Residual Analysis for Fingerprint Orientation Modeling

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Abstract

This paper presents a novel method for fingerprint orientation modeling, which executes in two phases. Firstly, the orientation field is reconstructed through fitting to a lower order Legendre polynomial basis to capture the global orientation pattern. Then the preliminary model around the singular region is dynamically refined by fitting to a higher order Legendre polynomial basis. The singular region is automatically detected through the analysis on the orientation residual field between the original orientation field and the orientation model. The method has been evaluated using the FVC 2004 data sets and compared with state-of-the-arts. Experiments turn out that the propose method attains higher accuracy in fingerprint matching and singularity preservation.

1. Introduction

As an important feature in fingerprint images, orientation pattern plays critical roles in fingerprint image enhancement, singularity characterization, fingerprint classification, fingerprint indexing, fingerprint recognition etc. There have been a large number of research efforts towards the reliable estimation of fingerprint orientation pattern from acquired fingerprint images, which can roughly be classified into two categories: local estimation and global modeling.

For local estimation methods, the orientation at a pixel is derived based on the information in a neighborhood of the pixel. The most frequently used local method is gradient estimation, which firstly calculates the gradient using the gradient operator (such as the Sobel operator) in digital image processing. Then the orientation is simply the direction perpendicular to the gradient. Despite of its numerical efficiency, the gradient operator is known to be sensitive to noise. To address this issue, a low-pass filter can be applied to the estimated orientation field for noise removal. There also has developed other methods for this problem, such as filter-bank [1,2], statistical techniques [3], structure tensor [4-6], local voting [7], integration operator [8] and ridge projection [9].

In practice, the quality of acquired fingerprint can easily be degraded for many reasons, for example, wet finger, dry finger, and finger with crease, wound, scar. Under these circumstances, the structure of fingerprint in a local region can be very weak and the local signal to noise ratio is very low, leading to difficulty for local estimation methods. On the other hand, since the fingerprint orientation is generally smooth except for a few points with singularities, it is possible to infer local structure using more global information. Pioneered in this direction is the zero-pole model by Sherlock et al [10], where singular points, cores and deltas, are modeled as zeros and poles in the complex plane, and the orientation is estimated by the summation of the influence of singular points. This model has received a number of interests and there have been several improvements. Vizcaya and Gerhardt [11] improved this zero-pole model to deal with more degree of freedom around the singular points. Gu et al [12-14] propose a combination model for orientation field representation, in which the global orientation is firstly constructed by a polynomial model and subsequently corrected by a Point-Charge model in regions near singular points. A similar idea has been presented in [15]. Very recently, a unified model is presented in [16] where the zero-pole model and its various generalizations can be regarded as special cases.

In spite of impressive results presented in the above works, these global modeling methods have a common limitation, i.e., they all require the prior knowledge on singular points in the acquired fingerprints. However, singular point detection by itself is a nontrivial issue in the characterization of fingerprints, which depends very much on the quality of the fingerprint image. For good quality fingerprints, Poincare index method would suffice in the localization of singular points. But for poor quality fingerprints, there would be a large number of spurious singular points if a simple singular point detection method, such as the Poincare index method, is used. In most of aforementioned global modeling methods, singular points are often detected manually, which evidently limits their application to realistic system. In [17], an SVM classifier is employed to remove the spurious points detected by the

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Poincare Index method, thus avoiding the manual detection for each fingerprint image. However, a set of training data with manually labeled singular points is necessary before the method can be used. In view of this problem, Wang et al. [18] present a fingerprint orientation model which fits the orientation field using a set of trigonometric polynomials. The method does not require the prior knowledge on singular points and has also been demonstrated to be advantageous over the combination model in fingerprint image enhancement and fingerprint matching. The method has recently been extended in [19], where Legendre polynomial is utilized and a step of singularity preservation using the Levenberg-Marquardt algorithm to minimize the modeling cost functional is introduced after the initial modeling. This method is advantageous in preserving singular points, but at cost of computation load.

In this paper, we will propose a method for fingerprint orientation reconstruction. The method basically consists of two phases: a preliminary modeling phase by a polynomial model, followed by a refined phase for fingerprint regions around singularities. What is different from the combination model is that the proposed method does not require the prior knowledge of fingerprint singularities. And more importantly, instead of having a fixed model for region with singularity, the model for region with singularity in the proposed method is dynamically updated through an iterative process, where the singularity region is gradually determined from the analysis of the residual field between the original orientation field and the global orientation model. The process is fully automatic and robust against various perturbations.

The rest of the paper is organized as follows. Section 2 gives a brief account on polynomial modeling for fingerprint orientation reconstruction, which serves as a preliminary modeling in the proposed method. After that, details on orientation residual analysis are given, including singular region detection as well as the refined model. In section 3, experiment for validating the proposed method and comparison with the state-of-the-art are presented. Finally the paper is concluded in Section 4.

2. Methods

2.1 Preliminary orientation modeling

A recent trend in fingerprint orientation modeling is to fit the orientation field using a set of functional basis, such as polynomial basis, and trigonometric functional basis. Usually the calculation is carried out in the cosine and the sine domain other than in the original orientation field directly. In addition, the orientation angle is doubled before the sine/cosine operation to avoid the problem of orientation cancellation [1]. For completeness, a brief account is given in the following. Firstly, let us denote the original orientation field as $\boldsymbol{\theta}$ and the transformed orientation field as

$$\mathbf{f}_c = \cos 2\boldsymbol{\theta}\,, \tag{1a}$$

$$\mathbf{f}_s = \sin 2\boldsymbol{\theta}\,. \tag{1b}$$

Then the transformed orientation field is approximated by a linear combination of a functional basis as:

$$\mathbf{f}_c \approx \mathbf{a}^T \boldsymbol{\varphi} \tag{2a}$$

$$\mathbf{f}_s \approx \mathbf{b}^T \boldsymbol{\varphi} \tag{2b}$$

where $\mathbf{a}$ and $\mathbf{b}$ are the parameters, and $\boldsymbol{\varphi}$ represents the set of functional basis. The parameters can be estimated through the least square or the weighted least square method. In this study, a lower order Legendre polynomial basis is utilized for preliminary modeling of the entire orientation field, which is subsequently analyzed in the orientation residual field and updated dynamically to refine the orientation pattern around true singularities in the original fingerprint image.

2.2 Orientation refining through residual analysis

For notational convenience, let us denote the transformed orientation field as

$$\mathbf{z} = \mathbf{f}_c + i\mathbf{f}_s \tag{3}$$

Then, the analysis of the orientation field can be carried out in the complex domain. In this section, we will focus on the analysis of the residual orientation field $\mathbf{z}_{\text{residual}}$, which is the discrepancy between the original orientation field and the reconstructed one:

$$\mathbf{z}_{residual} = \mathbf{z} - \hat{\mathbf{z}}, \tag{4}$$

where $\hat{\mathbf{z}}$ is the reconstructed orientation field in the complex domain.

In order to preserve the true singularity in the original fingerprint, we present in the following a method for orientation refining, which consists of two stages: (1) detection of areas for orientation re-estimation and (2) orientation refinement. These two stages alternate in an iterative process to track the true fingerprint singularities and refine the orientation field accordingly. The method works in the residual field and consists of the following steps:

Step 1) Region mask estimation

As aforementioned, our interest is to refine the orientation field in the region around singular points. A simple method to detect this region is based on the orientation coherence [1]. If the value of coherence at a pixel is less than a predetermined threshold, that pixel will probably close to region with presence of singularity. The detected region represents the region with presence of high curvature and the corresponding orientation needs to be refined. For convenience, this region is denoted as R_S. To differentiate true singularities from those due to creases, the method for crease detection [20] are employed. The detected crease region is then removed from R_S. The left region is denoted as R_P.

Fig. 1 A low-quality fingerprint image (Row 1, left) and enhanced results by local estimation (Row 1, right), orientation modeling using LPLM (Row 2, right) and orientation modeling using ROM (Row 2, right) respectively.

Step 2) Orientation compensation

Since the purpose here is to re-estimate the orientation field in R_S, for clarity, we denote $\mathbf{x}_S$ as pixels located in R_S, and $z(\mathbf{x}_S)$ refers to the orientation field of $\mathbf{x}_S$. As aforementioned, the fingerprint structure in R_S is highly curved and the model of the orientation field here should contain higher frequencies than the model used in the step of preliminary modeling. Hence, a higher order polynomial model is employed in this step, but the modeling is carried out in the orientation residual field:

$$\mathbf{z}_{residual}(\mathbf{x}_S) = \mathbf{z}(\mathbf{x}_S) - \hat{\mathbf{z}}(\mathbf{x}_S); \qquad \mathbf{x}_S \in R_S, \tag{5}$$

which is approximated using a higher order polynomial basis:

$$\mathbf{z}_{residual}(\mathbf{x}_S) \approx \mathbf{a}^T \boldsymbol{\varphi}(\mathbf{x}_S) + i\mathbf{b}^T \boldsymbol{\varphi}(\mathbf{x}_S) = \tilde{\mathbf{z}}_{residual}(\mathbf{x}_S). \tag{6}$$

As aforementioned, the goal of orientation refinement is to preserve the orientation pattern with presence of true singularities in R_P and to reconstruct the orientation pattern with presence of false singularities in R_S. To that end, we need to reduce the impact of the false singularities in R_S upon the estimation of the higher frequency model. Therefore the residual orientation data in R_P is utilized for determining the model parameters in the refined model (6).

Recalling the preliminary modeling in the last section which estimates the low frequency information of the entire orientation field, here the higher order polynomial model in the residual domain essentially re-estimates the higher frequencies of the orientation field in the highly curved region. Thus, a "better" estimation of the orientation field in R_S is simply to add $\tilde{\mathbf{z}}_{residual}$ to $\hat{\mathbf{z}}$:

$$\hat{\mathbf{z}}(\mathbf{x}_S) = \hat{\mathbf{z}}(\mathbf{x}_S) + \tilde{\mathbf{z}}_{residual}(\mathbf{x}_S). \tag{7}$$

Step 3) The energy of residual (Er)

$$E_r = \sum_{\mathbf{x}_P \in R_P} \left| \mathbf{z}_{residual}(\mathbf{x}_P) \right|^2 \tag{8}$$

(which represents the modeling error) is computed, where $\mathbf{x}_P$ denotes the pixels in R_P. If Er is less than a predetermined threshold T_{Energy} or a maximum allowable iteration number (8 in this study) is exceeded, the iteration stops; otherwise, goes back to Step 1.

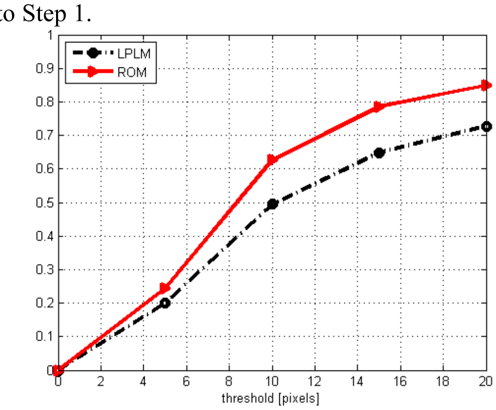

Fig. 2 Comparison of F-measure between ROM and LPLM for singular point detection on FVC 2004 Db1.

3. Experiments

To evaluate the performance of the proposed residual orientation modeling method (ROM), the fingerprint database FVC 2004 Db1 is employed in this study. The proposed method has been compared with the Legendre polynomial model with singularity preservation (LPLM) [19], which consists of preliminary modeling using Legendre polynomial followed by refinement based on the Levenberg-Marquard algorithm to preserve singularities.

An example is given in Fig. 1, where Row 1 left shows the original fingerprint which contains many creases. The enhanced image by gradient estimation is presented on the right of Row 1. It can be seen that the local estimation is insufficient when the acquired fingerprint is of low quality. Row 2 lists the enhanced images with global modeling by LPLM (left) and ROM (right) respectively. Both are significantly better than the local estimation solution. However, it is noted that the LPLM result still contains creases. Clearly, the proposed method yields better result.

Fig. 2 depicts the performance on singular point detection using two methods as evaluated by the F-measure, which is a trade-off between precision and recall [19]. The superiority of the proposed method to LPLM is clearly visible. In addition, fingerprint matching experiment has also been carried out, and the equal error rate on FVC 2004 Db1 is 5.95% for LPLM and 5.75% for ROM respectively.

4. Conclusion

In summary, this paper has presented a novel method for fingerprint orientation modeling, which is composed of the following two stages. Firstly, the orientation field is fitted to a lower order Legendre polynomial basis to capture the global orientation pattern in the fingerprint structure. Then the preliminary model around the region with presence of fingerprint singularities is dynamically refined using a higher order Legendre polynomial basis. The singular region is automatically detected through the analysis on the orientation residual field in an iterative fashion. And the detected singularity region is then utilized to dynamically update the refined model. The method does not require any prior knowledge on the fingerprint structure. To validate the performance of the method, experiments have been carried out in terms of fingerprint image enhancement, fingerprint singularity detection and fingerprint recognition using the FVC 2004 Db1. Compared with the existing Legendre polynomial model, the proposed method attains higher accuracy in fingerprint singularity detection and lower error rates in fingerprint matching.

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