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Segmentation and Recognition of Sclera trait using Adaptive Gabor Filter

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ABSTRACT

The rise in digital transition of connecting world via various online platforms has brought us to think on how to protect what's most important in this digital era. Among various security devices and applications available, biometrics is getting its attention on the smallest of devices possible to enhance the protection. Among various biometric technology, sclera is considered to be the newest trait researched today. In this paper, we propose an efficient sclera segmentation and recognition technique. We explored the use of adaptive Gabor filters to extract the texture features from sclera trait. The extracted texture features are represented in the form of bit strings. The similarity between the two bit strings are measured using normalized Hamming distance. The evaluation of the proposed method to check its efficiency is done using SSRBC 2016 dataset. The result of the proposed method is effective and feasible in sclera segmentation and recognition.

Keywords—Sclera;Texture Features;Adaptive Gabor Filter;Segmentation;Recognition

I. INTRODUCTION

Biometric mentions to an individual's automatic verification by using certain physical or behavioral characteristics that are relevant to him/her. When using biometric that particular person shall perform identification and verification rather than the ID card, password, etc [1]. Hence, biometric recognition system uses faces, retina, iris, fingerprints, hand geometry, gait, palmprint to define a person's identity. All these biometric modality has its own strength and limitations depending on the applications/environments. Many research work has been carried out over past decades on biometrics to recognize the individuals based on their physiological traits in terms of accuracy to the best extent possible. The physiological characteristics used for biometric authentication include fingerprints, DNA, face, palm geometry, retina, iris and ear [2, 3]. However, it is found that no biometric trait can be considered as genuine or can be applied universally. In order to cover larger crowds with lesser falsifying errors and higher recognition accuracy with various dimensions of environmental conditions, more research is needed on identifying newer biometric traits [4]. Biometric system is based on four components namely: Sensor module, feature extractor module, matching and decision module and finally database module [5]. Biometrics have many sources of uncertainty and variation like variance within persons, sensor age and calibration, differences in feature extraction that affect the performance of algorithms and data integrity. Identification of a human using the sclera offers several benefits over other vascular biometric traits.

Among the various biometric traits in the human physiological body, the sclera trait emerges to compliment the other traditional traits because of its unique characteristics. It is so unique that, the blood veins in the sclera region of the eye of every individual is different from others. Additionally, the vein pattern even differs from the left eye and the right of every individual. This uniqueness is so strong that the pattern of this sclera is even not the same for the identical twins [6, 7]. Furthermore, the distortion of this vein pattern does not alter much in person's lifespan [8]. Thus the high degree of randomness of these scleral region makes the sclera trait a very unique trait among other traits and is more protective in nature and avoids misrepresentation of authentication system. The advantage of choosing sclera is that it can be captured in any visible light, when

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compared to iris which requires IR illumination devices. These advantages of the sclera as biometric makes well-suited for noncompliant recognition situations. In sclera recognition system, sclera segmentation process is of highest importance as it segments the sclera area from iris and eyelids. It lets in four steps: Estimated glare area, Iris boundary detection, Sclera area detection and Refine eyelid and Iris. Fig. 1 presents the detailed steps involved in the process of segmentation and recognition of sclera trait.

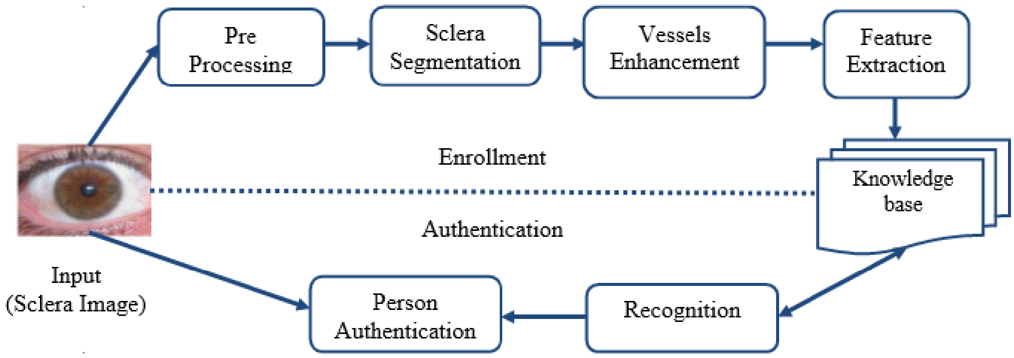

Figure 1:The process of Sclera Segmentation and Recognition.

An incorrect segmentation will reduce the region of the detected blood vessels or introduce new patterns, such as eyelids or eyelashes, which affect the overall accuracy of the complete system. The first method of segmentation was done using time adaptive active contour-based by [9]. Other methods of segmentation are sclera index measure, K-means and fuzzy logic etc.

The rest of the paper is organized as follows: section 2 presents the detailed related works on sclera segmentation and recognition. The proposed method which consists of 2 phases: segmentation and recognition phase is presented in section 3. The information about dataset used, experimental setup and results are presented in section 4. Section 5 draws the conclusion followed by the future scope of the proposed method.

II. RELATED WORKS

Segmentation and recognition of sclera trait involves various stages to recognize the individual identity. The segmentation in sclera recognition system plays a very important role. In literature, there are three ways of segmenting sclera images: manual, semi-automatic and automatic. In the beginning, segmentation of sclera is done manually [10]. this manual segmentation process is not reliable and does not suit for real time applications. To overcome these drawbacks, K-Means clustering algorithm was used as a semi-automatic segmentation method. Later, the eyelid and eyelash present in the sclera image is removed manually. Unfortunately, this process is very sensitive to human errors. The limitations of manual and semi-automatic segmentation methods are eliminated using fully automatic methods. The work proposed in [11, 12] segments the sclera using threshold. Another important work proposed by [13, 14] is Time Adaptive Self Organizing Map (TASOM) based active contour methods. The main objective of this methods is to extract the inner boundaries of this sclera. K-means clustering to segment the sclera by matching conjunctival vasculature of an eye is proposed by [10]. The enhancement of sclera vein pattern using adaptive histogram equalization is proposed by [6, 10, 15, 16]. A texture based Local Binary Pattern (LBP) feature and feature fusion techniques are proposed in [17]. Another important work by [18] explained how 2D Gabor filters can be designed to extract the texture features. The author highlighted the important characteristics of Gabor filter in combining the space and frequency. Thus, these characteristics can be explored to analyze the texture of images. This method found extensive applications in texture segmentation and classification [19], Finger Print recognition [20], Face recognition [21], Palm Print recognition [22], Iris Recognition [23] etc. For sclera recognition many existing methods are combined as an image enhancement technique (for example, Histogram Equalization (CALHE), Gabor Filter). These enhancement techniques will in turn result better recognition rate. Further, other local image descriptors like SIFT, LBP, HOG, GLCM, wavelet features are used to represent the sclera recognition [24 - 27]. Many researchers developed different automated segmentation techniques for sclera traits [28 - 31]. The results of the aforementioned works, recommended supervised segmentation techniques based on Convolution Neural Network (CNN) model are better when compare to the unsupervised techniques. [32] introduced a ScleraNet model for the computation of the image descriptor for sclera recognition.

III. PROPOSED METHOD

The proposed method consists of two phases: Segmentation followed by Feature Extraction Phase and Recognition Phase.

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A. **Segmentation Phase**

The main objective of the segmentation phase is to divide the image into its inherent parts and group the uniform pixels into clusters. There are many works published in the area of segmentation using clustering methods [33 - 36]. Among most of the clustering techniques the most widely used techniques are K-Means, Fuzzy C-Means and its variants. Even though fuzzy C-Means are capable of handling the vagueness to the certain extent, unfortunately they possess 2 challenges: fail to provide efficient results in presence of noise and limited in revealing non-Euclidean structure of the input data. To overcome these limitations, we use the Generalized Spatial Kernel-Fuzzy C Means (GSK-FCM) clustering [37] algorithms for sclera segmentation.The below Figure 2 presents the detailed steps involved in the proposed system.

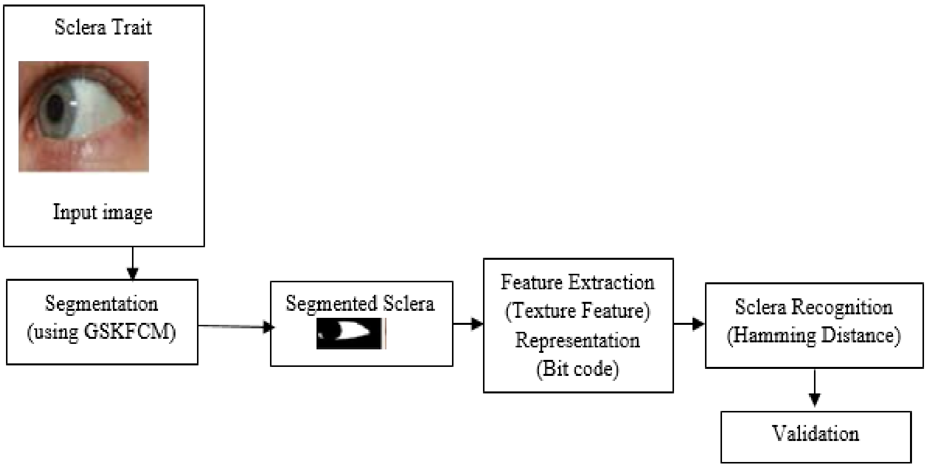

Figure2: The Proposed Method for Sclera Segmentation &Recognition.

The main intent of the GSK-FCM is to minimize the objective function as shown in Equation 1:

$$J = 2\sum_{i=1}^{c}\sum_{j=1}^{n} Z_{ij}^{m} d_{new}^{2}\left(x_j, v_k\right) \quad (1)$$

Where,

Z_{ij} : GSK –FCM membership function

d_{new} : distance function

c : number of clusters

n : number of data points

m : is a constant which controls the fuzziness of the resulting partition.

The detailed explanation of sclera segmentation using spatial kernel fuzzy clustering methods can be found in [37]. Similar to Fuzzy C-Means, GSK-FCM operates in the iterative process by updating membership and cluster center value. Further, the resultant sclera trait of the segmentation phase is used to extract the features followed by recognition.

Feature Extraction

The following section explain the process of feature extraction from the segmented sclera trait and subsequently followed by recognition.

The proposed feature extraction makes use of the texture of sclera vein and apply texture based feature extraction techniques. To extract the texture feature, we use the most popular Gabor filters. The main objective of the Gabor filters is to analyze the frequency component in the sclera veins in specific directions and in a local region of analysis/interest. The main advantages of using Gabor filters is because of the property of capturing frequency, discrimination and orientation representations of sclera veins. In the present research days, it has become obvious of using multiple Gabor filters to decide the wanted combinations. In the proposed work, we are using adaptive Gabor filter method [38] to represent the sclera vein features in bit string representation. Further, the adaptive Gabor filters uses the optimization algorithm that is capable of identifying the best parameter values for sclera vein recognition. The bit string representation is given to all the samples and the similarity of two bit strings is measured by using normalized Hamming distance [38].

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Adaptive Gabor filter for texture feature extraction

In the proposed work, we consider the texture based feature extraction on the sclera trait. In this work, we use adaptive Gabor filter to extract vein patterns for sclera recognition. [18, 39] proposed the 2D Gabor functions, which is responsible to do good spatial localization, frequency selectivity and orientation selectivity. The basic objective function of a circular 2D Gabor filter is given by

$G_{\sigma,u,\theta}(x,y) = g_{(x,y)}.exp\left[2\pi ju\left(xcos\theta + ysin\theta\right)\right]$ Where,

$$g_\sigma(x,y) = \frac{1}{2\pi\sigma^2}exp\left[-\left(x^2+y^2\right)/2\sigma^2\right]$$

Where,

$j = \sqrt{-1}$; u = frequency, θ = orientation, $g_\sigma(x,y)$ = Gaussian function and σ = standard deviation of the Gaussian envelope.

To analyze the 2D Gabor filter in terms of the real and imaginary parts, we express

$G_{\sigma,u,\theta}(x,y) = R_{\sigma,u,\theta}(x,y) + jI_{\sigma,u,\theta}(x,y)$ Where,

$R_{\sigma,u,\theta}(x,y) = g_\sigma(x,y).cos\left[2\pi u\left(xcos\theta + ysin\theta\right)\right]$; $I_{\sigma,u,\theta}(x,y) = g_\sigma(x,y).sin\left[2\pi u\left(xcos\theta + ysin\theta\right)\right]$

The input image which is filtered by 2D Gabor filters is normally tune to various resolutions and orientations. Unfortunately, they are not computationally effective to apply to the more number of filters having multiple resolution and orientations to an image.

Further, accurate recognition is possible only when the parameters defining 2D Gabor filters are appropriately chosen. To enter the right choice of the parameters, we make the ROI image into $(M \times M)$ non overlap blocks [38]. This makes to apply adaptive Gabor filters independently to each block. The size of each block is $(w \times w)$. If w is small, smooth area may be affected by noise, larger w will enhance the anti-noise ability of the block. Further, if w is too large, the block cannot reflect the detailed change of the image. As suggested by [38] we fix each block size as (16×16) and $M = 8$. Now, the challenge lies in selection of the filter parameters θ, u, and σ in each block.

In most of the cases, the orientation parameter, $\theta \in \left\{0, \pi/8, 2\pi/8, \ldots, 7\pi/8\right\}$ .However, in the proposed work, we found $\theta = \pi/8$ shall be an appropriate value and the same is found through empirically. The second parameter, distributed variance tends towards the normal distribution. Hence, we need to come out with a strategy in designing suitable statistics that is used to find suitable frequency. Based on the method followed in [38], we divide each block of the ROI image into three categories depending upon the change in the variance: stable area, slow change area and fast change area. Further, based on the empirical evaluation we fix 0, 0.008 and 0.2 respectively for each frequency blocks. The same can be formulated as:

$$u = \begin{cases} 0, if\ Var < H_1 \\ 0.08, if\ H_1 \le Var < H_2 \\ 0.2, otherwise \end{cases}$$

From the above formulation, Var refers to variance of block, H_1 and H_2 are two thresholds of piecewise function, and they are $I_\mu - I_\sigma$ and $I_\mu + I_\sigma$ respectively. Here, I_μ is a mean of the variance distribution and I_σ is the standard deviation of the mean. The third parameter is standard deviation of the Gaussian envelope. Neither too big or small the value of σ does not capture the blood vessel information in detail. Thus, by empirical evaluation we have fixed the value of $\sigma = 2\sqrt{2}$. This value is considered to be more optimal to preserve the vessel information.

Now, given a neighborhood window of size $s \times s$ for $s = 2k+1$, the discrete convolutions of $f(x,y)$ with respect to real and imaginary part at the sampling point (x,y) is given by

$C_R(x,y)_{\sigma,u,\theta} = \sum_{X=-k}^{k}\sum_{Y=-k}^{k} f(x+X, y+Y).R_{\sigma,u,\theta}(X,Y)$; $C_I(x,y)_{\sigma,u,\theta} = \sum_{X=-k}^{k}\sum_{Y=-k}^{k} f(x+X.y+Y).I_{\sigma,u,\theta}(X,Y)$

The discrete convolution is done until the whole ROI image is traversal.

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Lastly, the sample point in the filtered image is coded to two bit strings (V_R, V_I) by the following inequalities:

$$V_R(x,y) = \begin{cases} 1; if\ C_R(x,y)_{\sigma,u,\theta} \geq 0 \\ 0; if\ C_R(x,y)_{\sigma,u,\theta} < 0 \end{cases} \text{ and}$$

$$V_I(x,y) = \begin{cases} 1; if\ C_I(x,y)_{\sigma,u,\theta} \geq 0 \\ 0; if\ C_I(x,y)_{\sigma,u,\theta} < 0 \end{cases}$$

B. **Recogntion Phase**

Using the bit strings, the texture information in sclera traits is stored in the feature vector. Further, to find the relatedness between the 2 bit strings we used normalized Hamming distance [40]. To find the recognition rate, we used Random Forest, Support Vector Machine (SVM), Bayesian Network and Feedforward Neural Network. The aforementioned algorithms are tuned as recognition algorithms and we conduct the experiments on standard SSRBC 2016 competition dataset.

IV. EXPERIMENTAL RESULTS

The following section presents the details of dataset used and the various experimental settings and the results.

A. **Dataset**

To evaluate the efficiency of the proposed method, we used a competition dataset SSRBC – 2016 [31]. Basically the dataset consists of eye image captured from 30 individuals. The captured image resolution is of 1489×1105. While capturing the dataset, three different cases: blinked eyes, closed eyes and blurred eyes were considered. Further, every individual eye is captured in 4 different angles: Center, Left, Right and Up. Thus the dataset consists of 30 individual eye images captured in 04 different angles. In total, there are 120 eye images which are considered as ground truth images. The Figure 3 and Figure 4 presents the sample original sclera images and ground truth images respectively.

Figure3: Original Images from the dataset.

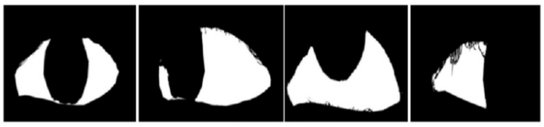

Figure4: Ground Truth Images.

- **Segmentation Results**

According to the segmentation phase that is explained in section III and to fix the optimal value of the parameters for GSK-FCM, we used four popular cluster validity indices: Partition Coefficient (V_{pc}), Partition Entropy (V_{pe}), Fukuyama-Sugeno function (V_{fs}) and Xie-Beni function (V_{xb}). Further, we fixed the Fuzzification factor $m = 2$ and stopping criteria $(\varepsilon = 0.00001)$ [37]. Figure 5 present the cluster validity results of GSK-FCM for different values of p and q.

From the fact of [37], we fix the value of $p = 1, q = 2, \sigma = 150$ and window size = 5 empirically. GSK-FCM achieves a Precision rate of 85.89 and Recall rate of 80.23 for the above experimental setup. Further, the cluster validity indices of segmentation achieved are $V_{pc} = 0.931$, $V_{pe} = 0.167$, $V_{xb}\left[1 \times 10^{-3}\right] = 59.65$, and $V_{fs}\left[-1 \times 10^{6}\right] = 390.67$ respectively.

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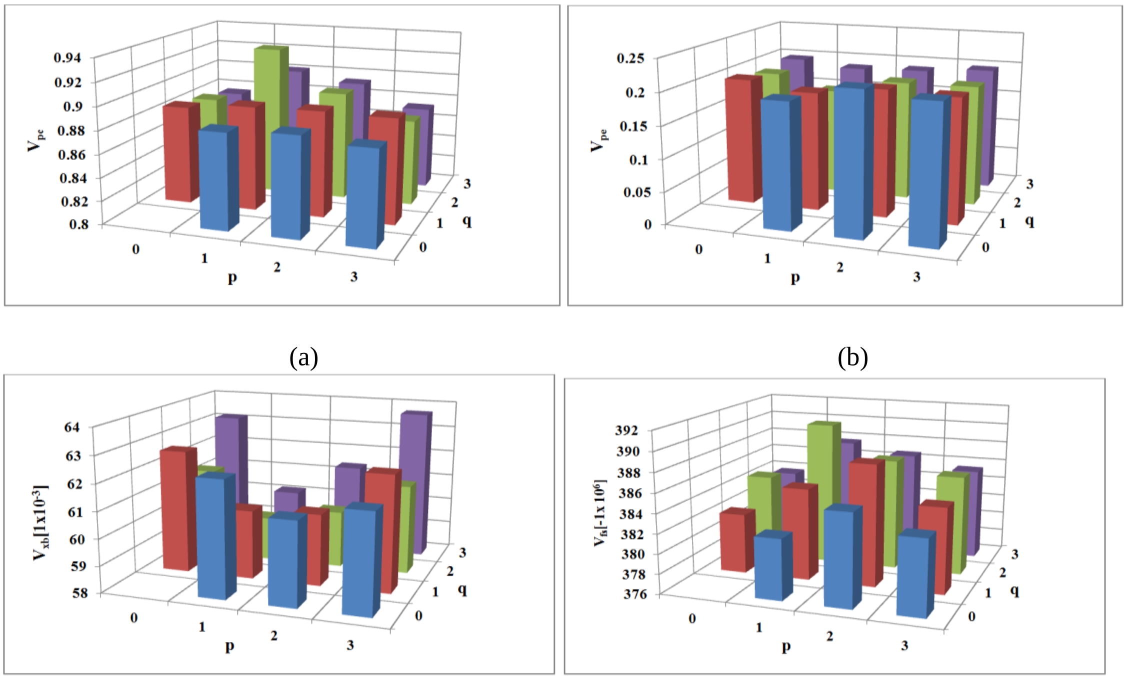

(a) (b)

(c) (d)

Figure5: Cluster validity indices for different values of p and q of GSKFCM on sclera segmentation (a) (V_{pc}), (b) (V_{pe}), (c) (V_{fs}) and (d) (V_{xb}).

- **Recognition Results**

The proposed model is experimented by using 50% of the sclera traits in the database for training and remaining 50% of the sclera traits of each person for testing. This is considered as set 1 experimentation. On the other hand, 60% of the sclera traits are considered for training and the remaining 40% of the sclera traits are considered for testing. This set of experimentation is termed as set 2. The splits in set 1 and set 2 are created through random selection process. The set 1 and set 2 experimentations are tested for five iterations and the best recognition rate out of five iterations is presented in Table 1. In each iteration the selection of training and testing split is through random process. To evaluate the proposed model, we used the Bayesian Network, Random Forest, Support Vector Machine and Feed Forward Network. From Table 1, we achieved a better recognition rate of 90.15% using Support Vector Machine (SVM) for 60:40 split. On the other hand, we also computed the Equal Error Rate (EER). The SVM achieved a EER of 0.46. This is equally good result achieved because lower the equal error rate value, the higher the accuracy of the biometric system. Further, we computed the overall time taken to compute the recognition rate of the proposed system. Unfortunately, SVM took more time in recognizing the individual. This is because of the reason that SVM will normally take more training time and it also depends upon various parameters. Table 1 presents the details of split used, Recognition Rate, Equal Error Rate (EER) and overall time taken to recognize the individual.

Table 1: Performance of the proposed method in terms of Recognition Rate, EER and Time

Algorithms	Split	Recognition Rate in %	Equal Error Rate (EER)	Overall Recognition Rate (in seconds)
Bayesian Network	50:50	79.63	0.77	0.56
	60:40	82.58	0.71	0.61
Random Forest	50:50	84.68	0.68	0.85
	60:40	85.95	0.62	0.89
Support Vector Machine	50:50	89.60	0.54	1.03
	60:40	90.15	0.46	1.09
Feed Forward	50:50	88.57	0.51	1.12

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Network	60:40	89.65	0.53	1.22

V. CONCLUSION AND FUTURE WORK

This paper proposes an efficient sclera segmentation and recognition method. The proposed method has two phases: segmentation and recognition phase. We used Generalized Spatial Kernel – Fuzzy C-Means to segment the sclera trait. Further, we use adaptive Gabor filter to extract the texture features and the same is represented in bit string format. The most widely used normalized Hamming distance is recommended to find the relatedness between the two bit strings. The advantage of the proposed method is that the sclera traits are represented in bit string format. This representation is very convenient in terms of speedy matching and takes less storage space. Further the experimental results revealed that the proposed method achieved encouraging performance in individual recognition through sclera trait. Following are the future possibilities that we can think of:

- To work towards the better preprocessing methods to enhance the quality of the images acquired.
- To work on the other texture features for the better recognition rate.
- To combine two or more algorithms to achieve better recognition rate.
- To validate the proposed method on other various sclera benchmark datasets.

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