

# A Neural Approach for Sclera Vein Recognition

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**Abstract:** This research involves the study of Sclera vein recognition, its shown to be a promising method for human identification. However, its matching speed is slow, which could impact its application for real-time applications. To improve the matching efficiency, we proposed a new parallel sclera vein recognition method using a two-stage parallel approach for registration and matching. We designed a rotation- and scale-invariant Y shape descriptor based feature extraction method to efficiently eliminate most unlikely matches. We developed a weighted polar line sclera descriptor structure to incorporate mask information to reduce memory cost. We designed a coarse-to-fine two-stage matching method. The experimental results show that our proposed method can achieve dramatic processing speed improvement without compromising the recognition accuracy.

**Keywords:** Line Descriptor, Morphological, Gabor Filter, Vein Pattern Enhancement, Feature Extraction, Template Matching.

## I. INTRODUCTION

The veins in the sclera the white part of the eyes can be imaged when a person glances to either side, providing four regions of patterns: one on each side of each eye. Verification employs digital templates from these patterns, and the templates are then encoded with mathematical and statistical algorithms. These allow confirmation of the identity of the proper user and the rejection of anyone else. Advocates of eye vein verification note that one of the technology's strengths is the stability of the pattern of eye blood vessels; the patterns do not change with age, alcohol consumption, allergies, or redness. Eye veins are clear enough that they can be reliably imaged by the cameras on most Smartphone. The technology works through contacts and glasses, though not through sunglasses. At least one version of eye vein detection uses infrared illumination as part of the imaging, allowing imaging even in low-light conditions. Several researchers have designed different Sclera vein recognition methods and have shown that it is promising to use Sclera vein recognition for human identification. Speed Up Robust Features (SURF) based method, minutiae detection, and direct correlation matching for feature registration and matching. Within these three methods, the SURF method achieves the best accuracy. It takes an average of 1.5 seconds using the SURF method to per-form a one-to-one matching.

## II. OVERVIEW OF SCLERA VEIN RECOGNITION

A typical sclera vein recognition system includes sclera segmentation, feature enhancement, feature extraction, and feature matching.



Fig 1 The diagram of a typical sclera vein recognition approach

Sclera image segmentation is the first step in sclera vein recognition. Several methods have been designed for sclera segmentation presents an semi-automated system for sclera segmentation. They used a clustering algorithm to classify the colour eye images into three clusters - sclera, iris, and background. Segmentation approach based on a normalized sclera index measure, which includes coarse sclera segmentation, pupil region segmentation, and fine sclera segmentation a skin tone plus "white colour"-based voting method for sclera segmentation in colour images and Otsu's thresholding based method for grayscale images.

After sclera segmentation, it is necessary to enhance and extract the sclera features since the sclera vein patterns often lack contrast, and are hard to detect. Used a bank of multi directional Gabor filters for vascular pattern enhancement. And contrast limited adaptive histogram equalization (CLAHE) to enhance the green colour plane of the RGB image, and a multi-scale region growing approach to identify the sclera veins from the image background. Applied a selective enhancement filter for blood vessels to extract features from the green component in a colour image.

Speed up Robust Features (SURF) which is based on interest-point detection, minutiae detection which is based on minutiae points on the vasculature structure, and direct correlation matching which relies on image registration. Designed a line descriptor based feature registration and matching method.

### Line Descriptor

The matching segment of the line-descriptor based method is a bottleneck with regard to matching speed. We briefly describe the Line Descriptor-based sclera vein recognition method. After segmentation, vein patterns were enhanced by a bank of directional Gabor filters. Binary

morphological operations are used to thin the detected vein structure down to a single pixel wide skeleton and remove the branch points. The line descriptor is used to describe the segments in the vein structure. Fig 2 shows a visual description of the line descriptor.

The individual components of the line descriptor are calculated as:

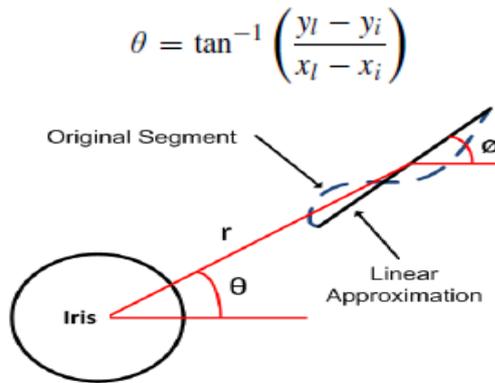


Fig 2 The Sketch of Parameters of Segment Descriptor

$$r = \sqrt{(y_l - y_i)^2 + (x_l - x_i)^2}$$

$$\text{and } \theta = \tan^{-1} \left( \frac{d}{dx} f_{\text{line}}(x) \right).$$

Here  $f_{\text{line}}(x)$  is the polynomial approximation of the line segment,  $(x_l, y_l)$  is the centre point of the line segment,  $(x_i, y_i)$  is the centre of the detected iris, and  $S$  is the line descriptor. In order to register the segments of the vascular patterns, a RANSAC-based algorithm is used to estimate the best-fit parameters for registration between the two sclera vascular patterns. For the registration algorithm, it randomly chooses two points one from the test template, and one from the target template. It also randomly chooses a scaling factor and a rotation value, based on a priori knowledge of the database. Using these values, it calculates a fitness value for the registration using these parameters.

After sclera template registration, each line segment in the test template is compared to the line segments in the target template for matches. In order to reduce the effect of segmentation errors, we created the weighting image from the sclera mask by setting interior pixels in the sclera mask to 1, pixels within some distance of the boundary of the mask to 0.5, and pixels outside the mask to 0. The matching score for two segment descriptors is calculated by:

$$m(S_i, S_j) = \begin{cases} w(S_i)w(S_j), & d(S_i, S_j) \leq D_{\text{match}} \\ & \text{and} \\ & |\theta_i - \theta_j| \leq \theta_{\text{match}} \\ 0, & \text{else,} \end{cases}$$

Where  $S_i$  and  $S_j$  are two segment descriptors,  $m(S_i, S_j)$  is the matching score between segments  $S_i$  and  $S_j$ ,  $d(S_i, S_j)$

is the Euclidean distance between the segment descriptors centre points,  $D_{\text{match}}$  is the matching distance threshold, and  $\theta_{\text{match}}$  is the matching angle threshold. The total matching score,  $M$ , is the sum of the individual matching scores divided by the maximum matching score for the minimal set between the test and target template. That is, one of the test or target templates has fewer points, and thus the sum of its descriptors weight sets the maximum score that can be attained.

$$M = \frac{\sum_{(i,j) \in \text{Matches}} m(S_i, S_j)}{\min \left( \sum_{i \in \text{Test}} w(S_i), \sum_{j \in \text{Target}} w(S_j) \right)}$$



Fig 3 The Weighting Image

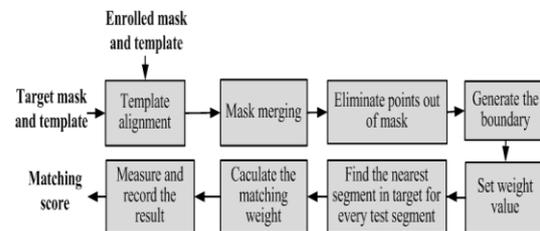


Fig 4 Module of Sclera Template Matching

#### Y Shape Sclera Feature for Efficient Registration

Currently, the registration of two sclera images during matching is very time consuming. To improve the efficiency, in this research, we propose a new descriptor the Y shape descriptor, which can greatly help improve the efficiency of the coarse registration of two images and can be used to filter out some non-matching pairs before refined matching. Within the sclera, there can be several layers of veins. The motion of these different layers can cause the blood vessels of sclera show different patterns. But in the same layers, blood vessels keep some of their forms. As present in Figure 5, the set of vessel segments combine to create Y shape branches often belonging to same sclera layer. When the numbers of branches is more than three, the vessels branches may come from different sclera layers and its pattern will deform with movement of eye. Y shape branches are observed to be a stable feature and can be used as sclera feature descriptor.

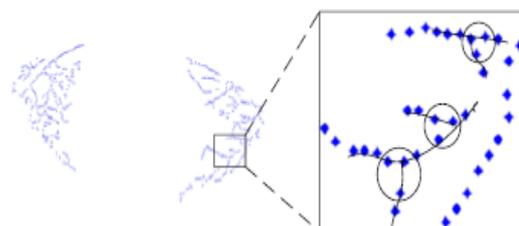


Fig 5 Y Shape Vessel Branch in Sclera

To detect the Y shape branches in the original template, we search for the nearest neighbours set of every line segment in a regular distance, classified the angles among these neighbours. If there were two types of angle values in the line segment set, this set may be inferred as a Y shape structure and the line segment angles would be recorded as a new feature of the sclera.

**Morphological**

Mathematical morphology (MM) is a theory and technique for the analysis and processing of geometrical structures, based on set theory, lattice theory, topology, and random functions. MM is most commonly applied to digital images, but it can be employed as well on graphs, surface meshes, solids, and many other spatial structures.

**Gabor Filter**

A Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Simple cells in the visual cortex of mammalian brains can be modelled by Gabor functions. Thus, image analysis with Gabor filters is thought to be similar to perception in the human visual system.

When matching, the registration RANSAC type algorithm was used to randomly select the corresponding descriptors and the transform parameter between them was used to generate the template transform affine matrix. To reduce heavy data transfer and computation, we designed the weighted polar line (WPL) descriptor structure, which includes the information of mask and can be automatically aligned.

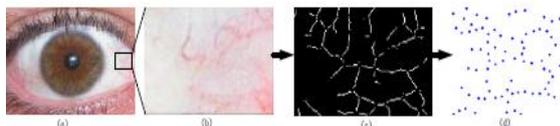


Fig 6(a) An eye image.

(b) Vessel patterns in sclera. (c) Enhanced sclera vessel patterns. (d) Centre of line segments of vessel patterns.

**Feature Extraction**

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

**Template Matching**

Template matching is a technique in digital image processing for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot, or as a way to detect edges in images.

**Sclera and Conjunctival Vasculature**

The Sclera and Conjunctival Vasculature the sclera is the white and opaque outer protective covering of the eye. The sclera completely surrounds the eye, and is made up of four layers of tissue the episclera, Stroma, lamina fusca, and endothelium. The conjunctival is a clear mucous membrane, made up of epithelial tissue, and consists of cells and underlying basement membrane that covers the sclera and lines the inside of the eyelids, the conjunctival vascular is hard to see with the naked eye at a distance. Shows an image of an eye under visible wavelength illumination with identification of the sclera vein patterns. For young children, the blood vessels in sclera area could be blue, but for adults, the blood vessels are red in colour. The structure of the blood vessels in the sclera are well suited to be used as a biometric they are an internal organ that is visible without undue difficulty and they are anecdotally stable over time and unique for each person. Therefore, the vein patterns in the sclera could be used for positive human identification.

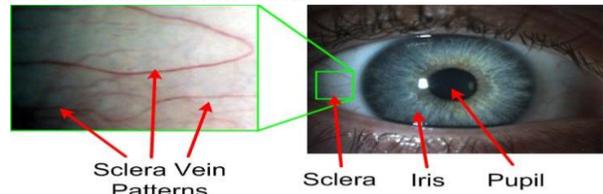


Fig 7 Structures of the Eye and Sclera Region

**Vein Patterns**

The two representative vein patterns, M and N, from vein layers X and Y, and then some of the myriad of individual layer deformations that these patterns can exhibit. The combination of the two patterns, M and N, due to the individual layer deformations can result in many different observable multilayered non-linear deformations.

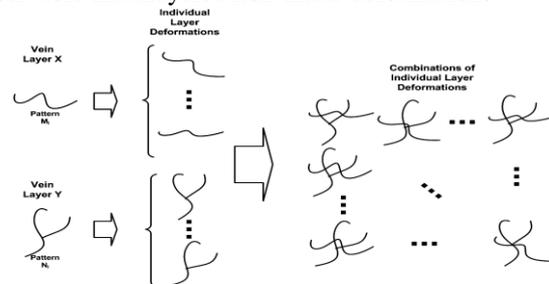


Fig 8 Illustration of How Different Patterns Can Emerge From Multiple Independent Layers

**Feature Enhancement**

Two general image enhancement techniques that are frequently used to perform preliminary image enhancement are contrast stretching and histogram equalization. Contrast stretching is a linear transformation

that increases the dynamic range of an image. Typically, this is done such that the lowest intensity value in the input image is mapped to an output value of '0', and the highest intensity value in the input image is mapped to an output value of '1'.

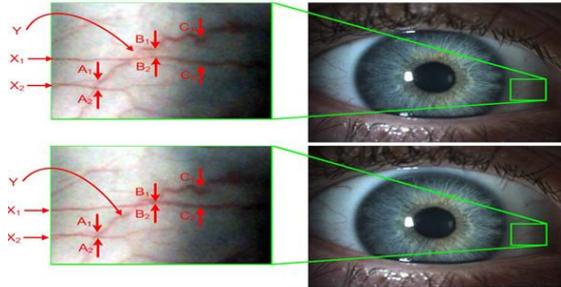


Fig 9 Layered Non-Linear Deformations in Multiple Images of the Same Eye

#### Gabor Filter Vein Enhancement

Segmented sclera area, which is highly reflective and hard to be accurately focused in the image acquisition process. As a result, the sclera vascular patterns are often blurry and have very low contrast. It is important to enhance the vascular patterns before feature extraction. Gabor filters, which are Gaussian weighted sinusoids, are good approximations of the vision processes of the primary human visual cortex.

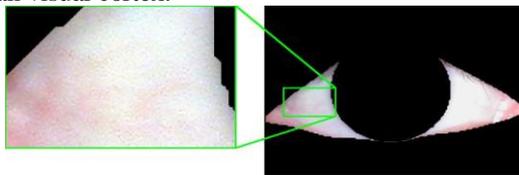


Fig 10 Segmented Sclera Region

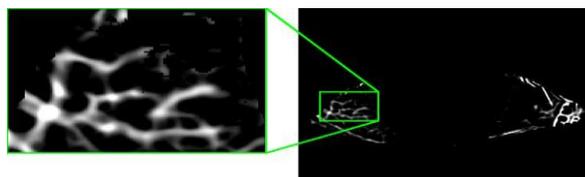


Fig 11 Gabor Enhancement

#### Direct Correlation Matching

The two images to be compared are first registered using an image alignment scheme and a direct correlation between corresponding pixels is then used to determine their similarity. Image registration is the process of finding a transformation that aligns one image with another. The regions of the sclera in the two images that are to be registered are cropped, and the images are padded to the same size.

The image with the smaller height is padded up and down with an equal number of rows. If the gaze direction of the eye is to the left, the image with the smaller width is padded to the right. If the gaze direction of the eye is to the right, the image with the smaller width is padded to the left. To detect the direction of the gaze, they coordinate of the centroid of the sclera region and the centroid of the pupil region is found and compared. This process results in a better overlap of the two sclera regions.

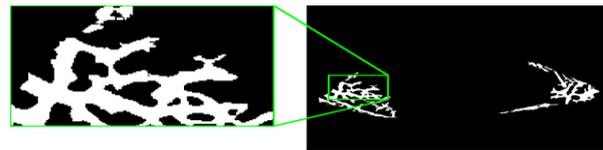


Fig 12 Otus Threshold Region

#### Minutiae Detection

Another technique to represent and match sclera images is based on the cross-over points of the conjunctival vasculature. We refer to these points as minutiae points based on the finger print bio-metric literature the large variations in intensity values and the low contrast between the blood vessels and the background, classical methods of segmentation based on edge detection are not robust and do not give good results. Used region growing method for segmenting the enhanced blood vessels based on the algorithm described in labelling of each pixel as pertaining to the conjunctival vasculature or background, is based on the information provided by the intensity value and the magnitude of the gradient of the pre-processed image.

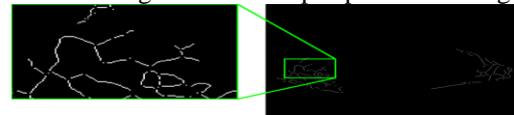


Fig 13 Morphological

### III. SIMULATED RESULTS

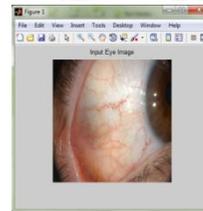


Fig 14 Input Eye Image

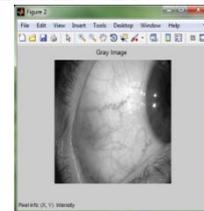


Fig 15 Gray Image

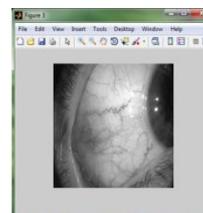


Fig 16 Depth Gray Image

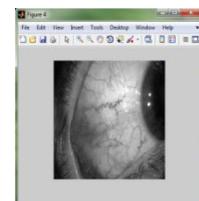


Fig 17 Segmented Sclera

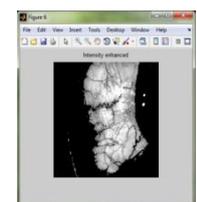


Fig 18 Intensity Enhanced



Fig 19 Convolved Image

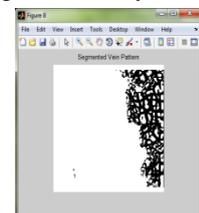


Fig 20 Segmented Vein Pattern

### Command window

EZW encoding took 1 second

y = 256 256

z = 128 128

Time for Gaussian scale space construction: 5.394 s

Time for Differential scale space construction: 0.019 s

Time for finding key points: 0.094 s

Total numbers of key points extracted are: 1703

Time for calculating descriptor: 1.370 s

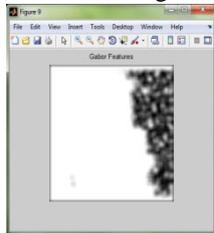


Fig 21 Gabor Features

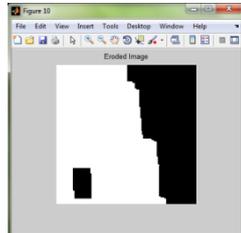


Fig 22 Eroded Image

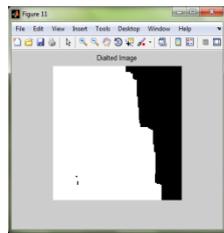


Fig 23 Dilated Image Representation

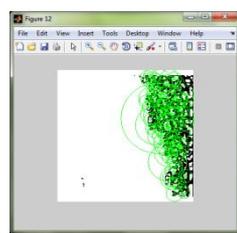


Fig 24 X, Y



Fig 25 Sclera Template

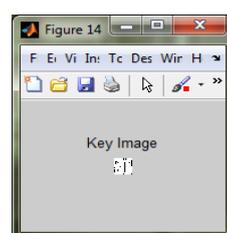


fig 26 Key Image



Fig 27 Identified Entry



Fig 28 login entry

### IV. CONCLUSION

This research work describes an improving recognition time and speed up the identification. We proposed a new method for sclera recognition a colour-based sclera region estimation scheme for sclera segmentation a Gabor wavelet-based sclera pattern enhancement method, and an adaptive thresholding method to emphasize and binarize the sclera vein patterns a line descriptor based feature extraction, registration, and matching method that is illumination, scale, orientation, and deformation invariant, and can mitigate the multi layered deformation effects exhibited in the sclera and tolerate segmentation error. The conjunctival is a clear mucous membrane, made up of

epithelial tissue, and consists of cells and underlying basement membrane that covers the sclera and lines the inside of the eyelids, the conjunctival vascular is hard to see with the naked eye at a distance. An eye under visible wavelength illumination with identification of the sclera vein patterns. The segments are described by three quantities the segments angle to some reference angle at the pupil center, the segments distance to the pupil centre, and the dominant angular orientation of the line segment.

### REFERENCES

- [1]. C. W. Oyster, (1999) *The Human Eye: Structure and Function*. Sunderland: Sinauer Associates.
- [2]. C. Cuevas, D. Berjon, F. Moran, and N. Garcia (2012), "Moving object detection for real-time augmented reality applications in a GPGPU," *IEEE Trans. Consum. Electron.*, vol. 58, no. 1, pp. 117–125.
- [3]. D. C. Cirean, U. Meier, L. M. Gambardella, and J. Schmidhuber (2010), "Deep, big, simple neural nets for handwritten digit recognition," *Neural Comput.*, vol. 22, no. 12, pp. 3207–3220.
- [4]. E. M. Arvacheh and H. R. Tizhoosh (2006), "IRIS Segmentation: Detecting Pupil, Limbus and Eyelids," in *IEEE International Conference on Image Processing*, pp. 2453-2456.
- [5]. H. Proenca and L. A. Alexandre (2006), "Iris segmentation methodology for non-cooperative recognition," *IEEE Proceedings Vision, Image and Signal Processing*, vol. 153, pp. 199-205.
- [6]. H. Proenca and L. A. Alexandre (2007), "Toward No cooperative Iris Recognition: A Classification Approach Using Multiple Signatures," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, pp. 607-612.
- [7]. H. Proenca (2009), "Iris Recognition: On the Segmentation of Degraded Images Acquired in the Visible Wavelength," *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- [8]. K. S. Oh and K. Jung (2004), "GPU implementation of neural networks," *Pattern Recognit.*, vol. 37, no. 6, pp. 1311–1314.
- [9]. M. Li, T. Tieniu, W. Yunhong, and Z. Dexin (2004), "Efficient iris recognition by characterizing key local variations," *Image Processing, IEEE Transactions on*, vol. 13, pp. 739-750.
- [10]. M. Vatsa, R. Singh, and A. Noore (2008), "Improving Iris Recognition Performance Using Segmentation, Quality Enhancement, Match Score Fusion, and Indexing," *IEEE Transactions on Systems, Man, and Cybernetics, Part b: Cybernetics*, vol. 38, pp. 1021-1035.
- [11]. P. Kaufman, and A. Alm (2003), "Clinical application," *Adler's Physiology of the Eye*.
- [12]. P. In Kyu, N. Singhal, L. Man Hee, C. Sungdae, and C. W. Kim (2011), "Design and performance evaluation of image processing algorithms on GPUs," *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 1, pp. 91-104.
- [13]. R. N. Rakvic, B.J. Ullis, R.P. Broussard, R.W. Ives, and N. Steiner (2009), "Parallelizing iris recognition," *IEEE Trans. Inf. Forensics Security*, vol. 4, no. 4, pp. 812–823.
- [14]. Z. Zhou, E. Y. Du, N. L. Thomas, and E. J. Delp (2012), "A new human identification method: Sclera recognition," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 42, no. 3, pp. 571–583.
- [15]. Z. Zhou, E.Y. Du, N. L. Thomas, and E. J. Delp (2013), "A comprehensive multimodal eye recognition," *Signal, Image Video Process.*, vol. 7, no. 4, pp. 619–631.
- [16]. Z. Zhou, E. Y. Du, N. L. Thomas, and E. J. Delp (2013), "A comprehensive approach for sclera image quality measure," *Int. J. Biometrics*, vol. 5, no. 2, pp. 181–198.
- [17]. Y. Xu, S. Deka, and R. Righetti (2011), "A hybrid CPU-GPGPU approach for real-time elastography," *IEEE Trans. Ultrason., Ferroelectr. Freq. Control*, vol. 58, no. 12, pp. 2631–2645.
- [18]. R. P. Wildes (1997), "Iris recognition: an emerging biometric technology," *Proceedings of the IEEE*, vol. 85, pp. 1348-1363.