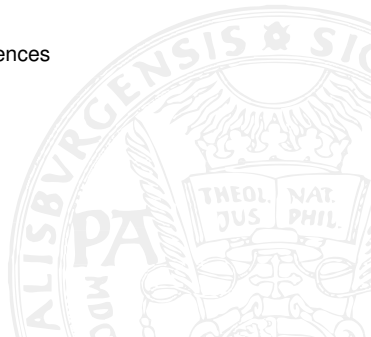


On the Extent of Longitudinal Finger Rotation in Publicly Available Finger Vein Data Sets

Bernhard Prommegger, Christof Kauba and Andreas Uhl

Department of Computer Sciences
University of Salzburg

October 17, 2019



What is longitudinal finger rotation?

- misplacement of the finger during acquisition

The Problem of longitudinal finger rotation:

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

The Problem of data sets:

- contain longitudinal rotation
- provide no information on the rotation angle

The Solution:

- detect or estimate the rotation angles



The Problem of Longitudinal Finger Rotation

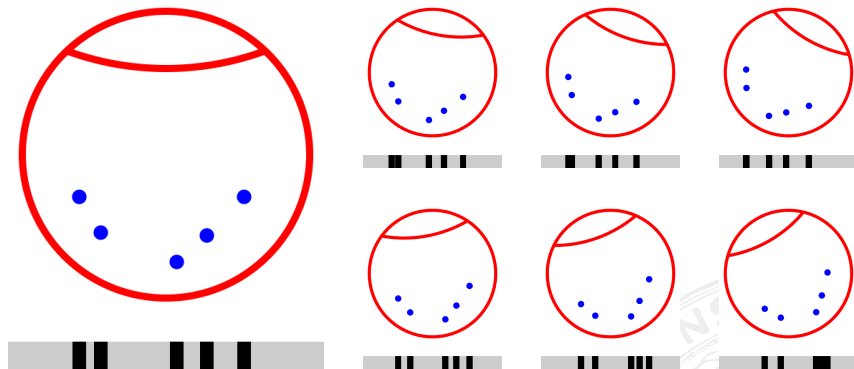


Figure: Longitudinal finger rotation principle: a schematic finger cross section showing five veins (blue dots) rotated from -10° to -30° (top row) and 10° to 30° (bottom row) in 10° steps. The projection of the vein pattern is different according to the rotation angle following a non-linear transformation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

Finger Rotation Detection

- Estimation of the rotation angle between two samples
- Rotate all images of the data set
 - range: $\pm 45^\circ$
 - step size: 1°
- Calculate GENUINE scores of
 - non-rotated first sample against all other rotated images
 - all non-rotated images against rotated first sample
 - Reference: first sample of every finger
- Rotation angle is selected where the highest correlation (score) is achieved

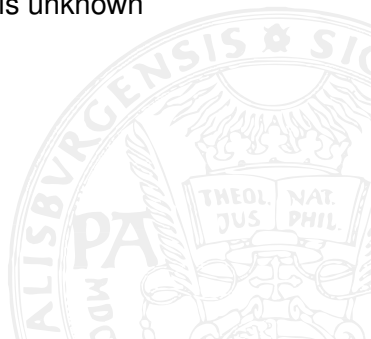
Finger Rotation

Problem: how to calculate the rotated version of the input images

- input images are a 2D projection of the vessels in the 3D space
- finger shape is not known
- depth of blood vessels within the finger is unknown

Assumptions:

- circular finger shape
- vessels on skin surface of finger



Finger Rotation

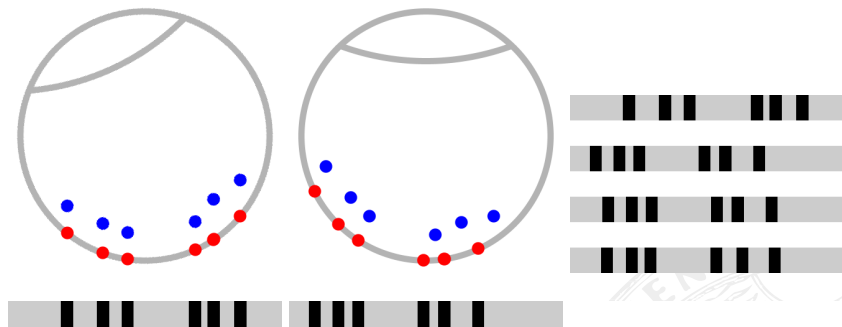


Figure: Principle of rotation correction. Left: finger rotated with 25°, middle: rotation corrected version, right (from top to bottom): rotated vein pattern, corrected vein pattern, corrected pattern shifted for the highest correlation to the palmar pattern.

Evaluated finger-vein data sets

Data Set	Subjects	Finger	Samples	Images	View
SDUMLA-HMT	106	6	6	3816	palmar
UTFVP	60	6	4 (2x2)	1440	palmar
FV-USM	123	4	12 (2x6)	5904	palmar
PLUSVein-FV3	60	6	5	1800	dorsal

SDUMLA-HMT [2]: Visually big differences in the images acquired from the same finger are visible. This also includes longitudinal rotation.

UTFVP [3]: Only visually considered, the UTFVP data set seems to have only little to no longitudinal rotation.

FV-USM [4]: The images of one session seem to be quite similar, while there are noticeable differences between the two sessions.

PLUSVein-FV3 [5]: The sensor was built in a way that requires the subject to place the whole hand flat on the sensor. Therefore, the data set is expected contain little to no longitudinal rotation. We only evaluate the dorsal images acquired by the laser version of the sensor.

Distribution of longitudinal finger rotation within the data sets

Rotation to mean	Data Set			
	SDUMLA-HMT	UTFVP	FV-USM	PLUSVein-FV3
0° - 5°	56.4%	85.2%	80.0%	98.4%
5° - 10°	21.5%	13.9%	15.3%	1.6%
10° - 15°	10.4%	0.8%	3.7%	-
15° - 20°	6.2%	0.1%	0.8%	-
20° - 25°	2.7%	-	0.2%	-
25° - 30°	1.6%	-	-	-
30° - 35°	0.8%	-	-	-
35° - 40°	0.4%	-	-	-
40° - 45°	0.1%	-	-	-

Statistical data on the degree of rotation present in the data sets

Data Set	Maximum Distance		
	Mean	Max	Std
SDUMLA-HMT	19.40	77.00	15.73
UTFVP	7.95	29.50	4.41
FV-USM	11.32	41.00	7.75
PLUSVein-FV3	4.46	12.50	2.44

Results III

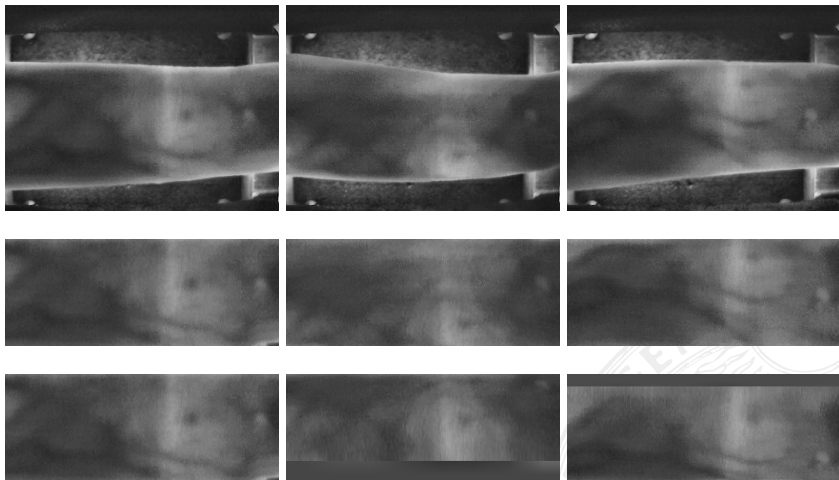


Figure: SDUMLA-HMT sample (left ring finger of subject #96). Left: sample #1 (reference), middle: #4 (rotation: 44°) right: #6 (rotation: -32°)

Result verification

Change (improvement) of recognition performance within the evaluated data sets:

- Reference: the original data set,
- Comparison 1: rotation corrected data set with respect to the first sample of each finger
- Comparison 2: rotation corrected data set with respect to the mean of the determined rotation angles of each finger.

Data Set	Version	Performance Indicators				
		EER	FMR100	FMR1000	ZeroFMR	RPI
SDUMLA-HMT	ORI	4.73 (± 0.22)	6.12	8.09	63.25	-
	ROT	1.07 (± 0.11)	1.13	1.72	59.91	341.6
	ROT Mean	1.14 (± 0.11)	1.18	1.82	47.77	315.8
UTFVP	ORI	0.42 (± 0.12)	0.23	0.65	3.11	-
	ROT	0.19 (± 0.09)	0.19	0.23	1.62	124.5
	ROT Mean	0.09 (± 0.06)	0.05	0.09	1.30	349.1
FV-USM	ORI	1.23 (± 0.08)	1.30	2.34	5.27	-
	ROT	0.56 (± 0.05)	0.48	0.93	2.47	120.1
	ROT Mean	0.77 (± 0.06)	0.69	1.42	3.93	59.4
PLUSVein-FV3	ORI	0.08 (± 0.05)	0.03	0.08	0.39	-
	ROT	0.06 (± 0.04)	0.00	0.06	0.25	50.0
	ROT Mean	0.08 (± 0.05)	0.00	0.08	0.22	0.9

Table: Recognition performance on the evaluated data sets and its corrected versions: ORI = original data set, ROT = rotation corrected to 1st image, ROT Mean = rotation corrected to mean of finger. Best achieved EER and RPI values are highlighted in bold.

Contribution

- Analysis of presence and degree of longitudinal finger rotation in four publicly available finger vein data sets
- Estimated rotation angles are available for download

Conclusion

- Different data sets show different degree of longitudinal finger rotation
- Influenced by
 - acquisition setup (e.g. scanner hardware)
 - acquisition protocol and its supervision

Future Work

- Analysis of additional data sets
- Analysis of inter/intra-session differences

Thank you!

Q & A



Influence of finger rotation on recognition performance

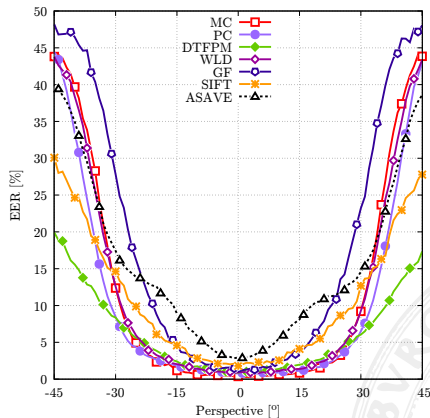


Figure: Trend of the EER across the different rotation angles (-45° to 45°) [6].

$$\begin{bmatrix} x_r \\ y_r \end{bmatrix} = \begin{bmatrix} \cos(-\varphi_{rotate}) & -\sin(-\varphi_{rotate}) \\ \sin(-\varphi_{rotate}) & \cos(-\varphi_{rotate}) \end{bmatrix} * \begin{bmatrix} x \\ y \end{bmatrix} \quad (1)$$

$$\varphi_{i,j} = \arg \max_{-45^\circ \leq \varphi_{rotate} \leq +45^\circ} score(i, j, \varphi_{rotate}) \quad (2)$$

$$\Phi_{i,1} = \text{avg}(\varphi_{i,1}, \varphi_{1,i}) \quad (3)$$

φ_{rotate}

rotation angle

x

row of the pixel in the image

y

$= \sqrt{r^2 - x^2}$

r

the approximated radius of the finger

$\varphi_{i,j}$

angle between the i^{th} and j^{th} sample

$score(i, j, \varphi_{rotate})$

score between the i^{th} and the rotated j^{th} sample

$\Phi_{i,1}$

calculated rotation angle of i^{th} sample

Additional Material III

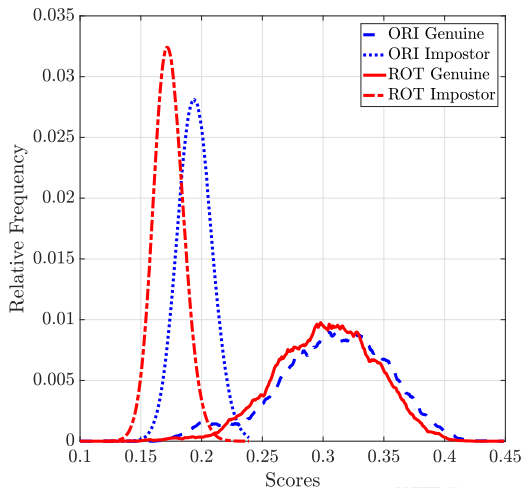


Figure: Distribution of genuine and impostor scores for SDUMLA-HMT: ORI = original data set, ROT = rotation corrected to 1st image

Additional Material IV

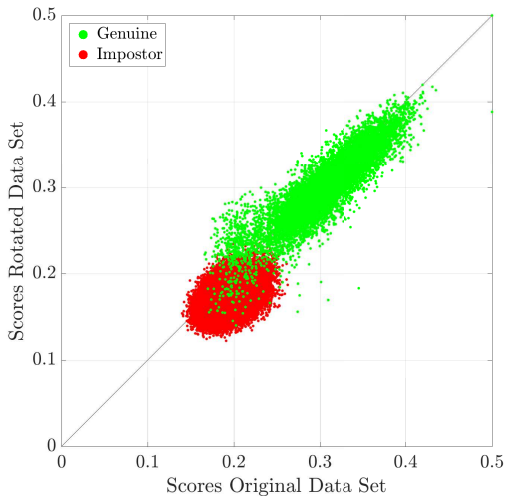


Figure: Changes in scores from the original data set to the rotation corrected data set

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- [2] Y. Yin, L. Liu, and X. Sun, “Sdumla-hmt: a multimodal biometric database,” *Biometric Recognition*, pp. 260–268, 2011.
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[Online]. Available: <http://doc.utwente.nl/87790/>
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- [5] C. Kauba, B. Prommegger, and A. Uhl, “Focussing the beam - a new laser illumination based data set providing insights to finger-vein recognition,” in *Proceedings of the IEEE 9th International Conference on Biometrics: Theory, Applications, and Systems (BTAS2018)*, Los Angeles, California, USA, 2018, pp. 1–9.
- [6] B. Prommegger, C. Kauba, M. Linortner, and A. Uhl, “Longitudinal finger rotation - deformation detection and correction,” *IEEE Transactions on Biometrics, Behavior, and Identity Science*, pp. 1–17, 2019.