

Detection of Singular Points from Fingerprint Images Using an Innovative Algorithm

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Abstract
Fingerprint scrutiny is typically based on the location and pattern of detected singular points in the images. These singular points (cores and deltas) not only represent the characteristics of local ridge patterns but also determine the topological structure (i.e., fingerprint type) and largely influence the orientation field. In this report, there is an innovative algorithm for singular points detection. After an initial detection using the conventional Poincare Index method, a so-called DORIVAC feature is used to remove spurious singular points. Then, the optimal combination of singular points is selected to minimize the difference between the original orientation field and the model-based orientation field reconstructed using the singular points. A core-delta relation is used as a global constraint for the final selection of singular points.
Keywords: Orientation field, Poincare´ Index, Singular points, topological structure.

1. Introduction

Fingerprint is the pattern of ridges and valleys on the surface of a fingertip. The ridges are black and the valleys are white. Its orientation field is defined as the local orientation the ridge-valley structures. The minutiae are defined as ridge endings and bifurcations. The singular points can be viewed as points where the orientation field is discontinuous, which can be classified into two types: core and delta. Fig. 1 lists five typical types of fingerprints with singular points noticeable. As an important topological characteristic for fingerprints, singular points can be used for fingerprint indexing (i.e., classification for fingerprint types) as well as for fingerprint arrangement and orientation field modeling and so forth.

Several previous works have addressed singular point detection and analysis in fingerprint images. They can be approximately classified into two groups.

The first approach is mainly based on using the Poincare´ Index to consider the irregular orientation distribution about singular points. This sort of algorithm usually calculates the sum of the orientation changes along a close circle about the point to judge whether it is a singular point.

The second form of approach uses probability analysis, ridge analysis, shape analysis, or template matching. Compared with these latter techniques, Poincare´ Index-based detection techniques are generally stronger to image rotation and relatively easy to compute, so they are more extensively used in real applications.

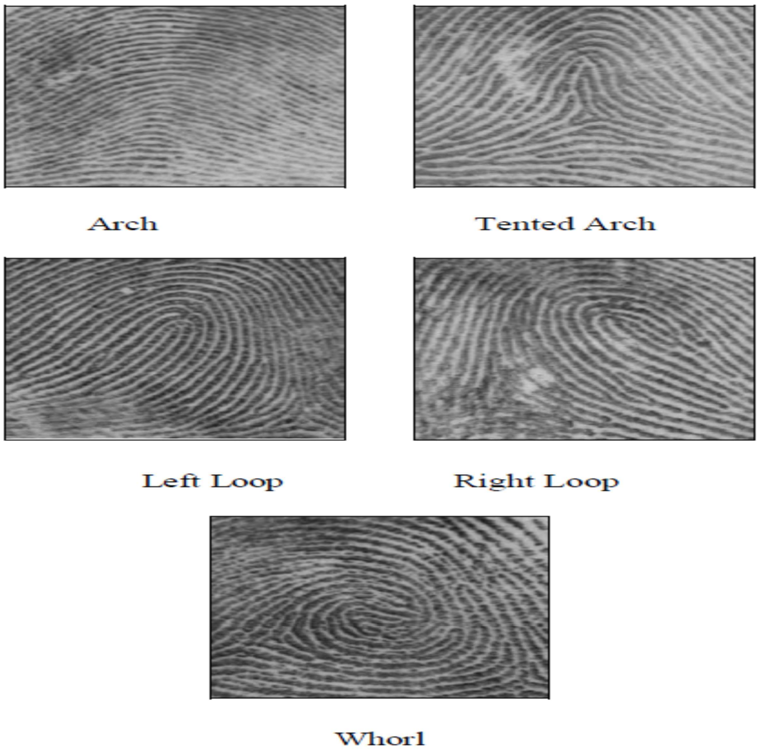

Fig 1: Various types of fingerprints with cores (marked with circles) and deltas (marked with triangles). (a) Plain arch. (b) Tented arch. (c) Left loop. (d) Right loop. (e) Whorl

Poincare´ Index-based algorithms usually result in many forged detections (especially for low-quality fingerprint images), even after post-processing. The forged detected points can greatly degrade the performance of these algorithms in lots of applications. The forged detections result because 1) the Poincare´ Index feature alone is not sufficient for accurate singular point detection and 2) most post-processing approaches use only local characteristic of singular points, which is not enough to discriminate true singular points from forged detections caused by creases, scars, blurs, damped prints, etc. In the orientation field, some forged detection actually has almost the same local patterns as true singular points. To accurately distinguish the genuine singular points, global discriminative information should be incorporated into the detection.

This paper, concentrate on to singular point detection based on an innovative so-called Difference of the ORIentation Values Along a Circle (DORIVAC) characteristic and global restrictions. Compared with previous studies, the contributions of this paper lie in the following aspects: 1) Paper is proposed using the DORIVAC feature for singular point verification, which can provide more discriminative information to get rid of forged detections and 2) based on an analysis of core-delta relationships, to select the best combination of singular points by global restrictions. The optimal singular points are selected to minimize the variation between the detected orientation field and model-based orientation field reconstructed using the singular points.

The rest of this paper is organized as follows: Part II analyses the topological structure of fingerprints. In Part III, the DORIVAC feature is proposed to remove forged SPs. Part IV discusses how to select the optimal combination of cores and deltas using global information. Part V finishes with conclusions.

2. Topological Analysis for Fingerprint Structures

2.1 Mathematical Background:

Definition. Let V (u, v) =p (u, v) + $i.\ q\ (u, v)$ be a continuous 2-dimensional vector field. Then, the Poincare´ Index of V (u, v) along an arbitrary simple closed path γ is defined as

$$I(\gamma) = \frac{1}{2\pi}\int_{(u,v)\in\gamma} d\emptyset(u,v) \tag{1}$$

where $\emptyset(u, v) = \arg V(u, v)$ is the angle at point (u, v) and $\emptyset \in [0,2\pi)$. The integration is taken anticlockwise along γ.

The Poincare´ Index is always an integer. By computing I beside a simple closed circle around a point P, one can find whether P is a singular point $(I \neq 0)$ or a common point$(I = 0)$.

Suppose that an area Ω has an exterior boundary, Γ_{Ext}, and an interior boundary, Γ_{Int} , as shown in Fig. 2. The singular points inside Ω are indicated by the circles,$\{\gamma_k | k = 1,2,3 \dots\}$. C is a simple closed path inside Ω. Two important properties of the Poincare´ Index can be formulated as follows and their evidence can be derived from Complex Function Theory.

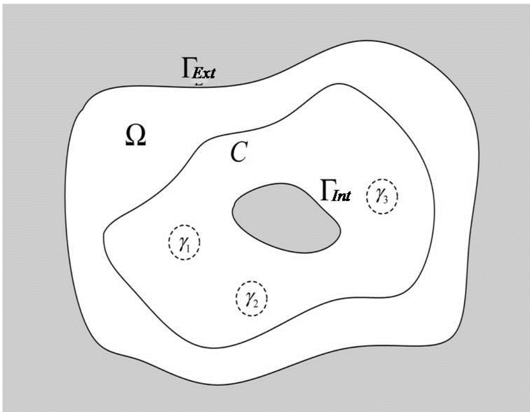

Fig. 2. Region Ω with its boundary $\partial\Omega = \Gamma_{Ext} \cup \Gamma_{Int}$ $\{\gamma_i, i = 1,2,3,\}$ are the circles around the singular points inside Ω. C is a simple closed path in Ω.

Property 1. The Poincare´ Index along the boundary of a given area is equal to the sum of the Poincare´ Indices of the singular points inside this area, i.e.

$$\sum_k I(\gamma_k) = I(\Gamma_{Ext}) - I(\Gamma_{Int}) \quad (2)$$

Property 2. If two simple closed paths are homotopic, and there are no other singular points between them, their Poincare´ Indices are the same. For example, $I(C) = I\,(\Gamma_{Ext})$, in Fig. 2.

2.2 Analysis of Fingerprint Images:

For oriented texture images, such as fingerprints and fluid flow, it is natural to establish their connection with 2-dimensional topology theory. This can relate the above definitions and properties on these images. The singular points in fingerprints are found to be steady with the singular points defined in topology. In Fig. 3, we list two typical singular points for fingerprints, their Poincare´ Indices, and their local patterns in the orientation field O.

A remarkable conclusion for fingerprints can be assumed based on Property 1. Since fingerprints usually do not have interior boundary Γ_{Int} and only have isolated singular points (cores and deltas) with known Poincare´ index (+1 for core, -1 for delta), (2) can be written as

$$N_{cores} - N_{deltas} = I(\Gamma_{Ext}) \quad (3)$$

where N_{cores} is the number of the cores, N_{deltas} is the number of the deltas, and Γ_{Ext} is the exterior boundary of the fingerprint.

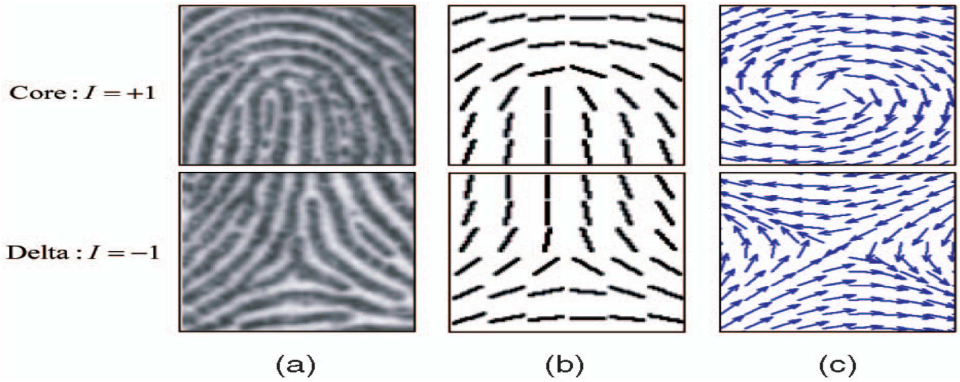

Fig. 3. (a) Singular points in fingerprints with the Poincare´ Indices, (b) their local patterns in the orientation field *O*, and (c) the vector field V.

Earlier works have pointed out that cores and deltas should appear in pairs. Two views of actual thumb are shown as an example in Figs. 4a and 4b with the cores and the deltas marked. For the simple closed path Γ_{Ext} consisting of this kind of boundaries, $I(\Gamma_{Ext}) = 0$, and then $N_{cores} = N_{deltas}$.

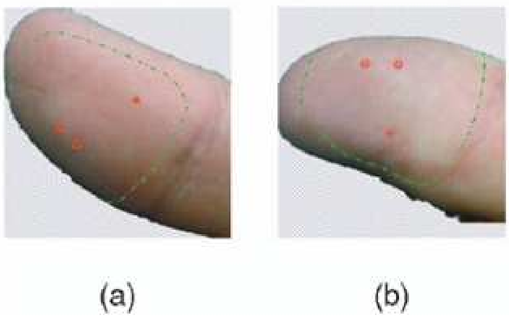

Fig. 4. (a) Left and (b) right views of a real thumb with singular points and boundary marked.

As for Property 2, we know that the Poincare´ Index can be calculated along any simple closed path as long as it is homotopic with the closed circle around the same points. This allows to adaptively choose the integral path for the boundary, for example, to choose the path where the orientation confidence is much higher.

3. Using DORIVAC Feature to Remove Forged Singular Points

3.1 DORIVAC Feature:

Many earlier researchers have shown that Poincare´ Index-based methods can usually detect nearly all true singular points when the Index is calculated along small area boundaries, but this also guides to much forged detection. If a bigger area is chosen, true singular points will be easy to miss. In order to get rid of forged detections while conserving a good detection rate, an innovative feature is advised here extended from the Poincare´ Index, which can provide more perceptive features and be used to confirm the trueness of each finding after using Poincare´ Index algorithm.

The Poincare´ Index is defined as the sum of the orientation differences beside a closed ring *L*. For a given point *P*, suppose that the set of sampled points along *L* is $\{T_1; T_2; T_3; \ldots; T_{N-1}\}$ and o_i is the orientation of point T_i. Then, the Poincare´ Index of *P* can be computed by

$$Ip \quad = \frac{1}{\pi}\sum_{i=i}^{N-1} f(o_{i+1} - o_i) \tag{4}$$

$$= \frac{1}{\pi} \sum_{i=i}^{N-1} f(\delta o_i),$$

$$f(x) = \begin{cases} x, & |x| \leq \frac{\pi}{2}, \\ \pi - x, & x > \frac{\pi}{2}, \\ \pi + x, & x < -\frac{\pi}{2}, \end{cases} \tag{5}$$

The Poincare´ Index is only the sum ofδo_i. It contains no information about the arrangement of $\delta o_i, i = 1,2,3, \ldots., N-1,$ and it cannot explain the singular point fully. So, when there are creases, scars, smudges, or damped prints in the fingerprint images, the Poincare´ Index method will easily outcome in many forged singular points. Post-processing steps are therefore frequently essential. In this paper, two simple set of laws are used through post-processing:

1) If a delta is too close to a core (the distance between them is smaller than 8 pixels), eradicate both of them as well as

2) In a very small area (a circular region with a radius of 8 pixels), if there is more than one core (or delta), an average core (or delta) can be calculated instead.

Suppose that there are *N* cores (or deltas) in such a area, $\{(u, v_i), i = 1,2, \ldots . N\}$ Then, the average core (or delta) (u, v) is calculated by

$$u = \frac{1}{N} \sum_{i=1}^{N} u_i \tag{6}$$

$$v = \frac{1}{N} \sum_{i=1}^{N} v_i \tag{7}$$

However, even after this post-processing step, much forged detection still remains. Fig. 5 shows two examples from a cheap-quality fingerprint, illustrating points that are wrongly detected as a core and a delta by using the Poincare´ Index method and this post-processing.

In order to additional remove the forged points, an innovative characteristic is used, which contains more information about the singular point. The characteristic on point *P*, which consists of the DORIVAC about *P*, i.e.,

$$\text{DORIVAC } (P) = [\delta o_1, \delta o_2, \ldots . \delta o_{N-1}] \tag{8}$$

Fig. 5. Two examples of forged singular points detected using a conventional Poincare´ Index-based method and post-processing steps, in which the false core is marked with a circle and the false delta is marked with a triangle.

As DORIVAC contains allδo_i, it can illustrate the singular point more absolutely. The Poincare´ Index can be seen as the summation of DORIVAC features and DORIVAC features can be considered as an extended form of Poincare´ Index. Fig. 6 shows six singular points detected by the Poincare´ Index method and their DORIVAC features are plotted as curves (among them, Figs. 6a, 6b, 6c, and 6d are true and Figs. 6e and 6f are forged detections).

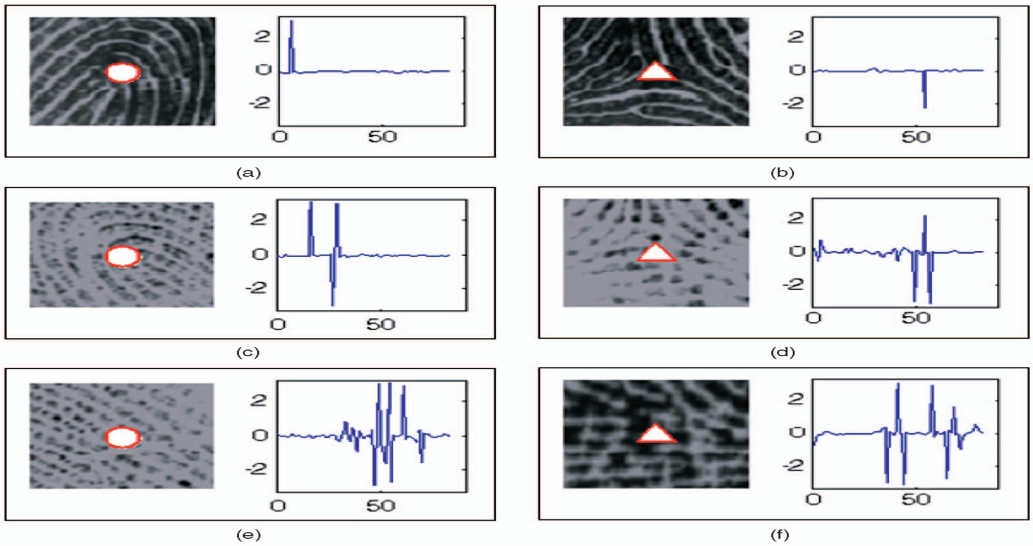

Fig. 6. Singular points detected by using the Poincare´ Index algorithm and their DORIVAC features (plotted as curves): (a), (b), (c), and (d) are true while (e) and (f) are forged.

Since the orientation field is defined in [0, π), there will be one DORIVAC feature pulse for each singular point (positive pulse for core, and negative pulse for delta) if the orientation field is detected completely. See Figs. 6a and 6b for examples. Although the noise around the true singular points may change the curves a little, there exists a clearly obvious difference between true and forged singular points. These phenomena can be observed in Fig. 6.

After post-processing steps, the detected singular points are isolated, i.e., there is only one singular point for any fairly large region. Thus, it is more suitable to calculate the DORIVAC features along a large circle. Then, *N* can be a large number, and accordingly, the curves of DORIVAC features will be more continuous.

3.2 Removing Forged Singular Points:

To distinguish true singular points from forged ones, a two-step classifier is projected as below. For each point with nonzero Poincare´ Index in the applicant set *S*, the DORIVAC feature is calculated. If there is exactly one pulse (i.e., positive pulse for core and negative pulse for delta) with the height nearly up to π, it is a legitimate singular point and will be kept in the final set *S* of singular points; otherwise, it will be removed from applicant set *S* and placed into an supplementary set *S'* of applicants for further processing. This process is outlined in Algorithm 1.

Algorithm 1:- Pseudo-code of the first step for removing forged SPs

for each detection point *P* in *S* do
  DORIVAC (*P*) =$[\delta o_1, \delta o_2, \ldots\ldots, \delta o_{N-1}]$;
 if $\exists!\, k \in [1, N-1], that\ |\delta o_k| > t, then$
   keep *P* in S;
 end
 else
   remove *P* to S´

8 end

9. end

The supplementary point set S' can contain a mixture of true singular point and forged detections. The classifier is designed, based on training samples to differentiate between the true points (e.g., Figs. 6c and 6d) and the forged ones (e.g., Figs. 6e and 6f).

Since it is time consuming to physically tag true and forged singular point samples for the training of the classifier, the taster learning methods are used suitable for small-numbered samples. The Support Vector Machine (SVM) is chosen to design the classifier. SVMs try to find a best separating hyper-plane in the feature space and lessen the classification error for the training data using a nonlinear transform function.

In this problem, the missed detection rate (classifying true singular points as forged ones) should be very small. The separating hyper-plane is defined by $a_i(i = 1,2 \dots . N)$ and b. In this paper, an optimal b_0 is selected to move the separating plane to a suitable position that will misclassify less than 2 percent of true singular points as forged ones and, meanwhile, decrease the error of classifying forged singular points as true ones.

From the definition of DORIVAC features, it is observed that this vector is sensitive to image rotation. To prevail over the influence of image rotation, the training set is enlarged by rotating each fingerprint sample image by 10 degree increments. All of the samples are used for training the SVM classifier to make it insensible to image rotation.

Based on the SVM result, the decision can be made whether a point P in S' should be moved back to the final candidate set S or not. After this two-step classification process, a set of the forged singular points are removed. For example, Figs. 6e and 6f can be successfully judged as forged singular points while the other four are kept as true ones.

4. Singular Points Selection with Global Information

As pointed out earlier, local features alone are not enough to fully distinguish the true singular points from forged detections, which can actually have similar local characteristics as the true ones. This inspires to incorporate more global discriminative information for detection.

4.1 Removing Invalid Combinations:

The core-delta relation deduced in Part II is used as a global restriction for selecting the best set of final singular points. In real applications, many fingerprint images captured by optical or capacitive sensors are not complete. Often they will lose one or two deltas. In this case, the number of cores is not necessarily equal to the number of deltas. Nevertheless, (3) still presents us a global topological restriction for singular points. Suppose the effective region of the fingerprints is Ω. By computing $I(\partial\Omega)$, we can know that only a few combinations of the singular points are valid. In Table 1, most of the possible combinations of singular points are listed for fingerprints with the Poincare´ Index and the possible types (PA—plain arch, TA—tented arch, LL—left loop, RL—right loop, TL—twin loop).

Table I. Frequent Combinations of Singular Points in a Complete Fingerprint

I($\partial\Omega$)	**Core**	**Delta**	**Possible Types**
0	0	0	PA
	1	1	LL,RL,TA
	2	2	TL,Whorl
1	1	0	LL,RL,TA
	2	1	TL, Whorl
2	2	0	TL, Whorl

By calculating the global Poincare´ Index I ($\partial\Omega$) some invalid combinations of singular points can be removed. For example, when the global Poincare´ Index is equal to 1, the combinations of 1-core-0-delta and 2-core-1-delta are calculated and other situations are not considered. This speeds up the algorithm greatly.

4.2 Selection of Optimal Singular Points:

As known, singular points can be used to determine the global structure of the orientation field of fingerprints. The basic idea is to select the best singular points by decreasing the difference between the original orientation field and the model-based orientation field rebuilt using the singular points.

Denote the original orientation field as O_0 and the rebuilt orientation field as O (ϴ.s), where ϴ is the model's parameter. The original orientation field, O_0, is calculated by the hierarchical gradient-based method. As for the model-based rebuilt orientation field, O(ϴ.s), the Zero-Pole model proposed by Sherlock and Monro is choose, considering both the model accuracy and the computational efficiency.

5. Conclusion

To sum up, the paper is focused on the detection of singular points in fingerprints. The contributions lie in two aspects. 1) a new feature, DORIVAC, in addition to the Poincare´ Index, which can successfully remove forged detections and 2) the topological relations of singular points is taken as a global restriction for fingerprints The optimal singular points can be selected by decreasing the difference between the original orientation field and the model-based orientation field rebuilt from the singular points.

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