Level Three Synthetic Fingerprint Generation

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1 Introduction

We propose a novel approach to create realistic, high-resolution synthetic fingerprints while maintaining control over the identity of the output images. Our goal is to foster further studies in this field without raising legal issues that come with real biometric data.

2 Synthetic Fingerprint Generation

To generate high-resolution synthetic fingerprints, we split our approach into two stages (Figure 1). The first stage concerns procedures required to create multiple instances of fingerprints, which we call **seed images**. The second stage consists of using CycleGAN to translate seed images into realistic L3 fingerprint.

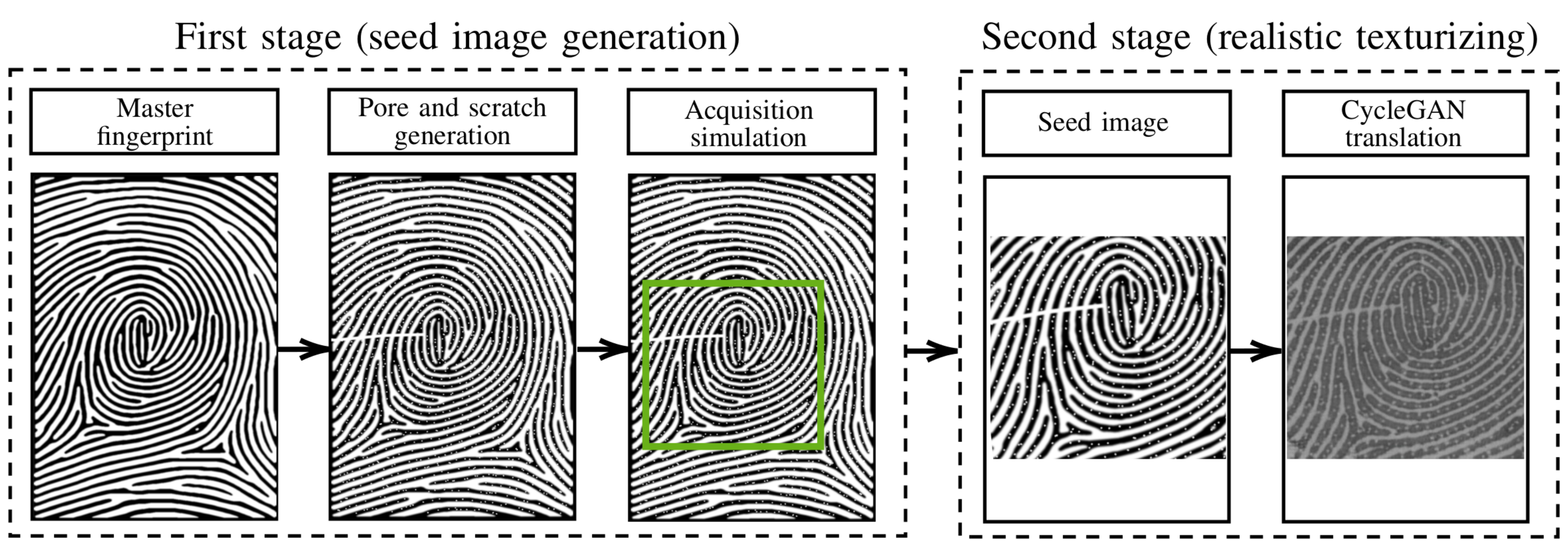
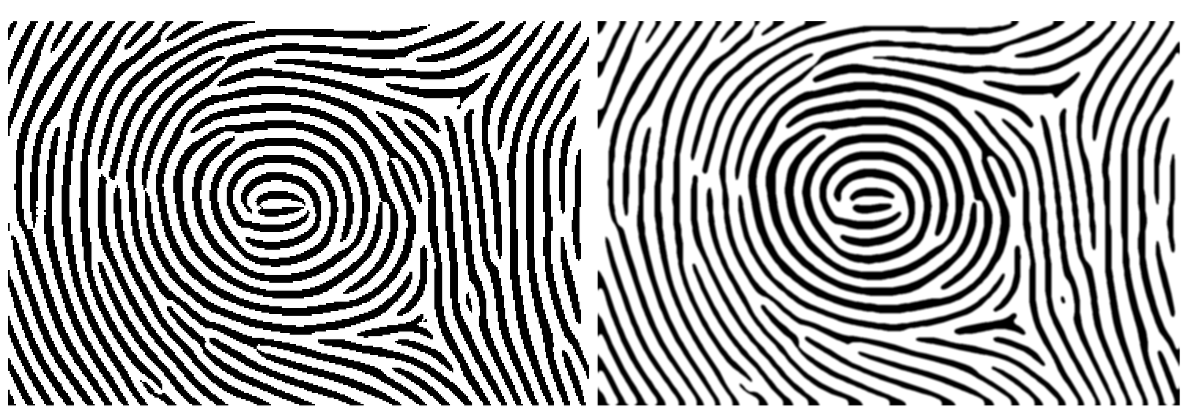


Figure 1: Flowchart with the steps to create a high-resolution synthetic fingerprint using the proposed approach.

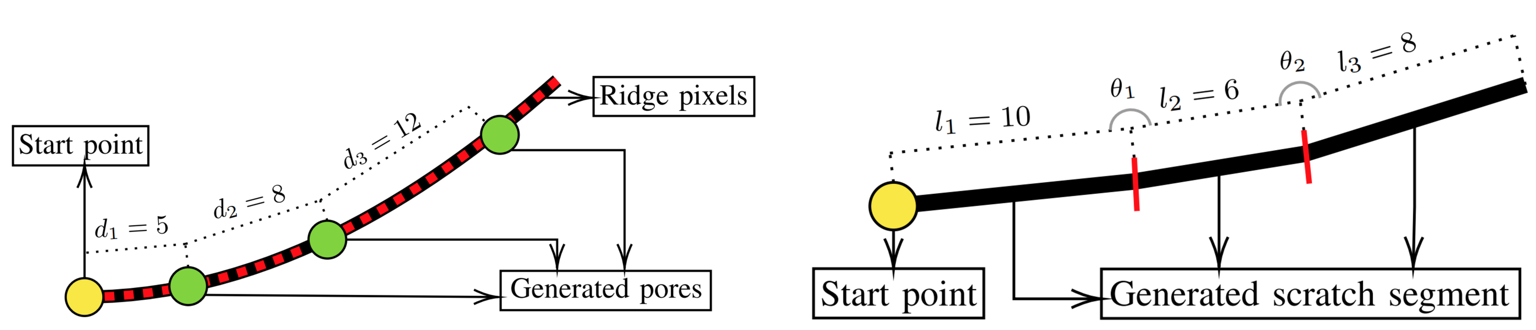
2.1 Master fingerprint



(a) Anguli output (b) Master fingerprint

Figure 2: Example of (a) an output of our modified version of Anguli and (b) its respective master fingerprint after ridge thickness sinusoidal perturbation. Note the ridge thickness variability in the master fingerprint.

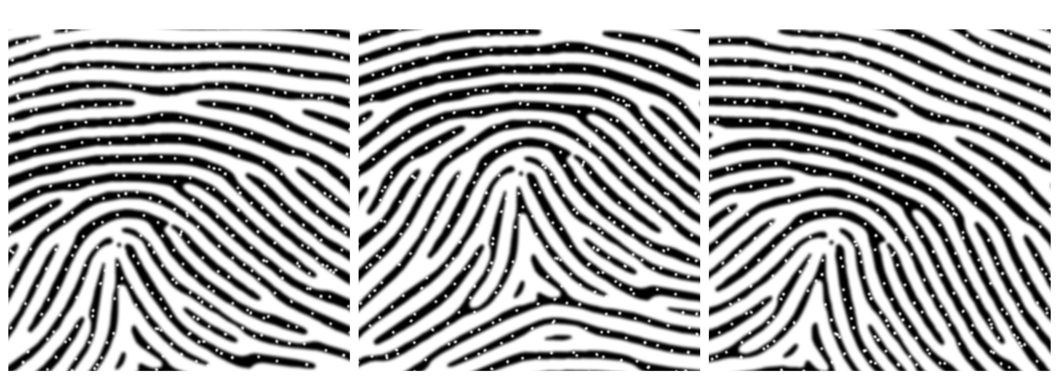
2.2 Pore and scratch generation



(a) (b)

Figure 3: a) Illustration of the pore generation process. (b) Illustration of the scratch generation process.

2.3 Acquisition simulation



(a) (b) (c)

Figure 4: Seed images generated from a single L3 master fingerprint, presenting distinct shifts and rotations.

2.4 CycleGAN translation

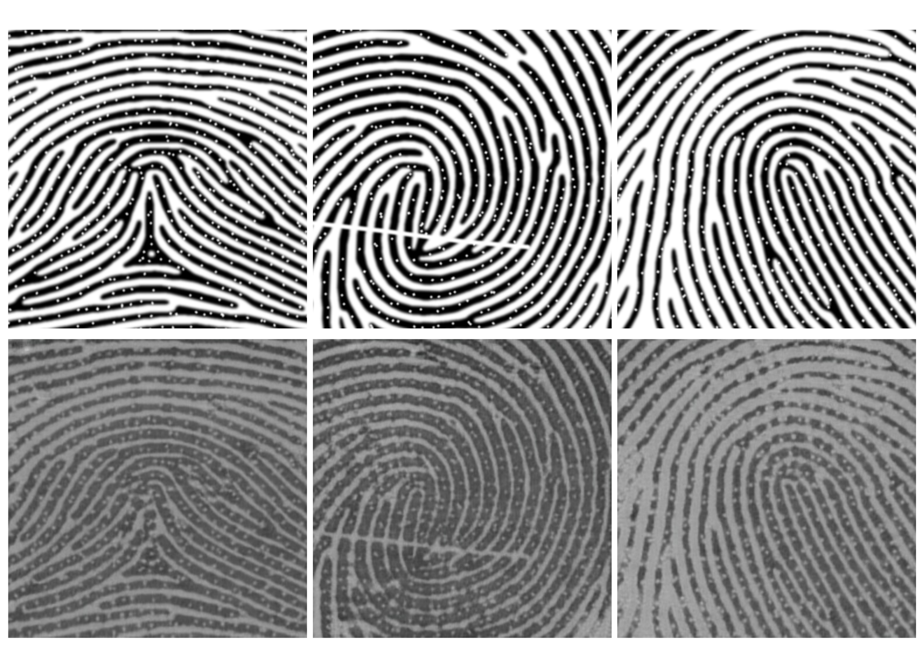


Figure 5: CycleGAN inference: seed images (top) and their respective results (bottom).

3 Qualitative results

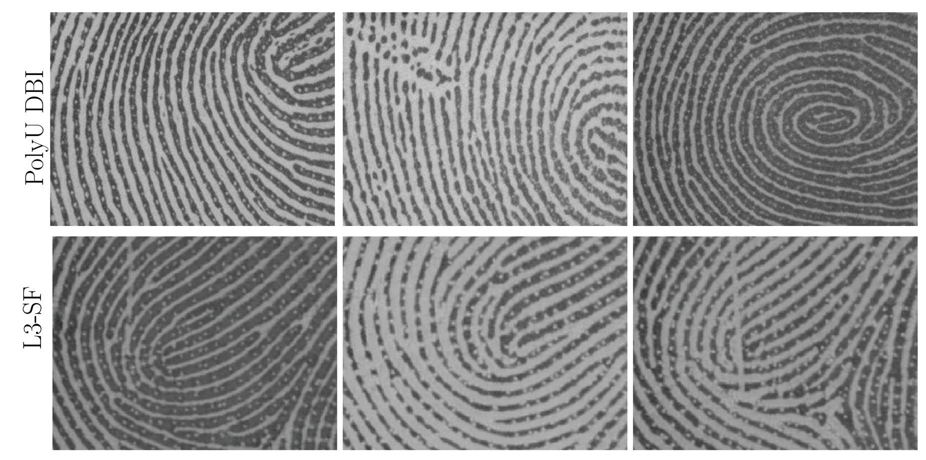


Figure 6: Visual comparison between real fingerprints from PolyU DBI (top) and synthetic ones from L3-SF (bottom).

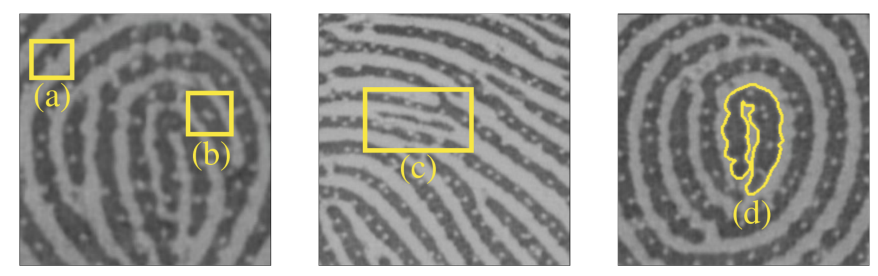


Figure 7: (a) and (b) are open and closed pores in an image of the L3-SF database. (c) shows an incipient ridge. (d) highlights an unique ridge shape.

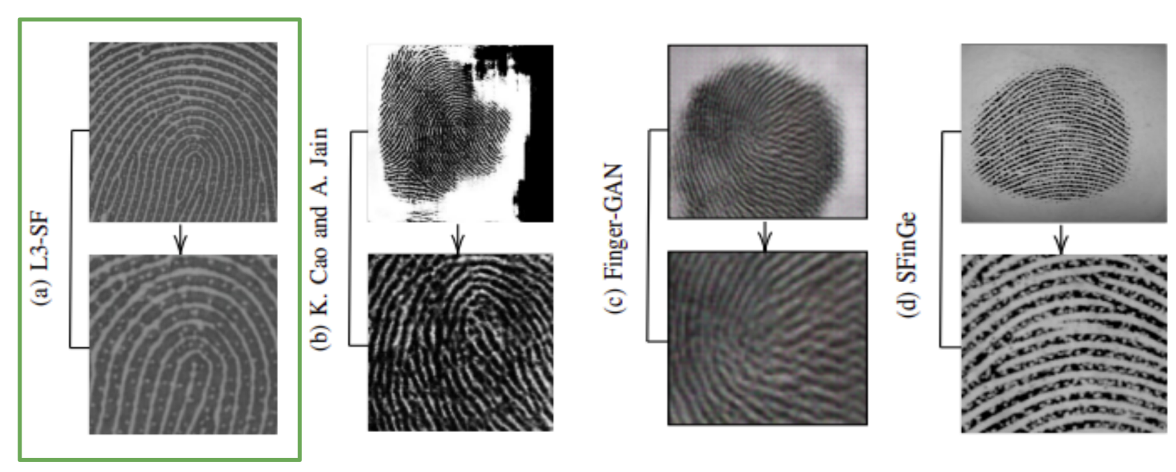


Figure 8: A visual comparison to existing approaches shows that our results are the new state-of-the-art. (a) the proposed approach, (b) SFinge [2], (c) Cao and Jain's method [1] and (d) Finger-GAN [3].

4 Quantitative results

The goal of our experiment was to compare real and synthetic images in terms of recognition performance. Ideally, both should have close results.

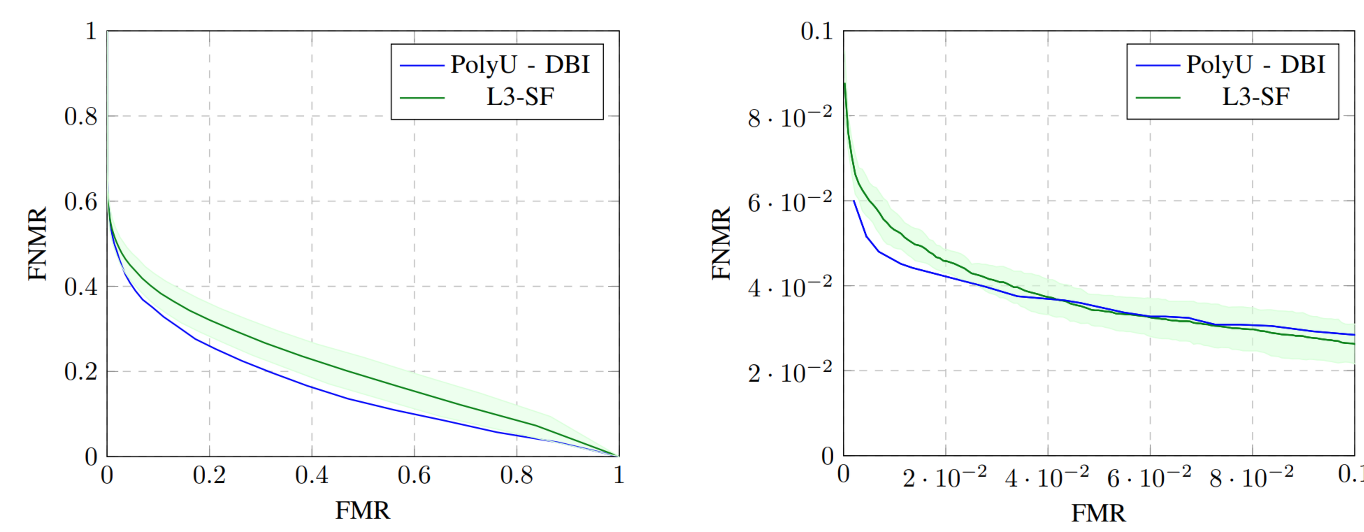


Figure 9: ROC curves from a minutiae-based matcher (left). ROC curves from a pore-based matcher (right).

We randomly show five real images and five synthetic fingerprints to the participants, which annotate the five images they consider false (see Figure 10).

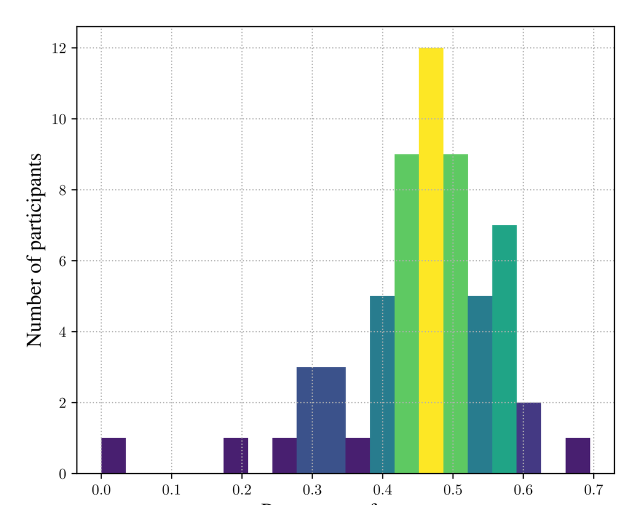


Figure 10: Histogram of the human perception experiment. Several participants had a classification accuracy close to random.

5 Main contributions and conclusions

- We created a novel hybrid fingerprint generation approach that combines a handcrafted identity generator and a learned texturizer to achieve realistic results and generate multiple images of a single identity.
- We created a public database of L3 synthetic fingerprint images with 7400 fingerprint images: `https://andrewyzy.github.io/L3-SF/`

References

[1] K. Cao and A. Jain. Fingerprint synthesis: Evaluating fingerprint search at scale. In *2018 International Conference on Biometrics (ICB)*, 2018.

[2] R. Cappelli. Sfinge: an approach to synthetic fingerprint generation. *International Workshop on Biometric Technologies*, Jan 2004.

[3] S. Minaee and A. Abdolrashidi. Finger-gan: Generating realistic fingerprint images using connectivity imposed gan. *arXiv preprint arXiv:1812.10482*, 2018.