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A multi-task fully deep convolutional neural network for contactless fingerprint minutiae extraction

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ABSTRACT

With the outbreak and wide spread of novel coronavirus (COVID-19), contactless fingerprint recognition has attracted more attention for personal recognition because it can provide significantly higher user convenience and hygiene than the traditional contact-based fingerprint recognition. However, it is still challenging to achieve a highly accurate recognition due to the low ridge-valley contrast and pose variances of contactless fingerprints. Minutiae points are a kind of ridge flow discontinuities, and robust and accurate extraction is an important step for most automatic fingerprint recognition algorithms. Most of existing methods are based on two stages which locate the minutiae points first and then compute their directions. The two-stage method cannot make full use of location and direction information. In this paper, we propose a multi-task fully deep convolutional neural network for jointly learning the minutiae location detection and its corresponding direction computation which operates directly on the whole gray scale contactless fingerprints. The proposed method consists of offline training and online testing stages. In the training stage, a fully deep convolutional neural network is built for the tasks of minutiae detection and its direction regression, with an attention mechanism to make the direction regression branch concentrate on the minutiae points. A new loss function is proposed to jointly learn the tasks of minutiae detection and its direction regression from the whole fingerprints. In the testing stage, the trained network is applied on the whole contactless fingerprint to generate the minutiae location and direction maps. The proposed multi-task leaning method performs better than the individual single task and it operates directly on the raw gray-scale contactless fingerprints without preprocessing. The results on three contactless fingerprint datasets show the proposed algorithm performs better than other minutiae extraction algorithms and the commercial software.

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1. Introduction

Fingerprint is a widely used biometrics characterized as the ridge friction patterns on finger tips. After more than forty years of research, automatic fingerprint identification system (AFIS) has achieved a great success for wide applications [1–3]. Traditional AFIS is usually based on contact fingerprints captured by pressing a finger on the scanner surface. With the outbreak and wide spread of novel coronavirus 2019 (COVID-19), World Health Organization (WHO) recommends to avoid contact with objects in public places to reduce the transmission of virus. Contactless fingerprints captured without any contact between a finger and sensor have become an important and highly promising prospect for personal recognition because of its significantly higher user convenience and hygiene than the traditional contact-based fingerprints. With the rapid advances of digital cameras, contactless fingerprints can be captured with the high-resolution and high-speed camera to provide higher-quality images. However, the acquisition of contactless fingerprints is significantly different from that of contacted fingerprint. Existing methods for contact-based fingerprint recognition cannot be directly used for contactless fingerprints.

There are some difficulties in contactless fingerprint recognition. First, since the fingerprint acquisition with camera is affected by lighting sources, the contactless fingerprints are usually low-contrast between ridge and valleys which may cause poor performance in extraction of feature points. Second, the presentation of fingers against sensors is often uncontrollable in acquisition, which results in the perspective distortion and pose variances of images. Fig. 1 shows some contactless fingerprints with poor qualities.
Thus, it is still challenging to achieve a highly accurate contactless fingerprint recognition. In recent years, there are many efforts made to address these problems and improve the performance of contactless fingerprint recognition [4–7].

Minutiae points are defined as the discontinuities of fingerprint ridge flows. There are several types of minutia points such as ridge ending and bifurcation. Minutiae location and direction are often used for fingerprint representation so that automatic recognition problem can be converted to comparison of minutiae sets between two fingerprints. Since most of existing fingerprint recognition algorithms rely on minutiae matching, minutiae points are considered as highly significant features for automatic fingerprint recognition. There are a lot of minutiae extraction methods proposed for contact-based fingerprints in the literature [2,8–11]. These methods can be broadly classified into two categories: traditional handcrafted methods and deep learning based methods.

The traditional handcrafted methods usually use the domain knowledge or heuristics to detect the minutiae points [2,8]. In these methods, fingerprint segmentation, enhancement, thinning and binarization are often performed before searching the minutia-like patterns of localized pixels for minutiae detection. Bansal, et al. [8] proposed a mathematical morphology method for minutiae extraction, which use the morphological Hit or Miss transform (HMT) on binary image to detect minutiae points. Farris, et al. [2] proposed to extract minutiae points on the skeleton binary fingerprint images. To overcome information lost caused by binarization and thinning processes, some methods were proposed to detect minutiae points from the gray-scale images obtained by fingerprint enhancement [12]. Although these traditional handcrafted methods can achieve good performance for minutiae detection on good quality fingerprints, they require strong prior knowledge to define the patterns of minutiae points and thus are sensitive to noises.

In recent years, deep learning networks such as Convolutional Neural Networks (CNNs) have successfully been investigated for fingerprint minutiae extraction [9–11,13]. Sankaran, et al. [9] proposed a minutiae extraction method for latent fingerprints by using the stacked sparse autoencoder to learn features for classification of image patches as minutia or non-minutia. Jiang, et al. [10] proposed a minutiae extraction approach based on two deep networks with a JudgeNet to select candidate patches followed by a LocateNet to determine the minutiae locations. This method can make use of representation ability of deep network and directly detect minutiae points from raw fingerprint images, but it cannot compute minutiae directions. Darlow, et al. [13] processed each pixel of input fingerprint by convolutional neural network to predict minutiae locations, and then minutiae directions were calculated by the principal axis of image gradients. Tang, et al. [11] proposed a FingerNet to combine the domain knowledge with deep learning. They first integrated some convolution kernels converted from traditional methods to form a shallow network with fixed weights, which is expanded to a full network for minutiae extraction. Nguyen, et al. [3] proposed to build a CoarseNet to generate a minutiae score map and estimate minutiae directions, followed by a FineNet to refine the candidate minutiae locations based on score map.

The above minutiae extraction methods can achieve good performance on the contact-based fingerprints with a clear distinction of ridges and valleys. However, they cannot work well on contactless fingerprints due to the low ridge-valley contrast. Earlier works on contactless fingerprint recognition tend to enhance the images and then extract minutiae features by using the contact-based methods. Lin, et al. [14] enhanced fingerprints with Gabor filtering and adaptive histogram equalization, followed by minutiae extraction with the algorithm in [1]. In [4], a ridge enhancement model was built to enhance the unwrapped contactless fingerprint images and the minutiae points were extracted with NIST mindct software [15] and Verifinger SDK [16]. Yin, et al. [5] proposed a contactless fingerprint matching algorithm based on minutiae features extracted with Verifinger SDK on the fingerprints pre-enhanced by intrinsic image decomposition and guided image filtering in [6]. More recently, Tan, et al. [7] proposed a deep network for minutiae extraction from raw contactless fingerprints. But the network was trained with the cropped patches, which cannot make use of the global information. In addition, the network detected minutiae and computed directions in two stages, which needed post-processing to refine and remove spurious minutiae.

In this paper, we proposes a multi-task fully deep convolutional neural network for minutiae extraction from the whole gray scale contactless fingerprints, which can jointly learn the detection of minutiae locations and the computation of minutiae directions. An attention mechanism is used to make the network concentrate on the direction regression of minutiae points. A new loss function is proposed to jointly combine the tasks of minutiae detection and its direction regression, which can help each other in the learning. Different from the patch based method, both the training and testing of the network operate on the whole fingerprints, which can make full use of global information for minutiae extraction. The proposed multi-task leaning method can simultaneously detect the locations of minutiae and compute their directions from the raw contactless fingerprints without preprocessing. The proposed method is tested on three publicly available datasets including direct evaluation versus ground truths, contactless fingerprint matching and contact-based to contactless fingerprint matching. The main contributions of this paper are summarized as follows.

- A multi-task fully deep convolutional neural network is proposed for minutiae extraction in contactless fingerprints. This is an end-to-end method by jointly learning detection of minutiae points and computation of minutiae direction, which is different from the two-stage methods with the minutiae detection followed by direction computation.
- Instead of cropping fingerprint into local patches, the proposed method operates directly on whole fingerprints in both training and testing stages, which can make full use of global fingerprint features for minutiae extraction in one shot.
- An attention mechanism is applied on the direction computation branch, which makes the network pay attention to the minutia points for more reliable direction computation. In addition, the minutia direction is represented with the cosine and sine values, which makes the loss function of direction regression optimized smoothly.

The rest of this paper is organized as follows: Section 2 present the proposed minutiae extraction method for contactless fingerprints in detail; Experimental results are presented in Section 3; Conclusion is given in Section 4.
2. Proposed method

In this section, we present the proposed minutiae extraction algorithm based on deep network for contactless fingerprints. First, we give an overview of the proposed algorithm. Next, the architecture of our deep network is presented with details. Finally, we present implementation details and minutiae extraction for test fingerprints.

2.1. Overview of the proposed algorithm

Minutiae are special patterns of the interleaved ridge and valley flows which are widely used as important features for fingerprint recognition. There are several types of minutiae points such as ridge ending and bifurcation. In this work, we will not discriminate the types of minutiae and all minutiae are considered as interest points. Minutiae extraction includes two tasks: detection of minutia location and computation of minutia direction. Thus, a minutia \( i \) can be represented as a triplet \((x_i, y_i, \theta_i)\), where \((x_i, y_i)\) denotes its location and \(\theta_i \in [0, 2\pi)\) denotes its direction. There are dozens of minutiae points in a fingerprint image.

Minutiae extraction is often considered as a kind of object detection where each minutia is an object to be detected. Over the past few years, deep CNNs have been widely investigated for object detection. Accordingly, minutiae extraction based on deep CNNs is usually divided into two steps: detection of minutiae points followed by computation of minutiae directions. The two-step methods train two deep networks separately, which is not only time-consuming but also unable to make use of the features from the tasks of location detection and direction computation.

To address the above problems, a novel minutiae extraction method is proposed based on multi-task fully deep convolutional neural network for contactless fingerprints, as shown in Fig. 2. Since the minutiae location detection and direction computation are two related tasks, we propose a multi-task deep network to jointly learn these two tasks and share their computations and representations. Different from the two-stage method on image patches, the proposed algorithm operates on the full-sized fingerprint image to locate the pixel-level minutiae points and compute their corresponding directions simultaneously. It consists of offline training and online testing stages.

In the offline stage, we train the multi-task fully deep convolutional neural network with the training data, which consists of the full sized contactless fingerprints and their corresponding minutia ground truths used as inputs and outputs of network, respectively. Since there are no publicly available contactless fingerprint database with the labelled minutiae coordinates and directions and labelling minutiae from scratch is very time-consuming and labor-sensitive, we use the commercial fingerprint recognition software to extract candidate minutiae followed by manual checking to generate the ground truths of minutiae. First, the COTS Verifinger SDK [16] is used to extract the minutiae locations and directions. Then, we develop a GUI tool to correct the minutiae points and directions in three ways: (a) add the new minutiae which are missed by Verifinger; (b) delete the spurious minutiae; (c) modify coordinates and directions which are not correctly labelled. Finally, the manually checked locations and directions are used as the ground truths of training images.

In the online stage, we simply feed the raw full-sized fingerprint into our trained network to generate two heatmaps: one for detecting the minutiae locations and the other for computing their directions. The local peaks on the location map are detected as minutiae points, and the values of direction map on detected points are used as the minutiae direction. The architecture of the multi-task network is presented in the following subsection.

2.2. The multi-task fully deep convolutional neural network

We design the architecture of the multi-task fully deep convolutional neural network called as ContactlessMinuNet with the Hourglass-shaped encoder-decoder network structure, as shown in Fig. 3. The deep network consists of three parts: the shared sub-network to learn the common representation and two branches for minutiae location detection and direction computation. First, a single shared encoder subnetwork is built to hierarchically process the input fingerprint images and learn the feature representation. After the encoder subnetwork, a shared decoder subnetwork is used to expand the representations back to higher resolution by upsampling. Finally, the network is split into two branches to learn the task-related weights with one for minutiae point detection and the other for minutiae direction computation. Thus, most of the network’s parameters are shared between two tasks to learn the relevant features.

2.2.1. The shared subnetwork

To learn image features, the shared subnetwork employs the Hourglass-shaped structure which can capture multi-level features and bring them together to generate pixel-wise predictions. Firstly,
the input contactless fingerprint image of size $W \times H \times 1$ is processed by 2 ResBlocks with each one followed by a $2 \times 2$ convolutional layer with stride=2 for downsampling. The ResBlock consists of two $3 \times 3$ convolutional layers with stride=1, and padding is used to keep the width and height of feature maps constant during convolution. The input of ResBlock is added to the output of the second convolutional layer by element-wise summation as skip connection. The feature maps of $W/4 \times H/4 \times C$ are generated for representation where C is the number of channels.

Then, an hourglass network [17] is added to the feature maps, which includes encoding and decoding paths. The encoding path consists of the repeated application of ResBlock and a $2 \times 2$ convolutional layer with stride=2 for downsampling the feature maps by half, while the number of feature channels is doubled. In each step of decoding path, a sub-pixel module [18] is applied to double the widths and heights of feature maps while the feature channels are reduced to half. The feature maps of encoding path is concatenated into those of decoding patch in the same level, which can make full use of multi-level features for minutiae extraction. All the convolutional layers in ResBlock are followed by a batch normalization layer and ReLU activation. The hourglass network preserves spatial information at each resolution since the deep network maps the low-level image to high-level feature space. After learning the rich features of fingerprint images, the network is split into two branches to learn task specific weights one for minutiae point detection and the other for minutiae direction computation.

2.2.2. The minutiae point detection branch

This network branch focuses on detection of minutiae points and the output of each pixel represents the probability of minutiae point. For minutiae point detection with the shared feature maps, one common method is to design an upsampling decoder back to full resolution via deconvolution operations. Unfortunately, upsampling layers tend to add a high amount of computation and can introduce the checkerboard artifacts. To reduce the computation, the minutiae point detection branch simply consists of a $1 \times 1$ convolutional layer, a batch normalization layer and a sigmoid layer. The sigmoid function is used as activation to generate minutiae location map of size $W/4 \times H/4 \times 1$. Each value of location map represents the probability of a minutia in a certain location, which stands for a cell of $4 \times 4$ pixels in the original fingerprint image. The points with local maximum probabilities are detected as minutiae points.

2.2.3. The minutiae direction regression branch

The direction regression branch is designed to predict the directions of minutiae, which is a phase angle $\theta_i \in [0, 2\pi)$. To facilitate the regression, the direction is represented as two components $(\cos \theta, \sin \theta)$ to be jointly predicted in this work. The feature maps learned from the shared subnetwork are input to the minutiae direction regression branch. To predict the minutiae direction more accurately, an attention based subnetwork is built to consist of an attention mechanism followed by a $1 \times 1$ convolutional layer, a batch normalization layer and a tanh layer. First, the attention mechanism is composed of two repeated Conv-BN-ReLU layers, and another convolutional layer with sigmoid activation function to transform the input feature maps into attention weight map for each point. The input feature map is then multiplied with the attention weight map to output the weighted feature maps which is further added with the input feature maps by element-wise summation as in [19]. After that, a $1 \times 1$ convolutional layer and a batch normalization layer are followed and hyperbolic tangent is used as activation function to limit the output of network to range of $[-1, 1]$. Finally, two-channel direction maps of size $W/4 \times H/4 \times 2$ is generated from the direction regression branch with each element of the direction map representing the cosine and sine values of a direction. To make sure that the elements of direction map meet the mathematical requirement $\cos^2 \theta + \sin^2 \theta = 1$, a normalization layer is added at the end of network by $(\frac{\cos \theta}{\sqrt{c^2 + s^2}}, \frac{\sin \theta}{\sqrt{c^2 + s^2}})$ where c and s are the predicted cosine and sine values of direction map, respectively. The final outputs of direction regression branch are two components $\cos \theta$ and $\sin \theta$ of minutiae directions $\theta$.

2.2.4. Loss functions

In this work, we apply multi-task learning strategy to jointly learn the detection of minutia points and computation of minutia directions by combining the losses of two network branches: one for minutia point detector $L_p$ and another for minutia direction regressor $L_d$. Firstly, minutiae detection is a severe class-imbalance problem because the number of non-minutia points is significantly larger than that of minutia points. If a regular binary cross-entropy loss function is adopted, the network training is inefficient as most locations are non-minutia that contribute no useful information. To solve this problem, a modified focal loss [20] is used to force the network training focus on minutia points with large classification weights. Let $\hat{P}$ and $P$ denote the predicted and ground truth minutia location maps, respectively, the minutia detection loss $L_p$ is computed as:

$$L_p = -\frac{1}{N} \sum_{x,y} \left\{ \left( 1 - \hat{P}_{xy} \right)^\alpha \log \left( \hat{P}_{xy} \right) + \left( 1 - P_{xy} \right)^\beta \log \left( 1 - P_{xy} \right) \right\} \quad \text{if } P_{xy} = 1$$

where $\alpha$ and $\beta$ are hyper-parameters in focal loss; $N$ is the number of minutiae points in input fingerprint. We set $\alpha = 2$ and $\beta = 4$ in our experiments.

Secondly, for direction regression, we only consider the minutiae points and their 8 neighborhoods while other locations have no directions and do not involve in regression, which can eliminate noises and reduce the computation. Let $\hat{\theta}$ and $\theta$ be the predicted and ground truth minutia directions, respectively. Since the phase angle $\theta \in [0, 2\pi)$ is a circular value, minutia points with angles of 0 and $2\pi$ have the same direction. If direct subtraction
is used to compute the difference between \( \hat{\theta} \) and \( \theta \), two phase angles with close directions would have a big difference. For computation of minutiae directions, some algorithms divide the range of direction into eight or more categories and classify the direction of minutiae into one category. But it may result in quantization error and the number of categories is large which make it challenging for classification. In the previous study for minutiae extraction [21], the smaller one of \( \hat{\theta} - \theta \) and \( 2 - (\hat{\theta} - \theta) \) is used to measure the distance between the predicted and ground truth directions, where the direction is normalized to \([-1, 1]\). This may result in the problem of gradient computation. In this work, instead of using the phase angle, the cosine and sine components \((\cos \theta, \sin \theta)\) are used to represent the minutiae direction \( \theta \). To achieve more precise direction prediction, the MSE loss function with both cosine and sine values of minutiae direction is used as the objective function of the direction regression, which is computed as:

\[
L_d = \frac{1}{N} \sum_{(x, y) \in \mathcal{R}} \begin{cases} 
(\cos \hat{\theta}_{xy} - \cos \theta_{xy})^2 + (\sin \hat{\theta}_{xy} - \sin \theta_{xy})^2 & \text{if its 8 neighbors exist} \\
0 & \text{otherwise}
\end{cases}
\]

where \( N \) is the number of available pixels for direction regression, which include all minutiae points and their 8 neighbors. With this loss function, the network predicts the cosine and sine components of the direction, which are further used to compute the phase angle.

Finally, for jointly learning the minutia location detection and direction regression, we combine the location probability prediction loss and direction regression loss as:

\[
L = L_p + \lambda L_d
\]

where \( \lambda \) is a weight term to balance these two losses.

2.3. Implementation details and minutiae extraction

The proposed algorithm is implemented with the PyTorch framework by Python programming. It consists of network training and minutia extraction for test images. Given the gray-scale contactless fingerprint image \( I \in \mathbb{R}^{W \times H \times 1} \), the proposed ContactlessMinuNet generates the minutia location and direction maps of size \( \frac{W}{4} \times \frac{H}{4} \), so we downsample the ground truth location and direction maps to \( P \in [0, 1]^{\frac{W}{4} \times \frac{H}{4} \times 1} \) and \( \Theta \in [-1, 1]^{\frac{W}{4} \times \frac{H}{4} \times 2} \), respectively. This can reduce the computation costs without sacrificing accuracy since there hardly exist two minutiae points in a cell of \( 4 \times 4 \) pixels for contactless fingerprints.

To generate ground truth location map \( P \in [0, 1]^{\frac{W}{4} \times \frac{H}{4} \times 1} \), we produce a heatmap \( H_{x,y} \in [0, 1]^{\frac{W}{4} \times \frac{H}{4} \times 1} \) for each minutia \((x,y)\) with a Gaussian kernel as:

\[
H_{x,y}(i, j) = \exp \left( \frac{-(i-x)^2 + (j-y)^2}{2 \sigma_{x,y}^2} \right)
\]

where \( \sigma_{x,y} \) is a standard deviation and is set to 1.5 in this work. The ground truth location map \( P \) is generated by applying elementwise maximum on \( H_{x,y} \) over all ground truth minutiae points, as shown in Fig. 4 (a). To generate ground truth direction map \( \Theta \in [-1, 1]^{\frac{W}{4} \times \frac{H}{4} \times 2} \), we compute cosine and sine values \((\cos \theta, \sin \theta)\) for the direction of each minutia. The location of each minutia and its 8 neighborhoods are assigned with value \((\cos \theta, \sin \theta)\), while other locations are assigned with \((0, 0)\), which indicates they do not have directions, as shown in Fig. 4 (b).

When training the proposed ContactlessMinuNet, the weights of convolutional layer and batch normalization layer are initialized by following the rules in [22]. The batch size is set to 4.

Adam optimizer [23] is used by setting \( \beta_1 = 0.9, \beta_2 = 0.999 \) and \( \epsilon = 1 \times 10^{-8} \). Warm-up training with learning rate \( 3 \times 10^{-4} \) is applied for the first 5 epochs, and then the network is trained for 200 epochs with the learning rate \( 1 \times 10^{-3} \). ReduceLrOnPlateau scheduler is adopted to reduce the learning rate with a factor until the loss does not drop.

For a given test contactless fingerprint, the network generates a location map of size \( \frac{W}{4} \times \frac{H}{4} \) and a direction maps of size \( \frac{W}{4} \times \frac{H}{4} \times 2 \). We choose the local peaks of location map as the locations of minutiae, and the phase angle of minutiae direction is computed as \( \arctan(\sin \theta / \cos \theta) \) with the predicted direction components at the minutiae location. Since the output location and direction maps are downsampled by 4 comparing to the input contactless fingerprint image of size \( W \times H \), the detected minutiae locations are mapped to the coordinates of input image with stride 4 based on receptive field theory [24].

3. Experimental results

In this section, we conduct experiments to test the effectiveness of the proposed algorithm for contactless fingerprint minutiae extraction. Firstly, we introduce the datasets and the settings used in the experiments. Secondly, we perform the ablation studies on the proposed ContactlessMinuNet to test the effectiveness of the multi-task learning, attention mechanism and loss function for minutiae extraction. Thirdly, we perform direct evaluation on extracted minutiae against the ground truths. Next, we perform matching experiments for both contactless fingerprint recognition and contact-based to contactless fingerprint recognition on three datasets and compare the results with other methods. Finally, discussion is provided to further compare the results with the recent published ones and demonstrate the generalization ability of proposed network using open-set protocol.

3.1. Datasets and settings

To evaluate the proposed method and compare with other methods, three contactless fingerprint datasets: PolyU Cross [25], Benchmark 2D/3D [26] and a dataset prepared by our laboratory are used for our experiments. The PolyU Cross dataset includes two sessions. The first session contains 2016 contactless fingerprint images acquired from 336 fingers with 6 impressions for every finger. The second session contains 960 fingerprint images from the corresponding 160 fingers with 6 impressions for each finger, which were captured from the same clients as the first session in about 2 to 24 months. For each contactless fingerprint image, PolyU Cross dataset provides the corresponding contact-based fingerprint image with also 6 impressions for each finger. Benchmark 2D/3D dataset consists of 9000 contactless fingerprint images acquired from 1500 fingers with three different views and 2 impressions for each view. We use 3000 unwrapped contactless fingerprint images for minutiae extraction with 2 impressions for each.
finger. Benchmark 2D/3D dataset also contains 6000 corresponding contact-based fingerprint images with 4 impressions for each finger. In addition, we have collected a dataset, which consists of 1320 contactless fingerprints and corresponding contact-based fingerprints. The dataset is acquired from 110 fingers with 12 impressions for each finger. All fingerprints are captured from the volunteers of our university. Fig. 5 shows some fingerprint samples of three datasets.

To train the proposed ContactlessMinuNet, we select the contactless fingerprints from fingers numbered from 1 to 136 in the first and second sessions of PolyU Cross dataset as the training set. Since there are some missing fingerprints in the second session, we have 1440 ((136 + 104) × 6) contactless fingerprints for training. The remaining 200 fingers with 1200 impressions in the first session of PolyU Cross dataset are used for testing the proposed method. For robust minutiae extraction with Benchmark 2D/3D dataset, a small set with 400 contactless fingerprints from 200 fingers are used for fine-tuning the pre-trained network based on PolyU Cross dataset, and the remaining 2600 contactless fingerprints from 1300 fingers are used for evaluation. For our dataset, 120 fingerprints from 10 fingers are used for fine-tuning the ContactlessMinuNet and the left 1200 fingerprints from 100 fingers are used for testing.

The goal of fingerprint minutiae extraction is to achieve reliable fingerprint recognition. Thus, we conduct fingerprint verification and identification experiments. To implement a complete process of fingerprint recognition, minutiae extraction is integrated with minutiae matching, which is automatically conducted using the existing Minutia Cylinder-Code (MCC) matcher [27] with the minutiae coordinates and directions as inputs.

For fingerprint verification experiments, we use FVC protocol to evaluate the performance. Each impression is compared against the remaining ones of the same finger to generate genuine pairs while the first impression of each finger is matched with the first impression of other fingers to generate impostor pairs. For contactless fingerprints from PolyU Cross dataset, we have 3000 (200 × 6 × 5/2) genuine pairs and 19900 (200 × 199/2) impostor pairs. For contactless fingerprints in Benchmark 2D/3D dataset, we have 1300 (1, 300 × 1) genuine pairs and 844350 (1, 300 × 1299/2) impostor pairs. For contactless fingerprints in our dataset, we have 6600 (100 × 12 × 11/2) genuine pairs and 4950 (100 × 99/2) impostor pairs. We combine the minutiae extraction with the MCC matcher to generate a matching score for each pair of contactless fingerprints. With the matching scores from all pairs of fingerprints, we calculate True Positive Rate (TPR) and False Positive Rate (FPR) and plot Receiver Operating Characteristic (ROC) curve as well as the area under the ROC curve (AUC) and Equal Error rate (EER) for each dataset to evaluate the fingerprint verification performance.

Different from verification, fingerprint identification is a one-vs-many matching process. For identification experiments, we use the first impression of each finger as the template, and the remaining impressions of each finger as the test fingerprints to match all template fingerprint images. A matching score is generated between a test and a template fingerprints. All matching scores are sorted in descending order and the templates are ranked for each test fingerprint. The Cumulative Matching Characteristic (CMC) curve, which plots the rank − k identification rate with k = 1, 2, 3, . . . , 20, . . . , is used to evaluate the performance of fingerprint identification.

Several state-of-the-art minutiae extraction methods including the COTS VeriFinger SDK [16], open source extraction software NIST mindct [15] and deep learning based method MinutiaeNet [3] are used to compare our proposed method. The VeriFinger and NIST minidct are directly used for minutiae extraction on the contactless fingerprints of test datasets. Since the released MinutiaeNet was trained on contact-based latent fingerprints, we retrain the network using the same contactless fingerprint training data as ours to make it effective on contactless fingerprints. All experiments are conducted on a single NVIDIA TITAN Xp GPU with 12 GB memory powered by Ubuntu-16.04-x84 system. Table 1 compares the computation requirements of different minutiae extraction methods used in the experiments.

### 3.2. Network ablation studies

This experiment is to test the effectiveness of the multi-task learning, attention mechanism and direction regression loss used in the proposed network through the ablation studies. In the first ablation study, we replace the multi-task learning with the traditional two-stage method which detects the minutiae points and compute the minutiae direction separately as in [7]. First, we remove the direction computation branch from the ContactlessMinuNet and thus the network only outputs the locations of minutiae. Then, the local patches of size 64 × 64 are cropped to be centered on the minutiae locations and a deep network is built for computation of minutiae direction. The second ablation study is to test the effectiveness of attention mechanism on the direction computation. In this study, we remove the attention module from the direction computation branch of ContactlessMinuNet while the other components of the network are retained. In the third ablation study, we replace the loss function of direction regression with that based on the phase angle from a recently published paper [21].

The training strategy for the ablation studies are same as what described in Section 2.3. We conduct both contactless fingerprint verification and identification experiments on Benchmark 2D/3D dataset since this dataset is more challenging than others. The verification and identification protocols follow with those in the above subsection. The comparisons of ROC and CMC curves by the proposed ContactlessMinuNet and three network ablation studies are shown in Fig. 6 and Fig. 7, respectively. In addition, we also compute the AUC and EER to evaluate the fingerprint verification performance as shown in Table 2. From the results, we can see that the multi-task learning, the attention mechanism and the direction regression loss all contribute to improvement of contactless fingerprint recognition accuracy. From Table 2, we can see that the multi-task learning, the attention mechanism and the novel direction loss achieve 1.59%, 2.71% and 5.61% improvements of AUC, and 1.08%, 2.40% and 4.75% improvements of EER, respectively.

![Fig. 5. Samples of contactless fingerprints (top) and contact-based fingerprints (bottom) from: (a) PolyU Cross dataset, (b) Benchmark 2D/3D dataset and (c) our dataset.](image)
### 3.3. Results on minutiae extraction

This experiment is to perform the direct evaluation of minutia extraction by comparing the minutiae points predicted by the proposed method with their ground truths. However, there are no ground truth minutiae points provided for the contactless fingerprint datasets. It is impractical to get a large number of fingerprints with minutia information labeled by human experts. For direct evaluation of minutia extraction, we have manually labelled the minutiae points of 100 fingerprint images randomly selected from the test set of Benchmark 2D/3D dataset as ground truths. First, we show the extracted minutiae points by different methods as well as their ground truths on two sample contactless fingerprints in Fig. 8. We can see that our proposed method can achieve more reliable minutiae extraction with less missing minutiae points than NIST mindct and MinutiaeNet, and also less spurious minutiae points than Verifinger.

Furthermore, we perform the direct evaluations as in the previous work [3]. We define the location error $D$ in pixel and direction error $\Theta$ in degree between the predicted and ground truth minutia as:

$$\begin{align*}
D &= \|l_e - l_g\|_2 \\
\Theta &= \min\left(\|o_e - o_g\|_1, 360^\circ - \|o_e - o_g\|_1\right)
\end{align*}$$

where $(l_e, o_e)$ and $(l_g, o_g)$ are coordinate $(x, y)$ and direction of extracted minutia and ground truth minutia, respectively. The predicted minutia is considered to be accurate if it satisfies $D \leq D_0$ and $\Theta \leq \Theta_0$. In our experiments, we set $D_0 = 12$ pixels and $\Theta_0 = 20^\circ$ as suggested in [3]. We calculate the precision (positive predictive value), recall (true positive rate) and F1 score to directly evaluate the accuracy and compare the proposed method with other methods as shown in Table 3. We have also provided more results on the number of correct minutiae, missed minutiae and falsely detected minutiae relative to ground truth as well as the running time of one fingerprint on average for extracting minutiae of different methods in Table 3. In addition, by adjusting the threshold of the network, the precision vs recall curves are compared for different methods in Fig. 9. Our results show that the proposed ContactlessMinuNet achieves higher accuracy than other methods. For running time, our algorithm is faster than Verifinger and MinutiaeNet although it is slower than NIST mindct.

### Table 1
Computation requirements of different minutiae extraction methods.

| Method              | Least requirements       | Resources used in this paper          |
|---------------------|--------------------------|---------------------------------------|
| ContactlessMinuNet  | GPU with at least 8 GB memory | NVIDIA TITAN Xp GPU with 12 GB memory |
| Verifinger          | CPU                      | Intel Xeon CPU                        |
| NIST mindct         | CPU                      | Intel Xeon CPU                        |
| MinutiaeNet         | GPU with at least 11 GB memory | NVIDIA TITAN Xp GPU with 12 GB memory |

### Table 2
AUCs and EERs of network ablation studies on contactless fingerprint identification in Benchmark 2D/3D dataset.

| Method                        | AUC(%) | EER(%) |
|-------------------------------|--------|--------|
| ContactlessMinuNet            | 98.24  | 4.28   |
| Two-stage learning            | 96.65  | 5.36   |
| Without attention             | 95.53  | 6.68   |
| Change direction loss         | 92.63  | 9.03   |

### Fig. 6
ROC curves of network ablation studies on contactless fingerprint verification in Benchmark 2D/3D dataset.

### Fig. 7
CMC curves of network ablation studies on contactless fingerprint identification in Benchmark 2D/3D dataset.

### Fig. 8
The extracted minutiae features of two sample fingerprints by different methods: (a) Proposed method, (b) Verifinger SDK [16], (c) NIST mindct [15] and (d) MinutiaeNet [3]. The blue circle and arrow denote the ground truth location and direction, while red ones denote the extracted location and direction with different methods. The green rectangle labels the missing minutiae and green ellipse labels the spurious minutiae. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Table 3
Minutiae extraction accuracy of different methods on the Benchmark 2D/3D contactless fingerprint dataset.

| Method           | Precision (%) | Recall (%) | F1 score (%) | #Correct | #Missed | #False | Time (s) |
|------------------|---------------|------------|--------------|----------|---------|--------|----------|
| ContactlessMinuNet | 79.16         | 80.94      | 80.04        | 3361     | 791     | 884    | 0.86     |
| Verifinger       | 46.52         | 76.75      | 57.93        | 3187     | 965     | 3663   | 1.10     |
| NIST mindtct     | 40.65         | 63.30      | 49.51        | 2628     | 1524    | 3837   | 0.32     |
| MinutiaeNet      | 23.14         | 17.23      | 19.75        | 715      | 3436    | 2376   | 1.20     |

Table 4
AUCs and EERs of different minutiae extraction methods on contactless fingerprint verification with three datasets.

| Dataset            | Method          | AUC(%) | EER(%) |
|--------------------|-----------------|--------|--------|
| PolyU Cross dataset| ContactlessMinuNet | 99.33  | 1.94   |
|                    | Verifinger       | 98.16  | 2.99   |
|                    | NIST mindtct     | 68.91  | 36.85  |
|                    | MinutiaeNet      | 93.03  | 13.35  |
| Benchmark 2D/3D    | ContactlessMinuNet | 98.24  | 4.28   |
|                    | Verifinger       | 95.44  | 9.02   |
|                    | NIST mindtct     | 81.84  | 22.93  |
|                    | MinutiaeNet      | 79.74  | 26.34  |
| Our dataset        | ContactlessMinuNet | 97.47  | 5.15   |
|                    | Verifinger       | 94.36  | 8.34   |
|                    | NIST mindtct     | 61.69  | 46.56  |
|                    | MinutiaeNet      | 80.77  | 24.29  |

3.4. Results on contactless fingerprint recognition

In this section, we conduct experiments to test the proposed minutiae extraction method on the contactless fingerprints from the test sets of PolyU Cross dataset, Benchmark 2D/3D dataset and our dataset. Both the fingerprint verification and identification experiments are performed to evaluate the performance of the minutiae extraction method.

For fingerprint verification, Fig. 10 compares the ROC curves of different minutiae extraction methods on three datasets. Table 4 compares their corresponding AUCs and EERs. From Fig. 10, we can see that the ROC curve of proposed ContactlessMinuNet is higher than other methods for all three datasets. From Table 4, we can see that our proposed ContactlessMinuNet achieves 1.05%, 4.74% and 3.19% decrease in EER for PolyU Cross dataset, Benchmark 2D/3D dataset and our dataset, respectively, when comparing to Verifinger. These results show that our proposed method performs better than other methods on contactless fingerprint verification.

For fingerprint identification, Fig. 11 compares the CMC curves of different minutiae extraction methods with PolyU Cross dataset, Benchmark 2D/3D dataset and our dataset. We can see that the CMC curve of the commercial Verifinger is significantly higher than those of other two methods on all three datasets. Nevertheless, comparing to Verifinger, our proposed method achieves the obvious and consistent improvements of identification performance on the Benchmark 2D/3D dataset and our dataset, and small improvements of identification performance on the PolyU Cross dataset. The rank-one accuracies of our proposed method are 89.61% and 94.10% for Benchmark 2D/3D dataset and our dataset, which increase 7.79% and 2.04% comparing to Verifinger, respectively.

From the results, we can see that the improvements of verification and identification performances by our proposed method for PolyU Cross dataset are less than those for other two datasets when compared with the Verifinger. This may be caused by the good fingerprint image quality of PolyU Cross dataset. The contactless fingerprint images of PolyU Cross dataset have less pose and
Fig. 10. ROC curves of different minutiae extraction methods on contactless fingerprint verification with (a) PolyU Cross dataset, (b) Benchmark 2D/3D dataset and (c) our dataset.

Fig. 11. CMC curves of different minutiae extraction methods on contactless fingerprint identification with (a) PolyU Cross dataset, (b) Benchmark 2D/3D dataset and (c) our dataset.
Fig. 12. ROC curves of different minutiae extraction methods on contactless to contact-based fingerprint verification with (a) PolyU Cross dataset, (b) Benchmark 2D/3D dataset and (c) our dataset.

Fig. 13. CMC curves of different minutiae extraction methods on contactless to contact-based fingerprint identification with (a) PolyU Cross dataset, (b) Benchmark 2D/3D dataset and (c) our dataset.
contrast variances than other datasets. Verifier can achieve very high performance with 98.16% of AUC and 95.51% of the rank-one accuracy for this dataset. Thus, our proposed method can achieve small improvements when compared to Verifier on other two datasets.

3.5. Results on contactless to contact-based fingerprint recognition

In addition to work well on the contactless fingerprint recognition, it is also important to test our proposed method on matching between the contactless and contact-based fingerprints since there are a number of contact-based fingerprint database developed to protect national borders and support e-governance programs. Both the verification and identification experiments are conducted to test the effectiveness of contactless to contact-based fingerprint recognition. To improve the adaptiveness of our proposed method on contact-based fingerprints, we fine-tune the ContactlessMinuNet with the FVC 2002 DB1A [28] and FVC 2004 DB1A [29] datasets as well as the minutiae ground truths publicly available from [30]. For contactless to contact-based fingerprint recognition, our proposed ContactlessMinuNet is used to extract the minutiae of contactless fingerprints while the fine-tuned ContactlessMinuNet is used to extract the minutiae of contact-based fingerprints.

For contactless to contact-based fingerprint verification, we adopt the same protocol as [26] in the experiments. The matching between the first contact-based and the first contactless impressions for each finger is considered as genuine pairs, while the first contact-based impression of each finger is compared with the first contactless fingerprint of remaining fingers as imposter pairs. For PolyU Cross dataset, there are 200 genuine pairs and 39800 (200 × 199) imposter pairs. For Benchmark 2D/3D dataset, there are 1300 genuine pairs and 1,688,700 (1300 × 1299) imposter pairs. For our dataset, there are 100 genuine pairs and 9900 (100 × 99) imposter pairs. Fig. 12 compares the ROC curves of different minutiae extraction methods on three datasets. The comparisons of AUCs and EERs are shown in Table 5. From the results, we can see that the accuracy of contactless to contact-based fingerprint verification is lower than contactless fingerprint verification, while the ROC curve of proposed ContactlessMinuNet is significantly higher than other methods. Table 5 illustrates that proposed ContactlessMinuNet achieves 7.72%, 8.68% and 7.24% decrease in EER for three datasets, respectively, comparing with Verifier. The results prove the effectiveness for our proposed method.

For contactless to contact-based fingerprint identification, we set the first contact-based impression of each finger as the template fingerprint, while the first contactless impression of each finger as the query fingerprint. CMC curves of different minutiae extraction methods are compared with three datasets in Fig. 13. From these results, we can see that our proposed method can achieve impressive and consistent improvements than other methods for all three datasets. The rank-one accuracies increase from 45.50%, 47.32%, 35.04% by Verifier to 65.05%, 54.61%, 63.08% by our proposed method on PolyU Cross dataset, Benchmark 2D/3D dataset and our dataset, respectively.

3.6. Discussion

In the above sections, we have made the comprehensive comparison of our proposed method with three state-of-the-art fingerprint minutiae extraction methods in terms of both minutiae extraction accuracy and fingerprint recognition performances. Our results for contactless fingerprint minutiae detection indicates that our proposed ContactlessMinuNet has achieved better performances than other methods. Recently, a deep neural network-based approach called as ContactlessNet [7] was proposed for contactless fingerprint minutiae extraction. Since their source codes or trained model are not released and it is not easy to implement the method, we directly use the results reported in the paper for comparison as shown in Table 6. The ContactlessNet [7] was tested on the Benchmark 2D/3D dataset, PolyU Contactless Fingerprint dataset and another dataset acquired during their work for experiments. The Benchmark 2D/3D dataset is same as our test dataset, but the other two datasets are not released for download. Thus, we compare the results of precision, recall, F1 score, AUC, EER and rank-1 accuracy on the Benchmark 2D/3D dataset in Table 6. It is worthy to note that the criterion to calculate precision and recall in [7] is looser than that in our experiments. The predicted minutia is considered to be accurate if its distance error to ground truth minutia is less than 16 pixels in [7] while it is less than 12 pixels in our results. Nevertheless, our results are better than those in [7].

In addition to the accuracy, the generalization is also important for the deep network. To demonstrate the generalization ability of our proposed method, we perform the fingerprint verification experiments using open-set protocol. Specifically, we directly use the model trained with Benchmark 2D/3D dataset without fine-tuning to predict the minutiae on other two datasets, i.e., PolyU Cross dataset and our dataset. The training and testing datasets are not overlapped. Fig. 14 shows the ROC curves of different models trained with and without fine-tuning processes, and the corresponding AUCs and EERs are compared in Table 7. From the results, we can see that the recognition performances are reduced about 2.5-4.5% with the open-set protocol because of the different data distribution between the training and test datasets. Nevertheless, the results still show the good matching performances, which proves the generalization ability of the proposed method. The performances could be further improved by fine-tuning.

![Fig. 14. Comparison of ROC curves by the proposed method with open-set protocol and fine-tuning on PolyU Cross dataset and our dataset.](image-url)
4. Conclusion

In this paper, we have proposed a deep learning framework based on multi-task fully deep convolutional neural network for contactless fingerprint minutiae extraction. Different from the traditional two-stage minutiae extraction, the proposed method can jointly learn and predict the minutiae location and direction from the whole contactless fingerprints by multi-task learning. The proposed method can make use of features learned from the minutiae detection and direction computation tasks. In addition, attention mechanism and a new loss function are used to improve the prediction of minutiae direction. The proposed method operates directly on the gray scale contactless fingerprints without any image processing. We test the proposed method on three fingerprint datasets. Experimental results demonstrate that our proposed algorithm achieves better performances than other methods for minutiae extraction on both contactless and contact-based fingerprints.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] A. Jain, L. Hong, R. Bolle, On-line fingerprint verification, IEEE Trans Pattern Anal Mach Intell 19 (4) (1997) 302–314.
[2] A. Farina, Z.M. Kovacs-Vajna, A. Leone, Fingerprint minutiae extraction from skeletonized binary images, Pattern Recognit 32 (5) (1999) 877–889.
[3] D.-L. Nguyen, K. Cao, A.K. Jain, Robust minutiae extractor: integrating deep networks and fingerprint domain knowledge, in: 2018 International Conference on Biometrics (ICB), IEEE, 2018, pp. 5–16.
[4] A. Babouei, S. Soleymani, J. Dawson, N.M. Nasrabadi, Deep contactless fingerprint unwarping, in: 2019 International Conference on Biometrics (ICB), IEEE, 2019, pp. 1–8.
[5] X. Yin, Y. Zhu, J. Hu, Contactless fingerprint recognition based on global minutia topology and loose genetic algorithm, IEEE Trans. Inf. Forensics Secur. 15 (2019) 28–41.
[6] X. Yin, J. Hu, J. Xu, Contactless fingerprint enhancement via intrinsic image Decomposition and Guided Image Filtering, in: 2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), IEEE, 2016, pp. 144–149.
[7] H. Tan, A. Kumar, Towards more accurate contactless fingerprint minutiae extraction and pose-invariant matching, IEEE Trans. Inf. Forensics Secur. 15 (2020) 3924–3937.
[8] R. Bansal, P. Sehgal, P. Bedi, Effective morphological extraction of true fingerprint minutiae based on the hit or miss transform, International Journal of Biometrics and Informatics (IJBBI) 4 (2) (2010) 71.
[9] A. Sankaran, P. Pandey, M. Vaica, R. Singh, On latent fingerprint minutiae extraction using stacked denoising sparse autoencoders, in: IEEE International Joint Conference on Biometrics, IEEE, 2014, pp. 1–7.
[10] L. Jiang, T. Zhao, C. Bai, A. Yong, M. Wu, A Direct Fingerprint Minutiae Extraction Approach Based on Convolutional Neural Networks, in: 2016 International Joint Conference on Neural Networks (IJCNN), IEEE, 2016, pp. 571–578.
[11] Y. Tang, F. Gao, J. Feng, Y. Liu, Fingerprint: an unified deep network for fingerprint minutiae extraction, in: 2017 IEEE International Joint Conference on Biometrics (IJCB), IEEE, 2017, pp. 108–116.
[12] L. Hong, Y. Wang, A. Jain, Fingerprint image enhancement: algorithm and performance evaluation, IEEE Trans Pattern Anal Mach Intell 20 (8) (1998) 777–789.
[13] L.N. Darlow, B. Rosman, Fingerprint minutiae extraction using deep learning, in: 2017 IEEE International Joint Conference on Biometrics (IJCB), IEEE, 2017, pp. 22–30.
[14] C. Lin, A. Kumar, A cnn-based framework for comparison of contactless to contact-based fingerprints, IEEE Trans. Inf. Forensics Secur. 14 (3) (2018) 662–676.
[15] C.L. Watson, M.D. Garris, E. Tabassi, C.L. Wilson, R.M. McCabe, S. Janet, K. Ko, User’s guide to nist biometric image software (nibs).
[16] Neurotechnology verifier sdk. https://www.neurotechnology.com/verifier.html.
[17] A. Newell, K. Yang, J. Deng, Stacked hourglass networks for human pose estimation, in: European conference on computer vision, Springer, 2016, pp. 483–499.
[18] W. Shi, J. Caballero, F. Huszár, J. Totz, A.P. Aitken, R. Bishop, D. Rueckert, Z. Wang, Real-time single image and video super-resolution using an efficient sub-pixel convolutional Neural network, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 1874–1883.
[19] H. Fukui, T. Hirakata, T. Yamashita, H. Fujiiyoshi, Attention branch network: learning of attention mechanism for visual explanation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 10705–10714.
[20] T.-Y. Lin, P. Goyal, R. Girshick, K. He, P. Dollár, Focal loss for dense object detection, in: Proceedings of the IEEE international conference on computer vision, 2017, pp. 2980–2988.
[21] B. Zhou, C. Han, Y. Liu, T. Guo, J. Qin, Fast minutiae extractor using neural network, Pattern Recognit 103 (2020) 107273.
[22] K. He, X. Zhang, S. Ren, J. Sun, Delving deep into rectifiers: surpassing human-level performance on imagenet classification, in: Proceedings of the IEEE international conference on computer vision, 2015, pp. 1026–1034.
[23] D.P. Kingma, J. Ba, Adam: A method for stochastic optimization, ArXiv preprint arXiv:1412.6980.
[24] V. Dumoulin, F. Visin, A guide to convolution arithmetic for deep learning, ArXiv preprint arXiv:1603.07285.
[25] C. Lin, A. Kumar, Matching contactless and contact-based conventional fingerprint images for biometrics identification, IEEE Trans. Image Process. 27 (4) (2018) 2008–2021.
[26] W. Zhou, J. Hu, I. Petersen, S. Wang, M. Bennamoun, A benchmark 3D fingerprint database, in: 2014 11th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), IEEE, 2014, pp. 935–940.
[27] R. Cappelli, M. Ferrara, D. Maltoni, Minutia cylinder-code: a new representation and matching technique for fingerprint recognition, IEEE Trans Pattern Anal Mach Intell 32 (12) (2010) 2128–2141.
[28] D. Maio, D. Maltoni, R. Cappelli, J.L. Wayman, A.K. Jain, Fvc2002: Second Fingerprint Verification Competition, in: Object recognition supported by user interaction for service robots, Vol. 3, IEEE, 2002, pp. 811–814.
[29] D. Maio, D. Maltoni, R. Cappelli, J.L. Wayman, A.K. Jain, Fvc2004: third fingerprint verification competition, in: International conference on biometric authentication, Springer, 2004, pp. 1–7.
[30] M. Kayaoglu, B. Topcu, U. Uludag, Standard fingerprint databases: Manual minutiae labeling and matcher performance analyses, ArXiv preprint arXiv:1305.1443.

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