Engineering Applications of Artificial Intelligence 46 (2015) 131–139

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Finger-vein pattern restoration with Direction-Variance-Boundary Constraint Search

Tong Liu*, Jianbin Xie, Wei Yan, Peiqin Li, Huanzhang Lu

College of Electronic Science and Engineering, National University of Defense Technology, Changsha 410073, Hunan, PR China

ARTICLE INFO

Article history:
Received 14 January 2015
Received in revised form
1 September 2015
Accepted 6 September 2015
Available online 29 September 2015

Keywords:
Biometrics
Finger-vein
Personal verification
Finger-vein recognition
Restoration

ABSTRACT

Finger-vein verification is an emerging biometrics technology. Its first task is extracting finger-vein patterns. Although existing algorithms can extract most finger-vein patterns robustly, some branch of these patterns always breaks, which leads to adverse effects for features extraction and matching. In this paper, a Direction-Variance-Boundary Constraint Search (DVBCS) model is presented to restore the broken finger-vein patterns. At the beginning, endpoints of broken finger-vein branches are located. Then, a direction constraint for searching candidate point set is demonstrated. Following the second stage, an optimal target point is selected from the candidate point set according to a minimum within-cluster variance criterion. Eventually, the boundary constraint and variance constraint are introduced as the termination conditions. Experimental results illustrate that, while maintaining low segmentation error, the proposed method can restore above 10% lost target points. Moreover, the equal error rate of finger-vein recognition is reduced from 0.57% to 0.29% when using the proposed method to restore finger-vein patterns.

1. Introduction

Biometric personal identification techniques, such as fingerprint (Jirachaweng et al., 2011), facial (Wang and Wu, 2010), iris (Roy et al., 2011), and vein pattern recognition (Wang et al., 2008), have attracted increased attention on various platforms with higher security and lower identification error rate requirements. Among these techniques, finger-vein verification has been paid growing attention in the biometrics community, because finger-vein features hold the merits of uniqueness, stability and anti-counterfeit (Yang and Zhang, 2012). The minutiae features of finger-vein patterns including bifurcation points and ending points are the common features used for finger-vein recognition (Yu et al., 2009; Yang et al., 2009; Qian et al., 2009; Khalil-Hani et al., 2012; Kang and Park, 2009; Lee et al., 2009), where finger-vein patterns need to be extracted from finger-vein images at first. However, it is difficult to extract the precise details of the depicted finger-vein patterns because of the low quality of finger-vein images (Yang et al., 2012). Although existed algorithms (Zhang et al., 2006; Yu et al., 2008; Ding et al., 2005; Mulyono and Jinn, 2008; Vlachos and Dermatas, 2008; Miura et al., 2004; Liu et al., 2013) can extract most finger-vein patterns, some branches of these finger-vein patterns always break. Therefore, finger-vein patterns extracted from different images of the same finger are far different from each other, and hardly match with each other in the process of features matching.

In order to avoid the influence by broken finger-vein branches, some finger-vein recognition methods (Xin et al., 2012) use features which are irrelevant to segmented image of finger-vein, and some ones (Gholami and Hassanpour, 2015) use features which are not sensitive to noise and broken branches in segmented image of finger-vein. For example, Ref. (Gholami and Hassanpour, 2015) applies Radon transformation to the segmented image, to extract features that are not sensitive to noise and broken finger-vein branches. However, the recognition methods by using the minutiae features of finger-vein patterns are very important because of the distinction of minutiae features. A clear and complete finger-vein pattern is very useful for improving the recognition performance of these methods. In this situation, we need to restore finger-veins with broken branches.

The proposed restoration methods can be categorized into two groups such as image level and feature level. In image restoration, a depth-dependent point spread function (DPSF) (Lee and Park, 2011) and a scattering removal method based on a biological optical model (Yang et al., 2012) are proposed, to remove scattering occurrence in biological tissue during imaging. Some image enhancement methods, such as even-symmetric Gabor filter (Yang and Shi, 2014), circle Gabor filter (Yang et al., 2009) and multi-scale matched filter (Gupta and Gupta, 2015), are introduced to sharpen the image contrast and enhance some blurred finger

* Corresponding author. Tel.: +86 135 74870542; fax: +86 731 84576465.
E-mail address: liutong1129@126.com (T. Liu).

http://dx.doi.org/10.1016/j.engappai.2015.09.004
0952-1976/

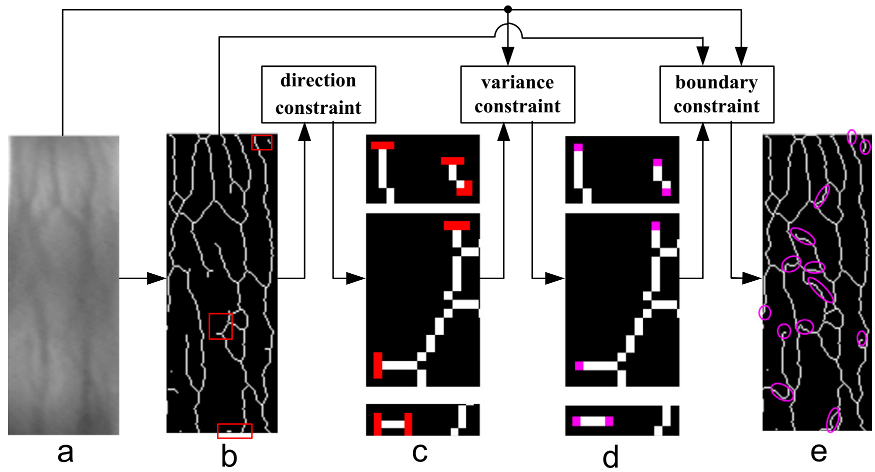

Fig. 1. Framework of our method. (a): finger-vein image; (b): finger-vein patterns extracted by traditional method, where the red rectangles show three example regions described in detail in (c) and (d); (c): candidate points (red points) confined by direction constraint of three example regions shown in (b); (d): optimal target points (purple points) confined by variance constraint of the three example regions; (e) restored finger-vein patterns confined by boundary constraint, where the purple ellipses show the different areas of finger-vein patterns before and after restoration. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

veins. Since these methods only pay attention to the global images but not to every vein, the finger-vein patterns extracted from images may still break due to low contrast in local area. The previous restoration methods at feature level are very few. If every vein is paid more attention and restored at feature level according to the gray distribution of veins, certain broken veins may be restored. However, there are a few restoration methods at feature level. The existed methods only use some filtering technology such as mathematical morphology and median filtering, to restore the segmented images (Yu et al., 2008; Liu et al., 2013; Yang and Shi, 2014). These methods restore veins with a distance metric. In this way, some veins with very short distance may be connected with each other, but noise may increase at the same time, and broken veins with little longer distance cannot be restored as before. That is to say, the finger-vein patterns may still break, which may reduce the performance of finger-vein recognition methods using minutiae features of finger-vein patterns (Yu et al., 2009; Yang et al., 2009; Qian et al., 2009; Khalil-Hani et al., 2012; Kang and Park, 2009; Lee et al., 2009).

In this paper, we present a Direction-Variance-Boundary Constraint Search (DVBCS) model, aiming to restore the broken finger-vein patterns, as shown in Fig. 1. One of the main contributions of this study is the development of a DVBCS model for the restoration of broken branches of vein patterns. The model involves endpoint location, direction constraint, minimum within-cluster variance criterion, variance constraint and boundary constraint. This model can be used to restore broken branches of finger-vein patterns. Moreover, comparative experiments and analysis are conducted in various methods. They also demonstrate that the proposed method can restore some broken branches of finger-vein patterns effectively, and improve the performance of finger-vein recognition significantly.

The rest of this paper is organized as follows: Section 2 describes the related works of finger-vein pattern extraction. In Section 3, the proposed DVBCS model is explained in details. Experiments and analysis are demonstrated in Section 4, together with a comparison between our method and the other related methods. Last but not the least, conclusions are summarized in Section 5.

2. Related works

As shown in Fig. 2, finger-vein patterns are commonly extracted with three steps, namely image segmentation, image smoothing, and image thinning (Yu et al., 2009; Yang et al., 2009; Qian et al., 2009; Khalil-Hani et al., 2012; Kang and Park, 2009; Lee et al., 2009). Image smoothing often uses top-hat morphological operators (Kumar and Zhou, 2012) while image thinning often employs hit-or-miss morphological operators (William, 2001). In the thinned image, every target point is minimally connected, which means the connectivity of the thinned image is destroyed if any target point loses (William, 2001). In other words, if p is a target point in the thinned image, the target point q connected to it must meet one of the conditions as follows:

- q is in the 4-connected field of p;
- q is not in the 4-connected field of p, and there is no target point in the intersection between the 4-connected field of p and the one of q.

Image segmentation has a significant impact on the extraction of finger-vein patterns. There are diversified kinds of image segmentation algorithms of finger-vein proposed in the past years. Zhang et al. (2006) constructed a local interconnection neural network with linear receptive field. It can detect straight-line feature in the small region like finger-vein pattern. But the algorithm needs appropriate samples to train the neural network, which makes it more complex and less robust. Yu et al. (2008) improved modification of the traditional templates into directional templates, and then gained results according to three separate threshold steps. But the threshold parameters are manually set, thus it lacks the flexibility to different light environment since the threshold value cannot change with the environment. Yang et al. (2009) adopted circular Gabor filter to enhance finger-vein images, and then used threshold method (Ding et al., 2005) to implement image segmentation. But the time consumption of Gabor filter is too large. Mulyono and jinn, (2008) introduced preliminary process to improve the image quality worsened by light effect and noise, and then implemented image segmentation by using adaptive threshold method. But the thresholds are less robust and the algorithm cannot achieve excellent segmentation performance when the width of finger-vein is small. Vlachos and Dermatas, 2008 executed finger-vein segmentation by using compound enhancement and crisp clustering. Image enhancement was performed at first by employing the second order local structure and the multidirectional response of a matching filter. After edge suppression, robust segmentation was achieved by using crisp