Towards Inpainting and Denoising Latent Fingerprints: A Study on the Impact in Latent Fingerprint Identification

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Abstract. In this paper, we provide a study about the impact of the most prominent inpainting and denoising solutions on the latent fingerprint identification. From an in-depth analysis, we show how some of the analyzed inpainting and denoising solutions can improve up 63% for Rank-1 and 26% for Rank-20 the fingerprint identification rates when state-of-the-art minutiae extractors are used. Nevertheless, it is necessary to create new denoising and inpainting solutions that are specifically built to deal with latent fingerprints and their associated issues.

Keywords: Latent fingerprint · Inpainting · Denoising · Deep learning

1 Introduction

Fingerprints are invaluable biometric features that have widely been adopted among law enforcement for verifying and identification of an individual. There exist two categories for clustering fingerprints: (i) impressions, which are acquired under controlled conditions; and (ii) latent fingerprints, which are unintentionally left by someone when manipulating objects and are thus particularly useful at crime scenes. However, due to the nature of the problem, latent fingerprints are usually incomplete and distorted images, presenting broken ridges and containing noisy background, which hinders their analysis during investigations due to their low-quality [14].

Figure 1 shows three examples of latent-rolled pairs of identified fingerprints from database NIST-SD27 [3]. Notice that latent fingerprints present incomplete and distorted images, containing noisy backgrounds. Consequently, as was recently reported in [14], the fingerprint identification rates are lower than 10%, 13 %, and 24% for Rank-1, weighted Rank-20, and Rank-100, respectively.

An idea to get better fingerprint identification rates is to improve the quality of latent fingerprints. Some authors [1,6,9,10,12] have been studying how

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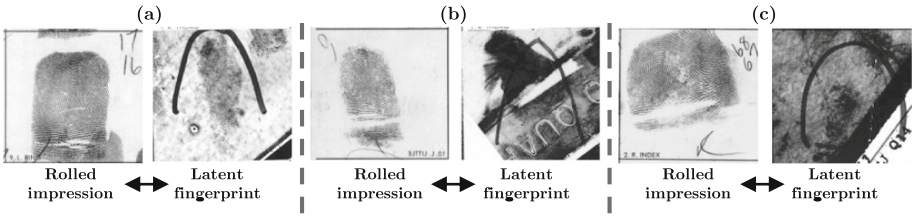

Fig. 1. Three examples of latent-rolled pairs of identified fingerprints from database NIST-SD27 [3]. Each latent fingerprints in NIST-SD27 is labeled according to its quality (a) good, (b) bad, and (c) ugly. Notice that, unlike the rolled impressions, the latent fingerprints contain partial information and higher levels of noise.

improving fingerprint impressions by using denoising and inpainting solutions. These solutions have positively impacted on the obtained accuracy for fingerprint verification. However, the literature has focused on studying denoising and inpainting solutions by using fingerprints obtained in controlled situations (impressions), which present higher quality than latent fingerprints.

As far as we know, there is no study on the impact of inpainting and denoising solutions for latent fingerprints. Hence, in this paper, we introduce the first study testing inpainting and denoising solutions on latent fingerprint databases.

Our study shows that fingerprint identification can be improved by using inpainting and denoising solutions, which were trained by using impressions. From our experiment result, we can conclude that the fingerprint identification rates can be improved up 63% for Rank-1 and 26% for Rank-20 when inpainting and denoising solutions are used. However, the fingerprint identification rates were not always improved by using inpainting and denoising solutions; or using some combination of them. Hence, we provide a set of recommendations for improving these solutions; and, consequently, the fingerprint identification rates.

This paper is organized as follows: Sect. 2 provides related work about inpainting and denoising solutions proposed for fingerprints. After, Sect. 3 presents our study related to the impact of the proposed inpainting and denoising solutions on latent fingerprints. Next, Sect. 3 provides our experimental setup as well as experimental results obtained from our study. Also, this section (Sect. 3) provides an in-depth analysis of the obtained results. Finally, Sect. 4 presents our conclusions and future work.

2 Related Work

Latent fingerprints are acquired from uncontrolled conditions (usually at crime scenes), hence containing noise, incomplete information, and perturbations produced by their forming mechanism. Besides, latent fingerprints suffer distortions due to their acquisition procedure. Unlike controlled fingerprint acquisitions, all these hostile conditions produce low-quality latent fingerprint images, which are vital for capturing criminals [14]. The acquired low-quality images motive

to machine learning researchers and fingerprint experts to create solutions for improving the quality of these images, and as a result, increasing the fingerprint identification rates [6]. Notice that fingerprint images are usually composed of thin ridges, and it is critical to preserve and keep them sharp during any restoration process for their reliable use during the fingerprint identification procedure. Any unintentional procedure that brakes or distorts the ridges can produce spurious minutiae, impacting negatively on the identification rate (a minutia is a minute detail on the ridges of a fingerprint, often ridge ending or bifurcation, which, together with other ones, are essential for the identification of people [14]).

One of the most prominent approaches for improving the quality of fingerprint images is to use denoising and inpainting solutions [1,6,9–12]. One of the pioneer solutions was proposed in [10], using the approach of *curvelet transforms*; which is a type of multiscale geometric transforms based on Fourier transformations for improving the quality of fingerprint images. Another solution was proposed in [12], where the authors use ridge orientation-based clustered dictionaries for creating a sparse denoising framework.

An essential advance on Machine Learning was the beginning of the Neural Artificial Network-based approach. However, the most significant progress was made when the CNN-based approach arrived, which has gained an enormous attraction in recent years. Consequently, several denoising and inpainting solutions based on CNNs were proposed for improving the quality of fingerprint images [1,6,9,11].

One of the pioneers and most prominent CNN-based solutions is U-Net, which was published in [11]. Figure 2 shows that U-Net's architecture contains two 3×3 convolutions, each followed by a rectified linear unit (ReLU) and a 2×2 max pooling operation with stride 2 for down-sampling. At the final layer, a 1×1 convolution is used to map each 64-component feature vector to the desired number of classes. In total, the network has 23 convolutional layers. Although this CNN was initially proposed for biomedical image segmentation, specifically for cell tracking challenge, its architecture has been a template for creating new CNNs by using its encoding and decoding procedure. It is essential to highlight that U-Net allows obtaining good fingerprint identification by improving the quality of fingerprint images.

The following three solution for improving the fingerprint images are based on the U-Net's architecture:

CVxTz was proposed in [6], which is similar to the U-net's architecture, excepting that CVxTz pad the input with zeros instead of mirroring the edges. CVxTz's architecture is suitable for improving the quality of fingerprint images because it takes into account a more broad context when predicting a pixel [6], and also it uses additional data augmentation. CVxTz was trained and tested by using a synthetic dataset[1] containing 84,000 fingerprint images (275×400 pixels), which were generated using a synthetic fingerprint generator

[1] This dataset can be downloaded from http://chalearnlap.cvc.uab.es/dataset/32/description/.

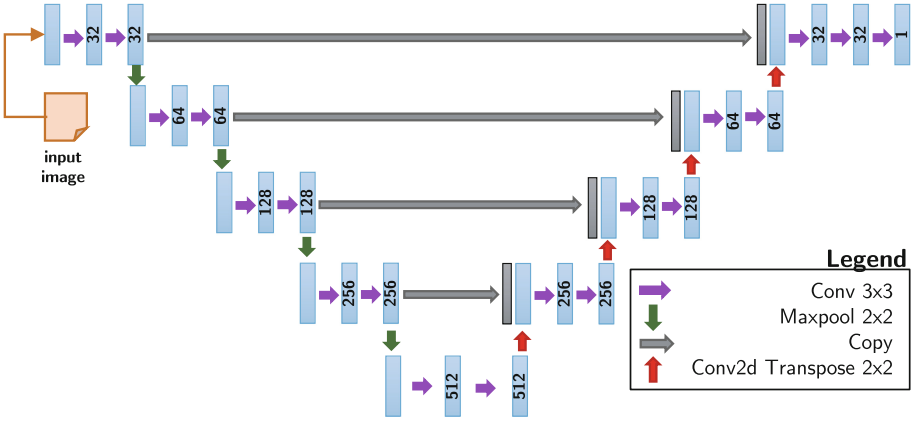

Fig. 2. U-net's architecture [11]. Its encoding and decoding procedure has widely been used to create other CNNs for improving the quality of fingerprint images.

(Anguli) [4]. All generated images were artificially transformed by adding background and random filters (blur, brightness, contrast, elastic transformation, occlusion, scratch, resolution, and rotation). The generated dataset contains 168,000 fingerprint images (84,000 fingerprint images - one ground-truth and one degraded image - per fingerprint). The results were assessed by using the mean absolute error (MAE) measure, where CVxTz allows obtaining the lowest MAE value (0.0189). The main drawback of CVxTz is that the used fingerprints were generated artificially, which means that the performance could significantly be degraded if the trained model is applied to real latent fingerprints.

U-Finger (a.k.a rgsl888) [9] was recently proposed as an alternative for denoising and inpainting on fingerprint images. U-Finger's architecture contains an encoding module where each convolutional layer is followed by spatial batch normalization and a ReLU neuron. From top to down, the four convolutional layers have 128, 32, 32, and 128 kernels of size 3×3, 1×1, 3×3, and 1×1, respectively. U-Finger's architecture's decode module provides a similar architecture as the encoding module excepting that the number of kernels in the four convolutional layers: 256, 64, 64, and 256. U-Finger was trained and tested by using the same dataset above mentioned for training the CVxTz solution. From experimental results, U-Finger obtains a worse MSE value (0.023579) than CVxTz (0.0189).

FDPMnet [1] was recently proposed for improving the quality of fingerprint images by using denoising and inpainting solutions. The encoding module consists of repeated two blocks of 3×3 convolutional layers, batch normalization layer, and ReLU activation. The decoding module is similar to encoding module, excepting that max-pooling is replaced by an upsampling layer which helps to reconstruct an output image. The final layer is a 1×1 convolution layer with a sigmoid activation function which gives the reconstructed output image. FDPMnet was trained and tested by using the same dataset above mentioned

for training and testing the CVxTz and U-Finger solutions. From experimental results, FDPMnet obtained the worst MSE value (0.0268) compared to CVxTz (0.0189) and U-Finger (0.23579). The main reason why CVxTz reached better results against the two other ones could be that it presents almost double the network depth as compared to other proposals, and also it uses additional data augmentation.

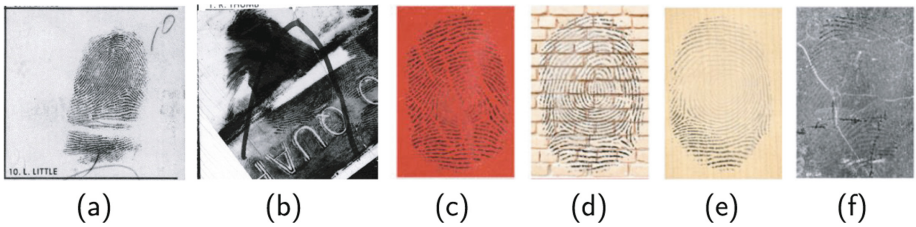

Fig. 3. Examples of fingerprints taken from the NIST-SD27 database [3] and the artificial dataset generated using Anguli [4]. An example of impression (a) and latent fingerprint (b), taken from a real scenario. From (c) to (f) contain fingerprints generated artificially.

Although the solutions above mentioned have managed impressive results, they have only been trained on fingerprints obtained in very controlled conditions, or on fingerprints generated synthetically by pieces of software. In Fig. 3, we show a set of fingerprints taken from a real database and other ones generated artificially. Notice that the quality of fingerprints generated artificially (c–f), which were transformed by using some filters, look like more the quality of an impression image (a) than the quality of a real latent fingerprint (b). Notice that the real latent fingerprint (b) contains some spots without visible ridges, different background textures, and different shades of gray.

From the reviewed papers and the analysis of Fig. 3, an novel avenue of study is open since there has been little research of fingerprint denoising and inpainting using latent fingerprints encountered in real-life situations instead of those taken from controlled situations or generated artificially. Hence, we proposed to analyze the performance of the most prominent denoising and inpainting solutions by using real latent fingerprints.

3 Studying the Impact of Inpainting and Denoising Solutions on the Latent Fingerprint Identification

This study aims to analyze the impact of the most prominent inpainting and denoising solutions on the latent fingerprint identification. To do so, we will analyze each solution separately as well as combinations of them by using two real latent fingerprint databases.

For a better understanding of our study, we have structured this section as follows: Sect. 3.1 presents our experimental setup, where databases, tested algorithms, and the methodological framework are described. Section 3.2 provides our experimental results and an in-depth analysis of these results.

3.1 Experimental Setup

For our experimentation, we have selected two latent fingerprint databases. On the one hand, NIST-SD27, which is a public database widely used in latent fingerprint studies [5,14]. On the other hand, we have a non-public database taken from a crime laboratory (from here on, *Proprietary*), which contains 568 rolled fingerprints (284 latent fingerprints and 284 impressions).

We selected three of the most prominent and popular minutiae extraction extractors, which have reported reasonable identification rates. Fingernet [13] and MinutiaeNet [8], which are based on convolutional networks; and Verifinger [7], a proprietary minutiae extractor developed by Neurotechnology.

We selected three of the most popular inpainting and denoising solutions for analysing their impact on the latent fingerprint identification: FDPMNet[2] [1], CVxTz[3] [6], and U-Finger[4] [9] (see Sect. 2 for more details).

We selected Minutia Cylinder-Code (MCC) [2] as a representation and matching technique for latent fingerprint identification. MCC has proven to obtain better identification rates than other several solutions. The authors of MCC provide a free and public SDK (SDKMCC[5]) for research purposes.

In our experiments, we use the identification rates plotted in the cumulative match characteristic (CMC) curve computed according to ISO/IEC 19795-1, which is the most used measure for assessing the fingerprint identification [14].

As the goal of this study is to analyze the impact of the most prominent inpainting and denoising solutions on the latent fingerprint identification, we will test every selected denoising and inpainting solution by themselves. After that, we will test all possible combinations of them (i.e., first run the solution A, then use the outputs as the inputs for solution B, and so on). Consequently, we will execute 15 combinations for each database (30 in total).

As representation and matching technique is the same, and we will only change the selected minutiae extractors as well as the combinations of the selected inpainting and denoising solutions, we will be able to see the following: (i) if the inpainting and denoising solution that were previously tried only on fingerprint impressions also work well with latent fingerprints; (ii) what is the combination of inpainting and denoising solutions improving the latent fingerprint identification rate; and (iii) what is the best combination among minutiae extractor and inpainting and denoising solutions for latent fingerprint identification.

[2] http://github.com/adigasu/FDPMNet.
[3] http://github.com/CVxTz/fingerprint_denoising.
[4] http://github.com/rgsl888/U-Finger-A-Fingerprint-Denosing-Network.
[5] http://biolab.csr.unibo.it.

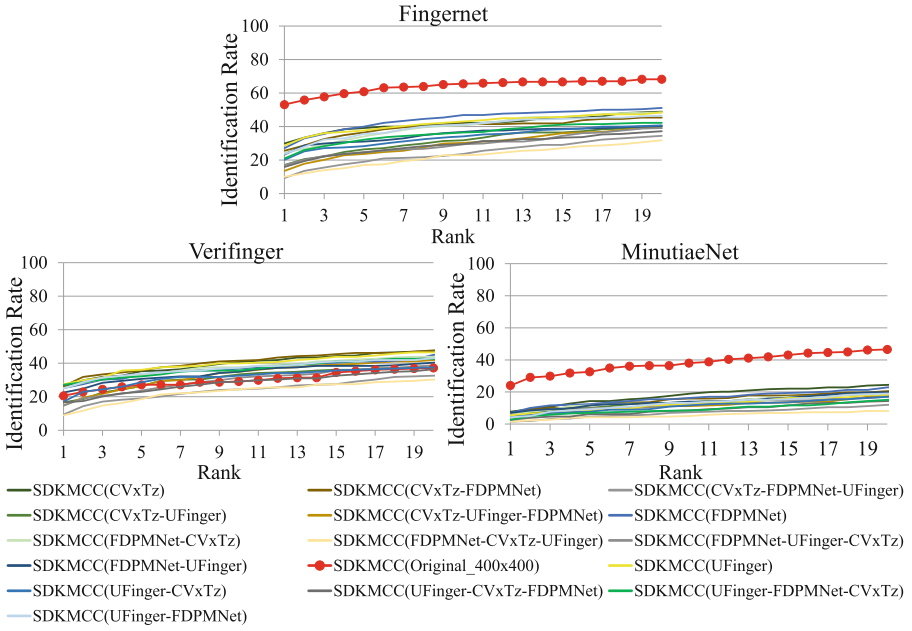

Fig. 4. CMC results for the NIST-SD27 database.

3.2 Experimental Results

Figure 4 shows the identification rates by using CMC curves (from Rank-1 to Rank-20) for each tested minutiae extractor on the NIST-SD27 database. This figure quantifies the ratio of correct identifications in the first place and among the 20 first ranks, respectively. From Fig. 4, we can notice that using Fingernet as a minutiae extractor, it allows obtaining the best results without using any inpainting and denoising solutions. The second-best result was obtained by only using FDPMNet, which presents an identification rate decrease of 48.91% (from 53.10% to 27.13%) for Rank-1 and an average identification rate decrease of 30.59% (from 63.91% to 44.36%) throughout the first-20 ranks.

From Fig. 4, we can notice a similar result to the one obtained by Fingernet but when MinutiaeNet is used. For MinutiaeNet, the best results come from not using any inpainting and denoising solutions. The second-best result was obtained by only using CVxTz, which presents an identification rate decrease of 67.74% (from 24.03% to 7.75%) for Rank-1 and an average accuracy decrease of 52.85% (from 38.02% to 17.93%) throughout the first-20 ranks.

Regarding the findings mentioned above, in Fig. 4, different results can be seen when Verifinger is used for extracting minutiae. The best result is coming from using CVxTz firstly and after, FDPMNet. This combination allows for obtaining an accuracy increase of 28.30% (from 20.54% to 26.36%) at Rank-1 and an average accuracy increase of 35.05% (from 30.08% to 40.62%) throughout

the first-20 ranks. Also, notice that only the combinations FDPMNet-CVxTZ-UFinger and FDPMNet-UFinger-CVxTZ do not improve the results obtained by Verifinger without using any inpainting and denoising solutions.

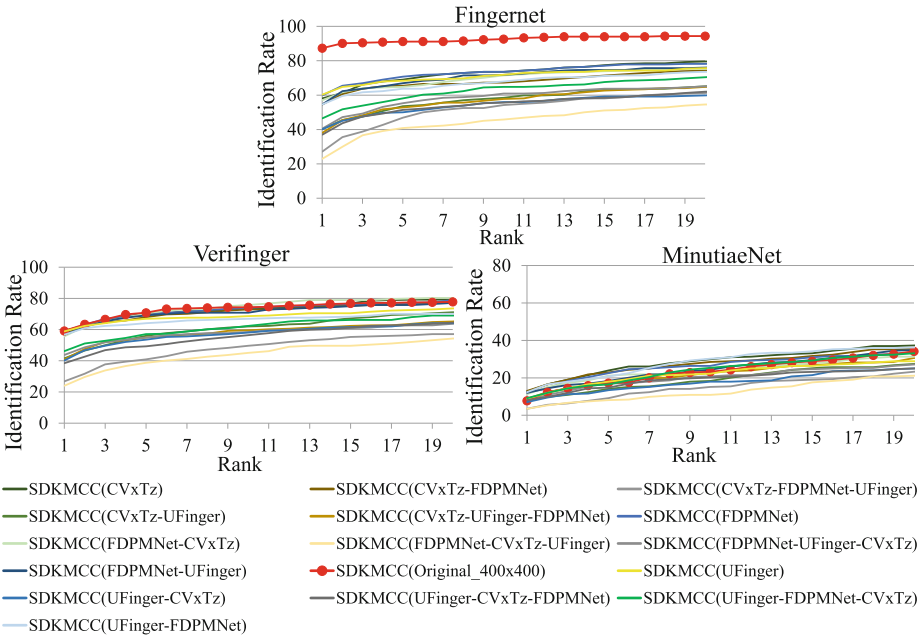

Fig. 5. CMC results for the Proprietary database.

Figure 5 shows from Rank-1 to Rank-20 identification rates by using CMC curves for each tested minutiae extractor on the Proprietary database. This figure quantifies the ratio of correct identifications in the first place and among the first-20 ranks, respectively. From Fig. 5, we can notice that using Fingernet as a minutiae extractor, it allows obtaining the best results without using any inpainting and denoising solutions. The second-best result was obtained by only using FDPMNet, which presents an identification rate decrease of 31.45% (from 87.32% to 59.86%) for Rank-1 and an identification rate decrease of 20.78% (from 92.45% to 73.24%) throughout the first-20 ranks.

From Fig. 5, we can notice that Verifinger obtains the best results from Rank-1 to Rank-8 without using any inpainting and denoising solutions. However, from Rank-9 to Rank-20, the best result is coming from using FDPMNet firstly and after, CVxTz. This combination decreases the identification rate in 5.95% (from 59.15% to 55.63%) for Rank-1, increases the identification rate in 1.06% (from 73.24% to 74.01%) throughout the first-20 ranks, and an identification rate increase of 3.29% (from 76.20% to 78.71%) from Rank-9 to Rank-20.

Other findings that we can notice from Fig. 5 is that, when using MinutiaeNet to extract minutiae from the proprietary database, the best results are coming

from using CVxTz. Nevertheless, it is very close to the results obtained by the combination of using U-Finger firstly and after FDPMNet. When compared MinutiaeNet with and without using any inpainting and denoising solutions, CVxTz increases the identification rate of 63.67% (from 7.75% to 12.68%) for Rank-1 and, on average, increases the identification rate of 22.83% (from 23.36% to 28.70%) for the first 20 ranks. On the other hand, the combinations U-Finger and FDPMNet increase the identification rate of 59.09% (from 7.75% to 12.32%) for Rank-1 and, on average, increases the identification rate of 21.02% (from 23.36 to 28.27%) for the first 20 ranks. It is essential to highlight that the results obtained by MinutiaeNet (without using any inpainting and denoising solutions) fall drastically when the Proprietary database is used, which could indicate that MinutiaeNet is biased in NIST-SD27.

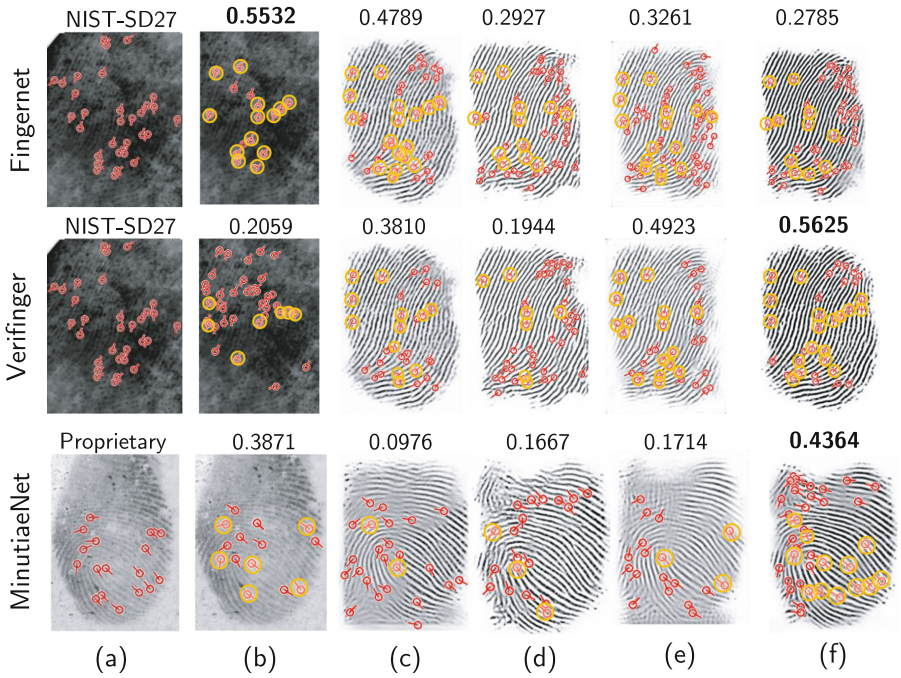

Fig. 6. Ground-truth minutiae and their matches (yellow circles) using different minutiae extractors, inpainting and denoising solutions, and two latent fingerprints. (a) latent fingerprint having minutiae extracted by a fingerprint expert. (b) the same latent fingerprint of (a) but having minutiae extracted by some of the three tested minutiae extractor (Fingernet, Verifinger, and MinutiaeNet). (c) it is the latent fingerprint (a) but filtered by CVxTZ. (d) it is the latent fingerprint (a) but filtered by FDPMNet. (e) it is the latent fingerprint (a) but filtered by U-Finger. (f) it is the latent fingerprint (a) but using the best combination of the tested inpainting and denoising solutions. Each latent fingerprint image having matched minutiae contains its associated F1 score value on top. (Color figure online)

For an in-depth analysis, Fig. 6 shows a comparison of the obtained results by using the ground-truth minutiae and their matches (yellow circles), the three tested minutiae extractors, the three tested inpainting and denoising solutions, and two latent fingerprints taking from the tested databases. From this figure, we can notice that FingertNet obtains the best F1 value for the NIST-SD27 database when inpainting and denoising solutions are not used. Also, we can see that Verifinger obtains the best F1 value for the NIST-SD27 database when the combination CVxTz and FDPMNet is used. Also, notice that Minutiae obtain the best F1 value for the Proprietary database when the combination FDPM-Net and U-Finger is used. All these findings can be corroborated by Figs. 4–5. Also, from Fig. 6, notice that the image quality for combination column (f) is better than using inpainting and denoising solutions alone. Furthermore, we can see that CVxTz (c) and U-Finger (e) provide blur on images, which makes it difficult to extract matched minutiae. Finally, from this figure, we can observe that Fingernet obtains the lowest number of spurious minutiae when inpainting and denoising solutions are not used. Nevertheless, for both Verifinger and MinutiaeNet, some inpainting and denoising combinations allow obtaining the best ratio between matched and spurious minutiae.

4 Conclusions

Denoising and inpainting solutions for fingerprint are of utmost importance since the fingerprint identification serves a crucial role in aiding police investigations for verifying and identifying people. However, most research on fingerprint denoising and inpainting focus on using fingerprint impressions, which contain less distortion than latent fingerprints, and they are obtained in controlled situations.

In this paper, we analyzed the impact of the most prominent inpainting and denoising solutions on latent fingerprint identification by using two latent fingerprint databases and three of the most popular minutiae extractors. From our results, we have found that using fingerprint denoising and inpainting solutions improve, in most cases, the identification rate of latent fingerprints even when dealing with images containing a noisy background and undefined ridges. On the one hand, the best denoising and inpainting solutions for NIST-SD27 are FDPM-Net when Fingernet is used, CVxTz when MinutiaeNet is used, and CVxTz firstly and after FDPMNet when Verifinger is used. On the other hand, the best denoising and inpainting solutions for Proprietary are FDPMNet when Fingernet is used, CVxTz, and the combination U-Finger firstly and after FDPMNet when MinuatiaeNet is used, and the combination FDPMNet firstly and after CVxTz when Verifinger is used.

From the analyzed solutions, we can conclude that they can improve up 63% for Rank-1 and 26% for Rank-20 the fingerprint identification rates when Verifinger or MinutiaeNet are used. Nevertheless, fingerprint identification was not always improved when these solutions were used jointly with Fingernet.

Our results and analysis open the door to future research aimed at studying and creating of denoising and inpainting solutions that are specifically built to

deal with latent fingerprints and their associated issues. Another avenue of future research is to inspect further how existing techniques can be improved by data augmentation and deblurring using generative adversarial networks.

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