Singular Candidate Method: Improvement of Extended Relational Graph Method for Reliable Detection of Fingerprint Singularity

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SUMMARY The singular points of fingerprints, viz. core and delta, are important referential points for the classification of fingerprints. Several conventional approaches such as the Poincaré index method have been proposed; however, these approaches are not reliable with poor-quality fingerprints. This paper proposes a new core and delta detection employing singular candidate analysis and an extended relational graph. Singular candidate analysis allows the use both the local and global features of ridge direction patterns and realizes high tolerance to local image noise; this involves the extraction of locations where there is high probability of the existence of a singular point. Experimental results using the fingerprint image databases FVC2000 and FVC2002, which include several poor-quality images, show that the success rate of the proposed approach is 10% higher than that of the Poincaré index method for singularity detection, although the average computation time is 15%–30% greater.

Key words: singular candidate method, singularity detection, extended relational graph, fingerprint, core, delta

1. Introduction

For many years, fingerprint identification has been a well-known and attractive identification method. Due to the progress of PCs and embedded processors, fingerprint identification can now be automatically accomplished with a stand-alone system. Fingerprint identification technology is widely applied in personal recognition systems, for example, door lock control systems and PC user management systems [1], [2].

When the number of registered users in a fingerprint identification system is large, the number of comparisons required for fingerprint identification increases drastically. Therefore, the required processing for identification increases with the size of the database. The time required for the identification process, which involves comparing the input fingerprint with the registered fingerprints in the database, can be reduced if the time required for each comparison is reduced. A common strategy to achieve this objective is to partition the fingerprint database into several subsets on the basis of a fingerprint classification system. Generally, the classification of fingerprints is performed on the basis of the global features of the ridge direction patterns of the fingerprint. Figure 1 shows five typical fingerprint classes. The most evident structural characteristic of a fingerprint is the pattern of interleaved ridges and valleys. In Fig. 1, the ridges are indicated with dark curves, whereas the valleys are indicated with bright curves. Some parts of the ridge curves resemble semicircles, whose centers are called core points. There are also triangular patterns in the fingerprints, whose centers are called delta points. The core and delta points are defined as the singular points of a fingerprint. References [2]–[9] show that there is a strong relationship between the fingerprint points and the locations of the singular points. It is known that the singular points of a fingerprint are important reference points for its classification. A reliable approach to the detection of singular points is required to classify fingerprints conveniently.

The Poincaré index method is the most primitive and famous approach to the detection of the singular points in fingerprints [3]. By using this method, the core and delta points are extracted on the basis of differences in the local ridge directions between the adjacent blocks. Since the algorithm of the Poincaré index method is quite simple, the computation overhead is rather small. However, singularity detection is considerably difficult when the fingerprint images contain local image noise and are of poor-quality. This may lead to faulty identification of singular points because the Poincaré index method uses only the local features of the fingerprint. Although some improved versions of the Poincaré index method have already been proposed to improve the success rate in singularity detection [4]–[7], the tolerance to local image noise is not sufficiently high.

The extended relational graph method [10]–[12] was proposed to improve the success rate of singularity detection by using the global features of the ridge directional image. In Refs. [10]–[12], an extended relational graph that reflects the global ridge distribution was proposed. The success rate of singularity detection is improved because the global features of the ridge distribution can be extracted by extended relational graph analysis, even if images of poor-quality are...
used. However, when the ridge curves contain strong non-linearity, the detected core and delta points are away from the actual locations. Furthermore, the precision of the singular point position is degraded when there is rather wider segment along the singular point. The precision tends decrease with the sensing area of the fingerprint sensor. Therefore, the positional precision is still not sufficiently high.

In this paper, a new singular point detection method is proposed. The proposed method is the improved version of the native extended relational graph method [10]–[12] in order to realize the high positional precision of the singularity detection. Three kinds of singular candidates are proposed to achieve higher positional precision. This method uses singular candidate analysis with an extended relational graph to realize fast computation and reliable detection. In this approach, both the local and global features of the ridge direction are extracted for singularity detection. To evaluate the local features of the ridge orientation field with tolerance to local image noise, we extract the singular candidates — positions where there is a high probability of the existence of singular points. Three types of singular candidate models are proposed to realize tolerance to local image noise. We have already reported the basic concept of the singular candidate method in Ref. [13]. This paper presents the complete algorithm and a precise evaluation of the singular candidate method. To evaluate the global features of ridge distribution, we adopt extended relational graph analysis.

The experimental results show that a success rate improvement of more than 10% is achieved for singularity detection using the standard fingerprint image databases FVC2000 and FVC2002 [7], which contain several images of poor-quality with creases, scars, smudges, dryness, and dampness. The average processing time is only 15%–30% greater than that of the Poincaré index method.

2. Singular Candidate Method

2.1 Objective of Singular Candidate Method

Poincaré index method [3]–[7] is the simplest and most primitive approach to detect singular points, which uses only the local ridge direction. However, if the local degradation is higher than the allowance to error caused by the local image noise, it is impossible to achieve high reliability in singularity detection.

There is also another kind of the conventional approach, called the extended relational graph method [10]–[12], to realize the tolerance to the local image noise by using the global distribution of the ridge direction. The extended relational graph is generated by the extraction of the global distribution of the ridge direction. However, it cannot realize the higher positional precision of the singularity detection because the native extended relational graph method only uses the global distribution of the ridge direction. The outline of the native extended relational method is shown in Appendix A.

The proposed method is an improvement of the extended relational graph method and improves the positional precision of singularity detection. The key feature of the proposed method is the tolerance against the error that occurs because of local image noise while the ridge orientation differences around the block are evaluated. Both the global ridge distribution and the local ridge direction are taken into account in order to achieve a reliable detection.

Although singular points identified by the Poincaré index method completely satisfy the condition that the differences in ridge orientation around the specified block should be $-180^\circ$, $+180^\circ$, or $+360^\circ$, the proposed approach introduces several allowances in the ridge directional condition in order to realize the tolerance to local image noise. Because of the tolerance against local image degradation, the accuracy of singularity detection with the proposed method is higher than that with conventional approaches, which involves only local ridge direction.

In this approach, three types of candidates, viz. core candidate, delta candidate, and whorl candidate, are proposed to make the tolerance against the local image degradation caused by noise. The proposed candidate models are shown in Fig. 2. A candidate model is similar to the mask pattern used for evaluating the rotation angle of the ridge direction around the specified block. According to the density of the singular candidates, the core and delta positions are computed as the averaging point of each candidate region, which is a set of singular candidates placed adjacently. Since singular candidate analysis — in which the singular candidates and their density are extracted — is performed in the detection process, the method can realize precise detection of the core and delta points. Furthermore, a few misjudgments in core and delta discrimination occur because the ridge directions around specified blocks are actually evaluated using singular candidate models that are larger than the mask pattern used in the Poincaré index

![Fig. 2](image)

Three models of singular candidates in proposed approach.

Fig. 2 Three models of singular candidates in proposed approach.
method. In the proposed method, the extended relational graph generated from the fingerprint image is also analyzed to determine whether the core and delta loops exist, and the results are used to obtain the distribution of the global ridge direction. However, if the singularity is located solely using global ridge direction, precise detection of the singular point location becomes difficult. Therefore, the reliable detection requires a combination of the global and local information on the ridge distribution.

2.2 Overview of Singular Candidate Method

The overview of the proposed approach is shown in Fig. 3, which includes four steps.

**Step 1 Pre-processing:** Pre-processing is performed to improve the image quality of the fingerprints. It is the conventional approach to eliminate image noise [1], [2], [7].

**Step 2 Extended relational graph analysis:** In step 2, an extended relational graph is generated from the directional image in a similar way to the native extended relational graph method [10]–[12]. The overview of the native extended relational graph method is summarized in Appendix A. In this step, each of the core and delta loops — where the labels along the loops continuously range from 0 to 3 (refer to Fig. 2 (d)) — is extracted by the depth-first search against the extended relational graph. An actual example is shown in Fig. 4, where each node corresponds to a segment in the directional image. The edge indicates the relationship between adjacent segments. Each node has a direction label for the corresponding segment. After generating the graph from the directional image, extended relational graph analysis is performed. It can be observed that the ridge direction around the core continuously ranges from 0 to 3 if a core or delta exists. Loop rotation is detectable on the basis of the segment center location along the loop. When the ridge direction is anticlockwise, it can be confirmed to be a core loop. When there is a loop where the ridge direction label continuously ranges from 0 to 3 and the loop direction becomes clockwise on the basis of each segment center along the loop, it can be defined as a delta loop.

**Step 3 Singular candidate analysis:** Step 3 is the most important procedure to emphasize the tolerance to noise for the singularity detection. In this step, three types of singular point candidates, viz. core candidates, delta candidates, and whorl candidates, are extracted from the ridge directional images using singular candidate models in order to attain tolerance to local image degradation. The procedure estimates the differences in ridge orientation between the neighboring blocks along the hatched blocks for each specified block (i, j) shown in Fig. 2. For each block with a size of 8 × 8 located at the segment boundaries, the differences in ridge orientation are verified for the extraction of the core, delta, and whorl candidates. The total ridge directional difference \( \Theta(i, j) \) is defined as

\[
\Theta(i, j) = \sum_{k=0}^{15} (\theta_k - \theta_{(k+1) \mod 16})
\]

where \( \theta_k \) indicates each ridge direction of the hatched block in Fig. 2. \( \Theta(i, j) \) represents the total rotation angle around a specified block. When there is no noise, \( \Theta(i, j) \) is equal to 180° in case that a core exists at the location of the specified block (i, j). \( \Theta(i, j) \) ranges from 135° to 225° to realize the
tolerance to noise while summing the orientation differences around each block; this relaxation in \( \Theta(i, j) \) values is done to tolerate the noise by using the core candidate model. Using the core candidate model realize a method with \( \pm 45^\circ \) tolerance to local image noise. When there is no noise, \( \Theta(i, j) \) is equal to \(-180^\circ\) in case that the delta exists at the location of the specified block \((i, j)\). \( \Theta(i, j) \) ranges from \(-225^\circ\) to \(-135^\circ\) to realize the tolerance to noise by using the delta candidate model. This means that the delta candidate model realizes a method with \( \pm 45^\circ \) tolerance to local image noise. When the whorl exists at the location of the specified block \((i, j)\) without noise, \( \Theta(i, j) \) is equal to \(360^\circ\). To realize the tolerance to noise in this case, \( \Theta(i, j) \) ranges from \(270^\circ\) to \(450^\circ\). Using the whorl candidate model realize a method with \( \pm 90^\circ \) tolerance to local image noise.

The singular candidates are grouped on the basis of their connectivity. The adjacent candidates are assigned into the same candidate group. On the basis of candidate types, connected candidates are assigned to a specific candidate group. A candidate region is defined as a rectangle that includes such a candidate group within the specified margin, as shown in Fig. 5. Candidate regions are categorized into the core candidate region or delta candidate regions when they mainly contain core and delta candidates, respectively. When a candidate region contains whorl candidates, whorl candidate evaluation is performed to generate the whorl candidate region. The overview of the procedure is shown in Fig. 6. In case the core candidate region contains whorl candidates and the number of whorl candidates is less than 10, all the whorl candidates in the specified candidate region are removed in order to divide the core candidate region into two individual regions, as shown in Fig. 6 (a). If the core candidate region contains whorl candidates, whose number is greater than or equal to 10, such a core region is converted into a whorl candidate region, as shown in Fig. 6 (b). After the construction of all the candidate regions, all the segment labels in each region are compared with the node numbers of the core and delta loops in the extended relational graph. If all the labels in these loops are not included in a candidate region, such a candidate region is defined as a false candidate region. Every false candidate region is eliminated. Figure 7 shows an example which contains several false candidate regions that must be eliminated.

**Step 4) Extraction of singular points:** In step 4, the singular point is detected at the averaging point of the candidates in each candidate region. The type of the singular point is determined on the basis of the majority of singular candidates in the candidate region. Figure 8 shows an actual example of singular point extraction by the candidate method.

### 3. Experimental Results

To evaluate the performance of the singular candidate method, the two conventional methods for the singularity detection, viz. the modified Poincaré index method [4], [7] and the native extended relational graph method [12] were applied to fingerprint image databases FVC2000 and FVC2002 and the extracted singular points compared with those manually marked by fingerprint recognition experts. Section 3.1 provides a discussion on the success rate and the processing time, and a discussion on the reliability of
the singularity detection are presented in Sect. 3.2.

3.1 Success Rate and Processing Time

To evaluate the success rate of detection, this approach is applied to several actual fingerprint images. Figure 9 shows the experimental results of the detection of the core and delta against four typical fingerprint classes in the FVC2000 database [7] by the proposed approach. FVC2000 is a famous and public fingerprint image database; however, many of its fingerprint images are damaged by local image noise. According to Fig. 9, reliable singular point detection can be achieved using the proposed approach.

Singularity detection in noisy or poor-quality fingerprints is difficult. The proposed approach has also been applied to the fingerprint images in famous databases such as FVC2000 and FVC2002 [7]. Each database contains 3200 samples, and every fingerprint image contains the local image noise due to creases, scars, smudges, dryness, and dampness. The properties of each database are shown in Table 1. In particular, the fingerprint images in the FVC2000 DB3 and FVC2002 DB2 databases contain more noise than the images in other databases.

The use of the native Poincaré index method like Ref. [3] may lead to the detection of false singularities where the image quality is poor. Since regularizing the direction image by local averaging is often quite effective in preventing the detection of false singularities, modified versions of Poincaré index method [4], [7] are applied in conventional systems. For comparison with the proposed approach, modified Poincaré index method, aiming to reduce the effect of local image noise [4], [7] is investigated. The extended relational graph method [12], which uses the global distribution of the ridge direction, is also investigated for comparison. Every method uses the same pre-processing algorithm to refine the fingerprint image quality. All answer locations of singular points for each fingerprint are determined by human expertise in this evaluation. A successful detection is defined as one in which each singular point is extracted in an allowance region with a size of 16 × 16 around each correct singular point.

![Fig. 8](image.png)

**Fig. 8** Actual results of singular point extraction by singular candidate method.

![Fig. 9](image.png)

**Fig. 9** Examples of experimental results by the singular candidate method.

The success rates of core and delta detection (SR) for each database are summarized in Table 2. Evidently, when the fingerprint image contains little noise, every approach can achieve a success rate of almost 100% for singularity detection. However, there is a decrease in the success rate when each fingerprint image contains local image noise.

According to Table 2, the Poincaré index method is very sensitive to local image noise. Table 2 also shows that the proposed approach can achieve a success rate of higher than 80% for singularity detection. Since the extended re-
Table 1: Several public fingerprint image databases [7].

| Database name | Sensor type | Resolution | Number |
|---------------|-------------|------------|--------|
| FVC2000 DB1   | Optical Sensor | 300 x 300  | 800    |
| FVC2000 DB2   | Capacitive Sensor | 256 x 364  | 800    |
| FVC2000 DB3   | Optical Sensor | 448 x 478  | 800    |
| FVC2000 DB4   | Synthetic    | 240 x 320  | 800    |
| FVC2002 DB1   | Optical Sensor | 388 x 374  | 800    |
| FVC2002 DB2   | Optical Sensor | 296 x 560  | 800    |
| FVC2002 DB3   | Capacitive Sensor | 300 x 300  | 800    |
| FVC2002 DB4   | Synthetic    | 288 x 364  | 800    |

Table 2: Experimental results of success rate of singularity detection.

| Database name | Poincaré index method [4], [7] | Extended relational graph method [12] | Singular candidate method |
|---------------|--------------------------------|--------------------------------------|--------------------------|
| FVC2000 DB1   | 74.8%                          | 70.8%                                | 84.0%                    |
| FVC2000 DB2   | 86.3%                          | 79.6%                                | 89.0%                    |
| FVC2000 DB3   | 71.1%                          | 55.8%                                | 80.8%                    |
| FVC2000 DB4   | 96.8%                          | 87.1%                                | 97.8%                    |
| FVC2002 DB1   | 87.0%                          | 78.6%                                | 91.7%                    |
| FVC2002 DB2   | 79.6%                          | 74.9%                                | 92.6%                    |
| FVC2002 DB3   | 90.0%                          | 85.6%                                | 94.0%                    |
| FVC2002 DB4   | 93.4%                          | 83.9%                                | 94.1%                    |

Table 3: Experimental results of computation time.

| Database name | Poincaré index method [4], [7] | Extended relational graph method [12] | Singular candidate method |
|---------------|--------------------------------|--------------------------------------|--------------------------|
| FVC2000 DB1   | 0.033 s                         | 0.035 s                              | 0.044 s                  |
| FVC2000 DB2   | 0.038 s                         | 0.046 s                              | 0.049 s                  |
| FVC2000 DB3   | 0.077 s                         | 0.071 s                              | 0.095 s                  |
| FVC2000 DB4   | 0.031 s                         | 0.032 s                              | 0.040 s                  |
| FVC2002 DB1   | 0.057 s                         | 0.059 s                              | 0.073 s                  |
| FVC2002 DB2   | 0.034 s                         | 0.034 s                              | 0.044 s                  |
| FVC2002 DB3   | 0.046 s                         | 0.040 s                              | 0.053 s                  |

false singular points $R_{false}$ is defined as

$$R_{false} = \frac{N_{fs}}{N_t} \times 100\% \quad (2)$$

where $N_{fs}$ is the number of results that contain false singular points, and $N_t$ is the number of completely evaluated fingerprints. The local image noise tends to generate false singular points. Therefore, $R_{false}$ tends to be higher when the amount of the local image noise is higher. $R_{false}$ indicates the tolerance of false detection.

It also tends to miss the singular detection when the amount of local image noise is higher. The rate of results with missed singular points $R_{missed}$ is defined as

$$R_{missed} = \frac{N_{ud}}{N_t} \times 100\% \quad (3)$$

where $N_{ud}$ is the number of results that contain undetected singular points. It is necessary to evaluate not only $R_{false}$ but also $R_{missed}$ for analyzing the causes of the detection errors. $R_{missed}$ denotes the tolerance of the missed detection.

The positional precision of singular detection strongly depends on the nature of the detection approach. The rate of results with a location error larger than the allowance range $R_{loc}$ is defined as

$$R_{loc} = \frac{N_{pe}}{N_t} \times 100\% \quad (4)$$

where $N_{pe}$ is the number of results with high positional errors, which is greater than the specified allowance. $R_{loc}$ denotes the degree of the positional precision error of singular detection.

The local image noise tends to generate a false decision in the case of a core or a delta. The rate of results with false decision in the case of a core or a delta, $R_{decision}$, is defined as

$$R_{decision} = \frac{N_{fd}}{N_t} \times 100\% \quad (5)$$

where $N_{fd}$ is the number of results that contain missed decisions regarding the core or the delta. $R_{decision}$ denotes the tolerance of the false decision to the local image noise.
Table 4  Summary of detection error causes by singular candidate method for FVC2000 and FVC2002.

| Database name  | $R_{false}$ | $R_{missed}$ | $R_{loc}$ | $R_{decision}$ |
|----------------|-------------|--------------|-----------|----------------|
| FVC2000 DB1    | 9.8%        | 3.9%         | 2.1%      | 0.0%           |
| FVC2000 DB2    | 5.8%        | 2.5%         | 3.6%      | 0.1%           |
| FVC2000 DB3    | 15.1%       | 2.8%         | 3.0%      | 0.0%           |
| FVC2000 DB4    | 1.4%        | 1.1%         | 0.0%      | 0.0%           |
| FVC2002 DB1    | 3.6%        | 5.8%         | 0.0%      | 0.1%           |
| FVC2002 DB2    | 5.6%        | 1.9%         | 0.1%      | 0.0%           |
| FVC2002 DB3    | 1.9%        | 4.3%         | 0.0%      | 0.0%           |
| FVC2002 DB4    | 0.1%        | 5.8%         | 0.0%      | 0.0%           |

Table 5  Summary of detection error causes by Poincaré index method [4], [7] for FVC2000 and FVC2002.

| Database name  | $R_{false}$ | $R_{missed}$ | $R_{loc}$ | $R_{decision}$ |
|----------------|-------------|--------------|-----------|----------------|
| FVC2000 DB1    | 25.2%       | 24.5%        | 0.8%      | 0.0%           |
| FVC2000 DB2    | 13.7%       | 11.6%        | 1.1%      | 3.0%           |
| FVC2000 DB3    | 28.9%       | 27.5%        | 2.8%      | 1.9%           |
| FVC2000 DB4    | 3.2%        | 3.3%         | 0.1%      | 0.0%           |
| FVC2002 DB1    | 13.0%       | 8.7%         | 5.1%      | 0.1%           |
| FVC2002 DB2    | 20.4%       | 17.3%        | 2.8%      | 0.8%           |
| FVC2002 DB3    | 10.0%       | 5.5%         | 4.6%      | 0.0%           |
| FVC2002 DB4    | 6.6%        | 1.8%         | 4.9%      | 0.0%           |

Table 6  Summary of detection error causes by extended relational graph method [12] for FVC2000 and FVC2002.

| Database name  | $R_{false}$ | $R_{missed}$ | $R_{loc}$ | $R_{decision}$ |
|----------------|-------------|--------------|-----------|----------------|
| FVC2000 DB1    | 12.8%       | 4.1%         | 12.1%     | 3.8%           |
| FVC2000 DB2    | 8.9%        | 1.0%         | 9.8%      | 2.4%           |
| FVC2000 DB3    | 13.1%       | 5.3%         | 30.1%     | 2.1%           |
| FVC2000 DB4    | 2.0%        | 1.6%         | 8.4%      | 1.3%           |
| FVC2002 DB1    | 11.3%       | 11.6%        | 7.9%      | 3.1%           |
| FVC2002 DB2    | 10.3%       | 6.9%         | 9.4%      | 8.5%           |
| FVC2002 DB3    | 4.6%        | 3.8%         | 7.1%      | 2.3%           |
| FVC2002 DB4    | 5.9%        | 9.3%         | 9.1%      | 2.6%           |

cauised by false detection, missed detection, positional precision error, or false decision. Therefore, there is a possibility of their occurring simultaneously.

Table 4 summarizes the causes of the detection errors obtained by the proposed approach with respect to FVC2000 and FVC2002. To compare with Table 4, the analytical results by the modified Poincaré index method [4], [7] and the extended relational graph method [12] are shown in Tables 5 and 6. The comparison shows that $R_{false}$, $R_{missed}$, $R_{loc}$ and $R_{decision}$ obtained by the singular candidate method are considerably smaller than those obtained by others. These results show that many causes of the false detection are eliminated by the singular candidate methods. They indicate that the proposed approach can accurately detect both the core and the delta points when there are creases, scars, smudges, dryness, and dampness on the fingerprint images. On the other hand, $R_{false}$ and $R_{missed}$ obtained by the Poincaré index method are considerably higher than the values obtained by the singular candidate method because the Poincaré index method is very sensitive to the local image noise. $R_{loc}$ and $R_{decision}$ obtained by the extended relational graph are considerably higher, although $R_{false}$ and $R_{missed}$ are smaller than those of the Poincaré index method. Since the extended relational graph method uses only the global ridge distribution, it still needs to use both global ridge distribution and local ridge direction to reduce $R_{loc}$ and $R_{decision}$ for reliable singularity detection.

To evaluate the tolerance to the image noise, this approach was applied to several actual poor-quality fingerprint images. Although the modified Poincaré index method cannot successfully perform singularity detection, the proposed approach can accurately detect both the core and the delta points. Figure 10 shows examples of singularity detection with poor-quality fingerprints.

There are also other recent studies that have been investigated [14], [15] for comparison with the proposed approach in the case of singularity detection for poor-quality fingerprints. A summary of the comparisons with recent works is given in Appendix B.

4. Conclusion

This paper has presented a new reliable core and delta de-
tection method using candidate analysis with an extended relational graph. Both the local and global features of the ridge orientation field are extracted to achieve reliable extraction of the core and delta points. Three types of candidate models are proposed (for core candidates, delta candidates, and whorl candidates) to obtain the local features of the ridge distribution with tolerance to local image noise. Further, the global features of the ridge orientation field are evaluated by extended relational analysis. The experimental results for the proposed approach showed that a success rate of higher than 80% was achieved for singularity detection using the standard fingerprint databases FVC2000 and FVC2002, even though these databases include poor-quality images. The computation time of the singular candidate method appears to be approximately 15%–30% longer than that of the Poincaré index method.

It will be contributed significantly to realize the reliable fingerprint classification [17], the reliable fingerprint alignment, precise fingerprint orientation modeling [18], [19] by improving the success rate of singularity detection against poor-quality images. It means that the expected processing time for matching can be reduced when the reliable classification can be realized. When the reliable alignment and the precise orientation modeling can be established, false minutia will be greatly reduced. As a matter of fact, the number of iterations will be reduced in the fingerprint acquisition process in case that false minutiae are reduced. Therefore, FRR (False Rejection Ratio) will be reduced by applying this approach. However, it is rather difficult to reduce FAR (False Acceptation Ratio) by the proposal method. In applications such as the door-lock system and user identification of PCs or cell phones, the fingerprints are occasionally captured as poor-quality images due to creases, scars, smudges, dryness, and dampness in the unclean fingerprint sensors. In such cases, the proposed approach of singularity detection can be applied effectively.

However, if the segments around the singular points in the directional image are significantly damaged by noise, the determination of the global information on the ridge distribution becomes difficult. Currently, we are developing a method for repairing damaged segments.

A method for the classification of fingerprints using the information on the core and delta locations with ridge distributions is currently under study.

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Appendix A: Overview of the Extended Graph Method

Since the Poincaré index method [4], [7] is sensitive to noise on the fingerprint image, the success detection rate of the Poincaré index method reduces when the input fingerprint image quality is poor. To improve the success rate of the singularity detection, it is necessary to avoid the effect of the local image degradation. The singularity detection approach using the extended relational graph, which includes the global feature of ridge distribution on the fingerprint, was proposed [10]–[12]. In this approach, the directional image based on an 8 × 8 block size is generated in a manner similar to that used in the Poincaré index method. The ridge direction is quantized into four quantized orientations, as shown in Fig. A-1 (b). The quantized directional image is computed by sliding the four direction masks over the binary
image of Fig. A-1 (a). Since the directional image has been segmented on the basis of the ridge direction, each segment contains a unique label. To improve the success detection rate in the case of poor-quality images, the extended relational graph, which includes the global feature of the ridge distribution on the fingerprint, is generated from the directional image. In Fig. A-1 (b), there are 7 segments in the directional image. Figure A-1 (c) shows the extended relational graph generated from Fig. A-1 (b). Each node corresponds to each segment in the directional image. The edge indicates the adjacent relationship between the segments. An edge is bridged between the corresponding nodes when two segments are placed adjacently. Each node has the direction label of the corresponding segment, and each edge has the coordinates set on the boundary between the corresponding nodes. Additionally, each node has segment center locations, which are computed by averaging between all block locations in the corresponding segment. Let us focus on the feature around the core shown in Fig. A-1 (b). Since the extended relational graph includes the global feature of the fingerprint ridge direction, this approach can detect the singularity of a fingerprint even when the image quality is poor.

The extended relational graph analysis is performed after generating the graph from the directional image. It can be observed that the ridge direction around the core continuously ranges from 0 to 3 if a core or a delta exists. The loop rotation is detectable depending on the segment center coordinates along the loop. It can be confirmed as a core loop when the rotation of the ridge direction is an anticlockwise rotation. It can be distinguished with the core loop when there is also a loop where the ridge direction label continuously ranges from 0 to 3 and the loop direction is clockwise based on each segment center along the loop. Such a loop is defined as a delta loop. The position of the core and the delta is computed as the averaging point among these segment centers along the loop. Since the extended relational graph contains the global feature of the distribution of the ridge direction, the success rate of the singular point detection is more than 94% against the fingerprint database FVC2004 DB4 [8].

However, when the boundary curves between the segments on the directional image contain a strong non-linearity, the averaging point of each segment along the loop is placed considerably away from the actual core or delta point. There still remains the problem of the positional precision error. Furthermore, in this case, it is rather difficult to judge if the loop indicates a core loop or a delta loop because the decision of the core loop or the delta loop is evaluated only on the basis of the averaging center point among segments along the loop in the extended relational graph. Therefore, sometimes, the core and delta decision is misjudged. There still remain the problems of core and delta discrimination.

Appendix B: Comparison of Recent Works with Proposal Method

There are also many recent studies that have been investigated [14], [15] for comparison with the proposed approach in the case of the singularity detection for low-quality fingerprints.

In one of the recent studies on singularity detection [14], the calculation of the closed line integral over a vector field gives the surface integral over the rotation of this vector field according to Green’s theorem. In practice, instead of summing up the angle differences along a closed path, the authors computed the rotation of the orientation image (through another differentiation) and then performed local integration (sum) over a small neighborhood of each element. Reference [14] also proposed a method for assigning a direction to each singularity. In this method, the directional image around each detected singular point is compared to the directional image of an ideal singularity of the same type. \( R_{\text{false}} \) is 13% and \( R_{\text{missed}} \) is 5% for FVC2000 DB2 by the approach of Ref. [14]. The total success rate \( SR \) in singularity detection is 82–87% for 800 fingerprints. \( SR \) of the singular point detection by the proposed approach is higher than that of Ref. [14]. Both \( R_{\text{false}} \) and \( R_{\text{missed}} \) in Ref. [14] are also higher than those of the proposed approach. The computational cost is much greater than that of the Poincaré index method because of the computation of vector analysis and PCA-based calculations.

In another recent study on singular point detection using a global orientation field [15], optimal singular points are selected to minimize the difference between the original orientation field and the model-based orientation field reconstructed from the singular points after the initial decision with the modified Poincaré index method [4], [7]. In Ref. [15], \( SR \) is 80.6%, \( R_{\text{false}} \) is 4.8%, and \( R_{\text{missed}} \) is 14.6% for FVC2000 DB1, DB2, and DB3, in which 2400 fingerprints are included. It is necessary to analyze both \( R_{\text{false}} \) and \( R_{\text{missed}} \) to evaluate the degree of the tolerance to the local image noise. \( R_{\text{false}} \) of the proposed approach is higher than that in Ref. [15], although \( R_{\text{missed}} \) is lower than that in the proposed method. Since the effect of false detection is smaller than that of the missed detection of singularity, the total success rate \( SR \) of the detection by the proposed approach is higher than that in Ref. [15]. The average processing time using an AMD 2.2-GHz PC for each fingerprint is around 0.10 s. It is possible to compare performances.
Table A-1  Comparison with the recent work I [14] and II [15] for public fingerprint databases.

| Database name | Measures | Recent work I [14] | Recent work II [15] | Singular candidate method |
|---------------|----------|-------------------|---------------------|--------------------------|
| FVC2000 DB2   | $R_{false}$ | 13.0%             | 5.8%                |
|               | $R_{missed}$ | 5.0%             | *1                  |
|               | $SR$       | 82–87%            | 2.5%                |
|               |            |                   | 89%                 |
| FVC2000 DB1, DB2, DB3 | $R_{false}$ | 4.8%             | 10.2%               |
|               | $R_{missed}$ | *2               |                     |
|               | $SR$       | 14.6%            | 9.2%                |
|               |            | 80.6%            | 84.6%               |

roughly among different platform PCs on the basis of the SPEC CPU 2006 benchmark test [16] although it is rather difficult to compare the performance of the processing time with that on other platforms because the performance of a PC depends on the memory size, kinds of processing tasks, OS performance, etc. Since the performance ratio between the Pentium 4 3.2-GHz platform and AMD 2.2-GHz platform is 0.9, these investigations show that $SR$ of the singularity detection by the proposed approach is greater than that in Ref. [15]. The computational cost of the proposed approach is smaller than or equal to that of those approaches.

The comparison of the proposed approach with two recent studies is summarized in Table A-1, where $SR$ indicates the success rate of the singular point detection; both items marked *1 and *2 are not described in Refs. [14] and [15] respectively.

These results implies that the quality of most failed fingerprints is poor. This can indicate that the proposed approach can reduce the number of failure detections for poor-quality images because $SR$ is higher than others. The improvement in $SR$ is higher when the ratio of poor-quality images in the fingerprint database is higher. Therefore, the proposed method is reliable to the local image noise in singularity detection even though the improvement of $SR$ is not very high.

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