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Minutia handedness: A novel global feature for minutiae-based fingerprint matching

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A B S T R A C T

Traditional minutiae-based matching algorithms are challenged by the probability that minutiae from different regions of different fingers may not be well matched, and hence lead to erroneous matching results. In this paper we introduce a novel feature called minutia handedness to deal with this problem. First, reference points are detected and additional checking conditions are added to ensure that genuine and accurate reference points can be found. Second, minutia handedness is defined for each minutia according to the bending degree of its associated ridges or the position of the reference points. There are three types of minutiae handedness: right-handed, left-handed and non-handed. Finally, the matching rules between different types of minutiae handedness are set up. The proposed method is tested on eight data sets of FVC2002 (2002) and FVC2004 (2004). The experimental results indicate that the performance of a convectional fingerprint recognition algorithm can be improved by incorporating minutia handedness with a small increment of template size.

1. Introduction

Fingerprint is much more reliable than most other biometrics such as signature, face and speech (Jain et al., 1997b), and has been widely used in many important applications such as electronic personal identification cards, and e-commerce. However, fingerprint recognition is still a challenging task. The performance of even a state-of-the-art matching algorithm is still much lower than most people's expectations and theory estimation (Pankanti et al., 2002). Therefore, much effort is still needed to improve the performance of the fingerprint recognition system.

Based on the features used in fingerprint matching, most existing algorithms can be classified into two categories: minutiae-based approaches and global feature-based approaches. It is widely believed that minutiae are the most discriminating and reliable features in fingerprints. Many matching methods based on minutiae have been proposed (Maltoni et al., 2009; Jain et al., 1997a). Since the relative transformation between two fingerprints is unknown in advance, the correspondence between minutiae is very ambiguous. Many researchers have tried to attach local features to minutiae to reduce ambiguity. These local features include ridge information (Jain et al., 1997a; He et al., 2003), local orientation features sampled around the minutiae (Tico and Kuosmanen, 2003) and local minutiae structure features (Chen et al., 2006; Ratha et al., 2000). Recently, He et al. (2006) proposed a global comprehensive similarity-based fingerprint matching algorithm, in which a minutiae-simplex, including a pair of minutiae as well as their associated textures, were employed to achieve fingerprint matching. He et al. (2007) extended this approach by representing a fingerprint as a graph, in which the comprehensive minutiae acted as the vertex set and the local binary minutiae relations were used to provide the edge set. Some researchers combined other local features to increase the discriminative ability between minutiae. Feng (2008) combined a texture descriptor and a minutiae descriptor to measure the similarity between minutiae. Wang et al. (2007a) defined two rotation and translation invariant features (OrientationCode and PolyLine) and fused them to calculate the similarity between corresponding minutiae. Local information can even be employed to generate an alignment-free cancelable template (Lee et al., 2007). Although incorporating more discriminative information into minutiae can reinforce the individuality of fingerprints and improve the system performance, two fingerprints from different fingers may contain similar minutiae, orientation and ridge features in a partial region. Fig. 1 shows an example of a pair of fingerprints from FVC2002 DB1. To intuitively solve this problem is to reject the input fingerprint with small overlapping region. However, this approach will result in a large false rejection rate because there may also be a small overlapping region for a genuine match as shown in Fig. 2.

Global features are widely used in identification, indexing (Chang and Fan, 2002) and classification (Shah and Sastry, 2004). Jain et al. (2000) proposed a fingerprint representation called the

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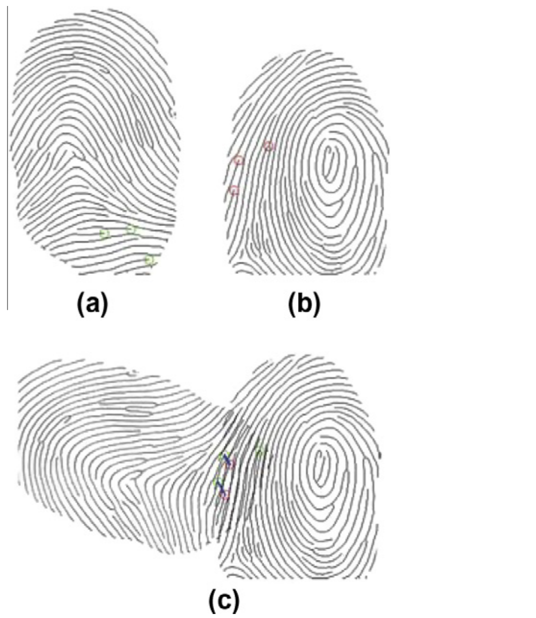

Fig. 1. An example of two fingerprints from FVC2002 DB1. Minutiae from different regions of different fingers are matched very well. The circles denote the matched minutiae: (a) thinned image of 56_1.tif; (b) thinned image of 98_1.tif; (c) registration of (a) and (b).

FingerCode. In this method, a reference point was first detected and a fixed-length feature vector was extracted by using Gabor filters in the region surrounding the reference point to represent the fingerprint. Lee and Wang (2001) proposed a local Gabor-based approach in which the Gabor filters were determined by using local information. Jin et al. (2004) integrated wavelet and Fourier–Mellin transform to produce a translation, rotation and scale invariant feature. Although these algorithms can solve the problem shown in Fig. 1, it is difficult to achieve the matching process when the reference point is missing.

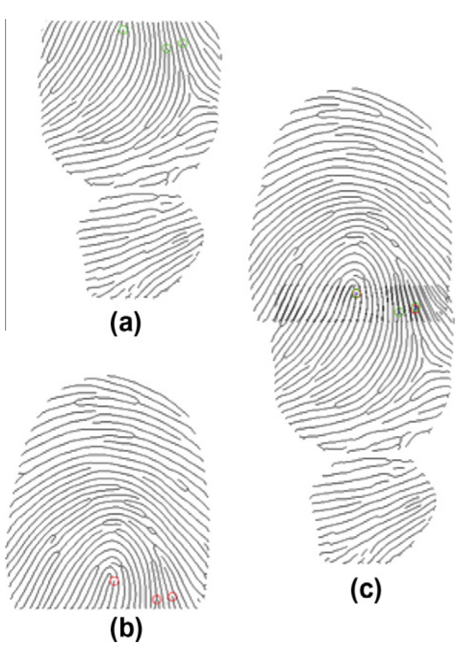

Fig. 2. An example of a pair of fingerprints from FVC2002 DB1 with a small overlapping region: (a) thinned image of 29_6.tif; (b) thinned image of 29_7.tif; (c) registration of (a) and (b).

Minutiae-based algorithms cannot characterize the overall ridge pattern of the fingerprint, whereas reference point-based global features are very sensitive to the accuracy of the reference point detection. It is desirable to explore robust fingerprint representation schemes which combine global and local information in a fingerprint to reinforce the individuality of fingerprints. Gu et al. (2006) proposed to combine the global structure (orientation field) and local cues (minutiae) to represent a fingerprint. Similarities based on the orientation field and minutiae were fused in the decision level to calculate the matching score. However, this method has the same shortcomings as the minutiae-based matchers that overlapping regions of different fingers may possess a similar orientation field, as shown in Fig. 1. Inspired by the conclusion that integration at the feature level provides better recognition results than other levels of integration (Jain et al., 2005), we propose a minutiae-based fingerprint matching algorithm by incorporating the global knowledge into minutiae descriptor. The contributions of our paper include: first, the reference point detection algorithm is improved and some additional checking conditions are added to ensure that accurate and genuine reference points can be found. Second, minutia handedness, which is determined by its associated ridges or the position of the reference points, is proposed to improve the matching performance. The proposed algorithm is tested on eight data sets of FVC2002 (2002) and FVC2004 (2004). The experimental results indicate that the performance of a convectional fingerprint recognition algorithm can be improved by incorporating minutia handedness.

The rest of this paper is organized as follows. Section 2 gives the definition of the feature of minutia handedness. Section 3 describes our matching algorithm with minutia handedness. Experimental results are reported in Section 4. Finally, the conclusions are drawn in Section 5.

2. Minutia handedness

In this section we introduce a novel feature called minutia handedness to capture global knowledge. It is defined for each minutia according to the bending degree of its associated ridge or the position of the reference points. Three types of minutiae handedness are defined in this paper: right-handed, left-handed and non-handed. A right-handed minutia means that all the reference points are on the right side of the minutia if we stand on the minutia point and turn our face to the minutia direction. Similarly, a left-handed minutia means that all of the reference points are on the left side of the minutia. Non-handed minutia means that the handedness cannot be determined for it. However, some fingerprint images may miss the reference point and the position of the reference point may be affected by noise. In this paper, we use the property that ridges generally bend backwards to the reference point is utilized to cover the shortage of an inaccurate reference point. If the ridge associated with a minutia has a large bending degree, the minutia handedness is determined by its associated ridge, otherwise by the reference point.

2.1. Minutia handedness determination by associated ridges

We first present the representation of the ridges associated with a minutia. Two widely used types of minutiae are ridge ending and ridge bifurcation. For a ridge ending, it has only one associated ridge. The ridge is sampled every qth point, and it is represented as $P = \{p_i = (x_i, y_i)\}_{i=1}^{n_p}$ as shown in Fig. 3(a), where n_p denotes the number of sampling points and p_1 denotes the ridge ending. As for a ridge bifurcation, it has three associated ridges and each ridge is first sampled starting from the minutia. In order to simplify the calculation, the two nearest ridges surrounding the angle of the