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Palm vein recognition based on multi-sampling and feature-level fusion

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ABSTRACT

For contactless palm vein images, particularly substantial changes in hand positioning between one image and the next, it is difficult to achieve a satisfactory recognition performance with geometry- or statistics-based methods due to issues such as non-uniform illumination and affine transformation. Therefore, with a multi-sampling and feature-level fusion strategy, a novel palm vein recognition method based on local invariant features is presented for addressing the aforementioned issues. As most of the contactless palm vein images are unclear and have low contrast, if a SIFT algorithm is directly adopted for feature extraction on the center region of a palm vein image, it will be difficult to obtain sufficient features for effective recognition. Therefore, in this paper, we first propose to take the entire palm as a Region of Interest (ROI) and perform new hierarchical enhancement on the ROI to ensure that additional features will be obtained from the subsequent feature extraction. Then, we take full advantage of the multiple samples collected in the registration stage to generate the registered template using feature-level fusion. Finally, bidirectional matching is proposed for mismatch removal. The experiments on the CASIA Palm vein Image Database and our palm vein database collected under the posture changes show that the proposed method was superior in terms of recognition performance, especially for palm vein image recognition under remarkable posture changes. In particular, the values of Equal Error Rate (EER) on the aforementioned two databases were 0.16% and 0.73%, respectively.

1. Introduction

With ongoing social and economic developments, the requirements for information security have been sharply increasing. However, traditional authentication methods, such as passwords and keys, are unable to satisfy these expectations because they are prone to be forgotten, lost or stolen. Because they are impossible to lose, forget, or counterfeit, identification and authentication based on biometric characteristics have gradually emerged as the most secure and convenient techniques. Face and fingerprint recognition have especially been widely utilized in financial and security domains, and evolved products have been developed for this purpose. However, these approaches are still not perfect in all application scenarios. It is well known that images of faces can easily be acquired, and face recognition systems are user-friendly, but such systems are more error-prone when identifying individuals with non-uniform illumination, from different viewpoints or expression, and in conjunction with other issues, including the influences of a hat, hair, eyes, beards, and so on. Fingerprints are highly discriminable, but they can easily be damaged. Furthermore, fingerprints are susceptible to reproduction, affecting the security of fingerprint recognition [1]. To address these issues, new biometric characteristics, such as finger knuckle prints, palm veins and irises, have emerged and received recent attention for use in identification and authentication techniques. The vein recognition technique is a new, contactless biometric recognition method that uses the blood vessels under the skin to establish identification. Due to the differences in the vessel networks among individuals, even identical twins, and the difficulties in counterfeiting these networks, vein recognition is highly reliable and secure [1]. Furthermore, contactless vein recognition is more hygienic and user-friendly than other methods, which improves user acceptance. Generally, vein images are collected from the finger, palm or dorsal area of the hand, with palm veins providing richer texture information, thereby improving the distinguishing ability and making them more convenient for acquisition, which is increasingly attractive to researchers. As with other single-modal biometrics, single-sample palm vein recognition has been intensively studied [2–4]. However, the limited biometrics information from a single biometric and single sample cannot

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satisfy the requirements of precision and reliability for recognition and authentication in real-world scenarios. Therefore, multi-biometrics recognition that is based on information fusion has emerged. According to the source of information, multi-biometrics can be divided into six categories: multiple sensors, multiple algorithms, multiple instances, multiple samples, multiple modes and hybrids. In terms of the fusion stage in the biometrics information fusion flowchart, multiple biometrics can also be classified as fusion prior to matching and fusion after matching. Fusion prior to matching includes sensor-level fusion and feature-level fusion. Fusion after matching includes dynamic classifier selection, score-level fusion, rank-level fusion, and decision-level fusion [5]. The lower the fusion level, the higher the processing complexity and the richer the information describing the input pattern.

The multi-modal approaches that are based on different biometric characteristics from different sensors have become increasingly attractive in multi-biometric studies because their underlying concept is clear and simple: the fusion of several single biometric characteristics at different levels. Jing et al. [6] adopted sensor-level fusion with face and palm print recognition. Some researchers have studied feature-level fusion, such as face and fingerprint fusion [7], face and palm print fusion [8], palm print and palm vein fusion [9], and finger vein and dorsal finger texture fusion [10]. Others have investigated multi-biometric recognition at the score-level fusion, such as dorsal hand triangle features and knuckle fusion [11]; ear and face fusion [12]; finger vein and finger facial texture fusion [13];and face, ear and signature fusion [14].

The feature information from different biometric images in multi-modal approaches is greatly complementary, and these methods are convenient and have outperformed in terms of recognition. However, these methods will increase the cost of acquisition equipment in multi-modal biometric recognition systems. As a result, many researchers have suggested the adoption of multiple algorithms to extract various features from a single biometric image, mining the complementary feature information from a single biometric image in multiple ways. Similar to multi-modal approaches, multi-algorithm approaches can fuse the obtained features at different levels. Some researchers have utilized feature-level fusion. For example, the Gabor feature and LBP feature were fused for face recognition by Tan et al. [15], and the global and local features of the finger vein were fused by Yang et al. [16]. Score-level fusion has also been investigated. Parket et al. [17] fused the global and local texture features from two Gabor filters for iris recognition. Qian et al. [18] fused the invariant moment features with seven different weights for finger vein recognition. Other researchers have used decision-level fusion. Prabhakar et al. [19] fused four different finger-matching algorithms for finger print recognition. Czyz et al. [20] fused several of the obtained recognition results to improve final face recognition performance. Gokberk et al. [21] fused the recognition results from two different classifiers for face recognition.

Compared with multi-modal approaches, multi-algorithm approaches ensure that richer biometric information will be extracted with cheaper acquisition instruments. However, the multi-algorithm approaches require substantial time for authentication, and the features must be complementary. Considering the above issues and several sample images captured in registration for a biometrics system, we present a novel palm vein recognition algorithm based on the multi-sampling and feature-level fusion strategies. In previous studies, only one palm vein image was selected from three or more samples as the registered template; however, in real-world scenarios, it is difficult to integrate the feature information from one palm vein image. Particularly with regard to contactless recognition, posture changes are relatively large, which means that the features between two captured palm vein images may be very different. If only one image is adopted for registration, it will negatively impact the system's recognition rate because of incomplete features. Therefore, we take full advantage of all sample images with different postures in the registration stage and conduct local invariant feature extraction on these images to generate the registered template. After feature fusion, we can obtain abundant invariant features in the registered template, which will result in better performance. The feature extraction of multiple samples and fusion of features will take more time; however, this time-consuming step only occurs at the registration stage, and only one to-be-matched image must perform feature extraction and matching in the matching stage. Therefore, our method does not substantially increase the time required for the matching stage.

The details of our proposed algorithm are as follows. In the offline registration stage, the image preprocessing is conducted, such as ROI extraction and image enhancement on the palm vein images with posture changes. Then, we adopt the SIFT to extract local invariant features from multiple samples and prune the redundant features from these samples by comparing the angles between their feature vectors. Finally, we fuse the remaining features as the registered template. In the online recognition stage, we adopt RootSIFT and bidirectional matching on the to-be-matched image and the registered template to establish identification. The flowchart of our proposed algorithm is illustrated in Fig. 1.

The remainder of this paper is organized as follows. In the next section, the image preprocessing method is introduced. In Section 3, we explain the feature extraction and fusion approaches. The feature matching and recognition strategies are presented in Section 4. In Section 5, the experimental results and discussions are reported. Finally, the conclusions of this paper are given in Section 6.

2. Image preprocessing

As there are few restrictions on the palm when the contactless mode is adopted for palm vein image acquisition, this method will

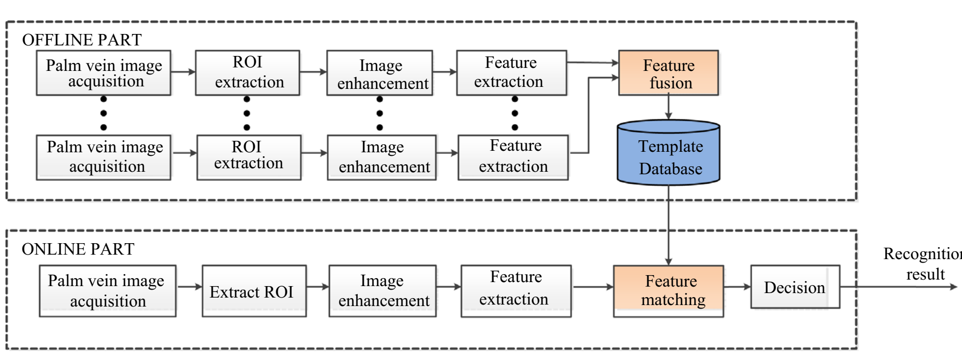

Fig. 1. System flowchart of our proposed algorithm.