

Development of Human Identification System Based on Simple Finger-Vein Pattern-Matching Method for Embedded Environments

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Abstract

Biometric techniques for authentication using body parts such as a fingerprint, face, iris, voice, and finger-vein have become increasingly important in the personal security field, including door access control, finance security, and electronic passport. Finger-vein images can be captured under various conditions, such as different temperatures and illumination, and noise in the acquisition camera. Difficulties in recognizing finger-vein images include the use of a complex algorithm for noise reduction, image reconstruction, and rotation invariance in the pattern-matching algorithm. In this paper, we use a compact CMOS camera with a penetrating infrared LED light source. In addition, we suggest a simple pattern matching method to reduce the calculation time for embedded environments. The experimental results show that our simple system has good results in terms of speed and accuracy for personal identification.

Keywords: *finger-vein identification, biometric techniques, pattern matching*

1. Introduction

Biometric recognition systems have been applied to many areas such as national ID cards, e-passports, border crossings, access authority, computer login systems, and smart cards. However, although hand-shape-based biometric techniques, such as fingerprints, palm prints, and finger-veins, are very popular, some weaknesses still remain. Hand-based biometric techniques depend on the surface conditions, as well as the degree of sweat and dryness of the user's body. In addition, these techniques suffer from the threat of easy forgery. The use of finger-veins as accurate and fraud-proof biometrics has drawn increasing attention from pattern recognition practitioners in recent years [1]. Veins in the body are unique and persistent, and thus authentication systems can utilize finger-vein patterns. Finger-vein recognition system can overcome the weaknesses of other hand-based biometric techniques. The advantages of a finger-vein recognition system were introduced in [2]. A finger-vein is a non-contact body part and, is less influenced by the surface conditions, and thus finger-vein recognition allows for a comparatively high level of security. Finger-vein patterns are internal features, and are therefore difficult to forge. Finally, vein can only can be recognized from a living body, and thus finger-veins can be applied to live-body identification. In this paper, we compare different popular biometric recognition techniques. Table 1 shows the comparison results of various biometric technologies [3]:

Table 1. Comparison Results of Various Major Biometric Recognition Methods [3]

Bio-metrics	Security		Convenience			
	Anti-	Accuracy	Speed	Availability	Acceptable	Cost

	forgery						
Finger print	N	N	G	I	I	G	G
Iris	N	G	N	N	G	I	I
Face	N	I	N	N	I	I	I
Voice	N	I	N	N	I	N	N
Finger Vein	G	G	G	G	G	N	N

G: Good N: Normal I: Insufficient

In the above comparison, a finger-vein recognition system shows a comparatively high level of security and convenience. However, authentication using a finger-vein still incur certain problems. The original images of a finger-vein usually have a low contrast. From a hardware perspective, the quality of the images may decrease under a poor environment, such as under low-temperature, high-humidity conditions, which have a negative influence on the camera acquisition system. On the other hand, among the image data from the same fingers, finger-vein images have a variety of translations, shifts, and rotations. To solve these problems, we will improve the performance of the image acquisition device and evaluate the algorithms for use in an identification method to overcome deformed data from noise or, the sensor device, distorted signals from environmental noise, the variability of the individual's physical appearance, and data with varying shifts and rotations [3, 4]. The design of a biometric system consists of five objectives: cost, user acceptance and environment constraints, accuracy, computational speed, and security [5].

In this paper, we introduce a finger-vein identification system based on a simple pattern-matching method for embedded applications that can achieve invariant pattern matching with a limited number of shifts and rotations. This simple pattern-matching algorithm allows for the use of a cheap and fast hardware system.

2. Finger-vein Recognition System

2.1 Image Acquisition System

Figure 1 shows our proposed authentication system. Our authentication device, use a low-cost camera, Logitech C920 Camera (1920 x 1080) with a CMOS sensor, for acquiring the finger-vein images, as shown in Figure 1.

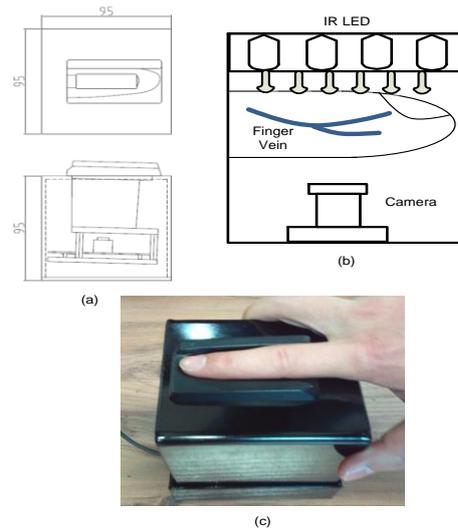


Figure1. The Finger-vein Authentication System (a) Design of the Mechanical System (b) Schematic of the Image Acquisition System (c) The Finger-vein Authentication System Detecting a Finger-vein Pattern

In our proposed device, we use a penetrating infrared LED with a wavelength of 700 to 1000nm as the light source. Because the infrared array LED is unable to penetrate the finger bone, and we must see the vessel beneath the bone, Infrared array LEDs are located along the side of the finger position and illuminate perpendicularly into the finger to collect the best quality finger-vein images. The minimum number of LEDs possible for even illumination and low cost is chosen.

The four finger-vein images in Figure2 were captured by our proposed image acquisition system.

Figure 2. Finger-vein Images Captured by Our Acquisition System

2.2. Image Deblurring Method

When we use a camera, every image is more or less blurry. Blurring always arises in the recording of a digital image. Captured finger-vein images are usually blurry and suffer from low contrast. The main reason for such blur and low image quality is that the light must penetrate the human body, and the human finger acts as a blurring filter. Image deblurring is therefore an inevitable step in an optical system to enhance the quality of an image. To find the exact blurring model of finger, we use an image from angiography and compare it with our finger image.

Optical blur models are mainly classified into spatially invariant blur and spatially variant blur. In our system, we consider illumination as spatially invariant. Spatial blurs can be classified into Gaussian distribution blur, uniform distribution blur, and so on. There are many kinds of optical blur models, and we tested a few deblurring models to select the best model for our application. Figure 3 shows the results of a few types of deblurring models.

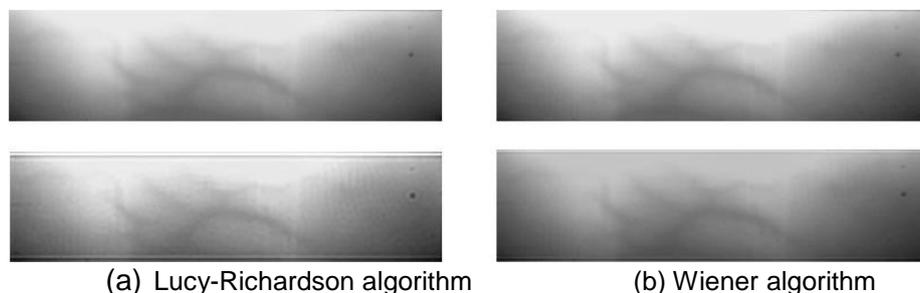


Figure 3. Images Results of Two Different Deblurring Algorithms

For finger-vein images, we choose a spatially invariant Gaussian distribution blur model, because, spatially invariant Gaussian blur usually occurs during the digital image processing in an optical system. In this paper, we use the following:

$$(1)$$

$$(2)$$

Here, $X_{i,j}$ is the gray value in the i^{th} column and j^{th} row of image X , Row and col are the height and width of image X , σ is the unit pixel length, and M is the size of the mask. We chose M to be 5 and σ to be 3.

Figure 4 shows deblurred finger-vein images with better contrast and sharpness after applying the Gaussian deblurring model, which can help make pattern-matching process easy to apply.

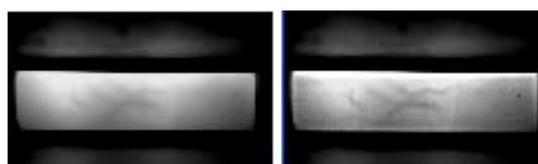


Figure 4. Images of Finger Vein Acquisition (a) Captured Blurred Finger-vein Image (b) Sharpened Image after Applying Gaussian Deblurring Model

2.3. Finger-vein Recognition Algorithm

Our proposed finger-vein recognition algorithm has three main steps, as shown in Figure 5. The first step is capturing images using the finger-vein image acquisition system. The second step is matching between the model and input images. In the second step, three important sub-steps, shown in Figure 5, are applied. The first sub-step is an image enhancement and, normalization after deblurring, the second sub-step is calculating the matching error, and the last sub-step is returning the matching error.

In the first step, the input images are captured twice by the evaluated image acquisition system. The histograms of two images are compared with each other. When they are similarly correlated, we choose one of the two images arbitrarily as an input image. When they are not similarly correlated, we acquire two more images to increase the success rate.

Figure 6 shows three different finger-vein images of the same finger. The histograms of Figures 6(a) and 6(b) are similar to each other; however, the histograms of Figure 6(c) differ with those of Figures 6(a) and 6(b).

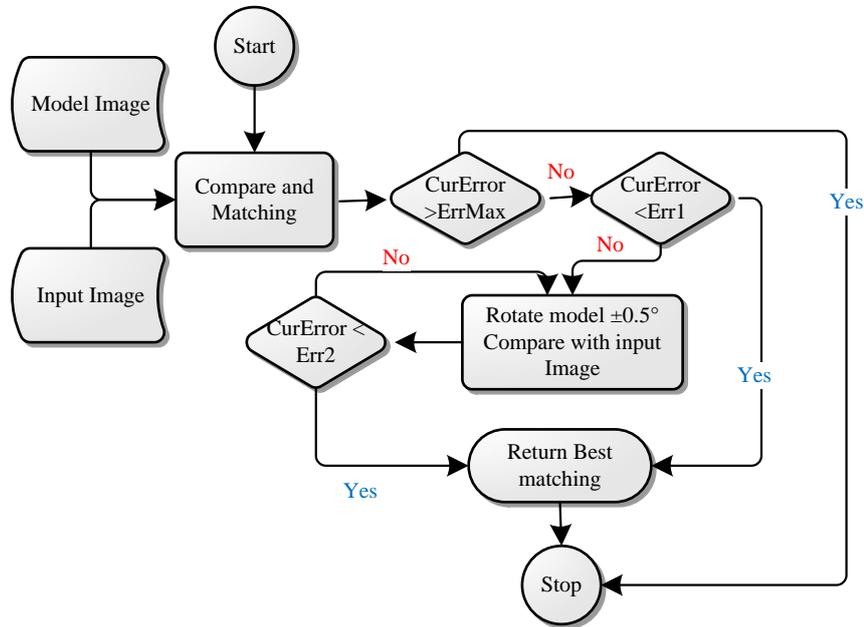


Figure 5. Schematic of the Algorithm used for Finger-vein Recognition

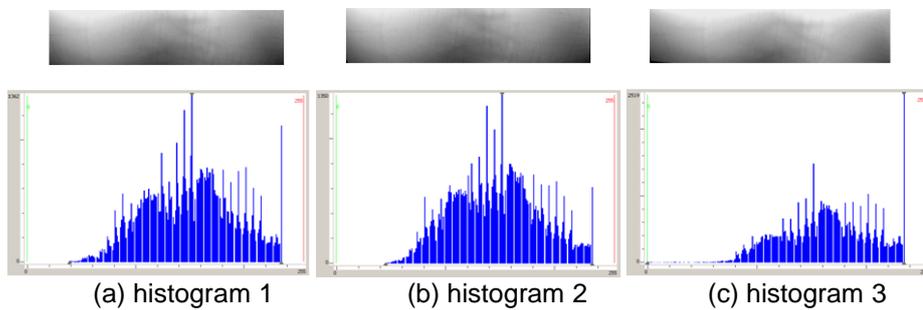


Figure 6. Histograms of Finger Vein from the Same Finger

The input images in our experiment consist of two types, model images and test images. Model images were captured and stored in the database in advance. Test images were captured during the authentication and compared with the model images in the database for recognition.

While capturing a finger-vein image, the finger of the user will usually shift or rotate in position. Our algorithm can solve the rotation pattern-matching problem by generating 20 rotation model images from -5° to $+5^\circ$ in $\pm 0.05^\circ$ steps. The rotated model images are generated using binary pixel interpolation. These rotated model images are stored in the database in advance.

The second step of our algorithm is a comparison and matching of the model images and with the test images. Our proposed method calculates the correlation between two images. As shown in Figure 7, this module has three main steps: (i) Image normalization, (ii) calculating the matching error, and (iii) return the matching Error.

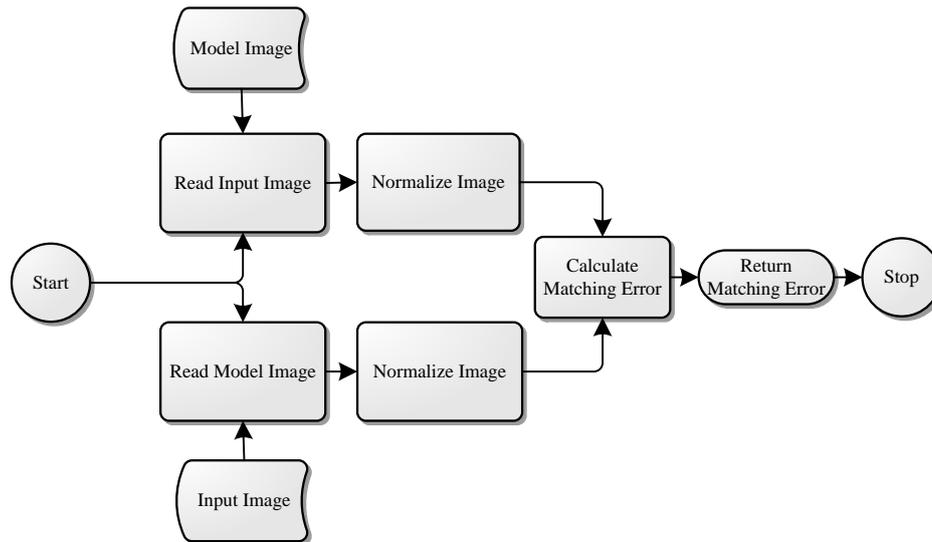


Figure 7. Flow-chart of the Calculation the Correlation

Before applying the matching algorithm, the images are normalized and deblurred after applying the image-capturing step to enhance the image quality, improve the system performance, and reduce the processing time. In our algorithm, the image normalization consists of some sub-modules, i.e., size correction, region of interest (ROI) extraction, and noise reduction, to improve the image quality. After this step, the size of the captured image is reduced from 640x480 pixels to 330x120 pixels to reduce the processing time and memory size. Figure 8 shows an example of input image normalization.

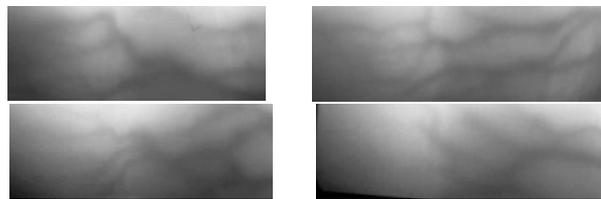


Figure 8. Examples of Input Images after Normalization

The next step is to calculate the correlation value between the model and test images. If the model and test images are of different fingers, the correlation value will be lower than when they are of the same finger.

At the end of this process, the matching error value is returned. This value is used in the next step of our algorithm and calculated through (3):

$$Error_{Matching} = \frac{\sum_{u,v} abs(I_{row-u,col-v} - M_{u,v})}{Area_M} \quad (3)$$

where, M is a model image, I is an input image, $Error_{Matching}$ is a matching error between input image I and model image M , $X_{i,j}$ is the gray value in the i^{th} column and j^{th} row of image X , u and v are chosen such that all points of the template will be reached, row and col are the height and width of image I , $Area_M$ is the area of image M . The values of u and v are the limits of the image shift are set to -5 to 5.

In the last step of the calculation, the correlation returns the best matching error. Our proposed algorithm uses 21 model rotated from -5° to $+5^\circ$ in $\pm 0.05^\circ$ step to resolve the

rotational image-matching problem, and applies pixel shifts of -5 to 5 to resolve the shift image problem. The minimum matching error chosen.

The value of the correlation is calculated to return the minimum matching error (as shown in Figure 5). Values such as *ErrMax*, *Err1*, and *Err2* are determined based on the system testing using image data. Our proposed algorithm shows a higher accuracy and speed.

3. Experimental Results

The finger-vein datasets for our experiments were generated by collecting finger-vein images from 100 individuals. Each finger-vein image of an individual was captured five different times. In total, the database contains 500 x 21 finger-vein model images because each model image was rotated 21 times.

Our proposed pattern-matching algorithm is a simple but fast image gray value correlation algorithm with a reasonably high accuracy and 97.60% success rate. Table 2 shows the results of our classification.

Table 2. Comparison of a Reference System and the Proposed Recognition System

Authentication System		Number of Total Trials	Number of Successes	Number of Fails	Ratio(%)
Reference System		500	451	49	90.20
Proposed method	Without Deblurring	500	473	27	94.60
	With Deblurring	500	488	12	97.60



Figure 9. Images with Unsatisfactory Results

To solve the complex pattern-matching problem for noise reduction, image re-construction and rotation and shift invariance in pattern matching, the main idea is to generate rotated images in advance and save them into database. It can be useful to apply a simple algorithm to implement the HW with a low cost CPU in an embedded environment. Normalization and deblurring are effective steps in our experiments. We compared the results of the algorithms when applying and not applying deblurring method and compared the performance of our system against a reference identification system (FDV - S570, Fit Design System, Japan). The experimental results show that our algorithm is very effective. We also analyzed images with unsatisfactory results, as shown in Fig. 9. The finger-veins in these images cannot be seen, and making it difficult to match and identify the images. To increase the success rate, we must increase the performance of the image acquisition system.

4. Conclusion

The greatest difficulty in a finger-vein recognition system is that the original finger-vein images have a low contrast and are blurry. To recognize the finger-vein images with a high success rate, a complex shift-invariant pattern-matching algorithm is needed for noise reduction, image re-construction, and rotation. However, we used a simple

identification device for acquiring the finger-vein images with a conventional Web camera CCD and lens, and proposed a simple pattern-matching algorithm, with low computational complexity. Our experimental results show that our proposed identification methods using finger- vein images has good results with accuracy of 97.60%. However, this success rate is still under 100%, which is insufficient for the personal security field, which requires 100% accuracy. In the future, our study will concentrate on developing image acquisition system to obtain better quality finger-vein images and use a different algorithm applied with a fusion technique.

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