# Latent Fingerprint Image Enhancement Based on Progressive Generative Adversarial Network

Xijie Huang, Peng Qian, Manhua Liu
Department of Instrument Science and Engineering, School of EIEE
Shanghai Jiao Tong University, Shanghai, China
{otaku_huang, qianpeng_1996, mhliu}@sjtu.edu.cn

## Abstract

*Latent fingerprints, a kind of fingerprints which are captured from the finger skin impressions at the crime scene, have been adopted to identify suspected criminals for a long time. However, poor latent fingerprint image quality owing to unstructured overlapping patterns, unclear ridge structure, and various background noise has brought a challenge to the recognition of latent fingerprints. Therefore, image enhancement is a crucial step for more accurate fingerprint recognition. In this paper, a latent fingerprint enhancement method based on the progressive generative adversarial network (GAN) is proposed. The powerful GAN structure provides an efficient translation from latent fingerprint to high-quality fingerprint. Our method consists of two stages: Progressive Offline Training (POT) and Iterative Online Testing (IOT). Progressive training makes our model not only focus on the local features such as minutiae but also preserve structure feature such as the orientation field. We extensively evaluate our model on NIST SD27 latent fingerprint dataset. With the help of orientation estimation task and progressive training scheme, our model achieves better recognition accuracy.*

## 1. Introduction

Fingerprints are one of the most important and reliable biometric modalities because of the characteristic that a person can be uniquely identified via it. Latent fingerprints, which are captured from the finger skin impressions unintentionally left at the crime scene by accident, are very useful in law enforcement and forensics applications. Latent fingerprint is a representative type of low-quality fingerprint. Compared to the rolled and plain fingerprints which are collected under controlled condition, latent fingerprints usually suffer from poor ridge structure and overlapping unstructured noise [9, 2]. Fig. 1 gives examples of latent, rolled, and plain fingerprint respectively.

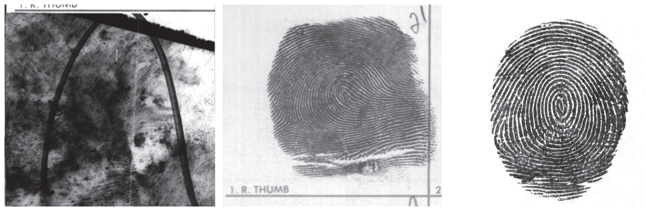

Figure 1. Examples of latent, rolled, and plain fingerprint images (from left to right), which are selected from NIST SD27 [5] dataset, NIST SD14 [21] dataset, and latent overlapped fingerprint dataset [3] respectively.

The Automated Fingerprint Identification Systems (AFIS [11]) have been widely adopted for fingerprints identification. Although AFIS achieves promising accuracy on plain and rolled fingerprints, the performance is still not satisfied for latent fingerprint images. As a result of the poor image quality of these fingerprint images, most of the common feature extraction techniques often fail to accurately extract useful features. To tackle these problems, fingerprint image enhancement is an important processing step to reduce the noise, recover the corrupted regions and improve the clarity of the ridge structure. When latent fingerprint images are enhanced, more efficient and accurate feature extraction is facilitated for better fingerprint matching and identification performance.

Classic fingerprint image enhancement methods focus on how to separate noise from the meaningful ridge pattern and remove it. Information in the frequency domain and orientation field are widely used because the orientation and frequency characteristics of noise are different from the ridge pattern part, which makes it easier to enhance the useful region.

During the past few decades, we have entered a new era and witnessed a huge revolution of artificial intelligence. Among all the breakthrough of artificial intelligence techniques, Deep neural networks (DNNs) achieved state-of-the-art performance in many image recognition and un-

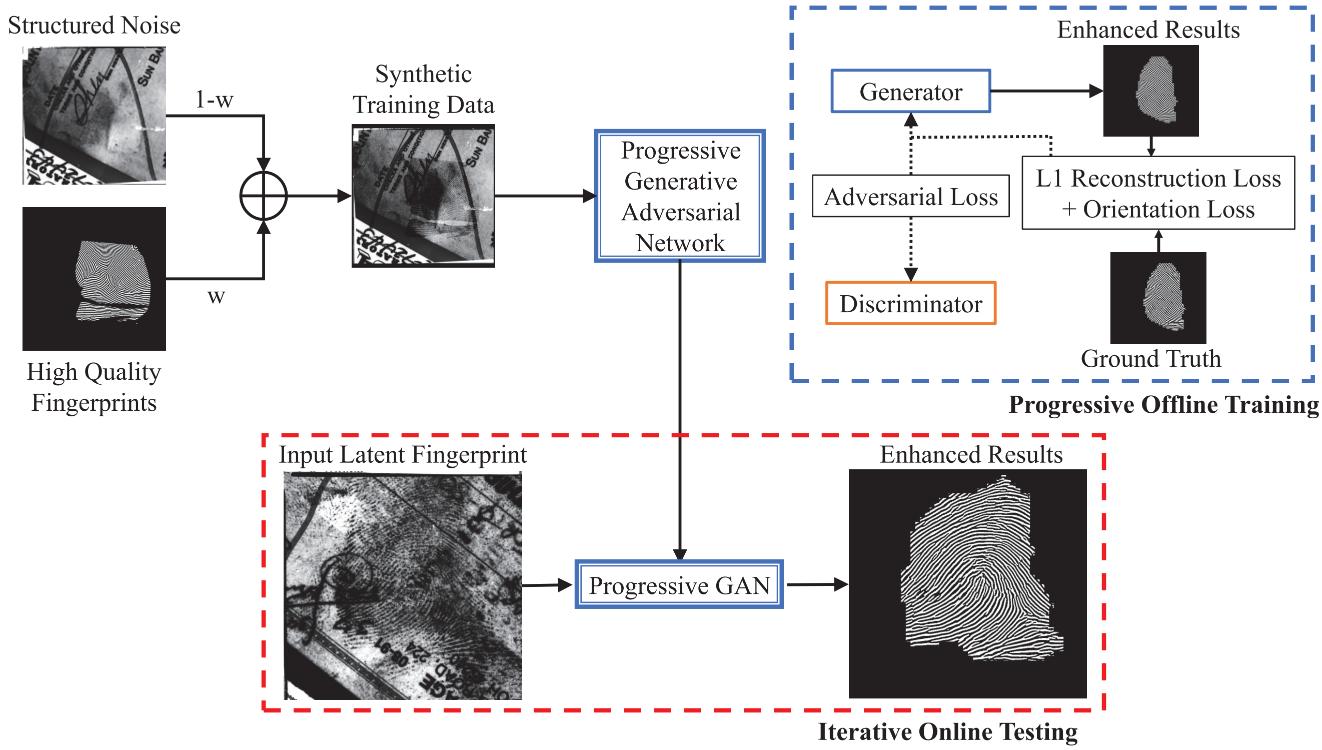


Figure 2. The flowchart of our progressive generative adversarial network based model. Our method can be divided into two stages: Progressive Offline Training (POT) and Iterative Online Testing (IOT). In the POT stage, the dashed lines denote the loss backpropagation path when training our GAN progressively. In IOT stage, the latent fingerprint images are enhanced by the GAN model.

derstanding applications, such as object detection [7] and face recognition [19]. Among all kinds of DNNs, Convolutional Neural Networks (CNNs) have been most widely used in image processing tasks, including image enhancement. Since LeCun et al. proposed the first CNN structure [13] and applied it to zip code recognition. Different CNNs have been emerging. Zhang et al. [27] proposed DnCNN model to handle blind Gaussian denoising with the residual learning strategy. Following the flourish of deep learning based image denoising and image restoration, latent fingerprint enhancement based on the deep neural network has also been a hot research topic recently.

Motivated by the idea that orientation estimation and fingerprint enhancement can share representation in the deep neural network, we proposed a multi-task based progressive generative adversarial network (PGAN) model. In our model, latent fingerprint enhancement can be denoted as an image-to-image translation problem and powerful representation capacity of a deep generative adversarial network can be applied to this task. The method we proposed can be decomposed into two stages: Progressive Offline Training (POT) and Iterative Online Testing (IOT). The deep GAN model is trained on POT stage and then is applied to IOT stage. The flowchart of our method is illustrated in Fig. 2.

In the POT stage, our GAN is trained with paired data. To generate the paired data of latent fingerprint and corresponding high-quality fingerprint, we simulate the latent fingerprint synthetically combining the noise and high-quality fingerprint images. Another problem is that generating performance of GAN is poor on high-resolution images and suffers from checkboard artifacts. This is because the generator of GAN follows an encoder-decoder structure, where deconvolution is applied in the decoder. To solve the problem, the progressive growing of GAN arise applied in the training process which can effectively boost the stability and performance of GAN.

In the IOT stage, the segmented latent fingerprint is input into the GAN trained in the POT stage. Generally, a fingerprint image after a single iteration of the image translation still suffers from unstructured noise. To solve this problem, we iteratively enhance the image until the fingerprint image quality achieves a satisfying result. In the latter iteration, the restored high-quality region can be good guidance for the enhancement of remaining low-quality regions.

To show the effectiveness and efficiency of our method, we extensively evaluate our model on NIST SD27 latent fingerprint dataset. From the Cumulative Match Characteristic (CMC) curve on NIST SD27 and three subsets, we can see our progressive GAN based method outperforms the previous model by a great margin. The key contribution of this paper can be summarized as follows:

- We propose a generative adversarial network based latent fingerprint enhancement method, which consists os two stages: Progressive Offline Training (POT) and Iterative Online Testing (IOT).
- We propose a progressive training method to boost the stability and performance of GAN, and propose a multi-task training method to fully exploit the information of the orientation field.
- We evaluate our model on NIST SD27 latent fingerprint dataset and show the Cumulative Match Characteristic (CMC) curve on NIST SD27 and three subsets.
- We compare our model with state-of-the-art latent fingerprint enhancement methods. Our results are better than other enhancement methods in terms of both effectiveness and efficiency.

# 2. Related Works

## 2.1. Latent fingerprint enhancement

To enhance the latent fingerprint images, Gabor filtering is proposed by Lin et al [8]. As the fingerprint consists of interleaved parallel ridge and valley flows with well-defined frequency and orientation, Gabor filtering can make full use of this information. Gabor filter can be defined as a sinusoidal plane wave tapered by a Gaussian to capture the periodic and non-stationary nature of fingerprint regions, which achieve promising effects on the improvement of ridge clarity [22].

Although Gabor filtering can improve the ridge clarity to some extent, it fails to restore the ridge structure influenced by unstructured noise precisely. To tackle this problem, the Global dictionary [4] was proposed to improve the accuracy of orientation field estimation. Liu et al. [15] proposed multi-scale patch based sparse representation with dictionaries. In their work, the dictionaries are made up of a set of Gabor elementary functions and the multi-scale sparse representation is applied to reconstruct high-quality fingerprint.

An image can be decomposed into the cartoon part and texture part according to the total variation (TV) model. To exploit this cue, image decomposition based on minimization of total variation has been researched to enhance the latent fingerprint images [26, 25]. The core idea of the TV model is that the texture component represents a meaningful structure of the image while the cartoon component is characterized as non-repeated structured noise. We can remove the cartoon component of the fingerprint image and keep the texture component as the enhanced result. Zhang et al. proposed an adaptive directional total variation (ADTV) model [26] to improve the effectiveness of fingerprint segmentation and enhancement. However, it is difficult to accurately restore the ridge pattern as cartoon component of the fingerprint image also contains some meaningful fingerprint pattern information. As a result, the enhanced fingerprint pattern is weak and suffers from missing information, which will lead to the poor performance of fingerprint matching and identification.

Moving to the era of deep learning, more learning-based latent fingerprint enhancement methods, especially CNN-based enhancement method are much more widely adopted. Cao and Jain [1] put forward orientation estimation as a classification problem and used the CNN for fingerprint orientation estimation. Inspired by their work, FingerNet [14] is proposed by Li et al. Following the pixels-to-pixels and end-to-end learning manner, FingerNet is a deep convolutional neural network based method to enhance latent fingerprints and achieve state-of-the-art accuracy on a various dataset. More recently, Qian et al. proposed a DenseUNet based latent fingerprint enhancement model [17]. In their work, they generate the paired training data with the aid of a TV model to separate structured noise. Skip connections are used in DenseUNet architecture which boosts the representation power of the network. Also, they use a quality control module as a switch of iterative testing, which effectively helps remove the noise in the latent fingerprint images.

## 2.2. Generative Adversarial Network

As one of the most important breakthroughs of deep learning recently, generative adversarial network (GAN) has achieved significant improvement in many computer vision tasks including image generation [6] and image-to-image translation [10, 28]. GAN is composed of two parts: generator $G$ and discriminator $D$. Discriminator $D$ learn to distinguish real sample and generated sample generated by generator $G$ while generator $G$ learn to "fool" the discriminator $D$.

Follow the core idea of GAN, researchers have attempted to improve fingerprint enhancement by the generative adversarial network. Svoboda et al. [20] are the first to use the generative network to predict the missing parts of the ridge pattern. More recently, COOGAN [16] is proposed to utilize the supervision of orientation and quality and achieve state-of-the-art performance on the NIST SD27 dataset. These approaches bring a new direction for latent fingerprint enhancement.

# 3. Proposed Method

In this section, we will first define the latent fingerprint enhancement problem and describe how to apply conditional GAN (cGAN) to the enhancement task. Then we will show the network architecture and some important hyper-parameter of our progressive GAN. Finally, the details of the progressive training of GAN will be given.

### 3.1. Problem Formulation

Latent fingerprint enhancement involves translating the original latent fingerprint images into high-quality fingerprint with a clear ridge structure. So it can be formulated as an image-to-image translation problem [10]. Our goal can be denoted as learning a mapping $f : D_L \rightarrow D_E$, where $D_L$ represents the latent fingerprint domain and $E$ represents the target domain where enhanced fingerprint lie in.

Generative adversarial networks can map a sample from a random distribution $P_{data}$ to the target domain. The generator $G$ is supervised by reconstruction loss (i.e. L1 or L2 loss) with corresponding ground truth in the domain $E$. Meanwhile, the discriminator $D$ learns to discriminate the generated sample from $G$ and the ground truth from the target domain. The generator $G$ tries to maximize the possibility of discriminator $D$ making a mistake [6]. The objective function can be denoted as:

$$\begin{aligned} L_{GAN} = E_{x \sim p_{data}}&[log(D(x))] \\ + E_{x \sim p_{data}}&[log(1 - D(G(x)))] \end{aligned} \tag{1}$$

In our application of latent fingerprint enhancement, the source domain is the given latent fingerprint rather than a random distribution. The input of the generator is real samples of latent fingerprint images. Also, the input sample serves as a condition of the discriminator. As the discriminator takes both the enhanced fingerprint generated by G and the ground truth of the high-quality fingerprint, the $G$ should learn to preserve the details and remove the noise to fool the discriminator $D$.

### 3.2. Generative Adversarial Network Architecture

Our proposed generative adversarial network is made up of generator and discriminator. An overview of the proposed GAN architecture is depicted in Fig. 3. The input of the generator is the original latent fingerprint image and the corresponding manually labeled segmentation, the output is the enhanced fingerprint image and the orientation field estimation. Then the output of the generator and the corresponding ground truth (ground truth fingerprint and orientation field) is input into the discriminator. The output of the PacthGAN discriminator is a probability map of the same size as the number of patches.

**Generator** The generator we use is a ”U-Net” structure [18]. In the ”U-Net” generator, there are skip connections connecting $i$th Conv layer and $n - i$th Deconv layer. The skip connection can pass the feature between the encoder and decoder which will help the preservation of the details such as ridge pattern. In our work, the kernel size of the Conv and Deconv layer is set to be 5×5 and the strides are set to be 1×1. The activation we use is ReLu activation. To suppress the noise in the image, the feature extracted by the Conv layer should be abstract, which requires the receptive field to be large. We also replace the pooling and unpooling layers with the Conv and Deconv layers. The kernel size of these layers is set to be 2×2 and the stride is also set to be 2×2. These Conv and Deconv layers have the same function of pooling and unpooling layers while learning more abstract representation. The output of the generator is the enhanced fingerprint image and the estimated orientation field.

**Discriminator** The discriminator we use is a ”Patch-GAN” [10] structure CNN classifier. Rather than output a single value of the possibility of true or fake, PatchGAN output a probability map. Each value in the map represents the probability of a single patch in the image. This architecture can help recover texture and preserve the details in the high-resolution image. The patch size we use is 70×70.

### 3.3. Objective Function

To train our generative adversarial network, the objective function should be given. In the proposed model, the loss function consists of three parts: adversarial loss, reconstruction loss, and orientation loss.

**Adversarial Loss** The objective function of GAN has been shown in Equ. 1. In the backpropagation process during the training, both the generator $G$ and discriminator $D$ minimize the adversarial loss. The generator will be penalized if the generated image is correctly identified. In our latent fingerprint enhancement application, we are using a conditional generative adversarial network (cGAN). Thus, the loss function should be modified as

$$\begin{aligned} L_{cGAN}(G, D, x) = E_{(x,y) \sim p(x,y)}&[log(D(x, y))] \\ + E_{x \sim p_x(x)}&[log(1 - D(x, G(x)))]. \end{aligned} \tag{2}$$

**Reconstruction Loss** The generator $G$ can translate latent fingerprint $x$ into enhanced high-quality fingerprint $y$, while the ground truth high-quality fingerprint is $y^*$. Reconstruction loss aims to preserve the similarities between the enhanced image and the corresponding ground truth. We use the L1 loss as the reconstruction loss, which can be formulated as:

$$L_{l_1}(G, x, y^*) = \|y^* - G(x)\| . \tag{3}$$

**Orientation Loss** Our model follows a multi-task learning scheme: generating enhanced fingerprint and output the

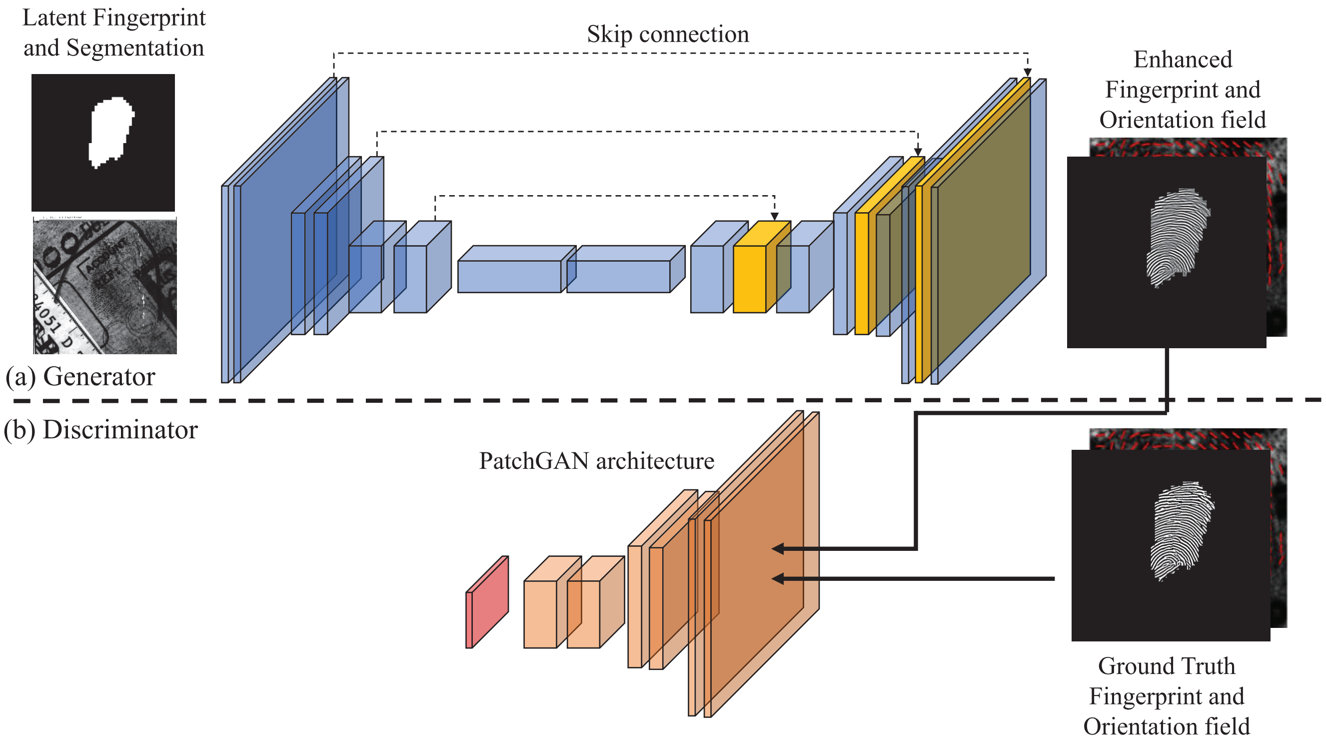


Figure 3. Generative Adversarial Network architecture. In the generator, each cuboid pair of the same size in the encoder part represents two consequent "Conv+Relu" layers. Each cuboid triple of the same size in the decoder represents two consequent "Deconv+Concat+Relu" layers, among which the concatenate layers are shown in yellow. The skip connection is between the $i$th Conv layer and $n-i$th Deconv layer. The output of the generator is the enhanced fingerprint image and the estimated orientation field. In discriminator, we use the PatchGAN architecture the same as pix2pix [10]. The output of discriminator is a probability map.

orientation field estimation. Since the orientation estimation and fingerprint enhancement share the same representation in the neural network, the multi-task learning from end to end can abstract more meaningful features than a single task. To reduce the dimension of the orientation feature, we down-sample the orientation field feature map and the corresponding ground truth generated by a gradient-based method same as [14]. For each patch with a given size, the neural network can predict an angle value in the range of $180°$, which makes up the estimation field $o_e$. If the ground truth orientation field is $o_g$, the orientation loss can be denoted as the cross-entropy (CE) between the estimated and ground-truth orientation field:

$$L_{ori}(o_e, o_g) = CE(o_e, o_g) = -\sum_i o_{g_i} log(o_{e_i}). \quad (4)$$

**Total Loss** Combining these three loss function, we can define our total loss as

$$L_{total} = L_{cGAN} + \lambda_1 L_{l_1} + \lambda_2 L_{ori}, \quad (5)$$

where $\lambda_1$ and $\lambda_2$ are weighing coefficient used to balance between the different components. Therefore, our training goal is to optimize the objective function:

$$G_{opt} = \min_G \max_D L_{total}. \quad (6)$$

### 3.4. Progressive Training

The progressive growing training of GAN is proposed by Karras et al [12]. The core idea of progressive training is to start training from a low-resolution and add new layers to the model increasingly. This training method can significantly stabilize the training of GAN. In our work, the input image is 816×816, which possesses a relatively high resolution. When training an image translation GAN on such high resolution, the generated image quality is low and the loss is hard to converge. To tackle these problems, progressive training is introduced in our latent fingerprint application. The process of progressive training is shown in Fig. 4.

As can be seen in Fig. 4, we first start training our GAN at a small scale with only a few Conv and Deconv layers. The spatial resolution of the first step is 22×22. The original training data is down-sampled into this resolution. After some iteration, we add a new Conv and a new Deconv layer to the two ends of the generator, add a new Conv layer to the discriminator. In the second step, the spatial resolution

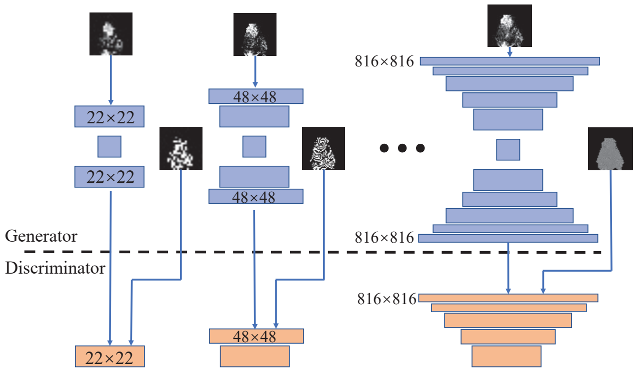


Figure 4. Progressive growing training of GAN. The blue rectangle represents the generator and the orange rectangle represents the discriminator. The training process is from left to right. The number $N \times N$ in the figure represent the spatial resolution of the input or the output.

is 48×48. After adding new layers for 5 times, the input resolution is 816×816, which is the spatial resolution of our generated data.

The model is trained on 30000 pairs of latent fingerprints and their corresponding ground truth. How to generate the training data will be disscussed in section 4.1. The optimizer we use is Adam Optimizer with learning rate 1e-4, $\beta_1$=0.9, and $\beta_2$=0.999. In the progressive growing stage, the GAN is trained for 1 epoch for each network scale and spatial resolution. After the growing training is completed, the GAN model is already converged. We further train the GAN for 3 epochs. The batch size is 8 and whole training process is finished on a single NVIDIA 1080Ti GPU in 10 hours.

## 4. Experiments and Results

### 4.1. Dataset

The dataset used in this work is collected or generated from NIST SD27 [5] and NIST SD14 [21]. The training set contains 30000 synthetic fingerprint images generated by combining noise from NIST SD27 and high-quality fingerprint from NIST SD14. The testing set contains 258 latent fingerprint images from NIST SD27.

It requires a large amount of paired training data to train a generative adversarial network from scratch. In our work, the paired training data includes the latent fingerprints and the corresponding enhanced images and segmentation masks. However, there is no publicly available database consisting of pairs of low quality latent and high quality enhanced fingerprint images for training. In addition, the number of available latent fingerprint images is limited comparing to rolled and plain fingerprint images. In NIST SD27 latent fingerprint dataset, there are merely 258 latent images and their corresponding template fingerprints. As a result, it is more widely accepted to use NIST SD27 as the test images dataset rather than the training dataset. To tackle the problem of training data scarcity, a solution is to synthetically generate the latent fingerprints by simulating the conditions in which a latent fingerprint is typically acquired such as in different overlapping patterns and backgrounds. Fig. 2 illustrates the process of generating paired training data for latent fingerprint enhancement. This procedure generally includes the generation of latent fingerprints and their corresponding enhancement ground truth, which are obtained with the good quality fingerprints from which the latent fingerprint are simulated. The samples in the training set simulate the structured noise and can represent the latent fingerprints acquired environment. Fig. 5 gives some examples of generated training data.

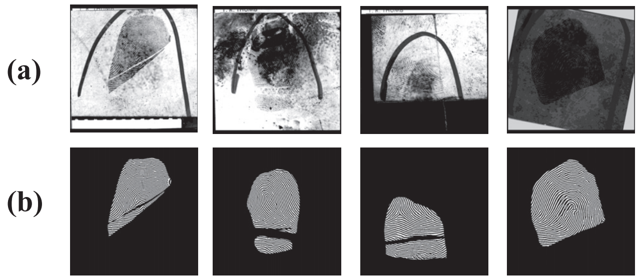


Figure 5. Examples of: (a) the generated Latent fingerprint images (b) enhanced binary fingerprints.

**Latent Fingerprint Generation** To generate the latent fingerprints, we simulate the conditions under which the latent fingerprints are usually captured by adding different noises and backgrounds into good quality fingerprints. Specifically, we synthetically add the high quality fingerprints with the structured noises to generate the latent fingerprints for training. Instead of NIST SD27, we use NIST SD14 to prepare the good quality fingerprints. NIST SD14 consists of 27,000 pairs of rolled fingerprints with various fingerprint types. We manually check and choose 200 high quality fingerprints from NIST SD14. Besides, we decompose the latent images of NIST SD27 into texture and cartoon components using the TV method [24] to simulate the various noise of latent images. The structured noises are obtained from the cartoon components.

After we have the noise pattern and high-quality fingerprint, the simulated fingerprint $I_l$ can be a linear combination as follows:

$$I_l = w \times I_g + (1 - w) \times I_s, \tag{7}$$

where $I_g$ represents the good quality fingerprint and $I_s$ is the decomposed noise pattern from the TV model. Weighting coefficient $w$ varies from 0.3 to 0.7 for whole patch noise. For data augmentation, we also add varying levels of Gaussian noise to the generated latent fingerprint and make some shifts and rotations of them. The final generated latent fingerprint images are of a size $816 \times 816$. Fig. 5 (a) shows some examples of generated latent fingerprint images.

The size of each fingerprint images in NIST SD27 is $768 \times 800$ pixels and we use image padding to change the size into $816 \times 816$ which is more suitable for training. Finally, we generate 30,000 pairs of latent fingerprint images and their corresponding binarized enhancement ground truth.

## 4.2. Evaluation Metrics

The ultimate goal for latent fingerprint enhancement is to improve the clarity of useful details and suppress various noises from the image for better recognition accuracy. Therefore, we can evaluate the effectiveness of our model using the accuracy of fingerprint identification. The matching database contains 258 fingerprints from NIST SD27 and 27000 fingerprints from NIST SD14. We use commercial fingerprint matchining software VeriFinger SDK 4.3 (https://www.neurotechnology.com/) for the feature extraction and matching. VeriFinger is commonly used by previous work and we can compare our model with the previous methods in the same environment. We use Cumulative Match Characteristic (CMC) curves to show the enhancement effectiveness of our model.

## 4.3. Results

We design some ablation experiments to evaluate the effectiveness of our method and compare the proposed enhancement method with previous methods. The first experiment is to test the effectiveness of the multi-task learning scheme and progressive growing training. In this experiment, we compare the proposed multi-task learning scheme with those without orientation estimation and progressive training as well as the raw image. From the results shown in Fig. 6 we can see that orientation estimation tasks and progressive growing training schemes can improve the re-

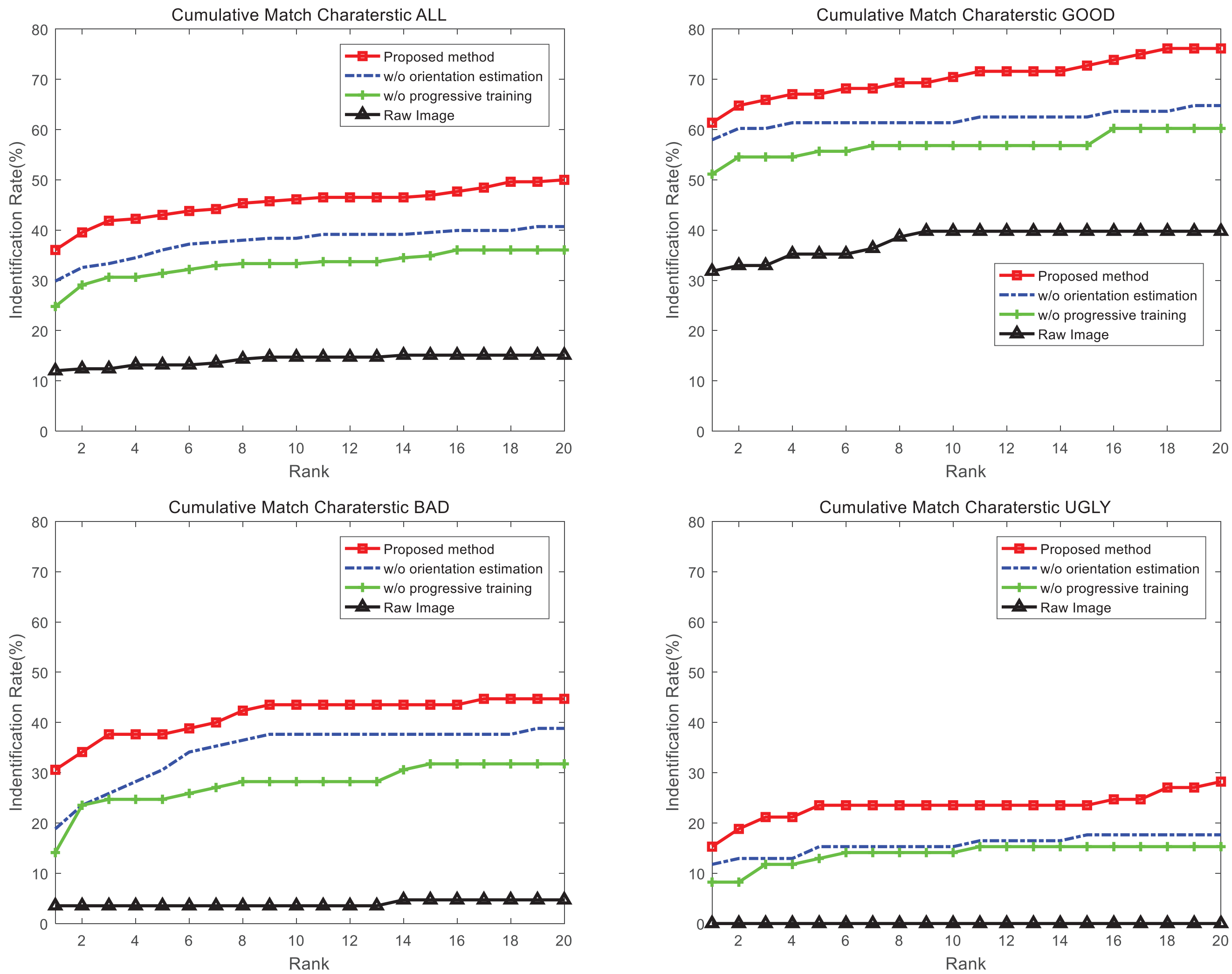


Figure 6. Ablation study experiment results on Orientation estimation task and Progressive growing training scheme

sults.

In addition, the second experiment is performed to compare the results with and without the iterative testing. Our iterative online testing (IOT) stage aims to iteratively enhance the latent fingerprint to make sure that the noise is removed as much as possible. From the enhancement results comparision shown in Fig. 7, we can see that the ridge pattern of an iteratively enhanced fingerprint is clearer and noise is removed to a greater extent.

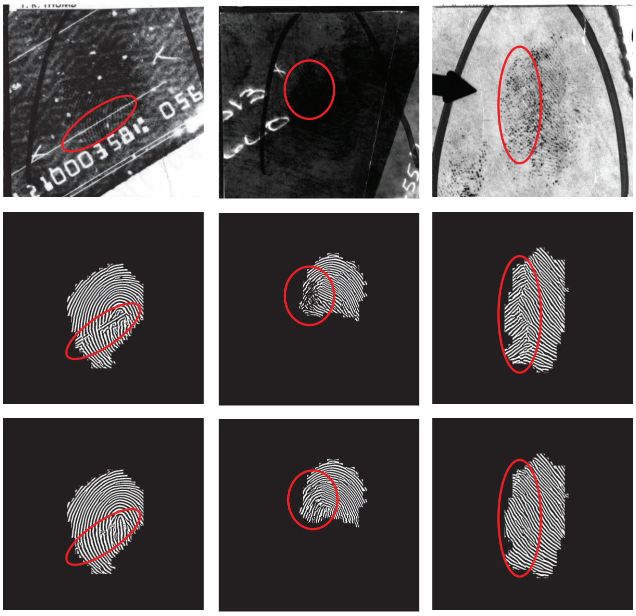

Figure 7. Ablation study on iterative online testing. Each column represents a sample from the three subsets from NIST SD27. The first, second, and third rows are the original latent fingerprint, the enhancement results without iteration, and the enhancement results with iteration resepectively. The red circle denotes the significant improvement of iterative testing.

Finally, we compare our proposed method to other methods published in the literature [17, 14, 4]. These methods were also tested on the NIST 27 database. We directly used the results reported in the literatures for comparison. The Cumulative Match Characteristic (CMC) curves comparsion on our test set are shown in Fig. 8. From the results we can see that our progressive GAN based method performs better than other enhancement algorithms significantly.

#### 4.3.1 Efficiency

To look into the efficiency of our method, we compare the test time for each image in different methods in the same configuration. As we can see in Tab. 1, our progressive GAN based method has a significant boost in efficiency over the previous methods. The high efficiency of our iterative online testing makes it possible for a more efficient realtime fingerprint identification system.

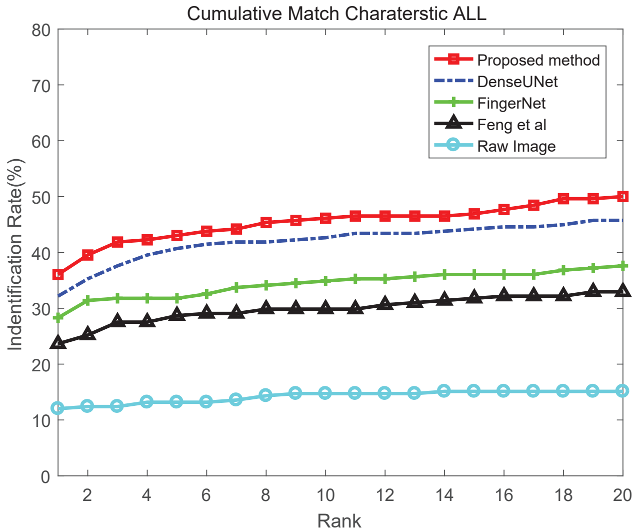


Figure 8. CMC curves comparing our method with previous latent fingerprint enhancement method DenseUNet [17], FingerNet [14], method proposed by Feng et al. [4], and the raw image.

Table 1. Test time per image

| Method | Computation time (sec) |
|---|---|
| ADTV [26] | 58.2 |
| Localized Dict [23] | 8.6 |
| Ours | 0.034 |

## 5. Conclusion

In this paper, we propose a GAN based latent fingerprint enhancement method. Our method is inspired by the multi-task learning and progressive growing training of GAN. Firstly, we give the problem formulation and define the latent fingerprint enhancement as an image-to-image translation problem. Then we design the multi-task GAN network to fully exploit the shared representation between orientation estimation and enhancement. Additionally, we propose a progressive growing training scheme which stabilizes the training of GAN. To show the effectiveness of our method, we evaluate our model on the NIST SD27 dataset and apply the enhanced result to the fingerprint matching application. The results shows that our method performs better than other methods.


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## References


[1] Kai Cao and Anil K Jain. Latent orientation field estimation via convolutional neural network. In *2015 International Conference on Biometrics (ICB)*, pages 349–356. IEEE, 2015.

[2] Tarang Chugh, Kai Cao, Jiayu Zhou, Elham Tabassi, and Anil K Jain. Latent fingerprint value prediction: Crowd-based learning. *IEEE Transactions on Information Forensics and Security*, 13(1):20–34, 2017.

[3] Jianjiang Feng, Yuan Shi, and Jie Zhou. Robust and efficient algorithms for separating latent overlapped fingerprints. *IEEE Transactions on Information Forensics and Security*, 7(5):1498–1510, 2012.

[4] Jianjiang Feng, Jie Zhou, and Anil K Jain. Orientation field estimation for latent fingerprint enhancement. *IEEE transactions on pattern analysis and machine intelligence*, 35(4):925–940, 2012.

[5] Michael D Garris and Michael D Garris. *NIST special database 27: Fingerprint minutiae from latent and matching tenprint images*. US Department of Commerce, National Institute of Standards and Technology, 2000.

[6] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[8] Lin Hong, Yifei Wan, and Anil Jain. Fingerprint image enhancement: algorithm and performance evaluation. *IEEE transactions on pattern analysis and machine intelligence*, 20(8):777–789, 1998.

[9] Suspect Identifies. A history of fingerprinting and criminal identijication, 2002.

[10] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1125–1134, 2017.

[11] Anil K Jain, Karthik Nandakumar, and Arun Ross. 50 years of biometric research: Accomplishments, challenges, and opportunities. *Pattern Recognition Letters*, 79:80–105, 2016.

[12] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*, 2017.

[13] Yann LeCun, Bernhard Boser, John S Denker, Donnie Henderson, Richard E Howard, Wayne Hubbard, and Lawrence D Jackel. Backpropagation applied to handwritten zip code recognition. *Neural computation*, 1(4):541–551, 1989.

[14] Jian Li, Jianjiang Feng, and C-C Jay Kuo. Deep convolutional neural network for latent fingerprint enhancement. *Signal Processing: Image Communication*, 60:52–63, 2018.

[15] Manhua Liu, Xiaoying Chen, and Xiaoduan Wang. Latent fingerprint enhancement via multi-scale patch based sparse representation. *IEEE Transactions on Information Forensics and Security*, 10(1):6–15, 2014.

[16] Yuhang Liu, Yao Tang, Ruilin Li, and Jufu Feng. Cooperative orientation generative adversarial network for latent fingerprint enhancement. In *2019 International Conference on Biometrics (ICB)*, pages 1–8. IEEE, 2019.

[17] Peng Qian, Aojie Li, and Manhua Liu. Latent fingerprint enhancement based on denseunet. In *2019 International Conference on Biometrics (ICB)*, pages 1–6. IEEE, 2019.

[18] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[19] Yi Sun, Ding Liang, Xiaogang Wang, and Xiaoou Tang. Deepid3: Face recognition with very deep neural networks. *arXiv preprint arXiv:1502.00873*, 2015.

[20] Jan Svoboda, Federico Monti, and Michael M Bronstein. Generative convolutional networks for latent fingerprint reconstruction. In *2017 IEEE International Joint Conference on Biometrics (IJCB)*, pages 429–436. IEEE, 2017.

[21] Craig I Watson. Nist special database 14. nist mated fingerprint card pairs 2 (mfcp2). Technical report, 2016.

[22] Jianwei Yang, Lifeng Liu, Tianzi Jiang, and Yong Fan. A modified gabor filter design method for fingerprint image enhancement. *Pattern Recognition Letters*, 24(12):1805–1817, 2003.

[23] Xiao Yang, Jianjiang Feng, and Jie Zhou. Localized dictionaries based orientation field estimation for latent fingerprints. *IEEE transactions on pattern analysis and machine intelligence*, 36(5):955–969, 2014.

[24] Wotao Yin, Donald Goldfarb, and Stanley Osher. A comparison of three total variation based texture extraction models. *Journal of Visual Communication and Image Representation*, 18(3):240–252, 2007.

[25] Jiangyang Zhang, Rongjie Lai, and C-C Jay Kuo. Latent fingerprint segmentation with adaptive total variation model. In *2012 5th IAPR International Conference on Biometrics (ICB)*, pages 189–195. IEEE, 2012.

[26] Jiangyang Zhang, Rongjie Lai, and C-C Jay Kuo. Adaptive directional total-variation model for latent fingerprint segmentation. *IEEE Transactions on Information Forensics and Security*, 8(8):1261–1273, 2013.

[27] Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE Transactions on Image Processing*, 26(7):3142–3155, 2017.

[28] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pages 2223–2232, 2017.