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Finger-vein recognition based on dual-sliding window localization and pseudo-elliptical transformer

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ABSTRACT

Uneven illumination occurs during finger imaging because of the influence of several factors, including the position and posture of the finger, the uniformity of near-infrared light, and the influence of ambient light. Existing phalangeal joint locating methods are sensitive to light illumination and cannot locate phalangeal joint stably. In this study, we propose a dual-sliding window model to accurately detect the position of the phalangeal joint of the finger-vein image, which is robust to light illumination, and to extract a more stable region of interest. Planar imaging generates different finger-vein images of the same finger at different acquisitions by space rotation of the finger. Thus, a pseudo-elliptical sampling model is proposed to retain the spatial distribution of vein patterns, to reduce the redundant information in finger images, and to reduce differences. Finally, a two-dimensional principal component analysis is used to project the transformed image for feature extraction. We calculated the Euclidean distance to measure the similarity between the test and training samples. Experiments in the three different databases show that the proposed method is effective and reliable and improves the performance of a finger-vein identification system.

1. Introduction

Personal identification technology using vein patterns, such as palm-vein and finger-vein, has been the focus of increasing attention (Khellat-Kihel, Abrishambaf, Monteiro, & Benyettou, 2016; Kumar & Zhou, 2011; Matsuda, Miura, Nagasaka, Kiyomizu, & Miyatake, 2016; Sierro, Ferrez, & Roduit, 2015; Xie, Lu, Yoon, Yang, & Park, 2015). Compared with traditional biometrics technology, vein pattern has the advantage of being contactless, live body identification, and high security. The finger-vein capture device can be more miniaturized and convenient, which ensures broad application of this biometric technology.

A typical finger-vein identification system consists of four steps, including image capturing, preprocessing (region of interest (ROI) and image enhancement), feature extracting, and matching. Among these steps, ROI extraction plays a critical role in an automatic finger-vein identification system, which directly affects the accuracy of finger-vein recognition (Kumar & Zhou, 2011; Yang, Yang, Zhou, & Yin, 2015; Yu, Shan, Yoon, Yang, & Dong, 2013).

However, many factors influence the quality and consistency of the finger-vein image, such as position and posture of the finger, uniformity of illumination under near-infrared (NIR) light, and influence of ambient light in the natural environment. These factors may lead to uneven illumination based on our experience in the study of palm-vein image acquisition devices (Liu, Zhou, Qiu, Qin, & Nie, 2015; Zhou et al., 2014). The ROI method should be robust and insensitive to the aforementioned factors. For convenience, uneven illumination caused by these factors is collectively referred to as interference of light in this study.

Several finger-vein ROI extraction methods have been proposed in the literature (Asaari, Suandi, & Rosdi, 2014; Raghavendra & Busch, 2015; Yang & Shi, 2012; Yang, Yang, Yin, & Xiao, 2013; Yang et al., 2015; Yu et al., 2013; Zuo, Wang, & Song, 2013). The existing methods can be classified into two types. One type is device positioning, which usually constrains the placement of the user's fingertip and finger-root by using the capture device. The middle region of the finger is acquired and used as the ROI image through cutting (Vlachos & Dermatas, 2015; Yang et al., 2015). This type would not be considered in this study, because it relies heavily on the finger-vein capture device and limits the practicality of the recognition systems. While the ROI method in

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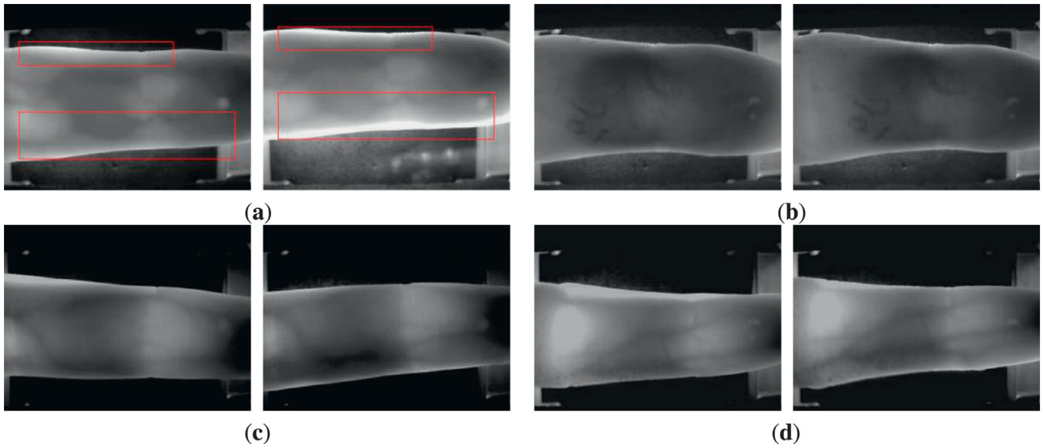

Fig. 1. Specificity of finger-vein images. (a) Gray value difference; (b) Plane shift; (c) Plane rotation; (d) Space rotation.

this paper (introduced in next paragraph) does not rely much on the capture device and provides more flexibility to the user.

The other type is algorithm positioning, which obtains the ROI area by using a certain algorithm. The more effective methods are fingertip or finger-root location (Asaari et al., 2014; Yang et al., 2015; Zuo et al., 2013) and phalangeal joint location (Yang & Shi, 2012; Yang et al., 2013; Yu et al., 2013). For the fingertip or finger-root location method, the entire finger with fingertip and finger-root should be acquired, which limits its use. Thus, the phalangeal joint location method is more common and effective.

Most methods are sensitive to finger position variation (finger plane shift and rotation, as shown in Figs. 1(b) and (c)) in practice. Yang and Shi (2012) proposed a ROI localization method based on the phalangeal joint of the human fingers to overcome this problem. A predefined window with a fixed height and width is used to locate a sub-region in the finger-vein imaging plane. Then, the gray values at each column image are accumulated in the sub-region. Finally, the maximum column-sum is identified to denote the position of the distal inter-phalangeal joint (hereinafter referred to as phalangeal joint) approximately. However, the phalangeal joint may not always be located in the column with higher gray value of the finger-vein image because of the effect of light illumination (Yang et al., 2013). Yang et al. (2013) improved the phalangeal joint detection method described in Yang and Shi (2012) by using a sliding window. They proposed a sliding window with a fixed size column by column from the left to the right of the key area of the finger-vein image and calculated the sum of the gray value in the sliding window. The position corresponding to the sliding window with the maximum gray value is estimated as the phalangeal joint in the finger-vein image. This method derives the sum of gray values in the sliding window, which is equivalent to smooth gray cumulative curves and is more effective than the method in Yang and Shi (2012). However, the aforementioned two methods are susceptible to light illumination (gray value difference, as shown in Fig. 1(a)). The aforementioned two methods cannot obtain the stable position of the phalangeal joint because of light interference. This study proposes a novel phalangeal joint localization method based on a dual-sliding window, which can effectively resist light interference. Thus, the ROI extraction area is stable.

The distribution of vein patterns in the fingers of humans is in the three-dimensional (3D) space, but is imaged to the plane by a camera under the illumination of NIR light. Therefore, the finger-vein image is in the two-dimensional (2D) space, which indicates that it is a plane image. As such, the distribution of the finger-vein pattern is flat. If the finger undergoes space rotation while being captured, then different plane finger-vein images of the same finger at different acquisitions are generated, as shown in Fig. 1(d). The larger the rotation angle is, the larger the difference. As such, the recognition accuracy decreases. Several methods are used to transform 2D plane images to maintain the space distribution of the finger-vein pattern and to reduce the difference caused by the space rotation of the finger. Huang, Dai, Li, Tang, and Li (2010) proposed a pattern normalization model to correct the distortion caused by the position of the finger. However, the nearest sampling method in Huang et al. (2010) may repeatedly sample at the same pixel point, increasing the amount of redundant information and decreasing the feature extraction speed. Huang, Liu, and Li (2012) proposed a method to reconstruct a 3D normalized finger model from 2D images, which mapped the 2D finger-vein images into a new 2D coordinate system. Then, the similarity between the probe and gallery images is determined by calculating the Hamming distance. However, the reconstruction method in Huang et al. (2012) is complex and needs several hardware parameters of the capture device (such as the view of the camera or the distance from lens focus to image plane), and considerable redundant information is obtained during normalization of the vein image.

In addition, the other biometrics systems such as fingerprint and human face recognition used an elliptical model or sampling model to overcome 2D distortion (An & Chung, 2008; Zhao, Jain, & Abramovich, 2011). An and Chung (2008) used an elliptical model to estimate a current pose of face for registration with the canonical frontal view image. But it is difficult to accomplish in finger-vein recognition because the rotation angle of finger is hard to be determined. In the fingerprint recognition system (Zhao et al., 2011), they proposed a 3D sampling technology such as direct sampling, cylinder model, and tube model. Each slice of the fingerprint is mapped to a 2D plane, which outputs a 2D equivalent fingerprint image. This method incorporates distortion into the unrolling process and improves the performance of the system compared with the traditional contact-based 2D fingerprints.

Thus, we propose a pseudo-elliptical sampling model to transform the enhanced finger-vein image. Transformation can restore the space distribution of the finger-vein pattern and benefit the feature extraction process. Consequently, the recognition accuracy is improved.

The flowchart of the finger-vein identification approach is shown in Fig. 2. First, we segmented the finger region from the background of the finger-vein image using the finger contour extraction (Fig. 3(b)) and correct the image by estimating the rotational angle of the finger (Fig. 3(c)), the detail can be seen in literature (Yu et al., 2013), and resized to the same size of