

A Central Point-based Analysis for Fingerprint Liveness Detection

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Abstract—To minimize security threats using fake fingerprints, various CNN-based fingerprint liveness detection methods have been proposed. However, since existing methods mainly employ a random crop method, key information of target fingerprint may be overlooked during the training process, which may lead to decreased detection accuracy. In this paper, we propose a new fingerprint liveness detection method based on central point analysis of fingerprints. The proposed method measures a central point of target fingerprint, extracts the crops with different sizes based on the central point, and fuses the liveness scores inferred from each crop-size model. As a result of validating our method using real datasets, it was confirmed that our method effectively detects fake fingerprints compared to existing methods.

Index Terms—fingerprint liveness detection, deep learning, central point, score fusion

I. INTRODUCTION

With the development of fingerprint recognition technology, fingerprint authentication systems have been used for building access, mobile banking, and payment services [1]–[3]. However, there have been reports of security threats using sophisticated fake fingerprints to disrupt fingerprint authentication systems. To solve this problem, a number of fingerprint liveness detection methods have been proposed, but they still provide limited performance in terms of accuracy.

Most of the recent fingerprint liveness detection methods employed convolutional neural networks (CNN) that automatically extract and learn key information from given fingerprint images [4] [5]. However, depending on target finger sizes, acquisition methods, and devices, the proportion of valid information areas in the fingerprint image can be different, which may affect the performance of CNN-based fingerprint liveness detection. For example, if the proportion of the fingerprint area in a given image for training is relatively smaller than the margin area (i.e., all areas except the fingerprint area), a CNN model may not extract sufficient information to learn, resulting in poor liveness detection performance [6]. Existing CNN-based fingerprint liveness detection methods have mainly relied on random crop methods, which may miss key information. Therefore, it is required to identify a valid fingerprint area in the given images, and train a model by focusing on the area expected to contain key information [7].

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In this paper, we propose a new fingerprint liveness detection method based on central point analysis of fingerprints. Our proposed method enables improvement of detection performance by minimizing the margin and maximizing the key information in a given fingerprint. Our proposed method extracts different sizes of crops based on the central points determined by region-of-interest (ROI) detection. Each crop is trained by a different CNN model, and each trained model infers a liveness score for each crop, respectively. Eventually, the liveness is determined by using score-level fusion.

The contributions of this paper are as follows: (1) Design of new fingerprint liveness detection method based on a central point analysis; (2) Prototype implementation of the proposed method; (3) Validation of the proposed method using real-world datasets.

This paper is organized as follows. Related work is discussed in Section 2. Section 3 presents our proposed method and Section 4 describes our experimental results. Conclusions are presented in Section 5.

II. RELATED WORK

Park et al. [8] proposed a CNN-based fingerprint liveness detection method using random crops. Their method showed similar performance compared to the existing methods, even with a smaller dataset, but did not focus on the area that could contain the key information of the fingerprints. Chugh et al. [9] extracted minutiae-centered local crops for CNN-based fingerprint liveness detection, reducing error rates compared to the state-of-the-art methods. However, their method is not suitable for real-time fingerprint authentication systems, because identifying a large number of minutiae-centered local crops inevitably increases computational costs [10].

III. OUR APPROACH

In this paper, we propose a novel fingerprint liveness detection method based on central point analysis of fingerprints. As shown in Fig. 1, our proposed method comprises two main steps: (1) Central Point Detection: Our method first detects an ROI of a given fingerprint and extracts the central point of the fingerprint from the coordinates of the detected ROI (i.e., bounding box). (2) Central Point-based Crop: In the training phase, our method extracts three different sizes of

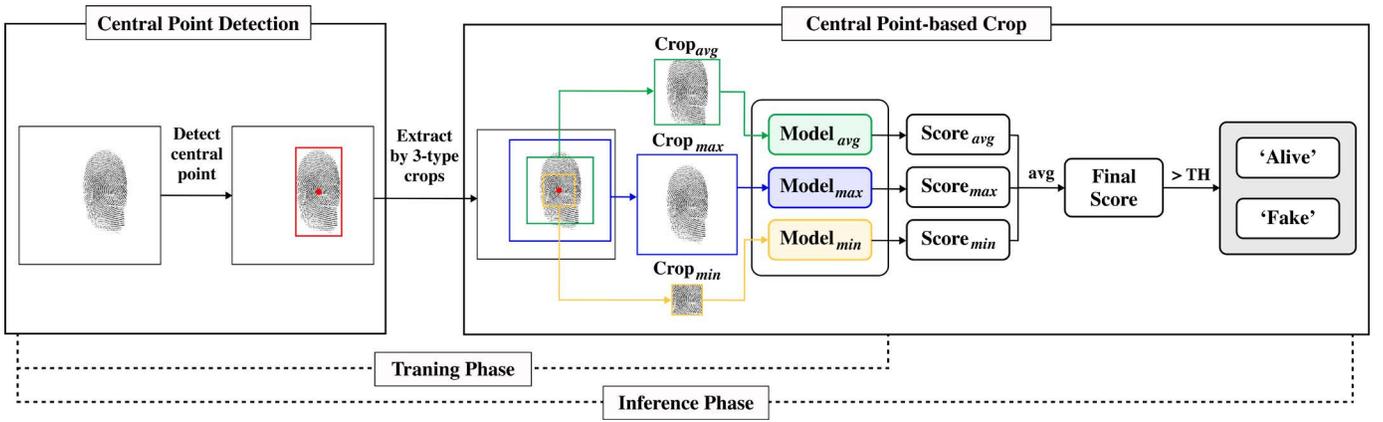


Fig. 1. An Overview of Our Proposed Method

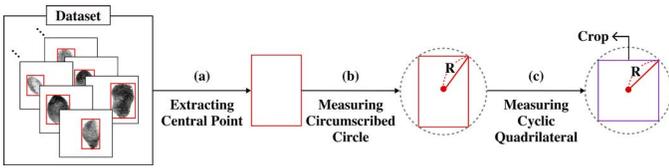


Fig. 2. Our Process for Extracting 3-type crops

crops (=3-type crops) based on the central point (=Crop_{min}, Crop_{max}, Crop_{avg}), and each size of crop is trained on a different detection model (=Model_{min}, Model_{max}, Model_{avg}), respectively. In the inference phase, our method also extracts 3-type crops based on the central point, and each trained detection model infers a liveness score (=Score_{min}, Score_{max}, Score_{avg}). As a final step, the scores are fused and compared against a pre-defined threshold to determine the liveness. The details of our method are as follows.

A. Central Point Detection

In general, the central area of the fingerprint contains relatively more key information that can be useful for detecting fake fingerprints (i.e., the thickness of a ridge, the direction of its curve) [6]. Hence, our method focuses on the central area of the fingerprint to improve the fingerprint liveness detection performance. A central point is obtained from the regional information of the bounding box (i.e., center coordinates, width, and height) detected by an object detection model. Considering that the fingerprint authentication system requires a prompt response, we selected YOLOv5, a real-time object detection model.

B. Central Point-based Crop

Our method uses 3-type crops (i.e., Crop_{min}, Crop_{max}, Crop_{avg}) based on the central point. If a model is trained with only a single fixed-size crop, the model may not learn enough information about the fingerprint. For example, if the size of a given fingerprint region is smaller than a fixed size, the crop may contain a relatively large amount of margin, which may affect the performance of the detection model. In the opposite case, a model may be generated in which key information

about a given fingerprint is not sufficiently trained. To solve this problem, our method uses 3-type crops.

Fig. 2 shows the process for extracting 3-type crops. Considering the fact that the shape of fingerprints is generally circular or elliptical, while deep learning requires a square image as input, our method adopts the concept of circumscribed and inscribed circles, extracting the crops containing sufficient information while minimizing margins. For each size value extracted from the bounding box (i.e., minimum, maximum, and average), our method (a) defines the center coordinate of the bounding box as a central point, (b) measures the circumscribed circle of the bounding box (which has a radius R), and (c) using R , measures the cyclic quadrilateral, which is determined as the size of the crop. Each model is trained by each crop size, respectively, and a liveness score is also inferred for each crop size. Our method ensembles these scores using a mean-based score-level fusion, and determines the liveness (i.e., alive or fake).

IV. EXPERIMENTAL EVALUATION

To assess the effectiveness of our approach in fingerprint liveness detection, we have conducted an evaluation that addresses the following research questions:

- **RQ#1:** How well does our proposed method perform compared to the existing crop method?
- **RQ#2:** Does the area near a central point of the fingerprint contain more information than others?

A. Experimental Setting

To evaluate our method, we selected LivDet 2015 dataset which contains both alive and fake fingerprints obtained from different sensors. (i.e., *GreenBit*, *Digital Persona*, *Biometrika*, and *Crossmatch*). To clearly observe the effectiveness of our proposed method, we targeted *Crossmatch* dataset containing images with wide margins and irregular fingerprint positions (2,983 train images and 2,948 test images) [11] [12]. With the *Crossmatch* dataset, we trained the ResNet-50 model with its original images (=non-crops), random crops, and central point-based crops (=our method), respectively, and compared

TABLE I
THE RESULT OF OUR EXPERIMENT

Method	Crop Size	Model	Accuracy (%)
<i>Non-crops</i>	(800, 750)	Model _{org}	77.95
<i>Random crops</i>	(581, 581)	Model _{max}	91.55
	(381, 381)	Model _{avg}	84.87
	(181, 181)	Model _{min}	62.58
	-	fusion	63.80
<i>Our method</i>	(581, 581)	Model _{max}	93.73
	(381, 381)	Model _{avg}	87.56
	(181, 181)	Model _{min}	87.80
	-	fusion	94.20

their accuracies. Note that, to extract the bounding box of fingerprints, we trained YOLOv5 with a manually-labeled *GreenBit* dataset (1,997 images).

The environment and hyperparameters used in this experiment are as follows: (1) YOLOv5: NVIDIA Tesla T4 GPU, Python 3.7.13, PyTorch 1.11.0+cu113, SGD, 16 batch size, and 160 epochs; (2) ResNet-50: NVIDIA GeForce RTX 3090 GPU, Python 3.8.0, Tensorflow 2.7.0, Adam, 8 batch size, and 20 epochs.

B. Experimental Results

(RQ#1) Effectiveness of our method: We evaluated our proposed method compared to the existing methods. Table I shows the differences in accuracy between *non-crops*, *random crops*, and *our method*. *Our method* showed improved accuracy (94.20%) compared to *non-crops* (77.95%) and the best accuracy of *random crops* (91.55%). The experimental results show that our proposed method can effectively detect fake fingerprints compared to existing methods.

(RQ#2) Importance of areas near a central point of fingerprint: We evaluated the performance of individual models (Model_{max}, Model_{avg}, Model_{min}) by crop method in terms of accuracy. As demonstrated in Table I, *our method* showed improved accuracy compared to *random crops*: Model_{max} (from 91.55% to 93.73%), Model_{avg} (from 84.87% to 87.56%) and Model_{min} (from 62.58% to 87.80%). The results imply that the smaller the random crop size, the lower the probability of including a central point of fingerprint, resulting in lower detection accuracy.

V. CONCLUSION

In this paper, we analyzed the central point of fingerprints to improve fingerprint liveness detection performance. Our proposed method enhanced detection performance by including key information from the central area of fingerprints. Experimental results showed that our method provided higher detection accuracy than *non-crops* and *random crops*. Our future work includes extensive evaluations of the effectiveness of our method by applying it to various detection models and datasets.

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