MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
8-30

Extraction of Finger-Vein Patterns Using Maximum Curvature Points in Image Profiles

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Abstract

A biometrics system for identifying individuals using the pattern of veins in a finger was previously proposed. The system has the advantage of being resistant to forgery because the pattern is inside a finger. Infrared light is used to capture an image of a finger that shows the vein patterns, which have various widths and brightnesses that change temporally as a result of fluctuations in the amount of blood in the vein, depending on temperature, physical conditions, etc. To robustly extract the precise details of the depicted veins, we developed a method of calculating local maximum curvatures in cross-sectional profiles of a vein image. This method can extract the centerlines of the veins consistently without being affected by the fluctuations in vein width and brightness, so its pattern matching is highly accurate. Experimental results show that our method extracted patterns robustly when vein width and brightness fluctuated, and that the equal error rate for personal identification was 0.0009%, which is much better than that of conventional methods.

1 Introduction

Personal identification technology is used in a wide range of systems for functions such as area access control and logins for PCs and e-commerce systems. Biometric techniques for identifying individuals, which include fingerprint, iris, and face recognition, are attracting attention because conventional techniques such as keys, passwords, and PIN numbers carry the risks of being stolen, lost, or forgotten.

A biometric system using finger-vein patterns, that is, patterns inside the human body, was previously proposed [1, 2]. This system has the advantage of being resistant to forgery. In this system, infrared light is transmitted from the rear of a hand. One finger is placed between the infrared light source and a camera, as shown in Fig. 1. As hemoglobin in the blood absorbs infrared light, the finger-vein patterns are captured as shadow patterns. The intensity of the light is adjusted using the captured image. After that, the outline of the finger is detected, the rotation of the image is corrected, and the vein pattern is extracted. Finally, the pattern is compared with registered patterns in a database.

A finger image captured using infrared light contains veins that have various widths and brightnesses, which may change with time because of fluctuations in the amount of blood in the vein, caused by changes in temperature, physical conditions, etc. To identify a person with high accuracy, the pattern of the thin/thick and clear/unclear veins in an image must be extracted equally. Furthermore, the pattern should be extracted with little or no dependence on vein width and brightness fluctuations.

Conventional methods such as the matched filter [3] and morphological [4] methods can extract patterns if the widths of veins are constant. However, these methods cannot extract veins that are narrower/wider than the assumed widths, which degrades the accuracy of the personal identification. The repeated line tracking method [2] can extract vein patterns from an unclear image, but it cannot sufficiently extract thin veins because the number of times that the tracking point moves on thin veins tends to be small statistically.

We propose a method that solves these problems by checking the curvature of the image profiles and emphasizing only the centerlines of veins. The centerlines are detected by searching for positions where the curvatures of a cross-sectional profile of a vein image are locally maximal. Our method of detecting the maximum curvature positions is robust against temporal fluctuations in vein width and brightness. The positions are connected with each other, and finally the vein pattern is obtained.

2 Algorithm

This section describes our algorithm for extracting finger-vein patterns from finger images.

This algorithm consists of three steps.

[Step 1] Extraction of the center positions of veins.
[Step 2] Connection of the center positions.

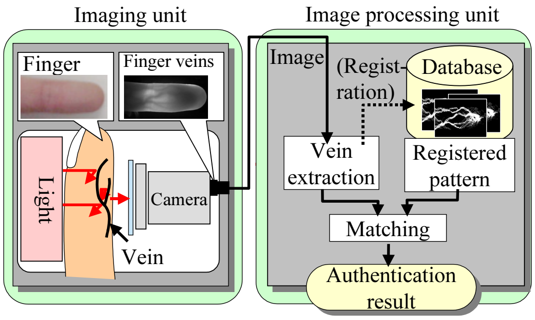


Figure 1: Flow of finger-vein personal identification.

[Step 3] Labeling of the image.

Each captured finger image is grayscale, 240 × 180 pixels, and has 8 bits per pixel. The image of the finger is captured horizontally, and the fingertip is on the right side of the image.

[Step 1] Extraction of the center positions of veins:

To extract the centerline of veins with various widths and brightnesses, our method checks cross-sectional profiles of a finger-vein image. The cross-sectional profile of a vein looks like a dent because the vein is darker than the surrounding area, as shown in Fig. 2. These concave curves have large curvatures.

Even if narrow/wide or bright/dark veins are shown in an image (positions A, B, and C in Fig. 2) and the center position of veins do not have a local minimum brightness (position C), the curvature of the profiles of the veins are large. Therefore, the center position of veins can be obtained by calculating local maximum curvatures in cross-sectional profiles.

The procedure for extracting vein centerlines is shown in Fig. 3. To make feature extraction robust against vein width fluctuation, only the positions of the centerlines of veins are emphasized. A score is assigned to each position, and it is larger when its dent is deeper or wider.

The details are described below.

[Step 1-1] Calculation of the curvatures of profiles:

F is a finger image, and $F(x, y)$ is the intensity of pixel (x, y). We define $P_f(z)$ as a cross-sectional profile acquired from $F(x, y)$ at any direction and position, where z is a position in a profile. For instance, $P_f(z)$ is acquired from $F(x, z)$ at a vertical direction, as shown in Fig. 3. To relate a position of $P_f(z)$ to that of $F(x, y)$, the mapping function T_{rs} is defined as $F(x, y) = T_{rs}(P_f(z))$.

The curvature, $\kappa(z)$, can be represented as

$$\kappa(z) = \frac{d^2 P_f(z)/dz^2}{\{1 + (dP_f(z)/dz)^2\}^{\frac{3}{2}}}. \tag{1}$$

[Step 1-2] Detection of the centers of veins:

A profile is classified as concave or convex depending on whether $\kappa(z)$ is positive or negative (Fig. 3). If $\kappa(z)$ is positive, the profile $P_f(z)$ is a dent (concave).

In this step, the local maximums of $\kappa(z)$ in each concave area are calculated. These points indicate the center positions of the veins.

The positions of these points are defined as z'_i, where $i = 0, 1, ..., N-1$, and N is the number of local maximum points in the profile.

[Step 1-3] Assignment of scores to the center positions:

Scores indicating the provability that the center positions are on veins are assigned to each center position.

A score, $S_{cr}(z)$, is defined as follows:

$$S_{cr}(z'_i) = \kappa(z'_i) \times W_r(i), \tag{2}$$

where $W_r(i)$ is the width of the region where the curvature is positive and one of the z'_i is located (Fig. 3).

If $W_r(i)$, which represents the width of a vein, is large, the probability that it is a vein is also large. Moreover, the curvature at the center of a vein is large when it appears clearly. Therefore, the width and the curvature of regions are considered in their scores.

Scores are assigned to a plane, V, which is a result of the emphasis of the veins. That is,

$$V(x'_i, y'_i) = V(x'_i, y'_i) + S_{cr}(z'_i), \tag{3}$$

where (x'_i, y'_i) represents the points defined by $F(x'_i, y'_i) = T_{rs}(P_f(z'_i))$.

[Step 1-4] Calculation of all the profiles:

To obtain the vein pattern spreading in an entire image, all the profiles in a direction are analyzed. To obtain the vein pattern spreading in all directions, all the profiles in four directions are also analyzed. The directions used are horizontal, vertical, and the two oblique directions intersecting the horizontal and vertical at 45°. Thus, all the center positions of the veins are detected by calculating the local maximum curvatures.

[Step 2] Connection of vein centers:

To connect the centers of veins and eliminate noise, the following filtering operation is conducted.

First, two neighboring pixels on the right side and two neighboring pixels on the left side of pixel (x, y) are checked.

If (x, y) and the pixels on both sides have large values, a line is drawn horizontally. When (x, y) has a small value and the pixels on both sides have large values, a line is drawn with a gap at (x, y). Therefore, the value of (x, y) should be increased to connect the line. When (x, y) has a large value and the pixels on both sides of (x, y) have small values, a dot of noise is at (x, y). Therefore, the value of (x, y) should be reduced to eliminate the noise.

This operation can be represented as follows.

$$\begin{aligned} C_{d1}(x, y) &= \min\{\max(V(x+1, y), V(x+2, y)) \\ &\quad + \max(V(x-1, y), V(x-2, y))\}. \end{aligned} \tag{4}$$

The operation is applied to all pixels.

Second, this calculation is made for each of the four directions in the same way, and C_{d2}, C_{d3}, C_{d4} are obtained.

Finally, a final image, $G(x, y)$, is obtained by selecting the maximum of C_{d1}, C_{d2}, C_{d3}, and C_{d4} for each pixel. That is, $G = \max(C_{d1}, C_{d2}, C_{d3}, C_{d4})$.

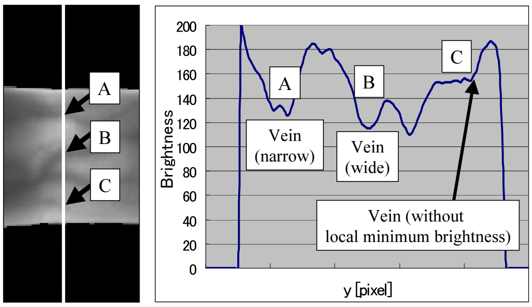


Figure 2: Cross-sectional profile of veins.

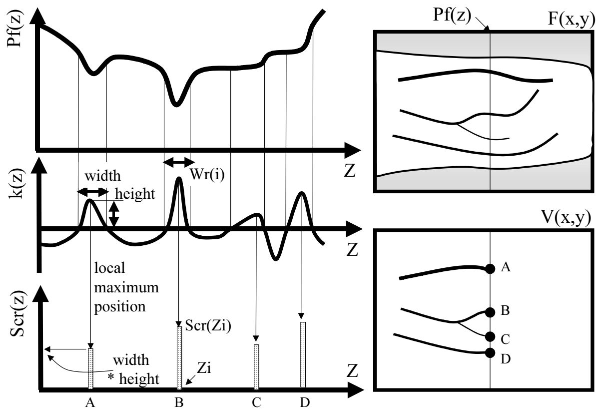


Figure 3: Relationship among profile, curvature, and probability score of veins.

[Step 3] Labeling the image:

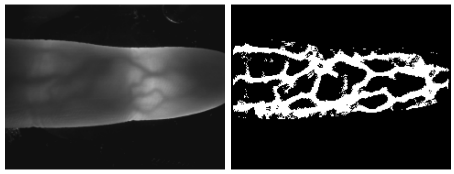
The vein pattern, $G(x, y)$, is binarized by using a threshold. Pixels with values smaller than the threshold are labeled as parts of the background, and those with values greater than or equal to the threshold are labeled as parts of the vein region. We determined the threshold such that the dispersion between the groups of values in $G(x, y)$ was maximized, assuming that the histogram of values in $G(x, y)$ was diphasic in form. An example of vein pattern extraction is shown in Fig. 4.

3 Experiments

In this section, experiments on the finger-vein extraction algorithm and the results are described. First, the sensitiveness of extracting the line pattern from test images is described. Second, we describe an investigation of the applicability of our identification method: an experiment using infrared finger images from 678 volunteers.

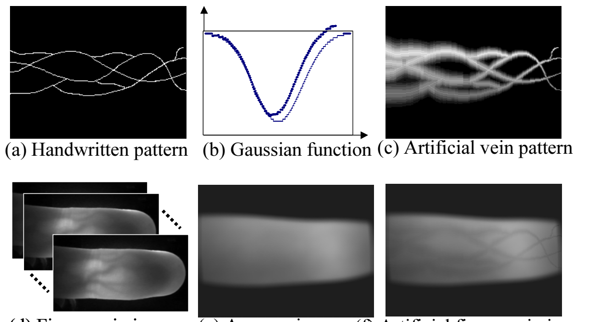
For comparison, three methods (our method, the line tracking method, and the matched filter method) were evaluated in the experiments.

The matched filter method uses two-dimensional filters [2, 3]. The filters are designed so that their profiles match the cross-sectional profiles of typical veins. The filters consist of four filter kernels, with each filter rotated to optimize for a different angular vein direction. Each filter is convoluted to the captured image independently, and all convolution values are added together.



(a) Original image (b) Extracted pattern

Figure 4: Result of vein extraction.



(a) Handwritten pattern (b) Gaussian function (c) Artificial vein pattern

(d) Finger-vein images (e) Average image (f) Artificial finger-vein image

Figure 5: Creation of test images.

The line tracking method tracks veins repeatedly, and the tracking starts at various positions [2]. A line is tracked by moving pixel by pixel along the veins, checking the cross-sectional profiles of the image. When a dark line is not detected, a new tracking operation starts at another position. This operation is executed repeatedly. Finally, the loci of the lines overlap, and the finger-vein pattern is obtained statistically.

Images were matched using a template matching method we previously proposed [2]. First, a binarized vein image is converted into three categories: Vein, Background, and Ambiguous.

Second, a stored pattern is overlapped with the vein image. The values of overlapping pixels are compared pixel by pixel. The pairs of pixels, where one is a Vein and the other a Background pixel, are counted. Such a pair is called a mismatch.

The ratio of the number of mismatched pairs to the total number of Vein pixels is defined as the mismatch ratio, and it quantifies the differences of two patterns.

3.1 Accuracy of the line extraction

First, we investigated the robustness of the methods against fluctuations in vein width and brightness. We used 32 test images created artificially, as shown in Fig. 5 (f). Each image contained vein-like lines with various widths and brightnesses (Figs. 5 (a) and (c)), and a background image of a finger (Fig. 5 (e)). Each image had a different average line width, ranging from 100% (normal width) to 200% (large width), as shown in Fig. 6. We call these percentages 'width ratios'. The line patterns were extracted from the 32 images, and each pattern was compared with a pattern whose width ratio was 150%.

Some examples of the patterns extracted are shown in Fig. 7. For comparison, the conventional methods (the matched filter and the repeated line tracking method) were also used to extract patterns. Our method extracted lines

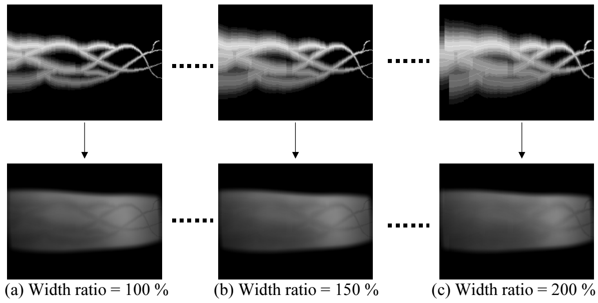


Figure 6: Test images with various widths.

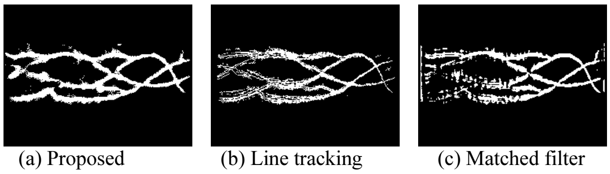


Figure 7: Line patterns extracted from test image.

with various widths and brightnesses more evenly than the other methods.

The mismatch ratio of our method was 2.83% on average. The matched filter and line tracking methods had the mismatch ratio averages of 4.62% and 4.56%. The mismatch ratio of our method stayed low even when the widths of the patterns were changed. Therefore, the pattern matching of our method is robust against vein width and brightness fluctuations.

3.2 Personal identification using finger vein patterns

To examine the performance of our method, we did an experiment to identify a large number of patterns. The experiment included an equal error rate (EER) evaluation, where the false acceptance rate (FAR) equals the false rejection rate (FRR), of a data set of infrared finger images.

The data set contained 678 different finger images, and two images were stored per finger. The FRR and FAR were obtained by calculating the mismatch ratios using both patterns of each finger and the patterns of different fingers.

The receiver operating characteristic (ROC) curve, which shows the relationship between FAR and FRR, is shown in Fig. 9. The EER of our method was 0.0009%. The EER for the repeated line tracking method was 0.0096%, and that of the matched filter method was 0.103%. Thus, our method had a lower personal identification error rate than the conventional methods. Furthermore, the EER in fingerprint systems ranges from 0.2% to 4% [5], so finger vein identification using our approach is much more effective.

4 Conclusion

We proposed a method of extracting vein patterns. To precisely extract patterns from vein images with various widths and brightnesses, the centerlines of the veins are extracted by calculating the curvature of the cross-sectional profile of the image. An evaluation of the robustness of our method against fluctuations in widths and brightnesses of

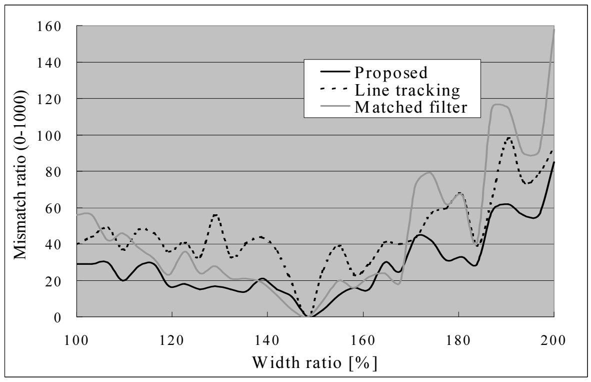


Figure 8: Mismatch ratios among test patterns of various widths.

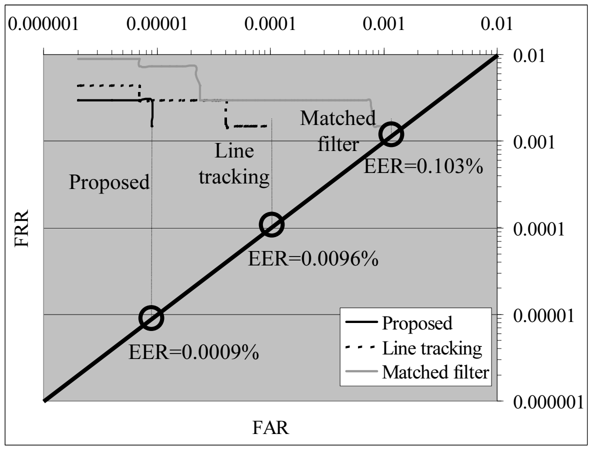


Figure 9: ROC curve.

veins showed that it is far superior to the conventional methods. A further experiment showed that the EER is 0.0009%, which means that the method is very effective for personal identification.

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