Alkassar S, Woo WL, Dlay SS, Chambers JA.

[Sclera recognition: on the quality measure and segmentation of degraded images captured under relaxed imaging conditions.](#)

IET Biometrics 2017, 6(4), 266 - 275.

Copyright:

© 2017 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

DOI link to article:

<https://doi.org/10.1049/iet-bmt.2016.0114>

Date deposited:

18/07/2017

Sclera Recognition: On The Quality Measure and Segmentation of Degraded Images Captured Under Relaxed Imaging Conditions

S. Alkassar^{1*}, W. L. Woo¹, S. S. Dlay¹, and J. A. Chambers¹

¹ School of Electrical and Electronic Engineering, Newcastle University

Newcastle upon Tyne, UK

Email: s.h.m.alkassar@newcastle.ac.uk

(Invited paper: IWBF2016)

Abstract

We propose a new method for sclera quality measure and segmentation under relaxed imaging constraints. In particular, for sclera image, we propose a new quality measure approach based on a focus measure. In addition, we propose a new fusion method for sclera segmentation which uses pixel properties of both the sclera area and the skin around the eye. Furthermore, sclera template rotation alignment and distance scaling methods are proposed to minimize the error rates when noisy eye images are captured at-a-distance and on-the-move, together with overcoming head pose rotation. Then, a performance analysis on exploited eye images using the Excellent, the Good, the Bad, and the Ugly (EGBU) classification technique for image quality is used to evaluate system performance. Eye images captured under relaxed imaging constraints using four camera devices within the UBIRIS.v2 and MICHE mobile databases are utilized to evaluate the proposed sclera recognition system, with the UBIRIS.v1 database as a reference. Results in terms of sclera image quality measure and sclera segmentation are promising and describe the effect and challenges of using relaxed imaging conditions on sclera recognition system.

Index Terms

Sclera Recognition, Biometrics, Image quality, Image Segmentation, Image colour analysis

I. INTRODUCTION

The eye biometric has received increased attention recently particularly with visible wavelength illumination due to the increased availability of camera-based devices. Capturing the eye using a normal camera has introduced three research topics, namely imaging and identifying the iris, periocular and sclera blood

TABLE I: The state-of-the-art literature on blood vein recognition within the eye

Method	Database (Sub./Img.)	Image Capturing Condition	Sclera Segmentation	Sclera Template Rotation Alignment	Sclera Distance Scaling
Derakhshani et al. [4]	In-house DB(6/12)	Constrained	Manual	No	No
Derakhshani and Ross [5]	In-house DB(50/300)	Constrained	Manual	No	No
Crihalmeanu et al. [6]	In-house DB(50/100)	Constrained	Semi-automated	No	No
Thomas et al. [7]	UBIRIS.v1 (241/1205)	Constrained	Automated	No	No
Oh and Toh [8]	UBIRIS.v1 (241/1205)	Constrained	Automated	No	No
Zhou et al. [9]	UBIRIS.v1 (241/1805)	Constrained	Automated	No	No
Lin et al. [24]	UBIRIS.v1 (241/1168)	Constrained	Automated	No	No
Das et al. [10]	UBIRIS.v1 (241/1350)	Constrained	Automated	No	No
Alkassar et al. [3]	UBIRIS.v1 all UTIRIS [25]	Constrained	Automated	No	No
Gottemukkula et al. [11]	In-house DB(226/904) UBIRIS.v1 (241/1205)	Constrained	Automated	No	Yes

veins [1]–[3]. The eye structure is shown in Fig. 1. Each aspect has been investigated in terms of capturing scenario, segmentation, image enhancement, feature extraction, and matching process. The sclera is the visible white part of the eye which surrounds the iris. The blood vessels within the sclera have different deformations and shapes which are used as distinctive features and ultimately can be used to verify and identify humans [4], [9].

Fig. 1: Eye anatomy consisting of pupil, iris, sclera and periocular regions.

A. Related work

First of all, it is noteworthy that blood vessel recognition within the eye has been named differently in recent research, as summarized in Table I, as sclera, ocular, and conjunctival vasculature recognition. However, they all have similarities in terms of extracting discriminative features from these vessels in order to recognize an individual. The first step was achieved by Darkshani et al. [4] where they investigated the feasibility of using these blood vessels within the eye for human recognition. They exploited manual sclera segmentation and minutiae detection was employed for feature extraction. Then, Derakhshani and Ross [5] developed a new method for blood vein feature extraction based on wavelets and used a neural network for classification. Sclera segmentation was achieved manually. In [6], the authors utilized a clustering technique for a semi-automated sclera segmentation method with a manual intervention for final refinement. In [7], [9], a new line descriptor for feature extraction is proposed. Local Binary Patterns (LBPs) were utilized by Oh and Toh [8] to extract the distinctive feature of the blood veins. Discrete Meyer wavelet filter banks and Local Directional Patterns (LDPs) were used in [10]. Alkassar et al. [3] proposed newly occluded eye detection for sclera validation along with sclera shape contour extraction. Gottemukkula et al. [11] developed a method for an ocular biometric which is suitable for smartphones. Finally, two competitions for the sclera segmentation were organised by Das et al. [12], [13] resulting in using a neural network classifiers to overcome some of noise factors.

B. Issues and challenges of sclera recognition

Recent research in sclera recognition has some drawbacks which can be summarized as:

- i. Images used are captured under controlled environments where most of the noise factors have been minimized such as capturing distance, blurring, gaze direction, pose direction, capturing on-the-move, and natural illumination conditions. As a result, reported results in terms of system performance and error rates may not be realistic in real life applications.
- ii. Various image qualities have not been evaluated in terms of sclera segmentation and recognition rates.
- iii. The only work on sclera image quality measure was conducted by Zhou et al. [14] where only images with constrained imaging conditions were considered. In addition, the quality measure involves discussing the occlusion cases and counting extracted features which not necessarily measure the image quality rather than feature extraction method quality.
- iv. Ocular vasculature using smartphone proposed by Gottemukkula et al. [11] has used only one mobile device and the dataset acquisition was indoor inside a lab environment with controlled illumination conditions and capturing distance.

TABLE II: Brief description for various eye databases captured under visible wavelength in terms of capturing devices and image properties

Dataset	Camera Type	Image size and Resolution	Capturing Distance
UBIRIS.v1 [16]	Nikon E5700 5MP	600×800 300 dpi ^a	20cm
UBIRIS.v2 [17]	Canon EOS 5D 13.3MP	300×400 72 dpi	5m-8m
MICHE iPhone 5 [18]	iSight with 8MP	1536×2048 72 dpi	13cm
MICHE Samsung Galaxy S4 [18]	CMOS with 13MP	2322×4128 72dpi	13cm

^a dpi: dots per inch

C. Contributions of our work

- In our previous work [15], we proposed a new method for sclera recognition when images are captured at-a-distance and on-the-move. However, in this work we propose developing the sclera segmentation and sclera rotation alignment and distance scaling.
- Image quality classification based on the Excellent, the Good, the Bad, and the Ugly (EGBU) has been introduced based on sclera image focus measure.
- Images captured at-a-distance, on-the-move, and under natural illumination conditions using ubiquitous camera-based devices are utilized to evaluate the proposed work.

The rest of the paper is described as follows: Section II describes the datasets used in this paper. Section III explains the proposed image quality measure based on focus measure whereas Section IV, shows the proposed sclera segmentation. The sclera template rotation alignment and distance scaling is described in Section V. Results are reported in Section VI while we draw our conclusions and future work in Section VII.

II. DATASET DESCRIPTIONS

As blood vein recognition within the eye is a developing area, it is noteworthy that there is no explicit database for this emerging biometric. Therefore, recently published work used either In-home database i.e., database created by authors and is not publicly available, or databases proposed for iris evaluation under visible wavelength spectrum. The following are a brief description of databases used to evaluate the proposed system:

- The UBIRIS.v1 database [16]: This database consists of 1877 images for 261 subjects. Two capturing sessions were used to collect eye images where session 1 has introduced minimal noise factors while

session 2 involved natural noise factors. This database has been used by many researchers for sclera recognition due to its public availability, high resolution, minimum noise factors, and ready ROI cropped which led to less preprocessing stages. However, it has received criticism over realism of the capturing scenario and minimization of noise factors. We therefore, used this database as a quality reference only for the Excellent classification. It is noteworthy that the UBIRIS.v1 database has another version of image resolution which is 200×150 . However, we have not used the images with the aforementioned resolution and hence, we ignored this resolution in Table II.

- ii. The UBIRIS.v2 database [17]: It has been designed to evaluate the feasibility of using iris recognition under visible wavelength for non-ideal conditions. These conditions include blurring, motion, different capturing distance, multiple eye gaze directions, eye-glasses images, and different illumination scenarios. This database consists of eye images captured at distances ranges from 4 to 8 meters for 261 subjects enrolling both right and left eyes resulting in 522 eyes and 11102 images. In this paper, we only used images captured at distances of 4, 5, and 6 meters.
- iii. The Mobile Iris Challenge Evaluation (MICHE) database [18]: This database was collected to assess iris recognition on mobile devices. Database images are captured using three mobile devices including iPhone 5, Samsung Galaxy S4, and Samsung Galaxy Tab 2 using both front and rear cameras. It includes a diversity of population, realistic acquisition scenarios which include indoor and outdoor imaging, and various noise factors resulting in an extreme challenge for eye mobile recognition. The total number of captured images is 3732 for 92 subjects. Some images are affected by several noise factors such as defocus, blur, occlusion, and specular reflection. Due to the low resolution of the front cameras of iPhone 5, Samsung Galaxy S4, and Samsung Galaxy Tab 2 (as Samsung Galaxy

Fig. 2: Examples of various eye databases under visible wavelength. The top row represents UBIRIS.v1 database samples, the middle row represents the UBIRIS.v2 database, while the bottom row represents the MICHE database.

Tab 2 does not have a rear camera), we therefore, have discarded images captured with these cameras resulting processing in only 1279 images.

Some of the properties of these databases and the camera devices used to capture their eye images are summarized in Table II. In addition, examples of collected images for the aforementioned databases are shown in Fig. 2.

Fig. 3: Examples of three different quality images where the convolution with the Laplacian operator and the final fm value are shown. (a), (b), and (c) are L outputs of images from the UBIRIS.v1, UBIRIS.v2, and MICHE databases respectively, and (d) shows their fm values.

III. SCLERA IMAGE QUALITY MEASURE

In any biometric system, not checking the input image for a quality measure could affect the entire processing flow thus resulting high error rates. As datasets involved in this research have relaxed imaging constraints, therefore the quality of the dataset images must be examined in order to have more insight about the suitability of these images for the sclera segmentation process. We proposed classifying input images into four categories: Excellent, Good, Bad, and Ugly (EGBU) images inspired by the research by Phillips et al. [19] where face images are classified based on their matching difficulties into three categories only which are the (GBU) whereas we are adding another category where the quality is Excellent. We develop their work by proposing using a focus measure to determine sharp and smooth edges of an input image and hence, define its quality accordingly. For a real-time application, the employed quality measure must be fast to avoid adding an extra expensive processing time and introducing an impractical sclera recognition system. We used the second derivative method proposed in [20] to detect the sharp and smooth edges within the input eye image through passing the high frequencies.

Let the intensity of an input image be $I(x, y)$, then the focus measure is defined as

$$fm(I) = \sum_{i=1}^x \sum_{j=1}^y |L(x, y) - \bar{L}|^2, \quad (1)$$

where $L(x, y)$ is the convolution of $I(x, y)$ with the Laplacian operator L to detect I edges which is defined as

$$L = \frac{1}{6} \begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix}, \quad (2)$$

and $\bar{L}$ is the mean of the absolute value calculated as

$$\bar{L} = \frac{1}{xy} \sum_{i=1}^x \sum_{j=1}^y |L(x, y)|. \quad (3)$$

High and low frequency edges of three different quality images are shown in Fig. 3a, 3b, 3c, whereas examples of the fm measure for the same images are shown in Fig. 3d. For high resolution images where the edges are strong, the variance between image pixels is high in which the image texture is clear whereas for low resolution images, most of the image pixels present low frequency edges where only a few pixels have a high edge value. While for the blurry image, the majority of pixels have the same low edge value resulting in smooth edges as each pixel value is subtracted by $\bar{L}$. The quality based on EGBU classification will be assigned to each image according to some empirical results of the utilized datasets which will be discussed in subsection VI-A.

(a)

(b)

Fig. 4: The sclera segmentation and refinement processes. (a) a block diagram depicting the two main steps for sclera map extraction and sclera map refinement steps. (b) proposed sclera map extraction and refinement. Showing from the left top row, an eye image from the UBIRIS.v2 at a distance of 4 meters, the skin descriptors fusion map Sk_f mask, and the sclera area descriptors fusion map SA_f . While from the left bottom row, the first image represents the resulted sclera map S_f mask after applying the binary convex hull to refine the sclera shape, binary labelling process mask with p_1 and p_2 locations specified after applying iris map, and the final binary mask after removing all the spur pixels.

IV. PROPOSED SCLERA SEGMENTATION SCHEME

For a sclera recognition system, the segmenting process is the first challenging issue and has provoked much research interest (Table I). Although the sclera has an advantage over the iris in the visible-wavelength illumination being the brightest and the white part of the eye, however, many factors could degrade the segmentation results. These factors include motion, blur, gaze deviation, capturing distance, and illumination variation. As a result, an efficient sclera segmentation method which can minimize the aforementioned factors is required. We therefore, propose a fusion method which depends on sclera pixel properties and the skin area around the eye. A block diagram of the proposed segmentation method is shown in Fig. 4a. We used the integro-differential operator [21] to extract the iris position and radius (x_0, y_0, r) which will be used in sclera map extraction and refinement.

A. Sclera Map Extraction

The sclera map extraction consists of two stages defined as

- This step is focused on extracting a sclera map depending on the skin around the eye. In our previous work in [15], we proposed a single skin classifier which resulted in satisfactory results. However, variation in illumination when capturing eye images and the variety in skin colour pixels could affect the skin segmentation. Therefore, we proposed a fusion method for multiple skin classifiers in [22] to improve the segmentation rate by using skin classifiers in different colour spaces. The eye skin descriptors fusion consists of six multiple colour spaces include RGB, rgb, HSV₁, HSV₂, HSI, and YCbCr. The final map which denoted as $\mathbf{Sk}_f$ is defined as

$$\mathbf{Sk}_f(x, y) = \begin{cases} 1, & \text{if } \sum_{i=1}^6 s_{ki}(x, y) \geq th_s \\ 0, & \text{otherwise} \end{cases}, \quad (4)$$

where s_{ki} is a single skin descriptor and th_s is the threshold of how many correct pixels of the six skin descriptor required for generating the final correct pixel. The implementation the eye skin descriptors fusion is explained in details in [22].

- The second part of the proposed algorithm utilizes sclera area pixel properties to extract a sclera map. The fusion of sclera area descriptors is also developed by fusing two maps generated from the HSV and YCbCr colour spaces. The first map extracted from the HSV colour space is explained thoroughly in [15] and can be denoted as $\mathbf{SA}_1$. The second map $\mathbf{SA}_2$ is extracted from the YCbCr colour space empirically as

$$\mathbf{SA}_2 = \begin{cases} 1, & \begin{aligned} 68 \leq Y \leq 137 \\ 119 \leq Cb \leq 136 \\ 131 \leq Cb \leq 156 \end{aligned} \\ 0, & \text{otherwise} \end{cases}. \quad (5)$$

Then, $\mathbf{SA}_2$ is inverted and the binary convex hull is applied to refine the extracted sclera area. After that, both sclera area maps ($\mathbf{SA}_1, \mathbf{SA}_2$) are fused using AND operation resulting $\mathbf{SA}_f$.

Finally, after acquiring the two sclera binary maps, the fusion process is achieved as

$$\mathbf{S}_f(x, y) = \begin{cases} 1, & \text{if } \mathbf{Sk}_f(x, y) \ \& \ \mathbf{SA}_f(x, y) = 1 \\ 0, & \text{otherwise} \end{cases}. \quad (6)$$

Fig. 5: Examples of eye corner and gaze estimation applied on an image captured at 5 meters along. (a) shows the detected eye corners, (b) represents eye gaze estimation where w_l and w_r are the width of left and right sclera areas respectively.

B. Sclera Map Refinement

Due to some variation in light and noise factors, fusing the two sclera maps will still introduce a template with misclassified pixels. In addition, for noisy images, applying a binary morphological operation to remove spur pixels is not efficient. Therefore, post-processing is required. We first apply a binary convex hull to refine the shape of the sclera extracted parts within the map S_f . Then, we propose a method to label each part of the sclera binary map S_f . The process is initiated by finding connected objects in S_f and creating a label matrix for the connected parts within the sclera map. After that, we select sclera areas which overlap with predefined points referring to the location of sclera regions which are predicted to be around the iris. Based on the eye gaze direction, if the eye gaze is frontal (F_G), then the two predefined points p_1 and p_2 are assigned based on the iris centre position. More information about how to determine p_1 and p_2 is available in [15].

Examples of the sclera fused map, sclera refinement process, and proposed labelling and selecting method are shown in Fig. 4b. Noting that if the eye gaze is deviated to the left (L_G) or to the right (R_G), only one point is required depending on the gaze estimation. We used the eye gaze detection method for unconstrained imaging conditions proposed by Alkassar et al. [23]. Eye corner detection and gaze estimation are shown in Fig. 5a and 5b.

V. PROPOSED SCLERA TEMPLATE ROTATION ALIGNMENT AND DISTANCE SCALING

For relaxed imaging conditions where the subject may walk back and forward to the camera, changing the head pose to the left and to the right with different eye gaze directions could affect the recognition

Fig. 6: Examples of sclera areas rotation alignment and distance scaling. (a) shows sclera template rotation alignment where internal sclera corners c_1, c_2, c_3 and c_4 represented as red and blue dots are estimated, the internal angles $\theta_1, \theta_2, \theta_3$ and θ_4 are calculated, and the detected eye corners (c_l, c_r) are shown in green dots, and (b) the extracted sclera templates with (R_G) at three distances 4, 5 and 6 meters are scaled using bilinear interpolation. The top row images correspond to distance 4 meters, the middle row images 5 meters, and the bottom row images at 6 meters before and after scaling.

process. Therefore, and for the non-corruptive user scenario, we need to mitigate these challenges in order to produce an efficient sclera recognition system. We therefore, developed our method for Sclera Template Rotation Alignment and Distance Scaling (STRADS) [15] which is invariant to pose rotation and capturing distance. The first step is to initiate the rotation alignment of an input sclera template. The rotation alignment process for (F_G) is depicted in Fig. 6a. For a deviated eye gaze image, only the visible right or left parts of the sclera is aligned. This is explained thoroughly in [15].

While for the distance scaling, an extraction method based on RGB thresholding to extract final sclera template is defined as

$$Sclera\ area = \begin{cases} true, & \text{if } (R > 30, G > 25, B > 44) \\ false, & \text{otherwise} \end{cases}. \quad (7)$$

Then, the extracted areas of the sclera templates at different distances are resized using bilinear interpolation into a unified size depending on the requested resolution. Eye corner points (c_l, c_r) and internal corner points (c_1, c_2, c_3, c_4) are utilized as a reference points to align each sclera part into fixed position. Distance scaling examples are shown in Fig. 6b.

Fig. 7: Boxplots of fm measure for the UBIRIS.v1.S1, UBIRIS.v2 at 4-5-6 meters, and MICHE iPhone 5 and Samsung Galaxy S4 databases.

Fig. 8: Histogram distributions of fm values for constrained and unconstrained eye image datasets.

VI. RESULTS AND DISCUSSION

A. fm Measure for Employed Datasets

For the sclera image quality measure, we used the fm measure to classify each image according to the sharpness and smoothness of the edge components within the image. Most recent work on sclera recognition which achieved high recognition rates has used the UBIRIS.v1 database. Therefore, we used it as an Excellent reference to other exploited databases in this paper. Boxplots of the fm measure for

(a)

(b)

Fig. 9: Sclera segmentation accuracy evaluation for different skin descriptor threshold th_s . Examples of using different skin descriptors for sclera segmentation. The left column represents from the top to bottom images from the MICHE iPhone 5, MICHE Samsung Galaxy S4 and UBIRIS.v2 at 4 meters databases. The middle column is the resulting sclera map when $th_s = 1$ while the right column is when $th_s = 6$.

the exploited databases are shown in Fig 7. The horizontal solid red line represents the median value, the bottom and the top of boxes are the first and the third quartile of fm values, the top and bottom whiskers are the extreme fm values, while the red cross represents outliers. It is observed that the median value for the constrained UBIRIS.v1 database is higher than the top extreme values and some of the top outlier values for the unconstrained imaging databases. This confirms how challenging it is to employ relaxed captured images in sclera recognition. However, trying to overcome these challenges will pave the way for practical sclera recognition system for real-time application. In addition, Fig. 8 shows the histogram distributions of the utilized datasets. For the constrained images, the majority of fm values are greater

TABLE III: Sclera segmentation accuracy of the proposed sclera segmentation with respect to GBU classification

Database	G			B			U		
	Correct	Fair	Poor	Correct	Fair	Poor	Correct	Fair	Poor
MICHE iPhone 5	43%	35%	22%	29%	40%	31%	18%	21%	51%
MICHE Samsung Galaxy S4	40%	36%	24%	25%	39%	36%	15%	28%	57%
UBIRIS.v2 at 4m	66%	22%	17%	42%	32%	26%	32%	40%	28%
UBIRIS.v2 at 5m	53%	18%	29%	37%	45%	18%	25%	35%	40%
UBIRIS.v2 at 6m	33%	43%	24%	30%	41%	29%	17%	37%	46%

than 200 whereas for unconstrained images, most of the fm values fall below the 100.

To classify each image according to the EGBU categories and for relaxed imaging capturing, we proposed the following classifier

$$Image\ condition = \begin{cases} E & \text{if } fm > 150 \\ G & \text{if } 100 \leq fm \leq 150 \\ B, & \text{if } 50 \leq fm < 100 \\ U, & \text{otherwise} \end{cases}, \quad (8)$$

where for each image condition, fm thresholds have been set empirically.

B. Sclera Segmentation Under EGBU Hypothesis

For the proposed sclera segmentation, first we compared the segmentation accuracy for each image according to their condition in terms of G, B, and U. We discarded the E category which mostly apply on the UBIRIS.v1 as we already evaluated the sclera segmentation on this database in [3], [22]. We manually segmented and labelled 250 images for each database resulting a total of 1000 images divided approximately equally among GBU image conditions. For the authentication protocol for sclera segmentation, a pixel binary classification method is used to calculate the total error pixels and accuracy defined as

$$Ep = \sum_{k=1}^n \sum_{i=1}^{w_o} \sum_{j=1}^{h_o} xor(bw_g(i, j), bw_t(i, j)), \quad (9)$$

$$Acc = 1 - \left(\frac{Ep}{n \times w_o \times h_o} \right) \times 100\%, \quad (10)$$

where Ep is the total number of incorrectly segmented pixels, n is the total number of segmented images, w_o and h_o are the width and the height of an input image respectively, and bw_g and bw_t are the binary maps for the ground truth and segmented sclera image respectively.

As shown in Table III, the sclera polynomial offset is classified for each GBU categories into correct where $Ep < 10$, fair where $10 < Ep < 30$, and poor where $Ep > 30$ pixels. It is expected that the G images have the highest correct segmentation rate where the UBIRIS.v2 at 4m has 66% and the rate decreased as the capturing distance increased. Whereas for the mobile images of the iPhone 5 and the Galaxy S4 achieved less segmentation rate where these images share most of the UBIRIS.v2 noise factors, but the lack of precise localization and fixed capturing distance introduced more challenge to sclera segmentation. While for the B and U classification, it is typical that the fair and poor segmentation are higher except for B images of the UBIRIS.v2 captured 4 meters where correct segmentation has the highest rate (42%).

In addition, we evaluated skin descriptors fusion for the unconstrained datasets in terms of a number of skin classifiers th_s required to achieve overall highest accuracy. As shown in Fig. 9a, for the UBIRIS.v2 at 4-5-6 meters, using at least any correct segmented pixel from the descriptor will achieve the highest accuracy while for the MICHE database for both devices, it requires all skin pixel descriptors to achieve the maximum segmentation accuracy. Some examples of the sclera segmentation with $th_s = 1$ and $th_s = 6$ for the skin descriptors are shown in Fig. 9b.

C. Sclera Template Rotation Alignment and Distance Scaling Evaluation

The simulations were performed using Matlab (version R2014a) on a PC with Intel core i5 3.0 GHz processor and 8.0 GB RAM. For the final part of the proposed system, we evaluated the STRADS method in terms of calculating the Equal Error Rate (EER), plotting ROC curves, and evaluating the processing times for the proposed system. For image enhancement, feature extraction and matching process, we

TABLE IV: The EER of the proposed sclera recognition with and without STRADS using the UBIRIS.v2 and MICHE databases

Method	With STRADS	Without STRADS
Database	EER (%)	
UBIRIS.v2 [17]	7.32	32.31
MICHE iPhone 5 [18]	7.69	36.54
MICHE Samsung Galaxy S4 [18]	9.06	34.07

Fig. 10: Normalized genuine and impostor scores for proposed STRADS using (a) the UBIRIS.v1, (b) the UBIRIS.v2, (c) MICHE iPhone 5, and (d) Samsung Galaxy S4 images.

used the complex-sclera method along with Kernel Fisher Discriminant Analysis (KFDA) with cosine similarity respectively proposed by Alkassar et al. [22]. For the UBIRIS.v2, the evaluation scenario has been achieved in multi-session contexts with F_G, R_G and L_G eye gazes. For each context, we used 2 images at a distance of 4 meters for training and 4 images at a distance of 5 and 6 meters for testing per user and gaze direction, and we averaged the resulting EER. While for the MICHE, we used 4 images for training and 4 for testing for both the iPhone 5 and Samsung Galaxy S4. K-fold cross-validation with the number of trials equal to five has been utilized in our evaluation.

Fig. 11: ROC curves of the proposed STRADS method for the UBIRIS.v2, MICHE iPhone 5, and MICHE Samsung Galaxy S4 datasets.

TABLE V: The process times of the proposed sclera system

Sclera Segmentation Steps	Run Times
Eye image fm measure	0.24 s
Sclera Segmentation	1.58 s
Eye gaze estimation	0.93 s
STRADS	0.16 s

As shown in Table IV, although the resulting EER after using the STRADS is not necessarily low, however, the average EER for the UBIRIS.v2 for 4,5,6 meters and the MICHE database have been improved significantly when applying the STRADS. The improvement rate is more than 25% for all exploited databases. This confirms the need for a rotation alignment and distance scaling method when dealing with sclera under relaxed imaging conditions. The normalized distribution of genuine and imposter scores using the UBIRIS.v1, UBIRIS.v2, and both MICHE iPhone 5 and Samsung Galaxy S4 images are plotted in Fig. 10. For the E images within the UBIRIS.v1 database, the distribution of genuine and imposter scores shows significant separation and thus low error rates. While for the GBU images, it is notable that as the UBIRIS.v2 images are less constrained in terms of the capturing process has not achieved by the participated users, therefore the matching score is better separated than the MICHE mobile devices images where users are responsible for capturing their images. In addition, ROC curves for the recognition rate as shown in Fig. 11 is evident that sclera recognition using relaxed imaging conditions and without user corporation is a major challenge which needs more investigation.

Finally, for the processing time evaluation, as shown in Table V, the proposed eye image quality measure and STRADS methods achieved significantly lower processing time (0.24s and 0.16s respectively). While the sclera segmentation process and eye gaze estimation consume higher times as the operation is pixel based and thus the greater the image resolution, the higher the processing time and the better sclera segmentation accuracy.

VII. CONCLUSION

In this paper, we proposed new methods for the quality measure metric, sclera segmentation and sclera template rotation alignment and distance scaling. The eye image quality measure is achieved by estimating the focus through high and low frequencies within the image using a practical method for real time application. Then, a fusion method involves fusing six eye skin descriptors and two sclera area maps is

utilized to overcome some artifacts introduced when a relaxed imaging capturing scenario is presented. Then, sclera template rotation alignment and a distance scaling method is proposed to tackle head pose and capturing distance variation. The evaluation process is achieved on the UBIRIS.v2 and MICHE iPhone 5 and Samsung Galaxy S4 databases and the results are promising in terms of how using unconstrained images could affect the sclera recognition and ways to overcome challenges introduced. Based on the reported results, there are some limitations which need to be considered when designing an efficient sclera segmentation. For instance, the segmentation process depends on the accuracy of the extracted iris position and centre. Another issue is that for higher resolution images, applying the proposed sclera segmentation is an exhausting process for mobile application as camera resolution is developing with time. In addition, fusing sclera features with iris and periocular features for unconstrained imaging capturing could lead to better recognition rates but more computational cost. All these factors need to be considered in future work.

VIII. ACKNOWLEDGEMENT

The first author would like to thank the Ministry of Higher Education and Scientific Research (MO-HESR), Iraq and Ninevah university for funding his PhD.

REFERENCES

- [1] Proenca, H., 'Iris Recognition: On the Segmentation of Degraded Images Acquired in the Visible Wavelength', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2010, **32**, (8), pp. 1502-1516
- [2] Smereka, J. M., Boddeti, V. N., Vijaya Kumar, B. V. K., 'Probabilistic Deformation Models for Challenging Periocular Image Verification', *IEEE Trans. Inf. Forensics Security*, 2015, **10**, (9), pp. 1875-1890
- [3] Alkassar, S., Woo, W. L., Dlay, S. S., Chambers, J. A., 'Robust Sclera Recognition System With Novel Sclera Segmentation and Validation Techniques', *IEEE Trans. Syst., Man, Cybern., Syst.*, 2016, (99), pp. 1-13
- [4] Derakhshani, R., Ross, A.: 'A new biometric modality based on conjunctival vasculature'. Proc. of Artificial Neural Networks in Engineering (ANNIE), 2006, pp. 1-8
- [5] Derakhshani, R., Ross, A.: 'A texture-based neural network classifier for biometric identification using ocular surface vasculature'. Int. Joint Conf. on Neural Networks (IJCNN), 2007, pp. 2982-2987
- [6] Crihalmeanu, S., Ross, A., Derakhshani, R.: 'Enhancement and registration schemes for matching conjunctival vasculature'. Proc. of the 3rd IAPR/IEEE Int. Conf. on Biometrics (ICB), 2009, pp. 1240-1249
- [7] Thomas, N. L., Du, E. Y., Zhou, Z.: 'A new approach for sclera vein recognition'. SPIE Defense, Security, and Sensing, 2010
- [8] Oh, K., Toh, K. A.: 'Extracting sclera features for cancelable identity verification'. 5th IAPR Int. Conf. on Biometrics (ICB), 2012, pp. 245-250
- [9] Zhou, Z., Du, E. Y., Thomas, N. L., Delp, E. J., 'A new human identification method: sclera recognition', *IEEE Trans. Syst., Man, Cybern. A*, 2012, **42**, (3), pp. 571-583
- [10] Das, A., Pal, U., Ballester, M. A. F., Blumenstein, M.: 'A new efficient and adaptive sclera recognition system'. IEEE Symp. on Computational Intelligence in Biometrics and Identity Management (CIBIM), 2014, pp. 1-8
- [11] Gottemukkula, V., Saripalle, S., Tankasala, S. P., Derakhshani, R., 'Method for using visible ocular vasculature for mobile biometrics', *IET Biometrics*, 2016, **5**, (1), pp. 3-12

- [12] Das, A., Pal, U., Ferrerc, M. A., Blumenstein, M.: 'SSBC 2015: Sclera segmentation benchmarking competition'. 7th Int. Conf. on Biometrics Theory, Applications and Systems (BTAS), 2015, pp. 1–6
- [13] Das, A., Pal, U., Ferrerc, M. A., Blumenstein, M.: 'SSRBC 2016: Sclera Segmentation and Recognition Benchmarking Competition'. 9th IAPR Int. Conf. on Biometrics (ICB), 2016, pp. 1–6
- [14] Zhou, Z., Du, E. Y., Thomas, N. L.: 'A comprehensive sclera image quality measure'. 11th Int. Conf. on Control Automation Robotics & Vision (ICARCV), 2010, pp. 638–643
- [15] Alkassar, S., Woo, W. L., Dlay, S. S., Chambers, J. A.: 'A novel method for sclera recognition with images captured on-the-move and at-a-distance'. 4th Int. Conf. on Biometrics and Forensics (IWBF), 2016, pp. 1–6
- [16] Proenca, H., Alexandre, L. A.: 'UBIRIS: A noisy iris image database'. Int. Conf. on Image Anal. and Process. (ICIAP), 2005, pp. 970–977
- [17] Proenca, H., Filipe, S., Santos, R., Oliveira, J., Alexandre, L. A.: 'The UBIRIS. v2: A database of visible wavelength images captured on-the-move and at-a-distance', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2010, **32**, (8), pp. 1529–1535
- [18] De Marsico, M., Nappi, M., Riccio, D., Wechsler, H.: 'Mobile Iris Challenge Evaluation (MICHE)-I, biometric iris dataset and protocols', *Pattern Recognition Lett.*, 2015, **57**, pp. 17–23
- [19] Phillips, P. J., Beveridge, J. R., Draper, B. A., *et al.*: 'An introduction to the good, the bad, & the ugly face recognition challenge problem'. IEEE Int. Conf. on Automat. Face & Gesture Recognition and Workshops, 2011, pp. 346–353
- [20] Pech-Pacheco, J. L., Cristóbal, G., Chamorro-Martinez, J., Fernández-Valdivia, J.: 'Diatom autofocusing in brightfield microscopy: a comparative study'. 15th Int. Conf. on Pattern Recognition, 2000, pp. 314–317
- [21] Daugman, J.: 'How iris recognition works', *IEEE Trans. Circuits Syst. Video Technol.*, 2004, **14**, (1), pp. 21–30
- [22] Alkassar, S., Woo, W. L., Dlay, S. S., Chambers, J. A.: 'Enhanced segmentation and complex-sclera features for human recognition with unconstrained visible-wavelength imaging'. 9th IAPR Int. Conf. on Biometrics (ICB), 2016, pp. 1–8
- [23] Alkassar, S., Woo, W. L., Dlay, S. S., Chambers, J. A.: 'Efficient Eye Corner and Gaze Detection for Sclera Recognition Under Relaxed Imaging Constraints'. 24th European Signal Processing Conf. (EUSIPCO), 2016, pp. 1–5
- [24] Lin, Y., Du, E. Y., Zhou, Z., Thomas, N. L.: 'An Efficient Parallel Approach for Sclera Vein Recognition', *IEEE Trans. Inf. Forensics Security*, 2014, **9**, (2), pp. 147–157
- [25] Hosseini, M.S., Araabi, B. N., Soltanian-Zadeh, H.: 'Pigment Melanin: Pattern for Iris Recognition', *IEEE Trans. Instrum. Meas.*, 2010, **59**, (4), pp. 792–804