Blood Vessel Detection from Sclera Images

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***Abstract*—After segmentation of the sclera area from the eye image, the next step for recognition of an eye is extraction of blood vessels within sclera, which do not change over time and is unique to every person. The method does not search for red patches on the sclera, but looks for line patterns on the sclera which are blood vessels, which is an essential requirement, as red patches for two eyes may appear similar under certain conditions. Contrast limited adaptive histogram equalization has been used to enhance the image. Images of detected vessels of two different images of same eye look very similar, even under low illumination. A trivial comparison logic is able to compare all images with minimal false accepts. Since the method is independent of colour of the vessels, it can be easily adapted to most real life situations.**

***Index Terms*—Blood Vessel Segmentation, Sclera Recognition, Pattern recognition**

I. INTRODUCTION

Sclera is a tough transparent membrane that covers almost eighty percent of the human eye-ball. The random arragement and interweaving of connective fibrils in sclera gives strength and flexibility to the eyeball. Sclera has a limited blood supply and is relatively inactive metabolically. Although some blood-vessels pass through the sclera to other tissues, it is considered avascular. Some of the nourishment of the sclera comes from the blood-vessels in the episclera which is a thin, loose connective tissue layer that covers the sclera. In [1] Anterior portion of the sclera is seen as the white portion in the visible part of the eye. Blood vessel pattern visible in the white of the eye contain relatively larger episcleral blood vessels. The pattern is referred to as sclera blood vessel pattern which is unique to every person and do not change over time. So the pattern can be used for eye recognition.

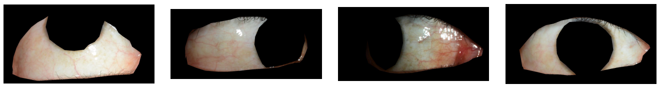
Detection of blood vessels from the sclera region of the eye-images is a relatively new reserach area and its applications include biometric, disease diagnosis and eye-image beautification. Eye-images from which blood vessels are to be detected contain iris and peri-ocular region in addition to sclera region. So sclera region when segmented manually or automatically from the eye-image, contain a few undesired patches of iris-portion and skin-portion along with eye-lashes.

In [2], methods have been reported which detect red pixels from white sclera and take them to be blood vessel pixels. They work well for eyes under normal conditions. But abnormal conditions like eye-disease, alcohol consumption or hypertension may result in red patches all over sclera. Hence identification of red pixels may not be suitable for blood vessel detection. Another problem is presence of very thin vessels. They are present almost everywhere in the sclera and are not visible always. Hence they are not being considered for recognition purpose. Undesired red patches and very thin vessels in sclera and hairs of eye-lashes occluding sclera must not be identified as sclera blood vessels. Last but not the least, poor illumination may result in low-contrast images and hence non-prominent vessel structure. All these together make detection of sclera blood vessel pattern a challenging task.

This work proposes a method for detection of blood vessels from sclera-segmented eye-images from which peri-ocular, most of hair, skin and iris portions have been removed. In most of the previous work, sclera blood vessel detection is done either by thresholding or by using Gabor wavelet based filters. Proposed method uses thresholding and feature extraction techniques. It gives good results on SSERBC Recognition dataset. The paper is organized as follows. Section II gives a brief review on related work; section III describes the proposed method; section IV presents experimental results; finally concluding remarks are given in section V.

II. PREVIOUS WORK

Following is a brief review on related work. In [1], Derakshani and others proposed a sclera recognition methodology based on manual sclera segmentation for a in-house database. They first applied CLAHE technique for enhancing the green plane of RGB image and then used a multiscale growing approach to identify sclera vessels. In [2], Zhou and others proposed a method in which automated sclera segmentation was done using pixel thresholding. UBIRIS database was used for recognition. The method estimated glare area, iris boundary, eyelid and detected sclera region. Gabor wavelet-based method was used to extract the sclera vessel patterns. In [3], Saranya and others proposed a Gabor wavelet based sclera pattern segmentation method, and an adaptive thresholding scheme to underscore and binarize the sclera vein patterns. Then proposed a line descriptor based registration that is scale, orientation, and distortion-invariant, and can moderate the multi-layered deformation effects and tolerate



(a) UpFront (b) Right (c) Left (d) Front

Fig. 1: Few images of the SSERBC dataset as input and their manually labelled gaze directions.

segmentation error. In [4], Rane and others proposed a method which segments sclera using otsu's thresholding and employs iris boundary detection, gaze detection, a filter used for feature extraction of vessel, adaptive thresholding methods are used to remove illumination. In [5], Athira and others proposed a method to estimate the potential sclera area by color distance map for both natural and flash illuminator. Gabor filter is used for filtering the blood vessels. In [6], Parab and others presented a paper in which they used the gabor filter for extraction of blood vessels within the sclera. The Red and Green layers of the RGB image is used as many people have blue coloured iris. Das and others organised a competition in a International Conference on Biometrics in 2017 [7]. Multi-Angle Sclera Dataset (MASD v1) was presented which comprised of 2624 images taken from both the eyes of 82 identities. Multiple methods were proposed by seven teams with the best results for recognition had an accuracy of 72.56% which used Pyramid Histogram of Oriented Gradients (PHOG) descriptor to extract the features from segmented sclera image.

III. Proposed Blood Vessel Segmentation Method

Since sclera vessel structure is a complex one, and detection of the same is not a trivial task, a short description of the structure is given here. Sclera contains a number of layers, viz. episclera, stroma, lamina fusca, and endothelium. Conjunctiva is the top-most transparent layer on sclera. From the frontal view of a sclera, it is difficult to identify the layer to which a blood vessel belongs. In general, the conjunctival vessels is hard to see with the naked eye at a distance and the prominent vessels seen in the sclera comes from the upper layers and the blurred vessels seen comes from the lower layers. For young children, the blood vessels in sclera area are observed to be blue in color, but for adults, the blood vessels are red in color.

The proposed work is described now. For this work, images from SSERBC-2017 dataset which were used for Sclera Recognition Competetion were used. A brief description of the dataset is given now. The dataset consists of images of 10 different eyes. For each eye 12 to 16 images are given. They are of 4 different gaze directions (looking straight, left, right and up). There are total 151 images. They are sclera-segmented colour images from which peri-ocular, hair, skin and iris portions have been removed. So an input image has coloured sclera region as foreground on a background which is completely black. Some images of the dataset are shown in Fig 1. As discussed before sclera has multiple layers, and top layers contain wide and prominent vessels. The question is whether blood vessels of every layer and every width is essential to detect for recognition purpose. It is seen by experimentation that prominent vessels vary in width from 5 to 10 pixels mostly. Vessels of smaller width are not prominent, seem to be scattered all over the sclera, and hence are not considered suitable for recognition. So prominent vessels of width 5 to 10 pixels are considered in our work. Blood vessels should be in high contrast to its surroundings, and hence contrast-limited adaptive histogram equalization (CLAHE) is performed separately on Red, Green and Blue planes of input RGB image twice. It is now observed that the Blue plane can easily distinguish the blood vessel from the sclera region. Removing the hairs in the eye-lashes that occlude the sclera region is a difficult task. This is done by forming a mask image.

A. Forming the Mask

To remove the hairs, a mask is formed which stores logical 1 for the true sclera region and logical 0 for the background. Mask creation is done in the following way. At first histogram equalized blue layer is converted to binary. Then the binary image is eroded by using a square of 10 pixels slided all over it. This removes the pixels in the sclera boundary, which contains small skin regions. The next step is thresholding of the RGB image. If R, G, B, are intensities of the red, green and blue layers of the RGB image, then the following thresholding removes the hair like structures to some extent along with few blood vessels.

$$|R-G| < 15 \; and \; |R-B| < 15 \; and \; |G-B| < 15 \; and \; R < 100$$

The mask is then eroded with square of 2x2 pixels to open the path of hair like structures to the black background. In order to recover the holes in the sclera region which are blood vessels, the mask is then complemented. Connected small components are removed, and complemented again to get sclera without any holes. Further the mask is eroded with a square of size 10 pixels. Further the following thresholding brings back the red blood vessels,

$$|R-G| > 15 \; and \; |R-B| > 15 \; and \; R > G \; and \; R > B$$

Mask so obtained is used in later stages. The process is described in a schema diagram given in Fig 2 and an example is given in Fig. 3.

B. Detection of Blood vessel like patterns

The other part of the algorithm uses the blue layer after applying CLAHE twice on the input image for feature extraction within blocks of the sclera region. The algorithm is designed so that it can be run on multiple threads, on multiple processing units independently. Patterns are considered blood vessels within the block if the middle most part of the block, longitudinally, contains the darkest pixels and longitudinally, the outer most part of the block gradually increases the intensity of the pixels. It is observed that most of the vessels are about 5 to 10 pixels in width. Fig 4 represents the skeleton of the block used.

$$Upper = \frac{\sum_{r=1}^{r=x-1} \sum_{c=1}^{Scol} [Pixel\_Intensity(r, c)]}{(x-1) * Scol} \quad (1)$$

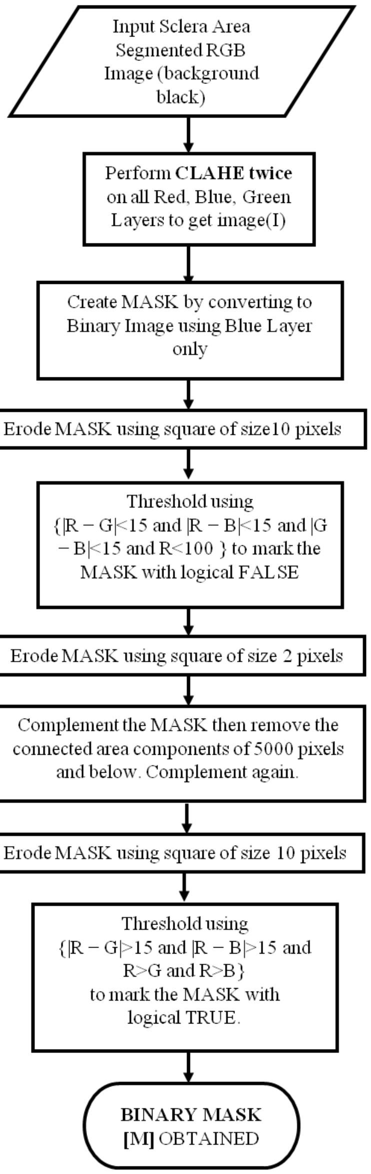
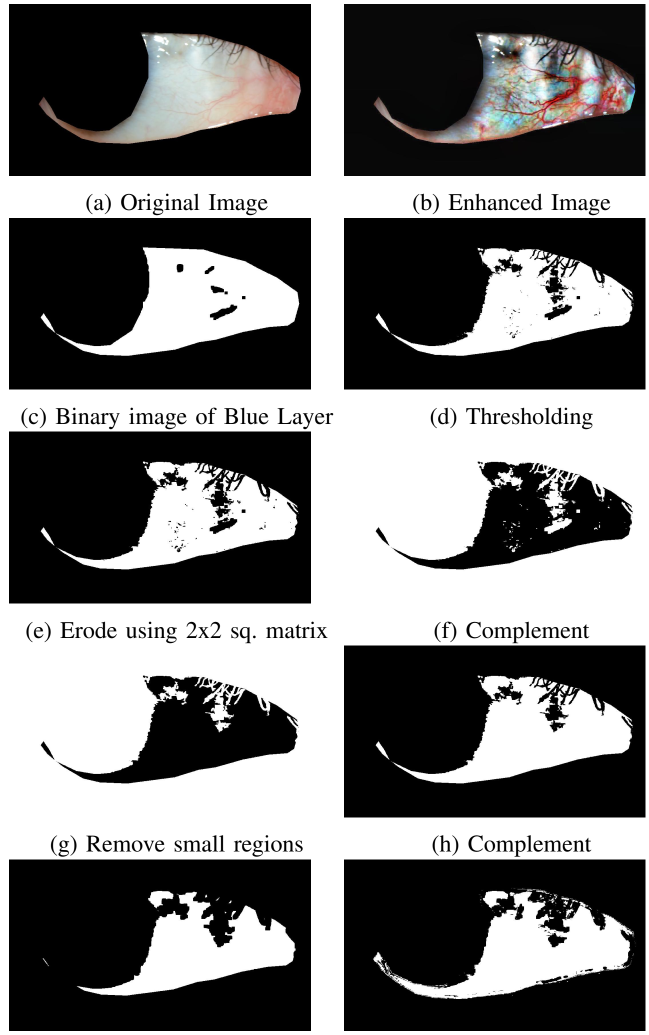


Fig. 2: Forming the MASK

$$Middle = \frac{\sum_{r=x}^{r=y} \sum_{c=1}^{Scol} [Pixel\_Intensity(r, c)]}{(y - x + 1) * Scol} \tag{2}$$

$$Lower = \frac{\sum_{r=y+1}^{r=Srow} \sum_{c=1}^{Scol} [Pixel\_Intensity(r, c)]}{(Srow - y) * Scol} \tag{3}$$

The equations 1, 2, 3, computes the average intensity of pixels of the upper, middle & lower part of the block. where, (Srow,Scol) is the dimension of the block, here (19 x 20), middle part of the block contains blood vessels, considered 7 th to 13 th row where x is 7 and y is 13, 'r' and 'c' represents row and coloumn number of the block, Pixel_Intensity(r,c) denotes the intensity of the pixel within the block of the image



(a) Original Image

(b) Enhanced Image

(c) Binary image of Blue Layer

(d) Thresholding

(e) Erode using 2x2 sq. matrix

(f) Complement

(g) Remove small regions

(h) Complement

(i) Erode using square matrix of size 10

(j) Threshold to get back the pixels of red color

Fig. 3: The MASK so formed shall be applied at a later stage

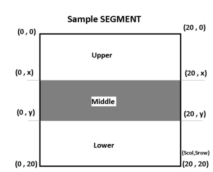


Fig. 4: Skeleton of a block

at row number 'r' and coloumn 'c'. Middle part of the block is considered to be blood vessel if

$$Upper - Middle > 10 \text{ and } Lower - Middle > 10$$

This process is continued for each possible block in the image. Since the method can detect only horizontal blood vessels, so the process is further continued after rotating the input image by 10, 20, 30, 50, 70, 90 degrees and -10, -20, -30, -50 , -70 degrees. Binary 'OR' is applied to resultant image from every angle. For each angle, an independent thread can also easily be executed and results of each thread, on applying logical 'OR', outputs the combined image. Fig 5 represents the entire process in detection of blood vessel like patterns.

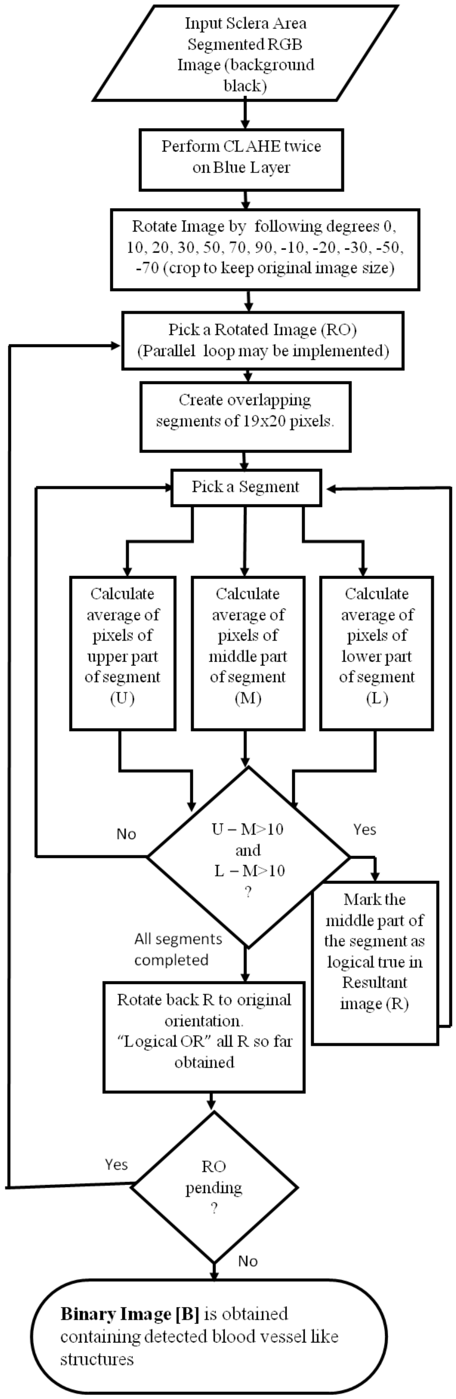


Fig. 5: Detection of Blood Vessel like patterns

C. Obtaining the Resultant Image

Logical 'AND' is performed on resultant image of Fig: 6 with the mask derived previously in fig: 3. Resultant image is mostly independent of hair and skin patches. Median filter and removal of connected area of below 1000 pixels is applied to remove small regions. It is seen that thick junctions of blood vessels are not detected. So, neighbouring pixels of the already detected vessels, with prominent red colour are considered by thresholding as in the following equation.

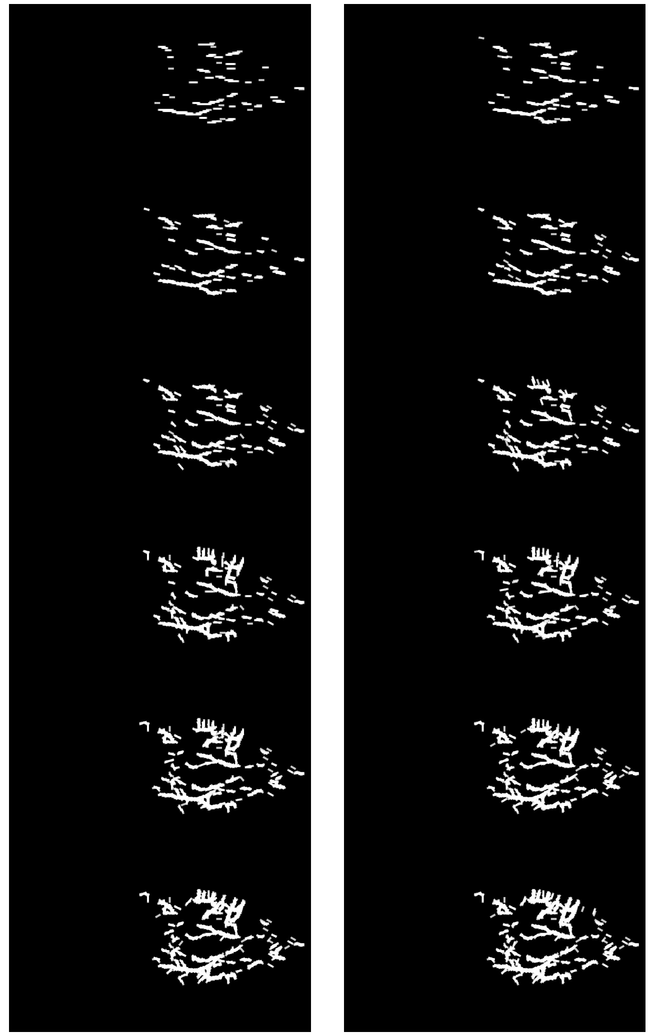


Fig. 6: Segments detected from blue layer obtained after CLAHE, as blood vessels for image rotated to angles in degrees : 0,10,20,30,50,70,90,-10,-20,-30,-50,-70

$$|R - G| > 50 \ and \ |R - B| > 30 \ and \ R > G \ and \ R > B$$

The combined image after applying median filter produces the resultant image. Skeletonisation is not performed. Fig: 7 describes the process.

D. Registration & Matching

The method used for registration is simple, but may not be suitable for every real life situations. In comparison, both binary images are cropped to a rectangular portion containing all the detected pixels. Both the images are compared by translating the image and comparing with the other image.

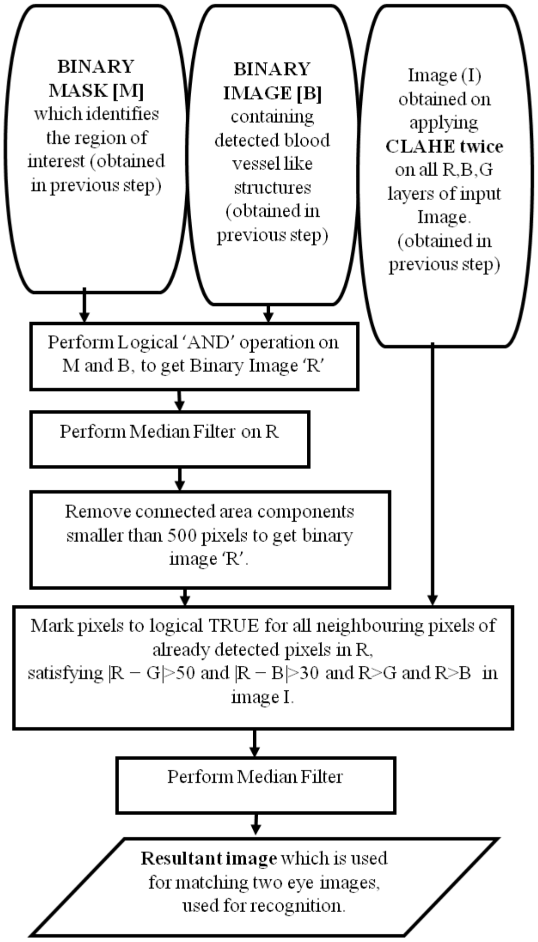


Fig. 7: Obtaining the Resultant Image

(a) Logical 'AND' with the Mask of Fig:3

(b) Smooth by applying median filter

(c) Search neighbouring red pixels

(d) Median Filter and removal of small components

Fig. 8: Resultant Binary Image Obtained

The image is translated both horizontally and vertically. In each iteration the translated image is compared with the other image, the comparison result is the number of ones after applying binary 'AND' operator to both images being compared. The number of ones in the result is compared with both the binary images being compared. Atleast 50% of number of ones in both binary images being compared, must be found in the resulting compared image after using 'AND' operator. In order to ensure sufficient detection of blood vessels within sclera to minimise false acceptance rate, comparison result of greater than 2500 matched pixels of both images is considered.

IV. Experimental Results

Experimental Results are given in two subsections, viz. Blood Vessel Detection and Matching.

A. Blood Vessel Detection

Training for blood vessel segmentation is not required in this method. The database used is as provided in SSERBC 2017. The database contains images of 10 distinct eyes where 8 eyes each has 16 images (4 images for every left, right, front and upfront gaze). 1(one) eye image has 12 images and another eye having 11 images consisting of only front and upfront gaze images. In total 16 x 8 + 12 + 11 = 151 images. Each RGB image in the dataset is manually segmented the sclera portion within the RGB image, and the region other than the sclera is considered as the black coloured background. Blood vessel Segmentation is carried out for all the images using a system having Intel i3 processor, 6GB of RAM, 500 GB optical hard disk, 64-bit Win7 OS. The time taken for computation is around 3 seconds for a single image. However the algorithm can run on multiple independent threads parallely. This method so described may run using 12 independent threads on a multi processor system. However increasing the number of threads increases the accuracy of detection while keeping the execution time constant. An image of SSERBC 2017 recognition dataset (Filename: s_1 (1).jpg) is used in this paper for description.

B. Matching

For SSERBC dataset, no ground truth images are available for vessel segmentation. So specificity, sensitivity, accuracy rates for results of vessel segmentation can't be provided. Segmented sclera vessels can be used for recognition purpose. Therefore retrieval of eye images using segmented sclera vessels are provided here. Each image is compared as a query image with all 151 images of the dataset. We have calculated FAR, FRR, Accuracy in respect of different gaze as in Table I. It is very clear that front gaze is unable to provide good results due to least visible vessels of sclera region. Table I represents the recognition rate at different gaze directions ('F' represents Front gaze, 'L' represents Left gaze, 'R' represnts Right gaze and 'U' represent UpFront gaze). 'A' is the number of images in the entire database at each gaze direction, which is manually counted. 'B' the total number of images in the

TABLE I: Results at different gaze directions

.	A	TP	FP	FN	O	TN	FAR	FRR	ACC
F	41	52	1	588	12	5550	.0001	.094	.90
L	32	92	0	404	60	4336	0	.083	.91
R	32	76	1	420	45	4335	.0002	.086	.91
U	46	115	0	566	69	6265	0	.081	.91

entire database which is 151. 'TP' is the number of images recognised by 'A' number of images, which are correctly identified(True Positive), when compared to all images of the dataset including itself. 'FP' is the number of images that are recognised but are not correct(False Positive), 'FN' is the number of images that are not recognised, but should have been recognised(FalseNegative) obtained using (No.of comparison with same eye image) - TP). 'O' represents the number of other images recognised (excluding itself), calculated by(TP-A). 'T' be the total number of comparisons obtained using (A*B). 'FAR' is False Accept Rate which is FP/T, 'FRR' is False Reject Rate which is FN/T. TN is True Negative calculated by T-FN-TP-FP. Accuracy(ACC) is measured by (TP+TN)/(TP+TN+FP+FN).

It is very well observed from column 'O', that 41 front gazed query images are able to identify only 12 more images correctly, moreover, one false positive detection is recorded. The best results are for Upfront gaze detections, where column 'O' depicts 69 more images were recognised using 46 upfront gazed query images, without any false accepts(FP). FAR depicts that the algorithm is quite robust in rejecting unrecognised eye images since, among 6946 comparisons, 115 were correctly recognised having no false accepts. Image s_7(4) which is front gazed, outputs s_9 (11) which is right gazed and vice versa. This image has introduced one(1) false accept(FP) each at front gaze and right gaze. This can be eliminated by thresholding further.

V. Conclusion

Most prominent blood vessels are well detected. Few vessels of lower layers of the sclera are also detected. The method does not depend only on color of the vessels, but detects pattern of blood vessels. False detection of vessels are minimised. Two same eye images with same gaze directions have very similar patterns of vessels even under low illumination or partial obstruction due to spectacle frames and can be easily distinguished with naked eye. The disadvantage is with very narrow curly shaped vessel structures which are sometimes detected as straight lines. But, overall vessel structure remains well aligned and well detected with minimum false detection of vessels. The database consists of images of left, right, front and upfront gaze. Best results are obtained when gaze is left, right and upfront. Front gaze images do not contain sufficient blood vessels visible in sclera area which makes it tough to identify an individual correctly. IRIS recognition should work well with front gaze.

The vessel patterns so detected can be compared with vessel pattern of another eye image to get good detection rates as false detection of vessels are minimised and vessel structures are well distinguished even with naked eye. The algorithm is rotation invariant for vessel detection, even under low ilumination. The parallel execution possibilities using multiple threads can minimise the computation time. The next part should focus on better registration of two images as images need to be translated, scaled or rotated to find their similarity for recognition purposes using RANSAC type or some other algorithm, which be our future work.

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