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Supervised Retinal Biometrics in Different Lighting Conditions

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Abstract— **Retinal image has been considered for number of health and biometrics applications. However, the reliability of these has not been investigated thoroughly. The variation observed in retina scans taken at different times is attributable to differences in illumination and positioning of the camera. It causes some missing bifurcations and crossovers from the retinal vessels. Exhaustive selection of optimal parameters is needed to construct the best similarity metrics equation to overcome the incomplete landmarks. In this paper, we extracted multiple features from the retina scans and employs supervised classification to overcome the shortcomings of the current techniques. The experimental results of 60 retina scans with different lightning conditions demonstrate the efficacy of this technique. The results were compared with the existing methods.**

I. Introduction

PRIOR work has reported the uniqueness of the shape of the retinal vasculature [1]. Blood vessels on the retina of a person are known to have distinctive patterns that can be used to identify an individual. The unique branching characteristics of the vessels are commonly employed as biometrics templates.

The variation observed in the retina scans taken in different time instance is largely contributed to uneven background illumination [2]. Current techniques require binary segmentation of the vessels which prone to segmentation error when non-uniform illumination exists in retina scans taken at different instance of time [2-4]. This lighting disparity caused by the positioning of the camera relatives to the retina of the subject [5]. A good retinal biometric system should be able to overcome the cases of this.

The works in [3] and [4] only demonstrated intra-individual performance and used noise to simulate inter-individual performance. The simulated noise may not be representative of the actual noise appears in retina scans. The systems also used optic disk detection (ODC) to identify the region of interest (ROI). The variation observed in the retina scans taken at different time instance largely contributes to the error in the ROI selection which results in high false positive rate.

Ortega et. al [2] proposed a system which does not require the localization of the ROI. Four-step algorithm has been used to join disconnected vessels prior to the bifurcation or crossover extraction. Following the feature extraction, intra-person features still does not result in a perfect match due to missing landmarks because of high variability in illumination and contrast. To overcome this problem, the authors introduced a novel similarity metrics. However, exhaustive selection of optimal parameters is needed to construct the best similarity metrics equation; they are manually chosen to fit the best outcome. Optimal similarity metrics for one database may not be the most favourable in other databases. The problem is evident for the unsupervised biometrics when tested on different databases; different algorithm parameter values were used for each database [6].

In this paper, we have proposed a novel method to identify the similarity between the retinal image of the unknown user and the images from the dataset. The technique involves image enhancement, image registration and developing a feature set to represent the uniqueness of the images. The image enhancement is based on the Frangi's vesselness definition [7], the image registration is based on Scale-Invariant Feature Transform (SIFT) [8] and Random Sampling Concensus (RANSAC) [9] algorithms. and the feature set is calculated using two-dimensional correlation. It consists of multiple features from the retina scans which increases the dimensionality of the feature space, and classified the unknown sample by using a supervised classification to overcome the shortcomings of the current techniques. For this purpose, the image was sub-divided into four quadrants and two-dimensional correlation features were extracted for each of these four blocks and one for the complete image to obtain a set of five features to represent the image. Supervised learning was then employed to construct the biometrics classifier. The proposed scheme does not require a manual choice of an optimal threshold, which is exhaustive and may be bias towards certain dataset.

It is hypothesized that the use of five features using a supervised learning will result in a more robust system than a single similarity metric. The experimental results of 60 retina scans with different lightning conditions demonstrate the efficacy of this technique. The results were compared with existing methods.

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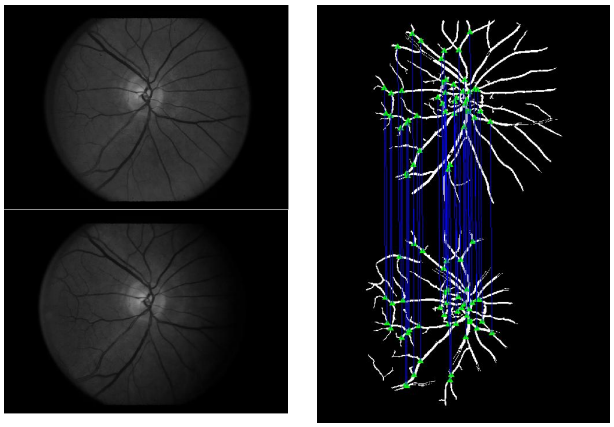


A) (B)

Fig. 1. Same retina taken from different angles, notice the difference in illumination and shadow occlusion in the scans result in missing bifurcations and branches. (a) Original images with different illuminations, (b) Segmented vessels showing missing landmarks on the right side of the image.

II. Materials and Methods

A. Image Preparation

This study was tested on a set of stereo images [10]. The stereo images were prepared by the Center for Eye Research Australia. It consists of 60 retina scans (2 scans each subject). The first shot was taken from left angle, and the second was from right angle. The angle of imaging differs by approximately 7 degrees. These two shooting points are considered as two cases where highly different lighting and shadow occlusion are generated. The differences are evident as shown in Fig. 1(a) and Fig. 1(b).

B. Vessel Enhancement

We employed the Frangi et al. [7] method to enhance the retinal vessel. This method has been validated by many proof-of-concept studies on vessel extraction [11, 12]. The vessels were enhanced based on the analysis of the eigenvalues of the Hessian. The algorithm first defines the scale-space representation, L which is the result of convolution of image intensity, f with a Gaussian function g,

$$L(x,y) = f(x,y) * g(x,y), \quad (1)$$

where (x,y) is the pixel location. The Hessian of an intensity image in scale space can be obtained at each point by convolving f with derivative-of-Gaussian kernel

$$H(x,y) = \begin{bmatrix} \frac{\partial^2 L}{\partial x^2} & \frac{\partial^2 L}{\partial x \partial y} \\ \frac{\partial^2 L}{\partial y \partial x} & \frac{\partial^2 L}{\partial y^2} \end{bmatrix}. \quad (2)$$

The vesselness measure according to Frangi is,

$$v_F = \begin{cases} 0, \lambda_2 > 0 \\ \exp\left(-\frac{A^2}{2\alpha^2}\right)\left(1-\exp\left(-\frac{S^2}{2\beta^2}\right)\right) \end{cases}, \quad (3)$$

where A is the ratio of the eigenvalues of the Hessian, λ_1 / λ_2, and S is the overall strength measure which differentiates between the vessels and the background. α and β are the constants.

C. Image Registration

The first step for image registration process is to extract possible candidates of the pixel location from the images, namely keypoints. Scale-Invariant Feature Transform (SIFT) [13] was employed for this purpose, the keypoints were processed based on the difference-of-Gaussian function of the pixels. A descriptor was then generated based on orientation, scale, and location of the keypoints.

Let f1 and f2 be the two retina scans to be registered, d1(i) and d2(j) are the descriptor vectors for the ith and the jth keypoints of f1 and f2, respectively. The main problem for image registration is to find the keypoints in f1 that match the keypoints in f2. The optimal candidates can be calculated based on the minimum Euclidean distance between d1 and d2.

Inconsistent matches were rejected using Random Sampling Concensus (RANSAC) [9]. In brief, RANSAC accepts the inliers and rejects the outliers by repeatedly samples a set of correspondences that are drawn randomly from the input set. Fig. 2 shows the correspondences from two same retinas taken at different times. The inliers were used as inputs to the non-reflective similarity transformation for image registration. It may include a rotation, a scaling, and a translation. If no inliers were detected, the matching scores were set to zero.

D. Features Extraction

This section explains how the proposed method extracted multiple features from a single enhanced-aligned image, and brief description of the previous methods that have been compared against.

To obtain multiple features from the retina scan, each enhanced-aligned retina image was divided into four blocks; top, bottom, left, and right. Features were calculated for the four blocks and the complete image based on two-dimensional correlation function. Fig. 3 illustrates an example how the image was split into two sections. Let *A(x,y)* and *B(x,y)* be the two sections to be matched.

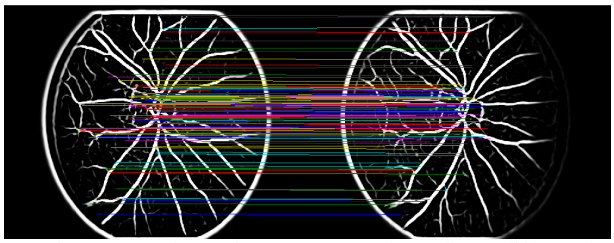
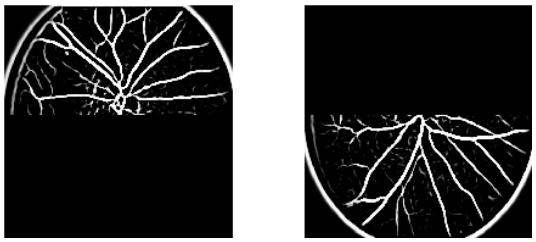


Fig. 2. The correspondences from two same retinas taken at different times, the lines show the inliers accepted from the RANSAC.



(a) (b)

Fig. 3. Examples of the separate sections of the enhanced-aligned retina image. (a) Top section, and (b) bottom section.

The proposed feature set is the two-dimensional correlation for each of the four quadrants and one for the total image. This leads to a feature set of length five to represent the image.

$$F_{whole|top|bottom|left|right} = \left[\frac{\sum_{x,y}[A(x,y)-\overline{A}][B(x,y)-\overline{B}]}{\sqrt{\left(\sum_{x,y}[A(x,y)-\overline{A}]^2 \sum_{x,y}[A(x,y)-\overline{B}]^2\right)}} \right], \quad (3)$$

where $\overline{A}$ and $\overline{B}$ are the means of A and B respectively. The centre point was calculated based on the centre of mass of the first image. All the five features were then fused to a classifier. Linear Discriminant Analysis Leave-One-Out (LDA-LOO) classifier was selected because of its ability to provide robust cross-validation of the huge amount of data, which is essential to avoid sampling bias when training the system without sacrificing the accuracy of the system. In addition, the use of a linear classification system further re-confirms the stronger discriminative abilities of the extracted retinal feature vectors.

The outcomes of this technique were compared with three existing techniques. Retina code [4] encodes the vessel structure surrounding the optic disc using concentric circles, which requires the identification of the optic disk. Matching is done using Hamming distance. Shape signature [3] on the other hand, uses the contour of the retinal vasculature to extract the uniqueness from the structure. It employs cross-correlation as similarity metric. Following this, in an effort to improve the robustness for images with less retinal area overlap (< 25%), Oinonen et al [6] proposed a novel principal bifurcation orientation (PBO) feature descriptor. This scheme employs the vessel direction information from the segmented vessel map for each of the considered image pairing. All the three techniques use binary segmentation of the vessels.

III. Results

The performance comparison for each technique is shown in Table 1. The accuracy is measured by false positive rate (FPR) and false negative rate (FNR) of the 3,540 comparisons (60 x 60 matching – 60 same-image matching). FPR and FNR were obtained using ROC curve analysis. The point closest to FPR=0% and FNR=0% in the ROC curve is defined as the optimal threshold.

Table 1
Performance comparison of different retinal biometrics on the stereo images.

Biometrics	Similarity Metrics / Classifier	FPR	FNR
Circular Coding Retina Code [4]	Hamming	6.6%	0%
Shape Signature [3]	Correlation	8.8%	33.3%
Proposed Supervised Biometrics	LDA-LOO	0%	0%
PBO Biometrics (no parameter fine-tuning was done from the original code) [6]	Self-defined metrics	96.5%	3.2%

Retina code and shape signature exhibits some degree of error; this may be resulted from the incorrect identification of the optic disk. The previous state-of-the-art method based on principal bifurcation orientation which reports 0% FPR and 0% FNR in the public dataset did not perform well with Stereo dataset. This may be due to the similarity metrics parameters being used needs manual support for optimization to different dataset as reported previously [6].

IV. Conclusion

This paper describes a supervised retinal biometrics approach which is based on the use of image registration, two-dimensional correlation and a fast classifier. The results are a marked improvement with zero FPR and zero FNR. In practice, FPR, which is the most essential characteristic in high security environment, may further be improved by adjusting the weight of the classifier favoring the FPR. The results in Table 1 indicate that the proposed system performed well without requiring manual parameters fine-tuning and exhaustive search. This indicates that by increasing the dimensionality of the feature space, the distance between different people would increase and would lead to reduced error in the classification.

We have developed and tested a novel methodology for retinal biometrics which does not require 1) optic disk detection to identify the region of interest, 2) binary segmentation of the vessels which prone to segmentation error when non-uniform illumination exists in retina scans taken at different instance of time, and 3) manual similarity metrics parameters selection. Cross-validation is also possible to find the best parameter values when fine-tuning the classifier.

Further investigation is warranted to test the scalability of the system and for that, we plan to assess the proposed system on multiple dataset including publicly available dataset [2].

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