Latent Fingerprint Enhancement using Generative Adversarial Networks

Indu Joshi[1], Adithya Anand[1], Mayank Vatsa[2], Richa Singh[2], Sumantra Dutta Roy[1], Prem Kumar Kalra[1]

[1]Indian Institute of Technology Delhi, India, [2]IIIT Delhi, India

[1]{Indu.Joshi, Adithya.Anand.cs116, pkalra}@cse.iitd.ac.in, [1]sumantra@ee.iitd.ac.in,
[2]{mayank, rsingh}@iiitd.ac.in

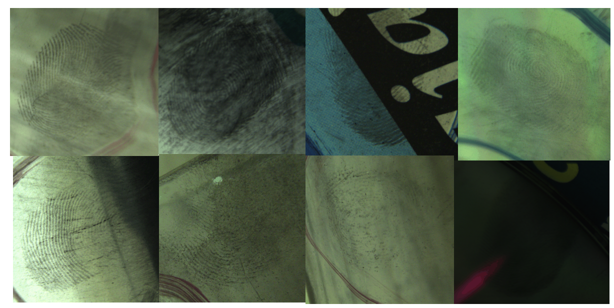
Abstract

Latent fingerprints recognition is very useful in law enforcement and forensics applications. However, automated matching of latent fingerprints with a gallery of live scan images is very challenging due to several compounding factors such as noisy background, poor ridge structure, and overlapping unstructured noise. In order to efficiently match latent fingerprints, an effective enhancement module is a necessity so that it can facilitate correct minutiae extraction. In this research, we propose a Generative Adversarial Network based latent fingerprint enhancement algorithm to amplify the ridge structure quality. Experiments on two publicly available datasets, IIITD-MOLF and IIITD-MSLFD show that the proposed enhancement algorithm improves the quality of fingerprint images while preserving the ridge structure. Using the enhanced images with standard feature extraction and matching algorithms further boosts latent fingerprint recognition performance.

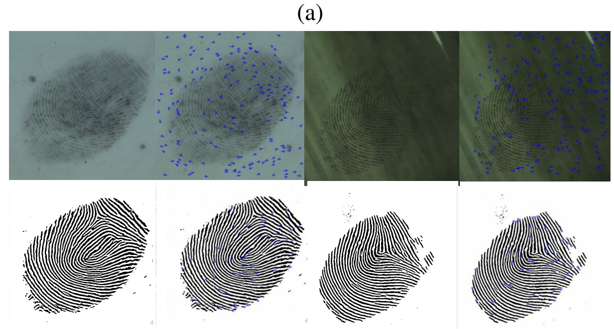
1. Introduction

Fingerprints are one of the most reliable biometric modalities since they can uniquely identify a person. They have been widely used in criminal identification and various access control applications. Unlike civilian applications where live scans are used, forensic applications require processing latent fingerprints lifted from crime scenes [20]. These impressions are left unintentionally when the subject touches an object and hence are usually of poor quality due to noise, overlapping background and sometimes overlapping fingerprints.

As shown in Figure 1 (a), latent fingerprints generally do not have a clear ridge structure. As a result, most of the standard fingerprints feature extractors often fail to accurately extract features (Figure 1 (b)) [19]. One of the important factors in successfully identifying latent fingerprints is reliable *enhancement* so that minutiae can be extracted efficiently and matching can be performed reliably. This paper focuses on latent fingerprints enhancement to facilitate efficient feature extraction for improved matching performance.



(a)



(b)

Figure 1: (a) Sample latent fingerprint images showcasing challenging factors such as background noise, poor ridge structure, textured background and overlapping fingerprints in the background. (b) sample cases illustrating the effect of (the proposed) enhancement step to improve minutiae detection. The first row shows the original latent impressions and minutiae detected using NBIS tool [1]. The second row shows that after enhancement, correct minutiae are detected.

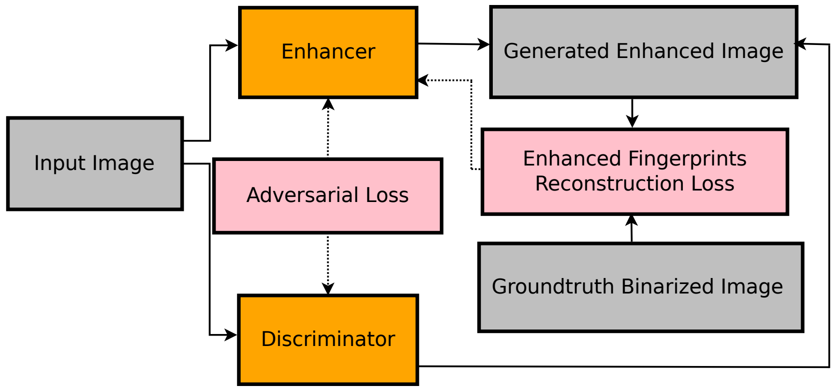


Figure 2: Proposed Latent fingerprints enhancement model. The dashed lines represent the backpropagation of losses while training the Enhancer and the Discriminator networks.

1.1. Related Work

Various latent fingerprints enhancement techniques have been explored in the past. Several of these enhancement methods use the knowledge of orientations to enhance the fingerprint quality. Feng et al. [10] proposed a patch based dictionary approach for orientation estimation. Yang et al. [24] claimed that only a certain class of orientations can lie at a particular location and introduced localized dictionaries. Chen et al. [9] created multiscale dictionaries to handle varying level of noise in latent impressions. Cao and Jain [5] posed orientation estimation as a classification problem and used the convolutional neural network for orientation estimation. Recently Li et al [15] proposed FingerNet, a deep convolutional neural network to enhance latent fingerprints.

Another interesting line of approach for latent enhancement is through reconstruction of the ridge structure. Svoboda et al. [22] recently proposed to utilize convolutional autoencoder for reconstructing latent impressions. However, the convolutional autoencoders had an explicitly defined objective function which aimed at minimizing the orientation and gradient difference between reconstructed and target enhanced image. This model was trained to simply minimize a $l2$ loss and did not accommodate perceptual quality. Further, the generated images had blurriness which affected the performance of fingerprint feature extraction. Thus, the resulting matching accuracy was not very high.

Generative Adversarial Networks (GANs) offer the flexibility to optimize the objective function for the problem at hand [13]. The optimization function can include adversarial loss along with other loss functions as per the requirements. Inspired by their success in generative applications, we propose a novel algorithm which leverages GANs for latent fingerprint enhancement.

1.2. Research Contributions

Generative Adversarial Networks have been successfully used in various applications such as synthetic image generation, image inpainting, and image denoising [13]. GANs generate sharper and enhanced images compared to other generative models including autoencoders. In this research, we propose a GANs based algorithm for latent fingerprint enhancement which improves the quality of fingerprints. It is our hypothesis that using the high quality fingerprints generated via GANs would improve the fingerprint matching performance of existing recognition algorithms, which otherwise do not yield very high performance on latent fingerprints. To the best of our knowledge, this is the first work which introduces Generative Adversarial Networks in the domain of latent fingerprints. We have evaluated the proposed algorithm on IIITD Multisurface Dataset [21] which has latent fingerprints extracted from eight different surfaces as well as the IIITD MOLF Datatset [17] which has over 4000 latent impressions. Evaluation on such challenging datasets demonstrates the effectiveness and generalization ability of the proposed algorithm.

2. Proposed Algorithm

Latent fingerprint enhancement involves generating fingerprint images with clear ridge structure so that it can facilitate accurate feature extraction and improved matching performance. In this paper, latent fingerprint enhancement is posed as a conditional image generation problem where the enhanced image is conditioned by the given latent. The mapping has to be learned in such a way that the ridges, valleys and other fingerprint features including minutiae are preserved. In order to achieve this, we have proposed to use an image to image translation model [14] which utilizes conditional GAN [16] for generating images. Figure 2 summarizes the steps involved in the proposed algorithm.

The proposed model consists of two networks: a latent

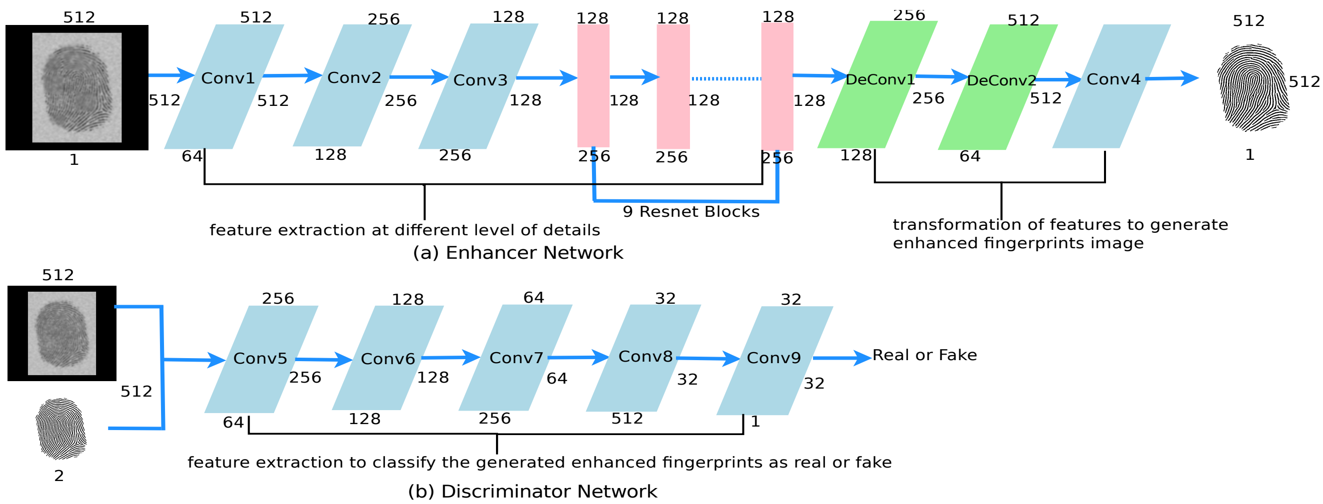


Figure 3: Architecture of Enhancer ($\mathcal{E}nh_L$) and Discriminator ($\mathcal{D}is_E$)

enhancer network ($\mathcal{E}nh_L$) and an enhanced fingerprint discriminator network ($\mathcal{D}is_E$). $\mathcal{E}nh_L$ is trained to produce an enhanced version of the given latent fingerprint x while $\mathcal{D}is_E$ is trained to classify whether the input image y is a real enhanced image or generated by $\mathcal{E}nh_L$.

2.1. Objective Function of GAN

In the proposed GAN model, there are two loss functions: (i) adversarial loss and (ii) enhanced fingerprint reconstruction loss.

Adversarial Loss: Both $\mathcal{E}nh_L$ and $\mathcal{D}is_E$ minimize the adversarial loss. Thus, the discriminator is penalized if it misclassifies the generated enhanced fingerprints as real. Similarly, the enhancer is penalized if the generated enhanced image is correctly classified as fake by the discriminator.

$$L_{adv} = E_{(x,y)\sim p(x,y)}[log\mathcal{D}is_E(x,y)] + E_{x\sim p_x(x)}[log(1-\mathcal{D}is_E(x,\mathcal{E}nh_L(x)))]$$

As a result, the enhancer learns the features required to generate enhanced fingerprints and the discriminator learns the discriminating features to distinguish between a real and a fake enhanced fingerprint image.

Note that the discriminator takes both image $\mathcal{E}nh_L(x)$ and x. Hence, it ensures that the enhancer must learn to preserve the ridge structure while generating the enhanced fingerprints. Thus, the enhanced fingerprints generated by the enhancer network have the same fingerprints features as the given input latent image.

Enhanced Fingerprint Reconstruction Loss:

$$L_{rec} = ||y - \mathcal{E}nh_L(x))||_1$$

This loss term ensures that $\mathcal{E}nh_L$ receives a penalty if the generated enhanced image $\mathcal{E}nh_L(x)$ deviates from the paired image y for the sample x in the training set. This loss thus helps the enhancer to better learn the global structure of the target binarized image. The motivation of using $l1$ norm is to generate sharp enhanced images unlike $l2$ norm which causes blurring.

Overall Loss: Using these two loss functions, the final objective function can be defined as:

$$min_{\alpha} min_{\beta} \;\; [E_{(x,y)\sim p(x,y)}[log\mathcal{D}is_E(x,y)]+ E_{x\sim p_x(x)}[log(1-\mathcal{D}is_E(x,\mathcal{E}nh_L(x)))] + \lambda||y-\mathcal{E}nh_L(x))||_1]$$

where, α represents the parameters of $\mathcal{E}nh_L$, β are the parameters of $\mathcal{D}is_E$, and λ controls the weight for reconstruction loss. Note that, in this research, we have used PatchGAN based strategy. The discriminator is trained to distinguish whether each 8×8 patch in the enhanced fingerprints image is real or fake. Discriminator takes both the latent fingerprint and the enhanced image, and classifies each patch as real or fake.

2.2. Network Architecture

The enhancer has an encoder-decoder architecture, Encoder part of the enhancer with Conv1, Conv2 and Conv3 blocks extract the coarse to the fine level of details in the latent fingerprint image. The nine Resnet blocks in the encoder part help the enhancer to better understand the local and global structures and also help in encountering the vanishing gradient in a deeper network and thus, help in generating more realistic enhanced images. On the other hand, the decoder part has Deconv1, Deconv2, and Conv4 blocks.

Table 1: Architecture of $\mathcal{E}nh_L$ and $\mathcal{D}is_E$.

Layer	Kernels	Size	Stride	Padding
Conv1[1]	64	7	1	3
Conv2[1]	128	3	2	1
Conv3[1]	256	3	2	1
ResNet Block[2]	256	3	2	1
Deconv1[2]	128	3	2	1
Deconv2[2]	64	3	2	1
Conv4[3]	1	7	1	3
Conv5[4]	64	4	2	1
Conv6[5]	128	4	2	1
Conv7[5]	256	4	2	1
Conv8[5]	512	4	1	1
Conv9[6]	1	4	1	1

These blocks learn to transform these features into a binarized/enhanced latent.

In Discriminator's architecture, enhanced image and latent are first concatenated along the input channel dimension and then passed through the network. The network architecture and its various parameters are given in Figure 3 and Table 1.

2.3. Training

For training the proposed model, the paired training examples i.e. latent fingerprints and the corresponding enhanced images for the same latent fingerprint image are required. All the publicly available datasets have latent fingerprint and good quality fingerprint of the same finger. However, none of the publicly available datasets have latent fingerprint and the enhanced fingerprint corresponding to that exact latent impression. Therefore, we have synthetically generated latent impressions by adding varying levels of Gaussian noise and different background into good quality fingerprints, to simulate the conditions in which a latent is typically acquired i.e. overlapping text, overlapping fingerprint, and varying surfaces. This step helps in training the proposed GAN model for latent fingerprint enhancement. Ground truth enhanced images corresponding to the latent images taken as the binarized images corresponding to the original good quality fingerprints from which the latent impressions are simulated.

1. For the proposed model to be invariant towards overlapping background text, fingerprints are blended with text images of varying font size and style.

2. While simulating latent impressions, different levels of noise is added into different patches of fingerprints. This is incorporated to learn invariance from smudging that might be present in a latent impression due to non-uniform powder content in various patches of latent. Good quality NIST SD4 [2] images with NFIQ2 [23] value greater than or equal to 70 are used as the training samples. Since these fingerprints are captured using ink, they also face a similar issue of non-uniformity. Further, many of these fingerprints have background text, these samples are good examples for the model to learn.

3. In order to make the model invariant to the surface from which the latent impression is extracted, different background images with varying textures are blended with the fingerprints. The samples of these surface include glass surface, wood-like texture, plastic and cardboard surface.

4. Finally, to eliminate line-like noise from latent images during enhancement, horizontal and vertical lines of varying width are added into the fingerprints.

The training set thus prepared is a representative sample of the conditions under which the latent fingerprints are typically acquired. Synthetic fingerprints obtained from an open source implementation [4] of SFinGe [8] are used to obtain the ground truth. Later, noise is added into them to simulate latent impressions. All the latent impressions obtained from a single good quality synthetic fingerprint had the same ground truth binarization, obtained using NBIS [1]. These binarized images serve as the enhanced image for learning the mapping.

The model is trained on 8423 fingerprints and their corresponding ground truth binarized images. Adam optimizer is used to train the network with learning rate 0.002, $\lambda = 10$, $\beta_1 = 0.5$ and $\beta_2 = 0.999$. The batch size is set to 2. The model is trained on two GPUs and each GPU is 2x NVIDIA K40 with 12 GB RAM and 2880 CUDA cores.

During training, the parameters of the enhancer and the discriminator networks are fine-tuned to generate the enhanced fingerprints. After the model is trained, the discriminator is discarded. Since the model is not trained on any real latent dataset, there is no limitation on the size of the training set. Moreover, the model is trained on binarized images, so it automatically learns the binarization of a given latent image.

3. Database and Experimental Evaluation

This section describes the databases and experimental setup used for evaluating the proposed algorithm.

[1] Conv layer + BatchNorm + ReLu
[2] Conv layer + BatchNorm + ReLu + Conv layer + BatchNorm
[3] Conv layer + Tanh
[4] Conv layer + LeakyReLu
[5] Conv layer + BatchNorm + LeakyReLu
[6] Conv layer

Figure 4: Sample training images: All seven fingerprints starting from top left have same binarized target image (bottom right). Different backgrounds with varying textures have been used during training to simulate the conditions under which a latent is typically acquired.

3.1. Dataset

The performance of the proposed algorithm has been evaluated on two publicly available datasets: IIITD-Multi-Optical Latent Fingerprint (MOLF) database [21] and IIITD-Multi-Surface Latent Fingerprint Database (MSLFD) [17].

1. IIITD-MOLF comprises of optical and latent fingerprints of 10 fingers pertaining to 100 different subjects. Fingerprints are acquired from different sensors. This dataset has a total of 4400 latent fingerprint samples.

2. IIITD-MSLFD has latent fingerprint impressions of 51 subjects acquired from 8 different surfaces such as ceramic mug, compact disc, hardbound book cover, and transparent glass. In total, the database contains 551 latent fingerprint samples.

Since the network is trained on images of size 512×512, the images from the two databases are preprocessed to obtain the regions of interest of size 512×512.

3.2. Experimental Setup

Two experiments are performed to demonstrate the effectiveness of the proposed algorithm towards latent fingerprints recognition.

1. Matching latent impressions to Multi-Sensor Fingerprints

2. Matching latent impressions to Multi-Surface Fingerprints

In the first experiment, latent impressions from the IIITD-MOLF database are matched with images across different galleries (DB1 and DB2) of the IIITD-MOLF database. Each gallery has fingerprints acquired from a different sensor. This experiment demonstrates the robustness of the proposed algorithm towards different fingerprints sensors.

The second experiment is designed to evaluate the robustness of the proposed enhancement algorithm towards different backgrounds and kinds of structured noise which are generally present in a latent fingerprint impression. In this experiment, the latent fingerprints of IIITD-MSLFD have been matched with the fingerprints acquired through a sensor. These latent images are captured from varying surfaces, have an overlapping background and are therefore very challenging to match.

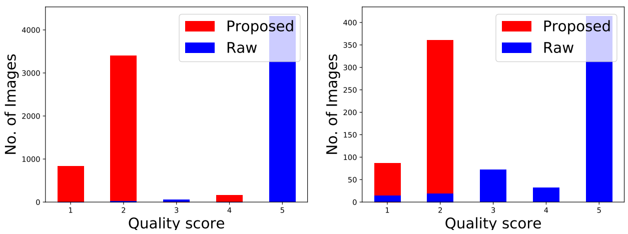
3.3. Evaluation Metrics

The objective of fingerprint enhancement algorithm is not only to improve the quality of fingerprint image but also preserve the ridge structure thereby improving the recognition performance. Therefore, the performance is evaluated using three different metrics.

1. **Fingerprint Quality Analysis:** To demonstrate that the proposed enhancement algorithm improves the quality of latent fingerprint image, the NFIQ module of NBIS [1] has been utilized. It gives a value between $1 - 5$ where one denotes the best quality and five denotes the worst quality. The performance has been evaluated based on the score distribution before and after the proposed enhancement algorithm, on the IIITD-MOLF latent images.

2. **Ridge Structure Preservation:** A key feature of any fingerprint enhancement algorithm is to preserve the ridge structure while enhancing the fingerprints. Structural Similarity Index metric (SSIM) [25] has been calculated on the reconstructions of synthetic data and their corresponding ground truth binarization. A high SSIM demonstrates that the structural similarity between the ground truth and reconstruction is indeed preserved, and thus the ridge structure is also preserved.

3. **Matching Performance:** In order to perform feature extraction and matching from latent fingerprints, two publicly available state-of-the-art feature extractors: ABR11 [3] and MINDTCT [1], and two publicly available matching algorithms: Bozorth [1] and



(a) (b)

Figure 5: Fingerprint image quality evaluated via the NFIQ module of NBIS [1] for latent fingerprint images of the (a) IIITD-MOLF database and (b) IIITD-MSLF database.

Table 2: Average NFIQ scores of the images from the IIITD-MOLF and IIITD-MSLFD datasets. Lower scores of the enhanced algorithm showcase that the proposed algorithm improves the fingerprint image quality.

Dataset	Enhancement	NFIQ Score
IIITD-MOLF	Raw Image	4.96
	Proposed	**1.88**
IIITD-MSLFD	Raw Image	4.48
	Proposed	**2.36**

MCC [6, 7, 11, 12] have been used. The performance has been reported in terms of the Rank-50 accuracies obtained by raw images and those enhanced by the proposed algorithm. The performance has also been compared with previously proposed enhancement algorithm by Svoboda et al. [22].

4. Results and Analysis

This section summarizes and analyzes the results based on the three metrics discussed above.

4.1. Fingerprint Quality Analysis

Figure 5 shows the histogram of NFIQ scores on the MOLF and MSLF databases. It can be observed that after enhancement, the distribution of fingerprint quality scores has shifted towards lower values (better quality). Further, Table 2 summarizes the average score across the entire database, before and after enhancement. The NFIQ score of original images is 4.96 and 4.48 on MOLF and MSLF databases, respectively. After applying the proposed GANs based image enhancement algorithm, the average quality score has significantly decreased (better quality) and the NFIQ scores of enhanced images are 1.88% and 2.36%, respectively. The improved quality signifies that the proposed algorithm enhances the ridge structure of the latent images which leads to the better quality scores.

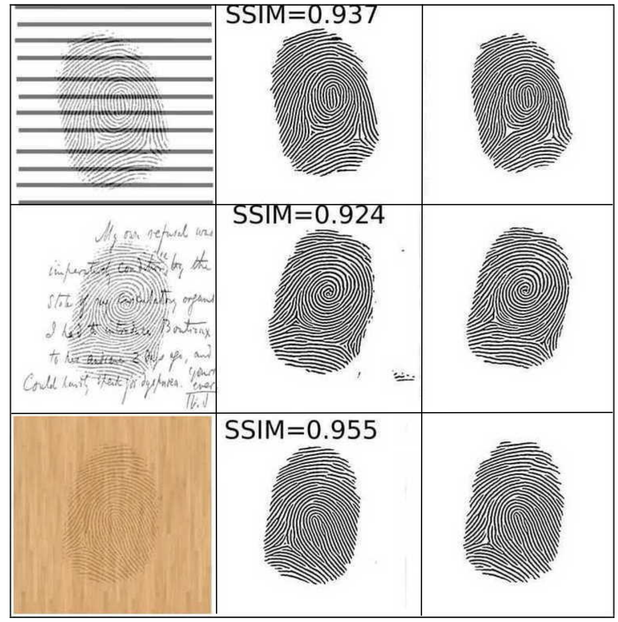


Figure 6: Left column: synthetic test latent, middle column: images generated using the proposed algorithm, Right column: ground truth. SSIM value is calculated between the proposed and ground truth. High SSIM values show that the proposed algorithm is able to preserve the ridge structure of latent images while enhancing them.

4.2. Ridge Structure Preservation

Figure 6 presents sample cases illustrating the effect of the proposed enhancement algorithm on the ridge structure and SSIM values. It can be observed that the SSIM values between the enhanced images generated by the model and the ground truth binarization for the synthetic latent test examples is very high. This demonstrates that the proposed model preserves the ridge structure and other fingerprint features like fingerprint pattern class, ridge orientation, and minutiae while enhancing the latent images. Additional successful examples of latent fingerprint enhancement by the proposed model are shown in Figure 9.

4.3. Matching Latent to Multi-Sensor Fingerprints

Tables 3 and 4 summarize the rank-50 accuracies obtained by matching latent impressions to fingerprint images captured by different sensors and Figure 7 showcases the CMC curves obtained across DB1 and DB2 from the IIIT-D MOLF database. It can be observed that the proposed algorithm leads to significant improvements in the matching accuracy. Matching raw images with MINDTCT+MCC yields 12.59% accuracy whereas, after enhancement, the performance with the same feature extractor and matcher improves to 35.66%. The comparison with existing algorithm shows that applying Svoboda et al.'s algorithm also

Table 3: Results of matching latent images of IIITD-MOLF across its DB1 fingerprints gallery.

Enhancement Algorithm	Features + Matcher	Rank-50 Accuracy
Raw Image	ABR11+MCC	5.45
	MINDTCT+BOZORTH	6.06
	MINDTCT+MCC	12.59
Svoboda et al. [22]	ABR11+MCC	22.36
	MINDTCT+MCC	18.36
Proposed	ABR11+MCC	28.18
	MINDTCT+BOZORTH	30.16
	MINDTCT+MCC	**35.66**

Table 4: Rank-50 accuracy (%) of matching latent images of IIITD-MOLF across its Lumidigm (DB1) and Secugen (DB2) fingerprints. Feature extraction and matching is performed using MINDTCT+MCC.

Enhancement Algorithm	DB1	DB2
Raw Image	5.45	5.18
Svoboda et al. [22]	22.36	19.50
Proposed GAN	**35.66**	**30.16**

improves the accuracy, however, the magnitude of improvement is much more by using the proposed algorithm. These results could be attributed to the fact that the proposed algorithm enhances the ridge structure of latent fingerprint images which helps in more accurate feature extraction and matching from enhanced fingerprints than the raw latent impressions.

4.4. Matching Latent Images to Multi-Surface Fingerprints

As mentioned earlier, the experiments are also performed to evaluate the performance with respect to multi-surface fingerprint matching. The CMC curves pertaining to this experiment are shown in Figure 8. It is interesting to observe that after the proposed enhancement, rank-50 identification accuracy increases from 11.43% to 15.24%. The accuracy on IIITD-MSLF database is lower than the IIITD-MOLF database, this can be attributed to varying and complex backgrounds in IIITD-MSLFD compared to the IIITD-MOLF. Moreover, in several images, the background has similar distribution of intensity values as the foreground fingerprints. This leads to spurious patterns in the enhanced images which adversely affects the feature extraction and thus the matching performance.

4.5. Challenges Observed

Across different experiments, we have observed that the proposed GAN based enhancement algorithm improves the

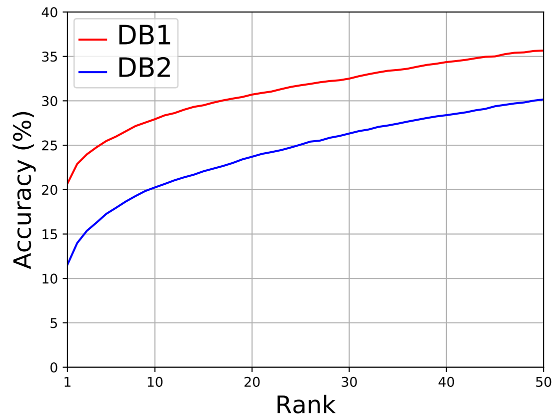


Figure 7: CMC curve for matching GAN enhanced images using MINDTCT+MCC on the IIITD-MOLF DB1 and DB2 galleries.

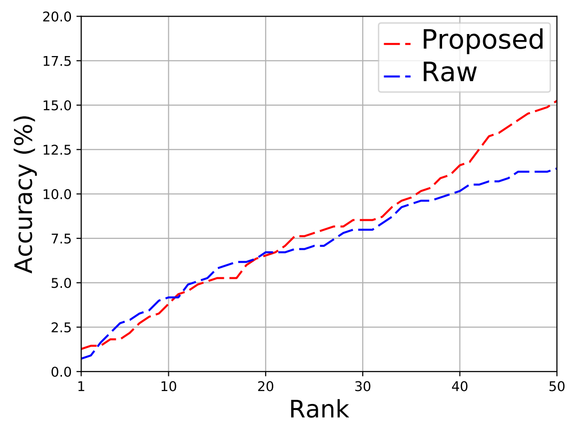


Figure 8: CMC curve for matching (using MINDTCT+BOZORTH) IIITD-MSLFD before and after enhancement by the proposed algorithm.

performance. However, as shown in Figure 10, we have encountered several challenging cases where the algorithm fails to yield good results. Here, we present an analysis of these cases.

- Analyzing the input images shown in Figure 10 reveals that if there is no ridge information in the input latent images, the algorithm is unable to reconstruct the enhanced fingerprints. Referring to the second and third samples of Figure 10, it can be observed that the proposed algorithm is able to enhance those portions of the fingerprints where there is some ridge information. We believe that in complete absence of ridge patterns, it will be challenging for any algorithm to meaningfully enhance the ridge patterns.

- For latent fingerprint matching, forensics experts first manually mark the region of interest and then perform

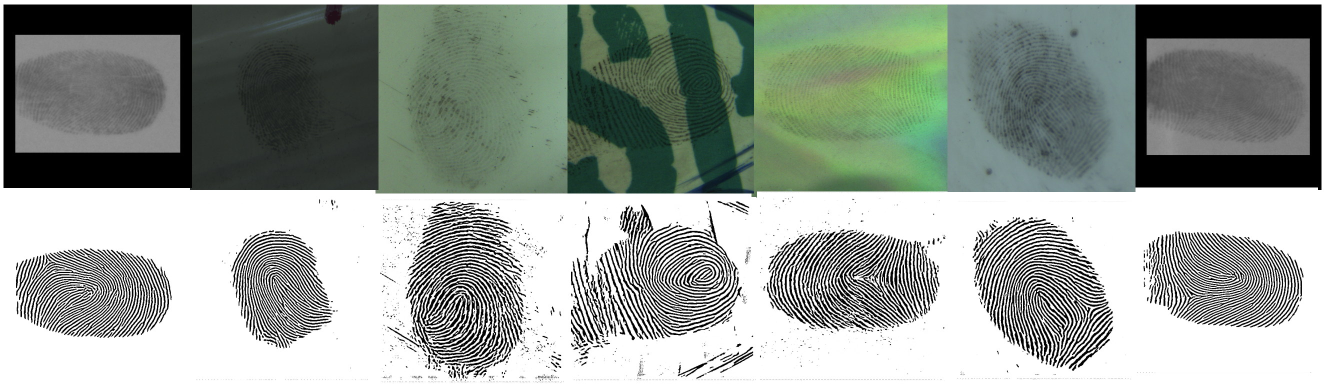


Figure 9: Samples of successful enhancement of latent fingerprints by the proposed model.

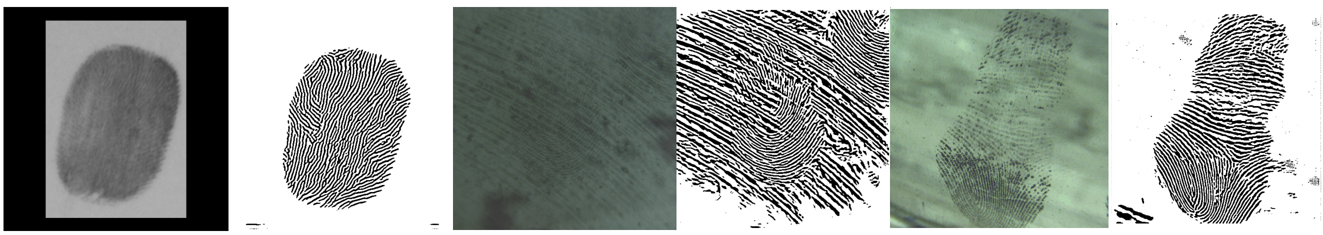


Figure 10: Some challenging cases for the proposed model.

matching. However, the proposed algorithm does not use ROI masks, rather it learns to identify the foreground and background and then enhances the foreground fingerprints. As a result, the algorithm sometimes misinterprets background as foreground when the background pixels have similar distribution of intensity values as the foreground fingerprints.

5. Conclusion

GANs are one of the most popular and promising architectures in image generative applications. Inspired by their success, we have posed latent fingerprint enhancement as an image-to-image translation problem and explored the possibility of using GANs to generate enhanced fingerprints which can facilitate accurate feature extraction. The proposed model has been trained using the enhancer and the discriminator as an adversarial network. Training is performed on both synthetic and real fingerprints. As a result, the model is not "fine-tuned" for a particular latent dataset and its utility is not limited by the availability of a large latent dataset. The proposed model has achieved state-of-the-art results on two challenging publicly available latent databases. While analyzing the enhanced fingerprint images few challenging cases are observed in which the algorithm generates spurious features when the ridge information in the latent image is insufficient. To address these limitations, the future work can explore the possibility of developing an algorithm that can decide the feasibility of reconstruction hence minimizing generation of spurious features. Furthermore, training the algorithm with larger texture and background variability in the database can help further improve the performance of the proposed model. Further, this algorithm can also be utilized in challenging scenarios like latent to latent fingerprint matching [18].

6. Acknowledgement

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