Patch-based Finger Vein Recognition using an Auto Encoder

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Introduction

Finger vein patterns are below the skin and can not be seen under visible light. So, they do not leave a trace, and it is difficult to alter or copy them, which adds to a biometric recognition system an additional security.

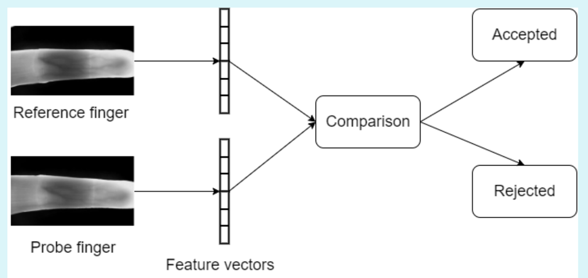

Figure1: Finger vein recognition

An auto encoder is trained to reconstruct its input through a series of compression and de-compression operations. During these series of operations, it learns a compact representation of the input data, without the need of labeled data..

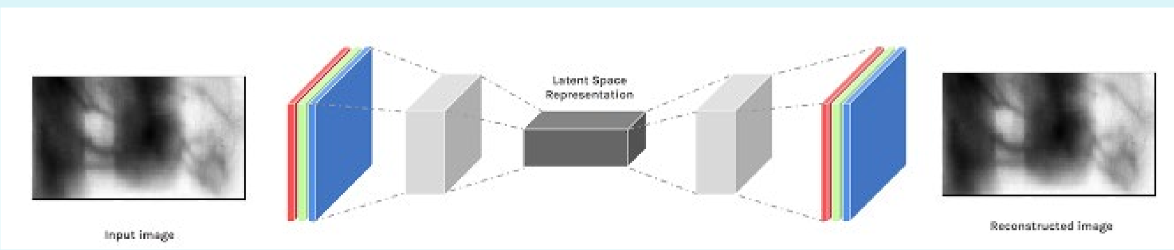

Figure2: Auto encoder

Ground-truth labels are hard to realise for large finger vein datasets. An unsupervised learning approach, such as Auto Encoder, could come in handy in this case.

Challenges
Auto Encoders vs. Finger Veins

Auto encoders are good at capturing global structures of a finger vein image such as joint shapes and illumination patterns, yet, vein patterns are not reconstructed well by the autoencoder[4].

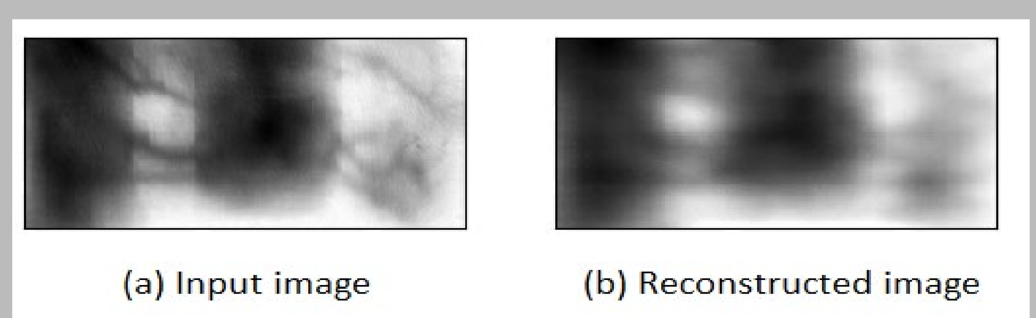

Figure3: Finger vein reconstruction with an auto encoder

Patch-based Finger Vein Recognition

Finger vein patterns have low contrast with the finger background, and due to their sparsity, they are dominated by global finger structures during training[4].

A solution to this problem is increasing the contribution of veins by extracting small vein patches. Further more, normalizing those small patches to zero mean and unit length improves the contrast.

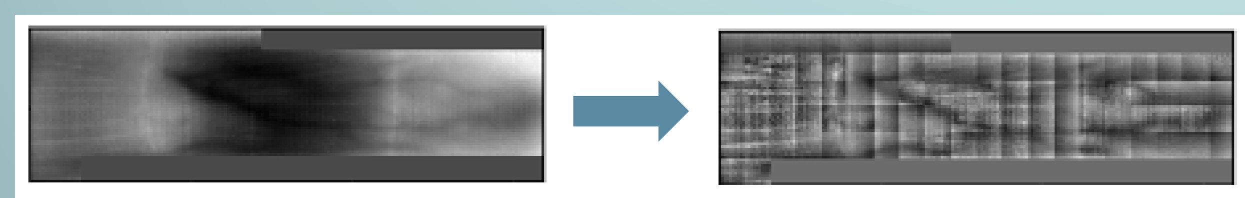

Figure4: Patch extraction and normalisation

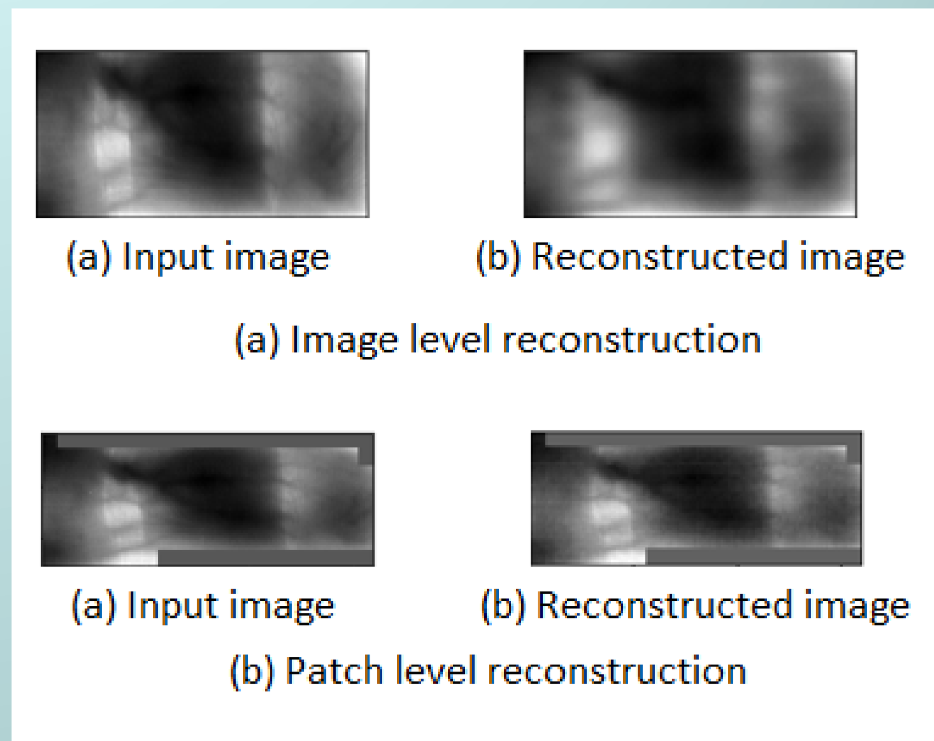

Figure5: Reconstruction comparison (a) Image level, (b) Patch level

Alignment is the Key

The patch based method is sensitive to alignment errors. Therefore, these errors should be corrected before comparison.

A sliding window approach is utilized in correcting the horizontal alignment between image pairs.

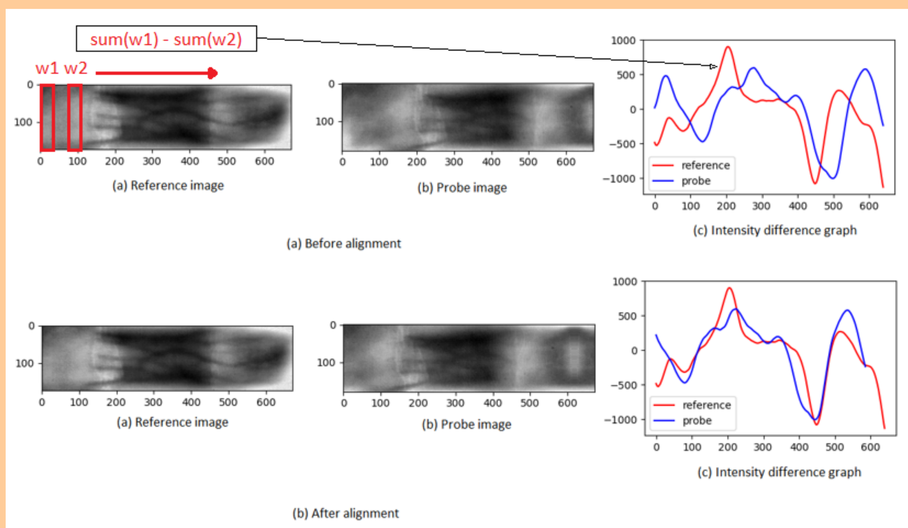

Figure6: Horizontal alignment

On the vertical axis, a simple structural similarity metric is used to find the correct alignment.

Are all patches informative?

Due to the sparsity of the vein patterns, not all of the extracted patches involve vein information. This case is likely to increase false acceptance.

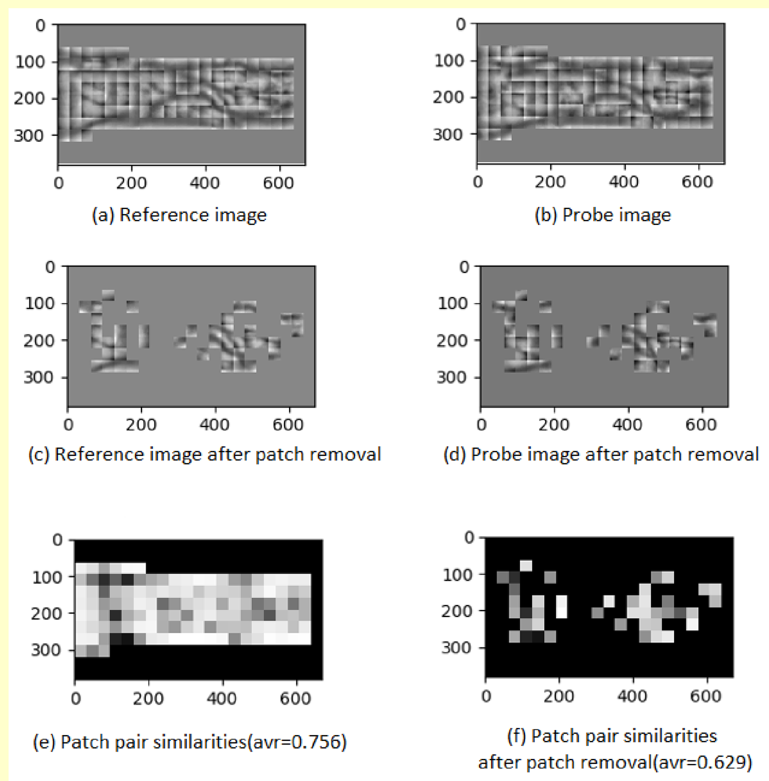

Figure7: Patch pair selection

A one-class SVM classifier is trained to remove non-informative patch-pairs based on an assumption that in an imposter pair, non-informative patch-pairs are likely to have high similarity scores.

Results

Evaluation is done on UTFVP dataset[3] by using 64 pixels patches. Cosine similarity is used to measure the similarity between patch pairs. Image pair similarity is the average similarity of the remaining patch pairs.

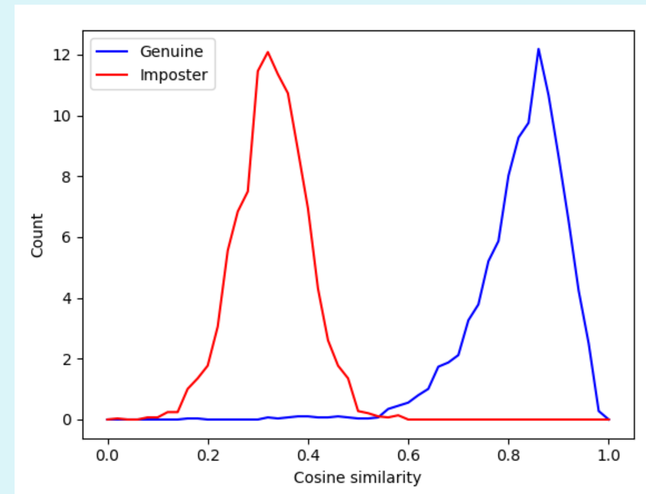

Figure8: image pair similarity histogram

Both the image pair similarity and the recognition performance expressed in EER indicates the potential of the patch-based approach.

	AUC	EER(%)
Image-based Recognition[4]	0.968	6.74*
Patch-based Recognition	0.998	0.83

Table 1: Performance comparison of image and patch-based approaches

Conclusion & Future Work

Although the performance of the patch-based approach is behind the state-of-the-art, the simplicity of it compared to literature[1],[2], and the recognition performance expressed in EER below 1% indicate the potential of the patch-based approach finger vein recognition.

Because of the simple vein patch reconstruction and comparison scheme, the patch-based auto encoder approach holds a great potential for cross-database finger vein recognition.

References

[1] Tang, Su, et al. "Finger vein verification using a Siamese CNN." *IET Biometrics* 8.5 (2019): 306-315.
[2] Song, Jong Min, Wan Kim, and Kang Ryoung Park. "Finger-vein recognition based on deep DenseNet using composite image." *Ieee Access* 7 (2019): 66845-66863.
[3] Ton, Bram T., and Raymond NJ Veldhuis. "A high quality finger vascular pattern dataset collected using a custom designed capturing device." *2013 International conference on biometrics (ICB)*. IEEE, 2013.
[4] Arican, Tuğçe, Raymond NJ Veldhuis, and Luuk Spreeuwers. "Finger Vein Verification with a Convolutional Auto-encoder." *41st Symposium on Information Theory and Signal Processingin the Benelux 2021*.
[5] Wang, Mingwen, and Dongming Tang. "A Study on Phalangeal Joint Reference Line Detection for Finger Vein Images." *2018 14th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*. IEEE, 2018.

* Log-likelihood ratio classfier