MODEL BASED ALGORITHM FOR SINGULAR POINT DETECTION FROM FINGERPRINT IMAGES *

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ABSTRACT

The detection of singular points (SP) is an important step for automatic fingerprint identification system (AFIS). In this paper, a model-based algorithm for singular points detection is proposed. Based on a model, which can describe the orientation fields around the singular point, a Hough transform is taken to compute the coefficients of the model, i.e., the exact position of the singular point. Since more information about singular point is used, the proposed algorithm is supposed to have a better performance than traditional Poincare index based algorithm. At the same time, the voting value of the Hough transform indicates the likelihood of the detected singular point, which can be used to eliminate spurious singular points. The experiments are taken to illustrate the algorithm's effectiveness.

1. INTRODUCTION

Among various biometric techniques, automatic fingerprint identification system (AFIS) is one of the most popular and reliable technologies for automatic personal identification.

Fingerprint is the pattern of ridges and valleys on the surface of a fingertip. The orientation field of fingerprint image is defined as the local orientation of the ridge-valley structures. The singular points can be viewed as the points where the orientation field is discontinuous. There are tow types of singular points, cores and deltas. Core points are the points where the innermost ridge loops are at their steepest. Delta points are the points from which three patterns deviate. Definitions may vary in deferent literatures, but this definition of singular point is the most popular one.

Singular point has important usage in AFIS. First, the fingerprints classification is mainly based on these critical points. The positions of cores and deltas are claimed to be enough to classify the fingerprints into six categories, which include arch, tented arch, left-loop, right-loop, whorl, and twin-loop. Although classification does not find out the exact fingerprint from a large database of fingerprints, it can greatly reduce the number of the fingerprints to be compared in the verification step. Because the number of singular points in a fingerprint is limited (often from two to four), the singular points can also be used as reference points to align the fingerprint images.

Most of the singular point detection algorithms are based on the orientation field estimation techniques and using Poincare index. For these algorithms, a point in the orientation field is classified as a singular point if along a closed curve around that point the orientation changes $\pm 180^\circ$. Attributing to the poor quality of fingerprint image and imprecise computation of the orientation field, the traditional Poincare index based algorithm often result in many spurious singular points. To remove these spurious singular points, some post-processing steps are adopted in [1]. And in [2], a multi-resolution method for singular points detection is proposed. It is shown that traditional method based on Poincare index cannot work well by a fixed resolution, because a trade-off must be made between the precision in the localization of the singular points and the probability of false alarm.

The traditional Poincare index based method just uses the orientation field on the curves, while our method is to integrate local orientation field to compute a likelihood value to determine whether a singular point is located in this area and find out its exact position. Because more information (not only the orientation on the closed curve but also a local area orientation around the point) is used to detect singular point, an improvement of singular point detection can be expected by using this algorithm, especially when combined with traditional methods.

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2. SINGULAR POINT MODELS

In order to use the information of local orientation field to detect singular points, the relationship between local orientation field and the position of singular point must be established first. It can be done by a so-called zero-pole model for orientation field based on singular points, which is first proposed by Sherlock and Monroe in [3]. In [4], an improvement is made by using a piecewise linear approximation model around singular points to adjust the effect of zero and pole points. In [5] and [6], one of us proposed a complex rational model and a combination model to describe the orientation field accurately, respectively.

This zero-pole model is a simple model for the interpretation of fingerprint topology. In this model, the fingerprint image is placed on a complex plane, and the core and delta points are regarded as poles and zeros of a rational polynomial function respectively. Noting that the ridge orientation far from the center of the image tends to be a constant value, a parameter θ_∞ named as background orientation is introduced too.

As we know that the Poincare index is -1 at each zero and +1 at each pole and the Poincare index of the core and delta is 1/2 and -1/2. So a function is defined as follows:

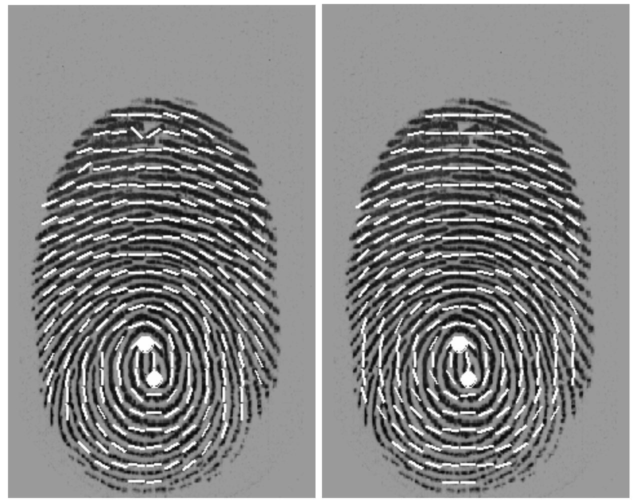
$$p(z) = e^{j\theta_\infty}\sqrt{\frac{(z-z_{c1})(z-z_{c2})....(z-z_{cm})}{(z-z_{d1})(z-z_{d2})....(z-z_{dn})}} \quad (1)$$

In this function, $z_{ci}(i=1...m)$ and $z_{di}(i=1...n)$ are the locations of the cores and deltas, respectively. So the orientation of the ridge at point z is the phase of this complex rational function's square root:

$$\begin{aligned}\theta(z) &= \arg(p(z)) \\ &= \theta_\infty + \frac{1}{2}[\sum_{i=1}^{m}\arg(z-z_{ci}) - \sum_{i=1}^{n}\arg(z-z_{di})]\end{aligned} \quad (2)$$

The main usage of this model is to provide a method to interpolate the orientation at any point, which can be used to unwrap the orientation, reconstruct a noisy image, etc [3]. This model is simple and effective, but lack of accuracy especially in the areas far from the singular points. Fig. 1 shows the orientation generated by this model for a fingerprint.

From Fig. 1, we notice that this zero-pole model can give a pretty good approximation to the actual orientation around the singular points. If more suitable θ_∞ and position of the singular points can be derived, the predicted orientation field can considerably approximate the actual local orientation field better. On the other hand, if we can get exact θ_∞ and actual local orientation field around a singular point, we can also compute the exact position of this singular point (e.g., by using Hough transform). It is the basic idea of the algorithm proposed in this paper.



(a) (b)

Fig 1. (a) the actual orientation field computed by gradient-based method, (b) the orientation field predicted by zero-pole model, with $\theta_\infty = \frac{\pi}{2}$.

3. MODEL BASED SINGULAR POINT DETECTION

When a singular point is not very close to other singular points, the influence of other points can be treated as a constant value in this point's neighborhood. So according to zero-pole model, the orientation field around this singular point (take core for example) can be presented as follows:

$$\theta(z) = \theta_\infty + \frac{1}{2}\arg(z - z_c) \quad (3)$$

Let (x_c, y_c) denote the coordinate of this core point. So we have $z_c = x_c + j \cdot y_c$. Then the orientation field in each certain pixel (x, y) around this core can be expressed by a linear equation of (x_c, y_c):

$$y - y_c = \tan[2\theta(z) - 2\theta_\infty](x - x_c) = K_c(x - x_c) \quad (4)$$

By the same derivation, around a delta point this equation can be reworked as follows:

$$y - y_d = \tan[2\theta_\infty - 2\theta(z)](x - x_d) = K_d(x - x_d) \quad (5)$$

The Hough transform (HT) is a method for detecting straight line in noisy digital images. And it can be extended to find general curves and shapes, which can be represented by an equation $f(x, y, \alpha, \beta) = 0$. In this equation, x and y denote the coordinate of feature point in the image, while α and β denote the parameters that we look for. Comparing Eqs. (4) and (5) with the equation used in HT, we will find that they have the same form. It hints that we can use the orientation field $\theta(z)$ and HT to compute the exact coordinate of singular points.

In HT, the orientation filed around the singular point forms the feature space, and the coordinate of the singular point forms the parameter space. Because of the consideration of computation, the parameter space is quantized into a series of integer pairs. According to Eq. (4) and (5), each point in the feature space corresponds to a line in the parameter space. So the orientation of every point around the singular point votes coherently into a series of accumulator counters which represent the position of singular point. Therefore, after the voting step, the accumulator with the largest numbers of voting indicates strong evidence for the position of the singular point. At the same time, the largest number of voting corresponding to the likelihood value is also obtained, which indicates how much the local orientation field resembles this singular point. If the number of voting does not reach a certain threshold value, we can make the decision that there is not a singular point according to the local orientation field.

Before using HT and zero-pole model to detect singular points, two problems have to be solved first. The first problem is how to determine the range of feature points. Because of the limitation of zero-pole model, only the orientation field that locates in a local region around the singular point can be regarded as the feature points used in HT. In order to solve this problem, a coarse detection of singular points is computed first by using traditional method based on Poincare index in a fixed resolution of orientation field. Then the orientation field around the detected singular point can be regarded as the feature points that will be used in Hough Transform.

The second problem that must be solved before using this algorithm is how to compute the background orientation. From Fig. 1 we can see that only when θ_∞ is appropriate, the orientation predicted by zero-pole model can approximate actual orientation field well. Following Eq. (5), we can sum up a rule as follows: If the singular point locates in the center of a rectangle area, the average orientation in this area equals to the background orientation θ_∞. But this rule cannot be used in practice, because the exact position of the singular point is just what we are looking for. But if we divide the local area into a series of rectangles, it has tremendous possibility that one of these average orientations equals to the real background orientation. And because HT can work well with the noisy data, the detection of singular point will not affect by other false background orientations.

The proposed model-based algorithm combined with traditional Poincare index based method is summed up as follows:

Step 1: Use Poincare index method in a fixed resolution of the orientation field to compute singular points in the fingerprint image first. Because a trade-off has to be made between the precision in the localization of the singular points and the probability of false alarm, the positions of detected singular points have to be refined and the spurious singular points have to be removed.

Step 2: Choose one of the singular points detected in Step 1. Let the local region be divided into a series of rectangles. The size of these rectangles is $wsize \times wsize$, and the number of these rectangles is $wnum \times wnum$. The parameter *wsize* and *wnum* have to be determined experimentally.

Step 3: Regard one of these averaged orientation fields as the background orientation. Let the orientation field in a square region with the size of $W \times W$ around the singular point be the feature points and using HT to make the corresponding accumulators in parameter space increased.

Step 4: If any averaged orientation has not been used in HT, go to step 3.

Step 5: In the parameter space, the accumulator with largest number of voting corresponds to the exact position of the singular point. And the maximum number of voting represents the likelihood value, which shows how much local orientation field resembles this singular point.

Step 6: If any singular point has not been computed, go to step 2.

Step 7: Compare the likelihood value of each singular point with a certain threshold. The singular points with the likelihood value below the threshold will be regarded as the spurious and removed from the result.

4. EXPERIMENTAL RESULTS AND CONCLUSIONS

The experiment is carried on a database of fingerprint images captured with a live-scanner, whose size is 512×320 (pixels). The fingerprint images in this database vary in different types and qualities.

We use the algorithm proposed in [1] as traditional method to compute singular points in the fingerprint images. The orientation field is computed by using average gradient vector method with the average window size of 15×15. The shape of closed curve is square with a length of 24 pixels. $wsize = 16, wnum = 3, W = 35$. The threshold of likelihood value is defined as the half of the maximum numbers of votes.

Some typical results are shown in Fig. 2. Because there is not a standard method of singular point detection that can give a judgment, the proposed method and traditional method has been evaluated by visually inspecting several detection results. The improvement of detection results can be observed in most test samples. It shows that when more information (not only the orientation on the closed curve but also the orientation in the local area) is applied to detect singular points, the improvement of accuracy can be expected. But deterioration is also observed in the dataset. There are two reasons for those results. The first reason is that the poor quality of some fingerprint images makes it impossible to compute exact orientation field. In those cases, neither traditional method nor model-based method can give an appropriate detection of singular point. The second reason is that for some fingerprint image with uncommon pattern of ridge-valley structure, the zero-pole model cannot describe their orientation field well.

In our future work, we will study on more flexible model, which has a better approximation for different kind of fingerprint images.

5. ACKNOWLEDGMENT

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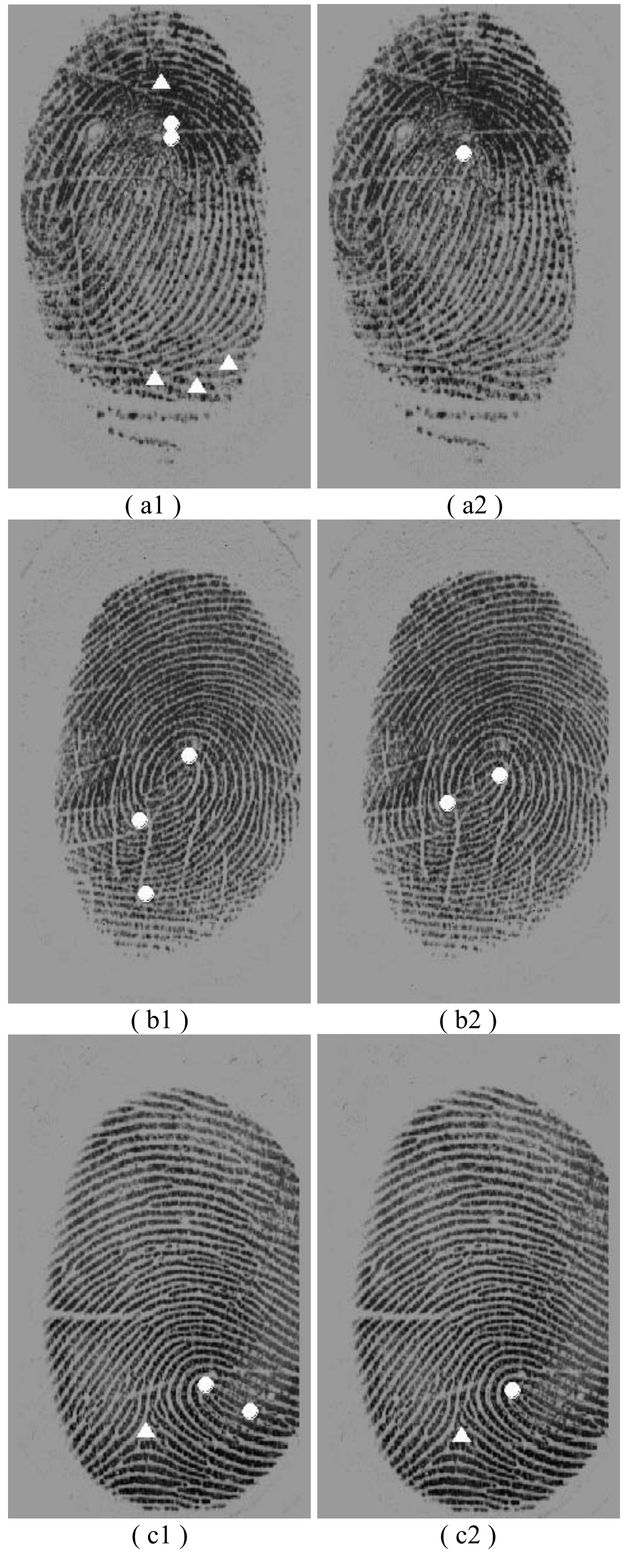

Fig 2. Experimental results of three fingerprint images. The singular points detected by the traditional algorithm [1] and the proposed model-based algorithm are given in left column and right column, respectively. Circles and triangles denote core and delta points, respectively.