Spectral Representation of Fingerprints

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Abstract

Most fingerprint recognition systems are based on the use of a minutiae set, which is an unordered collection of minutiae locations and directions suffering from various deformations such as translation, rotation and scaling. The spectral minutiae representation introduced in this paper is a novel method to represent a minutiae set as a fixed-length feature vector, which is invariant to translation, and in which rotation and scaling become translations, so that they can be easily compensated for. These characteristics enable the combination of fingerprint recognition systems with a template protection scheme, which requires a fixed-length feature vector. This paper introduces the idea and algorithm of spectral minutiae representation. A correlation based spectral minutiae matching algorithm is presented and evaluated. The scheme shows a promising result, with an equal error rate of 0.2% on manually extracted minutiae.

1 Introduction

Recognition of persons by means of biometric characteristics is an emerging phenomenon. Among various biometric identifiers, such as face, signature and voice, fingerprints have one of the highest levels of distinctiveness and performance [1]. Compared with most other biometric techniques, fingerprint recognition systems also have the advantages of both ease of use and low cost. All these reasons explain the popularity of fingerprint recognition systems.

Minutiae, which are the endpoints and bifurcations of fingerprint ridges, allow a very discriminative classification of fingerprints. Nowadays, many fingerprint recognition systems are based on minutiae matching [2], [3]. However, minutiae-based fingerprint matching algorithms have some drawbacks, which limit their application. First, due to the fact that minutiae sets are unordered, the correspondence between individual minutia in two minutiae sets is unknown before matching and this makes it difficult to find the geometric transformation (consisting of translation, rotation, scaling, and optionally non-linear deformations [3]) that optimally registers (or aligns) two sets. For fingerprint identification systems with a very large database [4], in which a fast comparison algorithm is necessary, minutiae-based matching algorithms will fail to meet the high performance speed requirements. Secondly, a minutiae representation of a fingerprint cannot be applied directly in recently developed template protections schemes [5] which require as an input a fixed-length feature vector representation of a biometric.

Spectral minutiae representation as proposed in this paper is a method which overcomes the above drawbacks of the minutiae sets, thus broadening the application of minutiae-based algorithms. Our method is based on the Fourier-Mellin transform, which allows a representation of images in a way that is invariant to translation, rotation and scaling [6], [7], [8]. By representing minutiae in such a spectral domain, we transform a minutiae set into a fixed-length feature vector, which is at the same time does not need registration to compensate for translation, rotation and scaling. By using a spectral minutiae representation instead of minutiae sets, we meet the requirements of the systems in which template protection is required and allow for faster matching.

The Spectral minutiae representation method can be easily integrated into a minutiae-based fingerprint recognition system. Minutiae sets can be directly transformed to this new representation, which makes this method compatible to the large amount of existing minutiae databases.

This paper is organized as follows. First, in Section 2, the concept of spectral minutiae representation is explained in detail. Next, the spectral minutiae matching algorithm is proposed in Section 3. Finally, we will present the experimental results in Section 4 and draw conclusions in Section 5.

2 Spectral Minutiae Representation

The Fourier-Mellin transform can be used to obtain a representation of an image that is invariant to translation, rotation and scaling. In [7], a Fourier-Mellin invariant (FMI) descriptor is given. First, the (fast) Fourier transform of an image is computed. Only the magnitude of the Fourier spectrum is retained, resulting in a translation invariant representation of the image. Next, the Fourier spectral magnitude is re-mapped onto a polar-logarithmic coordinate system with respect to an origin. In this way, the rotation and scaling become the translations along the corresponding coordinate axes. A similar procedure can be applied to minutiae sets in order to find a representation which is invariant to translation, rotation and scaling.

When implementing the Fourier-Mellin transform there are two important issues that should be considered. First, when a discrete Fourier transform is taken of a sampled continuous image, this results in a description of a periodic repetition of the original image. This is undesirable because it introduces errors. Second, the re-mapping onto a polar-logarithmic coordinate system after using a discrete Fourier transform introduces interpolation artifacts. Therefore we use analytical expressions that are evaluated at every grid point in the polar-log plane. These analytical expressions are obtained as follows. To each minutia a 2D function $m(x, y)$ is assigned. We select a delta function such that $m(x, y) = \delta(x - x_0, y - y_0)$, in which (x_0, y_0) is the location of the minutia. Its Fourier transform is given by:

$$\mathscr{F}\{m(x, y)\} = exp(-j(\omega_x x_0 + \omega_y y_0)) \tag{1}$$

Applying this operation to every minutia in the minutiae set, summing the results and taking the modulus of the combination, results in the analytic expression that can be evaluated in the polar-log plane.

The second step is to include the minutiae orientation into our representation. The orientation θ of a minutia can be incorporated by using the spatial derivative of $m(x, y)$ in the direction of the minutia orientation. A function $m(x, y, \theta)$ is assigned as the derivative of $m(x, y)$ in the direction θ. Its Fourier transform is given by:

$$\mathscr{F}\{m(x, y, \theta)\} = j(\omega_x \cos\theta + \omega_y \sin\theta) \cdot exp(-j(\omega_x x_0 + \omega_y y_0)) \tag{2}$$

The spectral representation of an entire minutiae set can be constructed by evaluating this expression on a predefined log-polar grid for each minutia, and taking the magnitude of the result after adding the complex values for all the minutiae. The resulting spectral minutiae representation is invariant to translation, and in which and scaling become translations along the log-polar coordinates.

Finally, we implement a point-wise multiplication with a Gaussian in the frequency domain. This equals to convolution with a Gaussian in the spatial domain. Applying this

Gaussian low-pass filter is to attenuate the higher frequencies in the spatial domain, thus reducing the influence of the minutiae location uncertainties.

In our algorithm, the following parameters have been used. The rotation axis ϕ in the polar-log plane is sampled in 256 steps, uniformly distributed between 0 and π (because of the symmetry of the Fourier spectra, only sampling from 0 to π is needed). The radius axis ρ is sampled in 128 steps, logarithmically distributed between 0.1 and 0.6. Examples of the achieved minutiae spectra are shown in Figure 1. For each spectrum, from left to right is the spectrum at different rotation angel (from 0 to π); from top to bottom is the spectrum with different frequency (from low frequency to high frequency).

3 Spectral Minutiae Matching

After representing fingerprints in the form of minutiae spectra, the next step is matching: the comparison of two minutiae spectra. The result of matching is either a 'match' (the two spectra appear to be from the same finger) or a 'non-match' (the two spectra appear to be from different fingers). Normally, in this step, we will first compute a numeric value (similarity score) which corresponds to the degree of similarity. Then, by using a threshold, we can make a match/non-match decision [9]. Based on the characteristics of the minutiae spectra, we applied a correlation-based matching algorithm for spectral minutiae matching. In the future, other similarity measures will be investigated.

Let $R(m,n)$ and $T(m,n)$ be the two sampled minutiae spectra in the polar-log domain respectively achieved from the *reference* fingerprint and *test* fingerprint. We use the two-dimensional correlation coefficient between R and T as a measure of their similarity. Thus, the matching score between R and T is defined as:

$$S_{\text{corr}}(R,T) = \frac{\sum_{m,n}(R_{mn}-\mu_R)(T_{mn}-\mu_T)}{\sqrt{(\sum_{m,n}(R_{mn}-\mu_R)^2)(\sum_{m,n}(T_{mn}-\mu_T)^2)}} \tag{3}$$

where

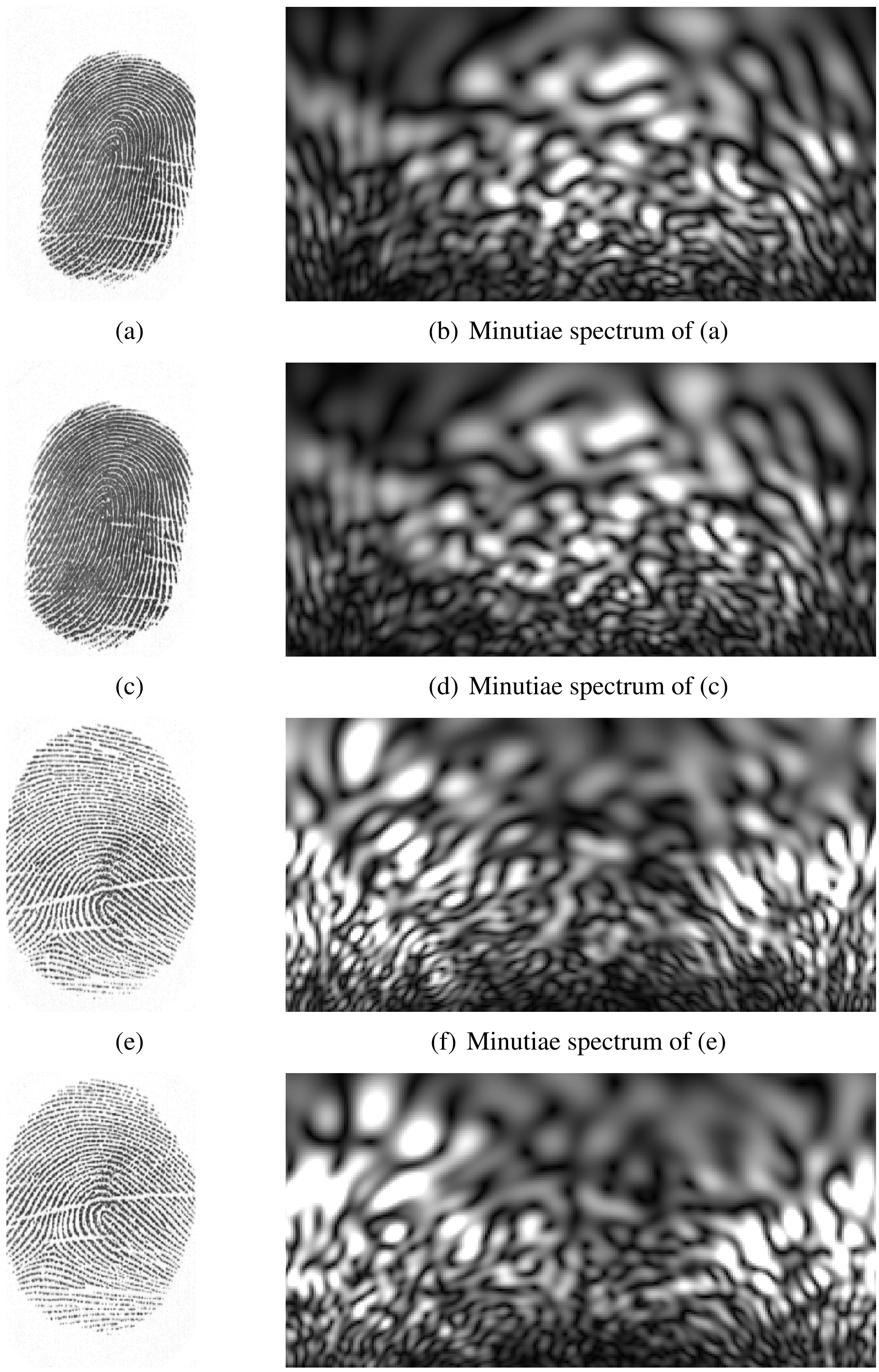
$$\mu_R = \frac{1}{MN}\sum_{m,n} R_{mn}, \qquad \mu_T = \frac{1}{MN}\sum_{m,n} T_{mn} \tag{4}$$

Since the minutiae spectra are translation invariant, but not rotation and scaling invariant, this method has to test a few different combinations of rotation and scaling, which are translations in the minutiae spectra (rotation becomes the translation in the horizontal direction and scaling becomes the translation in the vertical direction). In most fingerprint databases, there is no scaling difference between the fingerprints. Therefore, in practice only a few rotations have to be tested. We chose to test rotations from -15 units to +15 units in steps of 3 units, which corresponds to a range from -10° to $+10^\circ$. The maximum score from the different combinations is the final matching score between R and T.

4 Experiments

4.1 Measurements

We test the spectral minutiae representation in a verification setting. A verification system authenticates a person's identity by comparing the captured biometric characteristic with her own biometric template(s) pre-stored in the system. It conducts a one-to-one comparison to determine whether the identity claimed by the individual is true [1].



(a) (b) Minutiae spectrum of (a)

(c) (d) Minutiae spectrum of (c)

(e) (f) Minutiae spectrum of (e)

(g) (h) Minutiae spectrum of (g)

Figure 1: Examples of minutiae spectra. (a) and (c) are fingerprints from the same finger; (e) and (g) are fingerprints from the same finger.

(a) (b) (c) (d)

Figure 2: Examples of fingerprint samples in MCYT: (a) and (b) are the fingerprints that we accepted from MCYT;(c) and (d) are fingerprints that we rejected from MCYT because of the bad quality.

Table 1: Equal error rates.

	Data sets	EERs
1	FVC2000(DB2)	14.86%
2	MCYT(Automatically extracted minutiae)	5.80%
3	MCYT(Manually extracted minutiae)	0.20%

The matching performance of a fingerprint verification system is evaluated by means of several measures. The most commonly used are *the false acceptance rate* (FAR), *the false rejection rate* (FRR), and *the equal error rate* (EER). FAR is the probability that the system gives a 'match' decision for fingerprints that are not from the same finger. FRR is the probability that the system gives a 'non-match' decision for fingerprints that are from the same finger. EER is the rate at which FAR and FRR are equal. For simplicity, we use EER as the measurement of our scheme.

4.2 Results

The proposed algorithm has been evaluated by applying it to three different data sets. The first data set consisted of all the 110 identities from the FVC2000 database [10] folder 2. In this database, each identity has 8 samples. All the samples were collected by using the low-cost capacitive sensor "TouchChip" from ST Microelectronics. The second data set consisted of 100 identities from the MCYT Biometric Database [11], of which we used 10 samples per identity. All the samples we used were collected by using the optical sensor UareU from Digital Persona. The third data set contains exactly the same fingerprints as data set 2, but the minutiae have been manually extracted. For being able to manually extract reliable minutiae from fingerprint samples, we chose 100 identities from MCYT that have reasonable quality. The quality measurement that we used here is based on fingerprint's variance and coherence [12]. The variance and the coherence of a fingerprint reflect the clarity of its ridge-valley structures. In general, good quality fingerprints have higher variance and coherence than bad quality fingerprints. Some samples that we accepted and rejected from MCYT are shown in Figure 2.

For each comparison, we chose two fingerprints from the data set: one as a *reference* fingerprint, another one as a *test* fingerprint. The EERs we achieved from our algorithm are shown in Table 1.

From Table 1, we can see that the results achieved from the MCYT data set (2 and 3) are better than the one from the FVC2000 data set. The reason is that in the MCYT data set, all fingerprints are collected under control [11], that is, the fingerprints are relatively complete, and the translations and rotations are also limited. However, in FVC2000 folder 2, all prints are collected from untrained people, and the presence of the fingerprint cores and deltas is not guaranteed since no attention was paid to checking the correct finger position on the sensor [10]. For this reason, we notice that most samples contain only part of a fingerprint, and some even lost more than half. We assume that this causes a big increase in the EER. Moreover, the FVC2000 data set also contains many bad quality fingerprints, which makes the extracted minutiae very unreliable. To prove this, we also implemented a test on the first 30 identities from this data set (whose fingerprints have relatively better quality), and the EER is 9.66%, which is better than the whole set EER 14.86%.

Comparing the results from data set 2 and 3, we can see that the manually extracted minutiae lead to a much better result. The decrease of performance in data set 2 is mainly caused by the minutiae extraction errors (including the minutiae location errors, the missing and spurious minutiae). In case these errors were minimized (data set 3), we achieved an EER which was only 0.20%, and a false rejection rate FRR = 1.37% at FAR = 0%.

5 Conclusions

Spectral minutiae representation is a novel method to represent a minutiae set as a fixed-length feature vector, which enables the combination of fingerprint recognition systems and a template protection scheme and decreases matching time. This method avoids the minutiae registration difficulties by representing a minutiae set into a translation-invariant spectrum, in which rotation and scaling become translations, which can be easily compensated for. Moreover, this method is compatible with the large amount of existing minutiae databases and the additional cost to integrate this new scheme is relative low.

In this paper, we also presented the results of the spectral minutiae representation scheme. We achieved promising results with EER 0.20% for the manually extracted minutiae. However, from the results we can also see that this scheme is not reliable when there is little overlap between two fingerprints. Another challenge is how to overcome the influence of the minutiae errors, which are caused by an unreliable minutiae extractor. To cope with the limited overlaps and to be more robust to the minutiae errors are topics of further research..

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