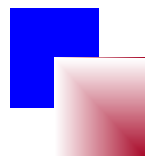


Less-Constrained ~~Unconstrained~~ and Contactless Palmprint Identification



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Department of Computing
The Hong Kong Polytechnic University, Hong Kong

✧ Contactless Palmprint Identification

➤ Applications

- Mobile Security and FinTech Applications
- Failure of Fingerprints → Manual Laborers, Elderly people, etc.



- Improving Performance → Multimodal Biometrics
- Medical Diagnosis of Some Diseases

✧ Contactless Palmprint Identification

➤ Public Security

Ivory Coast

Mexico

Pakistan

Thailand

USA

Hong Kong

✧ Contactless Palmprint Identification

➤ First Paper

- AVBPA03, Peg-free imaging using a hand-held camera



- Relative cooperation during imaging
- Simultaneous use of hand geometry features

✧ Contactless Palmprint Identification

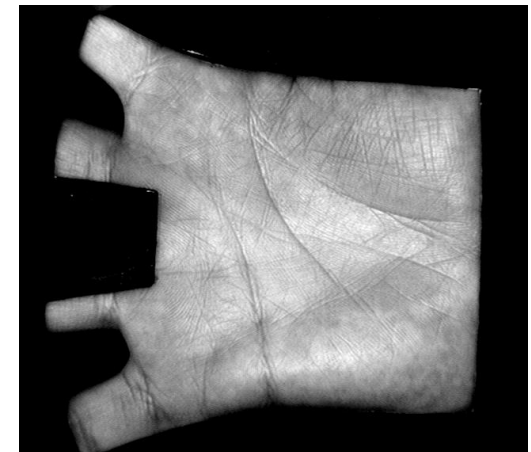
➤ Emerging Commercial Systems

- Amazon One, Fujitsu, BM Automation, PCS, ZKTeco, etc.



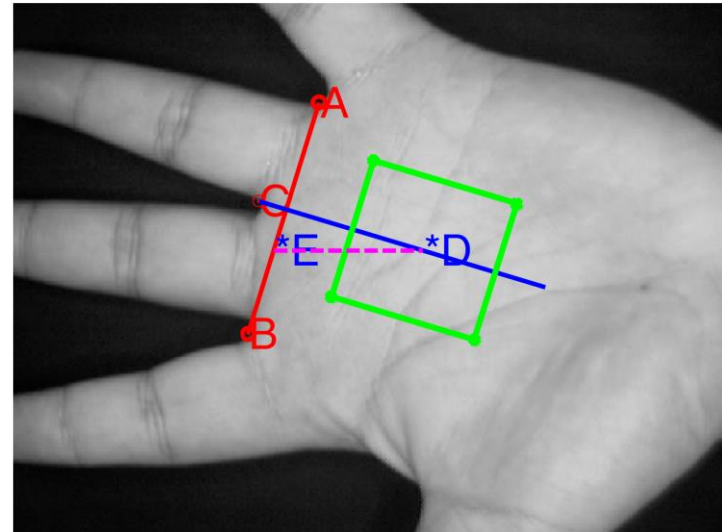
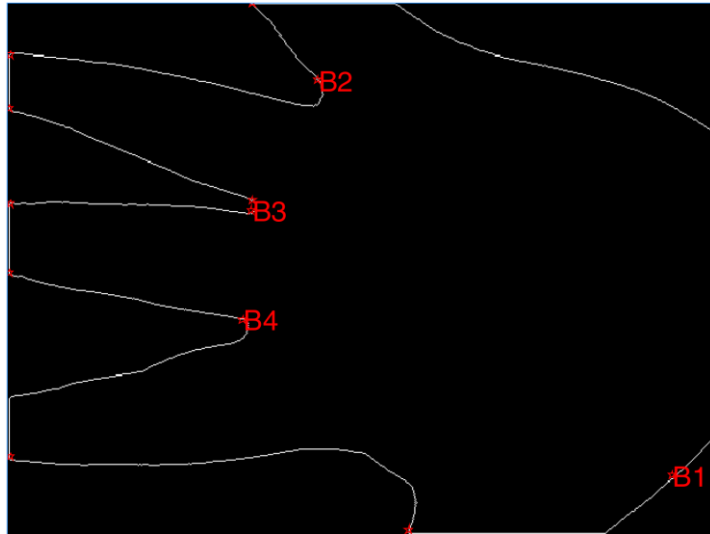
✦ Early Acquisition Devices

- Online → Immediate palm imaging
- Better **image quality**
- Pegs → Limits the rotation and translation
- More reliable and stable **coordination system**
- **Limitations** → Bulk, Cost



✧ Palmprint Segmentation – Earlier Work

- Several different ways to locate the ROI
 - Some detect the key-points first and then detect the ROI



✖ Palmprint Segmentation – Earlier Work

Limitations

- Only suitable for palm images acquired under **constrained and uniform environment**, such as the following images from several well know contactless palmprint datasets
 - The background is generally very different from the palm skin color
 - Images are usually acquired under stable/static environment



Sample from
CASIA dataset



Sample from
IITD dataset



Sample from
PolyU-IITD dataset

✧ Palmprint Segmentation – Earlier Work

Limitations

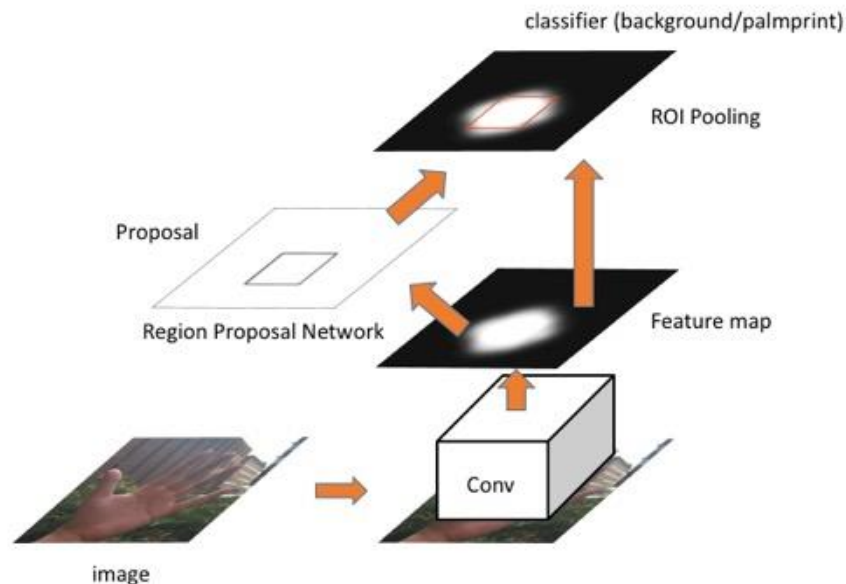
- Background can be unpredictable in a *real world* contactless palmprint image
- Sample images shown below are acquired under complex environments and are hard to detect/segment



Sample *contactless palmprint* images under *less-unconstrained* environments

✶ Palmprint Detection under Complex Backgrounds

- Current Palm Detectors → Keypoints, Pixel-wise Operators
- Fails → Completely Contactless Palm Detection
- Faster-RCNN Based Contactless Palmprint Detection



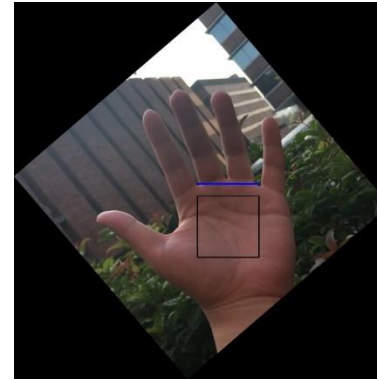
Y. Liu, A. Kumar, "A Deep Learning Based Framework to Detect and Recognize Humans using Contactless Palmprints in the Wild," arXiv preprint arXiv:1812.11319, 2018

S. Ren, K. He, R. Girshick, J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *TPAMI* 2017

✖ Palmprint Detection under Complex Backgrounds

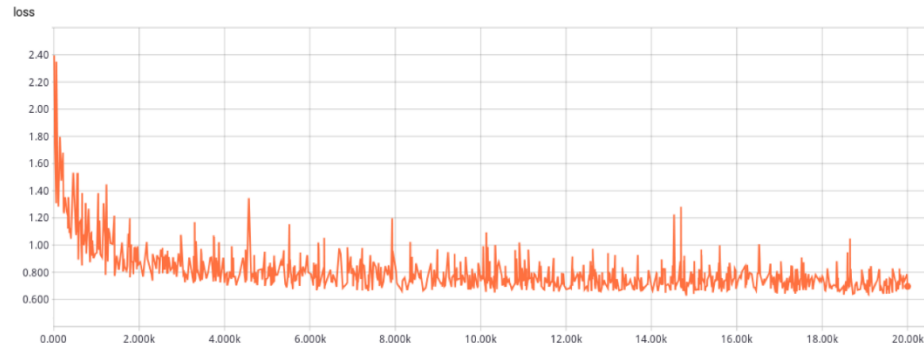
➤ Network Training

- Videos → 11 different backgrounds → Pose, Illumination
- Videos are segmented every 10 frames



Raw segmented frame

Aligned segmented frame



✖ Palmprint Detection under Complex Backgrounds

➤ Data Augmentation

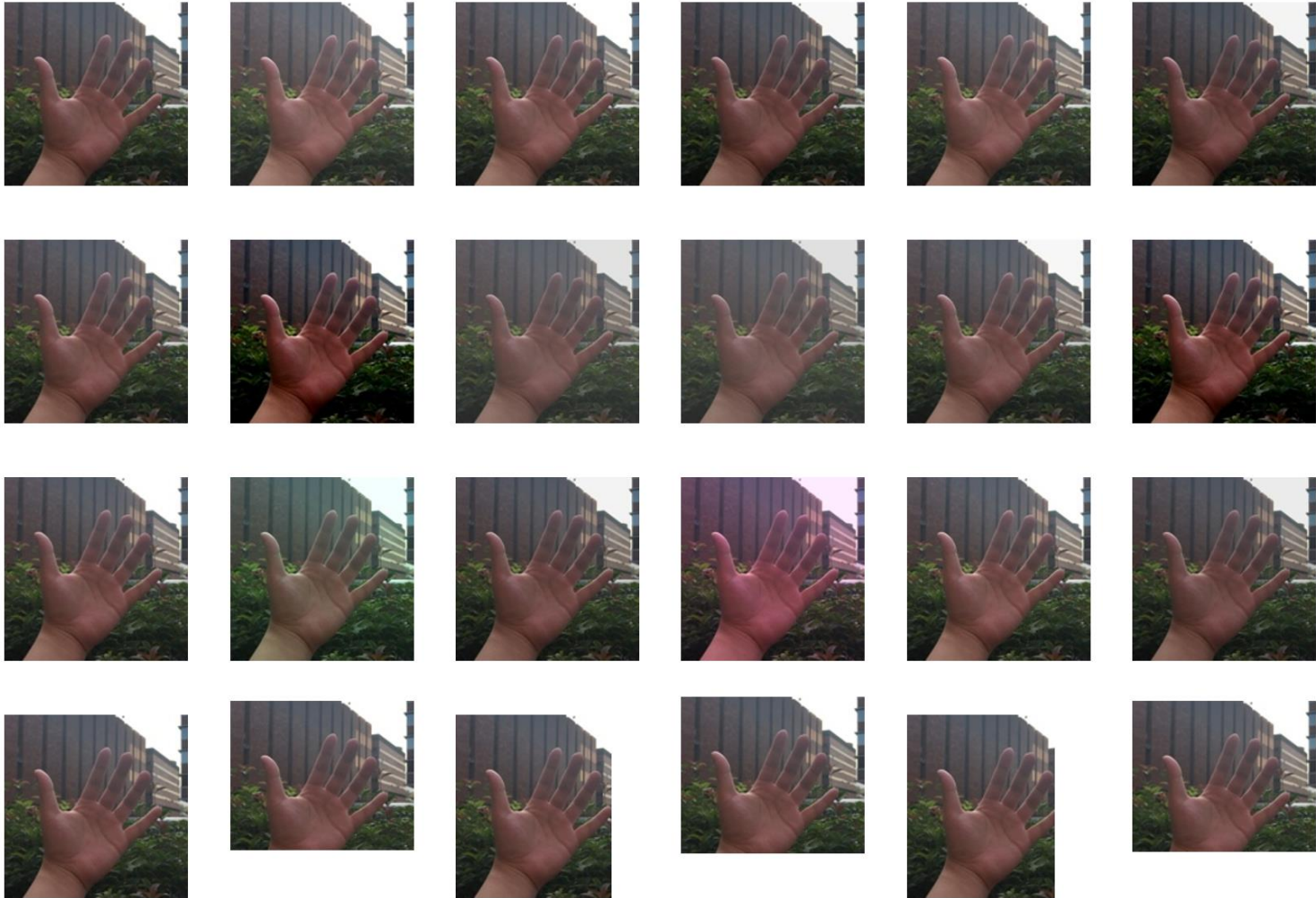
- Multiple traditional augmentation^[1] methods including
 - *Gaussian Blur*
 - *Randomly adding and multiplying on the three channel.*
 - *Contrast normalization*
 - *Additive Gaussian noise*
- Scale and Aspect ratio augmentation^[2]
 - *Random area ratio ($a=[0.08, 1]$)*
 - *Random aspect ratio ($s=[3/4, 4/3]$)*
 - *Crop size: $W'=\sqrt{W*H*a*s}$, $H'=\sqrt{W*H*a/s}$*
- Augmented **10** times to get totally **30K** dataset

[1] Weblink for downloading codes for Data Augmentation: <https://github.com/aleju/imgaug>

[2] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Rabinovich, A. (2015). Going deeper with convolutions. Proceedings of the *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 7-12-2015.

✶ Palmprint Detection under Complex Backgrounds

➤ Data Augmentation



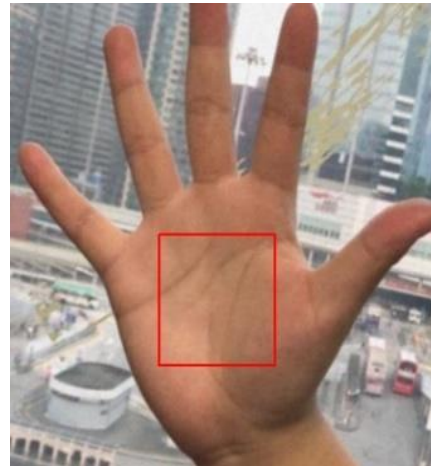
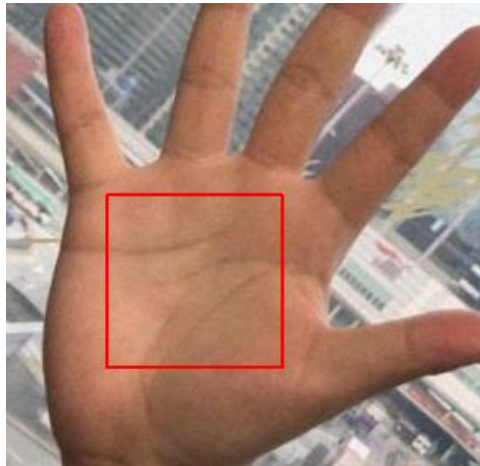
✖ Palmprint Detection under Complex Backgrounds



✖ Palmprint Detection under Complex Backgrounds

Limitations

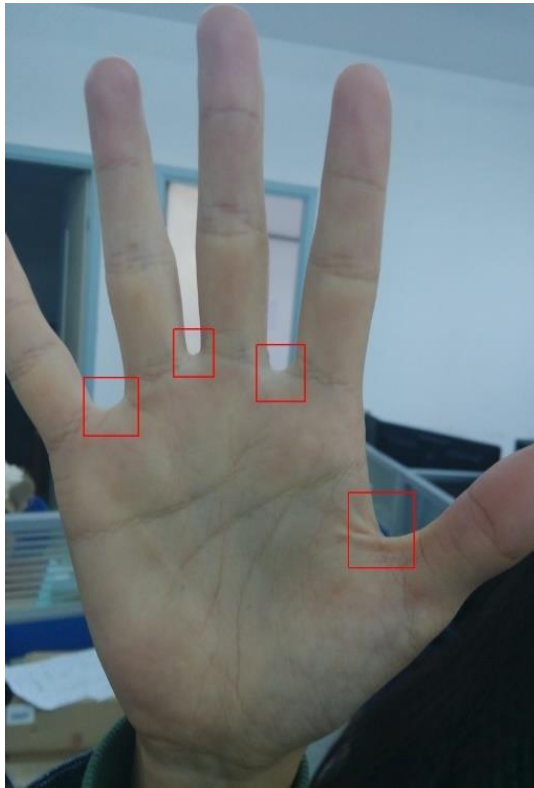
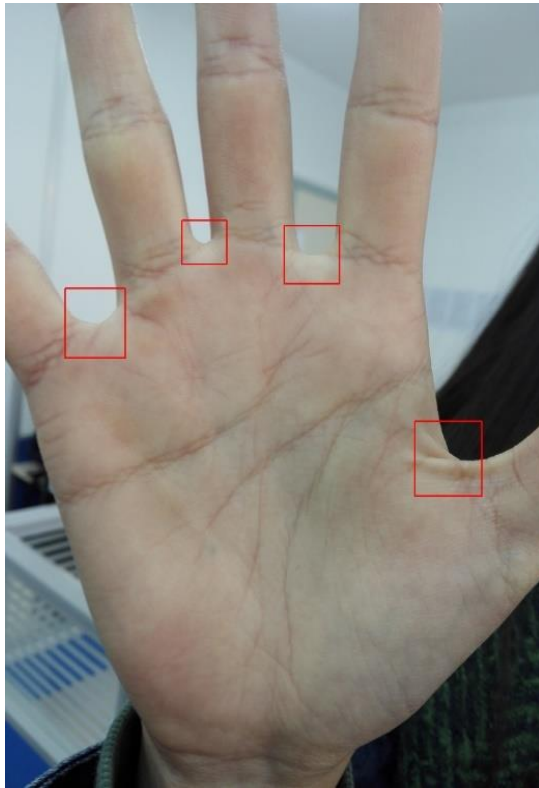
- Matching oblique palm images can be difficult and complex
- Sample images acquired/detected from the same hand/palm



- Observed ROI *rotation* can significantly degrade the match accuracy

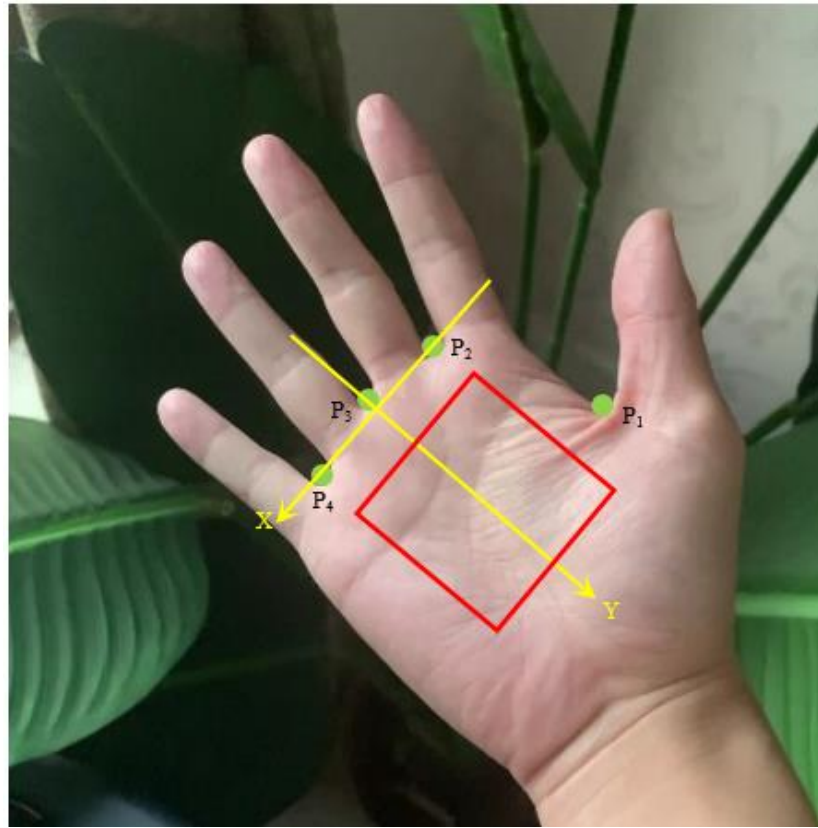
✖ Palmprint Detection under Complex Backgrounds

- Keypoint Detection using Object Detection Models
 - *Tiny Yolo v2, MobileNet + SSD, PeleeNet*



✧ Palmprint Detection under Complex Backgrounds

- Keypoint Detection using Object Detection Models
 - *ROI Extraction using Keypoint Detection*



✶ Palmprint Detection under Complex Backgrounds

➤ Tongji Mobile Palmprint Dataset (MPD dataset)

- *16000 Contactless palmprint images from 200 subjects*
- *288,577 images after augmentation*
- *Each rotated images are labelled on four finger gap points*



Sample images from MPD dataset

✧ Palmprint Detection under Complex Backgrounds

➤ Self Labelled Dataset (Ours)

- *4363 Contactless palmprint images from 20 different hands*
- *43630 images after augmentation*
- *Each rotated images are labelled on four finger gap points*



Sample images from our dataset

✧ Palmprint Detection under Complex Backgrounds

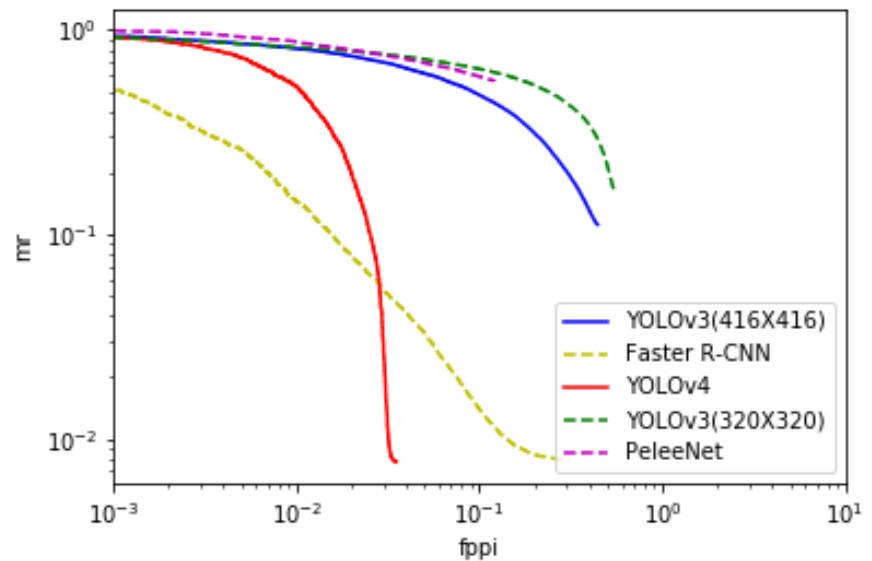
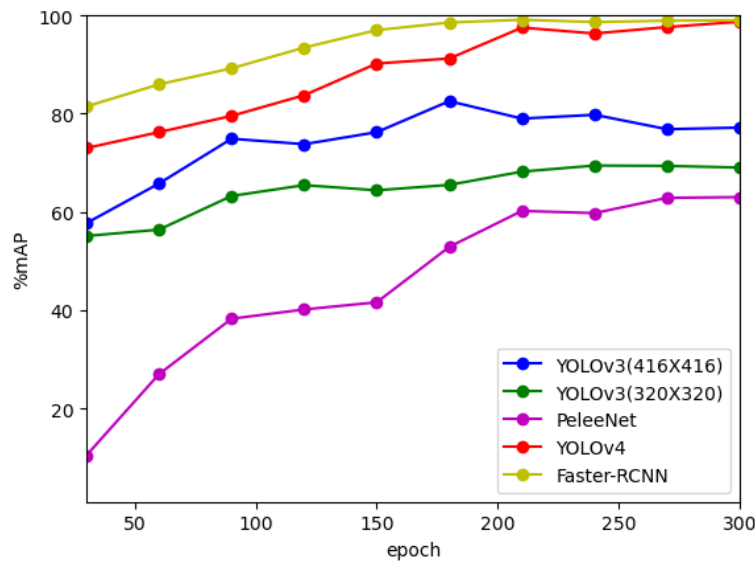
➤ Comparative Summary Between Datasets

	MPD	Self-labelled
Number of indoor images	16000	2839
Number of outdoor images	0	1524
Number of subjects	160	13
Imaging Distance	Varies slightly	Varies greatly
Images with closed finger	0	2058
Images with stretched finger	16000	2305
Total number of images	16000	4363

✶ Palmprint Detection under Complex Backgrounds

➤ Experimental Results (MPD Dataset)

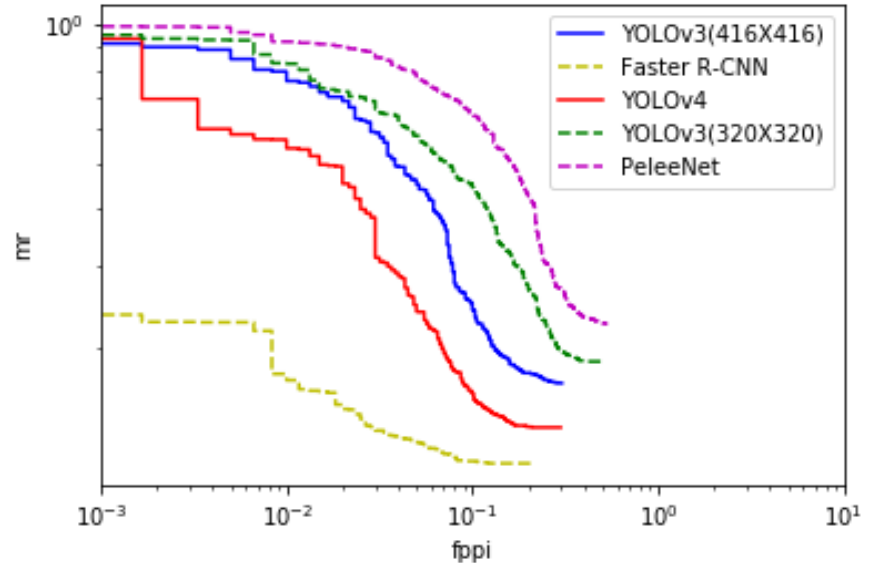
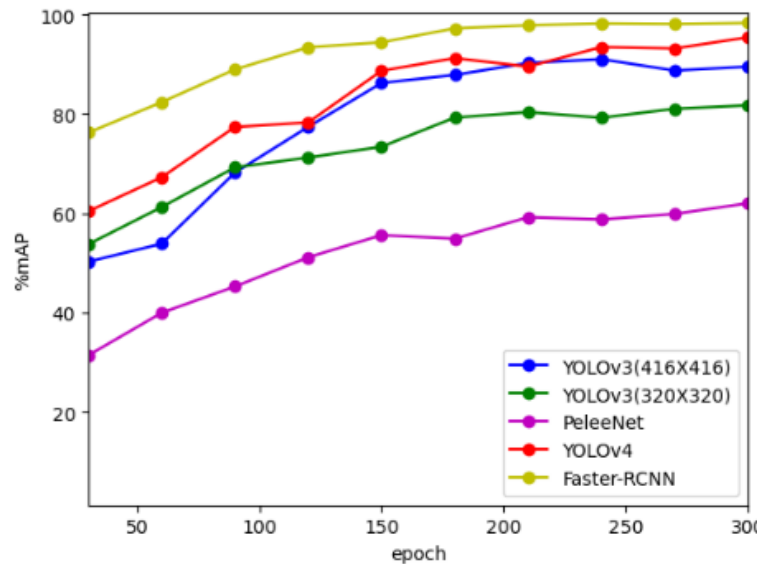
- MAP plot (*during training*) and FPPI Vs MR plot



✶ Palmprint Detection under Complex Backgrounds

➤ Experimental Results (Self Labelled Dataset)

- MAP plot (*during training*) and FPPI Vs MR plot



✖ Palmprint Detection under Complex Backgrounds

➤ Experimental Results

- Average time cost for the detection of one image

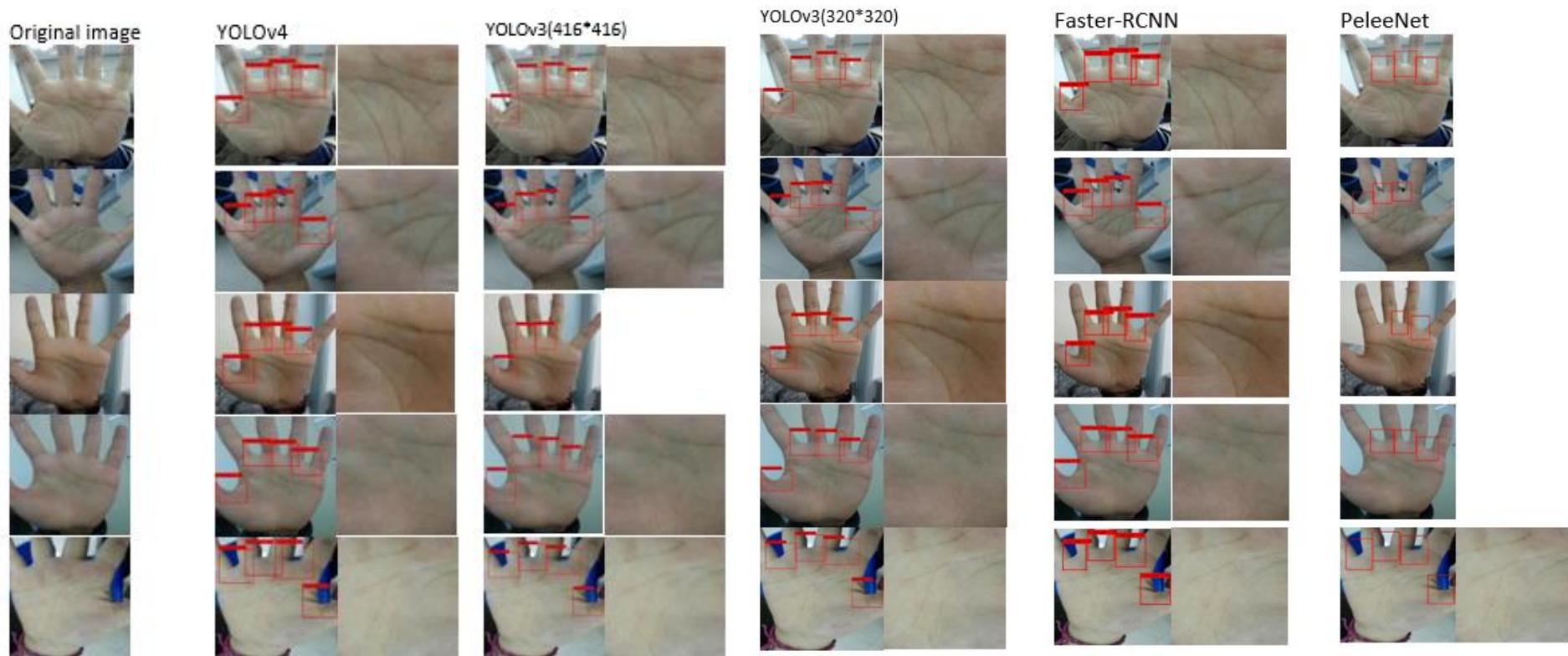
Detector	Time cost (ms)
YOLOv4	57.4
YOLOv3(416*416)	60.1
YOLOv3(320*320)	52.7
PeleeNet	37.2
Faster R-CNN	632.7

Linux version	3.10.0
CPU	Intel(R) Xeon(R) Silver 4108 CPU @ 1.80GHz
GPU	NVIDIA GeForce GTX 1080 Ti, 11GB
Hard ware acceleration	CUDA10.1 CUDNN 7.6.4

✶ Palmprint Detection under Complex Backgrounds

➤ Experimental Results

- *Comparative Results on MPD Dataset*



✦ Palmprint Detection under Complex Backgrounds

➤ Experimental Results

- *Comparative Results on Our Dataset*



Popular Methods - Theoretical Limitations

➤ Unified Framework for Palm Matchers

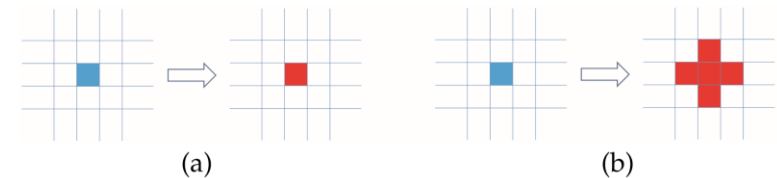
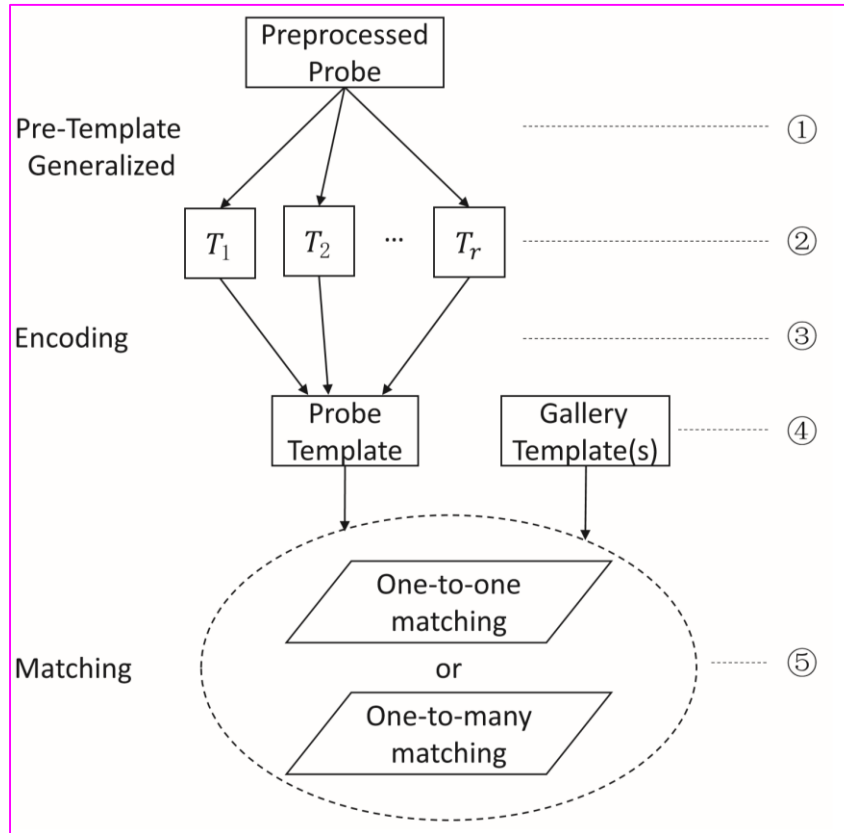


Fig. 2: (a) One-to-one and (b) one-to-many matching strategy.

TABLE 1: Summary of several competing 2D palmprint matchers.

Method	① Pre-template generating method	② Number of pre-template (r)	③ Encoding method	④ Number of encoding classes (λ)	⑤ Matching method
CompCode [10]	convolution	6	min	6	one-to-one
RLOC [7]	convolution	6	min	6	one-to-many
Ordinal Code [18]	convolution	2	max / min	2	one-to-one

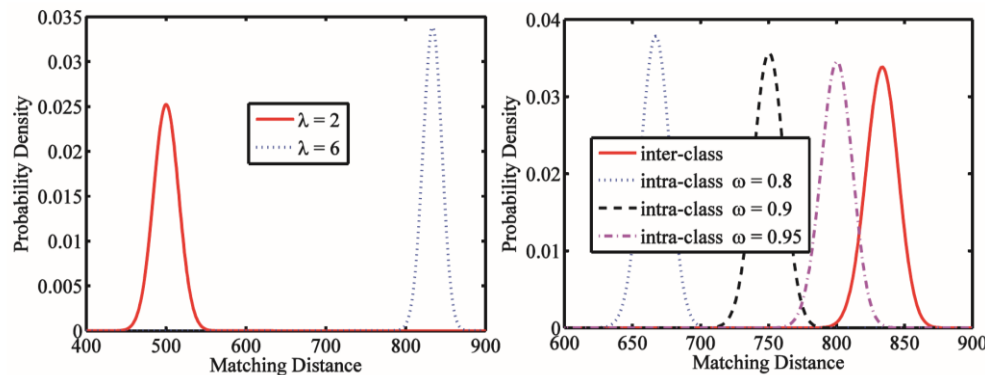
Popular Methods - Theoretical Limitations

➤ Modelling Matching Attempts among Templates

- Distribution of inter-class matching distances

$$D_{inter} \sim B(n_{inter}, p)$$

- Feature Templates (Uncorrelated), Inter-Class match $p = 1 - \frac{1}{\lambda}$.
- Let, $n_{intra} = \omega \cdot n_{inter}$ ($0 < \omega < 1$)



$$\omega \propto 1 - \frac{1}{\lambda^2}$$

➤ Desirable number of encoding classes $\rightarrow \lambda = 2$

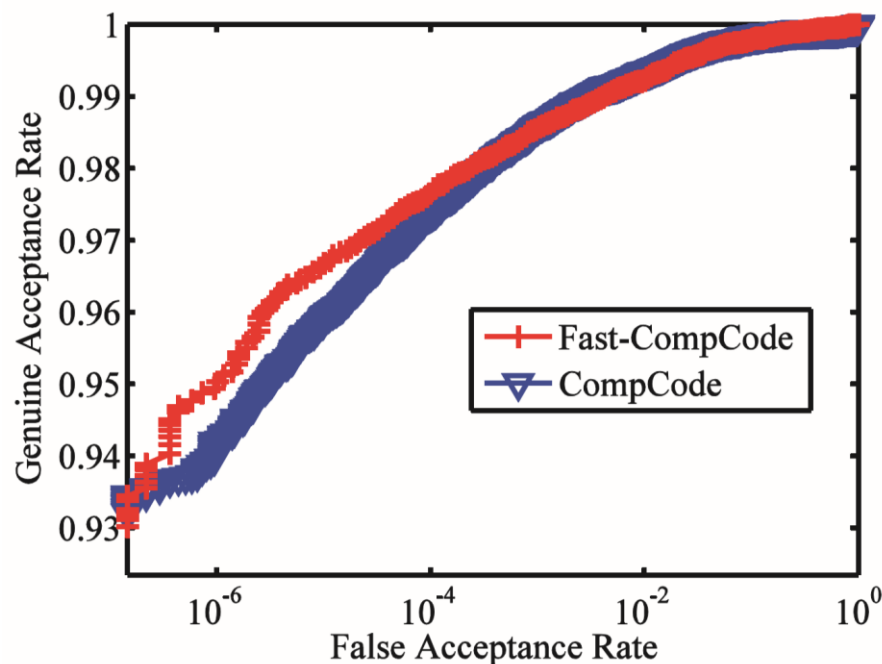
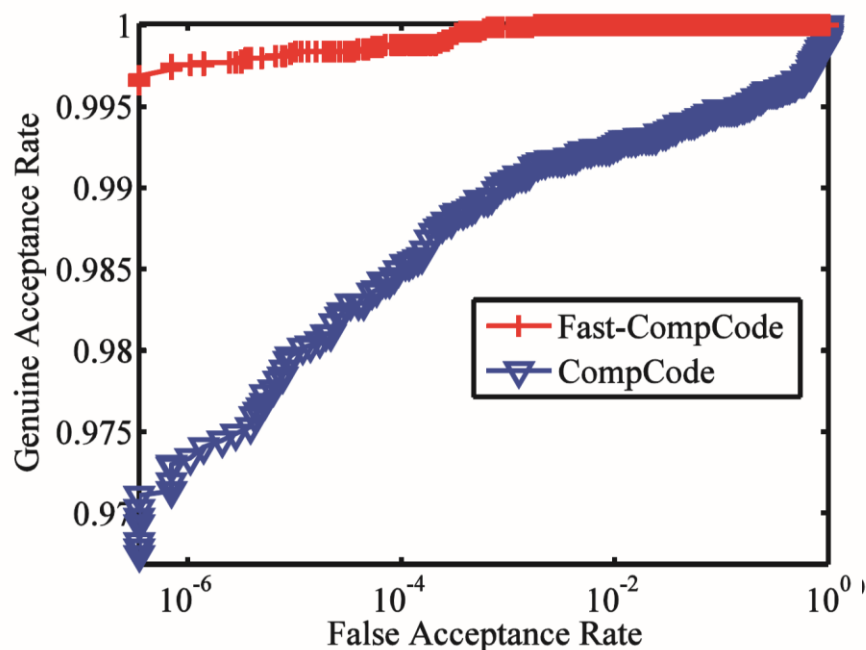
Experimental Results

➤ Fast-CompCode, Fast-RLOC

- Table: Comparative Results on PolyU Palmprint Database

Method	Fast-RLOC	RLOC (in [7])	RLOC	Fast-CompCode	CompCode (in [7])	CompCode
FAR (%)	4×10^{-5}	4×10^{-5}	4×10^{-5}	4×10^{-5}	4×10^{-5}	4×10^{-5}
FRR (%)	0.94	1.631	2.10	0.31	4.86	2.90
EER (%)	0.089	0.16	0.30	0.041	0.47	0.76

- Comparative ROC on Four Different Public Palmprint Databases



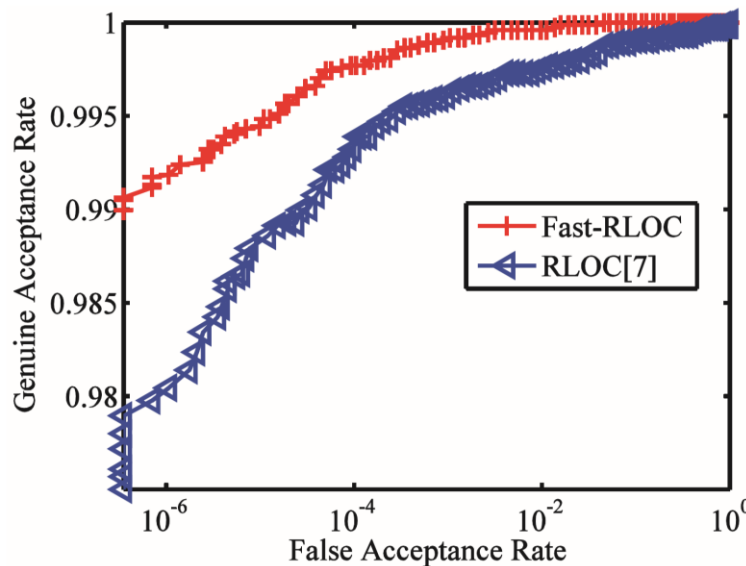
Experimental Results

➤ Fast-CompCode, Fast-RLOC

- Complexity Analysis (bytes, millisecond)

Method	Template Size	FeaExt	Matching
Fast-CompCode	128	1.3	0.017
CompCode	384	4.0	0.054

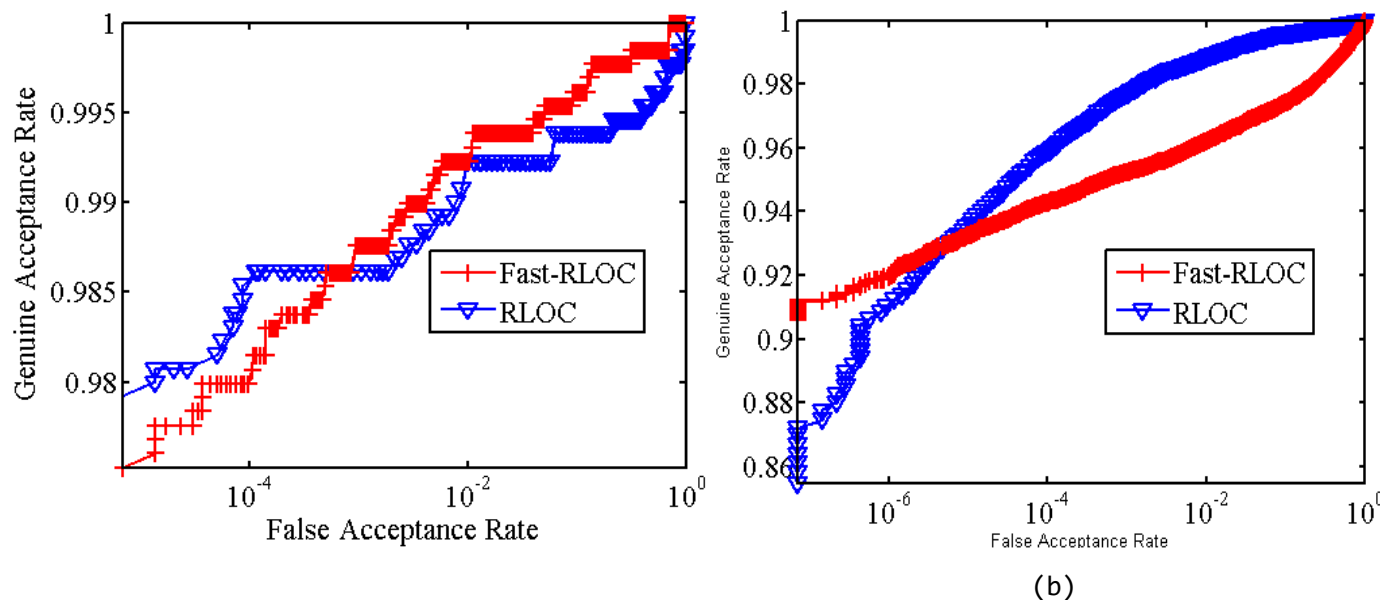
- Comparative ROC for Fast-RLOC on PolyU Palmprint Databases



Method	Matching
Fast-RLOC	0.017
RLOC	1.2

Experimental Results

- Fast-RLOC on Contactless Palmprint Databases
 - IITD (Left), CASIA (Right)

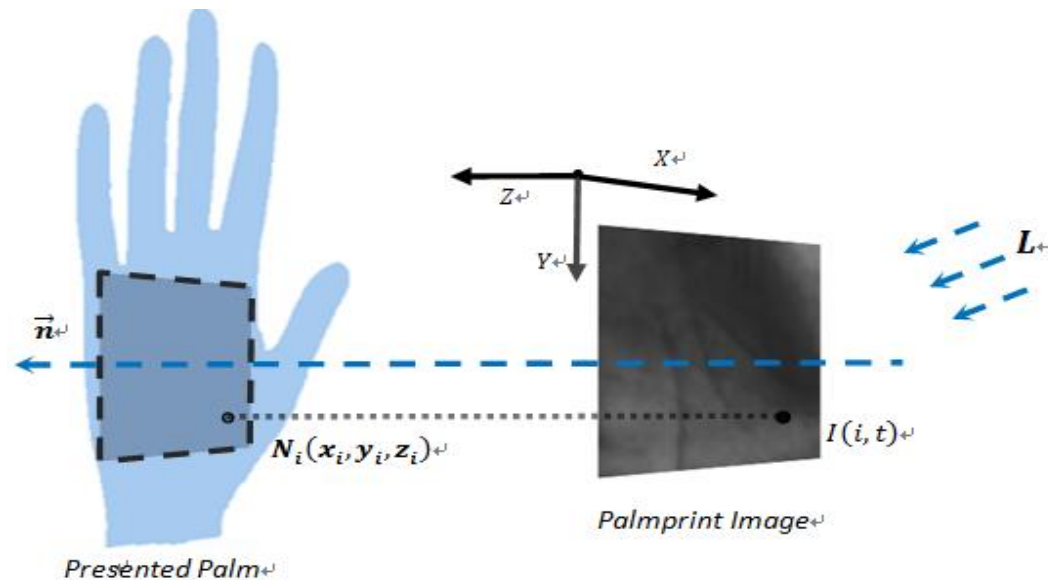


- Fully Reproducible, Download Codes → <https://www4.comp.polyu.edu.hk/~csajaykr/3DPalmprint.htm>

✶ Contactless Palmprint Feature Descriptor

➤ Difference of Vertex Normal Vectors (DoN)

- Recovers and Matches 3D Shape using a single 2D Image
 - *Ordinal Measure* → Difference of Neighboring point normal vectors
 - Theoretical Formulation & Support → Contactless Biometric Imaging



$$I(i) = k_d l_d \mathbf{L} \mathbf{n}_i$$

$$DoN(i) = \tau\left(\sum_{j \in R_i^1} z_j - \sum_{j \in R_i^2} z_j\right) \quad \tau(\alpha) = \begin{cases} 0, & \alpha < 0 \\ 1, & \alpha \geq 0 \end{cases}$$

✶ Contactless Palmprint Feature Descriptor

➤ Difference of Normal Vectors (DoN)

- Difference between Intensity → Two Regions

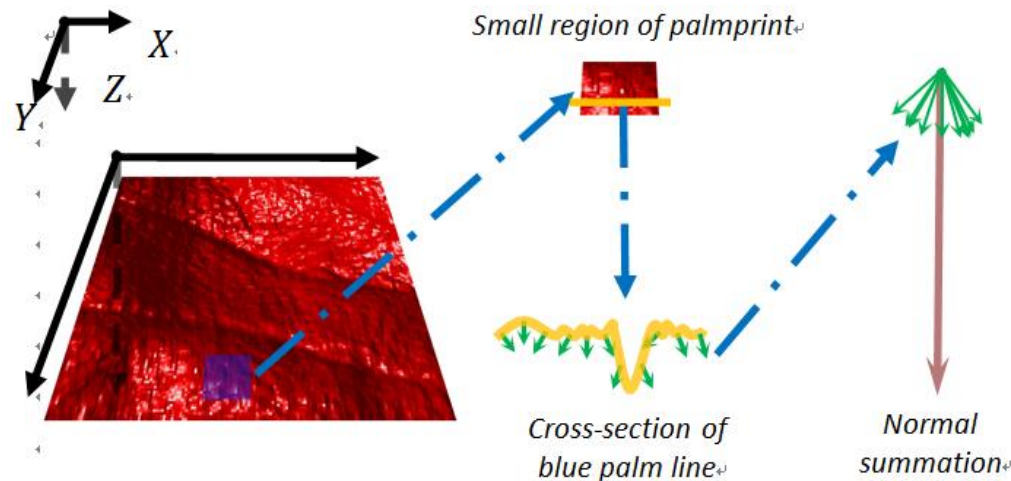
$$D(i) = \tau\left(\sum_{j \in R_i^1} I(j) - \sum_{j \in R_i^2} I(j)\right)$$

$$\begin{aligned} D(i) &= \tau(\Delta X_i a + \Delta Y_i b + \Delta Z_i c) \\ &= \tau(\Delta Z_i c) = \tau(\Delta Z_i). \end{aligned}$$

$$\begin{aligned} D(i) &= \tau(k_d l_d \mathbf{L}\left(\sum_{j \in R_i^1} \mathbf{n}_j - \sum_{j \in R_i^2} \mathbf{n}_j\right)) \\ &= \tau(\mathbf{L}\left(\sum_{j \in R_i^1} \mathbf{n}_j - \sum_{j \in R_i^2} \mathbf{n}_j\right)). \end{aligned}$$

$$|\Delta Z c_k| > |\Delta X a_k + \Delta Y b_k|$$

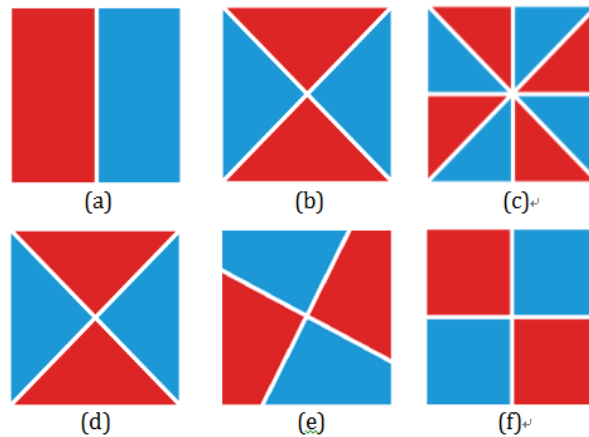
$$\frac{|c_k|}{|a_k|} > \frac{2|\Delta X|}{|\Delta Z|}$$



✧ Contactless Palmprint Feature Descriptor

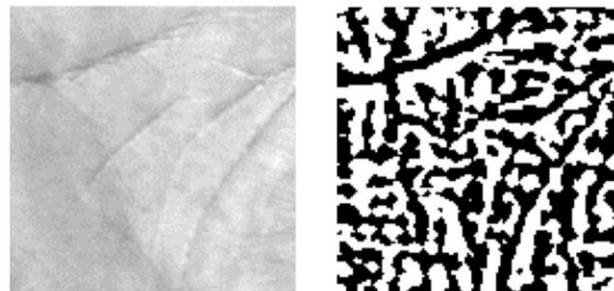
➤ Difference of Normal Vectors (DoN)

- Spatial Divisions → Candidate Feature Extractors
 - *Symmetry → Orthogonal or Parallel*



$$f_{i,j} = \begin{cases} 1 & |i| > |j| \\ -1 & |i| < |j| \\ 0 & \text{otherwise.} \end{cases}$$

$$\frac{\omega_1}{\omega_2} = \frac{1 - (1 - p_1)(1 - p_1)}{1 - (1 - p_2)(1 - p_2)}$$



I

F

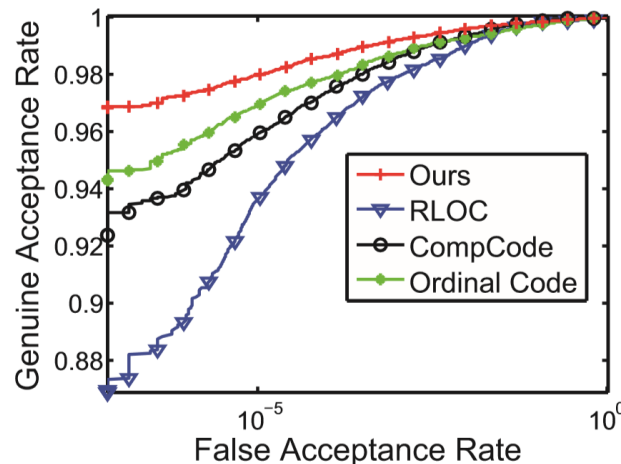
$$F = \tau(f * I)$$

Experimental Results

➤ Comparative Performance using DoN

■ Comparative Results on CASIA Contactless Palmprint Database

Method	Ours	RLOC	Competitive Code	Ordinal Code
EER	0.53	1.0	0.76	0.79



■ Complexity Analysis, *Smallest* Template Size (one-bit-per-pixel)

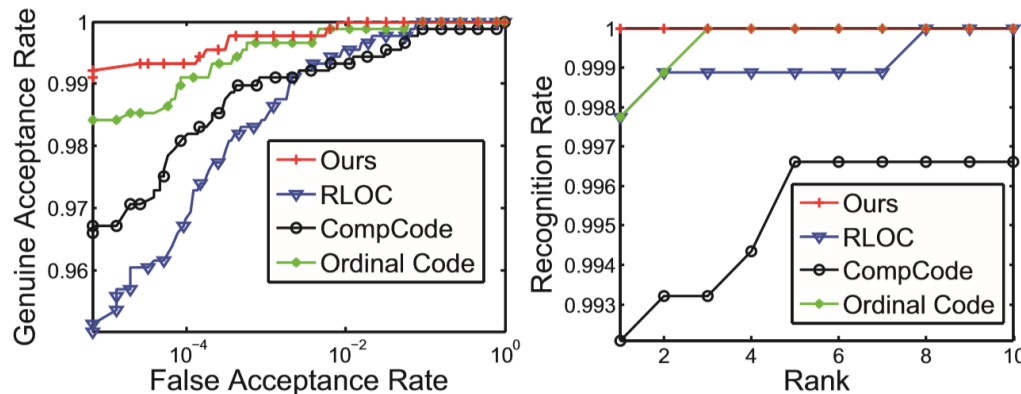
Method	Feature Extraction	Matching
Ours	1.1	0.054
RLOC	0.13	1.2
Competitive Code	4.0	0.054
Ordinal Code	3.2	0.054

Note: The experimental environment is: Windows 8 Professional, Intel(R) Core(TM) i5-3210M CPU@2.50GHz, 8G RAM, VS 2010.

Experimental Results

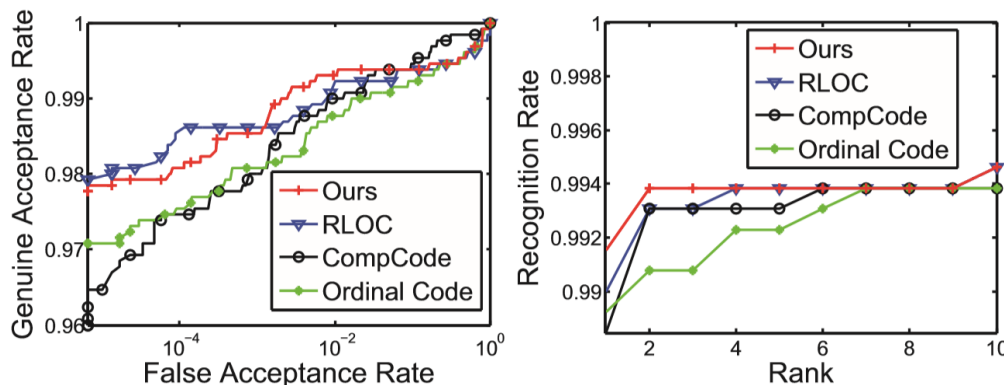
➤ Comparative Performance using DoN

■ PolyU 2D/3D Contactless Palmprint Database



■ IITD Palmprint Database

Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	0.22	0.64	0.68	0.33
Accuracy (%)	100	99.77	99.21	99.77



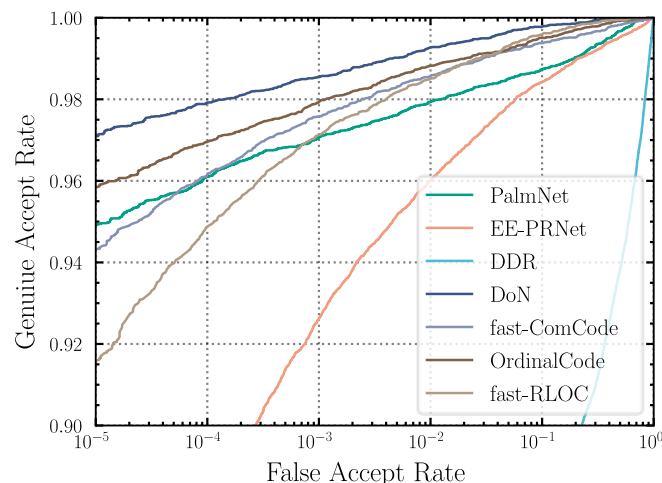
Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	0.68	0.88	1.0	1.25
Accuracy (%)	99.15	99.00	98.85	98.92

Experimental Results

➤ Comparative Performance using DoN with Recent Methods

- CASIA Contactless Palmprint Database, *Duplicate Subjects/Images* (19, 301)
- 300 Different Subjects, *Challenging Protocol* (all-to-all approach)
- 20608 genuine and 6,846, 412 impostor match scores

PalmNet (*TIFS*, Dec. 2019)
EE-PRNet (*TIFS*, Jan. 2020)
DDR (*PR* 2020)



Comparative performance with *all-to-all* protocol (CASIA)

	EER	GAR @ FAR= 10^{-4}	GAR @ FAR= 10^{-5}
PalmNet	1.85%	97.07%	96.10%
EE-PRNet	2.82%	92.62%	87.37%
DDR	11.88%	73.33%	8.16%
DoN	0.82%	98.54%	97.92%
fast-ComCode	1.32%	97.58%	96.17%
OrdinalCode	1.15%	97.93%	96.95%
fast-RLOC	1.34%	97.14%	94.89%

DoN →

In addition to huge computational simplicity!

✧ Cross-Sensor Contactless Palmprint Matching

➤ Different Palmprint Acquisition Devices

- MPD Contactless Palm Database, Several Sensors in PolyU-IITD Database

Sensor 1
(*Smartphone H*)



Sensor 2
(*Smartphone M*)



Experimental Results (Cross-Sensor Matching)

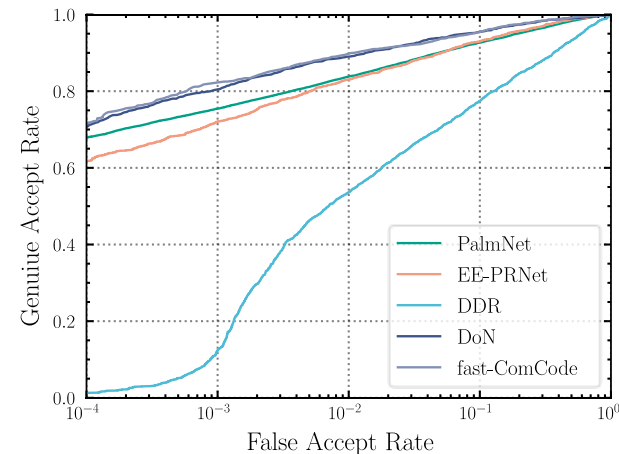
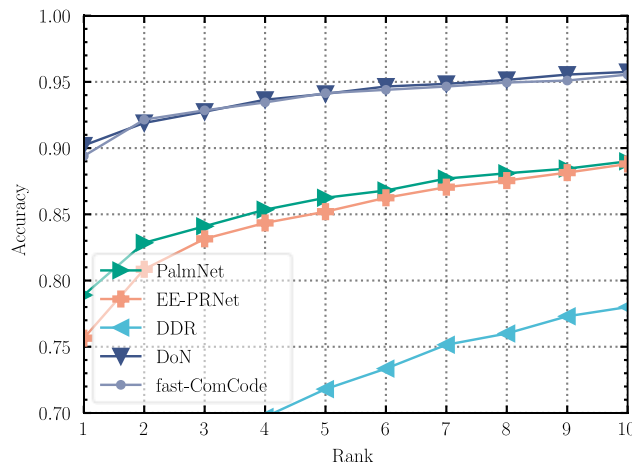
➤ Comparative Performance using DoN with Recent Methods

- MPD Contactless Palm Dataset Database, 200 Subjects (2 Sensors, H and M)
- Train: 1st Session Left Hand *H Sensor*, Test: 2nd Session Right Hand *M Sensor*
- 20,000 ($200 \times 10 \times 10$) genuine and 3,980,000 ($200 \times 199 \times 100$) impostor match score

The EER and Rank-1 accuracy for MPD dataset (HM)

Algorithm	Rank-1 Accuracy	EER	GAR@ FAR=10-3	GAR@ FAR=10-4
PalmNet	78.90%	8.03%	75.44%	67.84%
EE-PRNet	75.65%	7.69%	72.00%	61.60%
DDR	57.15%	17.19%	12.40%	1.30%
DoN	90.20%	5.74%	80.50%	70.70%
fast-ComCode	89.40%	5.94%	82.35%	71.65%

PalmNet (*TIFS*, Dec. 2019)
EE-PRNet (*TIFS*, Jan. 2020)
DDR (*PR* 2020)



Experimental Results (Cross-Sensor Matching)

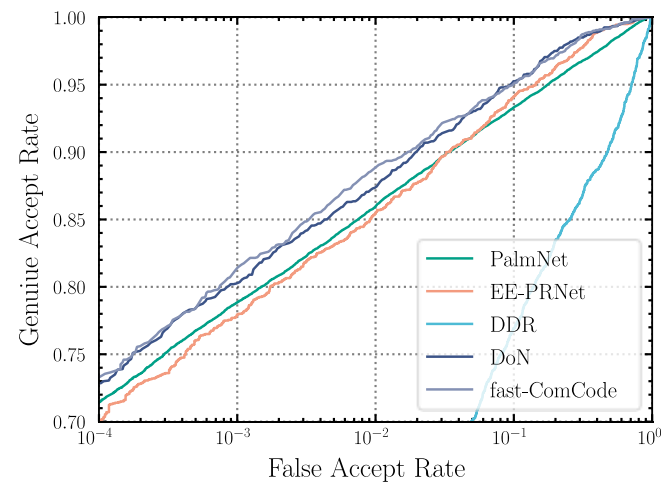
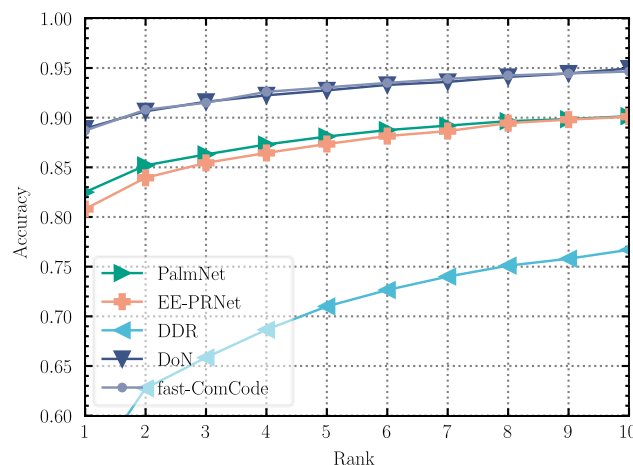
➤ Comparative Performance using DoN with Recent Methods

- MPD Contactless Palm Dataset Database, 200 Subjects (2 Sensors, H and M)
- Train: 1st Session Left Hand *M Sensor*, Test: 2nd Session Right Hand *H Sensor*
- 20,000 (200*10*10) genuine and 3,980,000 (200*199*100) impostor match score

The EER and Rank-1 accuracy for MPD dataset (MH)

Algorithm	Rank-1 Accuracy	EER	GAR@ FAR=10-3	GAR@ FAR=10-4
PalmNet	82.50%	7.56%	78.84%	71.44%
EE-PRNet	80.80%	7.25%	77.95%	69.90%
DDR	53.85%	17.82%	29.60%	13.60%
DoN	88.90%	6.35%	80.35%	72.85%
fast-ComCode	88.70%	6.10%	81.45%	73.30%

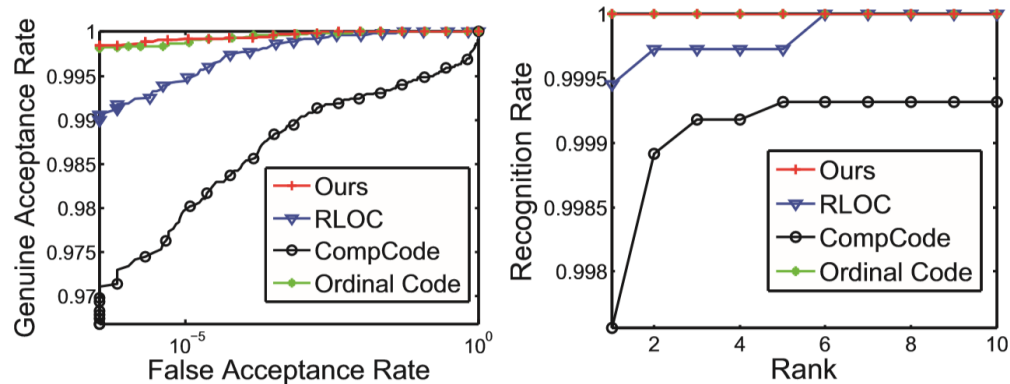
PalmNet (*TIFS*, Dec. 2019)
EE-PRNet (*TIFS*, Jan. 2020)
DDR (*PR* 2020)



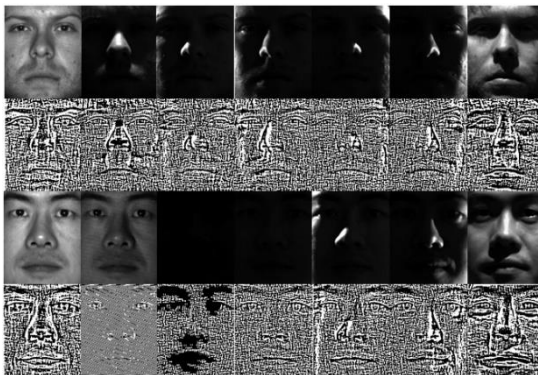
Experimental Results

➤ Comparative Performance using DoN

■ PolyU Palmprint Database



■ Extended Yale Face Database B



Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	0.033	0.089	0.076	0.038
Accuracy (%)	100	99.95	99.76	100

Method	Ours	PP+LTP/DT [19]	G_LDP [20]
Rank-1 rate (%)	99.3	99.0	97.9

Effective for a Range of Other Biometrics and Applications

✧ Cross-Spectral Palmprint Matching

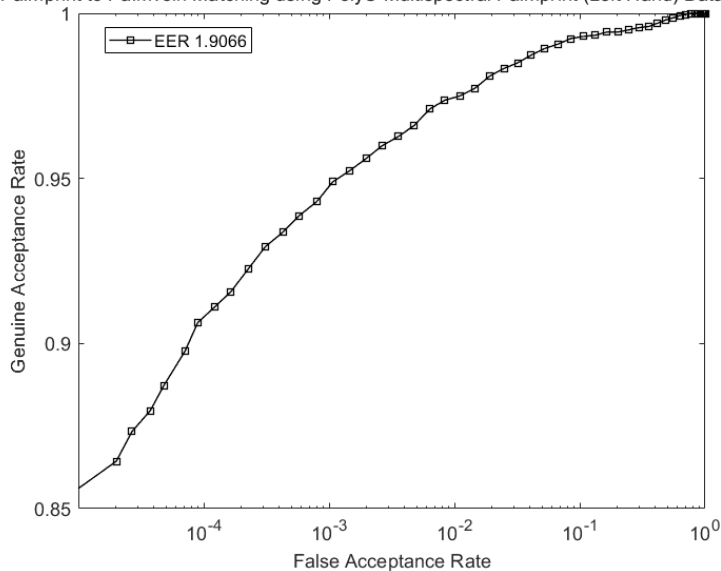
➤ Matching Palmprint with PalmVein Images

- PolyU Multispectral Database from 250 Different Subjects
- Train: 1st Session, Test: 2nd Session
- 1500 (250*6) genuine scores, 373500 (250*249*6) impostor scores

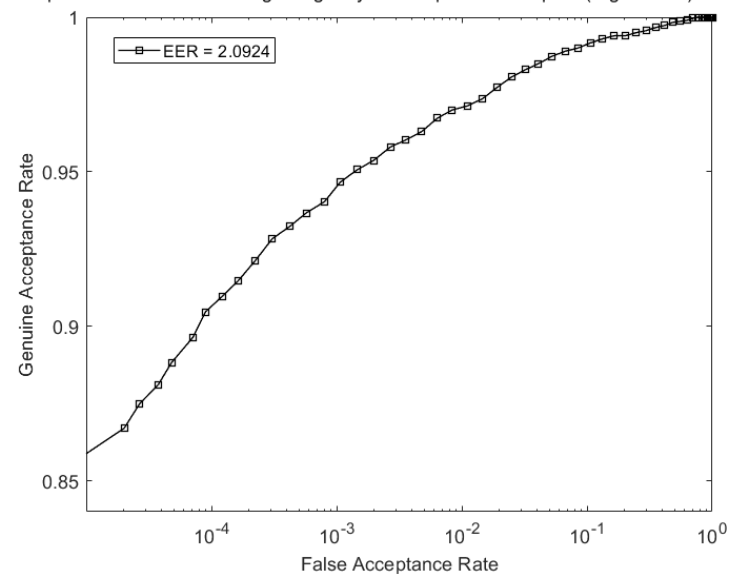
Sensor 1
(Palmprint)

Sensor 2
(Palmvein)

Palmprint to Palmvein Matching using PolyU Multispectral Palmprint (Left Hand) Database



Palmprint to Palmvein Matching using PolyU Multispectral Palmprint (Right Hand) Database

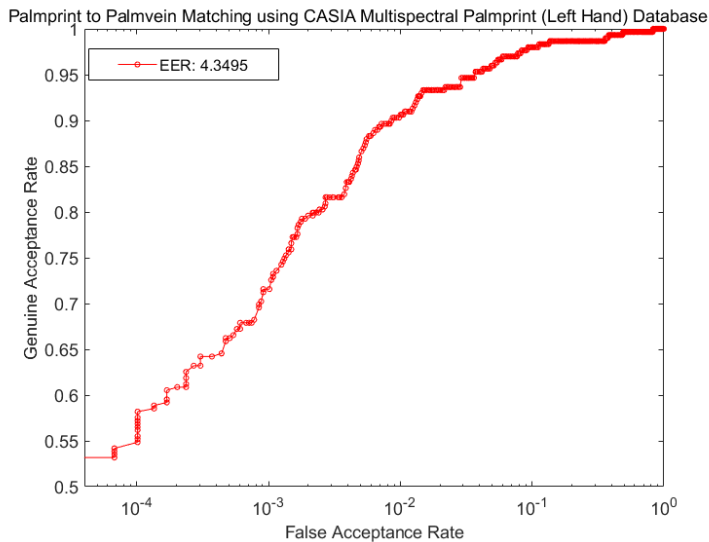


✧ Cross-Spectral Palmprint Matching

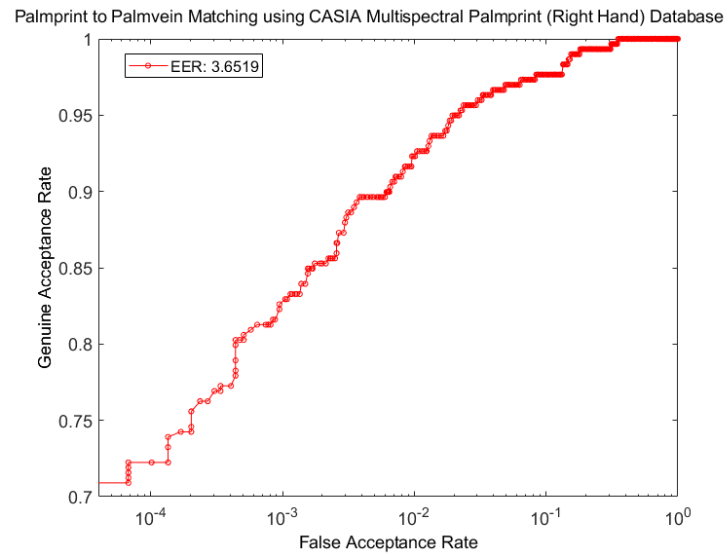
➤ Matching Palmprint with PalmVein Images

- CASIA Multispectral Palmprint Database from 100 Different Subjects
- Train: 1st Session, Test: 2nd Session
- 300 (100*3) genuine scores, 329700 (100*99*3) impostor scores

Sensor 1
(Palmprint)



Sensor 2
(Palmvein)



✧ Best Practices in Performance Evaluation

- Deep Neural Networks → Always provide *Cross-DB* Results
- Performance Evaluation → Use ROC (GAR Vs FAR using semi-log scale) not just EER
- Always use Masks or Clarify if Matching Palmprint or Palmprint+ (Noise/Background)
- Two Session Databases →
1st Session (Train/Registration), 2nd Session (Test/Evaluation)
- Single Session Databases: Challenging Protocol (*all-to-all*)
- Also use conventional baseline with *Public Codes* (e.g. DoN and stronger one if you know!)
- Present results on Left/Right hand palmprints *separately*,
Avoid enlarged database results *using* ($L+R$) images
- Present Template Size and Complexity

✧ Contactless Palmprint Databases (PolyU)

- *PolyU-IITD Contactless Palmprint Images Database (Version 3.0), 600+ Different Subjects*
<https://www4.comp.polyu.edu.hk/~csajaykr/palmprint3.htm>
- *The Hong Kong Polytechnic University Contact-Free 3D/2D Hand Images Database (Version 1.0), 177 Subjects*
http://www4.comp.polyu.edu.hk/~csajaykr/myhome/database_request/3dhand/Hand3D.htm
- *The Hong Kong Polytechnic University Contact-Free 3D/2D Hand Images Database (Version 2.0), 114 Subjects*
<http://www4.comp.polyu.edu.hk/~csajaykr/Database/3Dhand/Hand3DPose.htm>
- *IITD Touchless Palmprint Database, 230 Subjects*
http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Palm.htm

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➤ Collaborators

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- Yang Liu
- Qian Zheng
- Jiaxin Hu

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Questions?
