms for different sections of image. In AHE, the image is divided into small contextual regions called "tiles" and HE is applied. The resulting small tiles are then stitched back using bilinear interpolation method. It improves the local contrast of the image and enhances edges in each region. The disadvantage of AHE is, it over amplifies the small amount of noise in homogeneous regions.

In Contrast Limited Histogram Equalization (CLHE), the histogram is cut at some threshold and then equalization is applied. It improves the local contrast of image. In CLHE, since the peak of the histogram in each tile is clipped, the amount of over amplification is avoided.

Contrast Limited Adaptive Histogram Equalization (CLAHE) [27] method uses the concepts of AHE and CLHE. It uses small contextual regions called 'tiles' and the peaks of histogram are clipped. It increases the local contrast of the image and the noise amplification is avoided. The disadvantage of CLAHE method is it gives unsatisfactory results when there is unbalanced contrast and increased brightness [54]. Thus, here Enhanced CLAHE method is proposed by combining CLAHE with threshold technique.

3.2 THRESHOLDING

Thresholding is the one of the simplest, computationally faster method which is used in image processing for image segmentation [3]. Given image '*f*', the object can be extracted from its background with threshold '*T*' and create image '*g*' using the Eq.(3).

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{if } f(x,y) \le T \end{cases} \tag{3}$$

The above method is called as global threshold [3]. However if image has noise or illumination, global threshold would not give good results and variable thresholding has to be applied [3]. An optimal global thresholding is proposed by Otsu [3].

3.3 PROPOSED WORK

The proposed work in this paper has following steps:

1) First, create an illumination invariant face image by combining CLAHE and thresholding. The image obtained is termed as Enhanced Contrast Limited Adaptive Histogram Equalization (Enhanced CLAHE).
2) Second, the performance of the CLAHE and Enhanced CLAHE methods are compared. The face recognition of the two methods is tested using the three public databases AR, Yale and ORL. The train database and test database

are created for testing the two methods. The images in the test database are matched with images in train database using Fuzzy K Nearest Neighbour classifier. The face recognition accuracy rate percentage is the number of correct matches in test database divided by the total number of images in test database.

The face recognition accuracy rate percentage of CLAHE and the proposed method 'Enhanced CLAHE' are computed for three public face databases AR, Yale and ORL.

3) Third, the efficiency of the proposed method is compared with CLAHE by using the subspace projection method. The subspace projection method 'fisher face' is used here to extract the features from CLAHE and Enhanced CLAHE images. The feature extraction step is done in both train and test database images. The features in test database images are matched with features of train database image using cosine similarity measure. The face recognition accuracy rate percentage, Equal Error Rate (EER), Half Total Error, False Acceptance Rate (FAR) at 1%, 0.1% and 0.01% are calculated for both CLAHE and Enhanced CLAHE methods.

3.4 ENHANCED CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (ENHANCED CLAHE)

The illumination invariant face image termed as "Enhanced CLAHE" is created using the following steps.

3.4.1 Pre-Processing:

The input image is colour face image say '*I*'. The image '*I*' may contain noise. The average filter or mean filter is a simple method of smoothing images. It reduces the amount of variation between one pixel and the next. It is often used to reduce noise in images. The image '*I*' is processed with average filter of size 3×3 to filter the noise and an image say 'IF' is obtained. Then, Contrast-limited Adaptive histogram equalization [6] is applied on image 'IF' to create image 'EI'. The image 'EI' is the output of the pre-processing step.

3.4.2 Elliptical Face Image Creation:

1) The pre-processed face image 'EI' is further processed to create elliptical face mask using the following steps.
2) The image 'EI' is now segmented to obtain the binary image. The Otsu's global threshold [3] technique is applied on image 'EI' and binary image say 'B' is obtained.
3) The outer border from the binary image 'B' is extracted. The pixels within the outer border are filled with black colour and the pixels outside the outer border are filled with white pixels. This is called as binary mask 'BM'.
4) The binary mask 'BM' has some noise. It is processed with morphological operations like cleaning, majority, filling and dilating [3] to remove the unwanted pixels on the binary mask. The regional properties like centre pixels x_0 and y_0, major axis and minor axis are calculated from binary mask. The x intercept 'a' and y intercept 'b' is obtained from major axis and minor axis.
5) A translation invariant elliptical mask is created from binary mask 'BM' using the equation of ellipse given in 4.

$$\frac{\left(x-x_0\right)^2}{a^2}+\frac{\left(y-y_0\right)^2}{b^2}=1 \tag{4}$$

where, x_0 and y_0 are centre pixels, 'a' is x intercept and 'b' is y intercept.

6) The elliptical binary mask and input colour image '*I*' is added to create an elliptical colour face image say '*E*'. This image '*E*' is then converted into elliptical gray face image.

3.4.3 Segmentation:

1) The Enhanced Contrast Limited Adaptive Histogram Equalization (CLAHE) image is generated from gray face image '*E*' using the following steps.
2) The Contrast Limited Adaptive Histogram Equalization (CLAHE) with "tile size" 8×8 and clip limit 0.01 is applied on elliptical gray image '*E*'. It generates an image say '*f*'.
3) Let 'GT' is the mean of the image '*f*'.
4) Using Eq.(5), binary image '*g'* is obtained with threshold 'GT'.

$$g\left(x,y\right)=\begin{cases}1 \ \ if \ \ f\left(x,y\right)>GT\\ 0 \ \ if \ \ f\left(x,y\right)\le GT\end{cases} \tag{5}$$

5) The binary image '*g*', thus created contains noise. The morphological operations are applied on '*g*' to remove the noise and image obtained is say '*G*'. The image '*G*' is the output image called as Enhanced CLAHE image.

3.5 FUZZY K-NEAREST NEIGHBOUR CLASSIFIER

The fuzzy membership degree and each class centre are gained through FKNN [18] algorithm. Compute the membership degree to class '*i*' for j^{th} pattern using the expression proposed in the literature [21].

$$u_{ij}=\begin{cases}0.51+0.49\times(n_{ij}/k)\\ \quad 0.49\times(n_{ij}/k)\end{cases} \tag{6}$$

In the above expression n_{ij} stands for the number of the neighbours of the data (pattern) that belong to the class. u_{ij} satisfies two obvious properties:

$$\sum_{i=1}^{c}u_{ij}=1 \quad 0<\sum_{j=1}^{N}u_{ij}<N \tag{7}$$

The mean vector of each class is,

$$\widehat{m}_i=\frac{\sum_{j=1}^{N}u_{ij}^{\rho}x_j}{\sum_{j=1}^{M}u_{ij}^{\rho}} \tag{8}$$

where, ρ is a constant which controls the influence of fuzzy membership degree. Therefore, the class centre matrix *m* and the fuzzy membership matrix *U* can be achieved with the result of FKNN.

$$U=\left[u_{ij}\right], i=1,2\cdots c, j=1,2\cdots N \tag{9}$$

$$m=\left[\widehat{m}_i\right], i=1,2\cdots c \tag{10}$$

During testing process, for the given test image, the matching image from the train database is obtained by choosing the closest train image which has highest fuzzy membership value.

3.6 FISHER FACE SUBSPACE FEATURE EXTRACTION

Belhumeur et al. (1997) and Zhao et al. (1998) have proposed systems called as "Fisher faces" that is insensitive to large variations in lighting and facial expressions. The Eigen face method uses principal components analysis (PCA) for dimensionality reduction and it yields projection directions that maximize the total scatter across all classes, i.e., across all images of all faces [37]. The PCA projections are optimal for dimensionality reduction but it is not suitable for discriminating the classes of face images. The fisher face method maximizes the ratio of the between-class scatter and the within class scatter [2] [19]. Thus the fisher face method improves the face recognition accuracy since it increases the discrimination among the classes. The extracted fisher face features are matched using cosine similarity measure. The cosine similarity is used in machine learning to find the similarity among the two vectors. The cosine of two vectors [26] can be derived by using the Euclidean dot formula in Eq.(11).

$$a.b = \|a\|\|b\|\cos\theta \tag{11}$$

The cosine similarity cos(θ) for vectors A and B is represented using a dot product and magnitude as in Eq.(12).

$$\cos(\theta) = \frac{A.B}{\|A\|\|B\|} \frac{\sum A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(B_i)^2}\sqrt{\sum_{i=1}^{n}(A_i)^2}} \tag{12}$$

3.7 FACE DATABASES

The face recognition accuracy rate percentage of Enhanced CLAHE method is tested on AR, Yale and ORL databases.

3.7.1 AR Face Database:

The AR database (Martinez and Benavente, 1998, 2000) [22] contains colour images of 100 persons taken in two different sessions. It has 50 men and 50 women images. Each image size is 160×120. Neutral, expressions (anger, scream, and smile), illumination in (right, left and both sides) and occluded images are present. For testing, AR database subset is created with 14 images per subject for 100 subjects with a total of 1400 images. The Fig.1 shows the sample AR database subset images. The images in this database have varying brightness.

Fig.1. Sample AR face database subset image of same subject

3.7.2 ORL Database:

The Olivetti and Oracle Research Laboratory (ORL) Face Database [23] has 40 subjects with 10 different images per subject. There are totally 400 images. 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). All the images are gray scale images. It is taken in dark homogeneous background. The size of image in this database is 112×92. The Fig.2 shows the sample ORL face database image.

Fig.2 Sample ORL face database image of same subject

3.7.3 Yale Face Database:

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, with glasses, happy, left-light/no glasses, normal, right-light, sad and sleepy, surprised and wink [24] in database.

3.8 EXPERIMENTAL RESULTS OF ENHANCED CLAHE

The proposed method is implemented in MATLAB. The steps for creating Enhanced CLAHE image which is discussed in section 3.4 are implemented in all three databases. The results for Enhanced CLAHE in AR face database image are shown here. The results of pre-processing steps as discussed in section 3.4.1 are shown in Fig.3(a)-Fig.3(d). The results of creating elliptical face image steps as discussed in section 3.4.2 is shown in Fig.4(a)-Fig.4(d). The results of segmentation steps as described in section 3.4.3 are shown in Fig.5(a)-Fig.5(c). The final image obtained is the Enhanced CLAHE image and it is shown in Fig.5(c).

Fig.3. a) Colour image b) Gray c) Average filter d) Contrast Limited Adaptive histogram Equalization (CLAHE)

Fig.4. a) CLAHE plus Global Otsu b) Outer border c) Filled area d) Elliptical face image.

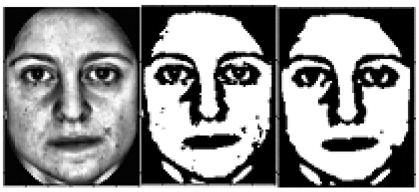

Fig.5. a) CLAHE elliptical image b) Binary CLAHE image c) Enhanced CLAHE image

The facial features extraction results of Otsu's thresholding technique, global threshold and CLAHE plus global threshold are compared. The input image used for this purpose is the full colour image. It is converted into gray image.

Fig.6. a) Original Colour image b) Gray Image

The colour image and gray image is shown in Fig.6(a) and Fig.6(b). The results of Otsu's global threshold technique and global threshold are shown in Fig.7(a) and Fig.7(b). Otsu's global threshold has less information, since some of the information details are lost while segmenting. The result of global threshold is better than Otsu threshold method. But, face shape and eyes details are lost in Fig.7(b). The CLAHE method plus global threshold with global mean is shown in Fig.7(c). Now, the outer shape and inner details are preserved, but noise is present. Thus CLAHE plus Global threshold has good results than Otsu and Global threshold method.

Fig.7. a) Otsu's global threshold b) Global threshold c) CLAHE plus Global threshold

Thus, the elliptical gray image 'E' is processed first with CLAHE, then Global threshold is applied on it. Now, to remove the noise, the morphological operations are applied. This removes the noise and image obtained is termed as Enhanced CLAHE image. It is shown in Fig.8. The facial features in Enhanced CLAHE are more effectively shown than the CLAHE image. The image shown in Fig.8 is unaffected by variations of light. The outer shape and information suitable for face recognition is preserved. The Enhanced CLAHE image highlights the facial features eyes, eyebrows, nose and mouth, face shape more clearly. This output is comparable with the outputs of homomorphic filter and gabor filter.

Fig.8. Enhanced CLAHE image

4. RESULTS AND DISCUSSION

The efficiency of the CLAHE and Enhanced CLAHE methods are compared by finding the face recognition accuracy of these two methods. The testing is done on three public face databases AR, Yale and ORL using Fuzzy K Nearest Classifier. The train database is created by varying the train images per subject from one to fifty percentage of the total number of images per subject. The test database is created using the remaining images of the subject. For example, in AR database, there are 14 images per subject. If the train database is created with first image for a subject, then test database contains remaining 13 images. Thus, train database has 100 images i.e. one image per subject and test database contains 1300 images i.e. 13 images per subject. Thus, there is no overlapping of images in train database and test database. The CLAHE method is implemented with following settings. The "tile" size is 8 by 8 and clip limit is 0.01. The input face images are cropped images.

While testing, the 'closest' image in the train database is chosen as the matching image using Fuzzy K Nearest Neighbour classifier. The count of the number of correct matches is found. The face recognition accuracy percentage rate is computed. The testing is done on AR, Yale and ORL databases. The performance results of CLAHE and Enhanced CLAHE methods using the Fuzzy K Nearest Neighbour classifier on AR, Yale and ORL databases are tabulated in Table.1-Table.3.

The face recognition accuracy rate percentage on AR database is shown in Table.1. The testing is done by changing the train images per subject from one to six. When using six train numbers per subject, the Enhanced CLAHE method has recognition accuracy of 85.37% on AR database. The CLAHE method has recognition accuracy of 71.12% using six train numbers per subject.

Table.1. Face recognition accuracy rate percentage on AR database using FKNN classifier

Total No. of test Images (100 subjects)	**AR Database**			
	Train images per subject	**Test images per subject**	**Recognition Accuracy %**	
			CLAHE	**Enhanced CLAHE**
1300	1	13	57.07	68.15
1200	2	12	58.25	69.41
1100	3	11	61.63	70.27
1000	4	10	66.80	76.40
900	5	9	72.44	79.55
800	6	8	71.12	85.37

The face recognition accuracy rate percentage on Yale database is shown in Table.2. The face recognition accuracy rate percentage of the proposed method in Yale database using five train images per subject is 88.88%.

The face recognition accuracy rate percentage on ORL database is shown in Table.3. The face recognition accuracy rate percentage of the proposed method in ORL database using six train images per subject is 74.37%. The Enhanced CLAHE method has highest recognition accuracy of 88.88% in Yale database using five train images per subject with FKNN classifier.

Table.2. Face recognition accuracy rate percentage on Yale database using FKNN classifier

Total No. of test Images (15 subjects)	Yale Database			
	Train images per subject	Test images per subject	Recognition Accuracy %	
			CLAHE	Enhanced CLAHE
150	1	10	24.67	40
135	2	9	32.59	74.07
120	3	8	36.67	84.16
105	4	7	36.19	87.62
90	5	6	47.77	88.88
75	6	5	42.67	86.66

Table.3. Face recognition accuracy rate percentage on ORL database using FKNN classifier

Total No. of test Images (40 subjects)	ORL Database			
	Train images per subject	Test images per subject	Recognition Accuracy %	
			CLAHE	Enhanced CLAHE
360	1	9	19.72	46.67
320	2	8	13.75	56.87
280	3	7	16.42	58.57
240	4	6	9.16	66.67
200	5	5	8.00	64.50
160	6	4	3.75	74.37

The performance analysis results of fisher face subspace method are tabulated in Table.4-Table.6 and its graphical results are shown in Fig.10.

The Performance analysis of Enhanced CLAHE method on AR, Yale ORL databases using fisher faces subspace method with different train numbers is shown in Table.4-Table.6. The performance measures Equal Error Rate, Half Total Error Rate, False Acceptance Rate at 1%, 0.1% and 0.01% are tabulated. The testing is done by varying the train images per subject from two to seven.

Table.4. Performance analysis of Enhanced CLAHE on AR database using fisher faces subspace method with different train numbers

Performance Measures in %	Enhanced CLAHE + Fisher face on AR database					
	Train Number					
	2	3	4	5	6	7
Recognition	73.42	76.09	79.50	82.89	90.75	92.14
EER	7.82	7.34	6.39	5.44	2.53	2.28
Half Total Error	7.48	6.65	6.26	5.00	2.37	2.23
1% FAR	80.33	81.18	84.60	88.44	96.00	96.0
0.1% FAR	62.00	67.36	70.90	75.11	87.50	89.71
0.01% FAR	43.75	52.18	54.10	61.67	80.50	83.00

Table.5. Performance analysis of Enhanced CLAHE on Yale database using fisher faces subspace method with different train numbers

Performance Measures in %	Enhanced CLAHE + Fisher face on Yale database					
	Train Number					
	2	3	4	5	6	7
Recognition	80	89.17	90.48	91.11	85.33	95.00
EER	9.58	4.02	2.86	2.22	5.62	1.85
Half Total Error	8.36	3.21	2.38	1.83	5.14	1.01
1% FAR	74.07	92.5	93.33	94.44	86.67	96.67
0.1% FAR	65.93	83.33	83.81	71.11	76.00	90.00
0.01% FAR	0.74	0.83	0.95	1.11	1.33	1.67

Table.6. Performance analysis of Enhanced CLAHE on ORL database using fisher faces subspace method with different train numbers

Performance Measures in %	Enhanced CLAHE + Fisher face on ORL database					
	Train Number					
	2	3	4	5	6	7
Recognition	67.81	70.71	78.75	82.50	85.00	87.50
EER	11.60	8.97	6.66	6.50	5.63	4.17
Half Total Error	10.49	8.37	6.26	6.10	5.39	3.84
1% FAR	65.00	75.00	82.08	86.00	86.25	89.17
0.1% FAR	48.75	59.29	67.50	67.00	75.63	79.17
0.01% FAR	34.06	44.64	54.17	53.50	65.63	0.83

The Equal Error Rate in AR, Yale and ORL database are 2.28, 1.85 and 4.17 respectively. The recognition rate in AR, Yale and ORL are 92.14%, 95% and 87.5% respectively. The FAR at 1% in AR, Yale and ORL are 96%, 96.67% and 89.17% respectively. The results tabulated in Table.4-Table.6 show that the fisher face feature extraction technique has higher performance results than the FKNN classifier. The proposed method "Enhanced CLAHE" performs better than the CLAHE method. The result of CLAHE vs. Enhanced CLAHE is shown in Fig.9.

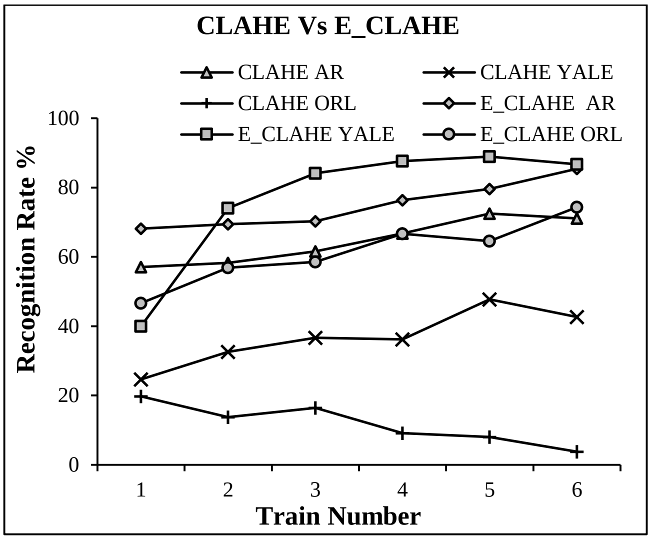

Fig.9. FKNN recognition results of CLAHE vs Enhanced CLAHE

The performance measures Recognition rate and FAR at 1% for Enhanced CLAHE method using fisher face sub space in AR, Yale and ORL database is shown in Fig.10.

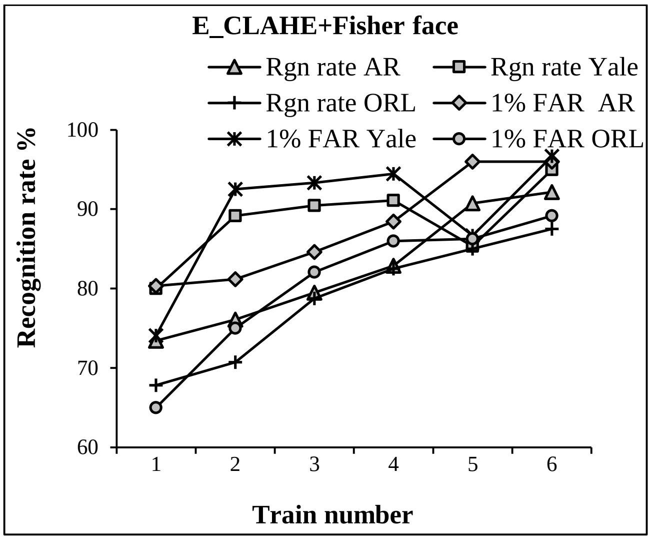

Fig.10. Fisher face recognition results of CLAHE vs Enhanced CLAHE

5. CONCLUSION AND FUTURE WORK

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 Enhanced CLAHE method using FKNN classifier on AR, Yale and ORL database has recognition accuracy percentage rates of 85.37%, 88.88% and 74.37% respectively.

Then, the subspace fisher face extracts the features from CLAHE and Enhanced CLAHE images. The subspace fisher face feature extraction from Enhanced CLAHE on AR, Yale and ORL database has highest recognition accuracy percentage rates of 92.14%, 95% and 87.5%. The AR database and Yale has images of varying illumination and contrast. This method works well in these two databases. However, ORL database images have small variations in illumination and have less performance than other databases. The face recognition accuracy can be tested using 2D PCA feature extraction and the dimensions used for recognition can be analysed. The future work is to reduce dimensions of features and increase the face recognition accuracy. To improve the face recognition accuracy in future, the features will be classified using SVM classifier.

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