

DCP-GAN: a Novel Deep Learning Network for Fingerprint Super-Resolution

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Abstract

Fingerprint recognition is currently one of the most commonly used biometric recognition technologies. At present, automatic fingerprint recognition systems have high accuracy in identifying fingerprints with good image quality. However, for low-quality fingerprint images, due to the presence of a large amount of noise interference, it is difficult to correctly extract features and the recognition accuracy is low. Therefore, we propose a fingerprint image super-resolution reconstruction algorithm based on a generative adversarial network with dense connection pyramids to address the issue of low accuracy in low-quality fingerprint recognition. Firstly, in order to maximize information sharing between convolutional layers, dense connection blocks are added to the generator. Secondly, the network adds pyramid blocks containing convolutional kernels of different sizes between Dense blocks, and extracts features at different levels using convolutional kernels of different sizes. Finally, this article proposes to reconstruct super-resolution reconstructed images of different magnifications based on parallel feature maps in a model. This multi magnification architecture can have the advantage of sharing underlying information during the training process.

1. Introduction

Fingerprint recognition as shown in Fig.1, an important branch of biometric recognition technology for identity recognition, has a long technological development history[20]. Despite the impressive results, the recognition performance for low-quality fingerprint images with low resolution and noises which often have unclear ridge structures and uneven image contrast remains suboptimal. Enhancing the quality of fingerprint images is crucial for reliable identification, and a widely adopted method is through fingerprint enhancement, which removes noise and accentuates the ridge patterns. Numerous algorithms aim to improve image fidelity by reducing background noise and boosting ridge contrast, leading to enhanced recognition capabilities. Although these enhancement techniques

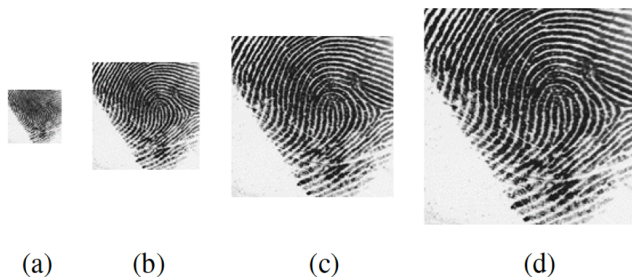


Figure 1. Fingerprint samples under different reconstruction resolutions: (a) 250 dpi, (b) 500 dpi, (c) 750 dpi, and (d) 1000 dpi.

[3, 5, 7, 18, 29] diminish noise and clarify details for more precise identification, they do not reconstruct the fine ridge details by augmenting the resolution of the image itself.

Currently, most fingerprint collection devices have a resolution of 500 dpi (Dots Per Inch). However, many low-cost or miniaturized sensors capture images at resolutions below 500 dpi. Low-resolution fingerprint images result in the loss of detailed features, thereby affecting fingerprint recognition performance[28]. Therefore, the issue of fingerprint super-resolution reconstruction[12, 24] remains a significant challenge in fingerprint processing. Additionally, when collecting infant fingerprints [1], the small area of these prints means that sensors designed for 500 dpi adult fingerprints capture images at resolutions less than 500 dpi, significantly reducing recognition performance. Using higher-resolution collection devices, on the other hand, entails higher cost implications.

Despite numerous challenges in recognizing low-quality fingerprint images, extensive research has focused on algorithms for removing background noise and enhancing fingerprint ridges to achieve better recognition performance. While fingerprint enhancement can reduce image noise and improve detail for more accurate recognition, it cannot reconstruct ridge details or recover them by increasing image resolution. Moreover, there has been limited research focused on fingerprint image super-resolution reconstruction (Super Resolution, SR) [12, 22]. Image super-resolution [15] reconstruction refers to the process of enlarging a low-

resolution (LR) image to a high-resolution (HR) image. It is a crucial image processing technique in computer vision and image processing. Super-resolution reconstruction technology has been extensively researched and applied in computer vision tasks. The most critical issue in super-resolution reconstruction tasks is how to reconstruct the details lost in low-resolution images.

The swift advancement in deep learning [31], has led to the emergence of various deep neural networks tailored for image super-resolution tasks. Among these, the SRCNN and its variant FSRCNN, were designed to perform an end-to-end mapping from bicubic-interpolated low-resolution images to their high-resolution counterparts. The success of residual CNNs in this domain inspired the adoption of the ResNet [13] architecture for image super-resolution, as proposed in recent studies. Moreover, the field has seen innovations like a densely connected deep network [30] for single-image super-resolution, capitalizing on the integration of features from various network layers to refine the reconstruction results. Recently, the integration of generative adversarial networks (GANs) into the realm of super-resolution has marked a significant milestone [17].

In the realm of computer vision, while a plethora of methods have been developed for image super-resolution, the specific area of fingerprint super-resolution remains underexplored [1, 22, 27]. To bridge this gap, this study introduces an innovative approach, the Dense Connected Pyramid Generative Adversarial Network (DCP-GAN), tailored for enhancing the resolution of fingerprint images across multiple scales. This approach leverages the strides made in deep learning for image super-resolution.

The methodology encompasses two distinct stages: offline training and online testing. The offline training phase begins with the collection of a substantial dataset of high-resolution fingerprint images (1000 dpi), which form the foundation for generating lower resolution counterparts through a downsampling process. Following this, the DCP-GAN is meticulously designed. It features a sophisticated generator network with dense connected pyramidal architecture, focused on the intricate task of image reconstruction. Complementing this is a feature-consistent discriminator, fine-tuned to enhance the model's accuracy. The network undergoes rigorous super-resolution training utilizing paired datasets, honing its ability to discern and enhance hierarchical features in the transformation from low to high-resolution fingerprints. During the online testing phase, this meticulously trained super-resolution network is deployed to generate fingerprints of significantly enhanced resolution. The primary contributions of this paper are summarized as follows.

- We present a novel fingerprint image super-resolution framework based on a Generative Adversarial Network (GAN) structure. This framework is adept at learning and

combining features across different levels, resulting in a highly effective high-resolution fingerprint reconstruction.

- We introduce a dense connected pyramid generative adversarial network specifically designed for the reconstruction of high-resolution fingerprint images. This deep network comprises a dense connected pyramid generator for image reconstruction and a feature-consistent discriminator. This marks the first application of GAN's deep network architecture in the realm of fingerprint super-resolution.
- Our approach achieves state-of-the-art results in both visual inspection and fingerprint recognition performance. This success is evident not only in adult FVC fingerprint databases but also in challenging child fingerprint databases. The performance improvements escalate with larger upscaling factors, making this the first work to demonstrate that image super-resolution can effectively enhance the recognition of challenging child fingerprints.

The rest structure of the paper is as follows: Section 2 describes the relevance work. Section 3 provides a detailed description of the proposed fingerprint super-resolution algorithm. Section 4 discusses our experimental setup and the results obtained. Finally, in Section 5, we conclude the paper with a summary of our findings and contributions.

2. Related Work

2.1. Low-quality fingerprint images processing

Before the rapid development of machine learning, fingerprint image enhancement typically utilized Gabor filtering algorithms[14]. Given that fingerprint images have distinct frequencies and orientations in their ridge and valley patterns, Gabor filters[14], known for their selectivity in frequency and orientation, were extensively researched for optimization in fingerprint enhancement. Feng *et al.* [11]proposed a method based on Gabor filtering to estimate the local ridge orientations in enhanced fingerprint images. Additionally, Chikkerur *et al.*[6] introduced a technique for fingerprint enhancement using two-dimensional Short Time Fourier Transform (STFT) analysis in the frequency domain. This method involves using STFT to estimate the probability of ridge directions and frequencies, ultimately enhancing the fingerprint based on these orientations, frequencies, and angles.

Beyond these, enhancement methods based on the Total Variation (TV) [32, 33] image model were also commonly used for fingerprint images. These methods decompose low-quality fingerprint images into texture and cartoon components. Building on this, a model based on Adaptive Directional Total-Variation (ADTV) was proposed [33]. This model enhances low-quality fingerprint images by integrating scale and directional features to eliminate struc-

tured noise. As machine learning technology continued to evolve, Dictionary Learning was first applied in studies related to the enhancement of low-quality fingerprint images. Cao *et al.* [4] developed a dictionary learning-based method to estimate the orientation and frequency fields of low-quality fingerprint images for enhancement. Moreover, Liu *et al.* [19] proposed a method using sparse representation of multi-scale image blocks for the segmentation and enhancement of low-quality fingerprint images. In this method, Gabor elementary functions were used to build a dictionary, and a sparse representation method based on multi-scale image blocks was iteratively applied to reconstruct fingerprint images.

2.2. Super-resolution reconstruction of deep convolutional neural networks

Although research on super-resolution reconstruction[31] of fingerprint images is scarce, a vast array of super-resolution reconstruction methods based on deep convolutional neural networks (CNNs) has been proposed in the field of computer vision. A critical aspect of this study is to explore how these novel super-resolution deep CNNs can be applied to the super-resolution reconstruction of fingerprint images. A deep CNN named SRCNN (Super-Resolution Convolutional Neural Network) [9] was the first to apply deep learning methods to image super-resolution tasks. This algorithm initially enlarges low-resolution images using bicubic interpolation and then employs three convolutional layers for feature extraction and representation, non-linear mapping, and reconstruction. In 2016, an improved version of SRCNN, known as FSRCNN (Fast Super-Resolution Convolutional Neural Network)[10], was proposed. This model inputs low-resolution images directly into the neural network and uses deconvolution operations to upscale the image, directly outputting high-resolution images. Shi *et al.*[25] proposed an enhanced structure, ESPCN (Efficient Sub-Pixel Convolutional Network), which replaces deconvolution layers with a sub-pixel convolution layer, rearranging feature maps to increase image resolution.

Kim *et al.*[13] introduced the ResNet structure into super-resolution reconstruction networks, proposing VDSR (Very Deep Super-Resolution)[15]. Building on this, Tong *et al.*[30], drawing inspiration from the DenseNet structure, proposed SRDenseNet, which deepens the network layers and tested three scales of SRDenseNet structures. Lai *et al.*[16] addressed the issues faced by single magnification super-resolution networks at high magnifications (such as 8x) and proposed LapSRN (Laplacian Pyramid Super-Resolution Network). Addressing the problem of high-frequency detail loss in super-resolution reconstruction tasks, Ledig *et al.*[17] introduced SRGAN (Super-Resolution Generative Adversarial Network), which uses

content loss functions and adversarial loss functions to enhance the visual effect of super-resolution reconstruction images. This comprehensive exploration of deep learning-based super-resolution techniques opens up new possibilities for enhancing the resolution of fingerprint images, a crucial aspect of biometric security and identification.

3. Methodology

3.1. Overview of the Proposed Algorithm

In this research, we focus on the deep learning-driven transformation of low-resolution (LR) to high-resolution (HR) fingerprint images using the Densely Connected Pyramid Generative Adversarial Network (DCP-GAN). Our approach is encapsulated in a comprehensive framework, illustrated in Fig.2, which outlines the process encompassing both offline training and online testing stages. Initially, in the offline training, we curate paired datasets of LR and HR fingerprint images. Subsequently, in the online testing phase, the network utilizes the learned mapping to process LR inputs and generate super-resolved HR fingerprint images. The ultimate goal of DCP-GAN is to master the intricacies of fingerprint details, enhancing the image quality for improved identification accuracy.

3.2. The Densely Connected Pyramid Generative Adversarial Networks (DCP-GAN)

In this study, we introduce a novel approach for fingerprint image enhancement using a Densely Connected Pyramid Generative Adversarial Network (DCP-GAN). This network employs a multi-level feature-extracting generator for image super-resolution and a discriminator that discerns the authenticity of the generated images. The adversarial process continues until a Nash equilibrium is reached, allowing the generator to create highly realistic high-resolution fingerprints. The detailed structures of both the generator and the discriminator will be discussed in subsequent sections, with their architectures depicted in Fig.3.

3.2.1 Densely Connected Pyramid Generator

Super-resolution networks differ from U-net structures in image segmentation, as they directly apply convolutions at high resolutions rather than using encoder-decoder architectures. Initially, these networks employed bicubic interpolation for upscaling, followed by convolution for reconstruction, leading to higher computational and memory demands due to the high-dimensional operations involved. To minimize high computational and memory costs, the network inputs low-resolution images and employs a deep convolutional network to learn and extract features, followed by an upsampling layer at the end for high-resolution reconstruction, forming the generator. The generator's architecture is

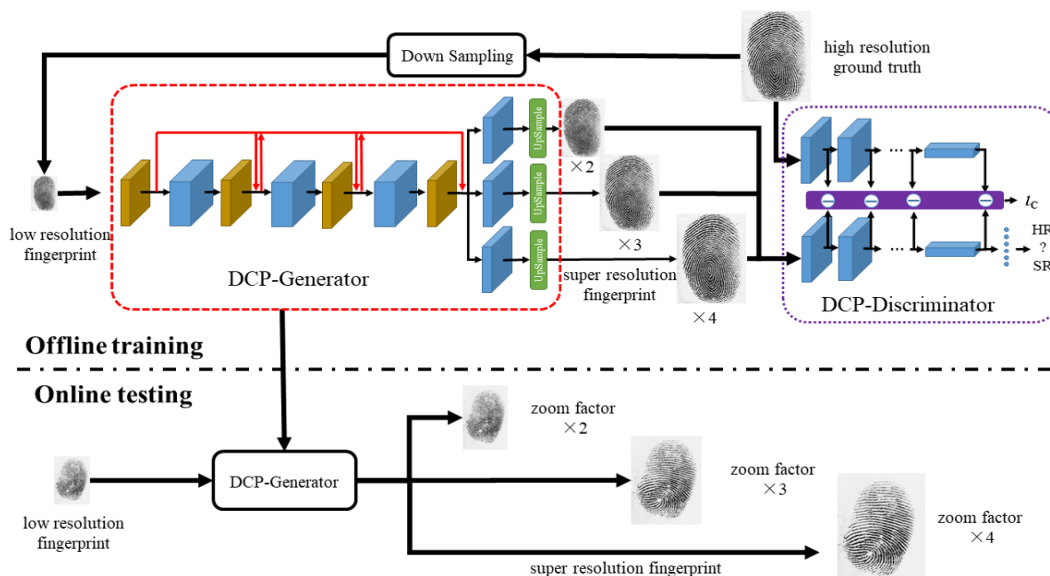


Figure 2. The whole framework of our proposed method for enhancing fingerprint images from low to high resolution using DCP-GAN.

showcased in Fig.3(a).

Dense Blocks for Enhanced Information Sharing:

The generator incorporates Dense Blocks to maximize inter-layer information sharing, contrasting with ResNet’s direct feature map summation. Short paths are established between each layer and every other layer in DenseNet, enhancing robust information and mitigating the vanishing-gradient problem. The introduced Dense Blocks concatenate feature maps from preceding layers, each containing 6 convolutional layers with a 1×1 bottleNeck layer, 3×3 convolution layer, and batch normalization, activated by LeakyReLU. Skip connections between these blocks facilitate feature fusion across levels.

Pyramid Blocks for Multi-Scale Feature Capturing:

DCP-GAN introduces Pyramid Blocks, and each Pyramid Block employs four kernel sizes (3×3 , 5×5 , 7×7 , 9×9) in parallel to integrate image details across various scales. Additionally, akin to DenseNet, we also employ a Dense block to densely connect the outputs between two pyramid blocks, which effectively harnesses information from various network layers, facilitating the construction of a densely connected pyramid generator. Subsequently, the concatenated feature maps from all pyramid blocks serve as input for the subsequent upsampling and reconstruction blocks.

Efficient Multi-Scale Upsampling: The model features a multi-scale architecture for different magnification levels, sharing foundational information during training. The upsampling layer uses sub-pixel convolution (PixelShuffle Layer) with a stride of r which denotes the upscaling zoom factor, more efficient than deconvolution, for rearranging the feature maps of size $W \times H \times (C \times r^2)$ to a

high-resolution image of $Wr \times Hr \times C$. The DCP-GAN’s three output layers set the scaling factor r to 2, 3, and 4 for 2x, 3x, and 4x magnification, respectively. For instance, a 128×128 input is upsampled to outputs of 256×256 , 384×384 , and 512×512 .

3.2.2 Discriminator Network

In the DCP-GAN framework, the discriminator plays a crucial role, tasked with distinguishing between authentic high-resolution fingerprint images and super-resolution reconstructed images produced by the generator. Given the generator’s capability to create super-resolution images at three different magnification levels, three distinct discriminators are designed, each tailored to a specific resolution. As illustrated in Fig.3(b), each discriminator is equipped with eight convolutional modules. These modules are a concatenation of a convolutional layer, batch normalization, LeakyReLU activation, and a maxpooling layer. The convolutional layers across all modules feature a kernel size of 3×3 and a stride of 1×1 . Except for the first maxpooling layer, all others are sized at 2×2 . For discriminators targeting magnification levels of 2x, 3x, and 4x, the first maxpooling layers are sized at 2×2 , 3×3 , and 4×4 , respectively. Following the convolutional layers, the network integrates a fully connected layer and a Sigmoid activation layer to output the classification result. An input of an authentic high-resolution image results in an output of 1, whereas a super-resolution reconstructed image yields an output of 0. Beyond the final output layer, this study also extracts intermediate feature layers, enhancing the discriminator’s ability

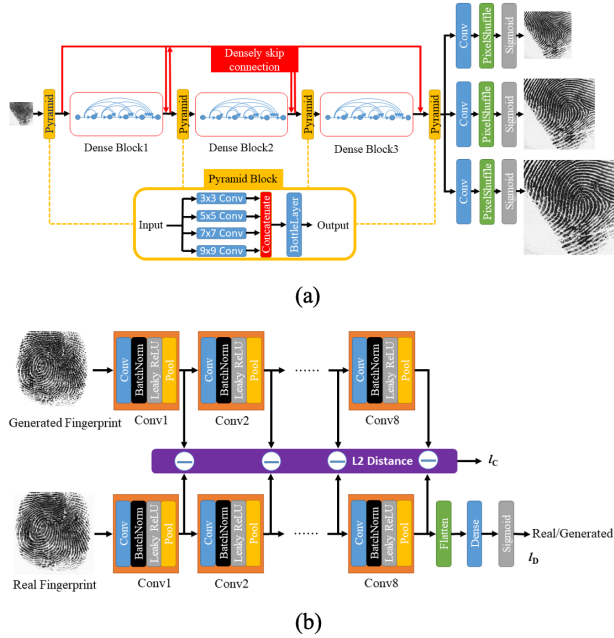


Figure 3. Two main components of the DCP-GAN architecture for fingerprint image super-resolution: (a) the densely connected pyramid generator, which is responsible for image reconstruction, and (b) the feature consistent discriminator, which evaluates the authenticity of the generated images.

to identify fingerprint features.

3.3. Loss Function

In order to quantitatively assess the effectiveness of the generated images and the performance of the network, the DCP-GAN model incorporates the Mean Squared Error (MSE) and the Structural Similarity Index (SSIM) as part of its loss function. The MSE measures the pixel-level differences between the super-resolution image and the original high-resolution image. Conversely, SSIM evaluates the structural similarity between the two images. The loss function of the discriminator in the DCP-GAN model for a single image is shown as follows:

$$\mathcal{L}_G = MSE(S, H) + \lambda_1 \frac{1}{N} \sum_{p=1}^N SSIM(S_p, H_p) \quad (1)$$

where S and H are the super-resolution and ground truth high-resolution fingerprint images, S_p and H_p are the local neighborhoods of pixel p in the generated and ground truth images; N denotes the total number of pixels in the fingerprint image, and λ_1 is a parameter used to adjust the weights of the Mean Squared Error (MSE) and the Structural Similarity Index (SSIM).

In addition to the adversarial loss, the DCP-GAN model utilizes a feature consistency loss, referenced in [23], to ensure that the super-resolution reconstructed images maintain consistency with the real high-resolution fingerprint images in terms of the hierarchical feature maps generated by the discriminator. The feature consistency loss is defined as:

$$\mathcal{L}_C = \sum_{s=1}^M ||F_s(S) - F_s(H)|| \quad (2)$$

where M is the number of feature vectors, and F_s represents the image feature vector generated by the discriminator. The objective during the training of the generator is to minimize the distance between the feature vectors of the generated images and those of the authentic high-resolution images. Conversely, the training objective for the discriminator is the opposite.

The adversarial loss is used to improve the ability of the discriminator to differentiate between authentic high-resolution fingerprint images and the super-resolution reconstructed images produced by the generator. The adversarial loss is formally defined as:

$$\mathcal{L}_D = E_{H \sim p_H} [\log(D(H))] + E_{L \sim p_L} [1 - \log(D(G(L)))] \quad (3)$$

where H is the high-resolution fingerprint as input of the discriminator and L is the low-resolution fingerprint as input of the generator; $G(\cdot)$ is the output of the generator and $D(\cdot)$ is the output of the discriminator; $\mathbb{E}(\cdot)$ denotes the expectation operator. The discriminator is tasked with classifying whether the input image is generated or a real high-resolution fingerprint and thus its output is a binary value.

Finally, the content loss, feature consistency loss, and adversarial loss are integrated to formulate the complete loss function for the DCP-GAN model. The combined loss function is defined as:

$$\mathcal{L}_{DCP-GAN} = \mathcal{L}_G + \lambda_2 (\mathcal{L}_C + \mathcal{L}_D) \quad (4)$$

where λ_2 is a parameter that balances the content loss and the adversarial loss. The final aim is to train the network to generate super-resolution images that are structurally and feature-wise similar to the original high-resolution images.

4. Experiments

4.1. Datasets

This chapter mainly uses the FVC database, fingerprint database of young children, and adult high-resolution fingerprint database for related algorithm research. The adult high-resolution fingerprint database is mainly used for deep neural network training data, while the FVC database and

fingerprint database of young children are mainly used for algorithm performance verification.

FVC Database: FVC databases are generally high-quality, and the official fingerprint matching standards are provided, making it a popular database for fingerprint matching algorithm research. The number of images in each database is 100 fingers in database A, 10 fingers in database B, and 8 images of each finger, collected by different sensors, with a resolution of about 500 dpi. To better compare with other methods, we choose FVC2000DB3_B and FVC2004DB3_B in our experiments.

Fingerprint Database of Young Children: Due to the smaller size and edge structure of young children's fingerprints compared to adults, if existing methods are directly used, the accuracy of young children's fingerprint recognition is lower than that of adults. Therefore, we established a fingerprint database collected from 200 fingers of 2-5 year old children to test the proposed algorithm. Figure 5 shows some examples of fingerprint images from the fingerprint database. The size of each fingerprint image is 600×800 , with a resolution of 1000 dpi. This fingerprint database contains 2000 1000dpi fingerprint images from 200 fingers, with 10 images per finger.

High Resolution Fingerprint Database: To train the proposed deep networks, a large number of training data is required including the paired low and high resolution fingerprint images, so we additionally collected and established a high-resolution fingerprint database. This database uses an optical single finger fingerprint capture device to capture single finger fingerprint images of volunteers, with an image size of 600×800 pixels, with a resolution of 1000dpi.

4.2. Experimental protocol

The DCP-GAN model proposed in this algorithm is built using Python programming language and PyTorch deep learning framework. Hardware environment usage Intel Xeon E5-2620v4@2.1GHz CPU And use NVIDIA GeForce RTX2080Ti GPU for acceleration operations. The model is trained using an Adam optimizer with an initial learning rate set to 0.001.

This chapter first conducts network structure ablation experiments on deep convolutional neural networks, mainly to verify the effectiveness of the proposed DCP-GAN partial structure in this chapter. The validation structures mainly include DenseBlock, PyramidBlock, and generative adversarial structures. Firstly, the generative adversarial part of DCP-GAN is removed, and only the content loss function used by the generator is retained. This structure is called DCP-Net; Next, remove PyramidBlock from the network structure, which is called DC Net. Finally, remove the DenseBlock from the network, and the network structure is called SR Net. Train SRNet, DC Net, DCP Net, and DCP GAN using the same training data to compare the per-

Network	PSNR			SSIM		
	500dpi	750dpi	1000dpi	500dpi	750dpi	1000dpi
SRNet	24.62	24.50	24.48	0.9012	0.8941	0.8853
DC-Net	27.13	26.93	26.85	0.9040	0.8999	0.8939
DCP-Net	27.52	27.32	27.24	0.9088	0.9035	0.8973
DCP-GAN	27.76	27.54	27.44	0.9111	0.9037	0.8977

Table 1. Psnr and ssim of different network structures on fingerprint database of young children.

formance differences of different network structures. The network structure ablation experiment mainly compares the peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) of the image.

This experiment uses the FVC database and fingerprint database of young children to verify the effectiveness of different super-resolution reconstruction methods on fingerprint matching. To facilitate comparison with other literature, this article uses the open-source C# fingerprint matching algorithm architecture. The matching algorithm uses M3gl[21] and adopts the same matching scheme: pairwise matching of the same finger, matching of different fingers using the same number, all images are downsampled to low resolution by magnification, and then reconstructed to 500dpi by super-resolution for matching. The accuracy index of matching is mainly obtained through the Detection Error Trade off (DET) curve. The main indicator of the curve is Equal Error Rate (EER). This experiment evaluates the super-resolution reconstruction effect through the above matching indicators, and the error rate parameters are as low as possible.

4.3. Ablation Study on Network Architecture

This section uses a high-resolution fingerprint database of 1000dpi for ablation experiments to verify the effectiveness of different network structures. Table 1 shows the PSNR and SSIM indicators of high-resolution fingerprint databases with different network structures. It can be seen that as the network structure becomes more complex, the PSNR and SSIM gradually improve.

Fig. 4 shows an example image of super-resolution reconstruction of fingerprint images with different network structures. From the figure, it can be seen that the images generated by SRNet have significant texture direction errors. The overall ridge direction field of the image generated by DC Net is basically accurate, but the adhesion of adjacent ridges leads to the appearance of incorrect ridges. The image lines generated by DCP Net are basically correct, but there are still errors in the detailed features. The image lines generated by DCP-GAN have accurate orientation, better restoring detailed features, and are closer to the target image. Through the above experiments, it has been proven that the addition of Dense Block, Pyramid Block, and Genera-

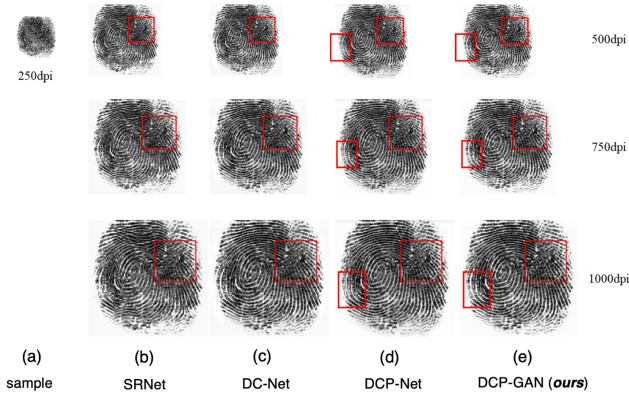


Figure 4. A sample of a 250 dpi low-resolution fingerprint and corresponding 500, 750, and 1000 dpi high-resolution images enhanced by different networks on FVC2000 DB3_B 101_1.

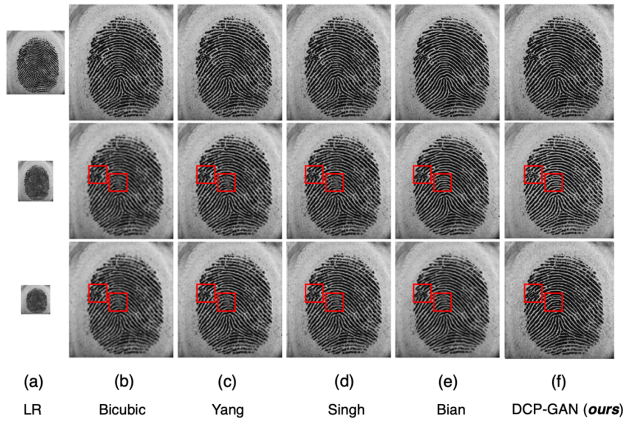


Figure 5. The low-resolution fingerprints of FVC2000DB3_B 101_1 downsampled by scale factors of 2, 3 and 4 from row 1 to 3 and the corresponding super-resolution results of 500 dpi generated by using different methods.

tive Adversarial Structure can effectively improve the effectiveness of fingerprint super-resolution reconstruction.

4.4. Comparison with other methods

In this experiment, we compare the proposed deep learning based method with other methods including the Bicubic interpolation method and the Yang’s method for fingerprint image super resolution on both the fingerprint database of young children and FVC database.

4.4.1 FVC database

Fig.5 shows the comparison of FVC2000DB3_B super-resolution reconstructed images generated by different methods. From the figure, it can be seen that the image generated by Bicubic is blurred. The images generated by Yang[8], Singh[26], and Bian[2] have higher sharpness, but

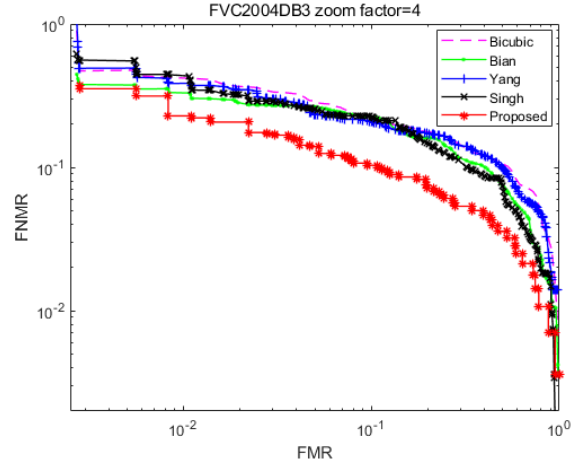


Figure 6. Comparison of the DET curves by different super-resolution methods with zoom factor 4 on FVC2000DB3_B.

Metrics	zoom factor	Method				
		Bicubic	Bian	Yang	Singh	Proposed
EER (%)	×2	8.31	5.46	8.31	6.17	4.52
	×3	9.98	8.73	9.09	10.81	7.04
	×4	17.22	16.09	17.18	17.04	9.76

Table 2. Comparison of EER of different zoom factors with different super resolution methods on FVC2000DB3_B.

they all have the problem of losing details, and Bian’s results have more loss of grayscale information. The DCP-GAN image proposed in this article is clearer and can better preserve detailed information.

In terms of fingerprint matching, this article conducted matching tests using the FVC2004DB3B database, and the matching DET curve is shown in Fig.6. The EER performance indicators are shown in Table 2. Due to the experimental approach of downsampling by magnification and reconstructing the super-resolution to 500dpi, the higher the magnification, the smaller the input image size and the greater the difficulty. Therefore, the higher the magnification, the higher the error rate of the experimental results. From Fig.6, it can be seen that the image DET curve generated by DCP-GAN is lower than that of the bicubic interpolation. From Table 2, it can be seen that compared to the bicubic interpolation, the EER of DCP-GAN at 2, 3, and 4 times magnification decreased from 5.46%, 8.73%, and 16.09% to 4.39%, 7.04%, and 9.76%, respectively. The larger the magnification, the more obvious the advantage.

4.4.2 Fingerprint Database of Young Children

This section evaluates various super-resolution algorithms using fingerprint database of young children. Fig.7 displays

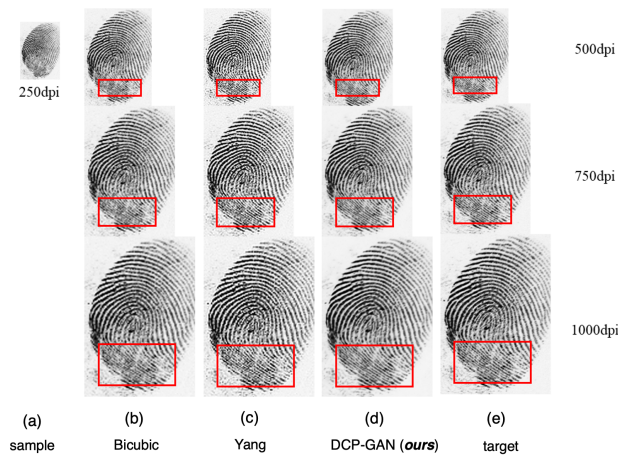


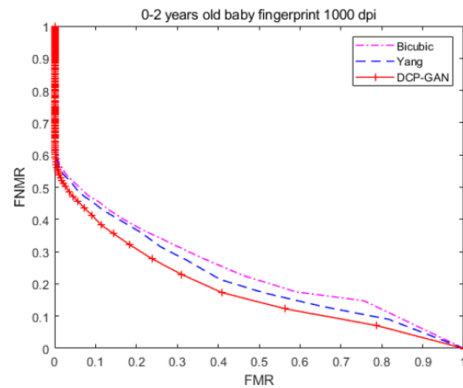
Figure 7. A sample of low-resolution fingerprint of 250 dpi and the super resolution results of 500, 750 and 1000 dpi from the first to the third row by using different methods on fingerprint database of young children.

Metrics	dpi	Method			
		Bicubic	Yang	Original	Proposed
EER (%)	500	9.45	8.12	7.42	7.87
	750	7.00	6.24	4.96	5.77
	1000	6.26	5.61	4.15	4.95

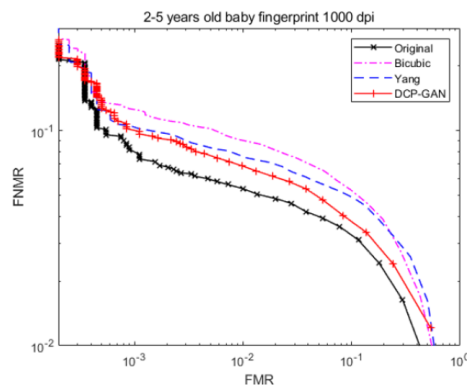
Table 3. Comparison of EER on the young children fingerprint images of different resolutions by different super resolution methods.

high-resolution young children fingerprint images produced by different methods. Notably, the Bicubic enlargement appears blurry, especially in densely textured areas (red box), hindering detailed feature distinction. Yang[8]’s enlargement exhibits improved sharpness but introduces severe noise, leading to unclear texture in the red box due to line accumulation. Contrastingly, DCP-GAN produces significantly clearer images, demonstrating high sharpness and smooth edges in sparse textures and effectively distinguishing ridges even in densely textured areas.

Subsequently, fingerprint matching is conducted on the infant database, resulting in DET curves (Fig.8) illustrating DCP-GAN’s superiority over Bicubic and Yang, aligning closely with the target high-resolution curve. Tables 3 present EER performance indicators, showing DCP-GAN outperforming other methods. For infants aged 0-2, DCP-GAN achieves EERs of 29.79%, 26.69%, and 26.19%, surpassing Yang’s 31.78%, 29.27%, and 29.29%. Similarly, for 2-5-year-olds, DCP-GAN achieves EERs of 7.87%, 5.77%, and 4.95%, outperforming Yang’s 8.12%, 6.24%, and 5.61%. Notably, DCP-GAN’s advantage becomes more pronounced with higher magnification and demonstrates lower matching error rates, emphasizing the efficacy of high



(a)



(b)

Figure 8. Comparison of the DET curves by different super-resolution methods with zoom factor 4 on young children fingerprint images.

dpi in reducing errors.

5. Conclusion

This paper has presented a densely connected pyramid generative adversarial network (DCP-GAN) for finger print super-resolution. The deep network of DCP-GAN consists of a densely connected pyramid generator for image reconstruction and a feature consistent discriminator for distinguish the input image as generated or real. The densely skip connections and pyramid convolution block are added to make the full use of multi-level features for reconstruction of high resolution fingerprints. In discriminator, a feature consistent component is added to enforce the feature consistency between the generated and real fingerprints. The proposed method is tested on the fingerprint database of young children and FVC database. The experiment results show that the proposed method achieved better performance than other methods. The super resolution method can provide an effective way to enhance the fingerprint recognition of young children.

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