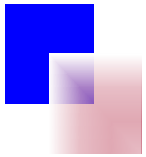
2025 Winter School on Biometrics
12th January 2025

Contactless Palmprint Recognition



Ajay Kumar

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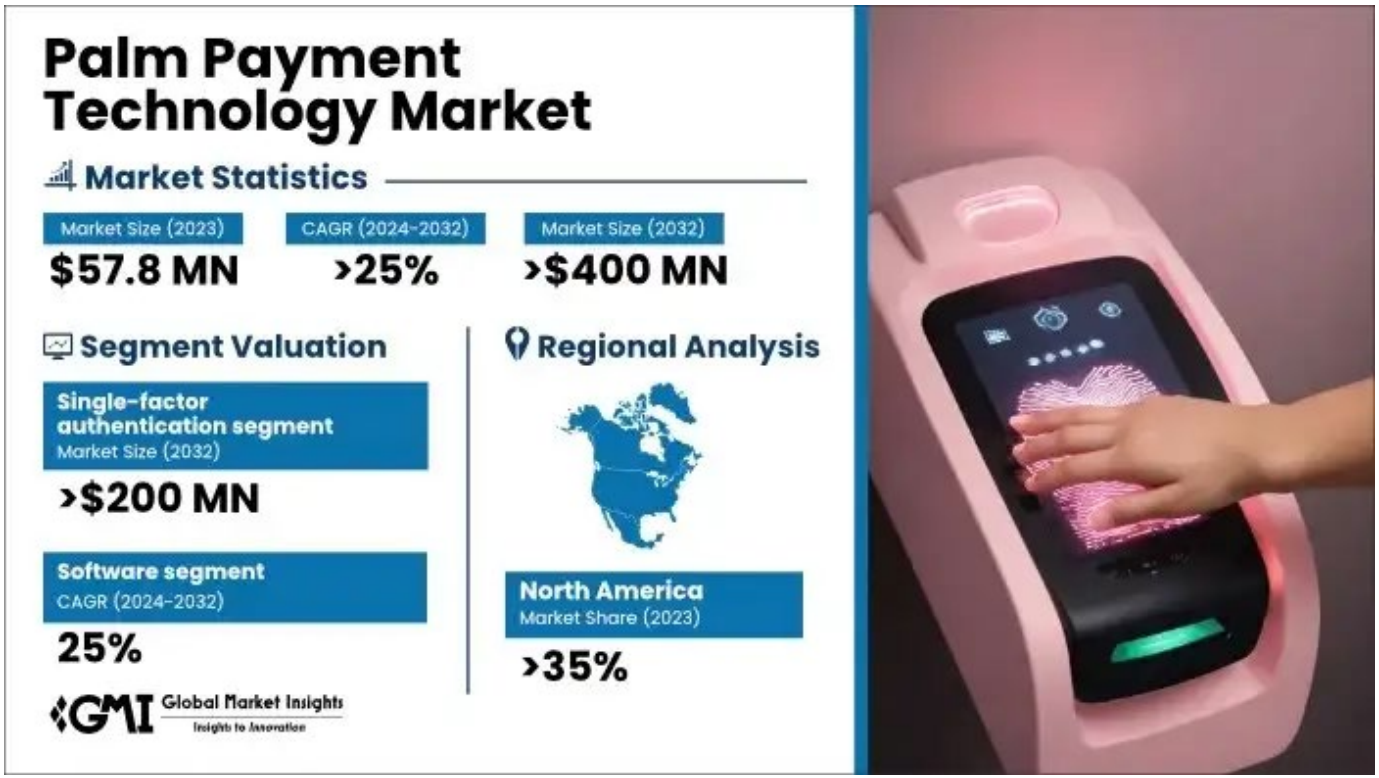
The Hong Kong Polytechnic University

Contactless Palmprint

- Estimated FinTech Market Size and Beyond



https://www.gminsights.com/industry-analysis/palm-payment-technology-market/market-size

Contactless Palmprint

- Applications
  - Mobile Security and FinTech Applications
  - Public Security and Surveillance
  - Medical Diagnosis of Some Diseases
  - Failure of Fingerprints $\rightarrow$ Manual Laborers, Elderly people, etc.
  - Improving Performance $\rightarrow$ Multimodal Biometrics

The History and Journey …

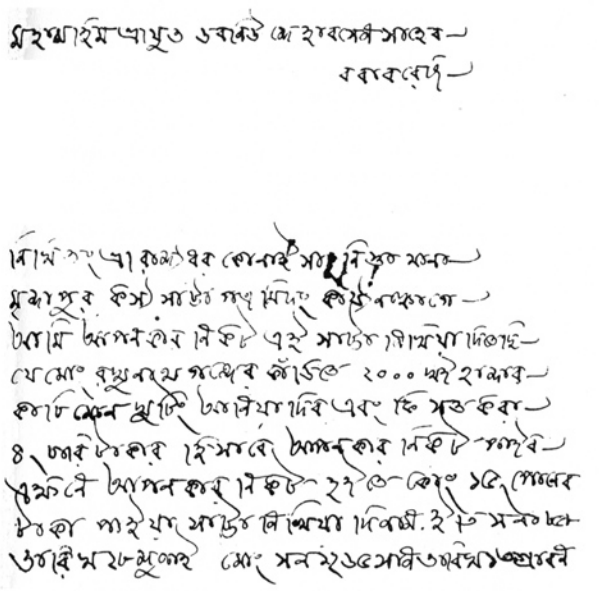
- Early Palm Evidences

https://onin.com/fp/fphistory.html

The History and Journey …

- Early Palm Evidences

KONAI's HANDPRINT
from the back of the contract
Bengal, India, 1858

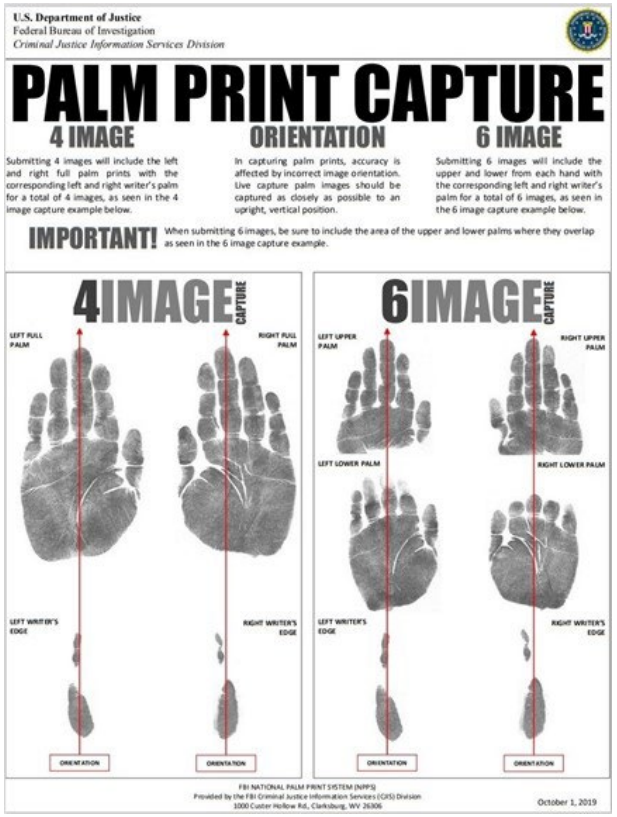


Contract for 2,000 maunds (165,200 Lbs.) of road-metalling,
between W.J. Herschel and Rajyadhar Konai, in Konai's handwriting

https://onin.com/fp/fphistmiru/hershcel_konai_contract.jpg

The History and Journey …

- Law Enforcement
  - Latent Palmprint Matching, Biometric Identification



https://issda.memberclicks.net/why-law-enforcement-agencies-in-iowa-should-capture-complete-palm-prints

Contactless Palm Acceptance

- Historical Perspective




- Cultural, Religious and Social Context
- Service, Power, Hope, Expectations, and Gesture
- Palmistry, Uniqueness, and Hygiene

Images from Google

Contactless Palmprint Identification

- Market Explosion, Opportunities and Challenges

Contactless Palmprint Identification

- First Paper
  - AVBPA03, Contactless and Peg-free imaging using a camera

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

A. Kumar, D. C. M. Wong, H. C. Shen, and A. K. Jain, "Personal verification using palmprint and hand geometry biometric," *Proc. 4th Intl. Conf. Audio- and Video-Based Biometric Authentication* (AVBPA), pp. 668-675, Guildford, UK, June 2003

Contactless Palmprint Identification

- Commercial Deployments
  - TenCent, Amazon One, Fujitsu, PCS, ZKTeco, Realme. *etc*.

  - From 1st Paper to Commercial Deployment in about 20 years!

Early Acquisition Devices

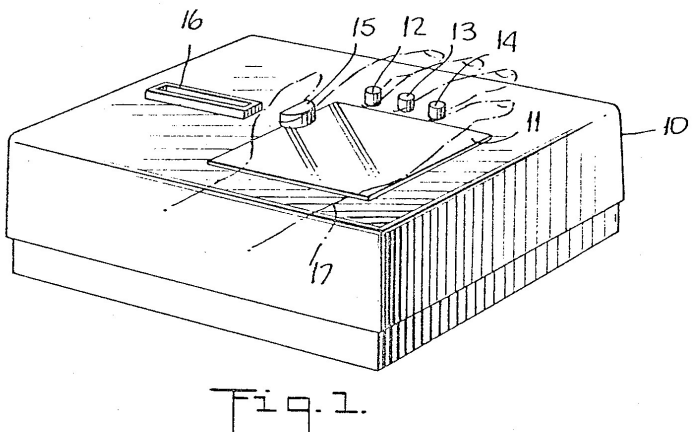
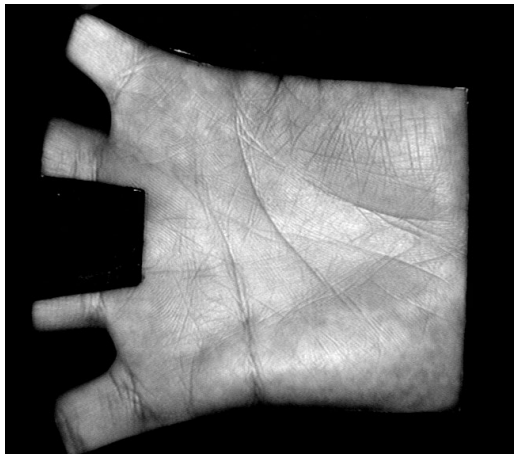


Fig. 1.

- Online → Immediate palm imaging
- Better image quality

- Pegs → Limits the rotation and translation
- More reliable and stable coordination system

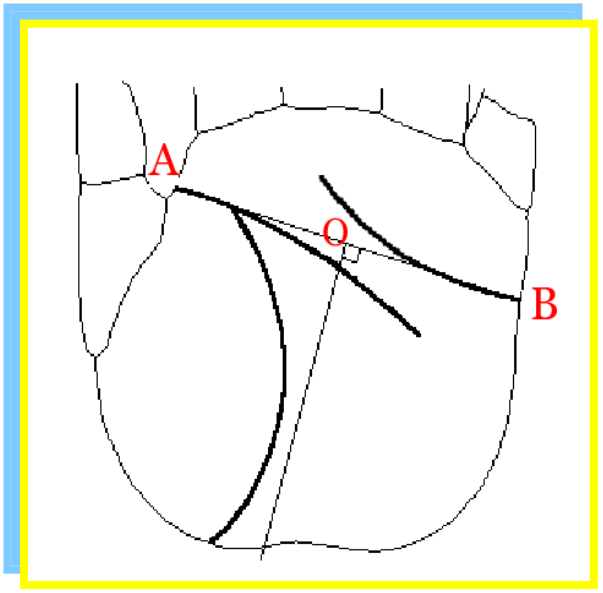


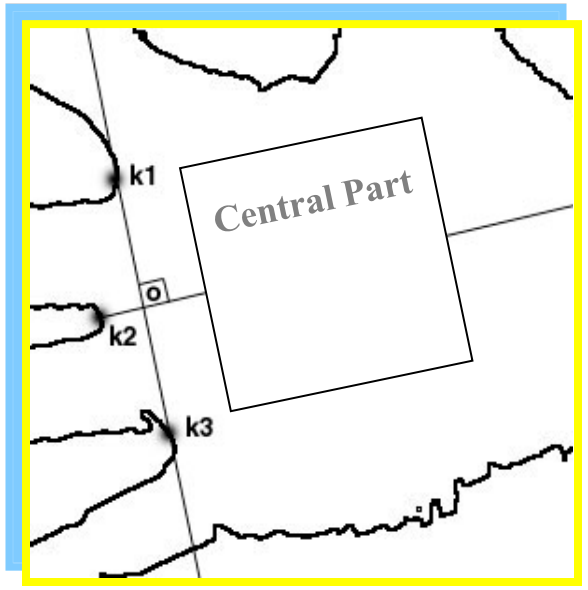
- Limitations → Bulk, Cost

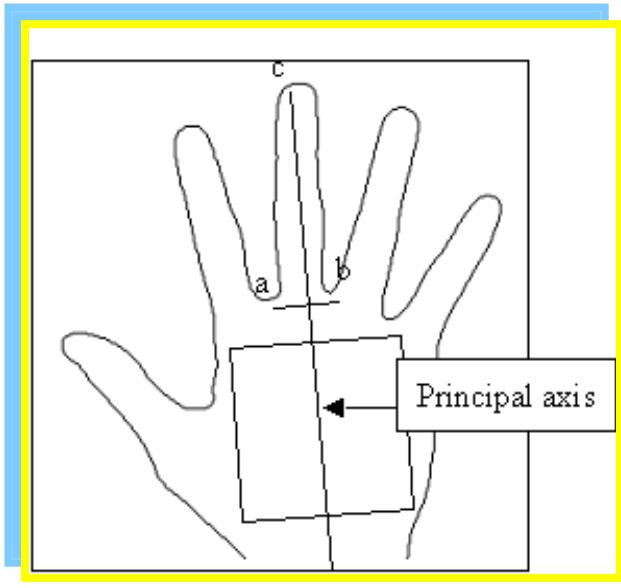
NG Altman, Palm Print Identification System, US Patent No. US3581282A. 1968

Palmprint Preprocessing

- Preprocessing
  - Rotational and Translational Changes → Normalization
  - Segmentation → Region of Interest Images







W. Shu and D. Zhang, "Automated Personal Identification by Palmprint," *Optical Engineering*, 1998.

W. Li, D. Zhang, and Z. Xu, "Palmprint Identification by Fourier Transform," *Intl. J. Pattern Recognition and Artificial Intelligence*, 2002.

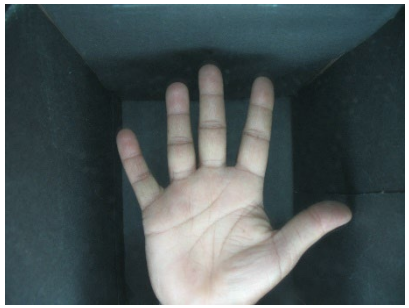
C. C. Han, H. L. Cheng, K. C. Fan and C. L. Lin, "Personal Authentication Using Palmprint Features," *Pattern Recognition*, 2003.

Palmprint Segmentation – Earlier Work

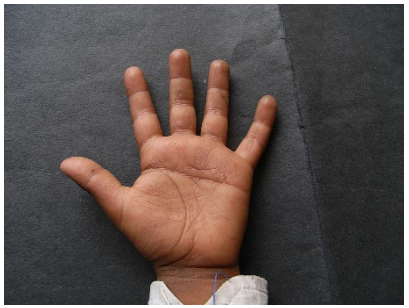
Limitations

- Only suitable for palm images acquired under constrained and uniform environments
  - The background is generally very different from the palm skin color
  - Images are usually acquired under a stable/static environment

Sample from CASIA dataset



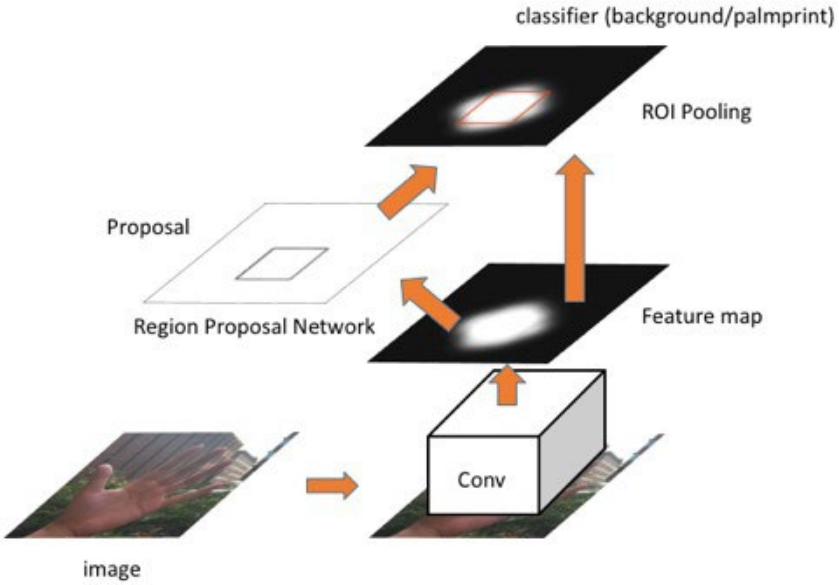
Sample from IITD dataset



Child-Palm Sample from PolyU-IITD dataset

Palmprint Detection under Complex Backgrounds

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

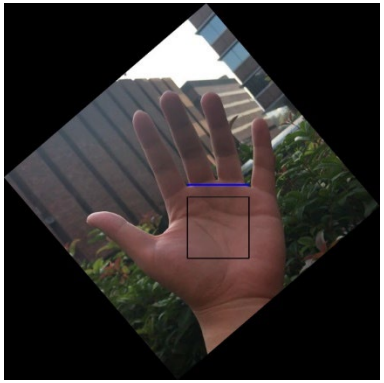


Y. Liu, A. Kumar, "A Deep Learning Based Framework to Detect and Recognize Humans using Contactless Palmprints in the Wild," arXiv preprint arXiv:1812.11319, 2018

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

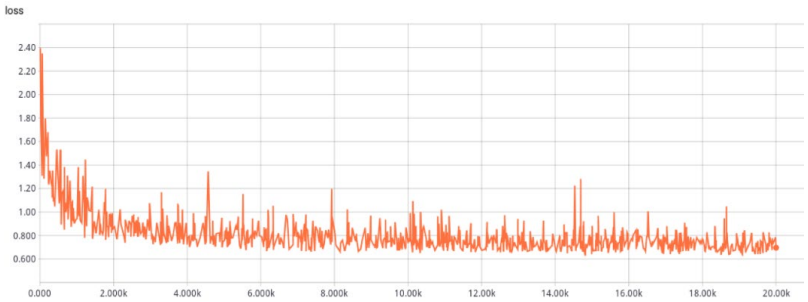
Palmprint Detection under Complex Backgrounds

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



Raw segmented frame

Aligned segmented frame



Y. Liu, A. Kumar, “Contactless Palmprint Identification Using Deeply Learned Residual Features," *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 2, no. 2, pp. 172-181, April 2020.

Palmprint Detection under Complex Backgrounds

➢ Data Augmentation

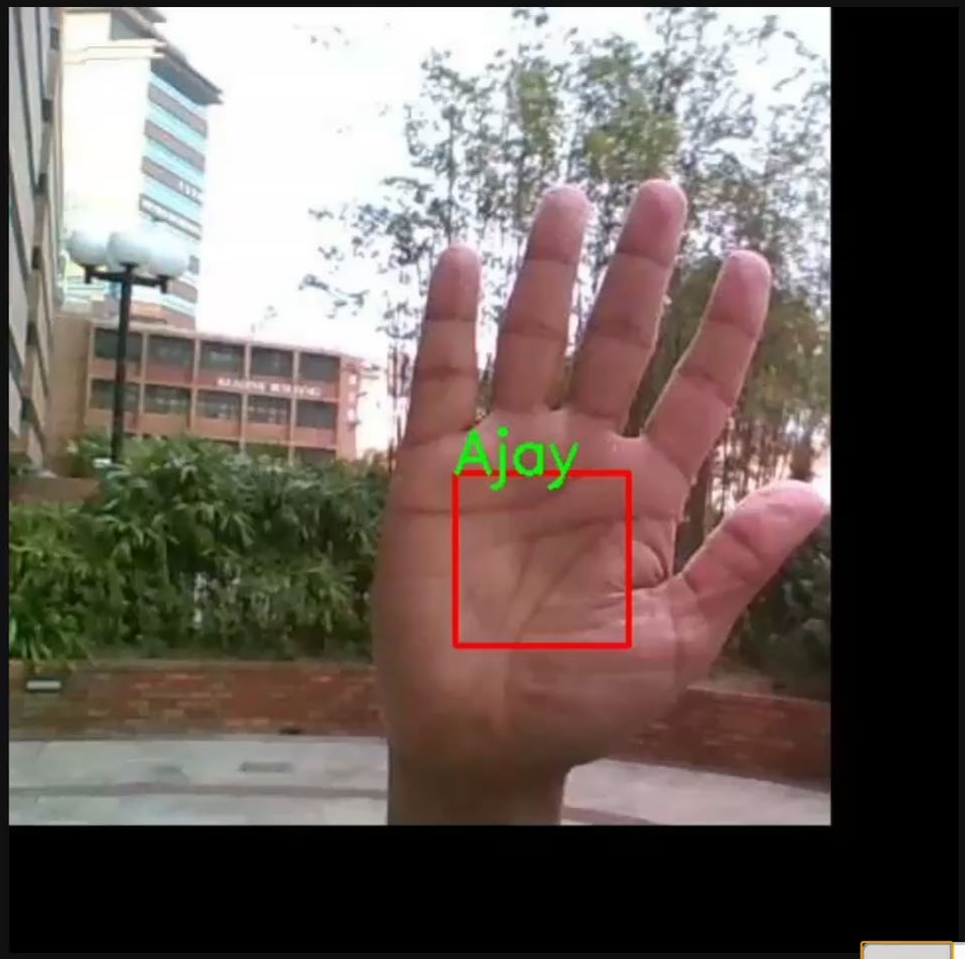
- Multiple traditional augmentation[1] methods including
  - *Gaussian Blur*
  - *Randomly adding and multiplying on the three channel.*
  - *Contrast normalization*
  - *Additive Gaussian noise*

- 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.

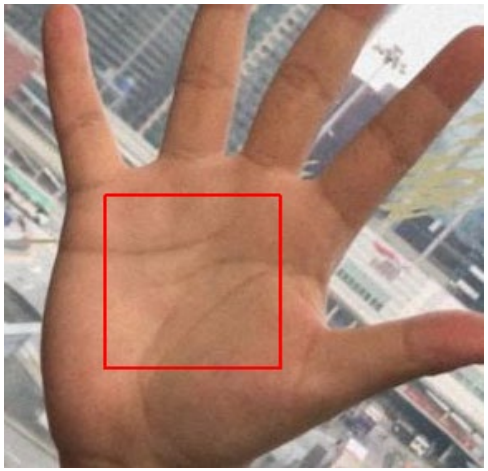
Palmprint Detection under Complex Backgrounds

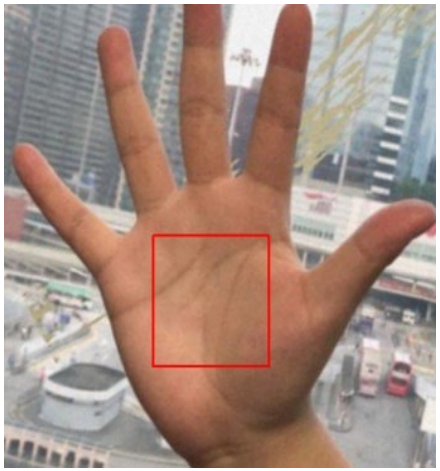


Palmprint Detection under Complex Backgrounds

Limitations

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

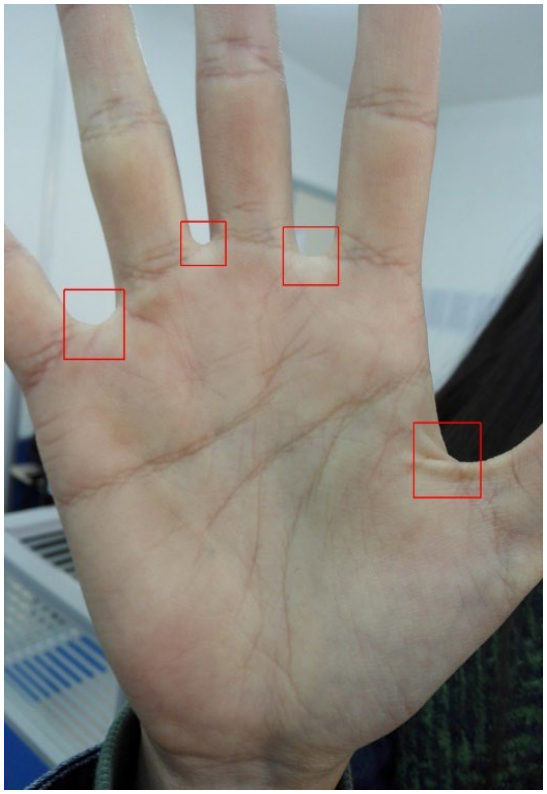


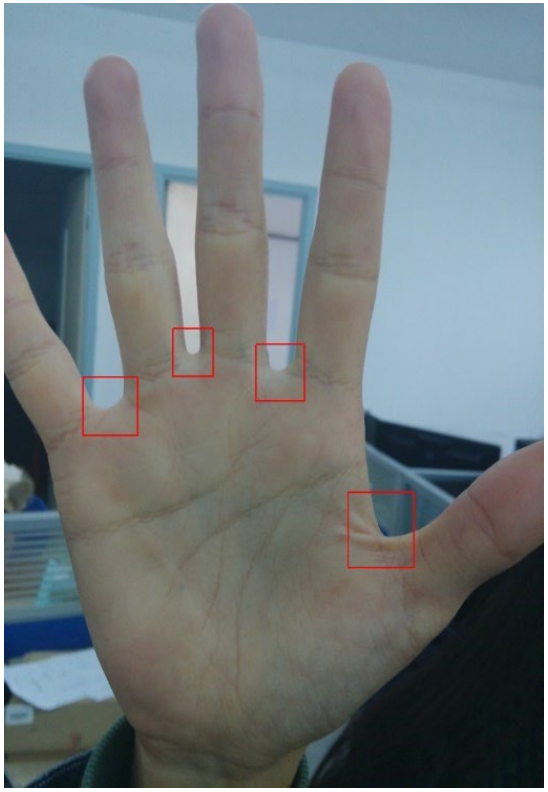


- Observed ROI *rotation* can significantly degrade the match accuracy

Palmprint Detection under Complex Backgrounds

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

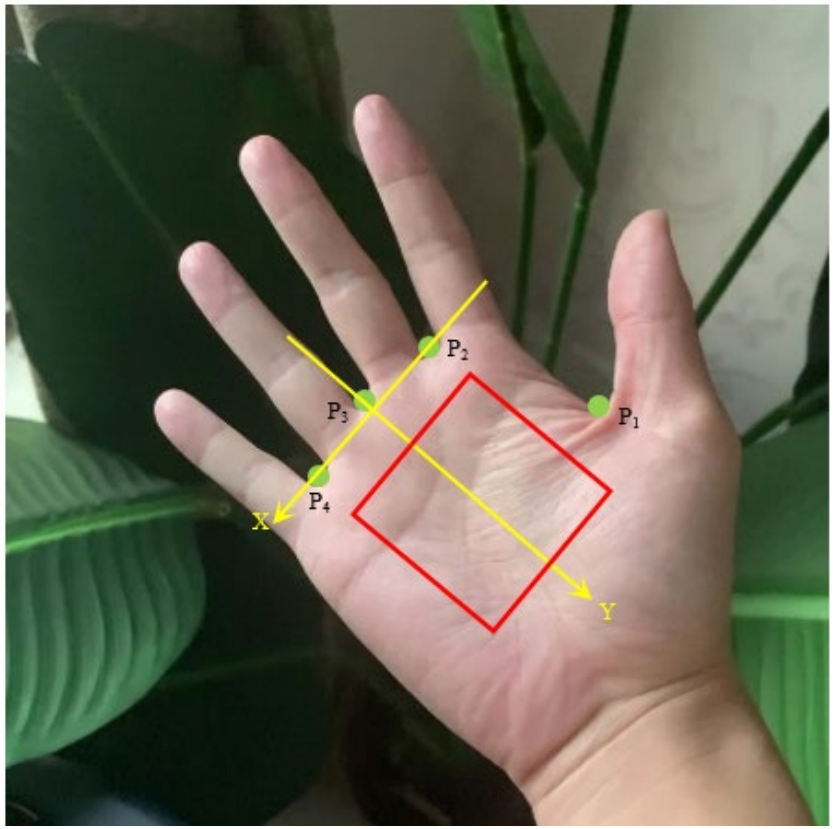




Y. Zhang, L. Zhang, X. Liu, S. Zhao, Y. Shen, and Y. Yang, “Pay By Showing Your Palm: A Study of Palmprint Verification on Mobile Platforms,” *Proc. ICME 2019*, pp. 862–867, July 2019.

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

Source: https://cslinzhang.github.io/deepmpv/

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

- *Average time cost for detection of one image*

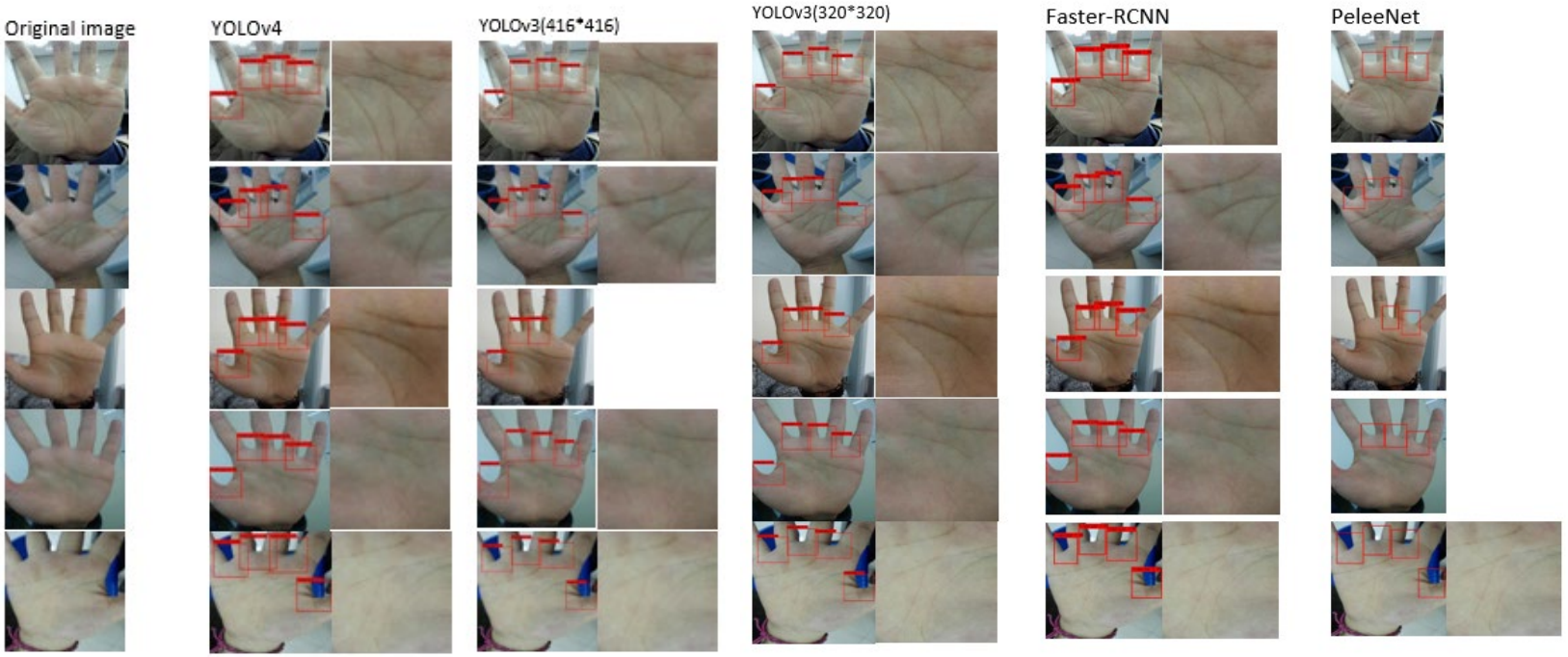
Detector	Time cost (ms)
YOLOv4	57.4
YOLOv3(416*416)	60.1
YOLOv3(320*320)	52.7
PeleNet	37.2
Faster R-CNN	632.7

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 and Performance Analysis*



Smartphone Based Contactless Palm Detection

- *MediaPipe* Based Contactless Palmprint Detection

I.

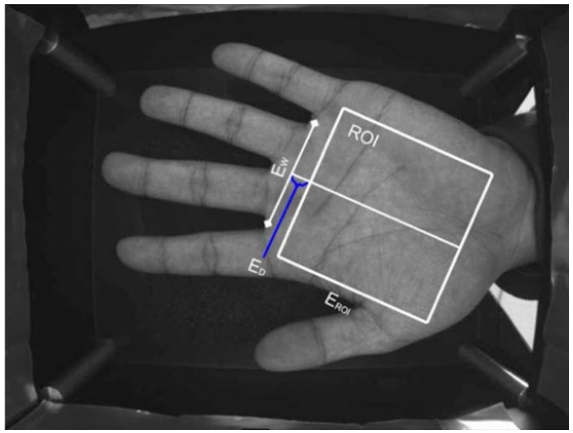


Figure 1: ROI (Zhou & Kumar, T-IFS 2010)

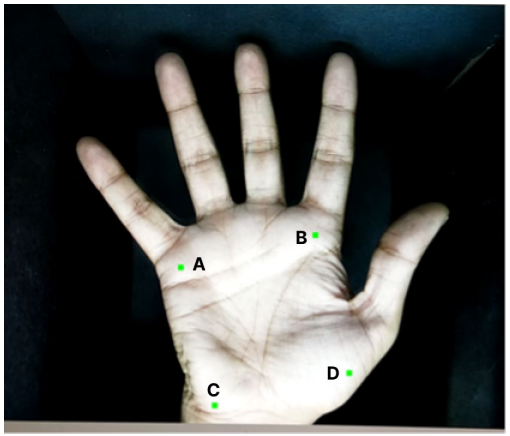
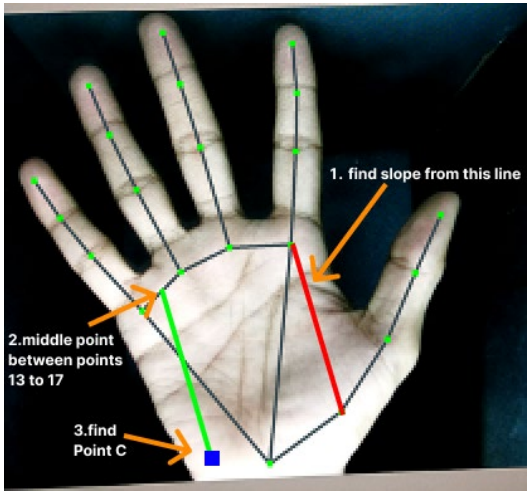
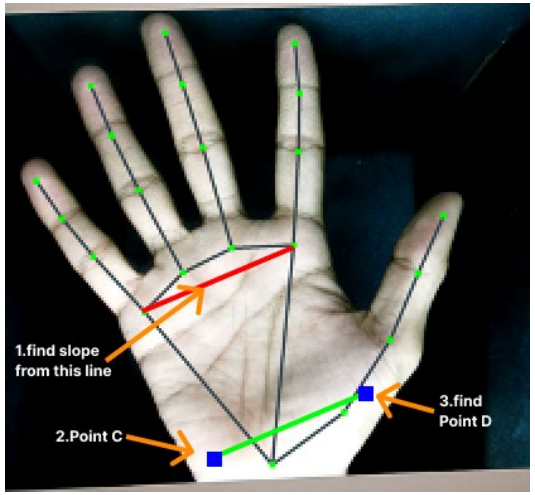


Figure 2: Palmprint Area Keypoints



(a)



(b)

Figure 3: Illustrate how to find points C in (a) and D in (b)

Smartphone Based Contactless Palm Detection

- Real World Challenges

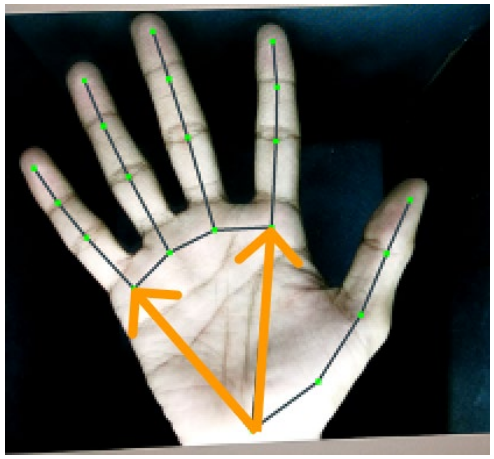
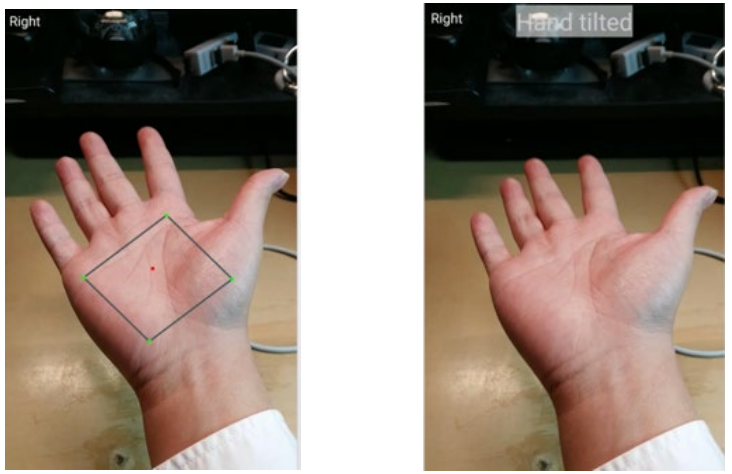


Figure A: Connection of Vectors

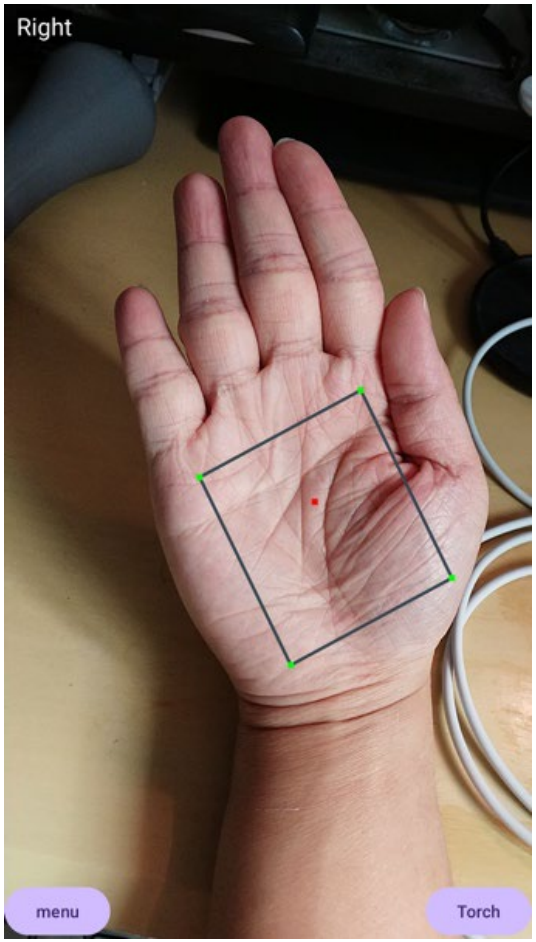


(a) (b)

Figure B: Experimental Results of Single Unit Vector

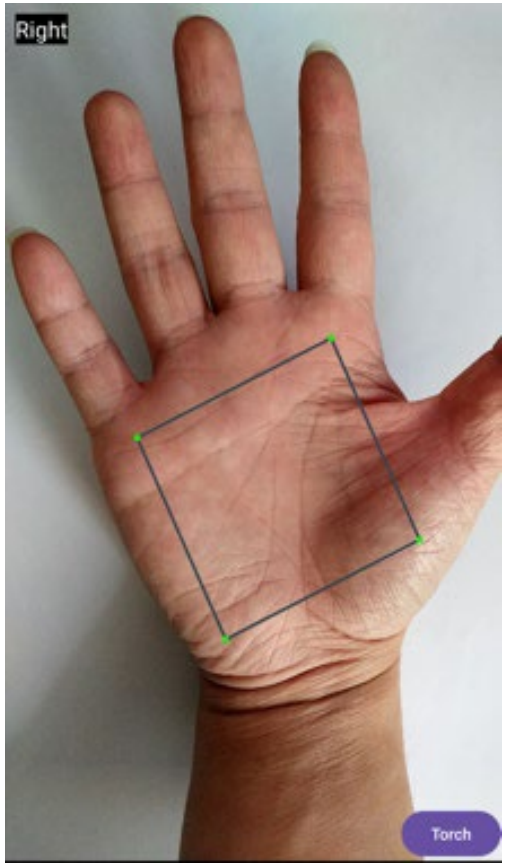
Smartphone Based Contactless Palm Detection

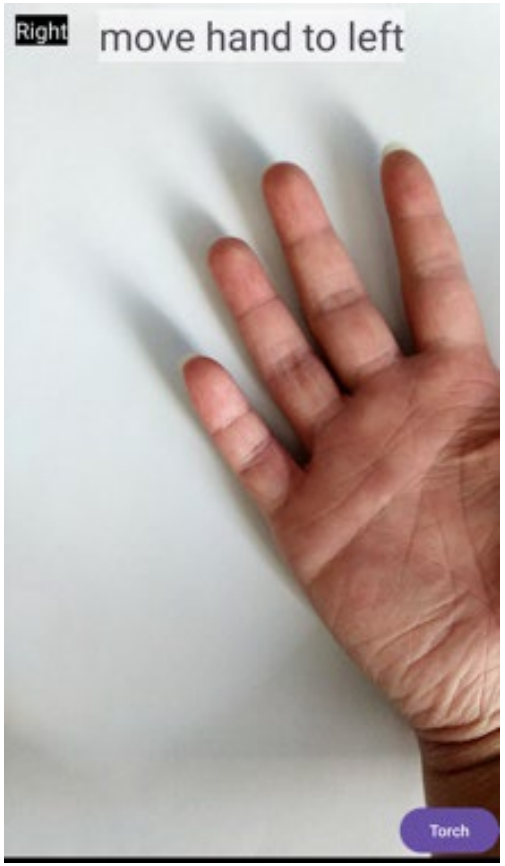
- Real World Challenges

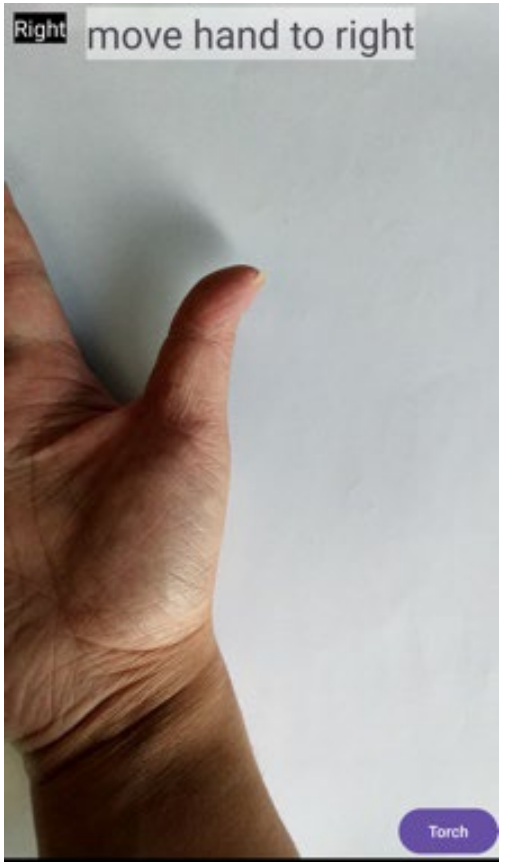


Smartphone Based Contactless Palm Detection

- Less-Constrained Contactless Palm Detection

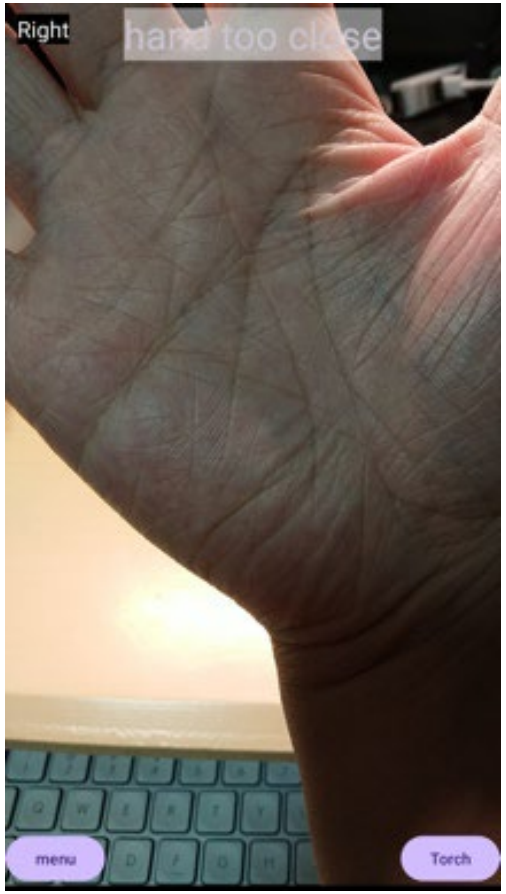


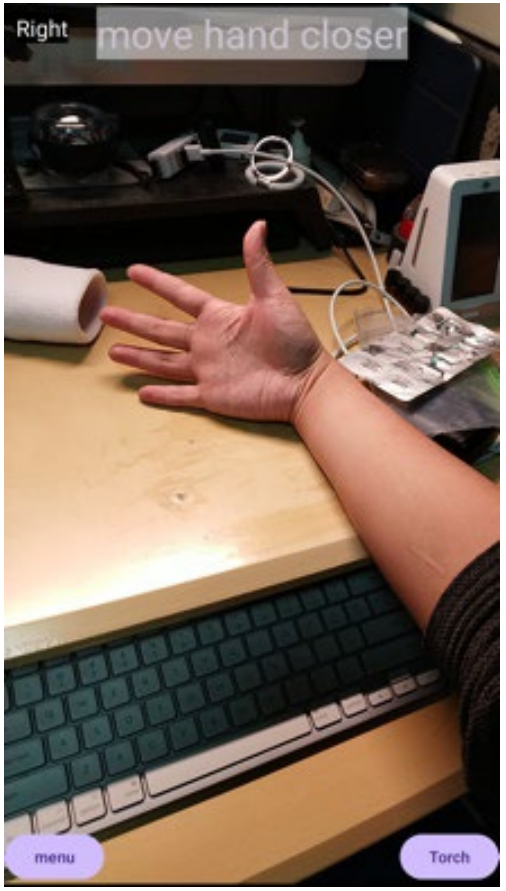




Smartphone Based Contactless Palm Detection

- Less-Constrained Contactless Palm Detection



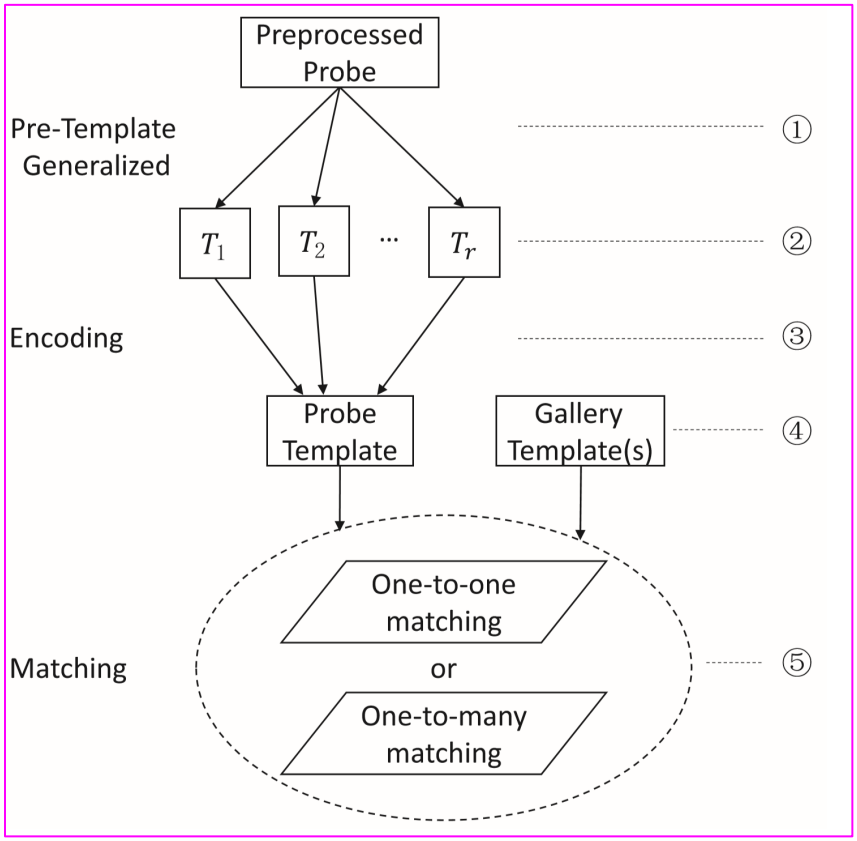


Smartphone Based Contactless Palm Detection

		Original Image	Zero Padding Image	
Database Name	Total	Success Result	Success Result	Image Type
CASIA-Palmprint [18]	5502	1164	4635	Palm Image
CASIA-Multi-Spectral-PalmprintV1 [24]	7200	7200	6514	Whole Hand Image
COEP [19]	1305	1305	1305	Whole Hand Image
IITD Palmprint V1 [20]	2601	2564	2571	Whole Hand Image
MPD [21]	16000	5945	13160	Palm Image
SMPD [22][25]	3677	487	1301	Palm Image
REST [23][26]	1948	1926	1946	Whole Hand Image

Popular Methods - Theoretical Limitations

- Unified Framework for Palm Matchers



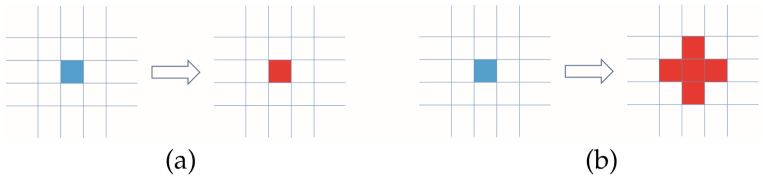


Fig. 2: (a) One-to-one and (b) one-to-many matching strategy.

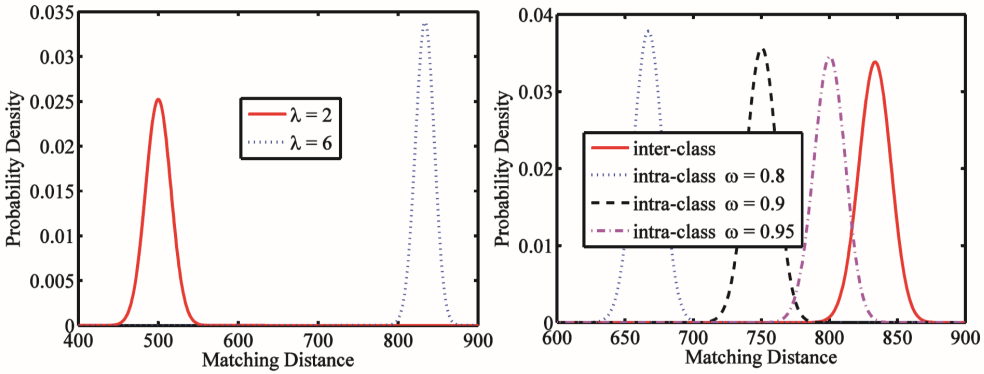
TABLE 1: Summary of several competing 2D palmprint matchers.

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, $n_{intra} = \omega . n_{inter}$ $(0 < \omega < 1)$



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

- Desirable number of encoding classes → λ = 2

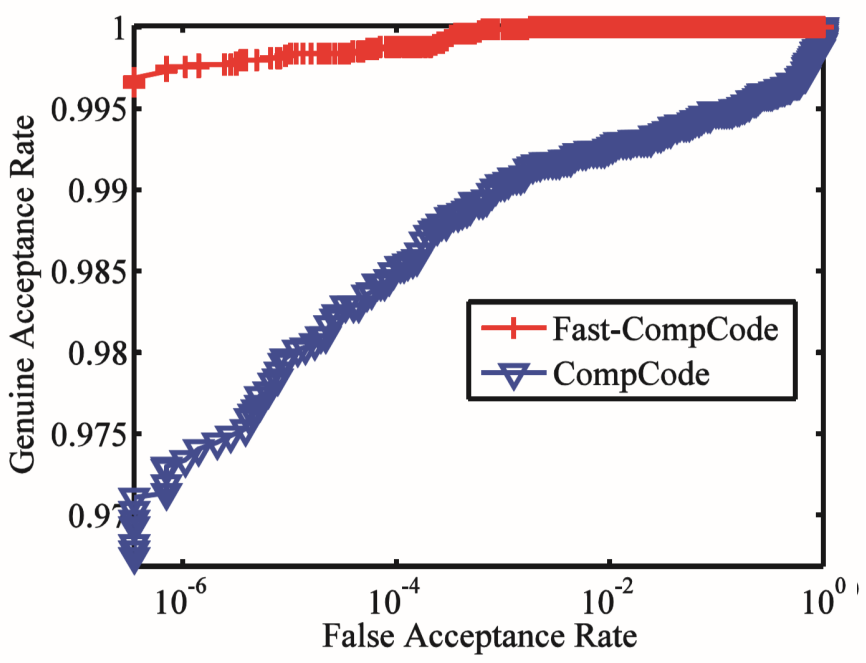
Q. Zheng, A. Kumar, G. Pan, "Suspecting Less and Achieving More: New Insights on Palmprint Identification for Faster and More Accurate Matching," *IEEE Trans. Info. Forensics & Security*, 2016

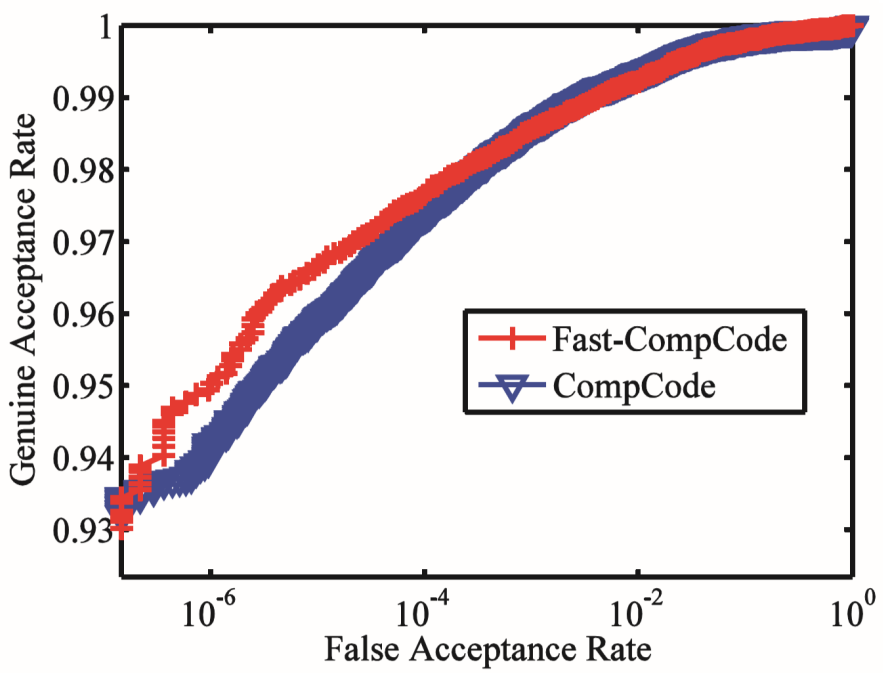
Experimental Results

- 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



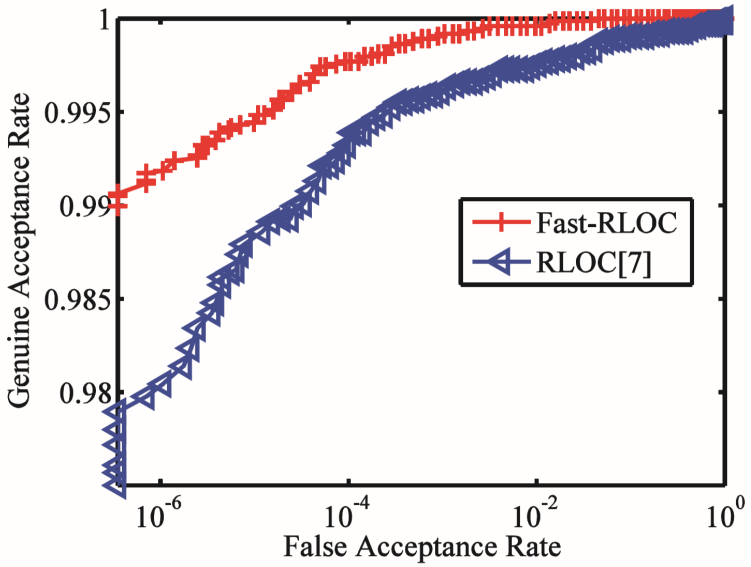


Experimental Results

- 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

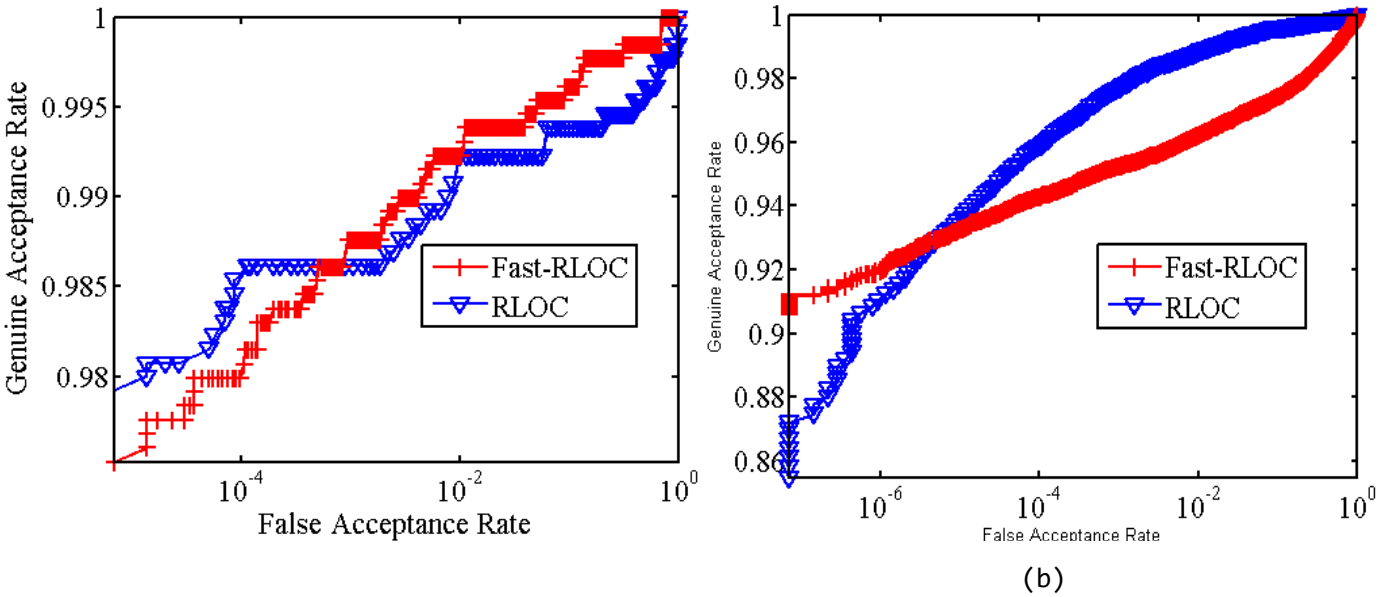


Method	Matching
Fast-RLOC	**0.017**
RLOC	1.2

Q. Zheng, A. Kumar, G. Pan, "Suspecting Less and Achieving More: New Insights on Palmprint Identification for Faster and More Accurate Matching," *IEEE Trans. Info. Forensics & Security*, 2016

Experimental Results

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

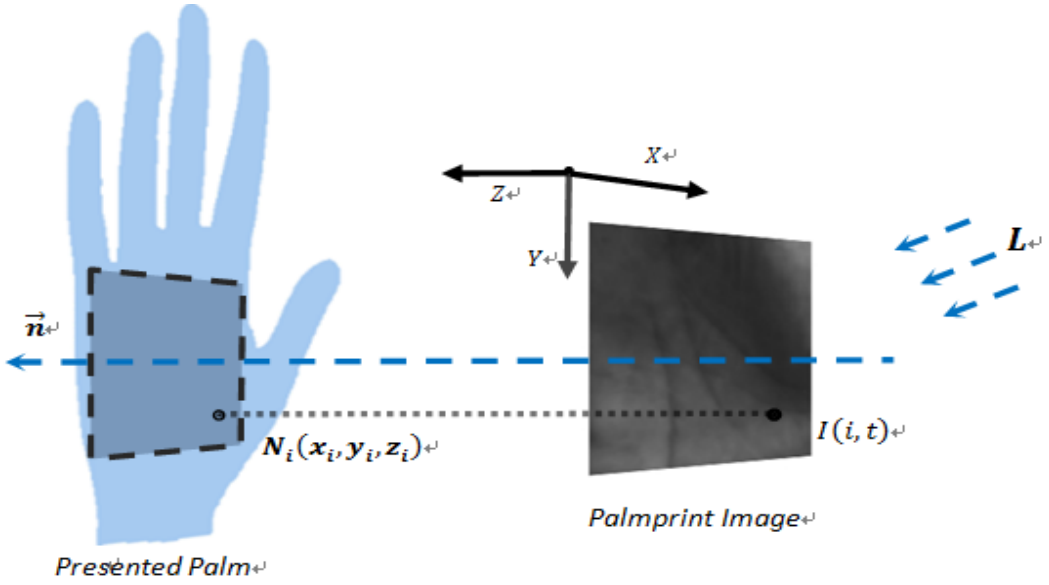


  - Fully Reproducible, Download Codes → https://www4.comp.polyu.edu.hk/~csajaykr/3DPalmprint.htm

Q. Zheng, A. Kumar, G. Pan, "Suspecting Less and Achieving More: New Insights on Palmprint Identification for Faster and More Accurate Matching," *IEEE Trans. Info. Forensics & Security*, 2016

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



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

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

Q. Zheng, A. Kumar, G. Pan, "A 3d feature descriptor recovered from a single 2d palmprint image," *T-PAMI*, 2016

Contactless Palmprint Feature Descriptor

- Difference of Normal Vectors (DoN)
  - Difference between Intensity → Two Regions

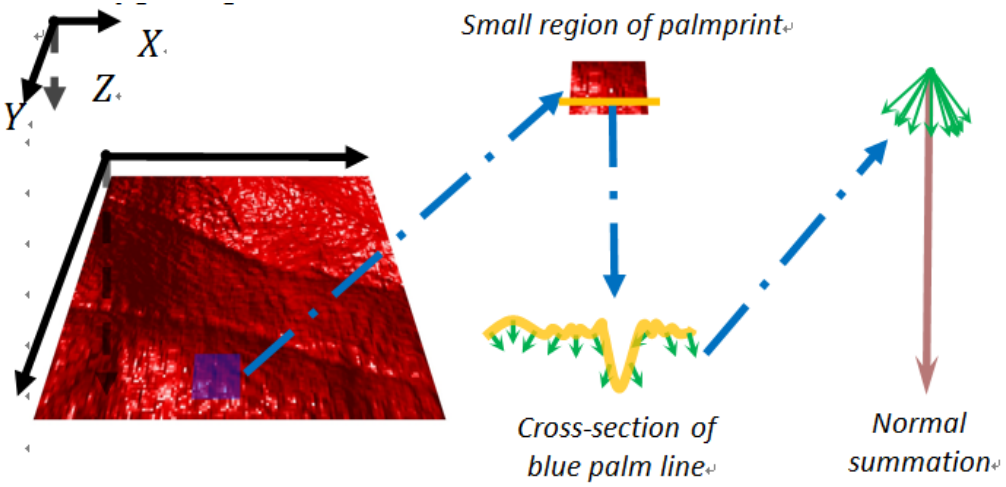
$$D(i) = \tau\Big(\sum_{j \in R_i^1} I(j) - \sum_{j \in R_i^2} I(j)\Big)$$

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

$$D(i) = \tau(\Delta X_i a + \Delta Y_i b + \Delta Z_i c)$$
$$= \tau(\Delta Z_i c) = \tau(\Delta Z_i).$$

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

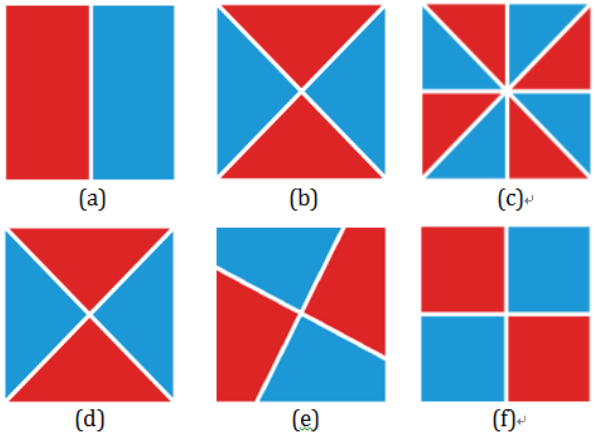
$$\frac{|c_k|}{|a_k|} > \frac{2|\Delta X|}{|\Delta Z|}$$



Q. Zheng, A. Kumar, G. Pan, "A 3d feature descriptor recovered from a single 2d palmprint image," *T-PAMI*, 2016

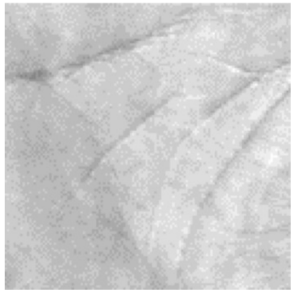
Contactless Palmprint Feature Descriptor

- Difference of Normal Vectors (DoN)
  - Spatial Divisions → Candidate Feature Extractors
    - *Symmetry → Orthogonal or Parallel*



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

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



I

F

$F = \tau(f * I)$

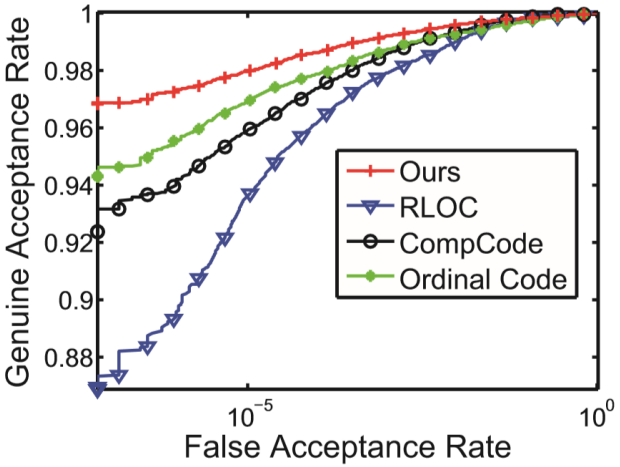
Q. Zheng, A. Kumar, G. Pan, "A 3d feature descriptor recovered from a single 2d palmprint image," *T-PAMI*, 2016

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)

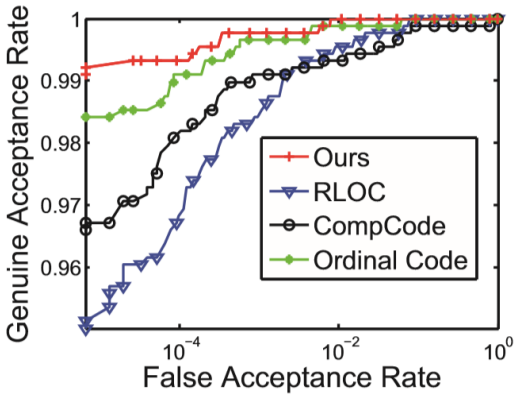
Method	Feature Extraction	Matching
Ours	1.1	**0.054**
RLOC	**0.13**	1.2
Competitive Code	4.0	0.054
Ordinal Code	3.2	0.054

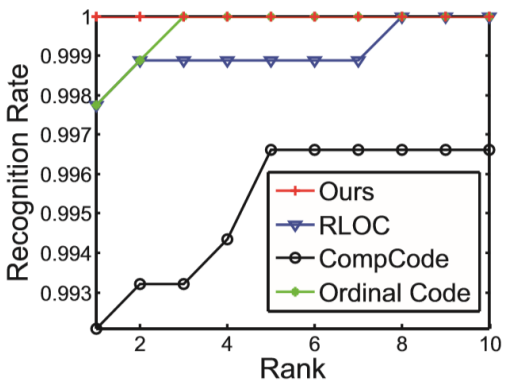
Note: The experimental environment is: Windows 8 Professional, Intel(R) Core(TM) i5-3210M CPU@2.50GHz, 8G RAM, VS 2010.

Experimental Results

➢ Comparative Performance using DoN

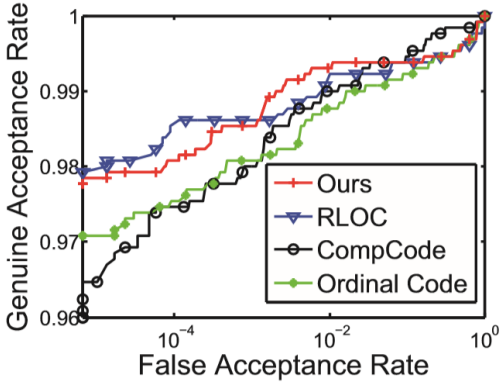
- PolyU 2D/3D Contactless Palmprint Database

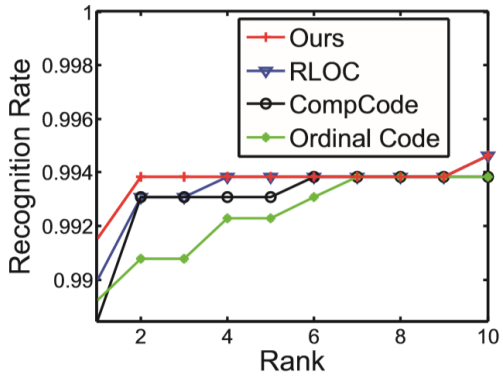




Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	**0.22**	0.64	0.68	0.33
Accuracy (%)	**100**	99.77	99.21	99.77

- IITD Palmprint Database



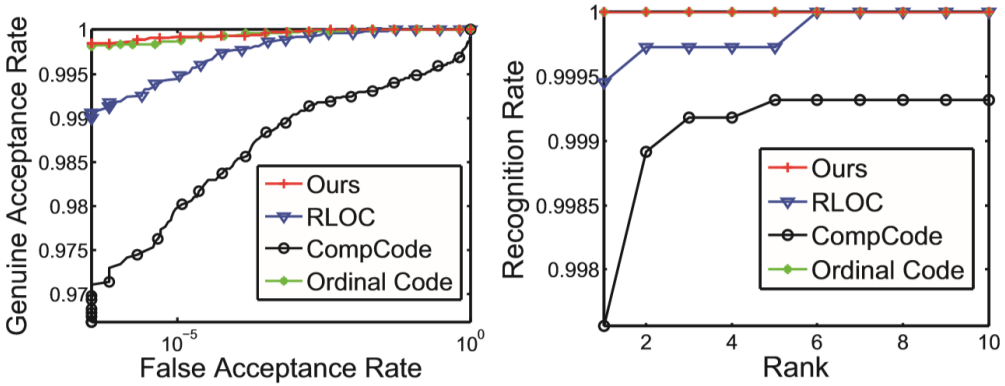


Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	**0.68**	0.88	1.0	1.25
Accuracy (%)	**99.15**	99.00	98.85	98.92

Experimental Results

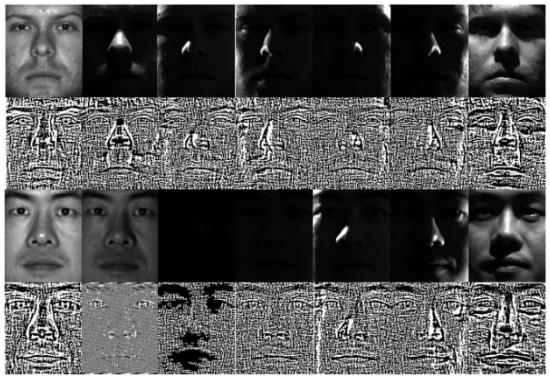
➢ Comparative Performance using DoN

- 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

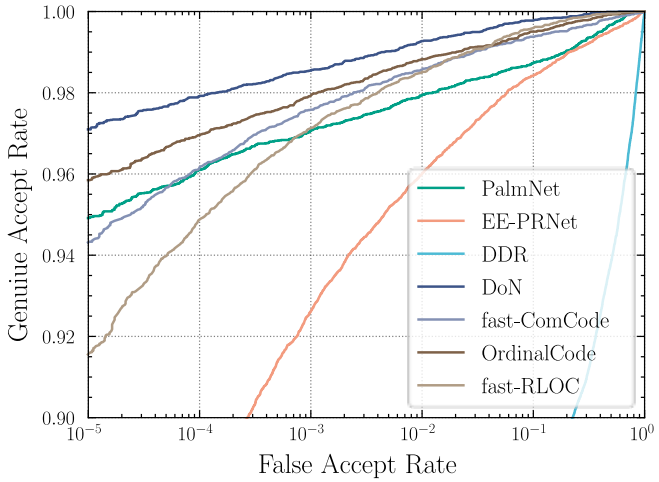
Effective for a Range of Other Biometrics and Applications

Fully Reproducible, *Download Codes* → https://www4.comp.polyu.edu.hk/~csajaykr/2Dto3D.htm

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*)

Y. Zhang, et al. “Towards palmprint verification on smartphones,” https://arxiv.org/abs/2003.13266v2, August 2020.

Experimental Results (Cross-Sensor Matching)

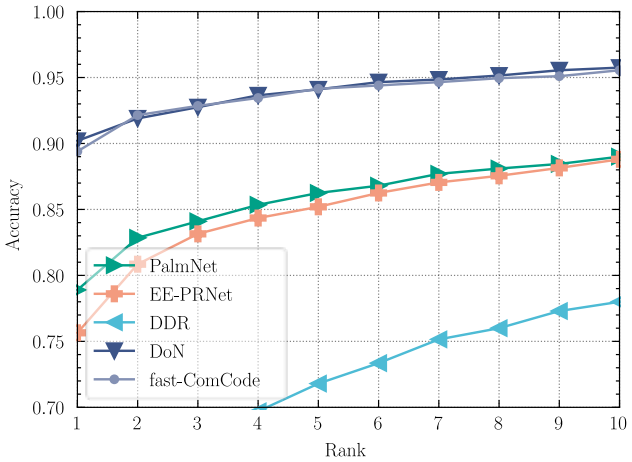
- Comparative Performance using DoN with Recent Methods
  - MPD Contactless Palm Dataset Database, 200 Subjects (2 Sensors, H and M)
  - Train: 1st Session Left Hand *H Sensor*, Test: 2nd Session Right Hand *M Sensor*
  - 20,000 (200*10*10) genuine and 3,980,000 (200*199*100) impostor match score

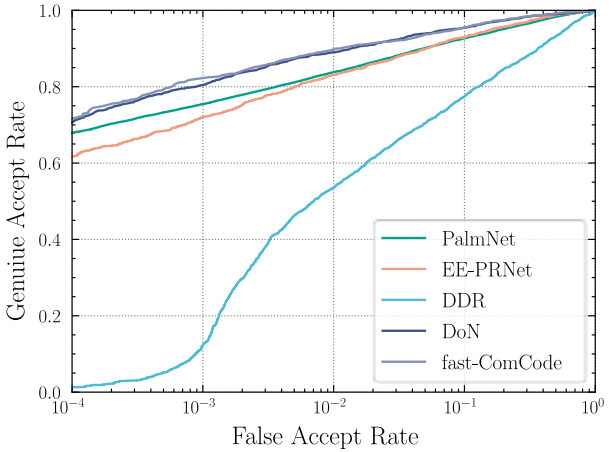
The EER and Rank-1 accuracy for MPD dataset (HM)

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%

DoN

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





Experimental Results (Cross-Sensor Matching)

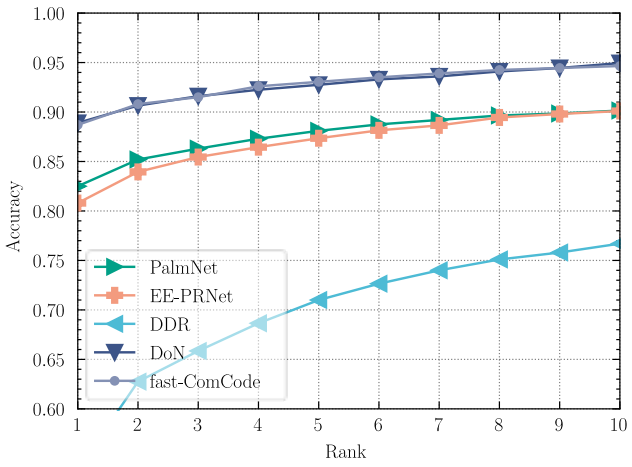
- Comparative Performance using DoN with Recent Methods
  - MPD Contactless Palm Dataset Database, 200 Subjects (2 Sensors, H and M)
  - Train: 1st Session Left Hand *M Sensor*, Test: 2nd Session Right Hand *H Sensor*
  - 20,000 (200*10*10) genuine and 3,980,000 (200*199*100) impostor match score

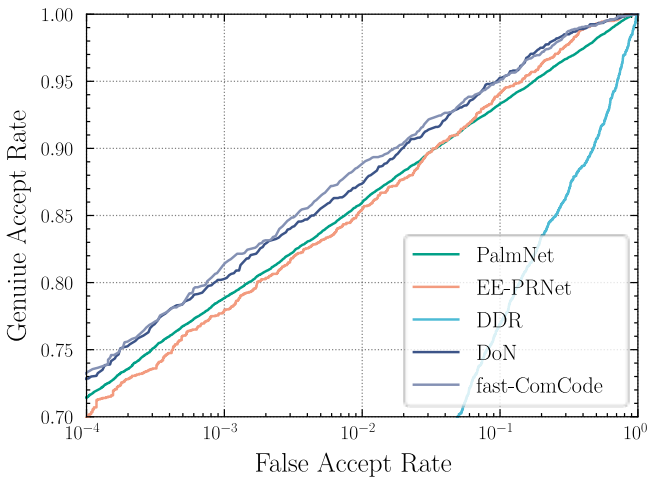
The EER and Rank-1 accuracy for MPD dataset (MH)

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%

DoN

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



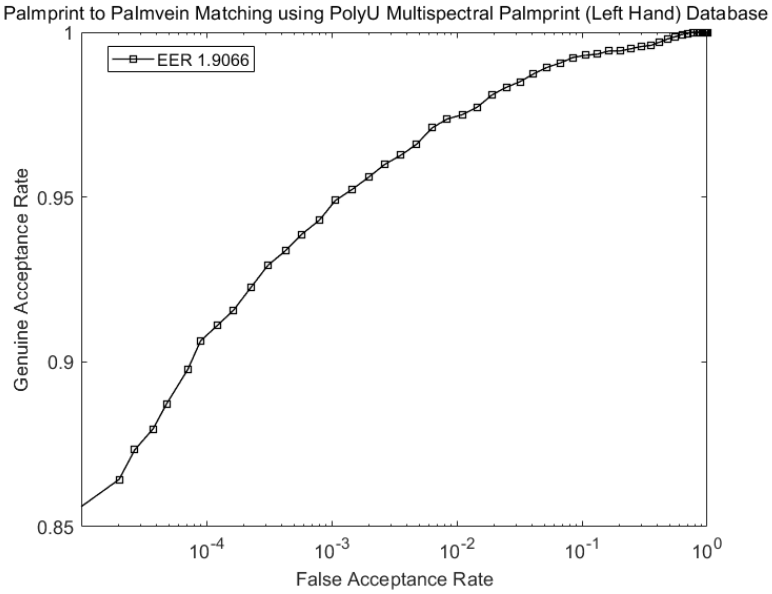


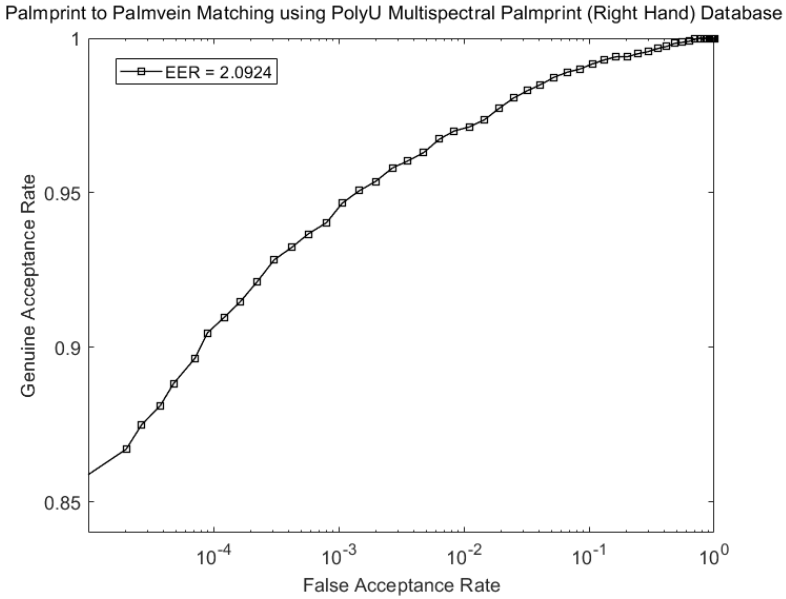
Cross-Spectral Palmprint Matching

- 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*)



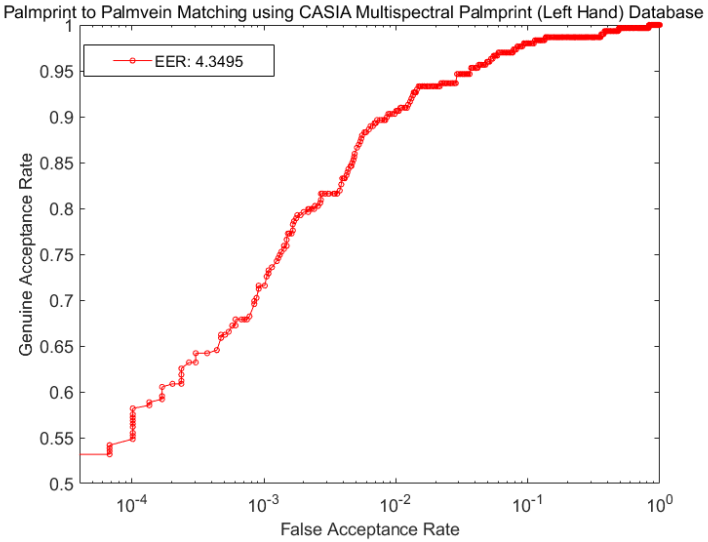


Cross-Spectral Palmprint Matching

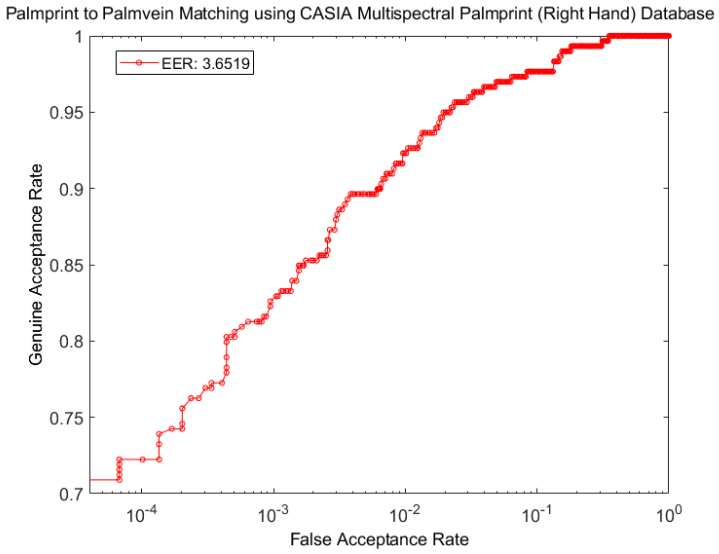
➢ Matching Palmprint with PalmVein Images

- 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)



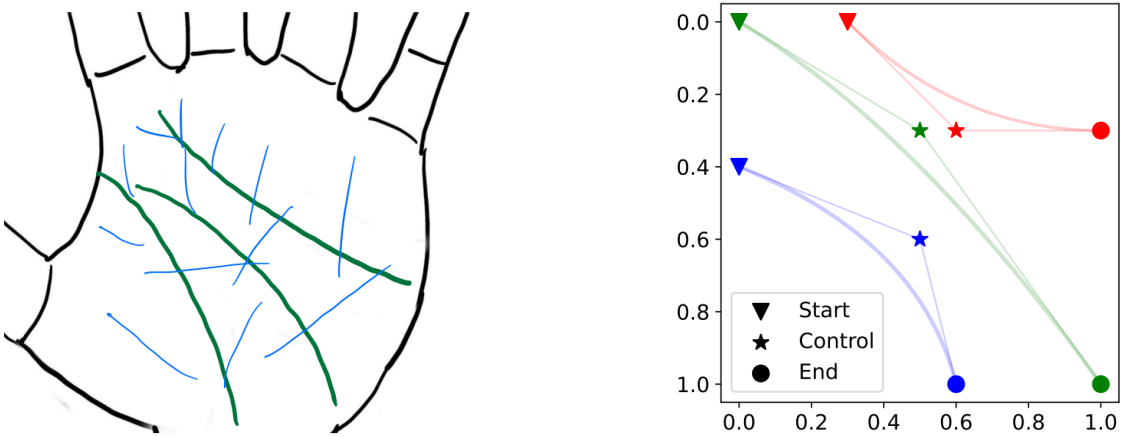
Sensor 2 (*Palmvein*)



A. Kumar, “Discriminative Micropattern Exemplars for Fine-Grained Biometric Recognition,” AVSS 2024

Palmprint Synthesis

- Synthesis of Large-Scale Datasets
  - Restrictions due to Privacy Regulations like GDPR
  - Deep Networks → Large Scale Datasets
  - Geometric Model → Palmar Creases with Parameterized Bezier curves



(a) A left palm with 3 principal (green) and several wrinkles (blue) (b) Control points (Start (▼), control (⋆) and end (●)) of principal lines.

Zhao et al., B´ezierPalm: A Free Lunch for Palmprint Recognition. ECCV 2022

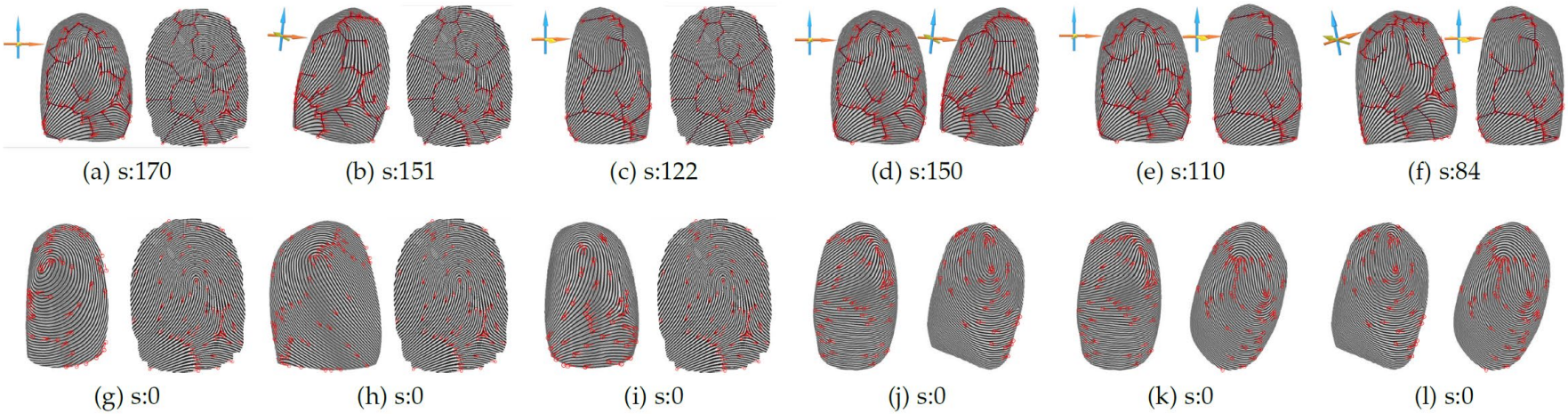
Palmprint Synthesis

- Synthesis of Large-Scale Datasets
  - Restrictions due to Privacy Regulations like GDPR
  - Geometric model, → Palmar creases with parameterized Bezier curves

Shen et al., 'RPG-Palm: Realistic Pseudo-data Generation for Palmprint Recognition, ICCV 2023

Contactless Palmprint Synthesis

- Synthesis of Large-Scale Datasets
  - Synthesis of Multi-View Contactless Palmprint Database



Chengdong Dong and Ajay Kumar, "Synthesis of Multi-View 3D Fingerprints to Advance Contactless Fingerprint Identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Nov. 2023

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 ones if you know!)
- Present results on Left/Right hand palmprints *separately*. Avoid enlarged database results *using* (*L*+*R*) images
- Present Template Size and Complexity

Acknowledgments

- Collaborators
  - Yulin Feng
  - Yang Liu
  - Qian Zheng
  - Vivek Kanhangad
  - Kuo Wang
  - Hu Jiaxin

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- Some more from (internet) open sources ..

Questions?