# Presentation Attack Detection in Finger and Hand Vein Biometrics using Video Sequences

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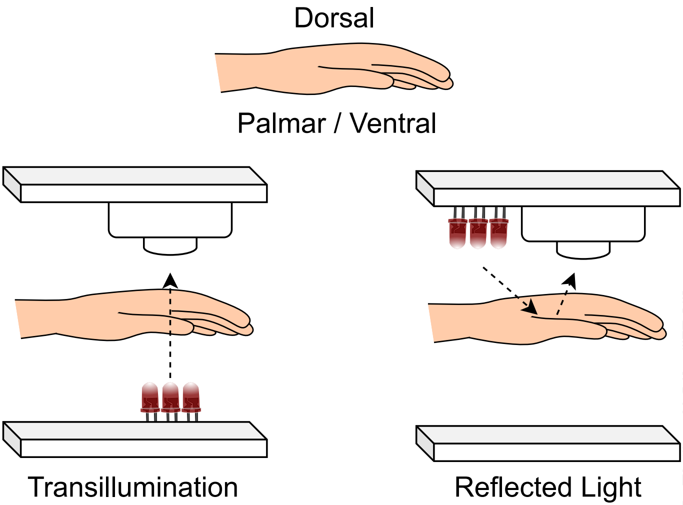



Figure: Near-Infrared Imaging.

# The Presentation Attack Problem

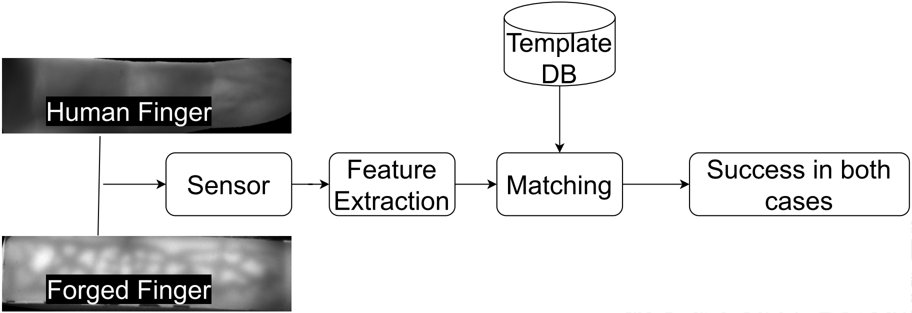



Figure: Block diagram visualisation of presentation attack problem

# Research Goals

Initial situation: 2 Video attack data sets.

- Threat Analysis: Potential to fool a real system?
- Attack Detection: Find methods to detect attacks.

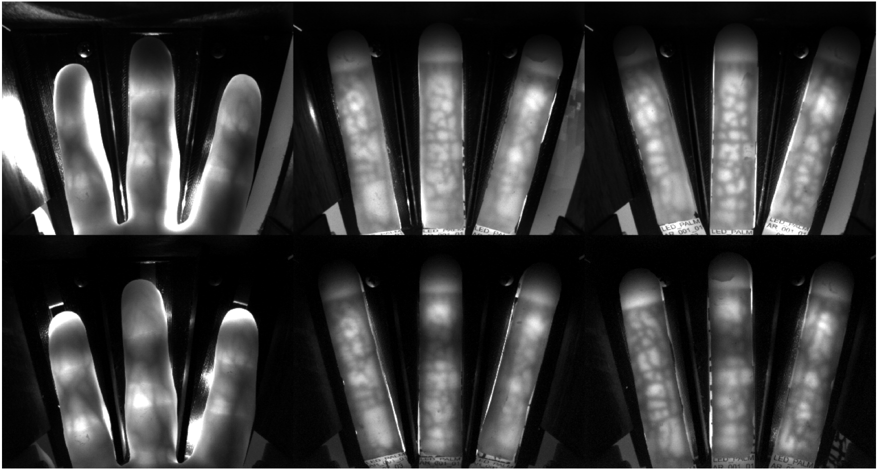


Figure: Example finger vein attack frames. Top row: LED. Bottom row: Laser. Column f.l.t.r.: Bona fide, Thin Attack, Thick Attack.

# The Data

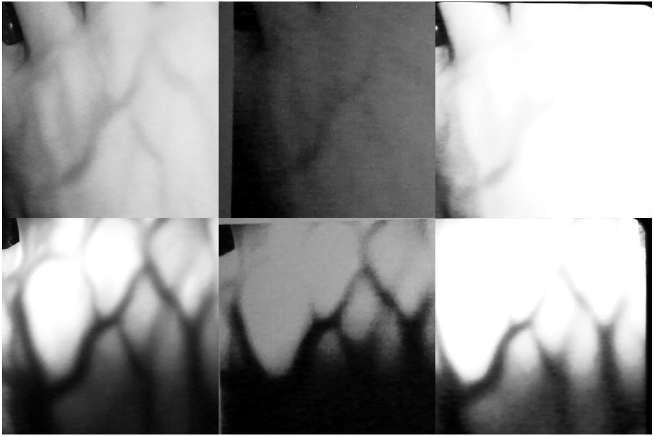


Figure: Example hand vein attack frames. Top row: Reflected Light. Bottom row: Transillumination. Column f.l.t.r.: Bona fide, Paper Attack, Display Attack.

# The Data

| Sample Type | Unique Fingers | Samples | Videos |
|---|---|---|---|
| Finger Bona Fide LED | 96 (16 * 6) | 5 | 480 |
| Finger Bona Fide Laser | 96 (16 * 6) | 5 | 480 |
| Finger Attack LED Thin Still | 96 (16 * 6) | 3 | 192 |
| Finger Attack LED Thick Trembling | 96 (16 * 6) | 3 | 192 |
| Finger Attack LED Thin Still | 96 (16 * 6) | 3 | 192 |
| Finger Attack LED Thick Trembling | 96 (16 * 6) | 3 | 192 |
| Finger Attack Laser Thin Still | 96 (16 * 6) | 3 | 192 |
| Finger Attack Laser Thick Trembling | 96 (16 * 6) | 3 | 192 |
| Finger Attack Laser Thin Still | 96 (16 * 6) | 3 | 192 |
| Finger Attack Laser Thick Trembling | 96 (16 * 6) | 3 | 192 |
| Hand Bona Fide Reflected Light | 26 (13 * 2) | 1 | 26 |
| Hand Bona Fide Transillumination | 26 (13 * 2) | 1 | 26 |
| Hand Attack Reflected Light Paper Still | 26 (13 * 2) | 1 | 26 |
| Hand Attack Reflected Light Paper Moving | 26 (13 * 2) | 1 | 26 |
| Hand Attack Reflected Light Display Still | 26 (13 * 2) | 1 | 26 |
| Hand Attack Reflected Light Display Moving | 26 (13 * 2) | 1 | 26 |
| Hand Attack Reflected Light Display Zoom | 26 (13 * 2) | 1 | 26 |
| Hand Attack Transillumination Paper Still | 26 (13 * 2) | 1 | 26 |
| Hand Attack Transillumination Paper Moving | 26 (13 * 2) | 1 | 26 |
| Hand Attack Transillumination Display Still | 26 (13 * 2) | 1 | 26 |
| Hand Attack Transillumination Display Moving | 26 (13 * 2) | 1 | 26 |
| Hand Attack Transillumination Display Zoom | 26 (13 * 2) | 1 | 26 |

Table: Overview scale of the video attack data sets

# Threat Analysis

## Threat Evaluation Metrics

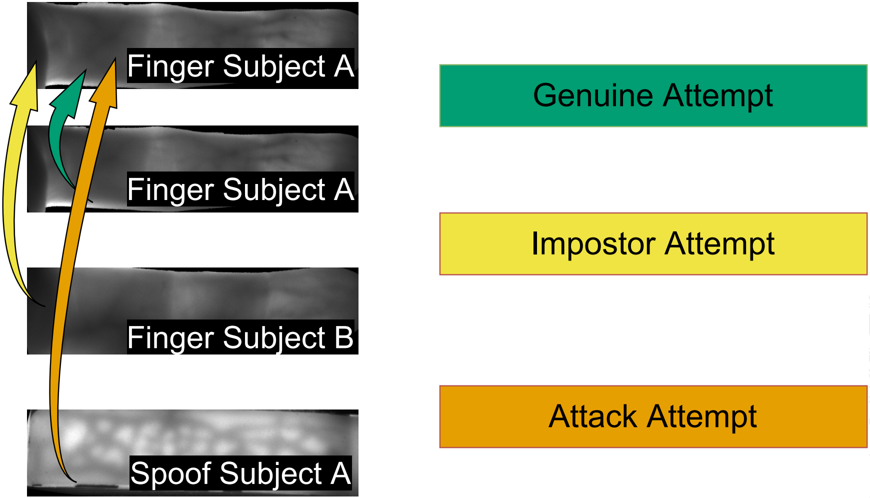



Figure: 3 Types of comparisons

# Threat Evaluation Metrics

- False Match Rate (FMR)

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

- False Non Match Rate (FNMR)

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

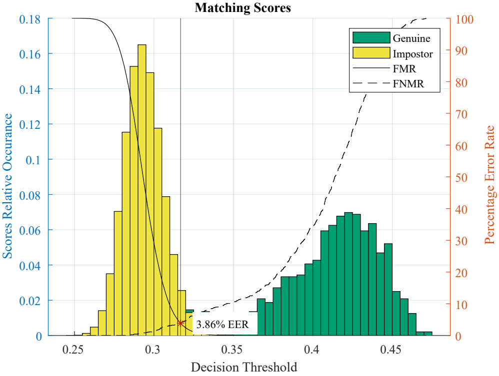
- Equal Error Rate (EER)

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

- Impostor Attack Presentation Match Rate (IAPMR)

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

# Threat Evaluation Protocol



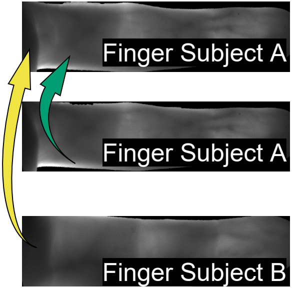
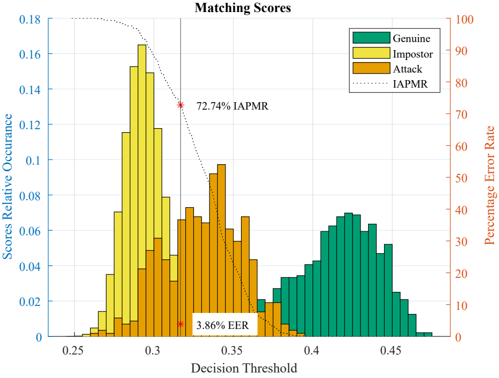




Figure: Step 1

# Threat Evaluation Protocol



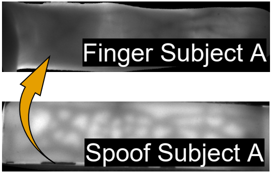
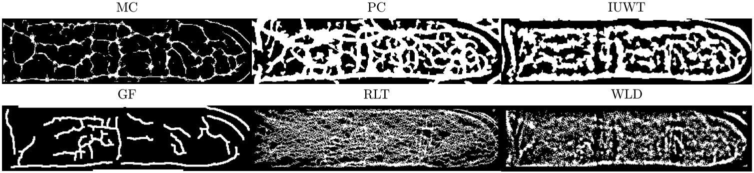




Figure: Step 2

- Binarized Vessel Network
  - Maximum Curvature (MC) [1]
  - Principal Curvature (PC) [2]
  - Wide Line Detector (WLD) [3]
  - Repeated Line Tracking (RLT) [4]
  - Gabor Filters (GF) [5]
  - Isotropic Undecimated Wavelet Transform (IUWT) [6]
  - Anatomy Structure Analysis-Based Vein Extraction (ASAVE) [7]

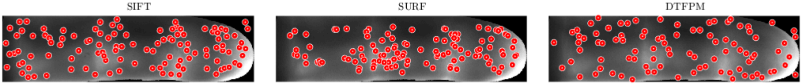
Figure: Binarized Vessel Networks



# Feature Extraction Algorithms

- Binarized Vessel Network
  - Maximum Curvature (MC) [1]
  - Principal Curvature (PC) [2]
  - Wide Line Detector (WLD) [3]
  - Repeated Line Tracking (RLT) [4]
  - Gabor Filters (GF) [5]
  - Isotropic Undecimated Wavelet Transform (IUWT) [6]
  - Anatomy Structure Analysis-Based Vein Extraction (ASAVE) [7]
- Keypoints
  - Scale Invariant Feature Transform (SIFT) based [8]
  - Speeded Up Robust Features (SURF) based [8]
  - Deformation Tolerant Feature Point Matching (DTFPM) [9]

Figure: Keypoints



# Feature Extraction Algorithms

- Binarized Vessel Network
  - Maximum Curvature (MC) [1]
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- Keypoints
  - Scale Invariant Feature Transform (SIFT) based [8]
  - Speeded Up Robust Features (SURF) based [8]
  - Deformation Tolerant Feature Point Matching (DTFPM) [9]
- Texture
  - Local Binary Pattern & Histogram Intersection (LBP) [10]
  - Convolutional Neural Network trained using triplet loss (CNN) [11]

# Threat Evaluation Results

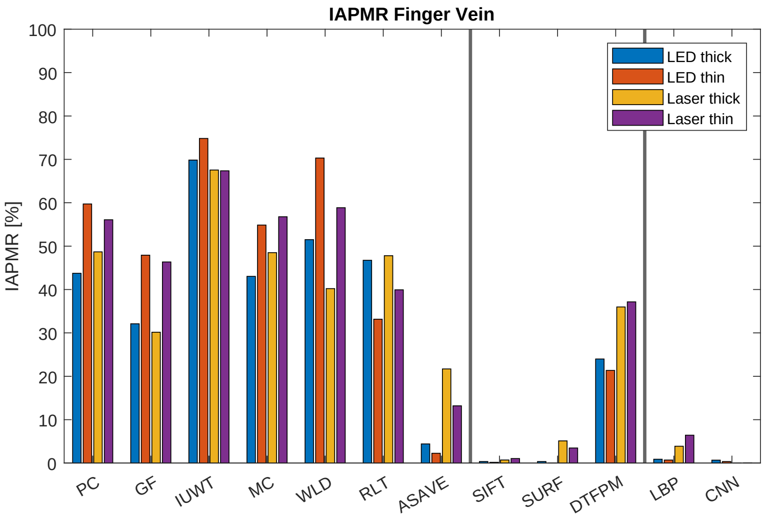



Figure: Results IAPMR Finger Vein Data

# Threat Evaluation Results

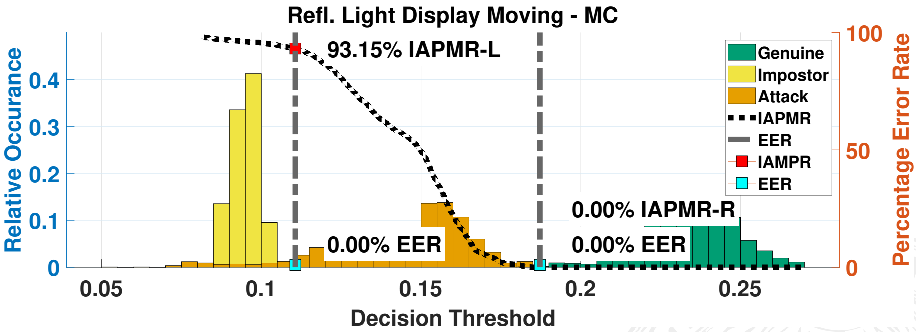
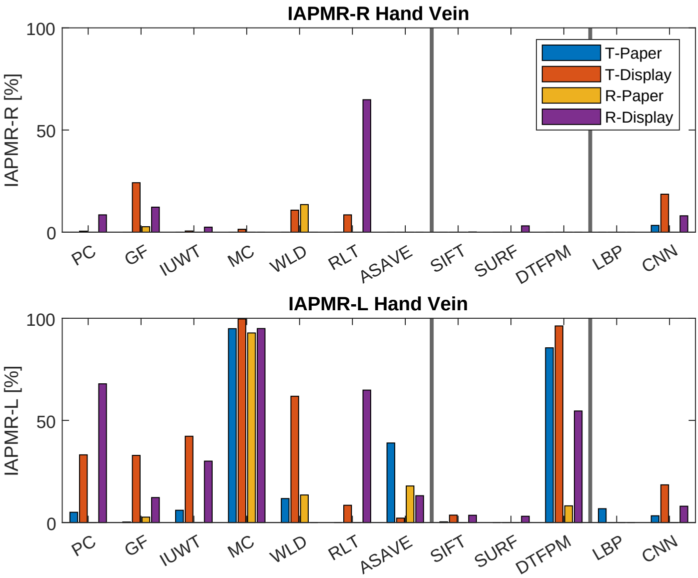


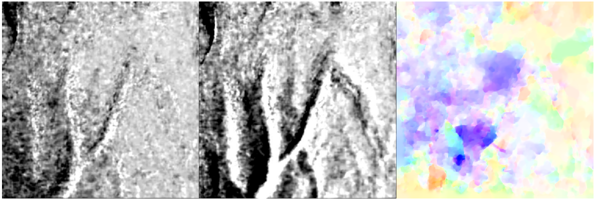

Figure: Exemplary visualization 2 scenario protocol used on hand vein data with maximum curvature.

# Threat Evaluation Results

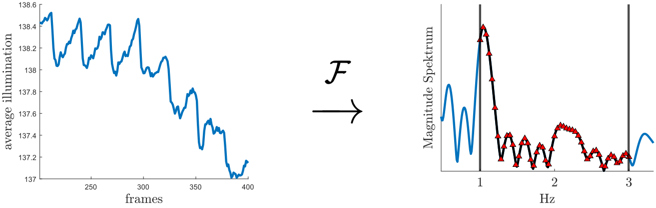


# Attack Detection

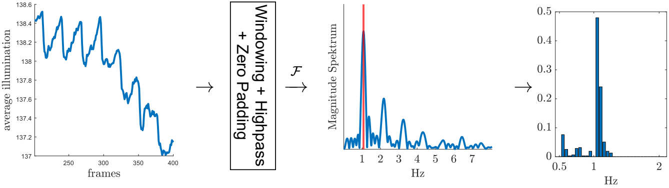
- Eulerian Video Magnification + Optical Flow by Raghavendra et al.[12]



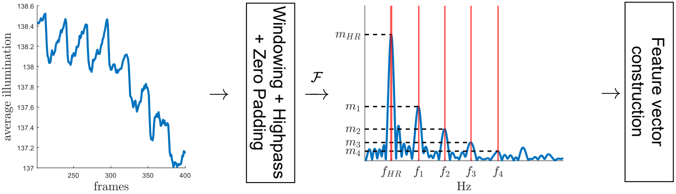
- FFT-based by Bok et al. [13]



- FFT-based by Schuiki & Uhl 1[14]




- FFT-based by Schuiki & Uhl 2 [14]



# Attack Detection Metrics

- Attack Presentation Classification Error Rate (APCER)

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

- Bona Fide Presentation Classification Error Rate (BPCER)

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

- Detection - Equal Error Rate (D-EER)

$$D - EER = \text{Point where } APCER = BPCER$$

# Attack Detection Results Finger Vein

| D-EER Attack Detection Finger Vein [%] | | | | | |
|---|---|---|---|---|---|
| | | Eulerian Video Magnification | PPG Bok et al. | PPG Schuiki & Uhl 1 | PPG Schuiki & Uhl 2 |
| LED | Thick Still | 3.57 | 4.49 | 3.74 | **0.52** |
| | Thick Trembling | 58.51 | 9.62 | 11.75 | **7.05** |
| | Thin Still | 3.31 | 1.85 | 6.60 | **0.43** |
| | Thin Trembling | 62.92 (37.08) | 23.38 | 23.38 | **10.90** |
| Laser | Thick Still | 6.52 | 12.12 | **1.05** | 1.94 |
| | Thick Trembling | 72.78 (27.22) | 26.48 | **16.84** | 24.62 |
| | Thin Still | 7.70 | 4.80 | 0.58 | **0.51** |
| | Thin Trembling | 73.48 (26.52) | 24.97 | 29.85 | **22.42** |

# Attack Detection Results Hand Vein

| D-EER Attack Detection Hand Vein [%] | | | | | |
|---|---|---|---|---|---|
| | | Eulerian Video Magnification | PPG Bok et al. | PPG Schuiki & Uhl 1 | PPG Schuiki & Uhl 2 |
| Refl. Light | Paper Still | 60.94 (39.06) | 9.75 | 23.08 | **7.69** |
| | Paper Moving | 87.10 (12.90) | 1.46 | **0.00** | **0.00** |
| | Display Still | 8.06 | 16.81 | 11.54 | **3.85** |
| | Display Moving | 41.02 | 7.63 | **3.85** | 7.69 |
| | Display Zooming | 53.08 | 0.37 | **0.00** | **0.00** |
| Transill. | Paper Still | 65.44 (34.56) | 15.66 | 15.38 | **3.85** |
| | Paper Moving | 86.81 (13.19) | **0.00** | 19.23 | **0.00** |
| | Display Still | 22.01 | 31.54 | **0.00** | **0.00** |
| | Display Moving | 74.18 (25.82) | 19.26 | **0.00** | 3.85 |
| | Display Zooming | 73.63 (26.37) | 7.60 | **0.00** | **0.00** |

# Conclusion / Future Work

Conclusion:

- We saw that for all of the video attacks at least one scenario exists where a system could potentially be fooled.
- Although often the newly developed methods for attack detection work quite well, there is room for improvement.

Future Work:

- Deep Learning Methods

# Thank You!
# Q & A

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