# A NOVEL FINGER-VEIN RECOGNITION METHOD WITH FEATURE COMBINATION

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## ABSTRACT

A novel method of exploiting finger-vein features for personal identification is proposed in this paper. First, the circular Gabor filter is used to enhance finger-vein region in an image. Then, image segmentation is implemented for finger-vein network extraction. To obtain the finger-vein skeleton, thinning operation is performed accordingly. Based on the extracted network and skeleton, finger-vein features on local moments, topological structure and statistics are exploited respectively. Finally, a fusion scheme is adopted for decision making. The experimental results show that the proposed method has good performance in personal identification.

***Index Terms***— Biometrics, finger veins, Gabor filter

## 1. INTRODUCTION

Finger veins are subcutaneous structures that randomly develop into a network and spread along a finger [1]. This physiological property makes the finger-vein characteristic very suitable for biometric applications. So exploiting finger-vein features for personal identification is becoming a new hot topic in biometrics-based identification research community. Compared with other traditional biometric characteristics (such as face, iris, fingerprints, etc.), finger veins exhibit some excellent advantages in application. For instance, apart from uniqueness, universality, permanence and measurability, finger-vein based recognition systems are:

- Immune to counterfeit: Finger veins hiding underneath the skin surface make vein pattern duplication impossible in practice;
- Active to liveness: Finger veins dying with tissue losing energy make finger-vein based recognition systems uncheatable by artificial veins;
- friendly to users: Finger veins imaging contactlessly make users free to contagion and unpleasant sensations.

Therefore, the finger-vein recognition is widely considered the most promising biometric technology in future.

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As finger veins are internal, visible lights are incapable of imaging them. To visualize veins in a finger, the near infrared(NIR) lights (760-850nm) are often used in finger-vein image acquisition systems, since they can penetrate a finger, and be absorbed greatly by the deoxyhemoglobin in veins [2, 3]. In practice, the captured finger-vein images in NIR-light imaging modes are with low contrast due to light attenuation arising from absorbtion of other tissues in a finger.

Nowadays, many works have been done for finger-vein based personal identification, and extracting features related to the finger-vein network is a common way in these works [3, 4, 5, 6, 7, 8]. However, the current methods are always sensitive to finger-vein image qualities, since the noises caused by processing low contrast finger-vein images can greatly reduce their stability and reliability in real applications. Moreover, opinions vary greatly in what kind of features can truly descibe finger-vein properties.

Hence, this paper makes an effort to find a method suitable to exploit the properties of finger veins for personal identification. Its contributions lie in: First, a reliable image enhancement method is designed for improve the quality of finger-vein images; Second, the features are extracted that can describe the diversity of the finger-vein networks, and a fusion scheme is adopted for finger-vein recognition.

For finger-vein image preprocessing, a circular Gabor filter specific to finger veins is designed to improve the quality of finger-vein images. Based on the filtered images, the finger-vein network is then segmented and thinned for obtaining the finger-vein skeleton.

For finger-vein recognition, the features related to a finger-vein network (such as local moments, topological structure and statistics, etc) are extracted firstly. Based on D-S evidence theory, finger-vein recognition is then implemented. The experimental results show that the proposed method has a good performance in personal identification.

## 2. FINGER-VEIN IMAGE PREPROCESSING

The current methods of finger-vein image enhancement can not effectively improve the contrast between vein region and nonvascular region in an image. This is not beneficial to segment a reliable finger-vein network in practice.

To enhance the vein information in an isotropic manner such that strengthen potential real veins as well as nonvascular region elimination, the circular Gabor filter proposed in [9] is used here. It is defined as

$$G(x,y) = K\exp(-\frac{(x^2+y^2)}{2\sigma^2})\exp(\hat{j}2\pi f_0\sqrt{x^2+y^2}) \quad (1)$$

where $K = 1/2\pi\sigma^2$, $\hat{j} = \sqrt{-1}$, $\sigma$ and $f_0$ respectively represent the scale parameter and the central frequency, which usually govern the optimal outputs of the Gabor filter. To make the Gabor filter specific to finger-vein enhancement, the relation of $\sigma$ and $f_0$ is determined by $\sigma f_0 = \sqrt{\ln 2/\pi}\cdot(2^{\triangle F}+1)/(2^{\triangle F}-1)$, where $\sigma$ is set five pixel width, $\triangle F$ denotes a half-magnitude bandwidth of Gaussian envelop. Thus, a filtered image can be output by computing the convolution of an original finger-vein image with $G(x,y)$. Fig. 1(b) illustrates some filtered results of finger-vein images, which show that the used circular Gabor filter is capable of enhancing image significantly.

For finger-vein network segmentation, a threshold image method proposed in [8] is used here. First, a threshold image is constructed pixelwisely by the statistics of pixels in $10\times10$ block. Based on a threshold image, the binary finger-vein network can be segmented adaptively, as shown in Fig. 1(c). To describing the topological structure of the finger-vein network conveniently, an image thinning method proposed in [6] is used to obtain the skeleton of finger veins. Some thinning results are shown in Fig. 1(d). The results shown in Fig. 1 illustrate that the adopted methods can preprocess finger-vein images effectively.

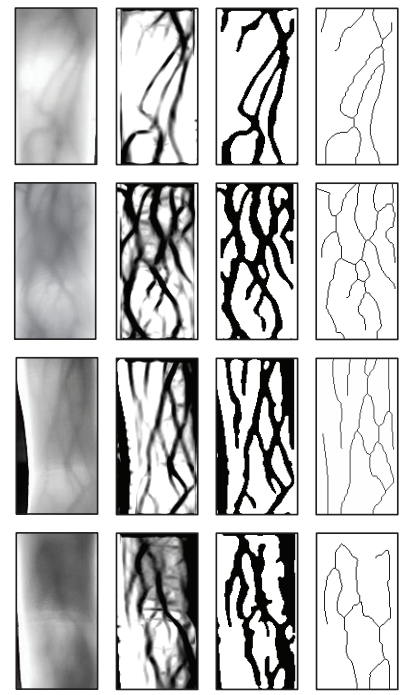



**Fig. 1**. Finger-vein image preprocessing. (a) Some original images normalized to $100\times180$ aspect. (b) Finger-vein image enhancement. (c) Finger-vein segmentation. (d) Finger-vein skeletons.

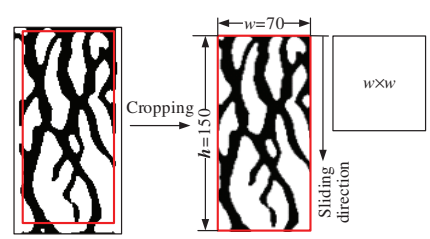



**Fig. 2**. Subimage extraction.

## 3. FINGER-VEIN FEATURE EXTRACTION

Fig. 1 also show that finger-vein patterns vary greatly in vessel diameters and networks. To describe this kind of variations, local moment feature, topological feature and vein-shape feature are exploited respectively in following.

### 3.1. Local moment feature

Moments are often useful in describing some invariant characteristics of a region [10]. Here, a local computation technique is adopted to make moment characteristics suitable to describe the finger-vein variations along a finger.

A $70\times150$ window (appearing red color in Fig. 2) firstly is used to crop a region from a finger-vein network image ($100\times180$ pixels). The cropped region contains the maximum number of pixels with zero while the window slides over a finger-vein network image globally. This is helpful to obtain a region that contains the richest finger-vein information.

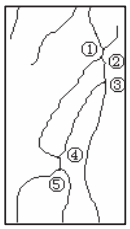
Then, a $w\times w(70\times70)$ square block slides along the height of the cropped region at a 20 pixel length step. Thus, five subimages ($70\times70$ each) are extracted when the block slide over. Computing the seven moments of every subimage, a matrix $\mathbf{M}_{5\times7} = [\boldsymbol{m}_1,\boldsymbol{m}_2,\boldsymbol{m}_3,\boldsymbol{m}_4,\boldsymbol{m}_5]^T$ (called local moment feature, LM-feature) is generated accordingly, where $\boldsymbol{m}_i$ denotes a row vector formed by seven moments of the $i$th subimage. Based on the properties of moments, it is clear that the matrix $\mathbf{M}_{5\times7}$ is capable of describing the finger-vein variations in vessel diameters and networks along a finger.

### 3.2. Topological feature

Moreover, the topological feature (T-feature) of a finger-vein network is also valuable for finger-vein recognition, since the finger-vein network can not be broken unless finger veins suffer rupture.

Based on the cross-points in a finger-vein skeleton, we propose a method that analyzes the topological characteristic of the finger-vein network. First, the cross-points in a finger-

vein skeleton are detected and numbered clockwise. The connectivity between adjacent cross-points is then determined and labeled. Fig. 3 clearly illustrates these two processes.




| | ① | ② | ③ | ④ | ⑤ |
|---|---|---|---|---|---|
| ① | 0 | 1 | 0 | 0 | 0 |
| ② | 1 | 0 | 1 | 1 | 0 |
| ③ | 0 | 1 | 0 | 1 | 0 |
| ④ | 0 | 1 | 1 | 0 | 1 |
| ⑤ | 0 | 0 | 0 | 1 | 0 |

**Fig. 3**. Topological information of cross-points.

The feature describing connection information(see the right of Fig. 3) obviously holds less discrimination. Therefore, the angles related cross-points are calculated; A diagram is shown in the right of Fig. 4, where a vector between any two numbered cross-points with connectivity can be built clockwise. Thus, the angle of two adjacent vectors is

$$\alpha_i = \frac{\vec{r}_i \cdot \vec{r}_j}{|\vec{r}_i| \cdot |\vec{r}_j|} \tag{2}$$

Clearly, the angle features can describe the invariant properties in rotation and scale of a finger. Collecting all angles depended on all cross-points can form a vector

$$A = [\alpha_1, \cdots, \alpha_i, \cdots, \alpha_n]^T \tag{3}$$

where $n$ is set to 15. So, the vector $A$ can represent the topological information of the numbered cross-points. Note that any component of $A$ is set to zero if it is not applicable.

### 3.3. Vein-shape feature

Vein-shape feature (VS-feature) is statistical characteristics of finger-vein curves connecting the cross-points in a finger-vein skeleton.

Assuming that $x$ axis correspond to a vector formed by any two adjacent cross-points, $y$ axis is determined in a manner shown in the left of Fig. 4. Let $f_x(x)$ denote a finger-vein curve function normalized by the area of the shadow region (see the left of Fig. 4), it can be viewed as a probability density function (p.d.f). Calculating the mean, the variance, the skewness coefficient and the Kurtosis coefficient of the p.d.f

$$\begin{cases} u_x = \sum x_k f_x(x_k) \\ \sigma_x^2 = \sum (x_k - u_x)^2 f_x(x_k) \\ \mu_3 = \sum (x_k - u_x)^3 f_x(x_k)/\sigma_x^{3/2} \\ \mu_4 = \sum (x_k - u_x)^4 f_x(x_k)/\sigma_x^2 - 3 \end{cases} \tag{4}$$

, the shape information of the finger-vein curve can be described using the following vector

$$s_i = [u_x^i, \sigma_x^i, \mu_3^i, \mu_4^i]^T \tag{5}$$

where $i$ represents the index of $\vec{r}_i$. Thus, a matrix $\mathbf{S}_{4\times n}$ can be constructed as

$$\mathbf{S}_{4\times n} = [s_1, \cdots, s_i, \cdots, s_n]^T \tag{6}$$

where $n$ is also set to 15. Undoubtedly, the matrix $\mathbf{S}_{4\times n}$ can describe the shape characteristic of the finger-vein skeleton. Note that any component of $\mathbf{S}_{4\times n}$ is also set to zero if it is not applicable.

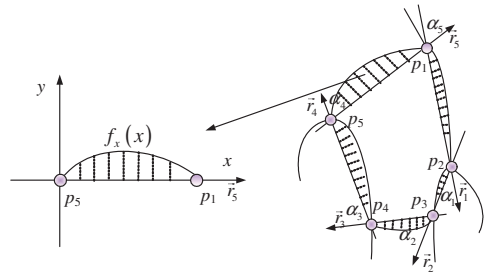



**Fig. 4**. Shape information analysis of finger-vein skeleton.

### 3.4. Finger-vein recognition

To test the discriminability of the extracted finger-vein features, the nearest cosine classifier here is adopted for classification. The classifier is defined as

$$\begin{cases} m = \arg\min_{v_i \in C_i} d(v, v_i) \\ d(v, v_i) = 1 - v^T v_i / (\|v\| \|v_i\|) \end{cases} \tag{7}$$

where $v$ and $v_i$ respectively represent an unknown sample and a template in the $i$th class, $C_i$ is the total number of templates in the $i$th class, $\|\cdot\|$ indicates the Eucliden norm, and $d(v, v_i)$ is the cosine similarity measure. Using similarity measure $d(v, v_i)$, the feature vector $v$ is classified into the $m$th class.

Fusion of the above features may generate better recognition results. Nowadays, many approaches have been proposed in multi-biometrics fusion, such as Bayes algorithm, KNN classifier, OS-Rule, SVM classifier, Decision Templates algorithm, Dempster-Shafer (D-S) algorithm, ect. Compared to other approaches, the D-S theory works better in integrating multiple evidences for decision making. Hence, the D-S theory here is adopted for finger-vein recognition. Details on D-S theory can be found in [11, 12].

## 4. EXPERIMENTS

Currently, there is no common finger-vein image database for finger-vein recognition. A finger-vein image database containing 54 individuals here is built using our homemade image acquisition system as shown in Fig. 5. In imaging subsystem (see the left of Fig. 5), the luminaire contains main NIR light-emitting diodes (LEDs) and two additional LEDs at a wavelength of 760 nm, and a CCD sensor was place under a finger. The additional LEDs are used only for enhancing the contrast between veins and other tissues.

In the database, each individual contributes 30 finger-vein images from three different fingers (fore, middle and ring fingers, 10 images per finger) of the right hand. 10 finger-vein images from one finger are selected as testing samples; the left are used for training. Using the nearest cosine classifier, the CCRs(Correct Classification Rate) and FARs (False Accept Rate) are given in Table 1.

**Table 1**. Finger-vein image classification

| (%) | LM-feature | T-feature | VS-feature |
|---|---|---|---|
| CCR | 97.51 | 96.44 | 98.50 |
| FAR | 0.092 | 0.154 | 0.065 |

From Table 1, we can see that the three kinds of features have good discriminability in finger-vein classification. This shows that the proposed features are reliable for describing the properties of finger-vein images. Moreover, the higher CCRs can effectively eliminate the "paradoxical phenomenon" in evidence fusion theory. Hence, decision fusion based D-S theory can greatly improve the performance of finger-vein based systems in personal identification.

To test the performance of the used fusion scheme in personal identification, the ROC (Receiver Operating Characteristic) curve is used to report identification result. In Fig. 6, the ROC curve gives a plot of various pairs of FAR (False Acceptance Rate) and FRR ( False Rejection Rate) under different threshold values for the decision making. Clearly, the used fusion method obtains a higher positive recognition rate, 99%(1-FRR), while the FAR is only 0.0086%. Although our finger-vein image database is small, the experimental results are exciting and meaningful for future works. That is, the features related to the finger-vein networks are worthwhile to further exploit, and the finger-vein recognition technology is worthwhile to pay further attention.

## 5. CONCLUSION

A new method for personal identification based on finger-vein features has been proposed in this paper. First, the circular Gabor filter was used to improve the quality of finger-vein images. Then the finger-vein network was segmented, and thinning operation was done to obtain the finger-vein skeleton. Based on the finger-vein network and skeleton, the features of local moments, topological structure and statistics of finger veins were extracted respectively. Finally, a decision fusion rule was adopted for finger-vein recognition. The experimental results show that the proposed method had a good performance in personal identification.

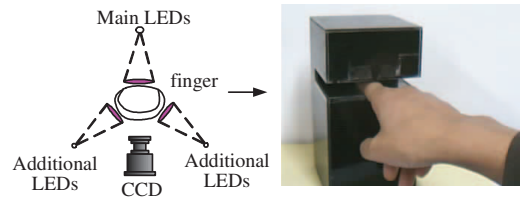



**Fig. 5**. A homemade finger-vein image acquisition system.

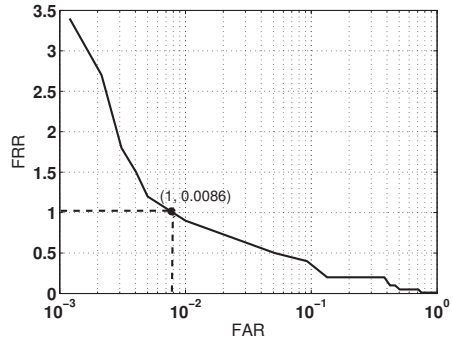



**Fig. 6**. ROC curve.

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