ROSE: real one-stage effort to detect the fingerprint singular point based on multi-scale spatial attention

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Abstract
Detecting the singular point accurately and efficiently is one of the most important tasks for fingerprint recognition. In recent years, deep learning has been gradually used in the fingerprint singular point detection. However, the existing deep learning-based singular point detection methods are either two-stage or multi-stage, which makes them time-consuming. More importantly, their detection accuracy is yet unsatisfactory, especially for the low-quality fingerprint. In this paper, we make a Real One-Stage Effort to detect fingerprint singular points more accurately and efficiently, and therefore, we name the proposed algorithm ROSE for short, in which the multi-scale spatial attention, the Gaussian heatmap and the variant of focal loss are integrated together to achieve a higher detection rate. Experimental results on the datasets FVC2002 DB1 and NIST SD4 show that our ROSE outperforms the state-of-the-art algorithms in terms of detection rate, false alarm rate and detection speed.

Keywords Singular point · One-stage effort · Spatial attention · Multi-scale

1 Introduction
The fingerprint singular point includes core points and delta points, on which the orientation field is not continuous, or the ridge curvature is the highest. The core points are usually associated with the points of maximum ridge line curvature.

There are multiple core points or no cores in a fingerprint image. The delta point indicates one of the points in a structure pattern resembling the Greek Letter Delta \( \Delta \) in a fingerprint image.

The fingerprint singular point plays an important role in fingerprint classification, indexing and registration [1]. Fingerprints can be classified by the number of the fingerprint singular point. This classification will reduce search space in large database [2]. It can be used as a reference point to register fingerprint images and participate in minutiae matching [3, 4].

Although the fingerprint singular point detection has been studied for many years, it is still a challenge to detect the singular point accurately and efficiently from fingerprints, especially from the low-quality ones [5]. The early fingerprint singular point detection methods are mainly non-deep learning methods, such as Poincaré Index (PI) methods [1, 6] and model-based methods [5, 7, 8], most of which can detect most singular points accurately from high-quality fingerprints. However, they require calculating the fingerprint orientation field before detection, which is time-consuming and they do not work very well for low-quality fingerprints.

In recent years, with its outstanding performance in computer vision, deep learning has been gradually used in the fingerprint singular point detection, and several detection
algorithms have been proposed based on fully convolutional network (FCN) [9] and faster-RCNN [10]. These deep learning-based methods improve the detection performance partly, but experimental results show limited benefit, especially for low-quality fingerprints. What is more, none of them is a real one-stage method.

In order to achieve higher accuracy and simplify the process, we use convolutional neural network to extract fingerprint singular point. Different from Poincaré Index (PI) methods [1, 6] and model-based methods [5, 7, 8], we do not need fingerprint orientation field. Different from deep learning methods [9–12], we can directly obtain the Gaussian heatmap of the singular point and decode the coordinates from it.

The main contributions of this paper are:

1. We adopt multi-scale spatial attention mechanism to extract regions of interest to improve feature representation in different-quality fingerprints, especially in low-quality ones.
2. We can get the pixel-level coordinates from the Gaussian heatmap predicted by the model.
3. Our model does not need to generate region proposals, and it is a Real One-Stage Effort (ROSE) to detect fingerprint singular points.

2 Related work

Most researches on singular point detection are based on traditional digital image processing algorithms. Now, with its wide application in the field of computer vision, deep learning has provided new solutions to the singular point detection problem. From this point of view, the existing singular points detection methods can be mainly divided into two categories: the methods with traditional digital image processing [1, 5–8, 13–15], and the ones with deep learning [9–12]. In the following, we shall give a thorough overview on detection methods.

Singular point detection methods on the traditional digital image processing can be further divided into three subcategories, including the methods on the Poincare index [1, 6, 13–15], the ones on filter and model techniques [8, 16–19] and the ones on the hybrid schemes [5, 7]. The Poincare index of a point is defined as the cumulative orientation differences counterclockwise along a simple closed [1], and it can be used to judge whether there are singular points in an orientation field block or not. Although the Poincare index methods have achieved, to some extent, satisfactory detection results for high-quality fingerprint, there are still limitations. For example, most of these methods require the high-precision fingerprint orientation field before detection, which means that the detection result is very dependent on the quality of the original image and the performance fingerprint pre-processing algorithm.

The filter and model techniques provide another way for detecting fingerprint singular points. Methods based on filter and model techniques detect cores and deltas generally by means of using the designed corresponding filters or the corresponding models, such as complex filtering methods [16, 17], multi-scale Gaussian filter [8] and multi-scale orientation entropy [18]. Most of these methods can obtain better performance in some experimental evaluations. However, it is worth noting that most of them need to visit every pixel or block to extract enough information to detect singular points [5], which is very time-consuming. At the same time, they cannot perform very well on low-quality fingerprint either.

The emergence of hybrid schemes makes it possible to achieve higher detection rate and faster detection speed. Qi et al. [19] develop a new hybrid index of singular points based on the definition of angle matching index (AMI) in vector fields. AMI is a specific polynomial model of orientation field, which could be also used in other areas, especially the vector field analysis. The AMI information of candidate singular points is collected, and the conventional convergence index filter framework is modified. Although these hybrid schemes can obtain better performance and higher efficiency in experimental evaluations, to a certain extent, they still depend on the quality of the fingerprint orientation field and do not work very well for low-quality fingerprint.

In recent years, much attention has been given to using deep learning models for fingerprint recognition [20], such as segmentation [21, 22], orientation field estimation [23, 24], minutiae extraction [25, 26] and minutiae descriptor extraction [27]. Qin et al. [9] firstly proposed the singular points detection method based on deep learning. They firstly design two convolutional neural networks in which one is used for classifying the core, the delta and the background and the other is used for estimating the positions of the core and the delta. Following this, a probabilistic method is used to determine the actual positions of singular points. However, the block classification method is somewhat rough, and this method has many processing steps. Its training process is also cumbersome including dividing the training images into many blocks and multi-scales. Hong et al. [28] also used the idea of block classification to automatically detect fingerprint singular points. However, its performance does not surpass Qin et al.’s [9]. They are inspired by the successful object detection in Liu et al. [11]. Liu et al. regard the singular point detection as the object detection problem and propose a deep learning detection algorithm via faster-RCNN. Liu et al.’s algorithm has a two-step strategy: some candidate patches, in which it is probable for singular points to exist, are chosen by one network in the first step, and the precise singular points are selected and located from the candidate patches in the second step. Compared to Qin et al.’s method,
Liu et al.’s method, the detection accuracy is still affected by anchor size, and low-quality small target detection is still a difficult problem [29]. That is to say, the faster-RCNN does not work very well for the fingerprint singular point detection, especially for the low-quality fingerprint. At the same time, it needs a large number of fingerprint images for training. In 2019, Geetika et al. [12] presented a macro-localization network and a micro-regression network to detect fingerprint singular points from coarse to fine, where the macro-localization network aims at extracting squares of size 43 × 43 pixels around singular points while the micro-regression network at regressing the accurate coordinates of singular points. They adopt the idea of semantic segmentation for extracting fingerprint singular points. However, the semantic segmentation network (i.e., macro-localization network) just segments the big coarse image block containing singular points. For more precise positioning, all the segmented image blocks need to be put into the non-semantic segmentation network (i.e., micro-regression network) for training again. Actually, the semantic segmentation plays a limited role in the whole method. Additionally, their twice training is time-consuming and laborious. What is more, the detection performance of Geetika et al.’s method, close to that of Liu et al.’s method, is still unsatisfactory. However, compared with methods on traditional digital image processing algorithms, those on deep learning have the advantage that the original fingerprint images are directly adopted instead of the orientation fields after processing images.

Through the above analysis, it can be seen that deep learning is one of the most important trends to improve the performance of fingerprint singular points detection. However, the design of current approaches based on deep learning is somewhat complicated and the training process consumes too much data and time. In addition, for the existing methods based on both traditional digital image processing and deep learning, their detection rate of singular points is still unsatisfactory, especially on the low-quality fingerprint. Thus, it is an important and challenging research problem to design a simple and effective network requiring easier training, fewer amounts of training data and yet retaining high singular point detection performance.

3 Proposed method

In essence, the fingerprint singular point can be regarded as the key point on a fingerprint image, say one of important fingerprint features. How to detect the singular point accurately, to a great extent, depends on the information representation of the singular point and its surrounding local area. In order to accurately locate the singular point, a multi-scale spatial attention mechanism is adopted in our network.

3.1 Multi-scale spatial attention

The attention mechanism is derived from the study of human vision. Different parts of the human retina have different levels of information processing capabilities, and the fovea of the retina has the strongest acuity. In order to make rational use of the limited visual information processing resources, humans will select a specific part of the visual area and then focus on it. According to this, the attention mechanism in deep learning mainly solves two aspects: how to decide which part needs to be paid attention to and how to allocate limited computing resources. Based on these two points, researchers have carried out a lot of work. RA-CNN [30] generates sub-regions iteratively and makes necessary predictions for these sub-regions; SENet [31] counts the global information of the image from the feature channel level; CBAM (Convolutional Block Attention Module) [32] integrates the attention of the spatial domain and the channel domain.

In this paper, considering the fact that the fingerprint scene is relatively single and the spatial information is more important in the singular point detection task, we adopt a relatively simple spatial attention mechanism, with the previous feature map into the attention module as input and output the position-related spatial weight map in different scales as output.

It is believed that the network should always pay attention to the singular point region of the fingerprint, that is, in the spatial weight map of different scales, the weight of the singular point area should always be maintained at a high level.

In our network, what we supervise is the joint weight of the spatial position, which guides the network to focus on the singularity area. This unique supervision method prioritizes the supervision of the attention modules of different scales and achieves the purpose of screening through the attention modules. After the weights of all levels are multiplied, any weight of the spatial position from the same position is determined by the weights of different levels, and this process can be regarded as the screening of the region of interest by the attention module of each level. If a certain region is always focused by the network, then this region is more likely to be the target region.

Based on the above principles, we adopt a space attention module, and its structure is shown in Fig. 1. With the feature maps from the feature extraction channel as input, two outputs are produced. One is the spatial attention map which tells where we should pay attention, and the other is the refined feature maps which improves the response of ROI (regions of interest). The generation mechanism of the spatial attention map is the same as CBAM. We first apply average-pooling and max-pooling operations along the channel axis and concatenate them to generate an efficient feature descriptor. After applying average pooling and max pooling
operations along the channel axis, the module concatenates them to generate a valid feature descriptor. The refined feature maps are generated by multiplying input feature maps and the spatial attention map.

The attention module is applied to multiple scales. Therefore, the model generates spatial attention maps of different scales. After these spatial attention maps are up-sampled, their scales are consistent with the original image. The final output is obtained by multiplying the spatial attention maps of different scales through upsampling.

### 3.2 Gaussian heatmap and NMS

Finally, we hope to get the numerical coordinates of the singular point in the target region, which can be regarded as the task of numerical regression of key points. Fully connected layers can directly output coordinates, but they are prone to overfitting, which hinders the generalization ability of the entire network [33]. It is difficult to obtain pixel-level coordinates through fully connected layers. The Gaussian heatmap integrated with NMS (Non-Maximum Suppression) is used to find the coordinate point corresponding to the peak. This method completes better than the form of fully connected regression coordinate points in generalization ability and accuracy, so it is widely used in the field of key points.

The Gaussian heatmap uses the singular point coordinates as the mean to generate a two-dimensional Gaussian distribution with a radius of 10. According to the coordinates \((x, y)\) of the singular point, the value of \((i, j)\) on the Gaussian heatmap can be determined. \(\sigma^2_s\) is the variance of the two-dimensional Gaussian distribution and is set to a constant of 12. The specific formula is as follows:

\[
H(i,j) = \exp \left( -\frac{\| (x, y) - (i, j) \|^2}{2\sigma^2_s} \right)
\]  

(1)

Through the simulation of Gauss function, the closer the pixel is to the singular point, the bigger the value is. The probability of singular points is directly regressed by the Gaussian heatmap. To a certain extent, each point provides supervision information, and the prediction of each pixel can improve the positioning accuracy [34].

In this way, the number of positive and negative samples can be balanced to a certain extent, and the spatial location of the singular point can be highlighted. Although this method will cause the offset of the numerical coordinates, the offset is within a controllable range. Meanwhile, such label form will cause the model to false detection during inference, but NMS algorithm will reduce this situation. The specific NMS algorithm is as follows [35], where \(n\) is 20.

**Algorithm 1: 2D \((n + 1) \times (n + 1) - Block NMS**

1. for all \((i,j) \in \{n, 2n + 1, \ldots\}^2 \cap [0, W - n] \times [0, H - n]\) do
2. \((m_i, m_j) \leftarrow (i, j);\)
3. for all \((i_2, j_2) \in [i, i + n] \times [j, j + n]\) do
4. if \(\text{img}(i_2,j_2) > \text{img}(m_i, m_j)\) then
5. \((m_i, m_j) \leftarrow (i_2, j_2);\)
6. for all \([m_i - n, m_i + n] \times [m_j - n, m_j + n] - [i, i + n] \times [j, j + n]\) do
7. if \(\text{img}(i_2,j_2) > \text{img}(m_i, m_j)\) then
8. go to failed;
9. Maximum At\((m_i, m_j)\);
10. failed

Then, the deformed focal loss in CornerNet [36] is used to supervise the training of the model, which is mainly to solve the problem that the proportion of positive and negative samples in one-stage objective detection is seriously unbalanced. In general, the number of fingerprint singular points is limited, which results in few positive samples in the Gaussian heatmap. Hence, we think that the variant of focal loss is suitable for the singular point detection. The formula of the variant of focal loss \(L_{\text{focal\_loss}}\) is as follows:

\[
L_{\text{focal\_loss}}(\hat{y}, y) = \frac{-1}{N} \sum_{i=1}^{h} \sum_{j=1}^{w} \left\{ \begin{array}{ll}
(1 - \hat{y}(i,j))^2 \log(\hat{y}(i,j)) & \text{if } y(i,j) = 1 \\
(1 - y(i,j))^2 \hat{y}(i,j)^2 \left( 1 - \log(\hat{y}(i,j)) \right) & \text{otherwise}
\end{array} \right.
\]  

(2)
where \( y \) is the true singular point heatmap, \( \hat{y} \) is the predicted singular point heatmap, \( N \) is the total number of targets in the map, \( h \) is the height of the heatmap, \( w \) is the width of the heatmap and \((i,j)\) is the coordinates of heatmap pixel.

### 3.3 Network structure

As shown in Fig. 2, ROSE is constructed by three branches—the feature extraction branch, the core multi-scale spatial attention branch and the delta spatial multi-scale attention branch, followed by an extra non-maximum suppression (NMS) layer. The feature extraction channel, which aims at extracting features from low-level to high-level, is composed of convolution operations and max-pooling operations. The core (or delta) multi-scale spatial attention branch, which is used to tell where we should pay attention and at the same time improve the representation of cores (or deltas) in different scales, is made up of the basic spatial attention and the upsampling operation. These two branches have the same structure. The NMS layer is at the end of ROSE and aims to remove redundant points and keep correct singular points simultaneously. Their details are as follows:

With the fingerprint image as input, the feature extraction branch is made up of 10 convolution operations and 4 max-pooling operations, whose layout and operation sequence are shown in Fig. 2. All the ten convolution operations have a certain number of \(3 \times 3\) filters with the same specifications, and the numbers of filters are 32, 32, 64, 64, 128, 128, 256, 256, 512 and 512, respectively. All the four max-pooling operations are set to window \(2 \times 2\) and stride 2 (non-overlapping window). From top to bottom, the scale of tensors decreases gradually and the information becomes more abstract. The outputs of the feature extraction branch are used as the inputs of the core and delta multi-scale attention branches described below.

Cores and deltas are two different fingerprint singular point. So two branches composed of spatial attention modules, with the same structure, respectively, extract cores and deltas. For the core multi-scale spatial attention branch, as shown in Fig. 2, the scale of each input and output decreases by 0.25 times from C1 to C5, which constitutes multi-scale inputs and outputs. The refined feature maps output by C1 to C4 are also used as inputs for the 4 max-pooling operations of the feature extraction channel, respectively, and the output of C5 is just one spatial attention map. Behind the basic attention modules (C2 to C5), upsampling operations on each spatial map are carried out one by one from C2 to C5 and the scales of these maps are unified as the original input fingerprint image. Branch of extracted deltas has the same structure. In a word, the proposed multi-scale spatial attention branch combines the basic spatial attention module and the upsampling operation, which provides more information for the subsequent fusion results. As one of the most important contributions of our ROSE in fingerprint singular point detection, it not only tells where we should pay attention in different scales, but also improves the representation of cores or deltas from low-level to high-level.
4 Experimental results

In this section, ROSE is evaluated on the public fingerprint datasets FVC2002 DB1 [37] and NIST SD4 [38] and then compared with four state-of-the-art singular point detection methods which include three deep learning methods [9, 11, 12] and one non-deep learning method [5]. The reason why we choose these two datasets lies in that these two different types of datasets are widely used in the evaluation of the singular point detection.

FVC2002 DB1 contains 800 images, and NIST SD4 contains 4000 images, a small number of which are low-quality ones. According to the quality evaluation method [39], there are 65 low-quality fingerprint images in FVC2002 DB1 and 179 low-quality fingerprint images in NIST SD4. Half of fingerprint images from each dataset are randomly chosen as training data, and the rest are used for testing. Due to lack of singular points location of fingerprint images in these two datasets, we have to manually calibrate all singular points for training and testing. In the training process, we choose Adam [40] as the optimization method. The learning rate is set to 0.01, and the momentum is set to 0.9. The experiment is carried out on a PC with Intel(R) Xeon (R) CPU E5-2630 (2.2 GHz), 128 GB of RAM, and GPU Tesla K40C.

In the testing process, the detection rate, the false alarm rate and the detection speed are chosen as the evaluation indicators and the evaluation criteria are the same as the Zhu et al.’s [5]. The total detection speed is defined as the average processing time.

With experiment results, a comparison is made between our ROSE and four state-of-the-art methods including walking point (WP) [5], block classification method (BC) [9], object detection (OD) [11] and SP-Net [12]. All the experiments are carried out under the similar conditions and follow the same evaluation criteria. The singular points detection accuracy of the five methods is shown in Table 1 and Table 2, while the singular points detection speed in Table 3. The bold values in Tables 1, 2, and 3 highlight our experimental results.

From Table 1 and Table 2, it can be seen that: (1) our ROSE is the best in the detection rate of both cores and deltas. Especially, our ROSE works much better than others in the detection rate of cores on NIST SD4, and it improves 3.6% compared to the best of the existing methods. (2) For the false alarm rate of both cores and deltas, our ROSE still works best. In a word, no matter which evaluation indicators considered ROSE performs best.

From Table 3, we can see that the detection speed of our ROSE is 20 ms per image averagely, which is much faster than other three deep learning methods [9, 11, 12] and even faster than the fastest non-deep learning method WP [5], which reflects the advantages of real one-stage of ROSE.

### Table 1 Performance of the four singular points detection methods and the proposed ROSE over the FVC2002 DB1

| Algorithm   | Detection rate (%) | False alarm rate (%) |
|-------------|--------------------|----------------------|
|             | Cores | deltas | Cores | deltas |
| WP [5]      | 94.8  | 97.8   | 0.9   | 4.2    |
| SP-Net [12] | 93.0  | 95.0   | 2.3   | 6.2    |
| BC [9]      | 95.2  | 98.1   | 1.2   | 4.0    |
| OD [11]     | 96.3  | 98.4   | 1.0   | 3.6    |
| Proposed ROSE | 97.1 | 98.6   | 0.8   | 3.2    |

### Table 2 Performance of the four singular points detection methods and the proposed ROSE over the NIST SD4

| Algorithm   | Detection rate (%) | False alarm rate (%) |
|-------------|--------------------|----------------------|
|             | Cores | deltas | Cores | deltas |
| WP [5]      | 84.6  | 90.9   | 5.4   | 4.7    |
| SP-Net [12] | 86.3  | 92.3   | 7.1   | 6.3    |
| BC [9]      | 88.2  | 94.5   | 5.8   | 4.2    |
| OD [11]     | 89.9  | 94.7   | 4.9   | 3.3    |
| Proposed ROSE | 93.5 | 95.1   | 4.2   | 3.1    |

### Table 3 The detection speed of the four singular points detection methods and the proposed ROSE

| Algorithm   | Ave. time (ms) |
|-------------|----------------|
| WP [5]      | 28             |
| SP-Net [12] | 253            |
| BC [9]      | 813            |
| OD [11]     | 214            |
| Proposed ROSE | 20            |
On low-quality fingerprint images, it is difficult to find fingerprint singular point through local features. The proposed method can rely on multi-scale spatial attention maps to predict the area of fingerprint singular point. This method ensures that even if there are blurs and deletions on low-quality fingerprint images, fingerprint singular point can be detected by the proposed method. To further illustrate the advantages of our ROSE in detecting the singular points out of low-quality fingerprints, in Fig. 3, we present the detection results obtained by different methods on two low-quality fingerprint examples in the test dataset from NIST SD4. Figure 3a and b shows the core detection results on F0318 and F0778. As can be seen from Fig. 3, all of OD, SP-Net and BC detect erroneous singular points, and WP and BC cannot even detect any point, while our ROSE can correctly detect the singular points.

To some extent, it can be concluded that our ROSE is more effective and robust for detecting the singular points out of fingerprints than other existing methods. Because multi-scale spatial attention maps will predict more relevant information and play a selective role. The area of fingerprint singular point is corrected step by step through the spatial attention map. Even if the pixel-level attention map is wrong, a larger-scale attention map maybe accurate and there will be no big deviations in the end.

5 Conclusion

Based on multi-scale spatial attention, in this paper, a new deep learning method, ROSE, is proposed to improve the accuracy and speed in the fingerprint singular point detection, and the experimental results on FVC2002 DB1 and NIST SD4 confirm the validity of our method. We think that the design idea and experimental advantages of ROSE may be helpful to other object detection researches based on deep learning.

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