A Watershed Algorithmic Approach for Gray-Scale Skeletonization in Thermal Vein Pattern Biometrics

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Abstract. In vein pattern biometrics, analysis of the shape of the vein pattern is the most critical task for person identification. One of best representations of the shape of vein patterns is the skeleton of the pattern. Many traditional skeletonization algorithms are based on binary images. In this paper, we propose a novel technique that utilizes the watershed algorithm to extract the skeletons of vein patterns directly from gray-scale images. This approach eliminates the segmentation stage, and hence prevents any error occurring during this process from propagating to the skeletonization stage. Experiments are carried out on a thermal vein pattern images database. Results show that watershed algorithm is capable of extracting the skeletons of the veins effectively, and also avoids any artifacts introduced by the binarization stage.

1 Introduction

Biometrics is the science of identifying a person using physiological or behavioral features [1]. During the past few decades, various biometric features have been utilized for person verification. The most popular ones are fingerprints, faces, and iris scans as well as handwritten signatures. Each of these biometrics have their strengths and weaknesses [2]. Recently, vein pattern biometrics has attracted increasing interest from both research communities [3,4,5,6] and industries [7,8].

A Vein Pattern is the vast network of blood vessels underneath a person's skin. Anatomically, aside from surgical intervention, the shape of vascular patterns in the same part of the body is distinct from each other [9], and it is very stable over a long period of time, as a person's pattern of blood vessels is "hardwired" into the body at birth, and remains relatively unaffected by aging, except for predictable growth, as with other biometrics such as fingerprints. In addition, as the blood vessels are hidden underneath the skin and are mostly invisible to the human eye, vein patterns are much harder for intruders to copy compared to other biometric features. The properties of uniqueness, stability and strong immunity to forgery of the vein pattern make it a potentially good biometric which offers greater secure and reliable features for person identity verification.

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A typical vein pattern biometric system consists of five individual processing stages [3]: *Image Acquisition, Image Enhancement, Vein Pattern Segmentation, Skeletonization and Matching*, as shown in Figure 1. During the image acquisition stage, vein patterns are usually captured using infrared imaging technologies. One of the practices is using a far-infrared camera to acquire the thermal vein pattern images of the back of the hand [3,4]. After obtaining the images, the system will segment the vein pattern from the background and binarize it for skeletonization to obtain the shape of the pattern. Finally, the system recognizes the vein patterns by various pattern recognition methods such as calculating the line segment Hausdorff distances [10].

However, during the vein pattern segmentation and binarization stage of the system shown in Figure 1, errors will be unavoidably introduced. These errors will then be propagated to the skeletonization stage, and subsequently degrade the performance of all the subsequent processing stages. This paper examines the problems brought up to the skeletonization stage by the segmentation and binarization process. A new solution is then proposed, whereby skeletonization is performed directly on the gray-scale vein pattern images using the morphological watershed algorithm, which produces better skeletonization results.

This research focuses on thermal vein pattern images processing, and the paper is organized in the following manner: Section 2 investigates in detail the problems introduced by the vein pattern segmentation process. A new system model for vein pattern biometrics is then proposed. Following this, in Section 3, an in-depth discussion of our approach using the watershed algorithm to extract the skeletons of the vein patterns from gray-scale images is presented. Experiments, and their results are reported in this section with some discussion of the problems encountered using the current watershed approach. Finally, Section 4 gives concluding remarks of this paper.

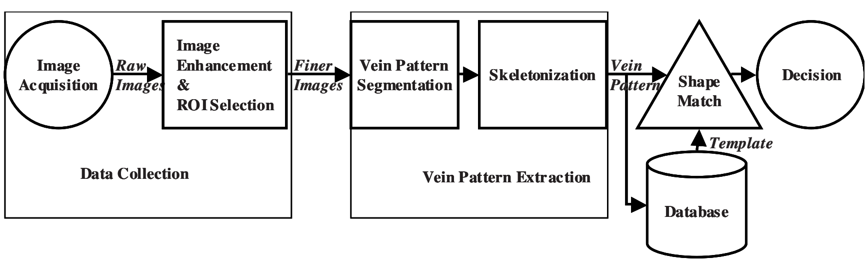

Fig. 1. A typical vein pattern verification system model

2 Traditional Binary-Based Skeletonization

2.1 Vein Pattern Segmentation

A typical thermal vein pattern image of the back of the hand is usually of low contrast and noise-prone. In addition, due to heat radiation, the tissue nearby

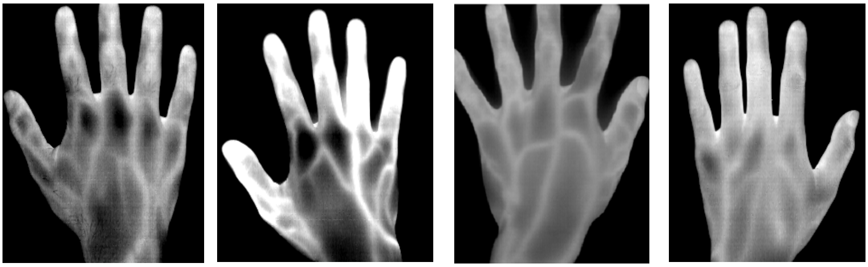

Fig. 2. Thermal vein pattern images of the back of the hands in a normal office environment

has similar temperature to the blood vessels, which results in veins being surrounded by many faint white region in the images (see Figure 2) . All these make separation of vein patterns from the background a difficult task. A popular class of segmentation methods: intensity thresholding, is usually utilized to tackle the problem, where each image pixel is classified either greater or less than or equal to a given intensity. However, 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. A more suitable method is via local adaptive thresholding, whereby the algorithm chooses different threhold values for every pixel in the image based on the analysis of its surrounding neighbors. Figure 3 shows the binary image of the vein pattern after applying our local thresholding algorithm, where for every pixel in the image, its threshold value is set as the mean value of its 13×13 neighborhood.

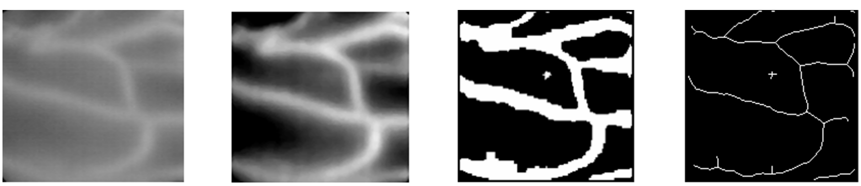

Fig. 3. From left to right: Original ROI of the vein pattern image; After image enhancement; After applying local thresholding; After skeletonization

It can been seen from Figure 3 that the shape of the vein pattern is well preserved in the binrary image after threholding. However, there are also many misclassifications of background points being the points of the vein, especially for those points near the edge of the veins. This is because the intensity thresholding method suffers from errors due to image inhomogeneities and the partial volume effect [11]. Furthermore, the choice of threshold level is subjective, and might not be optimum for all images.

The misclassification errors introduced by this binarization process will be propagated to the next stage, and may be magnified by the skeletonization algorithm, as is elaborated in the following section.

2.2 Binary Skeletonization

There are many skeletonization algorithms that can be used to thin the objects in the binary image. In this paper, we apply two different skeletonization algorithms [12,13] to the binary vein pattern images, and they give us very similar results. As can be seen in Figure 3, the misclassification points in the segmentation stage have led to numerous spur branches as well as isolated segments of skeletons. These false branches will in turn degrade the accuracy of the matching process. Whilst some pruning processes can be taken to remove some of the small artifacts, they generally have some negative impacts to the true skeletons.

2.3 Proposed New System Model

As discussed above, the binarization process of the thermal vein pattern image will result in many misclassification points, these points will create false branches during skeletonization, and hence degrade the performance of the subsequent processing stages. One solution is to improve the segmentation algorithms to reduce misclassification as much as possible. However, in this paper, we propose another solution to tackle this problem: performing skeletonization directly on the gray-scale vein pattern images. This will eliminate the segmentation stage, and hence will prevent any potential errors occurring at this stage being propagated to the subsequent stages. As a result, the system model in Figure 1 will now have 4 stages as shown in Figure 4.

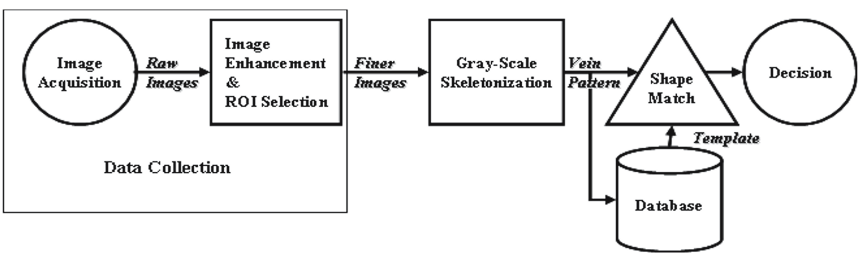

Fig. 4. The proposed new system model eliminates the segmentation stage

3 Gray-Scale Skeletonization Using the Watershed Algorithm

3.1 The Watershed Principle

The watershed concept is based on visualizing an image in three dimensions: two spatial coordinates versus gray levels, through which any grayscale image can be considered as a topographical surface. The basic idea of the watershed algorithm is a simulation of the immersion process [14,15]: At first, holes are pierced in all regional minima of the relief (connected plateaus of constant altitude from which it is impossible to reach a location of lower altitude without having to climb). Then by sinking the whole surface slowly into a lake, water springs through the holes and progressively immerses the adjacent walls. To prevent streams of water coming from different holds to intermingle, a dam is set up at the meeting locations. The flooding will eventually reach a stage when only the tops of the dams are visible above the waterline. These dam boundaries correspond to the divide lines of the watersheds.

Mathematically, this immersion process can be established by the definition of geodesic distance and geodesic influence zone [16]. The geodesic distance $d_A(x, y)$ between two pixels x and y in A is the infimum length of the paths P which join x and y and are totally included in A (Equation 1). Whilst the geodesic Influence zone is defined as: Suppose A contains a set B consisting of several connected components B_1, B_2,...,B_k. The geodesic influence zone $iz_A(B_i)$ of a connected component B_i of B in A is the locus of the points of A whose geodesic distance of B_i is smaller than their geodesic distance to any other component of B. This is expressed in Equation 2.

$$d_A(x, y) = inf\{l(P)\} \tag{1}$$

$$iz_A(B_i) = \{p \in A, \forall j \in [1, k]/\{i\}, d_A(p, B_i)\} \tag{2}$$

Hence, the watersheds can be obtained by finding the set of catchment basins of the gray-scale image I through the following recursion (Equations 3 and 4):

$$X_{h_{min}} = T_{h_{min}(I)}, \text{ where } T_h(I) = \{p \in D_I, I(p) \le h\} \tag{3}$$

$$\forall h \in [h_{min}, h_{max} - 1], X_{h+1} = min_{h+1} \bigcup iz_{T_{h+1}(I)}(X_h) \tag{4}$$

3.2 Application of Watersheds Algorithm to Vein Pattern Skeletonization

Traditionally, the watershed algorithm is used to find the contour of the objects for segmentation purposes. Therefore, it is usually applied to the gradient images. However, when we apply the watershed algorithm directly to the gray-scale vein pattern images, it is capable of locating the skeletons of the veins. The image in the center of Figure 5 shows the result of applying the watershed algorithm to the thermal vein pattern image. It is clearly visible that the result contains too many false ridges, and this is commonly referred to as over-segmentation, which is due to noise and other local irregularities.

Many researchers have addressed the over-segmentation problem for the watershed algorithm. Markers, for example, are widely used to reduce the effect of over-segmentation. In our approach, we perform morphological opening followed by closing operations to suppress the noise and local irregularities in the image prior to the application of the watershed algorithm (Equation 5). The image

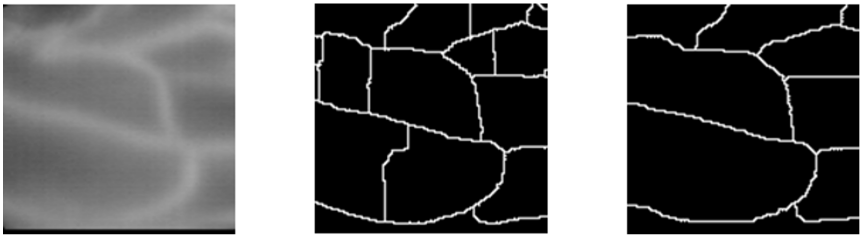

Fig. 5. From left to right: Original ROI image; Skeletons obtained by direct application of watershed algorithm, where over-segmentation is apparent; Skeletons obtained by applying morphological opening and closing first followed by the watershed algorithm

in the right side of Figure 5 shows the result with our approach, and it can be easily seen that the single pixel wide skeleton of the vein pattern is successfully extracted, and the number of false branches is significantly reduced.

$$I' = (I \circ B) \bullet B; \text{ where } B \text{ is the structuring element.} \tag{5}$$

3.3 Experiments

The watershed algorithm was investigated for gray-scale skeletonization on our thermal hand vein patterns database. Most of the vein patterns can be successfully skeletonized without losing any connectivity (as shown in the examples in

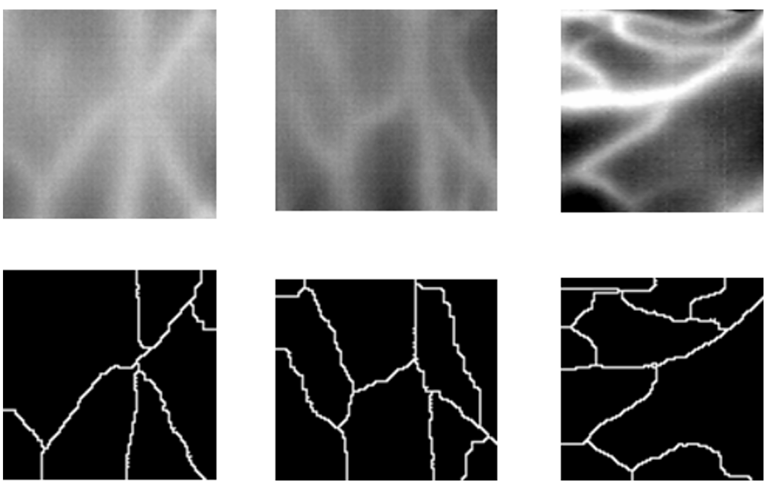

Fig. 6. Top: Original ROI images; Buttom: Skeletons obtained by applying the proposed watershed algorithm

Figure 6). However, there are some situations where the watershed algorithm fails to skeletonize the vein patterns properly:

1. when two veins are too close to each other, the watershed algorithm will tend to merge them together to become one line, as can be seen in the left image of Figure 7. This requires a better preprocessing algorithm to make the two veins more separable in gray level intensity.

2. when the vein patterns are not visually discernible, the watershed algorithm will not be able to extract any meaningful skeletons for the vein patterns . This can only be resolved by using alternative imaging devices, which is beyond the scope of this paper.

3. when the veins have floating endpoints in the image, the watershed algorithm is unable to extract this type of line, which is shown in the right image of Figure 7.

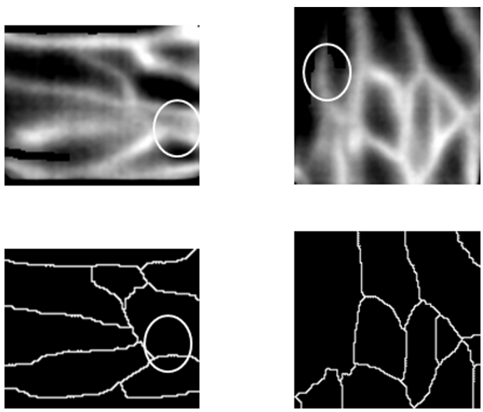

Fig. 7. Situations where watershed fails to extract the skeletons properly. Left: Two veins are too close to each other; Right: A vein has a floating endpoint in the image.

4 Conclusions

This paper presents a novel technique for extracting the skeletons of thermal vein patterns in vein pattern biometric systems. Traditional skeletonization algorithms require the object of interest to be firstly segmented from the background and binarized. However, the errors introduced during the binarization process will be propagated to the skeletonization stage, which can be magnified and degrade the system performance. The proposed watershed-based skeletonization algorithm works directly on the gray-scale vein pattern images. It eliminates the segmentation and binarization process, and hence prevents any potential errors being propagated to the subsequent stages. Experiments show that the watershed algorithm is capable of extracting the skeletons of veins from the gray-scale images. However, there are also a number of cases where the watershed algorithm fails to detect the proper skeletons, which remains an issue to be tackled in the future.

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