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Dorsal Hand Vein Recognition based on EP-Tree

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Abstract

Vein recognition, as an emerging biometric recognition approach, is becoming a very active topic in both research and practical applications. In our framework, the minutiae features is extracted from the dorsal hand vein patterns for recognition, which include end points and the distance between the two end points as measured along the boundary of the image. In addition, the end-points-tree (EP-tree) is proposed to accelerate the matching performance and evaluate the discriminating power of these end points for person verification purposes. We employed a total of 4,280 images of dorsal hand veins from 214 individuals in order to validate the proposed recognition method. In a comparison with three existing verification algorithms, the proposed method achieves the highest accuracy in the lowest matching time.

1. Introduction

Biometrics-based identity verification technologies are based on the distinctive information in human biometric traits including facial images, hand vein outlines, fingerprints, palmprints, retinal information, handwriting, signature, and gait [1]. Among them, vein recognition is tested as the most accurate manner of personal identification [2]. Therefore, nowadays many automatic security systems based on vein recognition have been deployed worldwide for border control, restricted access, and so on.

In general, dorsal hand vein images consist of many different features such as the geometric pattern, principal line, and minutiae. All these desirable properties (i.e., uniqueness, stability and non-invasiveness) make vein recognition suitable for highly reliable personal identification. Hsu et al. [3] successfully used modified 2-directional 2-dimensional principal component analysis ($(2D)^2$PCA) to obtain eigenveins, which is a low dimensional representation of vein pattern features. Lin et al. [4] proposed the use of multiple multi-resolution analysis features for analyzing palm-dorsal vein patterns. Lee [5] proposed an innovative, robust directional 2-D Gabor filters technique for the encoding of vein features in bit string representation. The fusion of multiple features [4-5] may improve recognition accuracy, but such approaches are time consuming. Geometry-based approaches [6-8] extract local features such as the locations and local statistics of the principal veins and minutiae points. Wang et al. [6] employed the minutiae features extracted from the vein patterns for recognition, which include bifurcation and ending points. These minutiae features are used as a geometric representation of the shape of vein patterns. Kumar et al. [7] presented a new approach to authenticate individuals using triangulation of hand vein images and simultaneous to extract the knuckle shape information. The resulting rotation and translation invariant feature vector is variable in length as determined by the number of identified triplets. Lee et al. [8] employed minutia-based alignment and local binary pattern for finger vein recognition. However, above the geometry-based methods are difficult to extract, represent, and compare, and it is time consuming to measure the similarity between the minutiae points.

In this paper, a new feature extraction approach for vein patterns is based on minutiae points where the positions of end-points from the skeletal representation of vein patterns are being used. The main contributions of this paper can be summarized as follows.

(1) Based on the minutiae points of vein images, we extracted end-point features and the boundary distances between the two end points along the boundary of every sub-image. The novel method of feature extraction offers the features compression of vein images and shows the vein characteristic properly. Further details of this strategy can be seen Section 3.
(2) To reduce matching cost, the end-point-tree (EP-tree) is proposed to search the similar vein image in the dorsal hand vein database. Therefore, we only match the similar images to further improve the computing time for vein recognition.

The rest of this paper is organized as follows. Section 2 briefly introduces the preprocessing of vein images. A detailed description of the proposed dorsal hand vein recognition method is given in Section 3. Experimental results are presented and discussed in Section 4, and conclusions are given in Section 5.

2. Vein Image Preprocessing

To ensure that the proper vein features can be extracted from the dorsal hand vein image, it is essential to preprocess the images. The dorsal vein hand database presented in this study is reported in [3]. The features of vein patterns extracted from the same region in different dorsal hand vein images are compared for verification. The extracted region is known as the region of interest (ROI). The ROI fixing process has a significant influence on the accuracy of verification. The preprocessing procedure employed in this study is comprehensively described in [3]. In addition, enhancing the performance of vein recognition requires the extraction of texture from the veins in the image background. In this paper, a global/local threshold algorithm [9] was used to segment the vein patterns from the background. The binary image in Fig. 1(b) illustrates the vein pattern has been successfully segmented from the original image after applying the global and local threshold algorithm.

Extracting the end points from the vein structures requires computational thinning of the vein patterns using mathematical morphology operators. This paper performed the thinning operation on vein binary image using the well-known Stentiford thinning algorithm [10]; however, even this was insufficient to satisfactorily reveal the structures associated with the vein patterns. This can be attributed to fact that the resulting binary pattern also contains redundant branches; i.e., isolated regions with negligible connectivity. Figure 1(c) presents the skeleton of the vein patterns extracted using the thinning algorithm. The most common approaches to overcome redundant branches are based on skeleton pruning methods. By using skeleton pruning algorithm [11] spurious segments induced by isolated regions with small connectivity are eliminated whilst the dominant veins are retained, as shown in Fig. 1(d). It can be seen that after the pruning process, the structures associated with the vein patterns have been effectively extracted while the shape of the vein pattern remains well preserved.

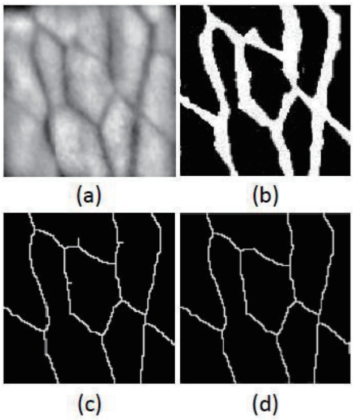

Figure 1. Skeleton of the vein pattern: (a) original ROI image, (b) binary image of vein pattern, (c) skeleton of pattern after thinning algorithm, and (d) vein structures extracted following pruning process.

3. Proposed Method

The proposed method presented in this paper for the recognition of dorsal hand veins involves two basic processes: feature extraction and matching. The procedures of two novel algorithms are stated as follows:

3.1. Extraction of minutiae features

Based on minutiae features, the vein pattern can be well represented using a number of end points in the dorsal hand vein image. Obtaining the end points from the skeleton of vein patterns involves partitioning the thinned image into four sub-images with different image dimensions (128×128 , 96×96, 64×64, and 32×32 pixels), as shown in Fig. 2. In each of the sub-images, the end points represent intersections of image boundaries and veins. The proposed method makes it possible to determine the number of end points and the distance between two end points along the boundary. However, in each sub-image, the number of end points and the distances along the boundaries are selected as main features with which to represent the vein properties. According to the above discussion, the entire feature extraction framework is given as follows:

Figure 2. Inward partitioning of thinned image resulting in four sub-images of various dimensions (128×128 , 96×96, 64×64, and 32×32 pixels)

(1) Vein images are partitioned into different dimensions. The sub-vein images are extracted from thinning image according to the size extract-window (128×128, 96×96, 64×64, and 32×32 pixels), respectively.
(2) The points at which the veins meet the four boundaries in each sub-image are extracted, and then the numbers of boundaries associated with each end point are calculated. The number of end points along the boundaries of the sub-image in Fig. 3 are 3, 1, 3, and 1 (clockwise from the top), respectively.
(3) The distances between two end points and between end points and vertices are then calculated. For example, the Fig. 3 shows the boundary distances as $L_1,\ L_2, \cdots, L_{12}$, respectively.
(4) Every sub-vein image can be found two feature sets based on the end points and boundary distances.
   - The first feature vector is extracted using end points, and resulting in $p1, p2, p3, p4, q1, q2, q3, q4, r1, r2, r3, r4, s1, s2, s3, s4$, respectively. $p1 \sim p4$ are the number of end points associated with the four boundaries in the 128×128 pixel sub-image. Thus, $q1 \sim q4$, $r1 \sim r4$, and $s1 \sim s4$ are the number of end points along the four boundaries in the sub-other images (96×96 , 64×64 , and 32×32 pixels), respectively.
   - The second feature vector is selected according to the boundary distances, as $i_1, i_2, \cdots, i_n,\ j_1, j_2, \cdots, j_m, k_1, k_2, \cdots, k_k, l_1, l_2, \cdots, l_x$, respectively. $i_1, i_2, \cdots, i_n$ are the distances along the boundaries of the 128×128 pixel sub-image. $j_1, j_2, \cdots, j_m$, $k_1, k_2, \cdots, k_k$, and $l_1, l_2, \cdots, l_x$ are the boundary distances of the other three images, 96×96, 64×64, and 32×32 pixels, respectively.

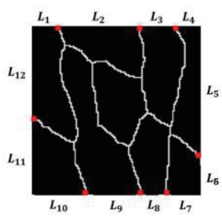

Figure 3. Extraction of end points and boundary distances from the skeleton of vein patterns.

The proposed method makes it possible to precisely determine the end points (feature points) and boundary distances (feature distances), such that the features present an accurate representation of the vein image. The method used for feature extraction does not involve searching the entire image, but only searching information related to the boundaries of images. Thus, the proposed method extracts the vein features precisely while reducing computational costs.

3.2. Matching of feature vectors

This paper proposes a novel matching algorithm which requires a comparison of similar feature vectors only. This reduces the computation time and increases recognition efficiency. The proposed matching method progresses along the following steps:

(1) Each level of the proposed EP-tree structure (based on the first feature vector) is defined by the number of end points of various dimensions. As a result, the four dimensions of the vein images are reflected in the four levels of the EP-tree.

(2) Using the EP-tree, every vein image can be rapidly matched to similar patterns. The description of the EP-tree (shown in Fig. 4) is as follows:

- The first level involves the quantity set of end points along the four boundaries in each sub-image of 128×128 pixels. We therefore assume that there are n vein images with the first sample $\{p1^1, p1^2, p1^3, p1^4\}$ and the last sample $\{pn^1, pn^2, pn^3, pn^4\}$.
- The second level is the quantity set of ends point along the four boundaries of each sub-image of 96×96 pixels. In the second level of the EP-tree, we assume that m vein images belong to the $p1$ class, the last sample is $\{qm^1, qm^2, qm^3, qm^4\}$, and p vein images belong to the $p2$ class, such that the last sample is $\{qp^1, qp^2, qp^3, qp^4\}$.
- The third level is the quantity set of end points along the four boundries of each sub-image of 64×64 pixels. In the third level of EP-tree, we assume that h vein images belong to the $p1$ and $q1$ class such that the last sample is $\{rh^1, rh^2, rh^3, rh^4\}$, and x vein images belong to the $p2$ and $q1$ class such that the last sample is $\{rx^1, rx^2, rx^3, rx^4\}$.
- The fourth level is the quantity set of end points along the four boundries of each sub-image of 32×32 pixels. In the fourth level of EP-tree, we assume that l vein images belong to the pn, $q1$ and rz class such that the last sample is $\{sl^1, sl^2, sl^3, sl^4\}$.
- Using the EP-tree, a test vein image is first matched to a group of similar images; i.e., different images may have the same number of end points along the four boundaries.

(3) The fact that group is not unique makes it necessary to use the second feature vector (boundary distances) to obtain accurate matches. EP-tree makes it possible to match a test vein image to similar vein image groups. However, the second feature vector of group has feature dimensions the same as the distances along the boundaries. Therefore, we determined the similarity between two feature vectors (based on boundary distance) using three different measurements : the Cosine and Euclidean distances, and the Hamming distance (HD). However, the HD refers to similarity between binary feature vectors. Thus, when using the HD, real-valued vein feature vectors were normalized between 1 and -1, and quantized as follows:

$$Q(f_i) = \begin{cases} 1, & f_i \geq 0 \\ 0, & f_i < 0 \end{cases}, \; i = 1,2,\cdots,n \qquad (1)$$

in which each element of the real-valued feature vector f_i becomes 0 or 1, depending on its sign, where f_i represents a ith real-valued element of a feature vector extracted from the distance between veins along a boundary.

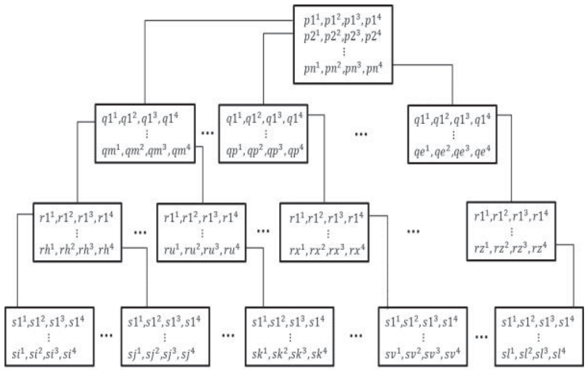

Figure 4. Structure of EP-tree

4. Experiment Results

The dorsal vein hand database employed in this study is reported in [5]. It includes 4,280 images from 214 volunteers (hence 214 different classes) with twenty images captured from each class. For each dorsal hand vein class, we selected eight samples from images taken in the first stage for training with all samples captured in other stages serving as test samples. A series of experiments was performed to evaluate the performance of the proposed method in identifying individuals based on a sequence of dorsal hand vein images.

The paper employed modern statistical methods to evaluate the performance of the biometric algorithms. Experiments were conducted in two modes: identification (i.e., one-to-many matching) and verification (i.e., one-to-one matching). In identification mode, the performance of the algorithm could be evaluated according to its correct recognition rate (CRR), which is the ratio of samples correctly classified to the total number of test samples. In verification mode, we adopted the well-known statistical pair, false acceptance rate (FAR) and false rejection rate (FRR) to evaluate the effectiveness of the proposed method. All experiments were executed using Matlab R2010a on a computer system of PIV 2.67GHz with 1GB RAM. The following subsections detail the experiments and results.

Experiment results demonstrate the effectiveness of the proposed method in the extraction of features from images of dorsal hand veins, with a CRR of 99.64% using the vein database. In this database [5], Cosine distance yielded the best performance, whereas the HD presented the worst performance. We then ascertained the effectiveness and robustness of the proposed approach with regard to identification and compared the results obtained using the algorithms proposed by Wang et al. [6] and Kumar et al. [7], due to the fact that this is currently the most popular algorithms based on minutiae points. We also compared the proposed algorithm with the method based on multi-resolution descriptors [4]. To further evaluate the effectiveness of the proposed method, we performed a detailed comparison of the proposed method with the above methods using the dorsal hand vein database [5]. Table 1 outlines our experiment results. It shows the CRR of the four algorithms using the dorsal hand vein database. According to the results in Table1, the proposed method provided the best performance, followed in order by [4] (Lin et al.), [7] (Kumar et al.), and [6] (Wang et al.). In Table 1, we also see that the proposed method produces better results than the other methods, thanks to its ability to characterize minutiae descriptors of the dorsal hand veins. The proposed representation also reduces the matching time required by the EP-tree, which makes our method superior to that of existing methods.

Table 1 Recognition results using four different methods

Methods	CRR (%)	EER (%)
Lin et al. [4]	98.31	1.77
Wang et al. [6]	93.87	5.88
Kumar et al. [7]	95.64	4.19
Proposed	99.64	0.74

5. Conclusion

This paper describes an efficient method to verify the identity of individuals from dorsal hand vein image. The minutiae features extracted include end points and the distance between them along boundaries of the images used. In addition, we proposed an EP-tree to accelerate matching performance and evaluate the discriminatory power of these feature points to facilitate the verification of identity. Our experiment results demonstrate the effectiveness of the proposed method. We also conducted a detailed comparison of performance with existing methods. Such comparisons and analysis are helpful in the further improvement of the performance of vein recognition methods.

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