Investigation of Dimensionality Reduction in a Finger Vein Verification System

Ei Wei Ting[1], M.Z.Ibrahim[1]* and D.J.Mulvaney[2],

[1]Faculty of Electrical and Electronic, University Malaysia Pahang,
26600, Pekan, Pahang, Malaysia
eweiting@rocketmail.com, *zamri@ump.edu.my,

[2]School of Electronic, Electrical and Systems Engineering, Loughborough University,
LE11 3TU, United Kingdom
d.j.mulvaney@lboro.ac.uk

Abstract. Popular methods of protecting access such as Personal Identification Numbers and smart cards are subject to security risks than result from accidental loss or being stolen. Risk can be reduced by adopting direct methods that identify the person and these are generally biometric methods, such as iris, face, voice and fingerprint recognition approaches. In this paper, a finger vein recognition method has been implemented in which the effect on performance has of using principal components analysis has been investigated. The data were obtained from the finger-vein database SDMULA-HMT and the images underwent contrast-limited adaptive histogram equalization and noise filtering for contrast improvement. The vein pattern was extracted using repeated line tracking and dimensionality reduction using principal components analysis to generate the feature vector. A 'speeded-up robust features' algorithm was used to determine the key points of interest and the Euclidean Distance was used to estimate similarity between database images. The results show that the use of a suitable number of principal components can improve the accuracy and reduce the computational overhead of the verification system.

Keywords: Finger Vein Recognition, Repeated Line Tracking, Principal Component Analysis, Speeded-Up Robust Features.

1 Introduction

It is becoming general recognized that with the increasing need to provide both physical and online security, allowing access according to what an individual is carrying or what an individual knows is less secure than limiting access depending on the characteristics of the individual themselves. To meet these demands, biometric personal identification and verification system such as fingerprint, voice, and iris recognition are gradually replacing smart cards and personal identification numbers. However, those systems have the major disadvantage that the biometric traits they measure can easily be duplicated as they depend on features that are visible to the naked eye [1]. A further drawback is that a number of biometric traits are known to change as a result of child development or ageing and it is often necessary to update the recorded biometric patterns at regular intervals, so introducing a potential security risk.

Information obtained from veins in the finger has been investigated as a possible biometric only relatively recently, but it has been recognized that as part of a security verification system they may have a number of advantages. Firstly, as the vein is located under the skin, it cannot be viewed directly, making the information harder to copy [2]. Secondly, although during an individual's lifetime the finger will grow and change appearance externally, the underlying vein pattern does not change. Finally, as the finger vein pattern can only be taken from a live body, the individual needs to be present during verification [3].

The use of finger veins for individual verification is currently being investigated by a number of researchers and a number of challenges remain in order to achieve appropriate accuracy and reliable performance. One main problem that affects the performance of all biometric identification systems is the quality of the data obtained during the acquisition process [4]. A finger vein verification system, shown in Fig. 1, typically consists of a suitable method of acquiring the image, preprocessing to reduce noise content, the use of feature extraction to reduce the dimensionality of the problem and matching against features obtained from previous finger vein images.

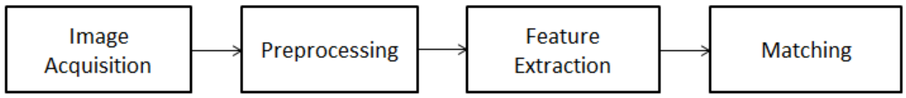


Fig. 1 The stages in a typical finger vein verification system

In previous studies, finger vein identification and verification has been able to deliver some success. Park *et al*. [5] implemented finger vein pattern extraction using local binary patterns combined with wavelet transforms and support vector machines. Wu and Liu [6] used principal components analysis (PCA) and linear discriminant analysis (LDA) for feature extraction in a finger vein identification system A substantial hurdle to the commercial realization of finger vein verification systems is that the reliability of the identification is significantly affected by the poor contrast in the images obtained by the available acquisition methods.

2 PROPOSED METHOD

This paper proposes pre-processing using noise filtering, region of interest segmentation and image enhancement to improve the finger vein image quality. The finger veins themselves are extracted using repeated line tracking and PCA to reduce the dimensionality of the feature vector. Speeded-up robust features (SURF) matching to extract key points of interest and classification is carried out using the Euclidean distances between points. Results were then obtained which allow the analysis of the effect of PCA on finger vein verification performance.

2.1 Finger vein database

The images were obtained from the SDMULA-HMT vein database. This database was found to be the most suitable among those available, with other candidate finger vein databases containing poor quality images, badly aligned images or images that were not useful as they has been obtained in a manner that made them suited to only specialized applications. The SDMULA-HMT vein database contains images obtained from 106 subjects with six images being provided for each subject, one for the fore, middle and ring fingers of each hand. The images are stored in the bitmap format and have a resolution of 320x240 pixels and samples are shown in Fig. 2.

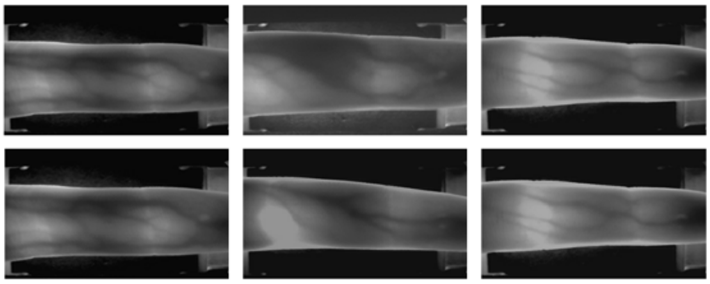


Fig. 2 Samples of finger vein images obtained from the SDMULA-HMT database

2.2 Image preprocessing

Image preprocessing stage is used to improve image contrast and quality. In this work, this includes image enhancement, edge detection, region of interest (ROI) detection, and noise filtering.

Firstly, each pixel in the finger vein image was converted from the red, green and blue pixel values in the bitmap RGB format to a luminance value (grayscale), using the formula shown in Equation 1.

$$Y=0.299*R+0.587G+0.114*B \tag{1}$$

Since finger vein images tend to be of low quality due to presence of bones and tissues, a good image enhancement method is important to improve image quality. In this work, the luminance image is enhanced using the conventional contrast-limited adaptive histogram equalization (CLAHE) proposed by Lu *et al.* [7] for contrast enhancement purposes. CLAHE computes several histograms, each of which corresponds to a distinct region of the finger vein image while simultaneously redistributing the brightness of the image.

Finger edge detection and finger region localization are then applied to remove unwanted regions and regions containing no finger information. Edge detection was achieved using a canny edge detection operator. The ROI was then cropped and resized to the required new width and height. Finally, a 3x3 median filter was applied in order to provide noise reduction. Fig. 3 shows the outcomes of each of the image preprocessing steps.

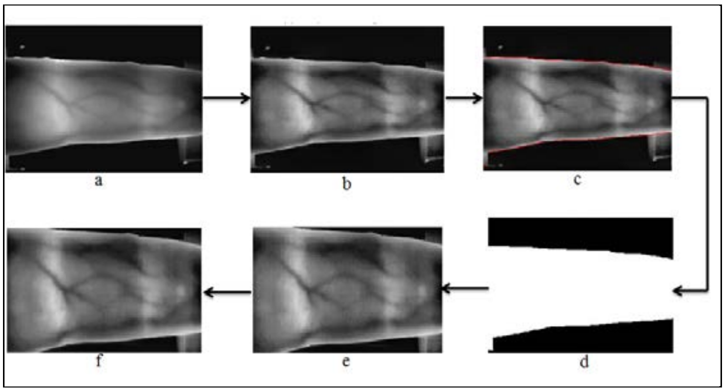


Fig. 3 Image pre-processing outcomes (a) original image, (b) CLAHE enhancement, (c) finger edge detection, (d) finger region detection, (e) cropped ROI of finger vein and (f) noise reduction following median filtering

2.3 Feature extraction

In this paper, the finger vein pattern was extracted using repeated line tracking (RLT) method proposed by Miura *et al.* [8] in their work on using finger veins for subject identification. In the current work, this technique was also found to be able to generate useful data for authentication from finger veins.

This method initially determines a starting point for line tracking and the tracking then follows connected pixels in the finger vein image according to a specified orientation and diameter requirements. The perpendicular to the direction of a vein has a luminance profile that includes a minimum near to the axis of the vein and so the line tracking involves moving to the next unexplored pixel that is the closest (in a straight line sense) local minima within a suitably small local region. By selecting a number of starting points it is possible to produce line segments that correspond to all the veins in the original image. The tracking ends when there remains no further minima to be processed.

2.4 DIMENSIONALITY REDUCTION

PCA is a linear approach to reducing data dimensionality. It is able to identify those variables in the data that are best at distinguishing between categories, while often also having the effect of removing those variables that only contribute to noise information that confuses the categorization process.

PCA and LDA were used by both Wu *et al.* [6] to extract finger vein patterns. The authors' results showed that the combination of PCA and LDA methods we able to reduce the dimensionally of an image and they obtained successful identification in 98% of cases when using seven PCA features and four LDA features.

2.5 SPEEDED UP ROBUST FEATURE (SURF) ALGORITHM

SURF is a robust local feature detector, that is part of the scale-invariant feature transform (SIFT). SURF includes a method for the rapid detection of sub-Hessians to detect feature points. In this paper, SURF was used to find key points between two finger vein patterns. This is followed by a right orientation of the key points to ensure a consistent vein pattern alignment between individual images. Matching is then carried out by measuring Euclidean distances between key points found in a new image and those in the database of stored images. The smaller the sum of the Euclidean distances between all pairs of key points in the images under comparison, the better the match.

3 EXPERIMENTAL RESULTS

The experiments used 20 finger vein samples from the SDMULA-HMT finger vein database, where each sample had three images for training and one for testing. The RLT method was used to extract the vein pattern of the fingers and Fig. 4 shows an example of the vein pattern of an image following RLT extraction.

Fig. 4 Vein pattern obtained following repeated line tracking

Fig. 5 shows the result of dimensionality reduction using PCA on finger vein patterns using different numbers of principal components. Fig. 5(a) shows the vein pattern with 32 principal components while Fig. 5(b) is the vein pattern obtained with 64 principal components. Although the veins in Fig. 5(a) appear less well defined and the images itself contain less information than in Fig 5(b), having fewer principal components gives an advantage in terms of reducing the length of the training vector and so shortening training time. Consequently, for a realistic implementation, will be necessary to determine a suitable compromise between parameter accuracy and computational practicality.

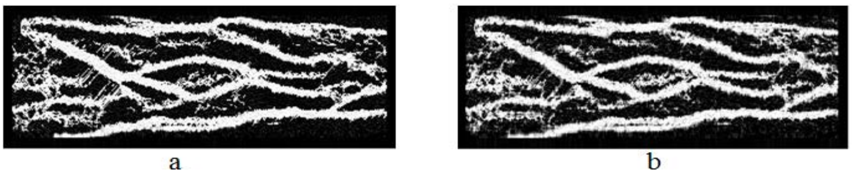


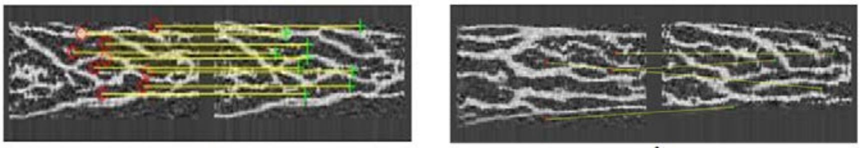
Fig. 5 Finger vein patterns constructed with (a) the first 32 principal components, (b) the first 64 principal components

Fig. 6 illustrates matches between pairs of images after applying SURF, but without the application of PCA. Fig. 6(a) shows an example of finger vein patterns for a pair of images obtained from the same subject. It was found that the matching points obtained were consistent between images from the same subjects and the Euclidean distances were found to be reliably small. Fig. 6(b) shows an example of an image pair obtained from different subjects and the Euclidean distances were found to be large in comparison with those obtained from same subject image pairs.

a b

Fig. 6 Comparison of pairs of images without the application of PCA obtained for (a) the same subjects, (b) different subjects

Fig. 7 shows the matching obtained between pairs of images after applying SURF, but in this case following the application of PCA. Due to the dimensionality reduction involved in PCA, the images in Fig. 7 are of a lower quality than the corresponding images in Fig. 6.



a b

Fig. 7 Comparison of pairs of images including the application of PCA obtained for (a) the same subjects, (b) different subjects

In biometrics, the performance of verification systems can be evaluated by the equal error rate (EER) when the false rejection rate is held at a zero false acceptance rate. The smaller the EER value, the better the performance of the verification system. In this paper, the experiment was carried out for finger vein verification both without PCA and with PCA for different numbers of principal components. Fig. 8 shows the receiver operating characteristic (ROC) curves that plot the number of false negative values against the false positive rates. The smaller the area under the curve (AUC) then the better is the accuracy of the identification. In Fig.8 it can be seen that the performance was improved by using PCA, but remains unsatisfactory for a practical system.

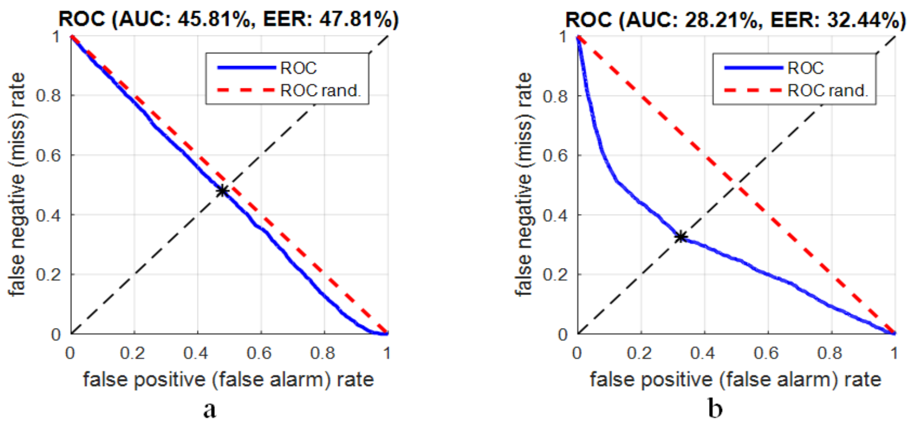


Fig. 8 ROC curve for the finger vein verification system (a) without PCA , (b) with the first 32 principal components

Further experiments were carried out and the performance was significantly improved when using only the first nine principal component and the first 16 principal components, as shown in Fig. 9. This demonstrates that PCA can reduce the quantity of data required for identification without losing important information and features.

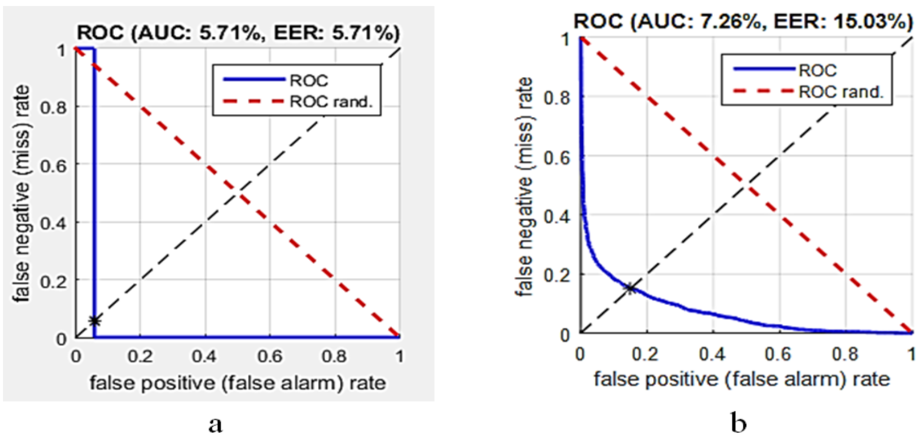


Fig. 9 ROC curve for the finger vein verification system for (a) the first nine principal components, (b) for the first 16 principal components

Table 1 summarizes the performances of the four different methods implemented for the finger vein verification system. It can be seen that the best performance was obtained after the most substantial PCA dimensionality reduction, with the implementation using nine principal components exhibiting both the smallest EER and AUC values.

Table 1. Performance comparison of the finger vein verification approaches

Method	EER (%)	AUC(%)
RLT Without PCA	47.81	45.81
RLT With PC=32	32.44	28.21
RLT With PC=16	15.03	7.26
RLT With PC=9	5.71	5.71

4 CONCLUSION

This paper has proposed an efficient finger vein based verification system using a PCA dimensionality reduction method. Experimental results have indicated that the finger vein verification system when using PCA was able to perform better than a system implemented without PCA. For the PCA verification system, the performance of the system was dependent on the number of principal components used, with the solution using only the first nine principal components performing better than systems using either the first 16 or 32 principal components. Although the vein patterns to which PCA was not applied contained more information than the vein patterns that did undergo PCA dimensionality reduction, PCA was nevertheless able to reduce the data to a set better suited for use in a vein verification system.

Acknowledgments

This work was supported by University Malaysia Pahang and funded by Ministry of Higher Education Malaysia under FRGS Grant RDU160108.

References

1. S. Damavandinejadmonfared, A. K. Mobarakeh, S. A. Suandi, and B. A. Rosdi, “Evaluate and determine the most appropriate method to identify finger vein,” Procedia Eng., vol. 41, no. Iris, pp. 516–521, (2012).
2. P. GOPINATH, “Human Identification Based on Finger Veins- a Review,” BEST Int. J. Humanit. Arts, Med. Sci. (BEST IJHAMS), vol. 2, no. 1, pp. 29–34, (2014).
3. L. Yang, G. Yang, Y. Yin, and L. Zhou, “A survey of finger vein recognition,” in Chinese Conference on Biometric Recognition, (2014), pp. 234–243.
4. E. C. Lee and K. R. Park, “Image restoration of skin scattering and optical blurring for finger vein recognition,” Opt. Lasers Eng., vol. 49, no. 7, pp. 816–828, Jul. (2011).
5. K. R. Park, “Finger vein recognition by combining global and local features based on SVM,” Comput. Informatics, vol. 30, no. 2, pp. 295–309, (2011).
6. J.-D. Wu and C.-T. Liu, “Finger-vein pattern identification using SVM and neural network technique,” Expert Syst. Appl., vol. 38, no. 11, pp. 14284–14289, (2011).
7. Y. Lu, S. Yoon, and D. S. Park, “Finger Vein Recognition based on Matching Score-Level Fusion of Gabor Features,” vol. 38, no. 2, pp. 178–182, (2013).

8. N. Miura, A. Nagasaka, and T. Miyatake, “Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification,” Mach. Vis. Appl., vol. 15, no. 4, pp. 194–203, (2004).