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A New Efficent and Adaptive Sclera Recognition System

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***Abstract*— In this paper an efficient and adaptive biometric sclera recognition and verification system is proposed. Here sclera segmentation was performed by Fuzzy C-means clustering. Since the sclera vessels are not prominent so, in order to make them clearly visible image enhancement was required. Adaptive histogram equalization, followed by a bank of Discrete Meyer Wavelet was used to enhance the sclera vessel patterns. Feature extraction was performed by, Dense Local Directional Pattern (D-LDP). D-LDP patch descriptors of each training image are used to form a bag of features; further Spatial Pyramid Matching was used to produce the final training model. Support Vector Machines (SVMs) are used for classification. The UBIRIS version 1 dataset was used here for experimentation of the proposed system. To investigate regarding sclera patterns adaptively with respect to change in environmental condition, population, data accruing technique and time span two different session of the mention dataset are utilized. The images in two sessions are different in acquiring technique, representation, number of individual and theye were captured in a gap of two weeks. An encouraging Equal Error Rate (EER) of 3.95% was achieved in the above mention investigation.**

Keywords—Biometric; Sclera Vessels Patterns; D-LDP; SVM; Bag of features, Adaptive Histogram Equalization; Discrete Meyer Wavelet.

I. INTRODUCTION

Security breaches due to miss-identification of individuals are among the greatest threats in the today's world. So, biometrics is the key solution in such scenarios. Biometrics is the science of identifying individual in a set of population by using physiological or behavioral or both characteristics possessed by the user. As opposed to knowledge-based and token-based security systems, cutting-edge biometrics-based identification systems offer higher security and less probability of forging. So, the need for biometric systems is increasing in day-to-day activities due to their ease of use by common people, e.g. in attendance systems of organizations, citizenship proof, door locks for high security zones etc. The financial sector, government, and reservation systems are also adopting biometric technologies for ensuring security in their own domains and to maintain a log activity of every individual. The earliest biometrics cataloging can be recorded in the year 1891 in Argentina when Juan Vucetich started collection fingerprints of the criminals. The first automatic biometric system was proposed in the late 19th century.

Till date various biometric systems have been proposed, such as digital fingerprints, retinal scans, facial characteristics, gait, and vocal patterns, these biometric characteristics are distinctive to each and every person. They are considered more reliable and capable than the traditional token-based or knowledge-based technologies in authenticating an individual. For the last few decades biometric have enjoyed a lot of encouragement by the researchers in academia, industry and government. Unfortunately, till date no biometric systems exhibit the properties of a perfect biometric system which can be applied universally and can be robust to change in different environmental condition.

Among various biometrics, the ocular biometrics is known to be one of the most accurate biometric. Retina is a popular ocular biometrics, which is not user-friendly. As in retina biometric system, eye needs to be scanned at a close distance which can be harmful for eye. Among the ocular biometrics, iris biometrics is believed to be the most reliable and safe biometric. Unfortunately iris biometric also poses some disadvantages, for example off-angle iris image deteriorate the system performance and even the recognition becomes tough. So in iris biometric high user participation is required which is quite tough for people with squint eye. So, further research on iris biometrics is required to make it more users friendly.

Apart from iris and retina, the human eye has an ocular surface known as the sclera, which contains a texture pattern due to the presence of blood vessels in its surface. The sclera patterns can be acquired easily along with iris in one sort and it is visible in even in off-angle eye scenario. So, by utilizing the texture of the sclera along with the vascular patterns evident on it, the performance of an iris recognition system can potentially be improved during non-ideal or off-angle eye recognition scenario.

However, in order to establish this concept of multi-modal eye biometric system combining iris and sclera patters, it is necessary to first assess that, if sufficient discriminatory information can be gained from the sclera and the accompanying vasculature pattern of the eye. It is also important investigation regarding it adaptively with respect to change in environmental condition, population, data accruing technique and robustness time span. To date, this biometric is relatively less studied and little is known regarding its usefulness. So, the state of the art related to them is not mature enough and still in its infancy. So, this work designs an image processing and pattern recognition module for evaluating the potential of the sclera biometric in regards to accuracy and adaptability with changes in conditions.

This work proposes a whole biometric system for personal identification based on sclera vessels. Here sclera segmentation was performed by Fuzzy C-means clustering. A new preprocessing approach for vein highlighting is proposed here by using a bank of Discrete Meyer Wavelet. Sclera feature extraction based on the Dense Local Directional Pattern (D-LDP) is also new in the literature. Support Vector Machines (SVMs) are used for classification.

The organization of the paper is as follows: - Section II reviews the works in sclera literature; Section III highlights the proposed sclera segmentation, vessel enhancement, feature extraction and classification techniques. In Section IV, the experimental methodology and results are described while Section V draws the overall conclusions.

II. SCLERA LITERATURE

The contributions of the different works that can found in sclera literature can be clustered in to four basic categories. They are sclera segmentation, sclera vessel enhancement and image registration, feature extraction and classification. The various techniques of the above mention steps are represented in the below figure 1.

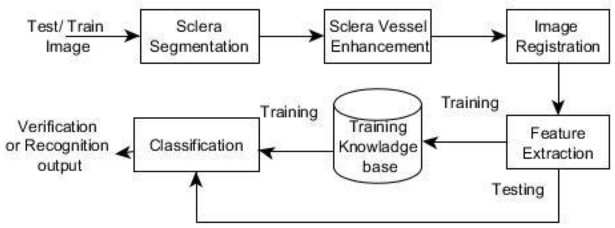


Figure 1. A block diagram of a typical sclera biometric.

The first recognized work on sclera biometrics is recorded in [1]. In this paper, the authors discuss methods for conjunctival image pre-processing by computing a Gaussian filters and Hessian matrix. In order to derive a suitable vascular template for biometric authentication, feature extraction is performed by a minutiae template. Here a small in-house dataset was used to establish the experiment.

In [6] first automatic sclera detection technique was proposed by a time adaptive active contour-based method. First automatic segmentation processes for sclera biometric was proposed in [4], Otsu's algorithm was used to segment the sclera from a gray image. Sclera segmentation based on color image was first proposed in [5], HSV model was used to segment sclera from a color eye image and a bank of Gabor filter was used to enhance the sclera.

Many features like LBP [9], GMCL [8] are used in the literature for sclera feature representation. First multi-angled sclera recognition was proposed in [2], further in [7] multi-angled sclera recognition was proposed using multispectral imagery.

First multi-modal eye recognition techniques using sclera and iris was proposed in [3]. Here a score fusion based technique was adapted to combine the sclera and the iris feature. Further in [5] a quality fusion technique was used to combine sclera and iris feature and in [10] feature level combination was used to establish sclera and iris based multi-modal biometrics. A survey on sclera recognition is recorded in [17].

It is evident form the survey, that sclera texture is a relatively new area of research in biometrics and therefore, it is essential to consider different feature extraction and matching techniques in order to determine an effective method to characterize this biometric and also to figure its addictiveness with change in conditions. So, in this work we investigated and proposed a recognition module for evaluating the potential of the sclera biometric in regards to accuracy and adaptability with changes in conditions.

III. PROPOSED APPROACH

In this section, the proposed sclera segmentation, sclera vein enhancement, feature extraction classification techniques are highlighted.

A. Sclera Segmentation

The sclera is a white region of connective tissue and blood vessels surrounding the iris. This blood vessel inside the sclera region is randomly-oriented which creates a pattern. This pattern can be used for biometric identification. Segmentation is the first step for most biometric related research. Similarly in sclera biometrics, accurate segmentation is very important, otherwise, an incorrect segmentation can not only reduce the pattern available, but also it can introduce other patterns such as eyelashes and eyelids which can influence the performance of the sclera pattern. Here sclera segmentation was performed by a Fuzzy C-means clustering-based segmentation proposed in [20]. Fuzzy C-means is a method of clustering which divide one cluster of data into two or more related clusters [18-19]. It is based on the minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij*} |\ x_i - c_i\ |^2 \quad \text{where} \quad 1 \leq \mathrm{m} < \infty \qquad (1)$$

Where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j as explained below in the equation (2) and (3).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left| \frac{|x_i - c_j|}{|x_i - c_k|} \right|^{\frac{2}{m-1}}} \qquad (2)$$

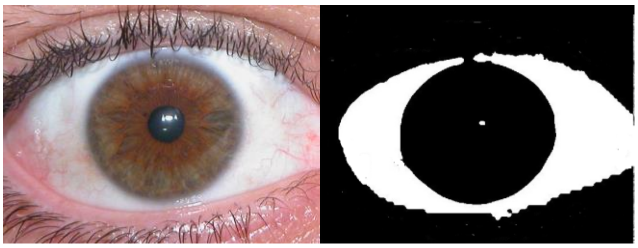
$$c_i = \frac{\sum_{i=1}^{N} u_{ij}^{m}.x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \qquad (3)$$

This iteration will stop when $max_{ij}\left\{ \left|u_{ij}^{\{k+1\}} - u_{ij}^{\{k\}}\right| \right\} < s$, where s is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. The performance of the level set segmentation is subject to appropriate initialization and optimal configuration of controlling parameters, which require substantial manual intervention. A new fuzzy level set algorithm was used in this paper to facilitate sclera segmentation. It is able to directly evolve from the initial segmentation by spatial fuzzy clustering. The controlling parameters of the level set evolution are also estimated from the results of fuzzy clustering. Moreover the fuzzy level set algorithm was enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried out on sclera images. The parameters that are affecting the level set segmentation are:

a. Controlling the spread of the Gaussian smoothing function
b. Controlling the gradient strength of the initial level set function
c. Regulator or direct function
d. Weighted coefficient of penalty term
e. Coefficient of counter length for smoothing
f. Artificial balloon force
g. Time set for level set initialization
h. Maximum iteration for level set evolution

Three indexes or cluster was considered for segmentation (assuming sclera area as one index, iris area as one index and the third index is the area around the eye.).

The results confirm its effectiveness for sclera image segmentation. Figure 2(b) shows the Fuzzy C means-based sclera segmentation of 2(a).



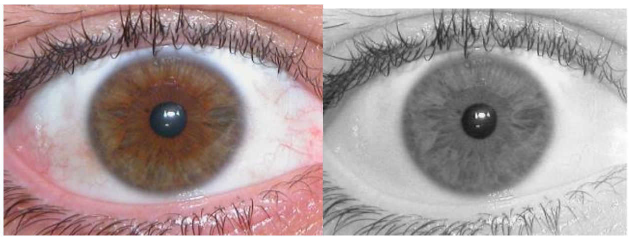
(a) (b)

Figure 2: A sclera image is shown in (a) and its fuzzy C- means based sclera segmentation is shown in (b).

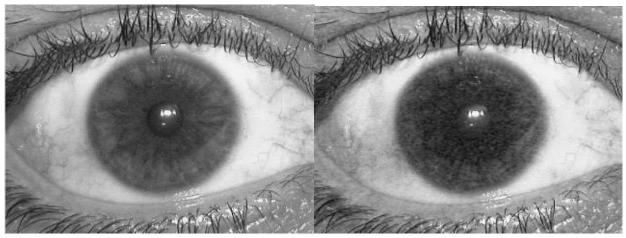
B. *Sclera vessel structure enhancement*

As the vessel patterns in the sclera are not prominent, so in order to make them clearly visible, image enhancement was required. Adaptive histogram equalization [21] was performed with a window size of 42 x 42 (the window value was selected by analysis, window value that produces the best result was use for experimentation) on the green channel of the sclera image (as the sclera vessel patterns are most prominent in the green channel as shown in figure 3(c)) to make the vessel structure more prominent as shown in Figure 4(a).

Further a bank of Discrete Meyer wavelet [22] was used to enhance the vessel patterns. Low pass reconstruction of the above mention filter was used to enhance the image. Figure 4(c) shows the vessel enhanced image after bank of filter been applied over the histogram equalized image.

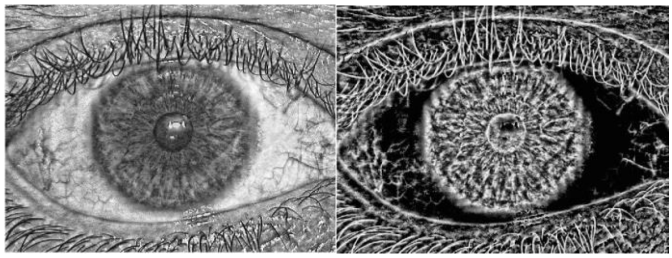


(a) (b)



(c) (d)

Figure 3 (a) The original RGB image, (b) The red channel component of (a), (c) the green channel component of (a), and (d) blue channel component of (a).



(a) (b)

Figure 4: (a) Adaptive histogram equalization of sclera image. (b) The vessel enhanced image.

C. *Feature Extraction Method*

In last years, the local patch based descriptors emerge as a way to improve feature extraction methods. It also worked efficiently in presence of distortion such as of scale, rotation, translation and occlusion. Its high discriminative capability and robustness attracted researchers in the area of biometrics. The variance of position of eyelids produces occlusions which are difficult to manage with traditional texture based methods. The robustness against occlusion is one of the most interesting factors in the application for sclera recognition. The local descriptor method applied in this paper is the Local Directional Pattern (LDP), which computes the edge response values in different directions and uses these to encode the image texture [11]. Considering the relative edge response values in different directions by eight different filters of each orientation as shown below in figure 5, the proposed LDP feature encodes the local neighborhood property of image pixels with a binary bit sequence.

$$\underset{\text{East } M_0}{\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}} \quad \underset{\text{North East } M_1}{\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}} \quad \underset{\text{North } M_2}{\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}} \quad \underset{\text{North West } M_3}{\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}$$

$$\underset{\text{West } M_4}{\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}} \quad \underset{\text{South West } M_5}{\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}} \quad \underset{\text{South } M_6}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}} \quad \underset{\text{South East } M_7}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}}$$

Figure 5: Eight Kirsch masks used to get the edge response in LDP.

Sclera feature extraction based on Dense Local Directional Pattern (D-LDP) was performed here. D-LDP patch descriptors of each training image are used to form a bag of features, which was finally used to produce the training model. For extracting the patch descriptors, each image was divided into a regular dense grid of 24x24 (The grid size was selected by analysis, the value that produces the best result was use for experimentation) locations with 24x24 (The patch size was selected by analysis, the value that produces the best result was use for experimentation) patch sizes as shown in figure 6(a).

Here histogram of bin size 512, for of each of this patches are calculated in multi-scaled of 1, 2 and 3. All the eight orientations of LDP are used here for calculating the LDP for each block in each scale. Finally the histogram of each patch and each scale are calculated and concatenated column wise to get the final descriptor. The blue cross in Fig.6 (a) represents the 24×24 D-LDP patches.

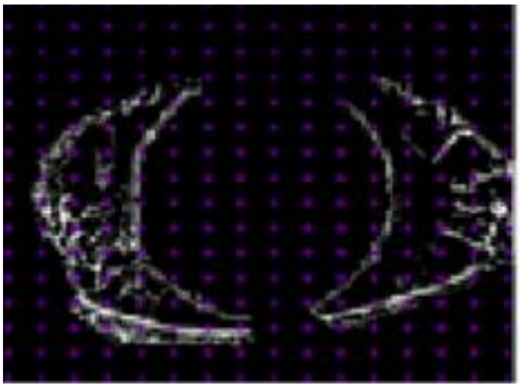


Figure 6: Image is divided into a 24x24 location of a 24x24 patch size for dense LDP descriptor.

Next, a k-means clustering technique was applied on the descriptors from the training set for the generation of the codebook. The typical vocabulary size for the clustering utilized in the experiment was 1024. Descriptors from each training image are used with the code book to form a bag of features, which was used to produce the training model.

The BoF (bag-of-features) histograms are computed within each of the 2^i segments of each patch k-means cluster, and all the histograms are finally merged to form a vector representation of the image by a spatial pyramid matching technique. Spatial pyramid matching is an extended version of the BoF model; it is simple and computationally efficient. In the BoF model, the spatial order of local descriptors was not considered, so it restricts the descriptive power of the image representation. The limitation of the BoF was overridden in the SPM [12] approach, which was successfully applied on image recognition tasks. An image was partitioned into 2^i *x* 2^i segments where i = 0; 1; 2, represents different resolutions. SPM reduces to BoF, when the value of the scale i = 0. Here, the pyramid matching was performed in two-dimensional image space and uses a traditional clustering technique in feature space. The number of matches at level i was given by the histogram intersection function I as below:

$$I\,(g(X); g(Y)) = \sum_{k=i}^{n} min(g_X(i); g_Y(i)) \qquad (4)$$

Finally, the representation of the image for classification was the total number of matches from all the histograms, which was given by the definition of a pyramid match kernel:

$$K(X;\, Y) = \sum_{i=1}^{l} 0.5^{i}\,(I_i - I_{i-1}) \qquad (5)$$

All total 21 (16+4+1) BoF histograms are computed from these three levels, next the histograms are concatenated to get the final vector representation of an image. The equation below represents the pyramid match kernel for three scales:

$$K_\Delta = I_2 + 0.5(I_1 - I_2) + 0.25(I_0 - I_1) \qquad (6)$$

D. Classification

Support Vector Machines (SVMs) [23] are used for classification. A SVM is a popular supervised machine learning technique which performs an implicit mapping into a higher dimensional feature space. This is also known as a kernel trick. After the mapping is completed, it finds a linear separating hyper plane with maximal margins to separate data from this higher dimensional space. The Library for Support Vector Machines (LIBSVM), Linear and Pegasus were used here for SVM implementation. Though new kernels are being proposed, the most frequently used kernel functions are linear, polynomial, and Radial Basis Function (RBF). This study uses the RBF kernel.

SVM or LIB-SVM makes binary decisions and multi-class classification for personal identification has been made in this study by adopting the one-against all techniques. We carried out grid-search on the hyper-parameters with 5-fold cross validation for selecting the parameters of the training sequences. The parameter settings that produce the best cross-validation accuracy were selected finally.

IV. EXPERIMENTAL RESULTS

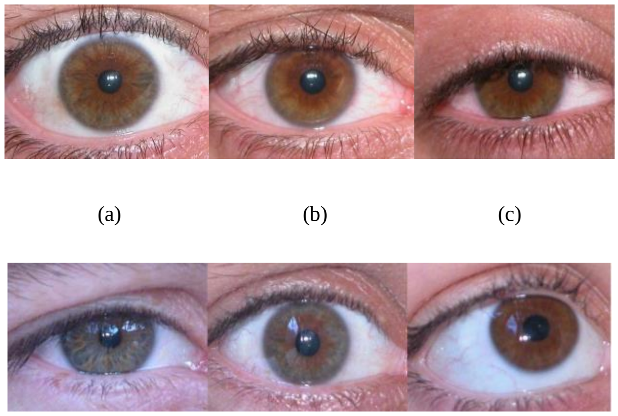
The experimental setup and the results of the proposed work are explained in this section. Various investigations regarding adaptively with respect to change in environmental condition, population, data accruing technique and time span are also highlighted in this section.

A. Data Set

In order to evaluate the performance of the proposed method, the UBIRIS version 1 database [13] was utilized in this experiment. This database consists of 1877 RGB images taken in two distinct sessions (1205 images in session 1 and 672 images in session 2), from 241 identities and images are represented in RGB color space. The database contains blurred images and images with blinking eyes. Both high resolution images (800 × 600) and low resolution images (200 × 150) are provided in the database. All the images are in JPEG format. We have used different quality images and some of the sample images are shown below in Figure 7.

In the first session image capture were with minimize noise factors, specially those relative to reflections, luminosity and contrast, by useing a image capture framework inside a closed room with controled artificial lighting. Whereas in the second session an enviromental change was brought by changing the capture enviriment, by introduceing natural luminosity factor inside the room along with the artifical lighting. This difference in the captureing enviroment produces heterogeneous images with respect to reflections, contrast, luminosity and focus. Images collected at second session simulate are captured by a vision system without or with minimal active participation from the subjects, adding several noise problems and their was a gap of two weeks in between the two session. Even the number of population was differnt for the two session. The first session consist of 241 users and in the second sesion there were 135 users. This changes in environmental condition, population, data accruing techniques and time span gap were utilized to investigate the addictiveness and adaptability of the sclera texture for biometric identification.

The dataset consist of different quality of images with respect to sclera region visibility. Some of the images are not occluded having good quality of sclera regions visible, some of them are of medium quality and the third type was of poor quality with respect to sclera region visibility. In the experiments all the closed eye image of the dataset were also used to assess the performance of the proposed system with occlusion, examples of such images are provided below in figure 8. The database also contains blurred images and images with blinking eyes as shown in figure 8. In the experiments all the images of sessions 1 and 2 are considered. Here single sessions as well as multi-session experiments were performed to prove the adaptively with respect to change in environmental condition. For the single session experiment, sessions 1 and 2 are considered separately, 3 images from each class of each session randomly chosen and utilized for training and the remaining 2 images for testing performance. Whereas for multisession experiments 5 images from session 1 were used for training and 5 images session 2 for testing and vice versa.

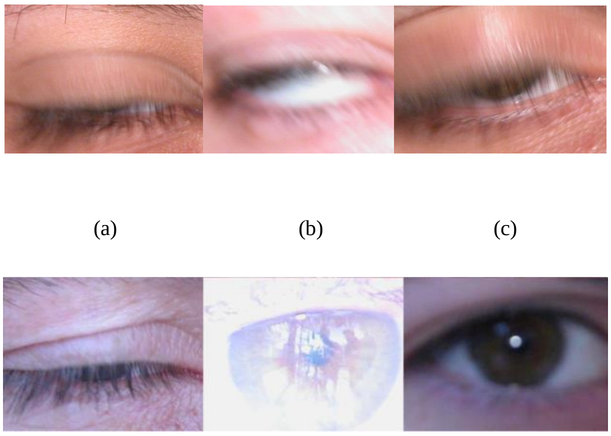


(a) (b) (c)

(d) (e) (f)

Figure 7: Different quality of eye images used.in the experiment (a) is the type of best quality image of Session 1, (b)) is the type of medium quality of Session 1 (c) is the type of Poor quality of Session 1, (d) is the type of below average quality image of Session 2, (e) is the type of average quality of Session 2 (f) is the type of best quality in of Session 2

For single session experiment a scores 241*2 for FRR and 242*241*2 score for FAR statistics were obtained for session 1 and whereas 135*2 scores for FRR and 136*135*2 score for FAR statistics were obtained for session 2. For multisession experiment 135*2 scores for FRR and 242*135*2 score for FAR statistics were obtained when session 1 was used for training and session 2 for testing and vice versa.



(a) (b) (c)

(d) (e) (f)

Figure 8: Example of closed and blurred eyes. (a),(b) and (c) are of session 1 and (d),(e) and (f) are of session 2.

B. Results of Segmentation

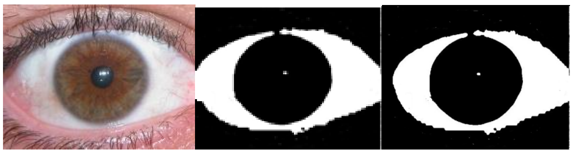
The parameters that are affecting the level set segmentation are:

i. Controlling the spread of the Gaussian smoothing function
ii. Controlling the gradient strength of the initial level set function
iii. Regulator or direct function
iv. Weighted coefficient of penalty term value set to 0.1
v. Coefficient of Counter length for smoothing value set to 5
vi. Artificial balloon force value set to -1.5
vii. Time set for level set initialization value set to 2
viii. Maximum iteration for level set evolution

A comparison between manual and automatic segmentation with the proposed method with the above setup are shown in figure 9. Quantitative results of both types of segmentation for the first 41 users from the dataset are reflected in Table I. In these experiments, different quality images were used. Some of them are not occluded having good quality of sclera regions visible, some of them are of medium quality and the third type was of poor quality with respect to sclera region visibility, some closed images are also used.

TABLE I. EQUAL ERROR RATE (%) OF THE DIFFERENT SEGMENTATION TECHNIQUES USED

Segmentation type	**EER**
Manual	0.04
Automatic	0.10



(a) (b) (c)

(d) (e) (f)

Figure 9: Examples of few manual segmented images. (a) & (d) are the original images, (b) & (e) are the manual segmented image and (c) & (f) are automatic segmented images.

Analyzing the influence of the segmentation on the recognition performance, it has perceptually been detected that for 14 images, wrong segmentation affected the identification. Examples of such images from session 1 and 2 and the mask created for them during segmentation are given below in Figure 10.

(a) (b)

(c) (d)

Figure 10: (a) & (c) are examples of poor quality images and (b) & (d) are the masks obtain during Segmentation.

C. Experimental Results on Sclera Vessel Enhancement and its Setup

In the experiments, it has been found that in the green channel of the images, the sclera vessel patterns are most prominent as indicated in Figure 3. So on the green channel of the sclera image, adaptive histogram equalization was performed with a tiled window size of 42 X 42 at a clip limit of 0.01, with full range and distribution exponential to get the best result.

Further, a bank of Discrete Meyer wavelet was used to enhance the vessel patterns. Low pass reconstruction with a cut off range of -0.9 * e^{10} and -0.5 * $e^{10}$and window size of 3X3.

Next, again adaptive histogram equalization with a tiled window size of 42 X 42 at a clip limit of 0.01, with full range and distribution exponential is imposed on the filtered image.

D. Experiments on Feature Analysis

For feature presentation analysis, a few local patch-based features such as Dense SIFT (Scale Invariant Feature Transform) [16], Dense LBP (Local Binary Pattern), and the proposed Dense LDP (Local Directional Pattern) are employed. The results in Table II reflect that dense LDP produces significantly better results.

TABLE II. EQUAL ERROR RATE (%) OF THE DIFFERENT TECHNIQUES USED FOR FEATURE EXTRACTION

Feature	**Equal Error Rate**		
	multisession	***Single session 1***	***Single session 2***
Dense SIFT	7.04	0.66	0.71
Dense LBP	5.05	0.71	0.83
Dense LDP	3.95	0.42	0.51

E. Classifer Analysis

For classification, SVMs are used as previously indicated. Three type of SVMs are used namely Library with RBF kernel, Pegasus and Linear. It can be inferred from the below table that Library SVM with the RBF kernel produces the best results.

TABLE III. EQUAL ERROR RATE (%) OF THE DIFFERENT SVMS USED FOR CLASSIFICATION

Kernel	Equal Error Rate		
	multisession	*Single session 1*	*Single session 2*
Lib SVM (RBF)	3.95	0.42	0.51
Pegasus	10.63	3.05	4.02
Linear	5.05	1.37	1.48

F. Time complexity

The average time complexity result of segmentation, vessel enhancement, feature extraction and classification are given below in Table IV. It can be inferred from the below table that the time complexity of the proposed technique was satisfactory. All the stimulated data reported here were developed in Matlab under Intel I5 processor in windows 7 environment

TABLE IV. TIME COMPLEXITY TABLE

Different Steps	*Time in Seconds*
Segmentation	0.14
Vessel enhancement	0.2
Feature extraction	0.41
Classification	0.15

F. Overall Experiment Results

The overall experimental results are summarized below in Table V.

TABLE V. EQUAL ERROR RATE (%) OF THE OVERALL RESULT USING THE DENSE LDP FEATURE

Feature	Equal Error Rate			
	Multisession session 1 training Session 2 testing	*Multisession session 2 training Session 1 testing*	*Single session 1*	*Single session 2*
Dense LDP	3.95	4.34	0.42	0.51

It can be inferred that the results of the single session experiments are very similar. It is the same for multisession experiment: the results are independent of the training and testing session.

The multisession experiment performs nearly 9 times worse than single session experiments. Two possible causes are: 1) differences in the acquisition conditions (lightning) between sessions and 2) difference in presence of eye lids and eye lashes due to time span difference in the feature computed.

The difference of EER between the two multi-session experiments and as well as single session experiment is very less, which infers the systems adaptively with respect to different change in environmental condition is quite promising

Below is the ROC (Receiver Operating Characteristic) curve for the best multi-session experiment. In the Y axis we have the genuine acceptance rate and the X axis represents the false acceptance rate.

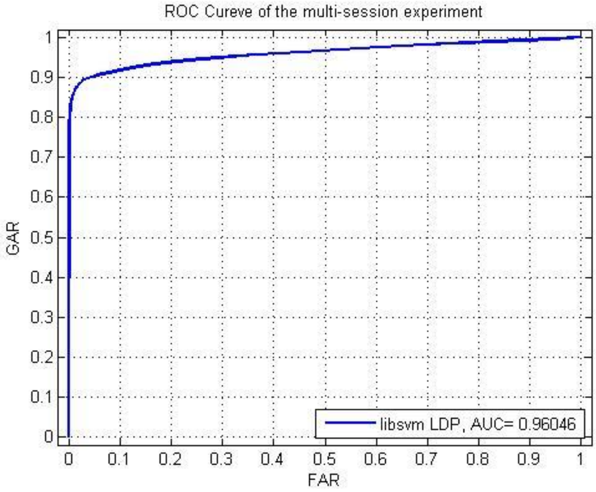


Figure 11: ROC curve of the multisession experiment

a. Comparism analysis with the state- of-art

The results of the proposed work are analysed with respect to the state-of-the-art by comparing it with the most similar work tested on UBIRIS version 1 that could find in the literature. Table VI reflects a state-of-the-art comparative analysis of the most similar work on UBIRIS version 1 dataset. From the table it can be reflected that the proposed system produces a better result than the method proposed by Zhou et al. [5] in and they have also used manual sclera segmentation for few images, as their automatic segmentation failed on those occasion, and the very poor quality (e.g., blur, blink, or no sclera-area image) images were also discarded form the experimentation.

In Oh and Toh [9], manual points were used for marking and connecting 333 images, even the experiment that they reported was not a multisession experiment, and the proposed system outperforms their result.

In [14] and [15] the authors have not used all the images from the mentioned dataset and even the experiments reported were performed a single session data. The authors in [16] have used all the images of session 1, but the images from the second session were not considered in the experiment.

Hence the proposed scheme is the most realistic one, since it did not discarded any images from the dataset used, the segmentation was fully automatic and the experiments was also performed with multisession data, where the sessions have variation in change in environmental condition, population, data accruing technique and time span gap.

Another significant novelty of this work is, the usage of statistical classifier like SVM in contrast to the other related work, where template matching was used for classification.

TABLE VI. A STATE OF THE ART COMPARISON OF OTHER PIECES OF WORK ON UBIRIS VERSION 1

Author	*Discard images*	*Segmentation*	*Multi session*	*Equal Error Rate (in %)*
Zhou et al. [4]	Yes	Some Manual	No	3.84
Oh and Toh [9]	Yes	Manual	No	0.47
Abhijit et al. [14]	Yes	Automatic	No	0.52
Miguel et al. [15]	Yes	Manual	No	0.04
Abhijit et al. [16]	No	Automatic	No	0.66
Proposed System	No	Automatic	No	0.42
Proposed System	No	Automatic	Yes	3.95

V. CONCLUSIONS

This paper has proposed a novel method of sclera recognition. For segmentation, a Fuzzy C–means based segmentation approach is proposed. Adaptive histogram equalization used for sclera preprocessing and a bank of low pass discrete Meyer wavelet reconstruction filter for establishing appropriate features was employed. Local Directional Pattern (LDP) provides information about the different pattern structures. Identification is achieved by SVM classification. The proposed approach has achieved good recognition accuracy without discarding images from UBIRIS version1 dataset, using fully automatic segmentation and multisession experiments. Even significant adaptation of sclera patterns for biometric identification, with respect to change in environmental condition are also proved from the demonstrated experiment.

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