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SSERBC 2017: Sclera Segmentation and Eye Recognition Benchmarking Competition

Abhijit Das[a,d], Umapada Pal[b], Miguel A. Ferrer[c], Michael Blumenstein[a,d], Dejan Štepec [e], Peter Rot[e], Žiga Emeršič [e], Peter Peer, Vitomir Štruc [e], Aruna Kumar S V[f] and B S Harish[f]

[a]Institute for Integrated and Intelligent Systems, Griffith University, Queensland, Australia
abhijit.das@griffithuni.edu.au, m.blumenstein@griffith.edu.au
[b]Computer Vision and Pattern Recognition Unit, Indian Statistical Institute, Kolkata, India
umapada@isical.ac.in
[c]IDeTIC, University of Las Palmas de Gran Canaria, Las Palmas, Spain
mferrer@dsc.ulpgc.es
[d]School of Software, University of Technology Sydney, Australia, michael.blumenstein@uts.edu.au
[e]Faculty of Computer and Information Science, University of Ljubljana, Ljubljana
dejan.stepec@xlab.si, Peter.Peer@fri.uni-lj.si, Ziga.Emersic@fri.uni-lj.si,
peter.peer@fri.uni-lj.si, vitomir.struc@fe.uni-lj.si
[f]Department of Information Science and Engineering, Sri Jayachamrajendra College of Engineering, Mysusru, Karnataka, India
arunkumarsv55@gmail.com, bsharish@sjce.ac.in

Abstract

This paper summarises the results of the Sclera Segmentation and Eye Recognition Benchmarking Competition (SSERBC 2017). It was organised in the context of the International Joint Conference on Biometrics (IJCB 2017). The aim of this competition was to record the recent developments in sclera segmentation and eye recognition in the visible spectrum (using iris, sclera and peri-ocular, and their fusion), and also to gain the attention of researchers on this subject.

*In this regard, we have used the Multi-Angle Sclera Dataset (MASD version 1). It is comprised of 2624 images taken from both the eyes of 82 identities. Therefore, it consists of images of 164 (82*2) eyes. A manual segmentation mask of these images was created to baseline both tasks.*

Precision and recall based statistical measures were employed to evaluate the effectiveness of the segmentation and the ranks of the segmentation task. Recognition accuracy measure has been employed to measure the recognition task. Manually segmented sclera, iris and peri-ocular regions were used in the recognition task. Sixteen teams registered for the competition, and among them, six teams submitted their algorithms or systems for the segmentation task and two of them submitted their recognition algorithm or systems.

The results produced by these algorithms or systems reflect current developments in the literature of sclera segmentation and eye recognition, employing cutting edge techniques. The MASD version 1 dataset with some of the ground truth will be freely available for research purposes. The success of the competition also demonstrates the recent interests of researchers from academia as well as industry on this subject.

1. Introduction

In the recent literature, ocular biometrics in the visible spectrum is extensively researched. Among them, iris, sclera and the peri-ocular are the employed traits. Peri-ocular is the area around the eye, which consists of pattern that can be used as a biometric trait [1]. The sclera is the white region in the eye, which contains blood vessel patterns that can be employed for personal identification [3]. The very recent literature refers to the success of sclera biometrics among other ocular biometric traits [4-6].

The major reason for the popularity of ocular biometric in the visible spectrum is due to its applicability in the mobile environment. The majority of the mobile available, their camera sensor capture images in the visible spectrum. The performance of iris biometrics in the visible spectrum for darker irises is very low. The sclera or peri-ocular biometric in conjunction with the iris biometric can enhance the relevance of the iris biometric in the mobile environment.

As emerging traits, it is first necessary to assess the biometric usefulness of the sclera and peri-ocular independently. Moreover, the research conducted on this subject is very limited. Additionally, sclera segmentation is found to be a very significantly important part of sclera biometrics. However, sclera segmentation has not been investigated as a separate topic in the most of the work reported in the literature, but mainly summarised as a component of a broader task.

Moreover, independent works on sclera segmentation, which are addressed in the literature, were evaluated employing independent in-house datasets or on public datasets with fewer challenging sclera images. Therefore, to set a common platform for the evaluation of sclera segmentation the 1st Sclera Segmentation Benchmarking Competition (SSBC 2015) and 1st Sclera Segmentation and Recognition Benchmarking Competition (SSRBC 2016) was organized in the context of the IEEE Seventh International Conference on Biometrics: Theory, Applications and Systems BTAS 2015 and 9th IAPR International Conference on Biometrics (ICB 2016). The successful organisation and the appreciating impact of these competitions have inspired the organisers to plan further competitions on sclera segmentation and eye recognition namely: SSERBC 2017. The competition also aimed to benchmark ocular biometric in the visible spectrum using a common dataset and common set of protocol. This benchmarking was required because of the several independent works performed on this subject using independent dataset, varying fusion technology and protocol. Therefore, this benchmarking and the protocol will help to set a platform for fair comparisons of the work on this subject.

The main aim of the competition is to establish a standard benchmark for eye recognition in the visible spectrum with a common dataset and also to record the recent developments of sclera segmentation that took place after SSRBC 2016. In addition, this competition was also aimed to attract the interest of researchers on this particular subjects. As the conceived competition is related to biometric research, so it was organised in the context of the International Joint Conference on Biometrics (IJCB 2017).

The rest of this paper is organised as follows. In Section 2 the competition schedule, the dataset for the competition and the performance evaluation technique adopted to evaluate and rank the participant's algorithm are described. In Section 3, various algorithms from the participants are described in details, in Section 4 the results achieved from the submitted algorithms and their detailed analysis is summarised. Finally, the last section i.e. Section 5, the overall conclusions are drawn and the future scope of this research is discussed.

2. The SSERBC 2017 competition

The competition schedule is shown in Table 1.

Table 1: Schedule of the competition

Different Phases	Dates
Competition website opens	10th December 2016
Registration starts	10th December 2016
Test dataset available	10th December 2016
Registration closes	15th May 2017
Algorithm/system submission	15th May 2017
Results announcement	31st May 2017

The competition was promoted through the website of the competition and further communications were made by email to the researchers. Sixteen participants registered for the competition from distinguished laboratories of academia and industry, located in different countries. Among them, five teams submitted their segmentation algorithms, one of them submitted their recognition algorithm and one of the team submitted both tasks. Table 2 reflects the name and the affiliation of participants who submitted their algorithms.

The Multi-Angle Sclera Database (MASD version 1) used in SSBC 2015 is employed in this competition for the segmentation task [8]. A graphical application was developed using Matlab 7 in the Windows 7 Operating System environment to generate manually segmented masks or ground truths of these sclera images in the dataset, in order to obtain a baseline to evaluate the automatic segmentation algorithms.

For the recognition task, segmented sclera images were developed by masking the eye images with their respective manual segmented masks. Iris and peri-ocular images were segmented by the same graphical application used to obtain the manually segmented sclera mask. A set of images at different angles, their manual segmented mask and the masked eye with manually segmented masks are shown in Figure 1.

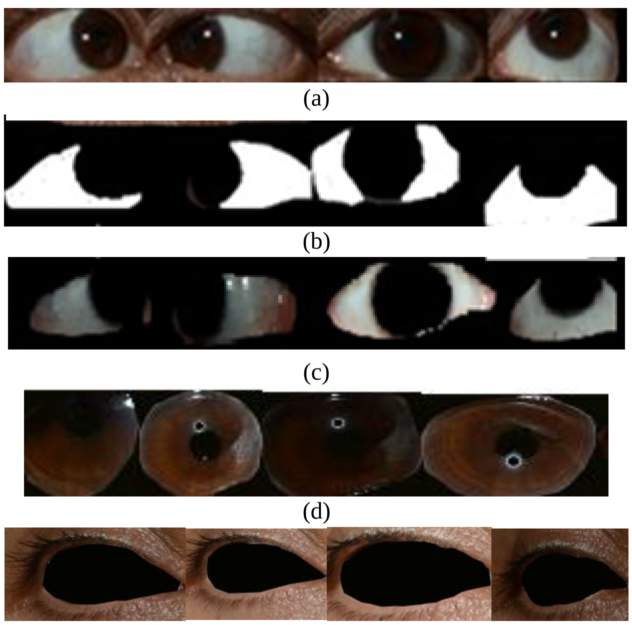
Table 2. Descriptions of the teams details those who submitted their system

Teams	Name (Institution)/ Task
1	Aruna Kumar S V, B S Harish (SJCE, Mysuru, Karnataka, India) /segmentation and recognition
2	Chandranath Adak (Griffith University, Australia / recognition
3	Rassoul Mesbah, Brendan McCane (University of Otago, New Zealand) /segmentation
4	Daniel Riccio[a,b], Nadia Brancati[b], Maria Frucci[b], Diego Gragnaniello[b] ([a]Universita' di Napoli Federico II, Naples, Italy, [b]Institute for High Performance Computing and Networking, National Research Council of Italy, Naples, Italy) /segmentation
5	Dejan Štepec, Peter Rot, Žiga Emeršič, Peter Peer, Vitomir Štruc, (Faculty of Computer and Information Science, Ljubljana)/segmentation
6	Sumanta Das, Ishita De Ghosh (Barrackpore Rastraguru Surendranath College, Kolkata, India) /segmentation
7	Abhishek Misra, Ashes Roy, Ishita De Ghosh (Barrackpore Rastraguru Surendranath College, Kolkata, India) /segmentation

For algorithm or system development purposes of segmentation task, a subset of the database and ground truths (1 image for each angle of the first 30 individuals i.e. 120) were provided to the registered participants of the competition. The participants were asked to provide a program that can read the images from a directory and writes the segmented mask in a particular directory with a naming convention. For the ease of evaluation and to maintain the real-time property of the submitted algorithm, the participants were asked to submit a system which does not take more than 10 seconds to segment and generate the mask for an image on an Intel Core i7 processor.

For the recognition task, 16 images i.e. 4 images for each angle of 10 subjects were provided. The participants were required to provide a program file that can read the images from a directory and generate the training model. Another separate program file that can read images from a directory prompts which class it belongs to.

The evaluation segmentation task can be done with respect to the manually segmented mask is a pixel level binary classification, so a precision and recall measure is employed as a performance measure. The recall is considered the measure for ranking the algorithms if the average precision of the submission is found to be same. The mathematical representation of the precision and recall for our scenario is shown in the following equations.



(a) (b) (c) (d) (e)

Figure 1: (a) A set of images with different angles, (b) their manual mask with only sclera region, (c) masked eye with manually segmented sclera, (d) manually segmented iris, (e) manually segmented peri-ocular.

$$\text{Precision } = \frac{\text{NPAM}}{\text{NPRS}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$\text{Recall in } = \frac{\text{NPAM}}{\text{NRMS}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where,
NPAM =Number of pixels retrieved in the sclera region by the automatically segmented mask
NPRS =Number of pixels retrieved in the automatically segmented mask.
NRMS =Number of pixels in the sclera region in the manually segmented mask

For the recognition task, the recognition accuracy was considered for the performance measure.

$$\text{Accuracy in \%}= \frac{\text{NCRS}}{\text{NS}} * 100 \quad \ldots\ldots\ldots..(3)$$

Where,
NCRS= Number of Correctly Recognised Samples
NS= Number of Samples.

3. Brief description of the submitted algorithm

The six segmentation and two recognition algorithms submitted by the six participants are described in this section.

3.1. Segmentation algorithm by participating team 1

The team proposed a modified intuitionistic fuzzy clustering algorithm for sclera segmentation. Intuitionistic Fuzzy Clustering (IFC) is a variant of traditional Fuzzy C-Means (FCM) and it is based on Intuitionistic Fuzzy Set (IFS) theory. Unlike FCM, the proposed clustering method uses both membership and non-membership values. They used modified Hausdorff distance metric to compute the distance between cluster centre and pixel.

3.2. Segmentation algorithm by participating team 3

The algorithm proposed by this team was based on a feed-forward deep convolutional encoder-decoder architecture. The module is trained based on the 32$\times$32 random samples from the grey scale colour map of the eye images. To generate the output image (labelled image), the module should be fed by 32$\times$32 cropped frames (non-overlapping) and all the pixels in the frame (1024 pixels) will be labelled simultaneously. It was implemented by torch7 (http://torch.ch/) and cutorch library (https://github.com/torch/cunn) installed on a Linux or OS X (Mac). For the ease of the implementation, the input images were greyscaled and resized to 700$\times$1000 pixels. GPU based training with 16 batch-sizes and learning rate 0.1 was used in this work.

Because of some technical problems due to the implementation platform and time constrain the system could not be evaluated on the total dataset. The mask generated by the test dataset distributed during the competition achieved around 90% of pixel-wise accuracy.

3.3. Segmentation algorithm by participating team 4

The proposed sclera segmentation algorithm was based on the assumption that the pixels belonging to the sclera have high grey level values in all three channels R, G and B. First step of this method is to highlight this feature and next the three channels are merged into a single grey level image. A clustering was performed to partition the image into different regions and a selection of the connected components is carried out to choose the regions representing the sclera. The algorithm is composed of the following steps: 1) image processing; 2) grey level clustering, and 3) connected components selection.

1) Image Processing-For each channel R, G and B, the grey level values are mapped in the range [0,1] using a "quasi-sigmoidal" function, to saturate grey level values that exceed a given threshold value. We compute such a threshold as:

$$mn = \min(nR, nG, nB), \qquad (4)$$

Where,
$nR = mean(R)+std2(R)/2$, $nG = max(G)+std2(G)/2$, $nB = max(B)+std2(B)/2$.

It was worth noting that, since the channel R has higher grey level values than G and B (for the presence of skin pixels), so the contribution of the red channel for the computation of the normalisation parameter should be lower than that given by green and blue channels. For this reason, the mean rather than maximum is considered in equation 4. The channels are merged to obtain a grey level image, using the relationship:

$$Qsc = B+G-R \qquad (5)$$

In the computation of the grey level image Qsc, the red component is subtracted, because its pixels assume high values in correspondence of both the sclera and the skin areas. Instead, we sum together the green and blue components, which are sensibly greater than zero only in the sclera area. Then, a full-scale histogram stretch of Qsc in the range [0,255] is performed.

2) Grey level Clustering: The clustering of Qsc is obtained taking into account the following features:
a) Weighted difference among gray level values $|p(gi)\, gi - p(gj)\, gj|$;
b) Real difference among grey level values $\log(|gi-gj|+1)$;
c) Sparsity σ (Igi, Igj).

3) Connected components selection: The foreground regions are detected on the basis of the following features:
a) Compactness of the region;
b) Ratio between area of region and area of the convex-hull enclosing the region;
c) Proximity to the centre of the image.
Based on these features, a score for each region of the foreground is computed. Finally, the regions are sorted in a descending order of score and the first region is marked as the sclera. Moreover, other regions are marked as sclera if the following conditions hold:
i) The score is greater than the 70% of the score of the first selected region;
ii) The regions are aligned along the horizontal axis.

3.4. Segmentation algorithm by participating team 5

This group from the University of Ljubljana (UL) participated in the sclera segmentation challenge using SegNet deep convolutional encoder-decoder [10]. The architecture was implemented in Caffe. They added 50 images (gathered "in the wild") with corresponding hand-made annotations to the existing 130 images in the training dataset. From each image out of those 180 images, 300 perturbations were made. Together they have generated approx. 54000 images. Perturbations were a combination of the following operations: cropping, Gaussian blur, additive Gaussian noise, brightness changes, contrast normalisation and affine transformations (scaling and rotation) similar as in [11]. Original images from train set and their perturbations were resized to 640 x480 pixels and were used as an input for the SegNet convolutional network. The model was trained with 30000 iterations (with a batch size 4). In the test phase, the first step is to resize images to 640x480 pixels and store the original size of each input image. The output of SegNet are masked where pixel value 0 corresponds to the prediction of background and 1 to the prediction of the sclera. The image size of those masks is as expected 640x480 pixels, so the final step is to resize those masks to the original sizes of input images.

3.5. Segmentation algorithm by participating team 6

The blue channel of the input RGB image was extracted and smoothed. Next, the smooth image was preprocessed by eliminating the corners of the image. If the image was too dark a histogram equalisation was performed, followed by calculating spatial colour relation. Spatial colour relation calculates the number of pixel colour pairs in the entire image (colour correlogram with distance 1). To get the gaze angle of the eye a distance matrix between the query image and mask of different gaze angle (already generated manually from other eye images) was calculated. The combination produced the minimum distance, the gaze of the corresponding manually generated mask was considered as the gaze. The input image was cropped from the top, bottom and left, right by 5% of width and length respectively. If the cropped image is very dark a histogram equalisation was performed. Next spatial colour relation of the cropped image followed by distance matrix calculation with the base image is performed. If distance value is less 1000, repeat all the steps performed. Further, repeat all the steps till the distance value of the iteration is not greater than previous iteration distance value. By this, it almost eliminates the background skin colours. The threshold was done to the processes image for getting the binary segmented image. The threshold is set to 160 for fair images and 65 for dark images.

3.6. Segmentation algorithm by participating team 7

Step 1: The input image was pre-processed.
Step 2: Apply dilation
Step 3: Filling the holes.
Step 4: Clear the border of the image.
Step 5: Apply erosion.
Step 6: Apply post-processing.
Step 7: Remove the small non-sclera area.

3.7. Eye recognition algorithm by participating team 1

The proposed sclera recognition system consists of two steps: Feature Extraction and Matching.
Feature Extraction: The proposed recognition system uses Pyramid Histogram of Oriented Gradients (PHOG)

descriptor to extract the features from segmented sclera image. PHOG is a spatial shape descriptor, which represents an image by its local shape. It also preserves the spatial information of that shape. PHOG feature extraction process consists of following steps:

Step 1: The image is divided into cells at several pyramid level. The grid at level *l* has 2^l cells along each dimension.

Step 2: The Histogram of Oriented Gradients (HOG) for each grid at each pyramid resolution level is computed

Step 3: The PHOG descriptor for an image is computed by concatenating all the HOG vectors at each pyramid resolution. A feature level fusion method was used to fuse sclera, iris and peri-ocular feature.

Matching: The proposed method adopts k-Nearest Neighbour (k-NN) as pattern classification technique. The nearest neighbour classifier is based on learning by analogy, that is by comparing a given test sample with training samples which are similar to it. During the training phase, PHOG features are extracted from the training images and further they are used to train the k-NN classifier. In the testing phase, k-NN classifier searches the pattern space for the k training samples which are closest to the test sample and assigns a class label based on voting strategy.

3.8. Eye recognition algorithm by participating team 2

The well-known Gabor features are extracted by this team. The team has set the number of scales (u=5), a number of orientations (v=8), no. of rows (m=39) and columns (n=39) of a 2-D Gabor filter. The feature vector is also down-sampled to a size of 720.

For this purpose, the team has used canny edge detection algorithms and has found the 3 types of density distributions over the sclera image. So, a density-based feature vector of size 3 has also been employed. The proposed method adopts the k-Nearest Neighbour (k-NN) as a pattern classification technique. A feature and image fusion level method were used to fuse sclera, iris and peri-ocular feature. Image level fusion outperformed in this scenario. A sclera pre-processing technique used in [9] was employed here. The red channel of the manually segmented iris images was used as the input.

4. Discussion and results

In this section, we summarised the results achieved after applying the submitted algorithms on the MASD version 1 dataset for segmentation and recognition tasks.

4.1. Sclera segmentation results and discussion

We maintained the protocol for submissions of the algorithm and then evaluated them by a common framework and ranked them to maintain a fair and unbiased competition among the participants. Through this publication, the participants can find the performance of their methods relative to the others. The results were obtained on the dataset comprised of 2624 images. In Table 3, the final quantitative results are presented for the five segmentation algorithms in the competition.

As far as our competition protocol was concerned, we ranked the results by the precision and further ranked by the recall for any duplicated ranks generated. We can conclude from the Table 3 that appreciable segmentation performance was achieved in the most of the submitted systems. The performance of the system submitted by team 5 was the best with respect to precision as well as recall performance. The performance gap with the next ranking system is about ~10% for precision and recall.

With qualitative analysis also the performance of the system from team 5 was found to be best. Therefore we further analysis masks generated by the system of team 5. Some examples of the mask and the corresponding images are given in Figure 2.

Table 3. Final results of the participants (in %).

Rank	Participating teams	Precision in %	Recall in %
1	5	95.34	96.65
2	4	85.59	64.60
3	7	76.45	62.89
4	1	55.72	88.16
5	6	53.91	49.92

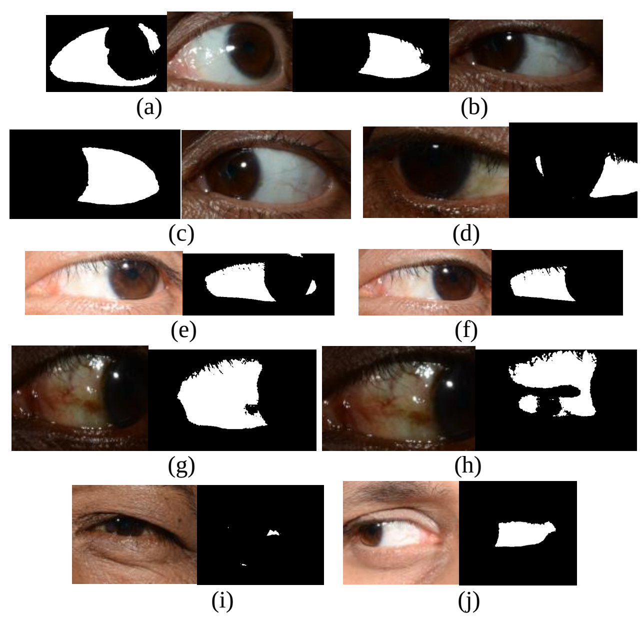


Figure 2: Examples of the mask produced by system of team 5 and the corresponding images

The major misclassification that can be found is: the dark vein or the sclera part are misclassified as the background 5(h), eye corner misclassified as foreground 5(a, j), and the skin area misclassified as in 5(i). The performance of the algorithm varied mainly due to illumination change and also due to the illumination distribution over the image 5(b and c). The most important highlighting part of the analysis is that the in some occasion the performance varied with similar illumination 5(e and f, g and h). Moreover, for a similar type of images in some occasion it worked 5(g), for the other cases it failed 5(h). Perhaps more rigorous training can solve these misclassifications.

For further analysis, we observed the best algorithms of SSBC 2015 and SSERBC 2016 [2, 8]. The performance of the algorithm of team 5 was found to be better in both the quantitative and qualitative aspect. Moreover, from the detailed experimental analysis, we found that the variations of illumination and other changes highlighted affected those algorithm more in comparison to the algorithms of team 5.

Therefore from the above mention analysis, we can conclude that the above-mentioned challenges i.e. the variation in illumination globally in the image as well as locally affected the performance of the sclera segmentation, and keeps sclera segmentation as an open research area. To solve some these challenges, preprocessing of the eye images could help (i.e. avoiding scenarios such as the introduction of sclera vessel patterns in the mask etc.).

4.2. Sclera recognition results and discussion

For training and testing, we divided the dataset irrespective of the gaze angle. Two images from four different gaze angles were used for training and the remaining two for testing. In Table 4 the final quantitative results are presented for the two recognition algorithms in the competition. As far as our competition protocol was concerned, we undertook the ranking by the accuracy percentage achieved by the algorithms.

Table 4. Final recognition results for each participant

Rank	Participating teams	Accuracy in %
1	1	72.56
2	2	72.01

It can be concluded from the above table that the recognition accuracy attended by both systems submitted was quite similar. The systems have not achieved higher performance with respect to the other algorithms proposed in SSRBC 1 and the work of [7] have achieved better performance. Perhaps cutting age featuring [12, 13] and classification method are required investigating this subject of research to attend better recognition performance.

5. Conclusions and Future Scope

The 1st Sclera Segmentation and Eye Recognition Benchmarking Competition, SSERBC 2017 was organised with the primary goals to record the recent advancements in sclera segmentation and eye recognition techniques in the visible spectrum. Moreover, it also aims to provide a common platform to evaluate sclera segmentation and eye recognition algorithms using a unique multi-angle eye dataset. Subsequently, the showcasing of the competition in one of the most recognised gatherings in the biometric community i.e. IJCB 2017 and promoting them via different electronic means of communications, have also increased the interest of researchers using this particular subject of research in biometric. Furthermore, the conceived competition has satisfactorily fulfilled all of the above aims, and the gain in popularity and interest of the participants were noteworthy. The algorithms submitted by the participants demonstrate appreciable results on our proposed dataset. We hope the critical analysis undertaken on the results of the different algorithms will also provide a way forward for further research.

One very important aspect of the research is the availability of datasets publicly, which is enriched with a wider variety of multi-angle or eye gaze scenarios. In addition, to the best of our knowledge, no such datasets are publicly available, and the availability of this proposed dataset will fill that gap.

The successful organisation and the appreciating impact of this competition have inspired the organisers to plan further competitions on the sclera and eye biometrics paradigm in the near future.

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