Rotation Tolerant Finger Vein Recognition using Convolutional Neural Networks

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Finger vein sensors

- single finger, palmar perspective
- suffers from different misplacements of the finger during acquisition
- apparatus to avoid finger misplacements

Longitudinal finger rotation

- causes a deformation of the vein pattern
- negatively effects recognition performance

Existing solutions for single camera systems

- detect and/or compensate finger rotation
- classical hand-crafted features only

Aim

- improve rotation tolerance using CNNs

The Problem of Longitudinal Finger Rotation

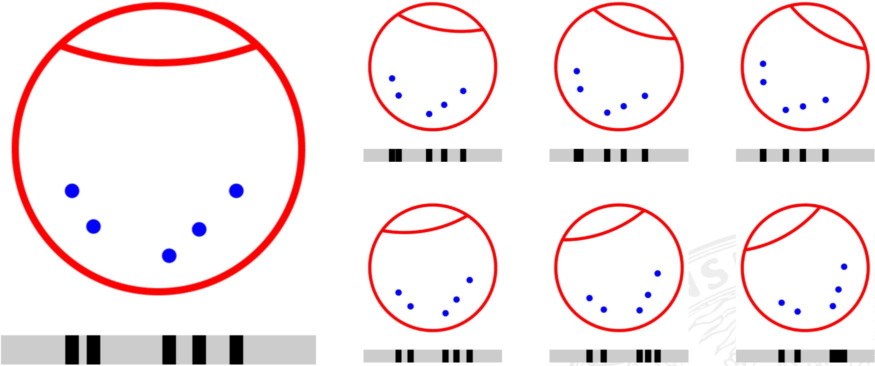


Figure: Longitudinal finger rotation principle: a schematic finger cross section showing five veins (blue dots) rotated from -10° to -30° (top row) and 10° to 30° (bottom row) in 10° steps. The projection of the vein pattern is different according to the rotation angle following a non-linear transformation [1].

Introduction III

Proposed solutions (not complete):

- Physical design of the sensor (e.g. Kauba *et al.* 2018 [2])
- Pre-aligning of the images (e.g. Lee *et al.* 2009 [3], Yang 2017 *et al.* [4])
- Pattern normalization (e.g. Huang *et al.* 2010 [5])
- Analysis of the geometric shape of the finger (Chen *et al.* 2018 [6])
- Deformation tolerant matching (e.g. Miura *et al.* 2004 [7], Matsuda *et al.* 2016 [8], Chen *et al.* 2017 [9])
- Pre-rotating enrolment perspectives with a fixed angle (Prommegger *et al.* 2019 [10])
- . . .

Rotation detection and correction (state-of-the-art)

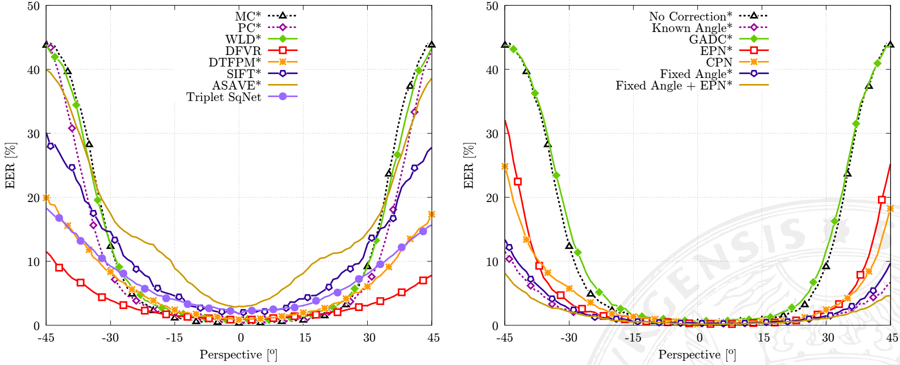


Figure: Trend of the EER across different rotation angles. Left: Performance of different finger vein recognition schemes, right: different rotation compensation approaches for the same scheme (MC) [10, 11]

CNN Architecture and Training I

CNN Architectures

- Squeeze-Net (SqNet) with triplet loss function
- DenseNet (DenseNet-161) with SoftMax loss

Data Sets

- PROTECT Multimodal Database (PMMDB) [12]
- PLUSVein-Finger Rotation Data set (PLUSVein-FR) [10]

Training Data

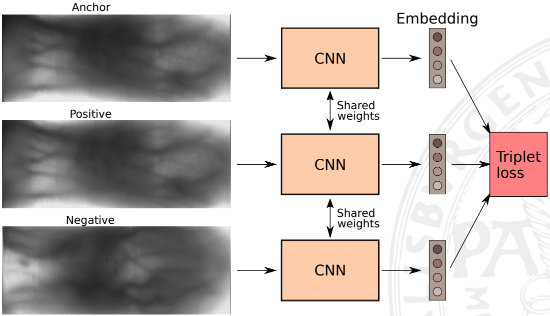
- Images acquired at different rotation angles vs
- Augmented images to simulate the rotation of the finger

Squeeze-Net (SqNet) with triplet loss function

- Groups images of the same class together
- Enforces a distance α to other classes
- Can be applied classes not included in the training set

$$L(A, P, N) = \max(||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 + \alpha, 0),$$

A .. Anchor, P .. Positive, N .. Negative, α .. margin, $f(x)$ .. embedding.



DenseNet (DenseNet-161) with SoftMax loss

- The SoftMax loss function is based on assigning classes to images (probability values to each class).
- Evaluation can only be applied to already trained classes.
- This is impracticable for biometric applications.
- To avoid this problem, the net is trained with the Soft-Max loss function and then employed as feature extractor for evaluation by using the CNN activations of intermediate layers.

CNN Training: Images acquired at different rotation angles vs augmented input data

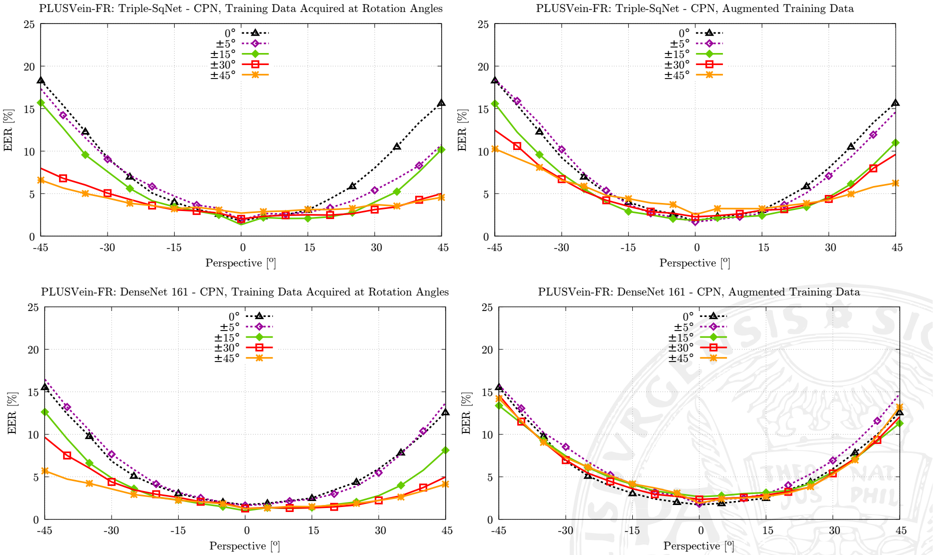
- Acquired images: Using images actually acquired at different rotation angles ($\pm 45°$ in steps of $1°$).
- Data Augmentation: Rotations are simulated by transforming images from the palmar view ($0°$).
  - Circular pattern normalization (CPN) [10]
  - Rotation corresponds to a vertical shift of the image.
- Reference: single camera system (training data acquired at palmar view = $\pm 0°$)
- Evaluations: Images from different rotational ranges ($\pm 5°$, $\pm 15°$, $\pm 30°$ and $\pm 45°$)

Experimental Setup

- CNN training on PMMDB
- Evaluation on PLUSVein-FR ($\pm 45°$)
- EER is computed using Similarity scores between images of the palmar view ($0°$) and images at rotation α ($\alpha \in [-45, 45]$)
- Relative performance degradation:

$$\text{RPD} = \frac{\text{ERR}_{rot} - \text{ERR}_{ref}}{\text{ERR}_{ref}}$$

Results I



Trend of EER for Triplet-SqNet and DenseNet-161

Comparison to state-of-the art hand-crafted methods

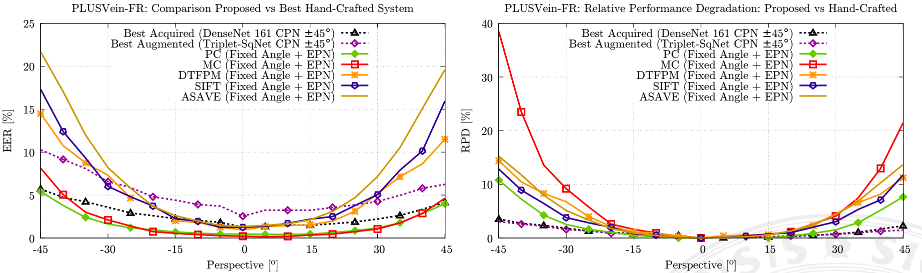


Figure: Performance degradation depending on the rotational difference. Left: absolute EER values, right: relative performance degradation

- inferior baseline performance @ palmar view
- lower performance degradation for increasing rotational distance

Conclusion I

Contribution:

- First CNN based rotation tolerant single camera system
- Two different training approaches:
  1. Images acquired at different rotation angles
  2. Artificial rotated versions of palmar images (data augmentation)
- Low (relative) performance degradation on the whole rotational range ($\pm 45°$)
- Augmented training data works only for Triplet-SqNet
- Baseline performance at palmar view still needs improvement

Thank you!

Bibliography I

[1] B. Prommegger, C. Kauba, and A. Uhl, “Longitudinal finger rotation - problems and effects in finger-vein recognition,” in *Proceedings of the International Conference of the Biometrics Special Interest Group (BIOSIG’18)*, Darmstadt, Germany, 2018.

[2] C. Kauba, B. Prommegger, and A. Uhl, “The two sides of the finger - an evaluation on the recognition performance of dorsal vs. palmar finger-veins,” in *Proceedings of the International Conference of the Biometrics Special Interest Group (BIOSIG’18)*, Darmstadt, Germany, 2018.

[3] E. C. Lee, H. C. Lee, and K. R. Park, “Finger vein recognition using minutia-based alignment and local binary pattern-based feature extraction,” *International Journal of Imaging Systems and Technology*, vol. 19, no. 3, pp. 179–186, 2009.

[4] L. Yang, G. Yang, Y. Yin, and X. Xi, "Finger vein recognition with anatomy structure analysis," *IEEE Transactions on Circuits and Systems for Video Technology*, pp. 1–1, 2017.

[5] B. Huang, Y. Dai, R. Li, D. Tang, and W. Li, "Finger-vein authentication based on wide line detector and pattern normalization," in *Pattern Recognition (ICPR), 2010 20th International Conference on*. IEEE, 2010, pp. 1269–1272.

[6] Q. Chen, L. Yang, G. Yang, and Y. Yin, "Geometric shape analysis based finger vein deformation detection and correction," *Neurocomputing*, 2018.

[7] N. Miura, A. Nagasaka, and T. Miyatake, "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification," *Machine Vision and Applications*, vol. 15, no. 4, pp. 194–203, 2004.

[8] Y. Matsuda, N. Miura, A. Nagasaka, H. Kiyomiu, and T. Miyatake, “Finger-vein authentication based on deformation-tolerant feature-point matching,” *Machine Vision and Applications*, vol. 27, no. 2, pp. 237–250, 2016.

[9] Q. Chen, L. Yang, G. Yang, Y. Yin, and X. Meng, “DFVR: Deformable finger vein recognition,” in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, March 2017, pp. 1278–1282.

[10] B. Prommegger, C. Kauba, M. Linortner, and A. Uhl, “Longitudinal finger rotation - deformation detection and correction,” *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 1, no. 2, pp. 123–138, 2019.

Bibliography IV

[11] B. Prommegger and A. Uhl, “A fully rotation invariant multi-camera finger vein recognition system,” *IET Biometrics*, pp. 1–12, 2021, accepted.

[12] C. Galdi, J. Boyle, L. Chen, V. Chiesa, L. Debiasi, J.-L. Dugelay, J. Ferryman, A. Grudzien, C. Kauba, S. Kirchgasser, M. Kowalski, M. Linortner, P. Maik, K. Michon, L. Patino, B. Prommegger, A. F. Sequeira, L. Szklarski, and A. Uhl, “Protect: Pervasive and user focused biometrics border project,” *IET Biometrics*, September 2020.