Rotation Tolerant Finger Vein Recognition using CNNs

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Abstract

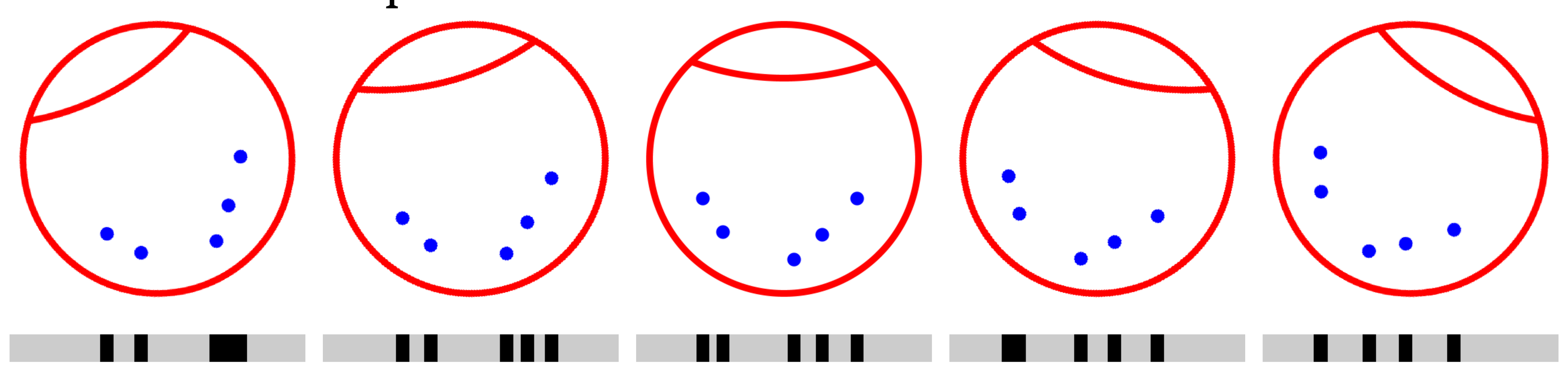
Finger vein recognition deals with the recognition of subjects based on their venous pattern within the fingers. The majority of the available systems acquire the vein pattern using only a single camera. Such systems are susceptible to misplacements of the finger during acquisition, in particular longitudinal finger rotation poses a severe problem. Besides some hardware based approaches that try to avoid the misplacement in the first place, there are several software based solutions to counter fight longitudinal finger rotation. All of them use classical hand-crafted features. This work presents a novel approach to make CNNs robust to longitudinal finger rotation by training CNNs using finger vein images from varying perspectives.

Conclusion

- First CNN based rotation tolerant single camera system
- Two different CNN architectures:
  - Triplet-SqNet
  - DenseNet-161 with SoftMax
- Two different training approaches:
  - Images acquired at different rotation angles
  - 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
- Rotation tolerance is based on training data and not on the CNNs architecture

Longitudinal Finger Rotation

- Misplacement of the finger during acquisition
- Can be reduced or prevented by the design of device (e.g. by adding support structures)
- Negative influence can be reduced during pre-processing, feature extraction or comparison

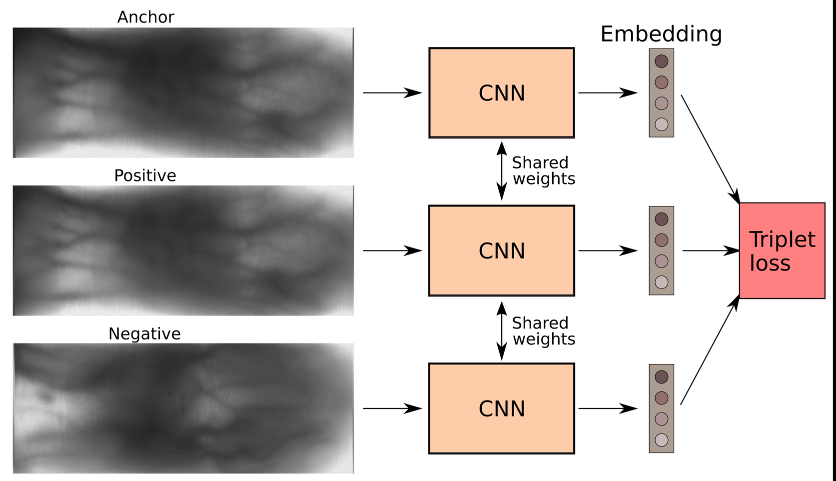


Longitudinal finger rotation principle: a schematic finger cross section showing five veins (blue dots) rotated from -30° (left) to +30° (right) in 15° steps. The projection (bottom row) of the vein pattern is different depending on the rotation angle.

CNN Architectures

Squeeze-Net (SqNet) with triplet loss function

- Groups images of the same class together in the output space
- Separates images from different classes
- Can be applied to classes that have not been included during training



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

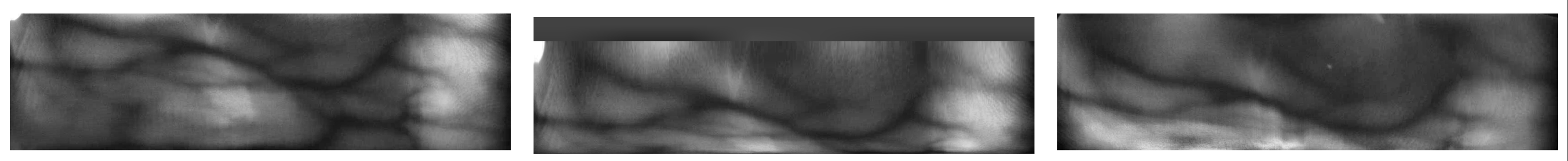
A .. Anchor, P .. Positive, N .. Negative, α .. margin, $f(x)$ .. embedding.

DenseNet (DenseNet-161) with SoftMax loss

- SoftMax loss function is based on assigning classes to images (probability values to each class).
- Evaluation can only be applied to already trained classes.
- Inpracticable 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.

Training Data

- Two data sets:
  - *PROTECT Multimodal Dataset*(PMMDB)
  - *PLUSVein-Finger Rotation Data Set*(PLUSVein-FR)
- Provide finger vein images all around the finger (360° in steps of 1°)
- Used subset: $\pm 45°$ around the palmar view (= 0°)
- PMMDB for training, PLUSVein-FR for evaluation



Acquired at 0° | Rotated to 45° | Acquired at 45°

Varying ranges from which the training images are taken:

- Only from a single perspective (palmar view, $\pm 0°$) = classical single camera recognition system
- Different rotational ranges (± 5 °, $\pm 15°$, $\pm 30°$ and $\pm 45°$)

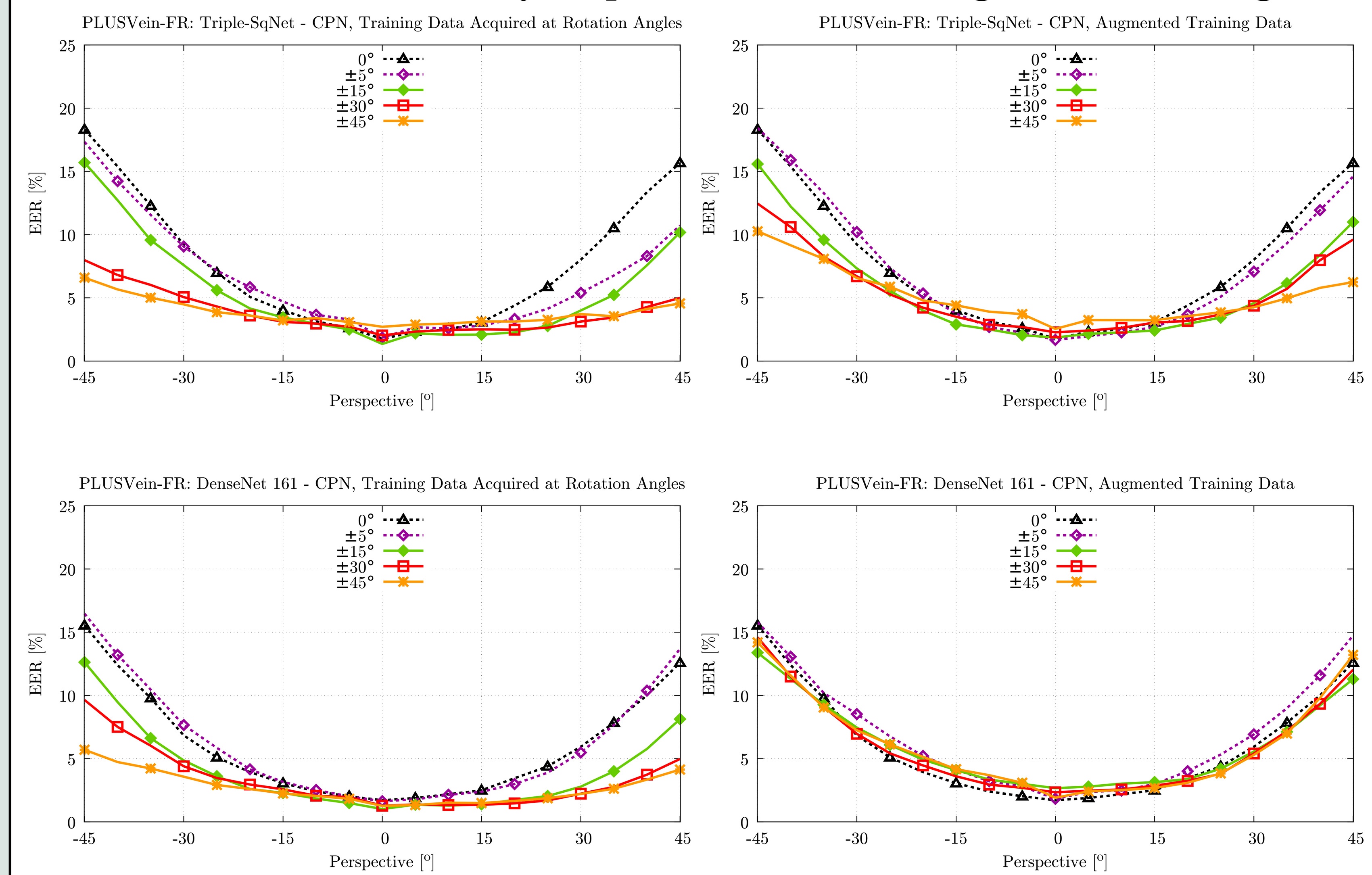
Two sources for rotated images:

1. Images acquired at different rotation angles
2. Augmented images simulating rotations of the finger (circular pattern normalization + shift)

Experiments / Results

Evaluation of the CNN's rotation tolerance

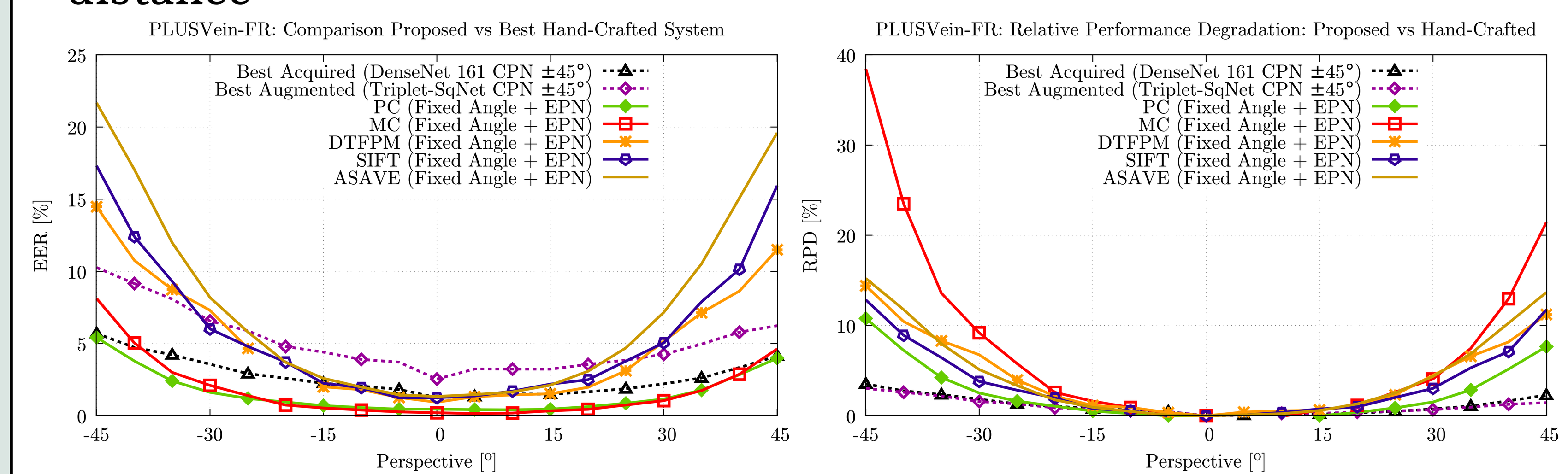
- CNNs: Triplet-SqNet (top row) and DenseNet-161 (bottom)
- Classical single camera recognition system with images acquired from a single view ($\pm 0°$))
- Training images taken in the range of $\pm 5°$, $\pm 15°$, $\pm 30°$ and $\pm 45°$
- Rotation source: actually acquired (left) and augmentation (right)



Trend of the EER across different longitudinal rotations applying Triplet-SqNet and DenseNet-161 trained with different rotational ranges

Comparison to State-of-the-Art

- Comparison to best performing methods of previous evaluations (Prommegger *et al.* 2019, 2020)
- Inferior baseline performance @ palmar view
- Lower (relative) performance degradation for increasing rotational distance



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

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