A Thermal Hand Vein Pattern Verification System

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Abstract. Many biometrics, such as face, fingerprint and iris images, have been studied extensively for personal verification purposes in the past few decades. However, verification using vein patterns is less developed compared to other human traits. A new personal verification system using the thermal-imaged vein pattern in the back of the hand is presented in the paper. The system consists of five individual steps: *Data Acquisition, Image Enhancement, Vein Pattern Segmentation, Skeletonization and Matching*. Unlike most biometric systems that carry out comparisons based on a pre-selected feature set, this system directly recognizes the shapes of the vein pattern by measuring their Line-Segment Hausdorff Distance. Preliminary testing on a database containing 108 different images has been carried out and all the images are correctly recognized.

1 Introduction

Public awareness of security issues has been greatly heightened since September 2001. This has led to a massive rise in demand for the personal identification systems. Traditional methods make use of smart cards or Personal Identification Numbers (PIN) etc to identify a person. However, these methods only offer limited security and are usually unreliable. Over the past few years, various biometric systems have been developed to overcome these disadvantages.

Biometrics is the science of identifying a person using its physiological or behavioral features [1]. These features range from physical traits like fingerprints, faces, retina etc. to personal behaviors (such as signatures). Compared to traditional methods, biometric features are much harder for intruders to copy or forge, and it is very rare for them to be lost. Hence, for identification systems making use of biometric features, they offer a much more secure and reliable performance.

During the past few decades, many researchers have carried out extensive studies on utilizing various biometric features (both physiological and behavioral) for personal verification. Amongst those biometric features, the most popular ones are fingerprints, faces, and iris scans for physiological biometrics, as well as signatures for behavioral one. Each of these biometric features has its strengths and weaknesses [2]. Recently, hand vein pattern biometrics has attracted increasing interest from both research communities [3–5] and industries [6]. Anatomically, aside from surgical intervention, the shape of vascular patterns in the back of the hand is distinct from each other [7], and it remains stable over a long period. In addition, as the blood vessels are hidden underneath the skin and are invisible to the human eye, vein patterns are much harder for intruders to copy as compared to other biometric features. All these special properties of hand vein patterns make it a potentially good biometrics to offer more secure and reliable features for personal verification.

In this paper, a new personal verification system using vein patterns in the back of the hand is proposed. The system consists of five individual processing stages: *Hand Image Acquisition, Image Enhancement, Vein Pattern Segmentation, Skeletonization and Matching*, as shown in Figure 1. The system captures the vein pattern images using a thermal camera. Unlike other vein pattern verification systems that compare the vein patterns based on a predefined set of features extracted using techniques like Multiresolution analysis [5], the proposed system recognizes the shapes of the preprocessed vein patterns by calculating their line segment Hausdorff distances.

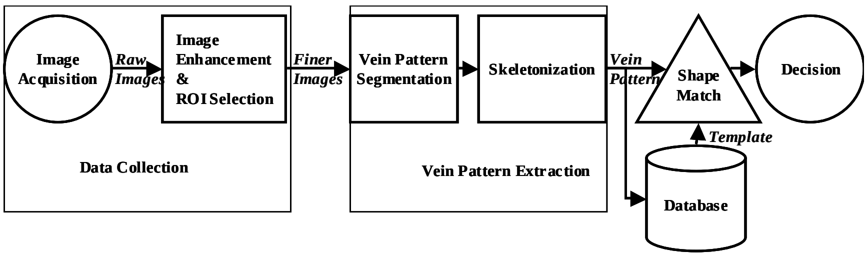

Fig. 1. Hand vein pattern verification system model

2 Data Collection

2.1 Image Acquisition

Veins are hidden underneath the skin, and are generally invisible to the naked eye and other visual inspection systems. However, human superficial veins have higher temperature than the surrounding tissue. Based on this fact, the vein pattern in the back of the hand can be captured using a thermal camera. In this work, an NEC Thermal Tracer is utilized to acquire thermal images of the back of the hand. Figure 2 shows some of the images collected from different people in a normal office environment ($20-25°C$), and it can be seen that the veins appear to be brighter in the images and are now visually distinguishable. A rectangular region in the hand images can be defined as the region of interest (ROI). The technique of locating the ROI is similar to the one proposed by Lin and Fan [5], where the landmarks of the hand such as finger tips and valleys between the fingers are first located, then a fixed size rectangular region is defined as the ROI based on the location of these landmark points. The image on the left of Figure 4 shows the result of the extracted ROI.

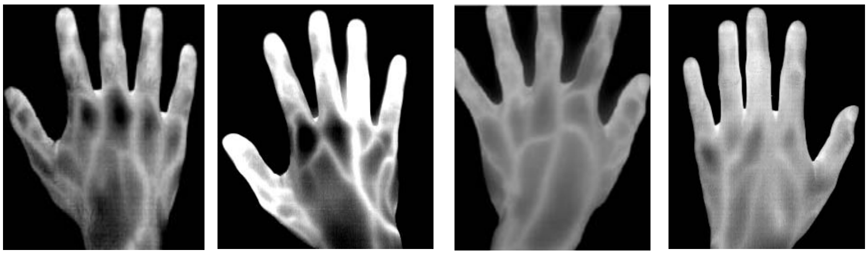

Fig. 2. Thermal images of the back of the hands in normal office environment

The images in Figure 2 were captured in a normal office environment, where the temperature and humidity are lower than outside. Figure 3 shows another set of images captured in a tropical outside environment ($30 - 34°C$ and $> 80\%$ humidity). It can be seen that the ambient temperature and humidity have a negative impact on the image quality, and the vein patterns in these images are now not easily visually distinguishable. Therefore, in our work, we use the image data collected in a normal office environment instead of an outside environment for better system performance.

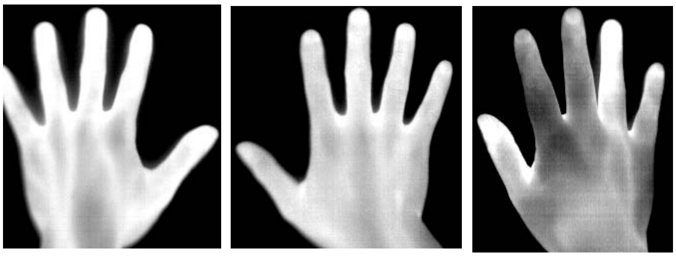

Fig. 3. Thermal images of the back of the hands in an outdoor environment

2.2 Image Enhancement

The clearness of the vein pattern in the extracted ROI varies from image to image, therefore, the quality of these images need to be enhanced before further processing. A 5x5 Median Filter was used to remove the speckling noise in the images. Then, a 2-D Gaussian low pass filter $H(u,v) = e^{-D^2(u,v)/2\sigma^2}$ with standard deviation $\sigma = 0.8$ was applied to the vein pattern images to suppress the effect of high frequency noise.

After removing the speckling and other high frequency noise, the vein pattern images are normalized to have pre-specified mean and variance values. The normalization process is to reduce the possible imperfections in the image due to the sensor noise and other effects. The method for normalization employed in this work is similar to the one suggested by Hong et al [8]. Let $I(x,y)$ denote the intensity value at position (x,y) in a vein pattern image. The mean and variance of image are denoted as μ and σ^2 respectively. For an image sized $N \times M$, they are computed using Equation 1 and 2.

$$\mu = \frac{1}{N \times M} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x,y) \ . \tag{1}$$

$$\sigma^2 = \frac{1}{N \times M} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - \mu)^2 \ . \tag{2}$$

Then the normalized image $I^{'}(x,y)$ is given by the pixel-wise operations in Equation 3, where μ_d and σ_d^2 are the desired values for mean and variance respectively.

$$I^{'}(x,y) = \begin{cases} \mu_d + \sqrt{\frac{\sigma_d^2 \cdot (I(x,y)-\mu)^2}{\sigma^2}}, & I(x,y) > \mu \\ \mu_d - \sqrt{\frac{\sigma_d^2 \cdot (I(x,y)-\mu)^2}{\sigma^2}}, & \text{Otherwise} \end{cases} \ . \tag{3}$$

Figure 4 shows the vein pattern image after normalization. It can be seen that the quality of the image has been improved significantly

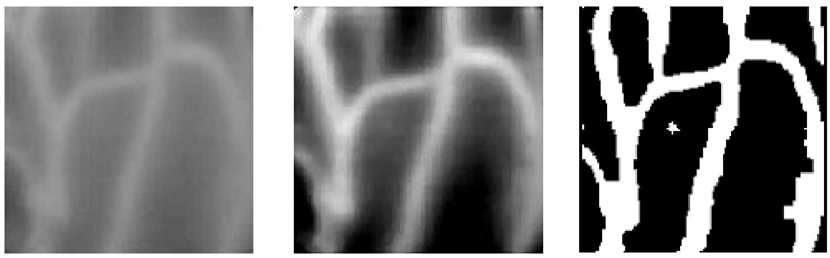

Fig. 4. Left: Region of interest; Center: After normalization; Right: After local threholding

3 Vein Pattern Extraction

3.1 Local Thresholding

After noise reduction and normalization, the quality of the image improves. However, the vein pattern is still surrounded by many faint white regions. To obtain a better representation of the shape of the vein pattern, it is necessary to separate the vein pattern from the image background. Due to the fact that the gray-level intensity values of the vein vary at different locations in the image, global threholding techniques do not provide satisfactory results. Hence, a locally adaptive thresholding algorithm was utilized to segment the vein patterns from the background. The algorithm chooses different threhold values for every pixel in the image based on the analysis of its surrounding neighbors. For every pixel in the image, its threhold value is set as the mean value of its 13×13 neighborhood. The binary image on the right side of Figure 4 shows the vein pattern has been successfully segmented from the original image after applying the local threholding algorithm.

3.2 Skeletonization

As the size of veins grow as human beings grow, only the shape of the vein pattern is used as the sole feature to recognize each individual. A good representation of the pattern's shape is via extracting its skeleton. Figure 5 shows the skeleton of the vein pattern after applying the thinning algorithm proposed by Zhang and Suen [9] . It can be seen that after the pruning process, the skeletons of the vein pattern are successfully extracted and the shape of the vein pattern is well preserved.

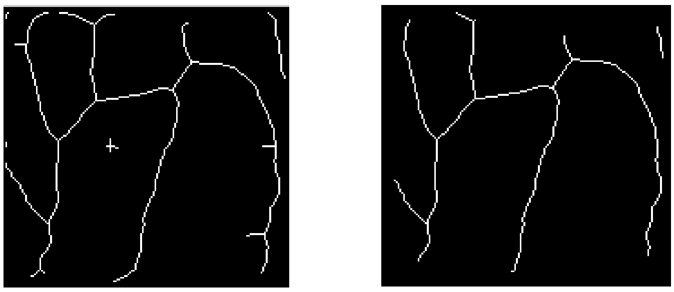

Fig. 5. Left: Skeleton of the vein pattern in Figure 4; Right: After pruning

4 Vein Pattern Matching

Vein pattern matching is done by measuring the line segment Hausdorff distance between a pair of vein patterns. Hausdorff distance is a natural measure for comparing similarity of shapes. It is a distance measure between two point sets, and Equation 4 and 5 give the definition for a modified version of Hausdorff distance.

$$H(M^p, T^p) = \max\left(h(M^p, T^p), h(T^p, M^p)\right) . \tag{4}$$

$$h(M^p, T^p) = \frac{1}{N_m^p} \sum_{m_i^p \in M^p} \min_{t_j^p \in T^p} \| m_i^p - t_j^p \| . \tag{5}$$

Hausdorff distance uses the spatial information of an image, but lacks local structure representation such as orientation when it comes to comparing the shapes of curves. To overcome this weakness, in this paper, the line segment Hausdorff distance (LHD) is calculated to match the shapes of vein patterns.

Line segment Hausdorff distance was proposed by Gao and Leung [10] for a face matching application. It incorporates the structural information of line segment orientation and line-point association, and hence is effective to compare two shapes made up of a number of curve segments.

Given two finite line segment sets $M^l = \{m_1^l, m_2^l, ..., m_p^l\}$ and $T^l = \{t_1^l, t_2^l, ..., t_p^l\}$, LHD is built on the vector $\overrightarrow{d}(m_i^l, t_j^l)$ representing the distance between the two line segment sets, and the vector is defined as

$$\overrightarrow{d}(m_i^l, t_j^l) = [\, d_\theta(m_i^l, t_j^l), \quad d_\parallel(m_i^l, t_j^l), \quad d_\perp(m_i^l, t_j^l) \,]^T \tag{6}$$

where $d_\theta(m_i^l, t_j^l)$, $d_\parallel(m_i^l, t_j^l)$ and $d_\perp(m_i^l, t_j^l)$ are the *angle distance, parallel distance and perpendicular distance* respectively. The numerical value of the distance is given by equation 7. The directed and undirected LHDs are defined in equation 8 and 9, where $l_{m_i^l}$ is the length of line segment m_i^l.

$$d(m_i^l, t_j^l) = \sqrt{(W_a \cdot d_\theta(m_i^l, t_j^l))^2 + d_\parallel^2(m_i^l, t_j^l) + d_\perp^2(m_i^l, t_j^l)} \tag{7}$$

$$h_l(M^l, T^l) = \frac{1}{\sum_{m_i^l \in M^l} l_{m_i^l}} \sum_{m_i^l \in M^l} l_{m_i^l} \cdot \min_{t_j^l \in T^l} d(m_i^l, t_j^l) \tag{8}$$

$$H_l(M^l, T^l) = \max(h_l(M^l, T^l), h_l(T^l, M^l)) \tag{9}$$

In this application, the vein patterns are divided into a number of curve segments. For each individual curve segment, a few points are sampled to represent the curve segment. Using these sample points as the end points, a set of line segments representing the shape of the vein pattern are obtained. By this means, the undirected LHD can then be calculated to measure the similarity of two vein patterns.

5 Testing Results

Testing was carried out on a vein pattern image database consisting of 108 images from 12 people (9 from each person). Prior to testing, three images for each person were selected randomly to form the class templates for that person.

During the verification stage, three undirected LHDs (H_1,H_2,H_3) are computed between the incoming vein pattern image and the three template images. The average value H' of H_1, H_2 and H_3 is then calculated, which is the similarity measure between the incoming vein pattern and the target class. Figure 6 shows the distribution of the genuine and intruder accesses against the value H'. It can be easily seen from the figure that the smaller H' is, the higher the probability the vein pattern belonging to the genuine class. By choosing 9.0 to be the threhold value, the system achieves 0% false acceptance rate (FAR) and 0% false rejection rate (FRR) for all the 108 images in both the testing set (containing 72 images) and the template set (containing 36 images).

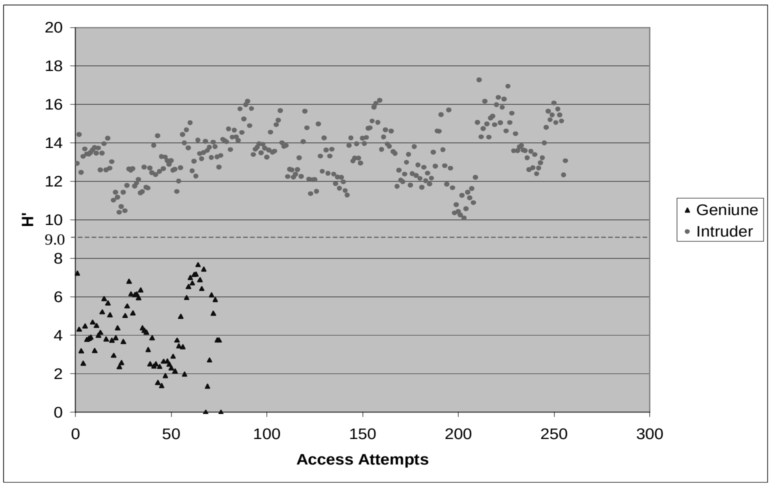

Fig. 6. Distribution of genuine and intruder accesses against similarity measure H'

The results of the experiment are encouraging. However, the images in the current database are taken in a more controlled manner, where the participants are fully cooperative and the image acquisition is carried out in a normal office environment with ambient temperature around $20°C$ and humidity of $< 50\%$. For a real life application, the surrounding conditions are unknown. Therefore the quality of the vein pattern images may reduce, and as a result, a decrease of verification accuracy can be expected.

6 Conclusions

This paper presents a biometric system that recognizes the shapes of the vein pattern in the back of the human hands captured using a thermal camera. Unlike other approaches, the system directly recognizes the shapes of the vein pattern using line segment Hausdorff distance. Preliminary testing results show that all the vein pattern images in the database have been correctly recognized, and it demonstrates the potential usefulness of such a system. Nevertheless, a number of research issues need to be addressed in the future. First of all, the clearness of the vein pattern in the image is affected by a number of factors such as ambient temperature, nearness of the vein to the skin etc. An investigation is needed into the impact of these factors on the quality of the vein pattern image. Secondly, more experiments need to be carried out using a larger image database for a thorough evaluation on the efficacy of hand vein pattern biometrics. Lastly, it is likely that the vein patterns will be used in conjunction with other biometrics in a multi-modal system.

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