



Windowed DMD as a Microtexture Descriptor for Finger Vein Counter-spoofing in Biometrics

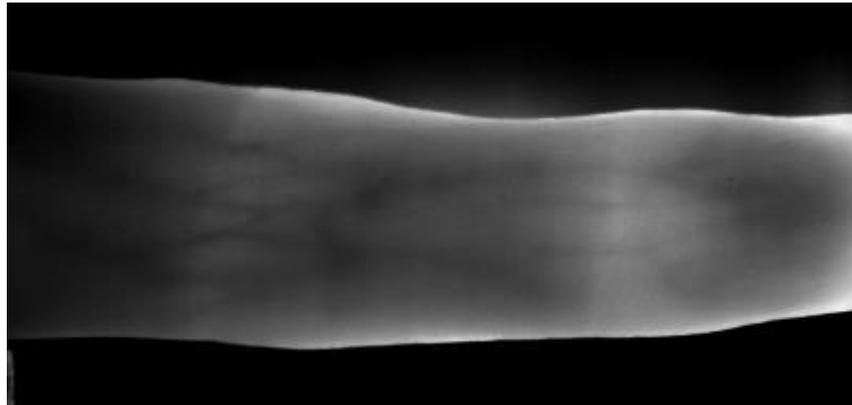
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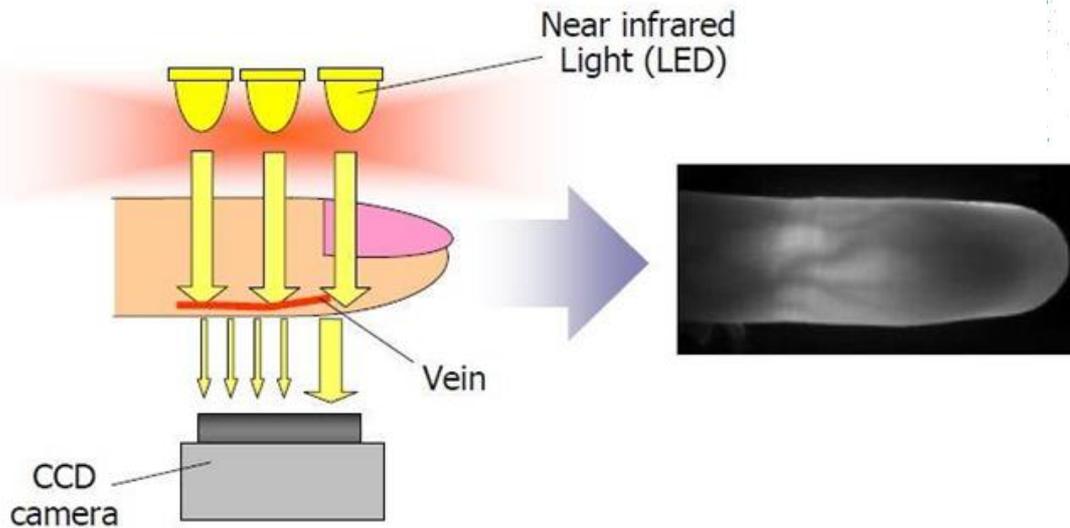
Finger Vein Biometrics

- Authentication system that matches the vascular patterns in an individual's finger.



- Blood vessel patterns are unique to each individual, as are other biometric data such as fingerprints or the patterns of the iris.

How it works





Importance



Finger vein Spoofing - Background

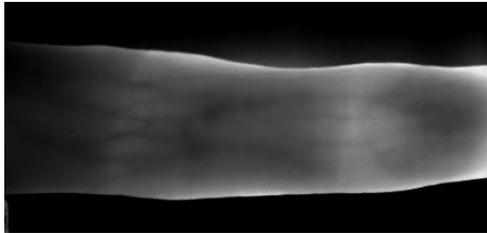


How to counter spoof ?

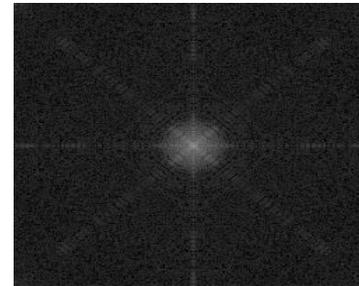
- Look for the ***cues and artefacts*** that differentiate valid from the spoof.
- Our Hypothesis:
 - Cues that differ ***light reflection*** properties.
 - micro-level artefacts that differ in ***quality***.
- How to identify these cues and artefacts?
 - Thanks to ***texture based methods***.

Texture methods

Spatial



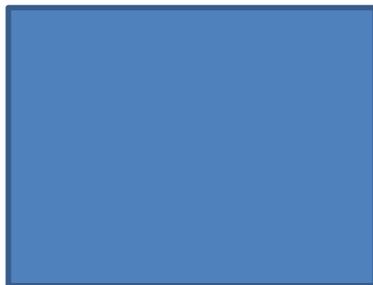
Frequency



vs

Band pass filtering

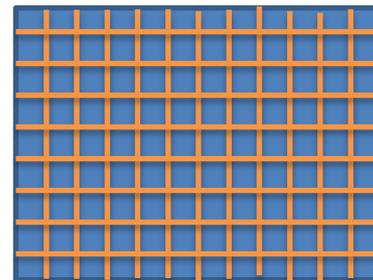
Global



Requires precise localisation

vs

Local



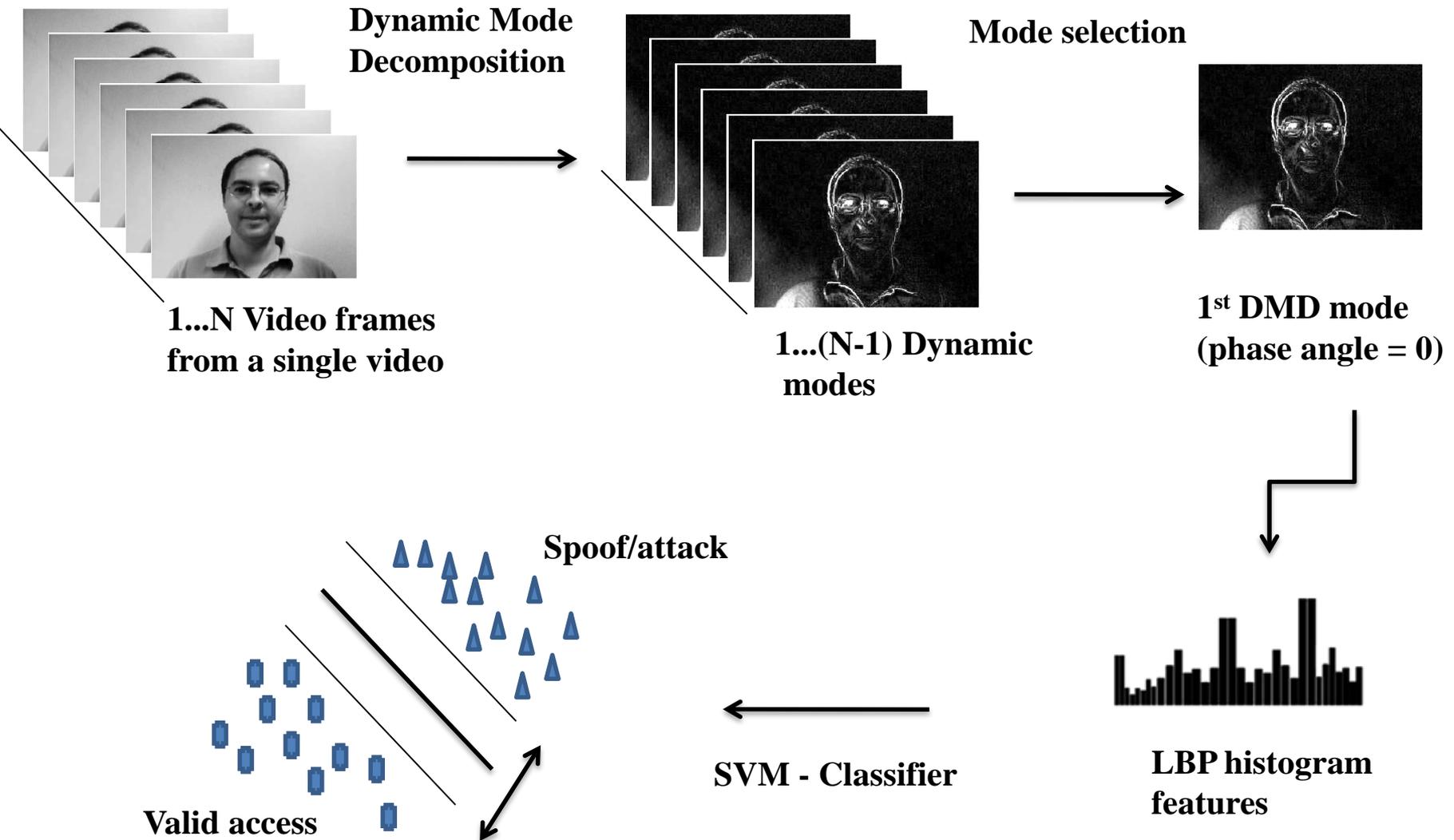
Robust to misalignment
Micro texture

Texture methods

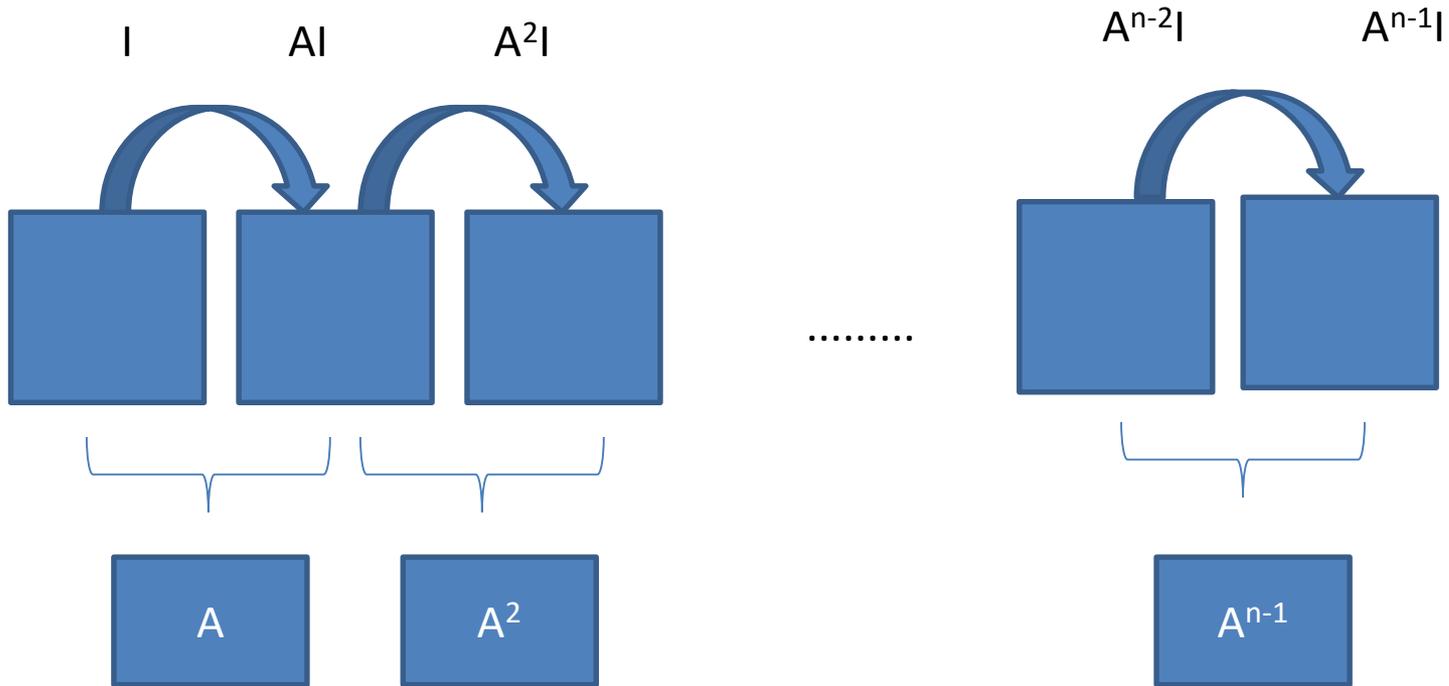
Our proposal

Texture methods	Spatial / Frequency	Local / Global
Windowed-Dynamic Mode Decomposition	Spatial	local
Discrete Wavelet Transform	Frequency	Global
Discrete Cosine Transform	Frequency	Global
Histogram of Gradients	Spatial	Global
Filters	Spatial	Local
Local Binary Patterns	Spatial	Local

DMD – Facial counterSpoofing



How DMD works?

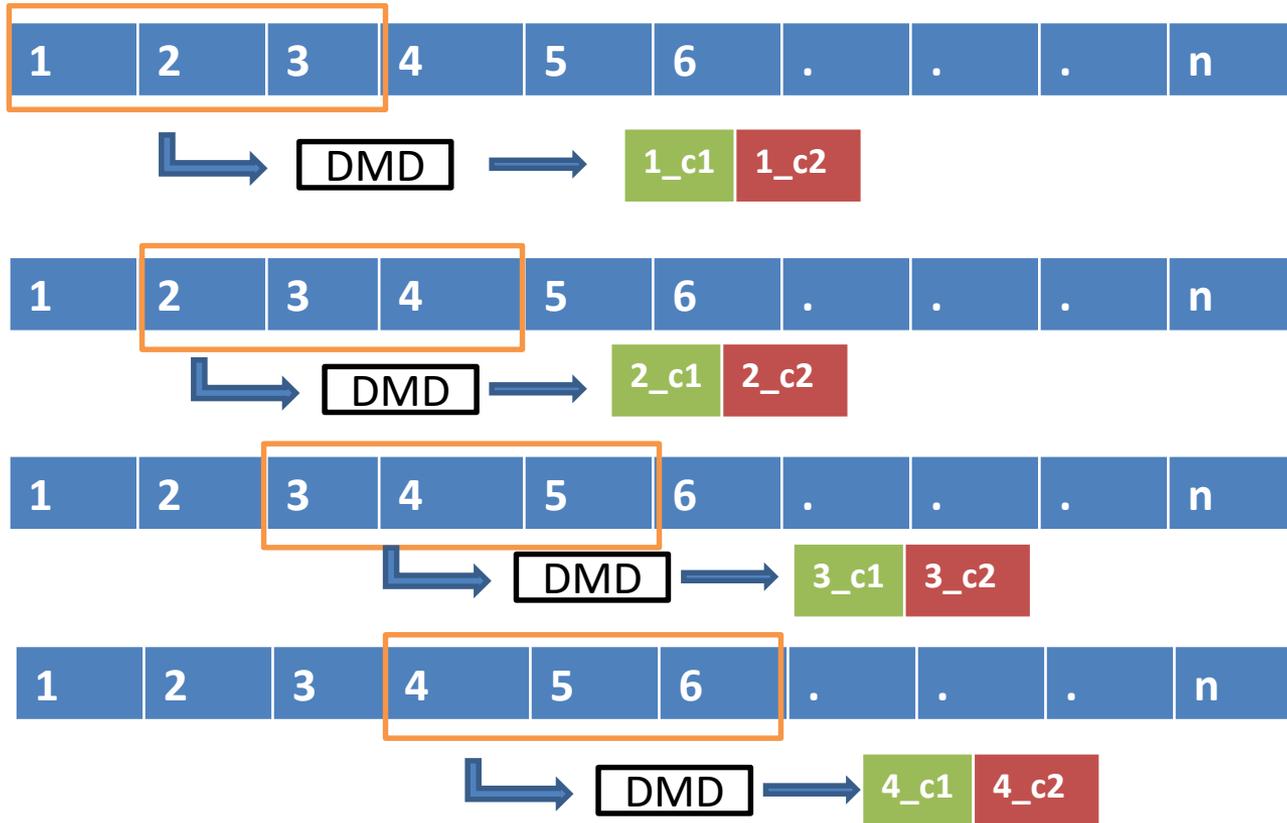


Find the unknown matrix A
 Solve for eigenvalues and vectors of A
 Generally using Arnoldi approximations.

How about images ?

- Our Proposal – Windowed DMD
- Research questions:
 - If DMD can capture principle movements videos then would W-DMD capture texture gradients from images?
 - What would be the effect of texture gradients on classification performance ?
 - How effective is the W-DMD compared to plethora of existing descriptors ?

Our proposal – Windowed DMD



W-DMD(c1)

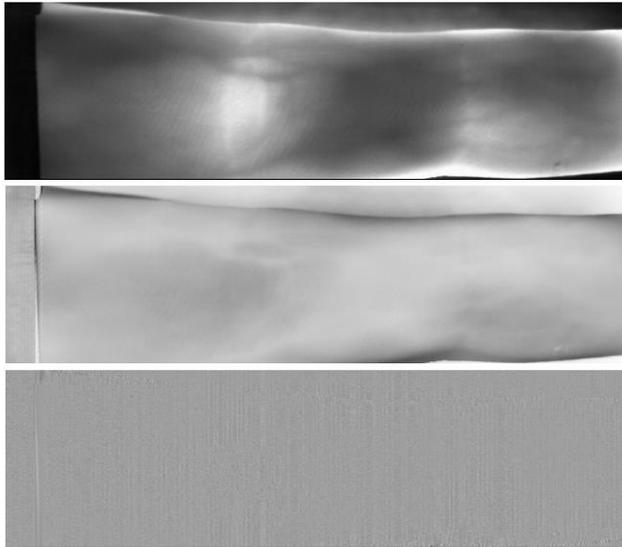
1_c1 | 2_c1 | 3_c1 | . | . | (n-2)_c1

W-DMD(c2)

1_c2 | 2_c2 | 3_c2 | . | . | (n-2)_c2

W-DMD on full finger vein images

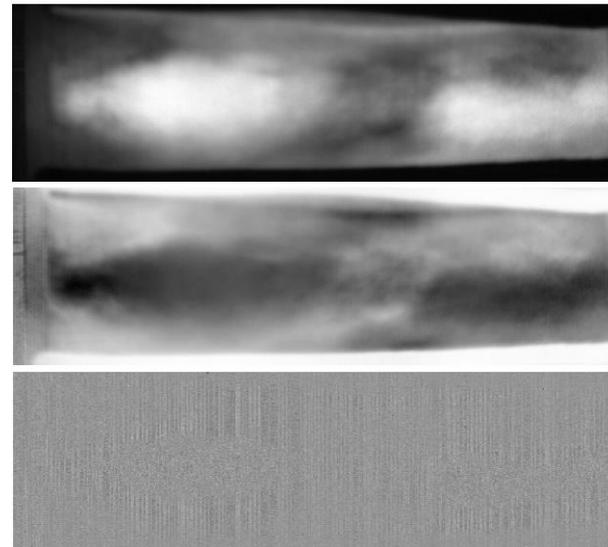
Real



W-DMD (C1)

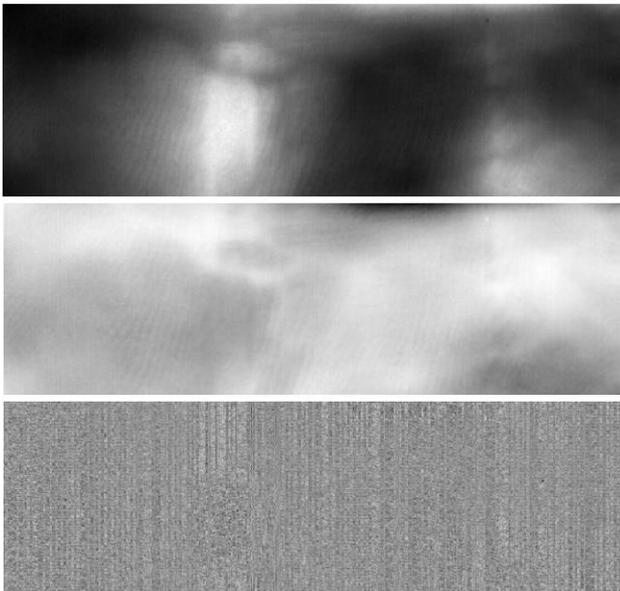
W-DMD (C2)

Spoof



W-DMD on cropped finger vein images

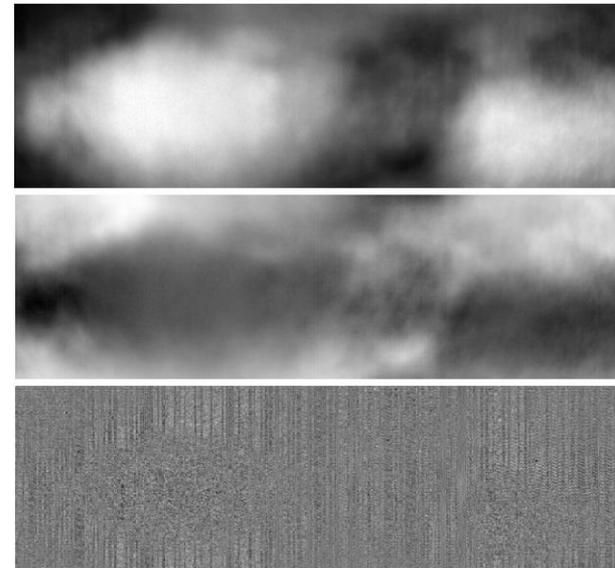
Real



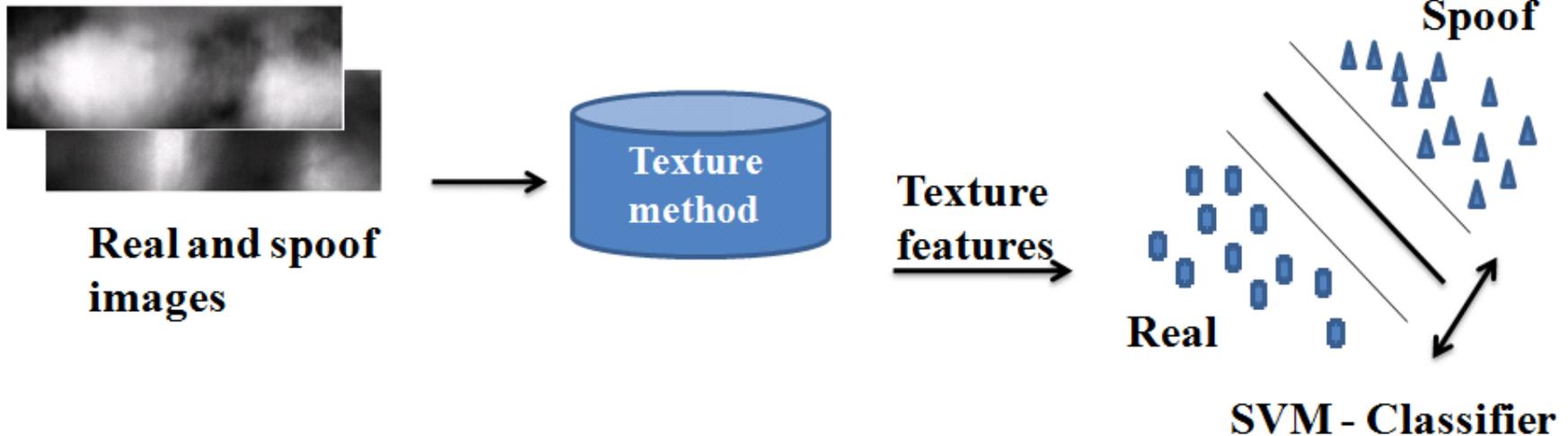
W-DMD (C1)

W-DMD (C2)

Spoof



Classification framework



Texture feature dimensions

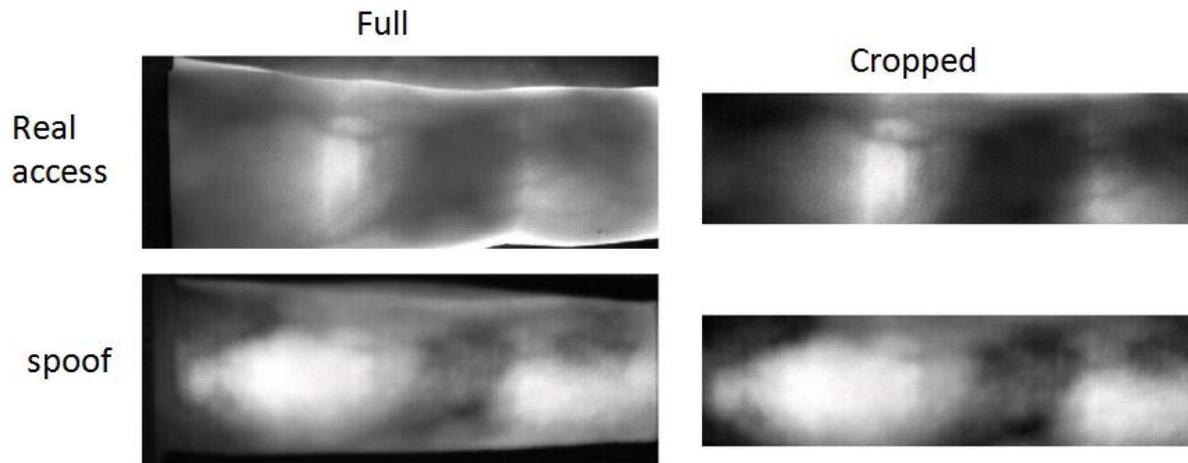
Texture Methods	Cropped	Full
LBP	1x531	1x531
DWT	1x36	1x70
DCT	1x400	1x400
HoG	1x81	1x81
Entropy	1x138	1x270
STD	1x138	1x270
Range	1x138	1x270
W-DMD	1x3330	1x6550
W-DMD+LBP	1x531	1x531

Minimum Intersection Kernel

$$k(x, y) = \sum_{i=1}^n \min(x_i, y_i)$$

Dataset

- IDIAP's Fingervein Spoofing Dataset



Protocol	Training set	Development set	Test set
full	120	120	200
cropped	120	120	200

Evaluation

- Equal Error rate based on F-ratio
- Larger F-ratio => higher separability.
- Measured even when no error is observed.
- F-ratio = $[\mu_C - \mu_I / \sigma_C + \sigma_I]$
 - Where C is real and I is spoof and μ is mean and σ is standard deviation.

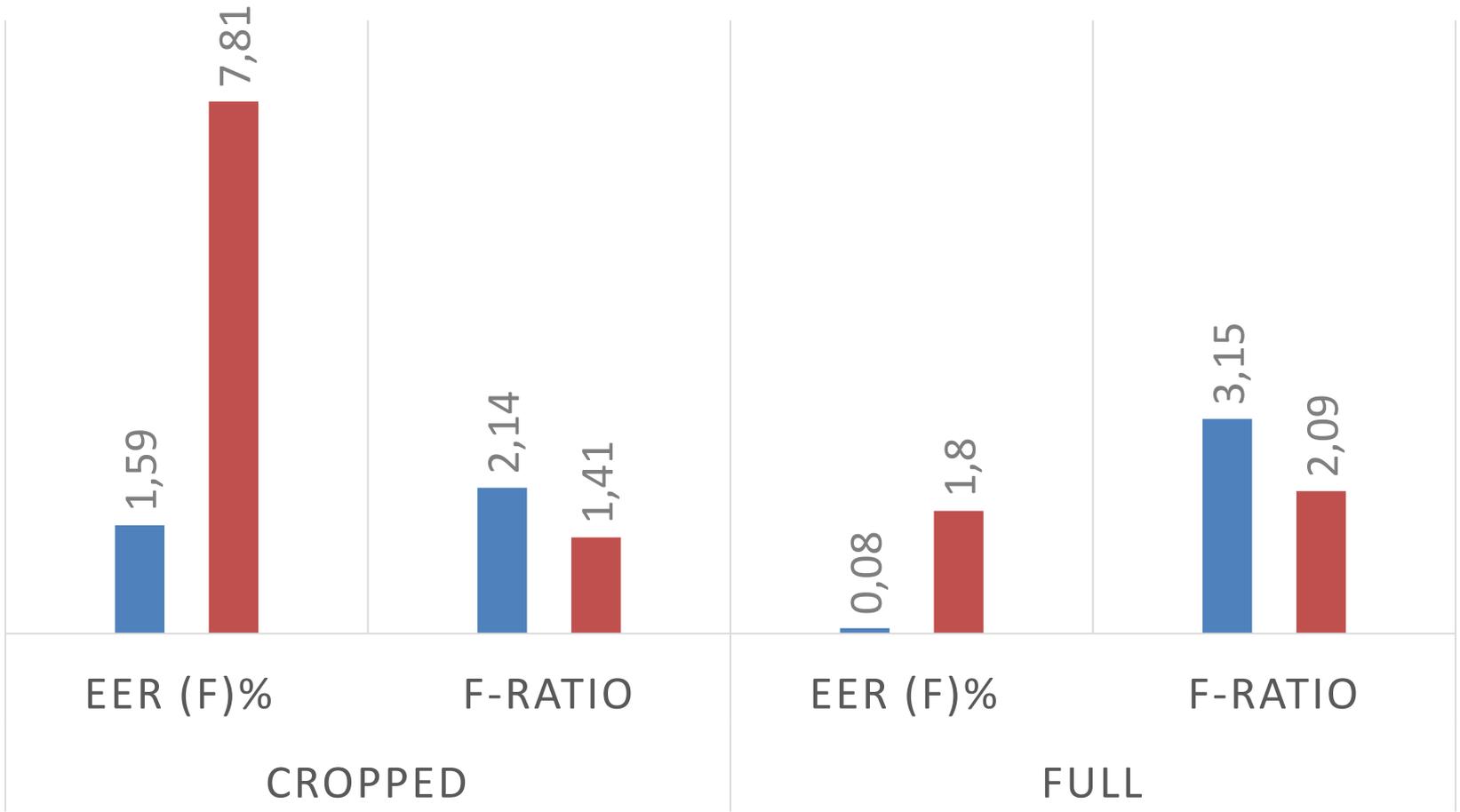


Experimental Hypotheses

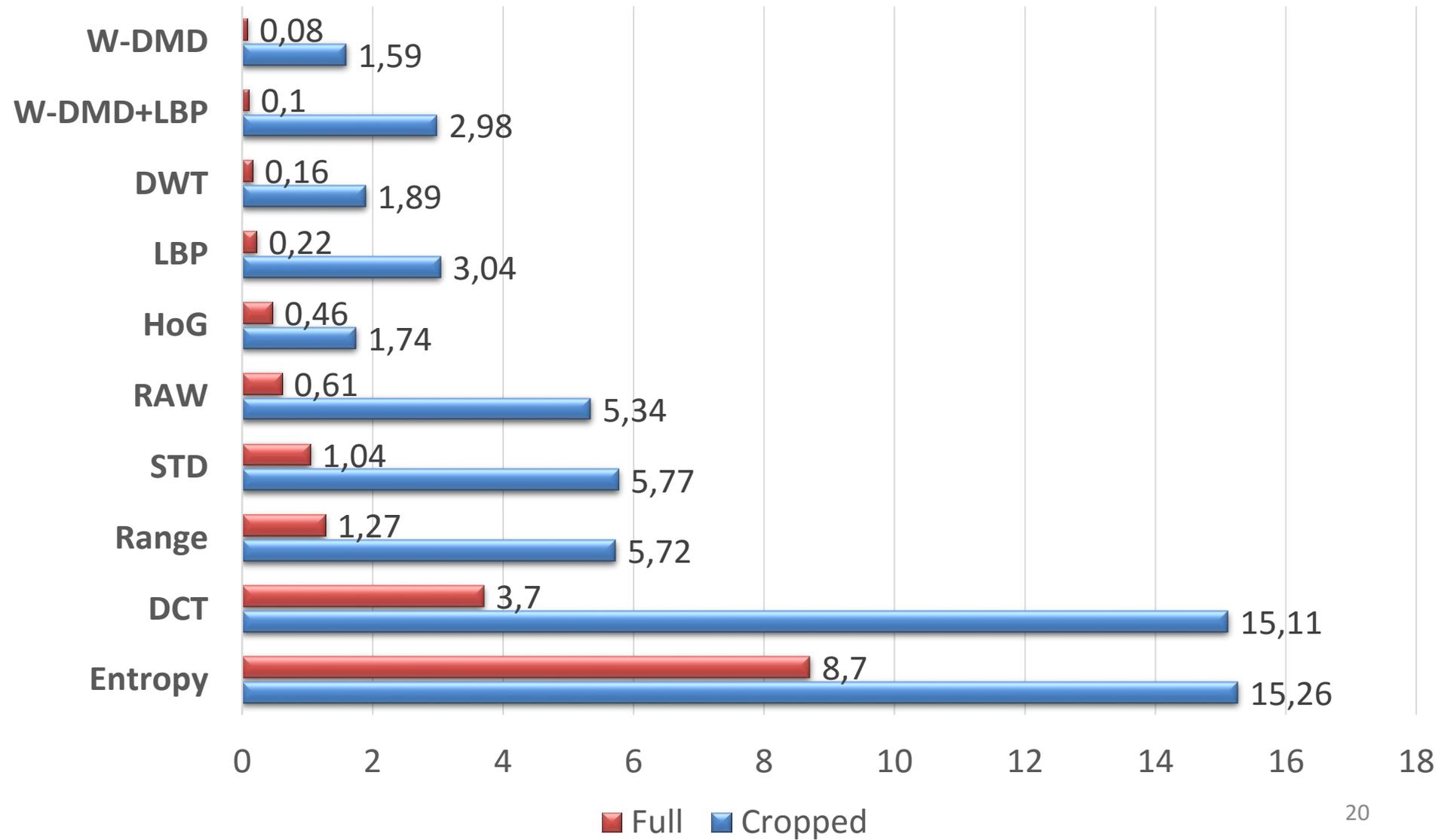
- Which DMD components?
- Comparisons with other methods?

Exp 1: Selection of the W-DMD component

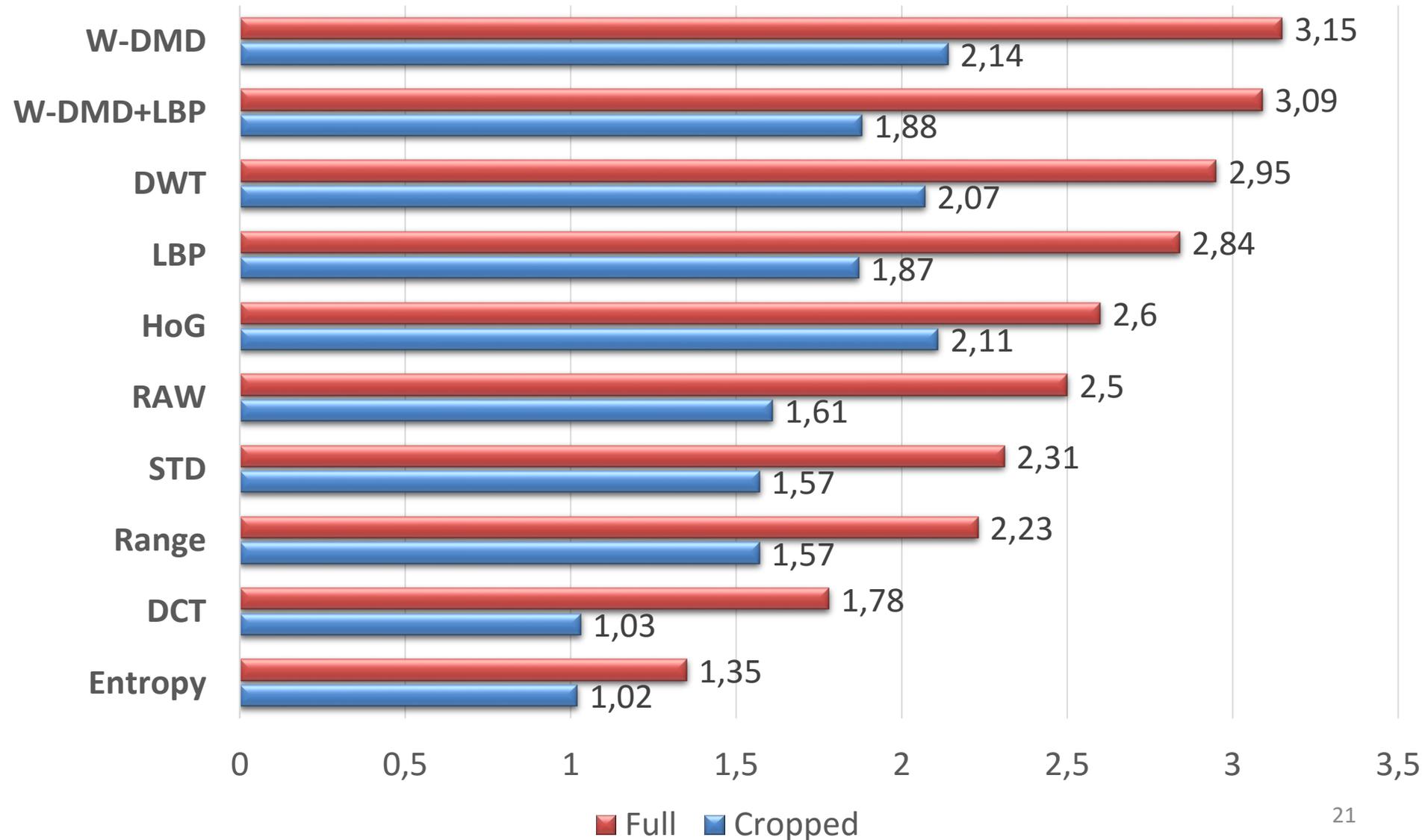
■ W-DMD (C1) ■ W-DMD (C2)



Exp 2. Results - EER(F)(%)



F-ratio



Conclusions

- Limitations – Size of the feature vector.
- Applied W-DMD on finger vein images for valid and print attacks from 110 clients (240 (training) + 240 (development) + 400(testing)).
- Significance of the W-DMD + SVM pipeline - effectively detect the spoof samples.
- The results were promising in tackling the print attack challenge.



Thank you

Any Questions ?

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