Confronting a Variety of Finger Vein Recognition Algorithms With Wax Presentation Attack Artefacts

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The Presentation Attack Problem

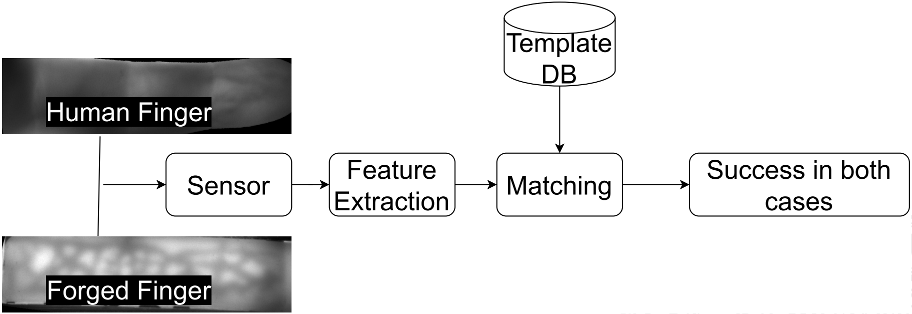

Figure 1: Block diagram visualisation of presentation attack problem

Scope of this research

State of research

- Currently 2 finger vein presentation attack databases available
  - The Idiap Research Institute VERA Fingervein Database [1]
  - South China University of Technology Finger Vein Database [2].
- Threat analysis commonly done using ”2 Scenario Protocol”
  - Maximum Curvature (MC) [3]
  - Wide Line Detector (WLD) [4]
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Scope of this research

- Reworked [6] presentation attack recipe using beeswax
- Generation of corresponding data set
- Extensive Threat analysis for this data set using 12 feature extraction & matching schemes that can be categorized into three meta types of algorithms

Presentation Attack Recipe

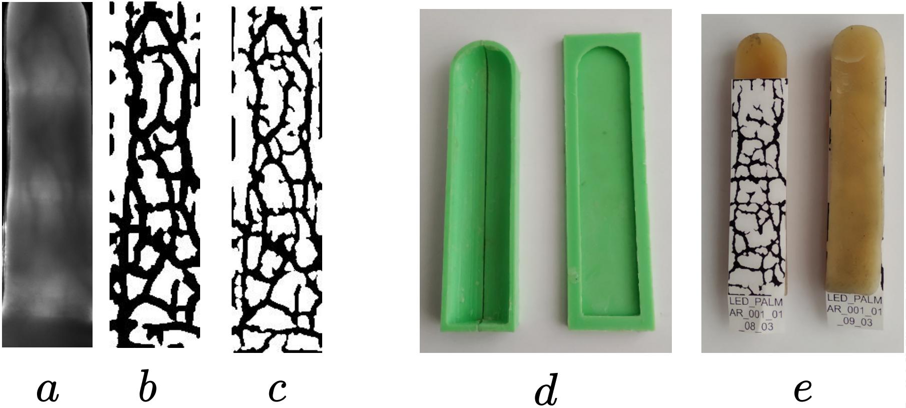


Figure 2: a) original finger from PLUS-FV3 database [7] b) & c) vein pattern extracted with Principal Curvature [8] d) 3D printed mould for beeswax e) sandwich-principle for PA generation

Data Collection

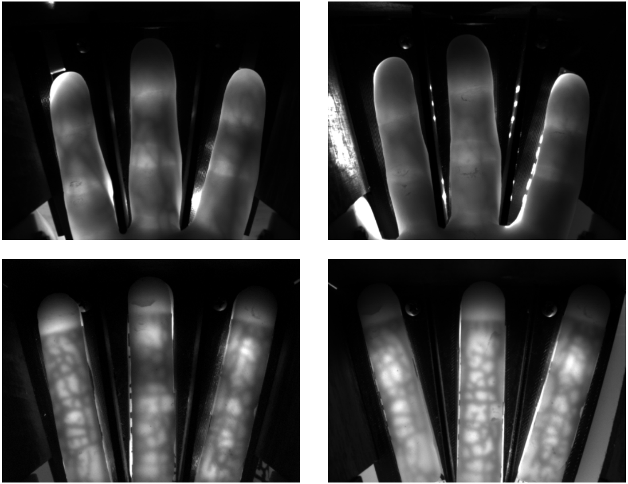


Figure 3: Top row: Bona Fide (PLUS-FV3 Data set), Bottom row: Presentation Attack. Left column: Laser illum., Right column: LED illum.

Data Collection

Sample Type	Unique Fingers	Samples	Images
PLUS-FV3 Bona Fide LED	132 (22 * 6)	5	660
PLUS-FV3 Bona Fide Laser	132 (22 * 6)	5	660
Presentation Attack LED thick	132 (22 * 6)	3	396
Presentation Attack LED thin	132 (22 * 6)	3	396
Presentation Attack Laser thick	132 (22 * 6)	3	396
Presentation Attack Laser thin	132 (22 * 6)	3	396

Table 1: Overview scale of wax presentation attack database

Metrics

- False Match Rate (FMR)

$$FMR = \frac{accepted\ impostor\ attempts}{all\ impostor\ attempts}$$

- False Non Match Rate (FNMR)

$$FNMR = \frac{denied\ genuine\ attempts}{all\ genuine\ attempts}$$

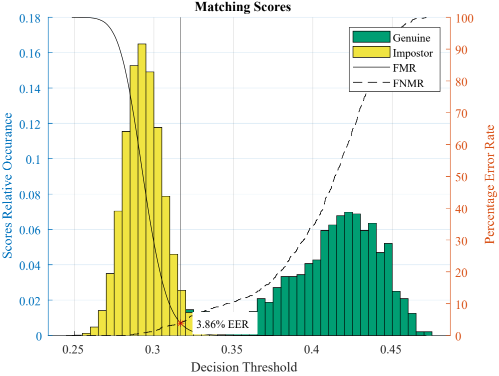
- Equal Error Rate (EER)

$$EER = Operating\ point\ where\ FMR = FNMR$$

- Impostor Attack Presentation Match Rate (IAPMR)

$$IAPMR = \frac{accepted\ attack\ attempts}{all\ attack\ attempts}$$

Threat Analysis: 2 Scenario Protocol



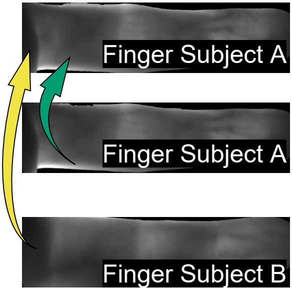
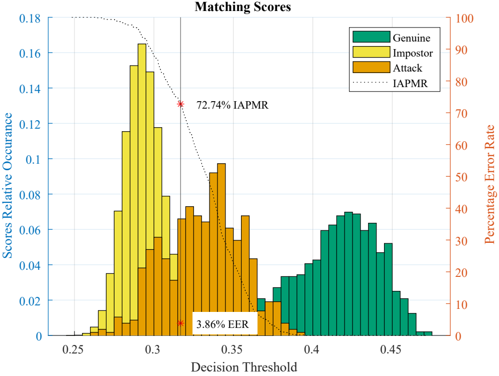


Figure 4: Scenario A

Threat Analysis: 2 Scenario Protocol



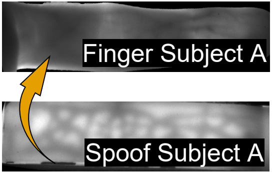


Figure 5: Scenario B

Threat Analysis: Matching Algorithms

- Binarized Vessel Network
  - Maximum Curvature (MC) [3]
  - Principal Curvature (PC) [8]
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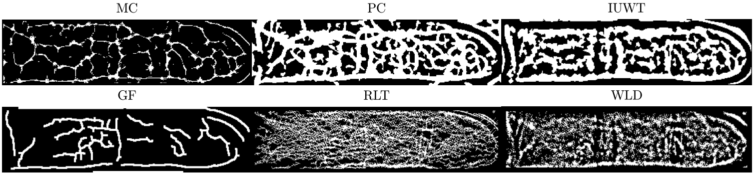
  - Gabor Filters (GF) [9]
  - Isotropic Undecimated Wavelet Transform (IUWT) [10]
  - Anatomy Structure Analysis-Based Vein Extraction (ASAVE) [11]

Figure 6: Binarized Vessel Networks



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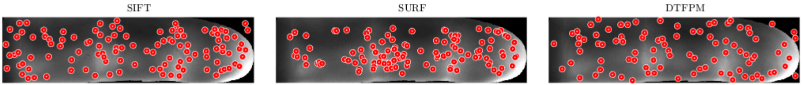
- Keypoints
  - Scale Invariant Feature Transform (SIFT) based [12]
  - Speeded Up Robust Features (SURF) based [12]
  - Deformation Tolerant Feature Point Matching (DTFPM) [13]

Figure 6: Keypoints



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- Texture
  - Local Binary Pattern & Histogram Intersection (LBP) [14]
  - Convolutional Neural Network trained using triplet loss (CNN) [15] [1]

[1] CNN trained on PROTECT data [16], everything else used implementation from OpenVein-Toolkit [17]

Experimental Results

Method	LED			Laser		
	EER	IAPMR thick	IAPMR thin	EER	IAPMR thick	IAPMR thin
MC	0.61	72.29	89.52	1.29	58.37	75.00
PC	0.62	71.24	80.93	1.90	55.17	64.27
WLD	1.13	69.28	84.22	2.80	57.73	78.66
RLT	4.91	43.40	36.49	6.59	23.75	17.30
GF	1.06	37.78	60.98	2.65	31.80	53.41
IUWT	0.53	79.35	90.03	1.97	79.82	84.34
ASAVE	2.35	24.31	19.07	2.59	8.81	1.89
DTFPM	2.20	16.99	16.16	2.64	5.62	6.31
SURF	3.43	0.00	0.00	3.49	0.00	0.00
SIFT	0.96	0.00	0.00	0.91	0.00	0.13
LBP	3.79	0.00	0.38	4.24	0.00	0.00
CNN	2.89	0.67	0.35	6.8	0.0	0.05

Table 2: EERs and IAPMRs when using different feature extraction and matching schemes.

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Future Work

- Can we use in-homogeneous behaviour of recognition algorithms for presentation attack detection?
- Transfer of vulnerability analysis to other publicly available finger vein presentation attack datasets

Thank you for your attention!

Thank You!

Q & A

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