Vulnerability Assessment and Presentation Attack Detection Using a Set of Distinct Finger Vein Recognition Algorithms

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The Presentation Attack Problem

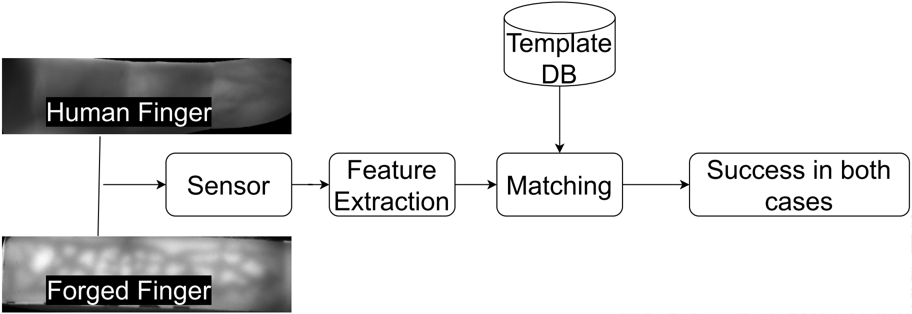


Figure: Block diagram visualisation of presentation attack problem

This Talk

- 3 Finger vein attack data sets
  - Paris Lodron University of Salzburg Finger Vein Spoofing Data Set (**PLUS-LED** and **PLUS-Laser**) [1]
  - The Idiap Research Institute VERA Fingervein Database (**IDIAP VERA**) [2]
  - South China University of Technology Spoofing Finger Vein Database (**SCUT-SFVD**) [3]
- Extensive threat analysis using 12 finger vein recognition schemes
- Presentation attack detection by fusion of similarity scores

Metrics

- False Match Rate (FMR)

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

- False Non Match Rate (FNMR)

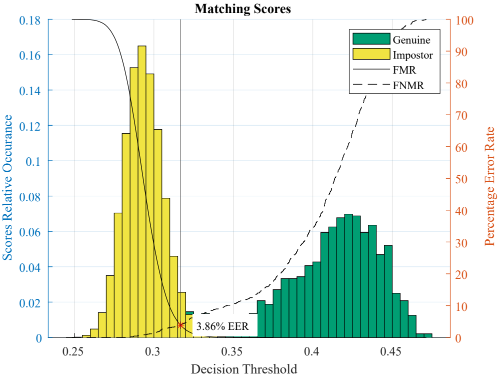
$$FNMR = \frac{\textit{denied genuine attempts}}{\textit{all genuine attempts}}$$

- Equal Error Rate (EER)

$$EER = \textit{Operating point where } FMR = FNMR$$

- Impostor Attack Presentation Match Rate (IAPMR)

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



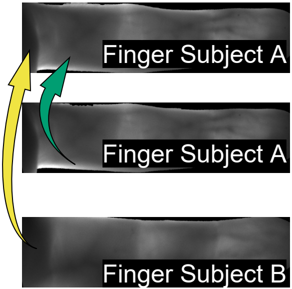
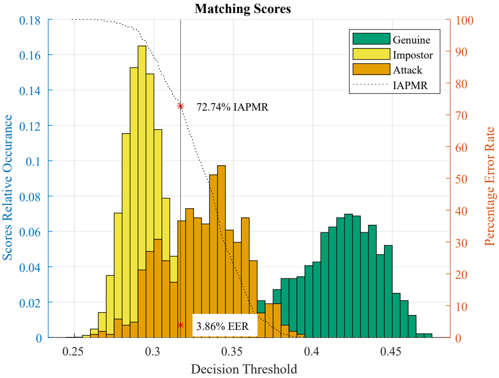


Figure: Step 1



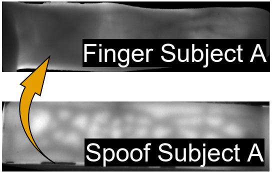
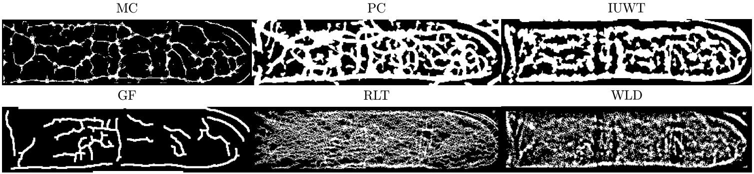


Figure: Step 2

- Binarized Vessel Network
  - Maximum Curvature (MC) [4]
  - Principal Curvature (PC) [5]
  - Wide Line Detector (WLD) [6]
  - Repeated Line Tracking (RLT) [7]
  - Gabor Filters (GF) [8]
  - Isotropic Undecimated Wavelet Transform (IUWT) [9]
  - Anatomy Structure Analysis-Based Vein Extraction (ASAVE) [10]

Figure: Binarized Vessel Networks



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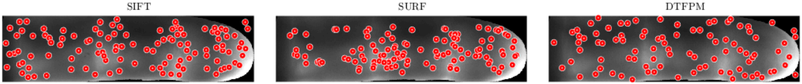
  - Anatomy Structure Analysis-Based Vein Extraction (ASAVE) [10]
- Keypoints
  - Scale Invariant Feature Transform (SIFT) based [11]
  - Speeded Up Robust Features (SURF) based [11]
  - Deformation Tolerant Feature Point Matching (DTFPM) [12]

Figure: Keypoints



Feature Extraction Algorithms

- Binarized Vessel Network
  - Maximum Curvature (MC) [4]
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  - Deformation Tolerant Feature Point Matching (DTFPM) [12]
- Texture
  - Local Binary Pattern & Histogram Intersection (LBP) [13]
  - Convolutional Neural Network trained using triplet loss (CNN) [14] [1]

[1] Everything except CNN used matching implementation from OpenVein-Toolkit [15]

PLUS-LED and PLUS-Laser Generation [1]

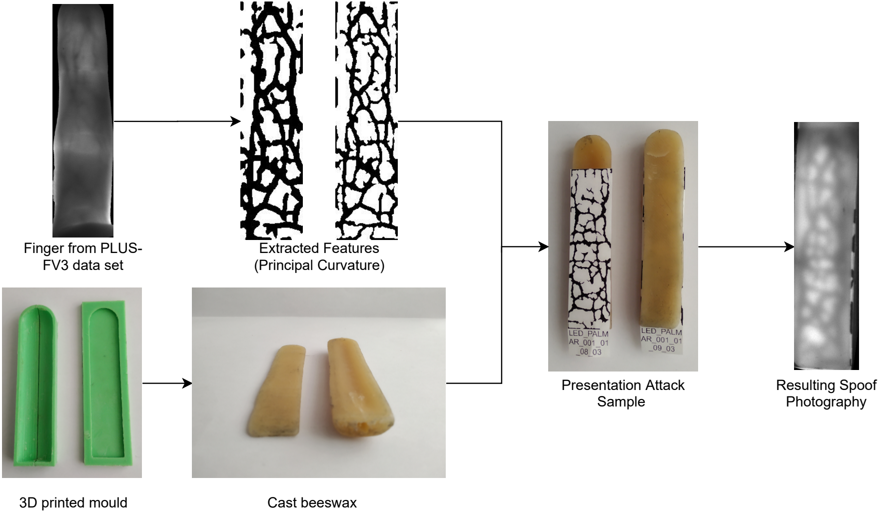

Figure: Presentation Attack generation from [1].

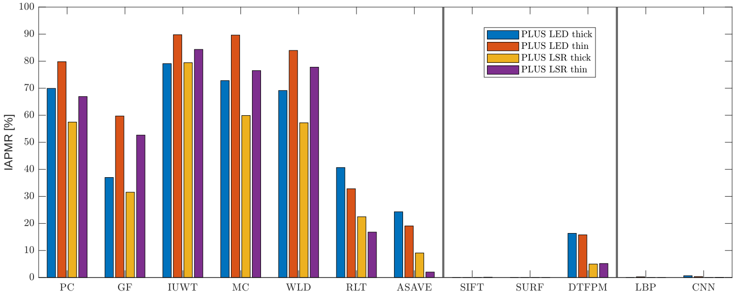

Figure: Results IAPMR PLUS LED and Laser

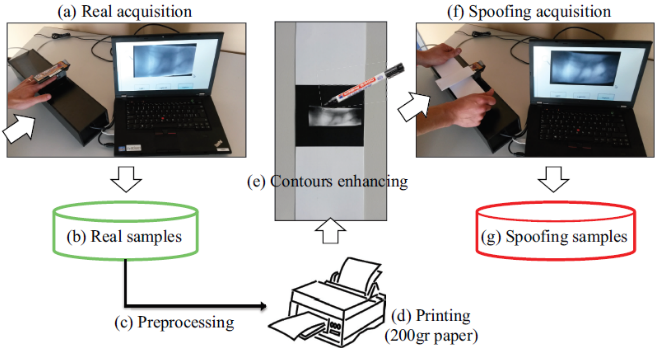

Figure: Presentation Attack generation flow diagram (screenshot from Tome et al. [2]) IDIAP database.

Threat Analysis: IDIAP VERA

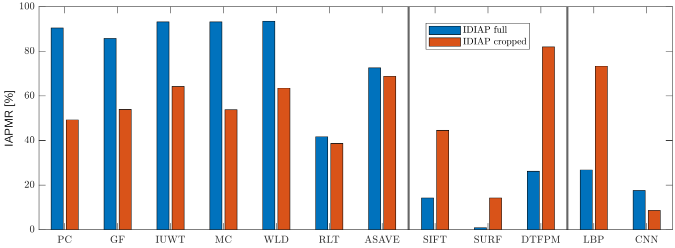

Figure: Results IAPMR IDIAP full and cropped

SCUT-SFVD Generation and Examples

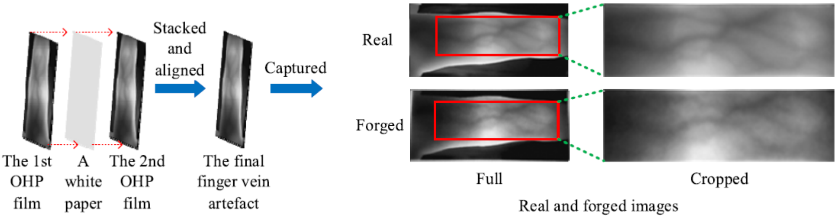

Figure: Presentation Attack generation (screenshot from Qiu et al. [3]) SCUT-SFVD database.

Threat Analysis: SCUT-SFVD

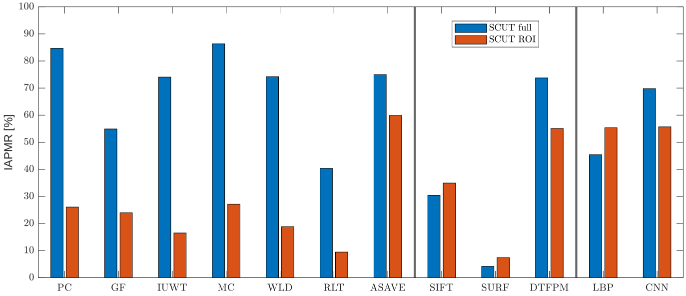

Figure: Results IAPMR SCUT full and cropped

Threat Analysis: Overview

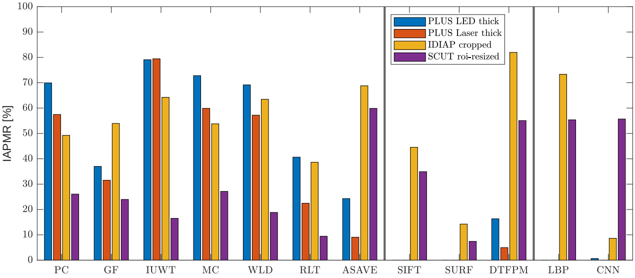

Figure: Overview IAPMRs; one case of every DB

Similarity Score Fusion Strategies

- *Sum-Rule Fusion*

$$f = \sum_{i=1}^{N} S_i \quad (1)$$

- *Min-Rule Fusion*

$$f = min(S_1, ..., S_N) \quad (2)$$

- *Max-Rule Fusion*

$$f = max(S_1, ..., S_N) \quad (3)$$

- *Support Vector Machine with linear and rbf kernel*

$$\vec{x} = (S_1, ..., S_N) \quad (4)$$

f ... fusioned score, S_i *... similarity score of recognition scheme i*

Score Normalisation

- *no-norm*

$$\textit{No normalisation applied} \tag{5}$$

- *z-norm*

$$S' = \frac{S - \mu}{\sigma} \tag{6}$$

- *tanh-norm*

$$S' = 0.5 * \left(tanh \left(0.01 * \frac{S - \mu}{\sigma} \right) + 1 \right) \tag{7}$$

Spoof Detection Metrics

- Attack Presentation Classification Error Rate (APCER)

$$APCER = \frac{spoof\ attempts\ classified\ as\ real\ finger\ attempts}{all\ spoof\ attempts}$$

- Bona Fide Presnetation Classification Error Rate (BPCER)

$$BPCER = \frac{real\ finger\ attmepts\ classified\ as\ spoof}{all\ real\ finger\ attempts}$$

- Detection - Equal Error Rate (D-EER)

$$D - EER = Point\ where\ APCER = BPCER$$

Best Reuslts

Database	D-EER	Fusion	Norm	MC	PC	WLD	RLT	GF	IUWT	ASAVE	DTFPM	SURF	SIFT	LBP	CNN
IDIAP VERA full	1.67	svm-lin	z-norm			✓				✓	✓	✓	✓	✓	✓
IDIAP VERA cropped	4.02	svm-lin	z-norm		✓			✓		✓	✓	✓	✓		✓
SCUT-SFVD full	0.75	svm-rbf	z-norm	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓
SCUT-SFVD roi-resized	1.09	svm-rbf	tanh-norm		✓		✓			✓		✓	✓	✓	✓
PLUS-LED thick	0.00	svm-rbf	z-norm										✓		✓
PLUS-LED thin	0.00	svm-lin	tanh-norm									✓	✓	✓	
PLUS-Laser thick	0.00	svm-lin	z-norm										✓		✓
PLUS-Laser thin	0.00	svm-lin	z-norm		✓						✓		✓		✓

Table: Selection of best working method constellations in terms of D-EER

Summary:

- 3 FV attack datasets were tested on threat they pose to 12 recognition algorithms; Similarity scores of matching experiments were used for score level fusion to achieve spoof detection.

Lessons learned:

- Every evaluated data sets poses a threat to at least some recognition schemes. However SURF seems to be overall very resistant to spoofing.
- We can combine similarity scores of different recognition schemes to achieve spoof detection (at least to some degree).

Thank You!
Q & A

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