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Singular value decomposition based minutiae matching method for finger vein recognition

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ABSTRACT

Recently, finger vein recognition has received considerable attention in the biometric recognition field. Originating from fingerprint recognition, minutiae-based methods are recognized as an important branch, which attempts to discover minutia patterns from finger vein images for matching and recognition. However, the accuracy of these methods is generally unsatisfactory. One of the most challenging problems is that, the correspondences of two minutia sets are difficult to obtain resulting from the rotation, translation and deformation of the finger vein images. Another critical problem is that, the current available feature descriptors for minutia representation are weak and insufficient. In this paper, we propose SVDMM, a singular value decomposition (SVD)-based minutiae matching method for finger vein recognition, which involves three stages: (I) minutia pairing, (II) false removing and (III) score calculating. In particular, stage I discovers minutia pairs via SVD-based decomposition of the correlation-weighted proximity matrix. Stage II removes false pairs based on the local extensive binary pattern (LEBP) for increasing the reliability of the correspondences. Stage III determines the matching score of the input and template images by the 'average' matching degree of all their precise minutia pairs. Extensive experiments demonstrate that our work not only performs better than the similar works in the literature, but also has great potential to achieve comparable performance to other categories of state-of-the-art methods.

1. Introduction

Finger veins are subcutaneous structures that randomly develop into a network and spread along a finger [1] and believed to be quite unique, even in the case of identical twins and even between the different fingers of an individual proved by [45]. As a biometric identifier, finger veins have many properties, such as universality, uniqueness, permanence, etc. In comparison with other biometric identifiers such as fingerprint, face, hand geometry and gait, finger veins demonstrate some excellent advantages in application [3–5]. (1) Live body identification: finger veins can only be identified on a live body without fake finger attacks in fingerprint recognition; (2) immune to counterfeit: finger vein patterns are internal features that are difficult to forge; (3) non-contact: finger veins are not influenced by surface conditions. Non-invasive and contactless data capture ensures both convenience and cleanliness for the users; and (4) smaller size of devices: most finger vein capturing devices are smaller in size as compared to palm vein based verification devices [6]. Therefore, the finger vein is widely considered as a promising biometric pattern for personalized identification, receiving lots of research interest and commercial applications [7–9].

In general, finger vein recognition involves four main procedures: image capturing, preprocessing, feature extraction and matching. In particular, image capturing visualizes veins in a finger [10,11]. Preprocessing mainly enhances images [12,13], extracts region of interest (ROI) [14,15], etc. Feature extraction detects the characteristics of the vein pattern for representation and matching measures the similarity between two finger vein images for recognition [29,42].

Given the advantages of finger vein recognition, lots of methods have been proposed, which fall into three categories according to their feature extraction rules: ROI-based methods, network-based methods, and minutiae-based methods.

In ROI-based methods [16–19], the features are extracted from the whole ROI without finger vein network segmentation. Although promising experimental results are reported in [16–19]; in practice, these ROI-based methods may suffer from some limitations. Firstly, image alignment, one of the most intractable problems in biometric recognitions field [2,15,20,21], is a critical step in most of these methods, resulting from the captured images generally varying in direction and position. Secondly, many features extracted from the non-vein regions are noisy, which inevitably reduces the recognition

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performance. Generally, the proportion of the veins in the ROI is relatively small, e.g., about 41.05% in the MLA database and 44.32% in the PolyU Database. Thirdly, these methods need relatively larger templates for storage, leading to low processing speed in the finger vein matching process. That is because their features come from the entire ROI instead of only the effective regions.

In network-based methods [2,22–26], the finger vein networks are segmented firstly, and then the features are extracted from the segmented networks. Due to the low qualities of finger vein images and the limitations of the segmenting algorithms, the segmentation results are often unsatisfying and thus degrade the recognition accuracy, though meanwhile most of the non-vein regions along with their noises can be removed in the segmentation process. Furthermore, many network-based methods are also sensitive to variations of the finger vein image. Though few methods are robust to these variations to some extent, such as the methods proposed in [25], they generally have high computation complexity in the matching process for the global structure registration of the vein network.

In minutiae-based methods [27–30], the point patterns are discovered from finger vein images for matching and recognition. Different from the ROI-based and network-based methods, minutiae-based methods concentrate the characteristic of the vein network to some discrete minutia points. Thus their templates are relatively small, resulting in high efficiency in storage and computation. In addition, the point pattern matching is generally more robust against image variations than the other matching methods, on the basis of the common hypothesis that the minutia points are able to capture the invariant and discriminatory information, along with the fact that each point corresponds to another point independently [31]. Thus the minutiae-based method is gradually recognized as an important branch in the biometric recognition field.

However, for existing minutiae-based methods, the accuracy is generally unsatisfactory. One of the most challenging problems is that, when matching two finger vein images, the correspondences between their minutia sets are difficult to obtain resulting from the rotation, translation and deformation of the finger vein images. Thus for the current available minutiae-based methods, their minutia correspondences are unknown or inaccurate. For instance, the method [29] adopts Hausdorff Distance (HD) to measure the similarity between two minutia sets for point pattern matching without establishing the minutia correspondences. However, HD is highly sensitive to the moderate shift of the finger vein images and the small perturbation of the point location. In addition, the methods [27,28,30] establish the minutia correspondences by scale-invariant feature transform (SIFT), demonstrating poor performance. One reason is that the types of the minutiae are unknown and many false pairs with different types could be identified. The other reason is that the minutia pairing is performed by matching the 128-dimensional vectors of the points and their accuracies depend on the amount of the texture around the points. If the textures are sparse, it will get incorrect pairs easily.

Another critical problem is that, in existing minutiae-based methods, the feature descriptors are weak and insufficient for point pattern matching. For example, in [25], the coordinate values of the points are used as the minutia features, which are very sensitive to the image variation and point perturbation. In [27,28,30], the SIFT feature is used for the matching, which is unstable in most cases.

Hence, this paper attempts to investigate a robust matching method for finger vein recognition, so as to remedy the limitations of existing solutions in the previous works. For this purpose, a Singular Value Decomposition (SVD)-based minutiae matching (SVDMM) method, which is an application of the SVD-based method proposed in [32] and further developed in [34], was proposed. The reasons why we chose the SVD-based method for finger vein minutia matching are listed as follows: firstly, the SVD method can satisfy both the exclusion and proximity principles set forth by Ullman [33] and can be straightforward implemented founded on a well-conditioned eigenvector solution which involves no explicit iterations. In addition, it can cope nicely with image rotation, translation and deformation [34]. Secondly, many applications of this SVD method have been extensively used in pairwise matching problems whether past or present [34–40], demonstrating the effectiveness of this method. Especially some state-of-the-art biometric recognition systems have utilized it for minutiae matching and achieved promising performances. For example, in [41], an SVD-based algorithm was used for palm print matching and received the best result. Thirdly, our problem differs from conventional SVD application scenarios in that comparing with the key points in the natural images, the minutiae in the finger vein images generally do not have enough 'character' to discriminate amongst them. Thus, in order to specifically cater for finger vein image so as to discover more reliable minutiae pairs; in this paper, we make improvement of SVD method by increasing the proportion of the correlation information in the proximity matrix G. In addition, a novel local descriptor LEBP attached to the minutiae is used to quantify the minutiae pairs discovered by the SVD-pairing algorithm so as to enforce the principle of similarity. Fourthly, our extensive experimental results demonstrate that the improved SVD method is efficient in handling the minutiae matching in finger vein recognition.

In this paper, we applied SVDMM to the minutiae-based finger vein recognition. In particular, we use two categories of minutia, bifurcation point (BP) and ending point (EP), from the skeletonized binary finger vein images with the method proposed in [29], and then we extracted three local descriptors, local average intensity (LAI), local intensity deviation (LID) and local extensive binary pattern (LEBP), as the features to represent each minutia for minutiae matching. LEBP is the combination of local multilayer binary pattern (LmBP) and local directional binary pattern (LdBP), which are two effective and complementary descriptors presented in this paper.

The SVDMM process involves three stages: (I) minutia pairing, (II) false removing and (III) score calculating. In stage I, we use the coordinate value, LAI and LID to represent each minutia, and then we construct a correlation-weighted proximity matrix G for two minutia sets $\boldsymbol{I}$ and $\boldsymbol{J}$ extracted from the target pair of finger vein images, where each element G_{ij} denotes the correlation between the i-th minutia in $\boldsymbol{I}$ and the j-th minutia in $\boldsymbol{J}$. Then we utilize a SVD-pairing algorithm to discover minutia pairs via decomposition of the matrix G. In stage II, we use LEBP to evaluate the correlation between each discovered pair of minutia, and recognize those minutia pairs with quite low LEBP-based correlation scores as false paring for removing. By effectively removing the false pairs, this stage can significantly improve the recognition accuracy and robustness. In stage III, we finally determine the matching score of the input and template finger vein images by the 'average' matching degree of all their precise minutia pairs and return. Extensive experiments are performed on two different finger vein databases, and the experimental results demonstrate our SVDMM-based finger vein recognition method not only performs better than similar category methods, but also can achieve comparable performance to other categories of state-of-the-art methods.

There are three main contributions of our work: (i) we present a novel minutiae matching method SVDMM for minutiae-based finger vein recognition. Its nice performance has been evidenced by extensive experiments; (ii) we present an SVD-based pairing algorithm to discover minutia pairs of two finger vein images