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Contactless Palmprint Identification

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Contactless Palmprint Identification

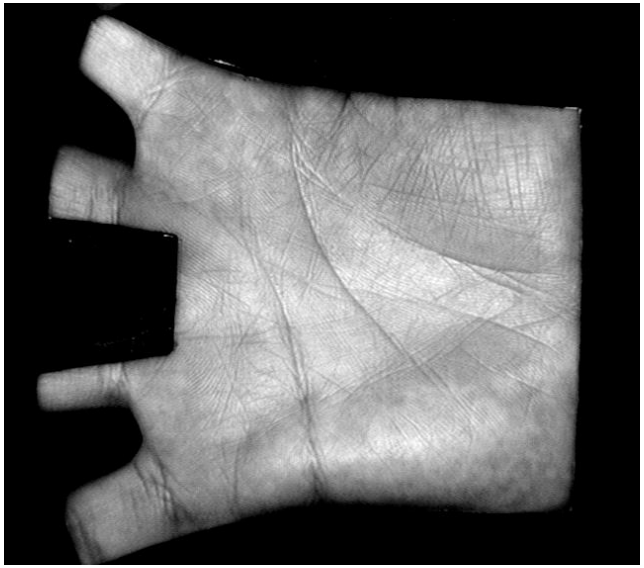
- Applications
  - Failure of Fingerprints $\rightarrow$ Manual Laborers, Elderly people, etc.
  - Improving Performance $\rightarrow$ Multimodal Biometrics
  - Mobile Security and FinTech Applications
  - Medical Diagnosis of Some Diseases
  - Public Security and Surveillance

Early Acquisition Devices

- Online → Immediate Palm image
- Better image quality

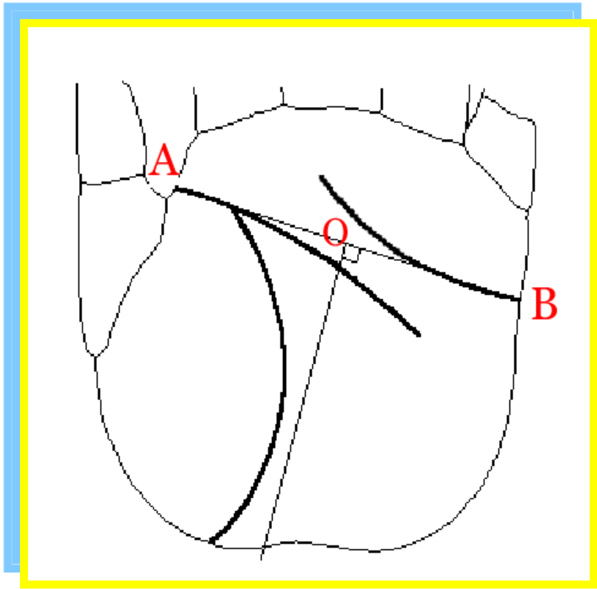
- Pegs → Limits the rotation and translation
- More reliable and stable coordination system

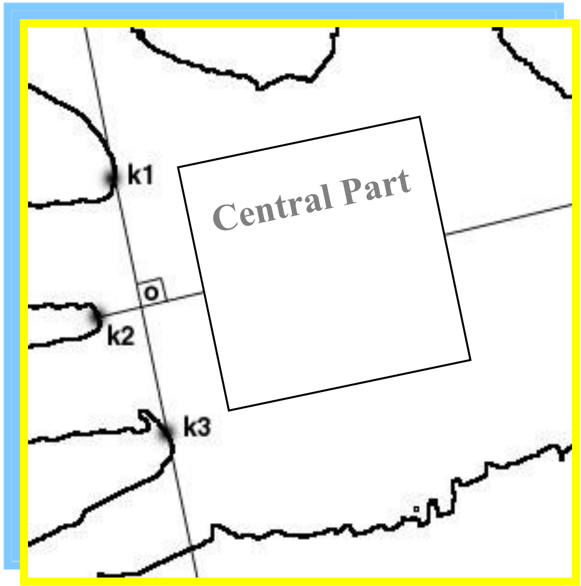
- Limitations → Bulk, Cost

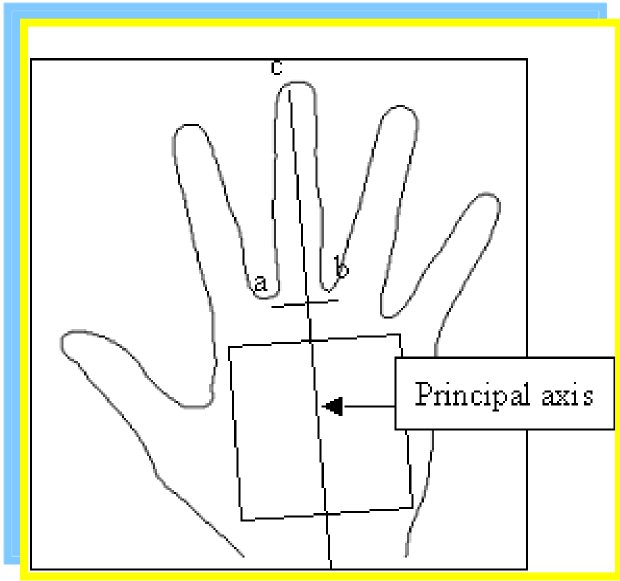


Palmprint Preprocessing

- 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.

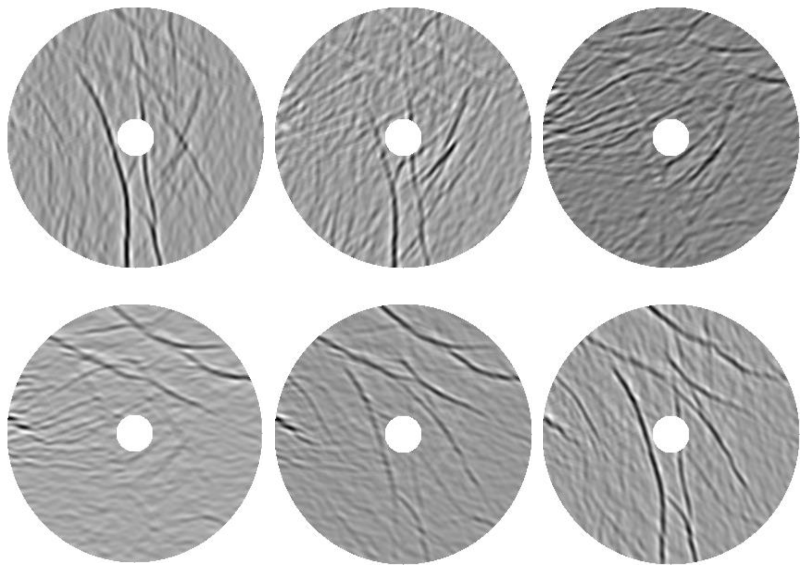
Feature Extraction Methods

Popular Methods (Over 10+ Years)

- PalmCodes
  - Gabor Phase Encoding → *Zhang et al*. (PAMI'03)
  - Gabor Amplitude Signatures → *Kumar & Shen* (ICIG'02)
- Competitive Coding → *Kong & Zhang* (ICPR'04)
- Ordinal Codes → *Sun et al.* (CVPR'05)
- RLOC → Jia *et al.* (PR'08)
- FisherPalms, FusionCode, BOCV, BLPOC, *etc*.

PalmCodes

- **ROI filtered from six (Even) Gabor Filters**

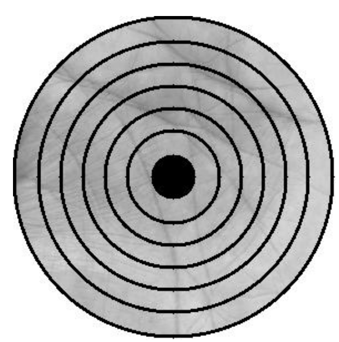


- **Rotational Invariance → Ring projection**

$$\mu_{\varphi}^{p} = \frac{1}{N_r}\sum_{r}\sum_{q} I'_{\varphi}(r\cos\theta_q, r\sin\theta_q)\ , \quad p = 1,2,\ldots Z$$

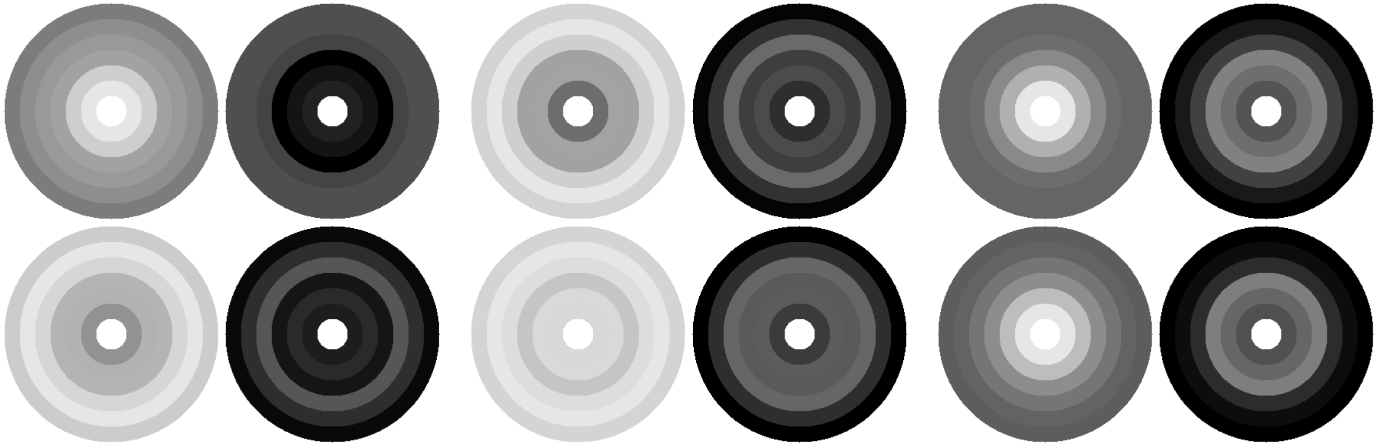
$$\sigma_{\varphi}^{p} = \sqrt{\frac{1}{N_r^2}\sum_{r}\sum_{q}\left(I'_{\varphi}(r\cos\theta_q, r\sin\theta_q) - \mu_{\psi}^{p}\right)^2}$$

$$\Omega_k = \left\{\mu_{\varphi}^{p}, \sigma_{\varphi}^{p}\right\}, \quad \forall\ p = 1,2,.., Z,\ \varphi = 0^0, 30^0, \ldots 150^0.$$



PalmCodes

❖ **Typical *PalmCode* (Gabor Amplitude Response)**



- Similarity Distance $\rightarrow$ Match Score

Training database from N users; $\mathbf{\Omega} = [\Omega_1, \Omega_2, ..., \Omega_N]$

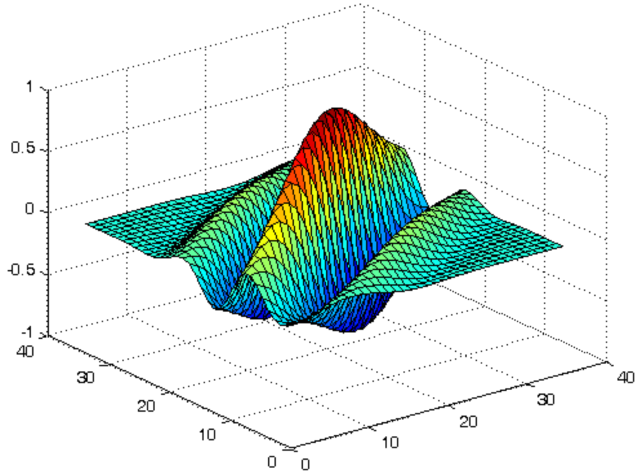
$$\beta_{\max} = \max_k \left\{ \frac{\sum_l \Lambda \Omega_k}{\sqrt{\sum_l \Lambda \sum_l \Omega_k}} \right\} \quad , \quad l = 1,2,...,6Z \ , \quad k = 1,2,..., N$$

- Similar to *FingerCode*

Feature Extraction and Matching

- PalmCode Features
  - Phase Encoding Using Gabor Filters

$$\psi(x, y, x_0, y_0, \omega, \theta, \kappa) = \frac{\omega}{\sqrt{2\pi}\kappa} e^{-\frac{\omega^2}{8\kappa^2}(4x'^2+y'^2)} \left(e^{\omega x'} - e^{-\frac{\kappa^2}{2}} \right)$$



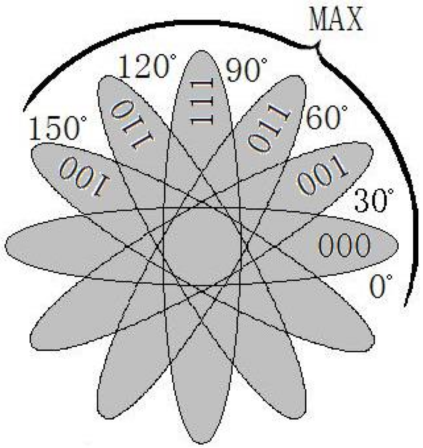
  - Hamming Distance $\rightarrow$ Match Score
  - Similar to IrisCode

D. Zhang, W. K. Kong, J. You, and M. Wong, "On-line palmprint identification," *IEEE Trans. Patt. Anal. Machine Intell.*, Sep. 2003.

Feature Extraction and Matching

- CompCode
  - Dominating Directional Encoding from Even Gabor Filters

$$j = \arg\max_{\theta} \iint I(x,y)F(x,y,\theta)dxdy$$



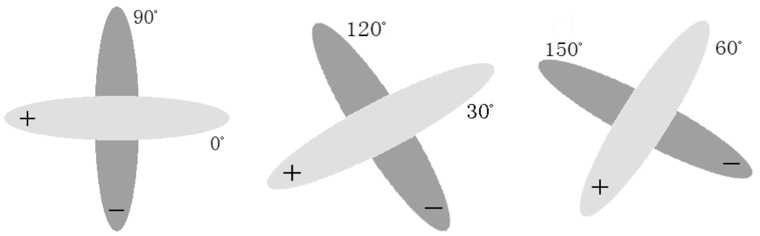
  - Encoding $\rightarrow$ Winning Direction (among six) as Binary Code
  - Hamming Distance $\rightarrow$ Match Score

W. K. Kong, D. Zhang, "Competitive coding scheme for palmprint verification," *Proc. ICPR 2004*, pp. 520-523, 2004,

Feature Extraction and Matching

➢ OrdinalCode

- Phase Encoding from Difference of Gaussian filters



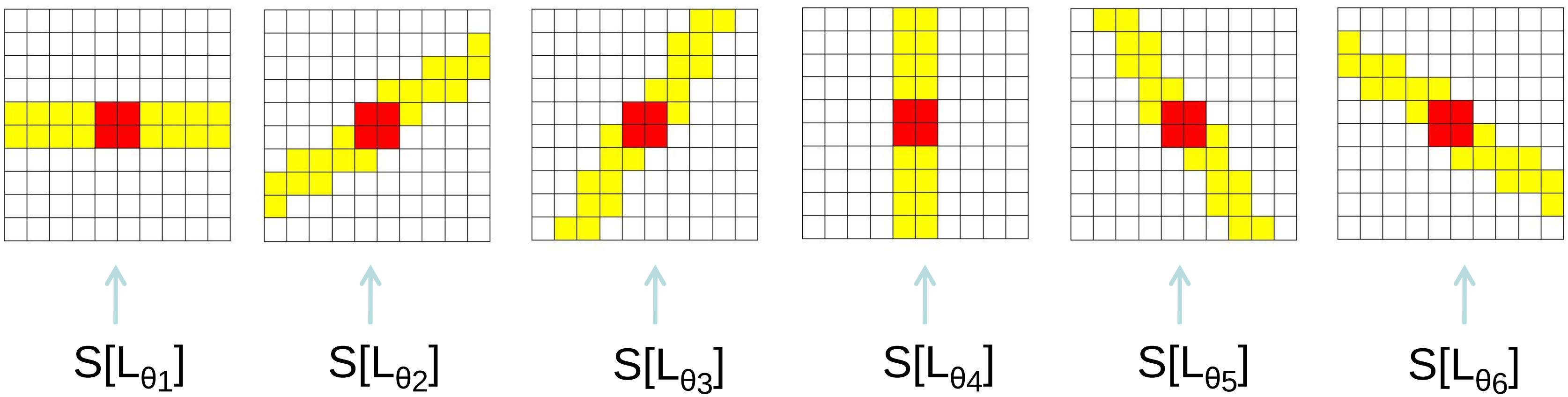
$$OF(\theta) = \iint I(x,y)F(x,y,\theta)dxdy - \iint I(x,y)F(x,y,\theta+\frac{\pi}{2})dxdy$$

$$= \iint I(x,y)(F(x,y,\theta) - F(x,y,\theta+\frac{\pi}{2}))dxdy$$

Z. Sun, T. Tan, Y. Yang, and S. Z. Li, "Ordinal palmprint representation for personal identification," *Proc. CVPR 2005*, 2005.

Feature Extraction and Matching

- Robust Line Orientation Code (RLOC)
  - Avoids Complex Gabor Filtering → Dominant Orientation



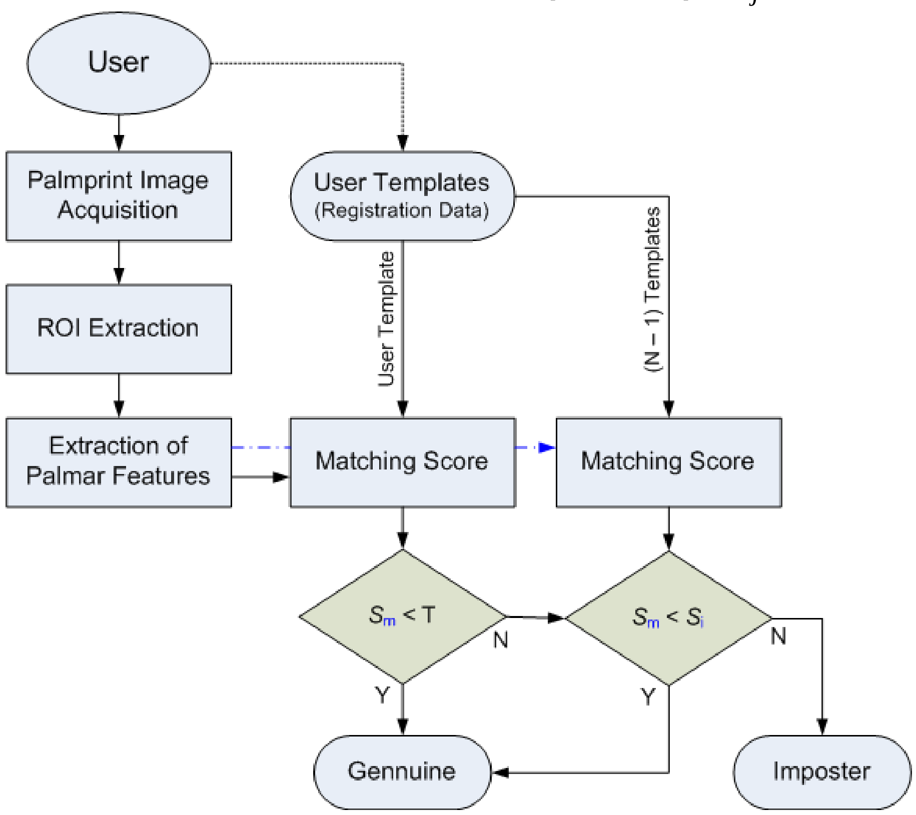
  - Matching → One to Many (Neighborhoods)
  - Simplified Feature Extraction, Complex Matching

W. Jia, D.-S. Huang, and D. Zhang, “Palmprint verification based on robust line orientation code,” *Pattern Recognitio*n, 2008.

More Accurate Contactless Palm Matching

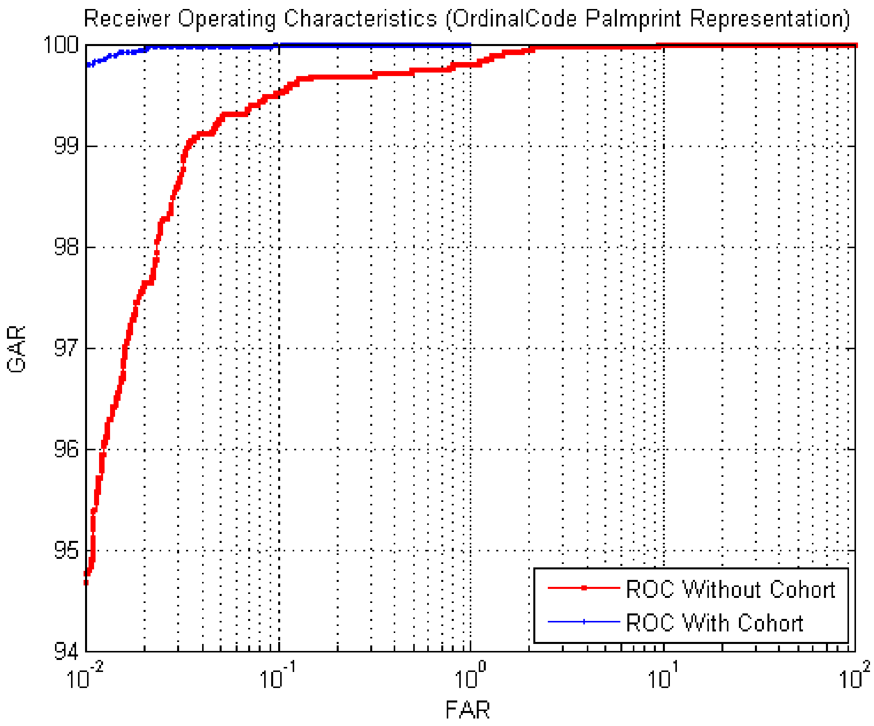
- Integrating Cohort Information
  - Limited Performance?
  - Also Consider Matching Scores from Imposter Samples
  - Matching Score S_i between two Palm Samples f_i^1 and f_i^2

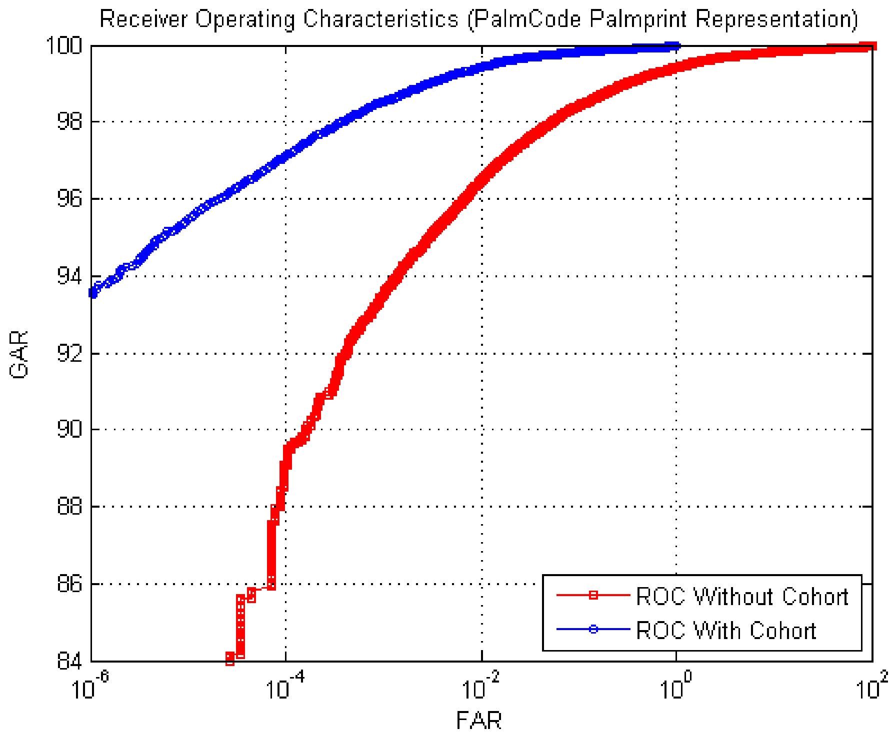
$$S_i = \Theta(f_i^1, f_j^2) \text{ where } i \neq j \text{ and } i = 1, 2, \ldots N$$



Experimental Results

- PolyU Palmprint Database
  - OrdinalCode and PalmCode Palmprint Representations





A. Kumar, “Incorporating Cohort Information for Reliable Palmprint Authentication,” *Proc. ICVGIP 2008,* pp. 583-590, 2008.

Experimental Results

- PolyU Palmprint Database
  - CompCode Palmprint Representation

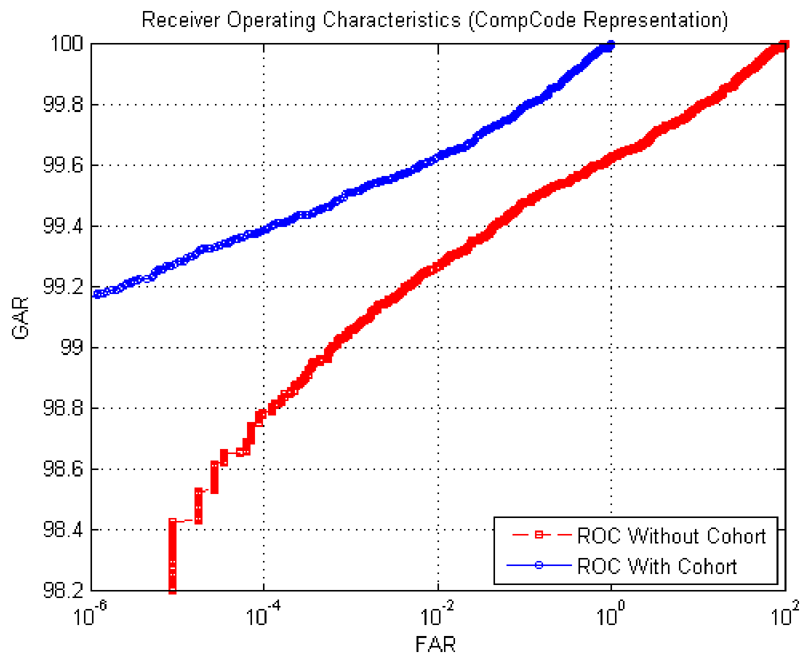


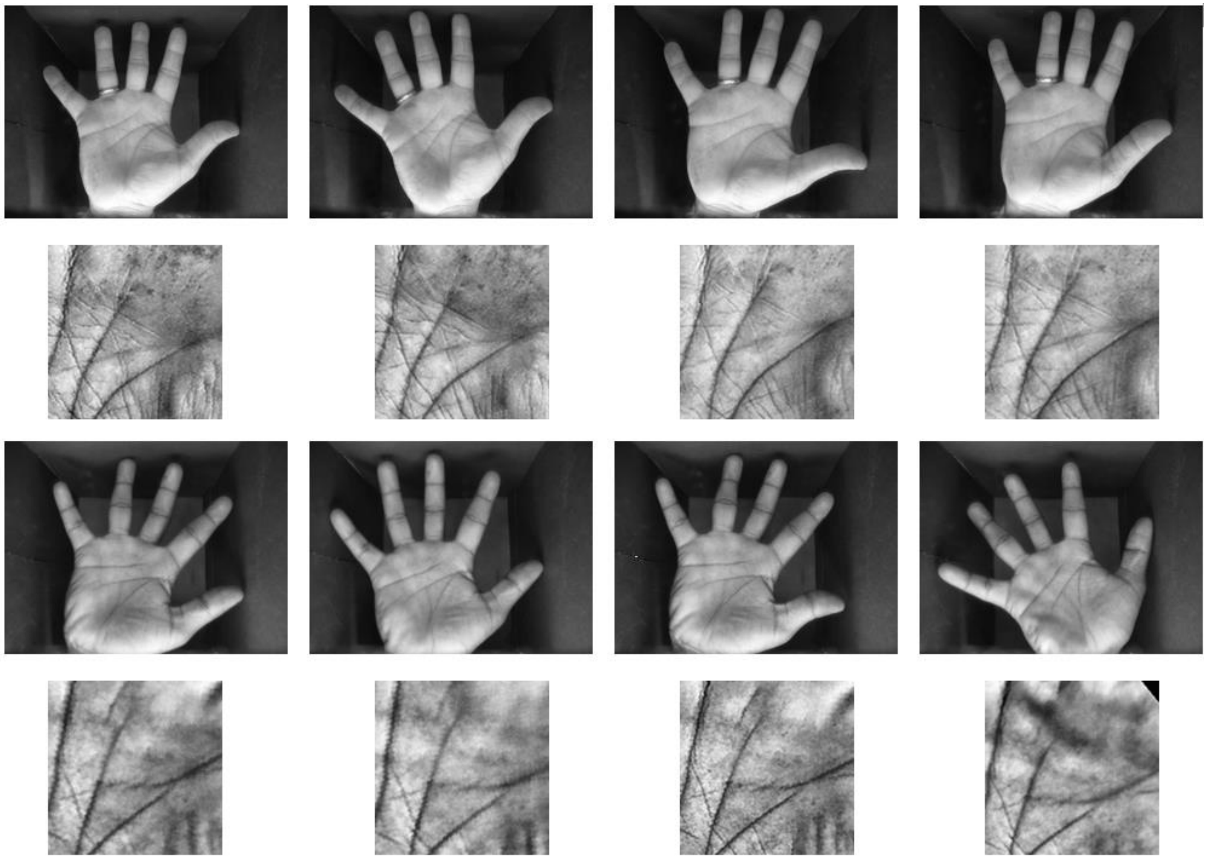
Table 2: Improvement in Equal Error Rate using Cohort Information

	PalmCode [4]	CompCode [6]	OrdinalCode [5]
Without Cohort	0.70	0.43	0.89
With Cohort	0.15	0.17	0.13

A. Kumar, "Incorporating Cohort Information for Reliable Palmprint Authentication," *Proc. ICVGIP 2008,* pp. 583-590, 2008.

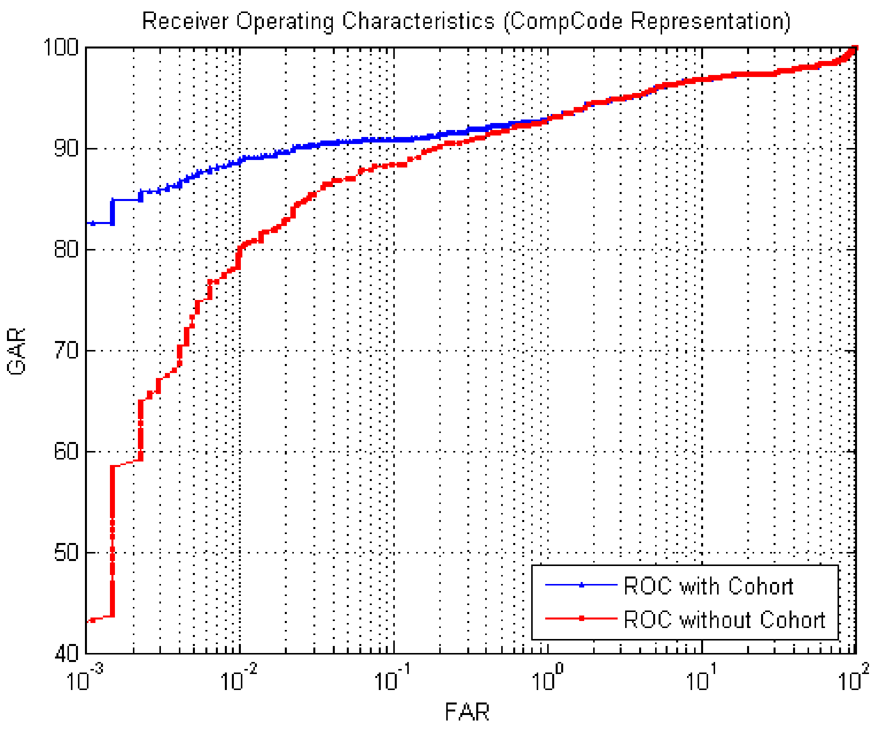
Experimental Results

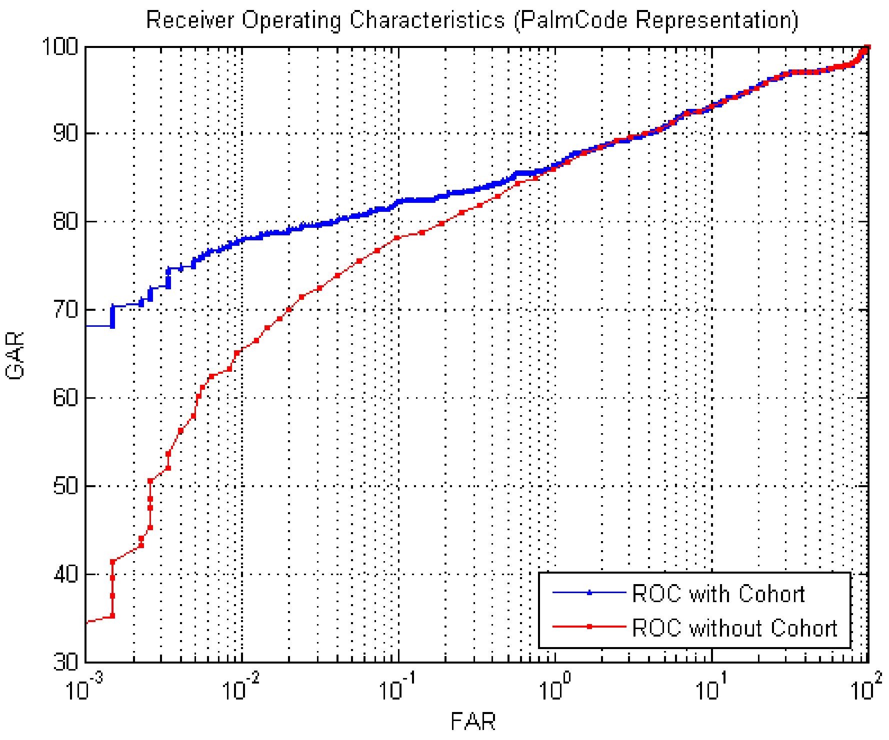
- IIT Delhi Palmprint Image Database
  - *Contactless* and *Peg-Free* Palmprint Database, Over 230 Subjects
  - Automatically Segmented/Normalized 150 × 150 Pixel Palmprints



Experimental Results

- *Pegfree* and *Touchless* Palmprint Image Database
  - Performance Improvement using CompCode and PalmCode

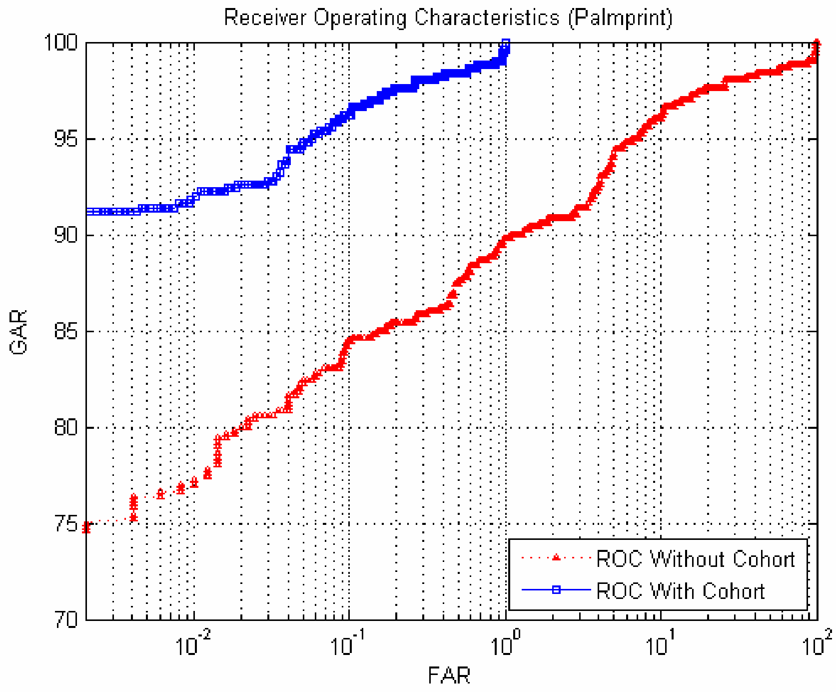


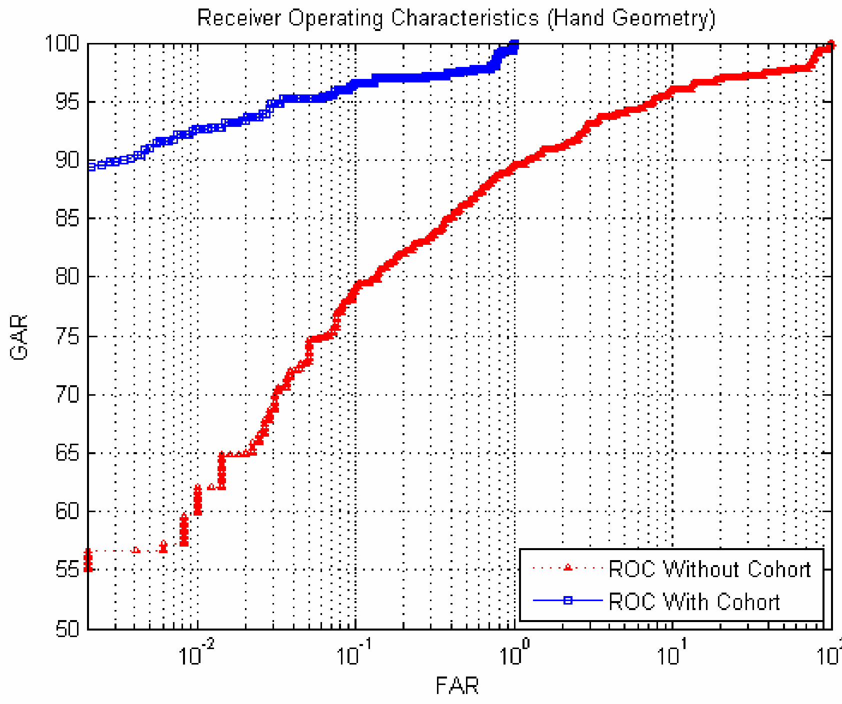


A. Kumar, "Incorporating Cohort Information for Reliable Palmprint Authentication," *Proc. ICVGIP 2008,* pp. 583-590, 2008.

Experimental Results

➢ Simultaneously Recovered Palmprint and Hand Geometry





A. Kumar, “Incorporating Cohort Information for Reliable Palmprint Authentication,” *Proc. ICVGIP 2008,* pp. 583-590, 2008.

Experimental Results

➢ Performance from Palmprint and Hand Geometry

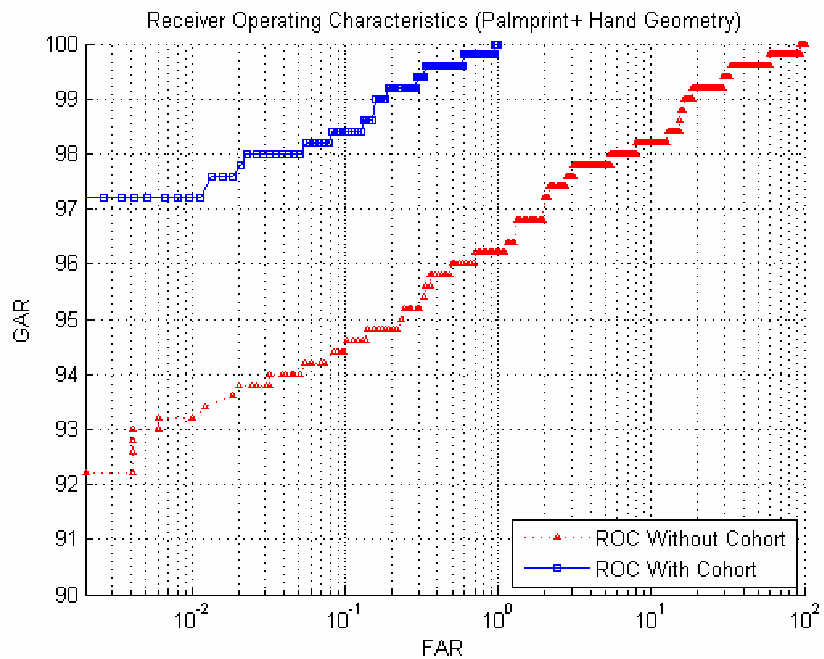


Table 1: Improvement in Equal Error Rate using Cohort Information

	Palmprint	Hand Geometry	Palmprint + Hand Geometry
Without Cohort	5.6 %	6.4 %	2.6 %
With Cohort	0.96 %	0.85 %	0.40 %

A. Kumar, “Incorporating Cohort Information for Reliable Palmprint Authentication,” *Proc. ICVGIP 2008,* pp. 583-590, 2008.

Match Score Distribution for Palmprints?

Palmprint Score Distribution Model

- Performance Estimation → Reliable Score Distribution Model
- Excellent Match Between Theoretical and Real Score Distribution
- *Empirical Estimation* from Real Matching Scores

- Beta Distribution → $B(\alpha,\beta)$

$$f(p_i|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p_i^{\alpha-1}(1-p_i)^{\beta-1}$$

- Binomial Distribution → $Bin(n_i,p_i)$

$$f(x_i|n_i) = \binom{n_i}{x_i} p_i^{x_i}(1-p_i)^{n_i-x_i}$$

- Beta-Binomial Distribution → $Betabin(\alpha,\beta,n_i)$

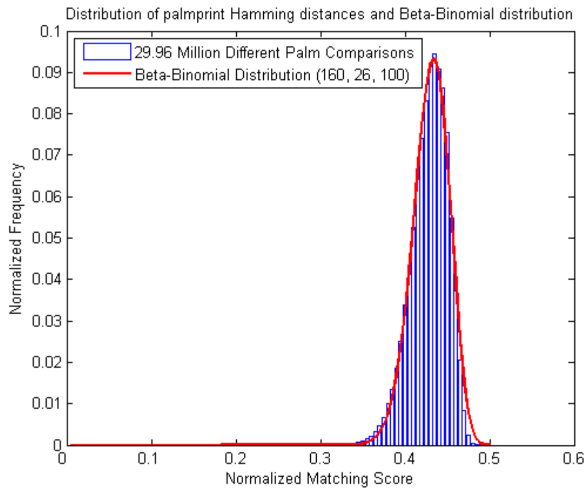
$$f(x_i|n_i,\alpha,\beta) = \binom{n_i}{x_i} \frac{B(\alpha+x_i,\beta+n_i-x_i)}{B(\alpha,\beta)}$$

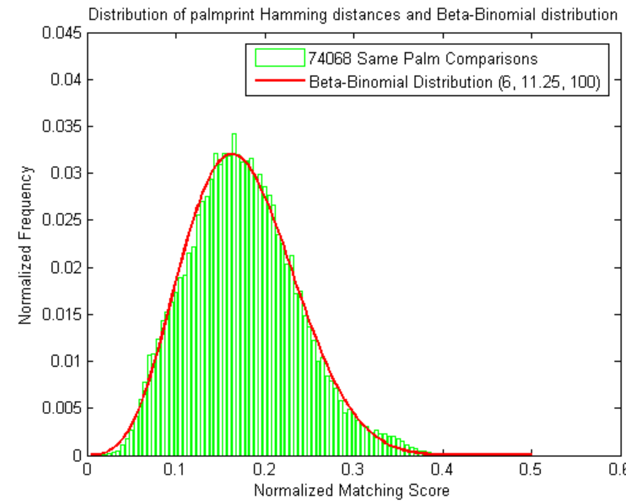
A. Kumar, “Incorporating Cohort Information for Reliable Palmprint Authentication,” *Proc. ICVGIP 2008,* pp. 583-590, 2008.

Distribution of Match Scores

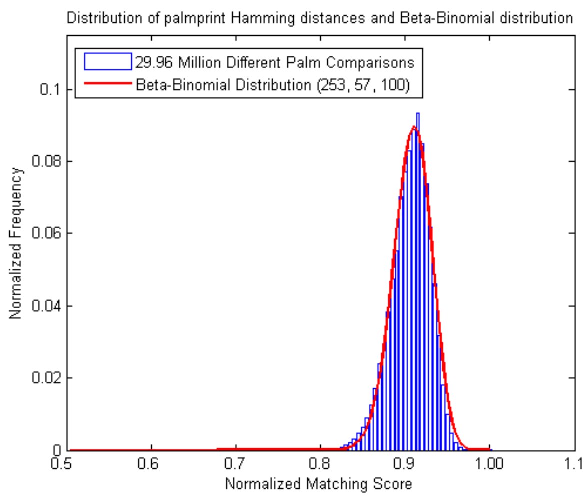
- Gennuine and Imposter Score Distribution

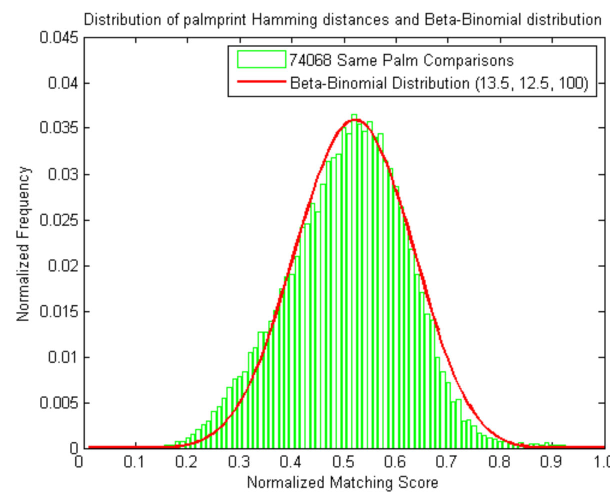
OrdinalCode Representation





PalmCode Representation

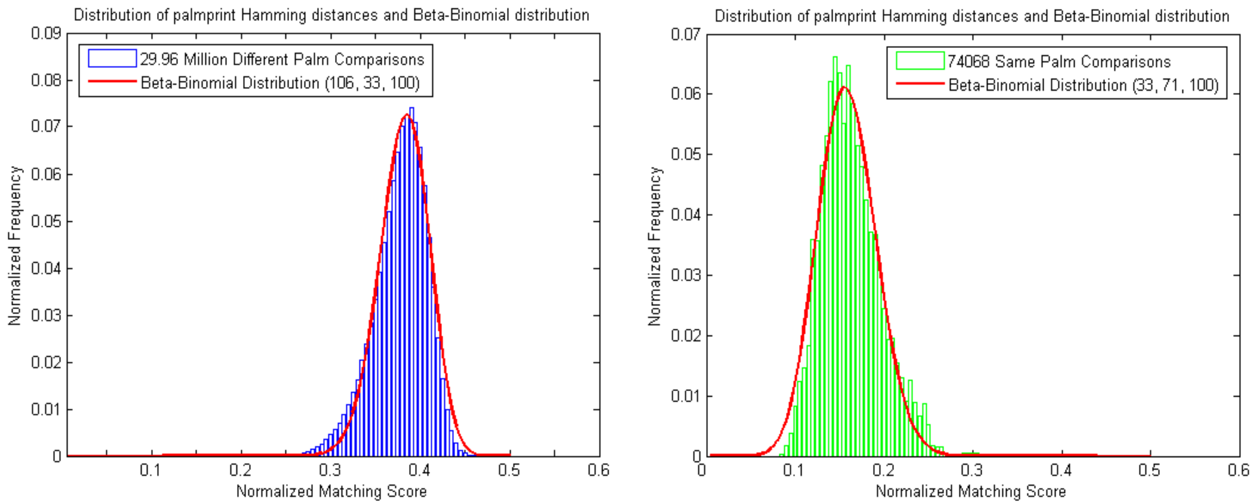




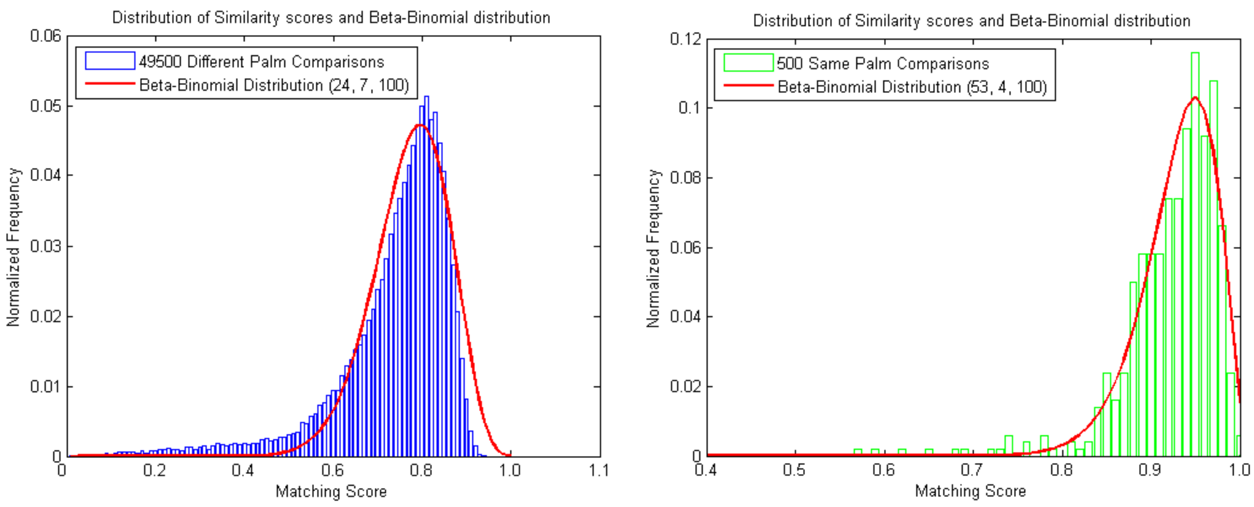
Distribution of Match Scores

- Gennuine and Imposter Score Distribution

CompCode Representation



DCT Representation



Distribution of Match Scores

- Estimation of Best Fit Score Distribution Model

Table 3: Norm of the error between the theoretical and actual score distributions

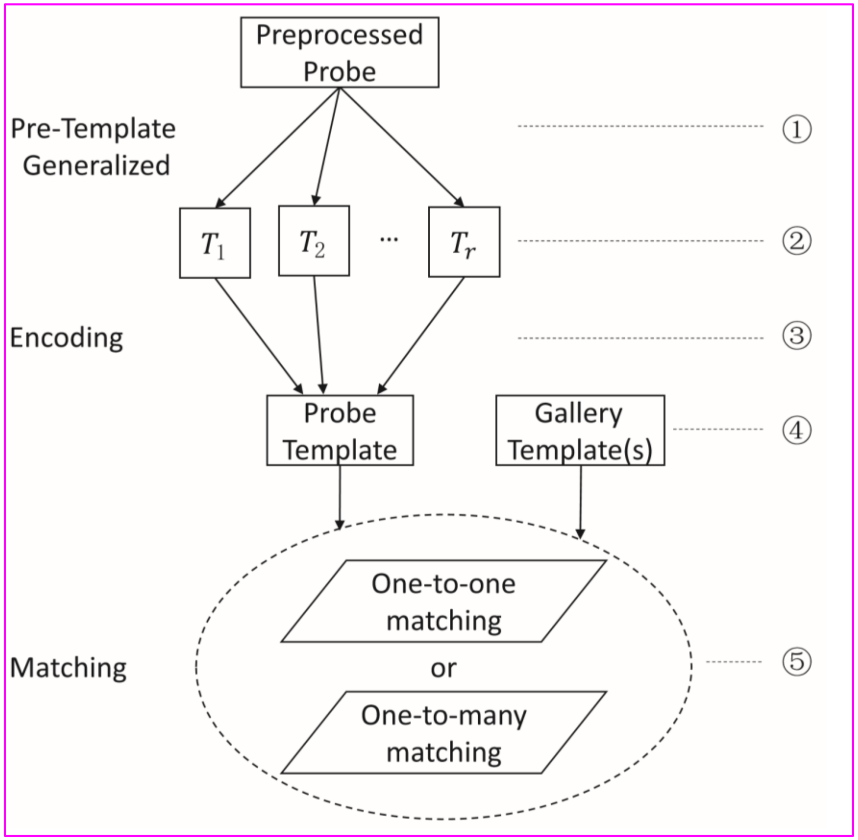
	Beta		Beta-Binomial		Binomial		Gaussian	
	G	**I**	**G**	**I**	**G**	**I**	**G**	**I**
Ordinal Codes [5]	0.0157	0.0567	**0.0088**	**0.0154**	0.1367	0.0674	0.0187	0.0409
PalmCode [4]	0.0172	**0.0099**	**0.0142**	0.0146	0.0999	0.0347	0.0161	0.0338
CompCode [6]	0.0265	0.0445	**0.0260**	**0.0197**	0.0457	0.0571	0.0402	0.0411
DCT Features [3]	0.0488	0.0626	**0.0463**	**0.0310**	0.1446	0.1276	0.1022	0.0780

G: Genuine, **I** - Imposter

Beta-Binomial Distribution → Minimum error in *most palmprint feature distributions*, both for genuine and imposter matches

Popular Methods - Theoretical Limitations

➢ Unified Framework for Palm Matchers



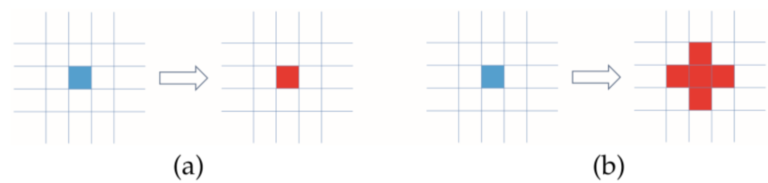


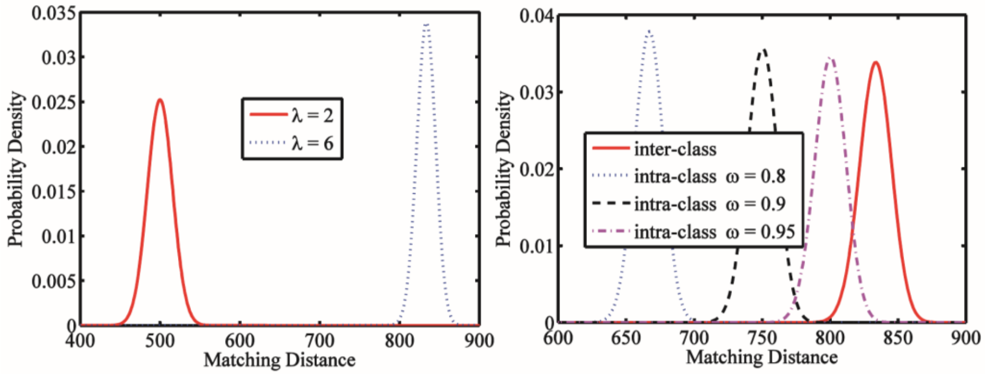
Fig. 2: (a) One-to-one and (b) one-to-many matching strategy.

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

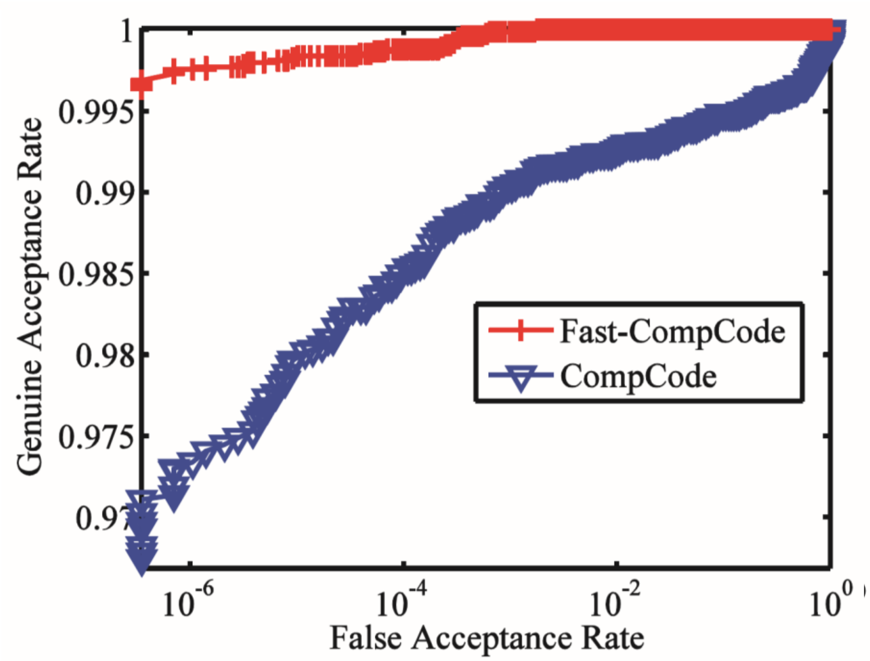
Q. Zheng, A. Kumar, G. Pan, “Suspecting Less and Achieving More: New Insights on Palmprint Identification for Faster and More Accurate Matching,” *IEEE Trans. Info. Forensics & Security*, 2016

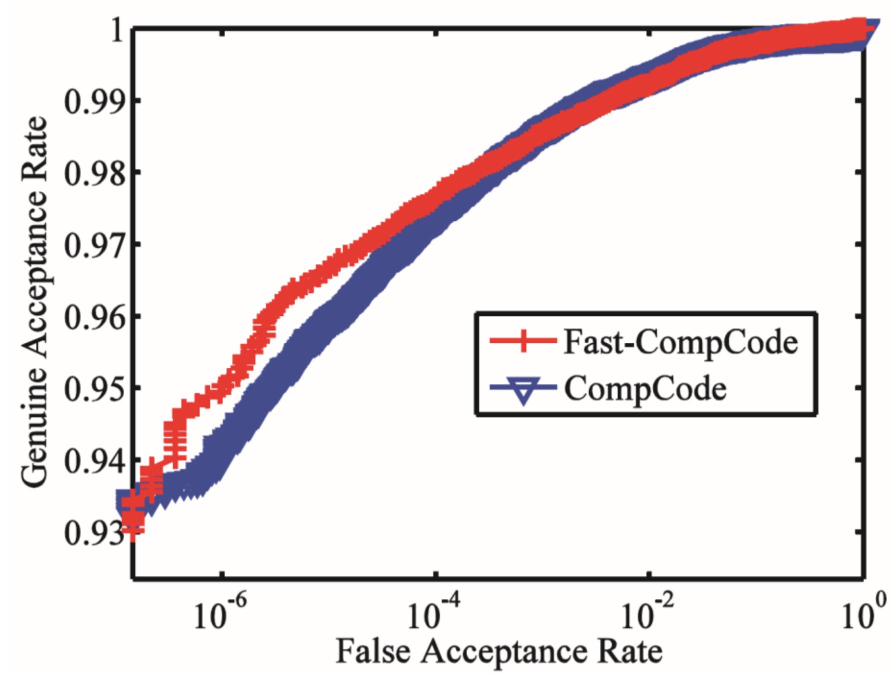
Experimental Results

- 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





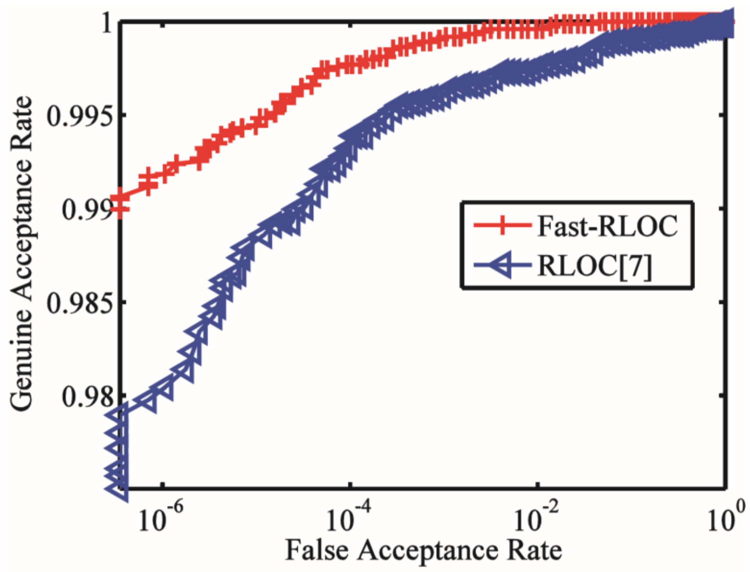
Experimental Results

➢ 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

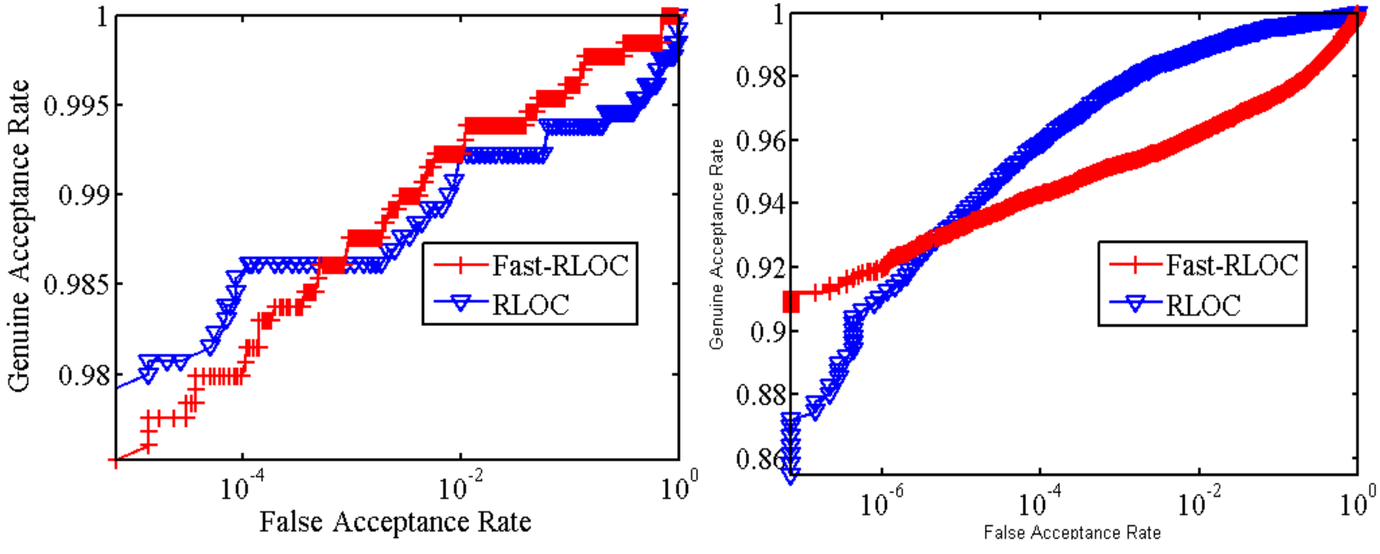


Method	Matching
Fast-RLOC	**0.017**
RLOC	1.2

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)



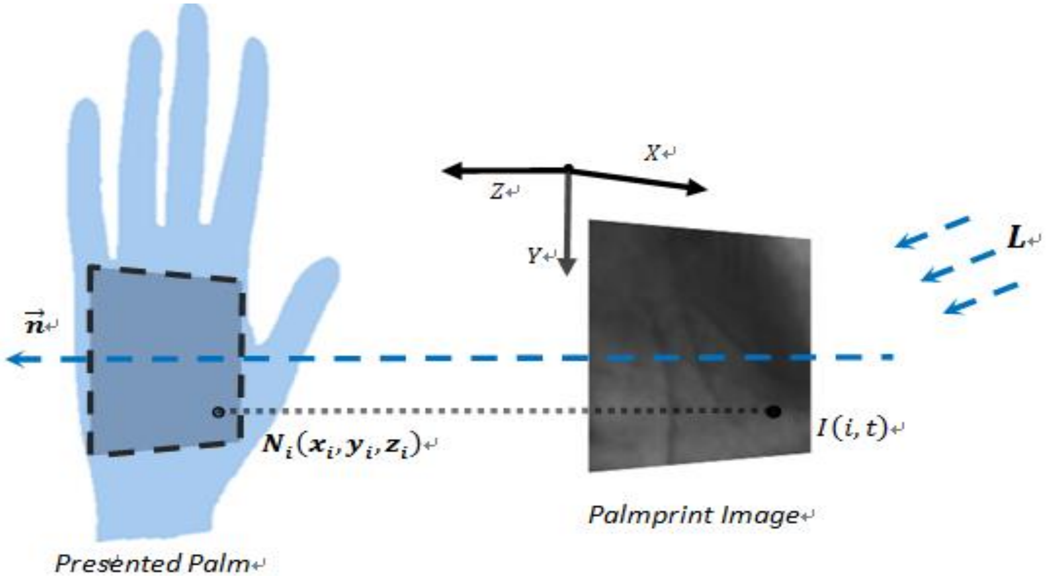
(b)

  - 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

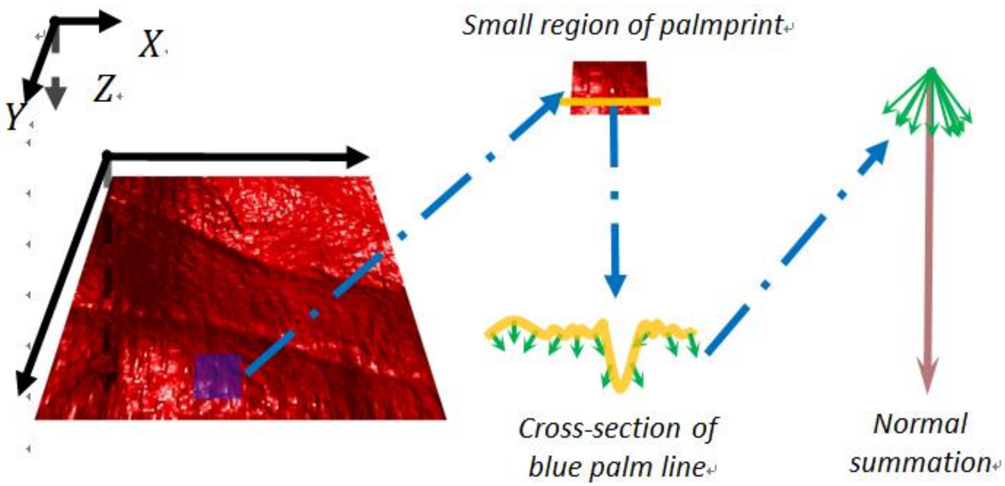
$$D(i) = \tau\Big(\sum_{j \in R_i^1} I(j) - \sum_{j \in R_i^2} I(j)\Big)$$

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

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

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

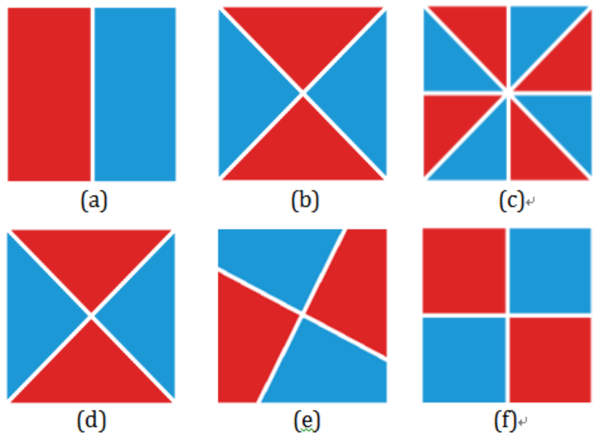
$$\frac{|c_k|}{|a_k|} > \frac{2|\Delta X|}{|\Delta Z|}$$



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

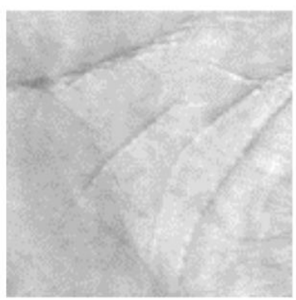
Contactless Palmprint Feature Descriptor

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



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

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



$F = \tau(f * I)$

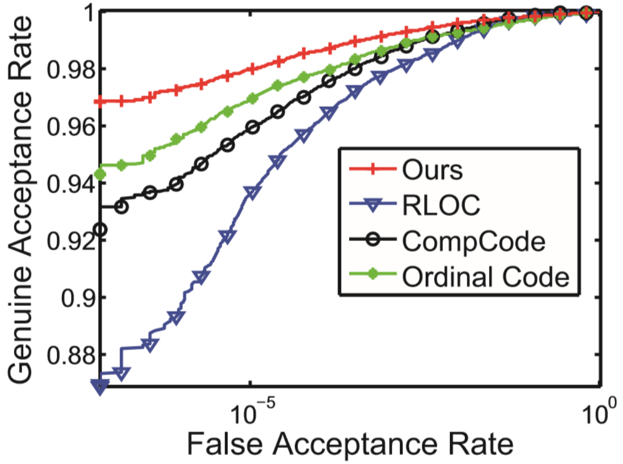
I F

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)

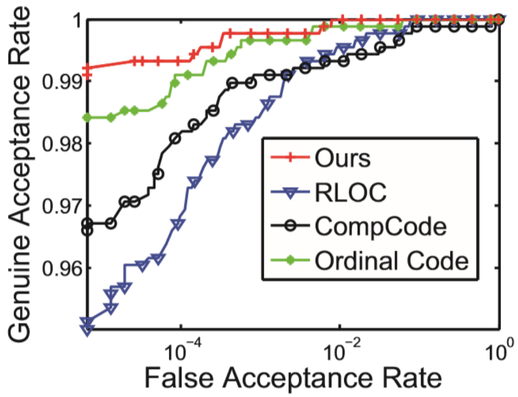
Method	Feature Extraction	Matching
Ours	1.1	**0.054**
RLOC	**0.13**	1.2
Competitive Code	4.0	0.054
Ordinal Code	3.2	0.054

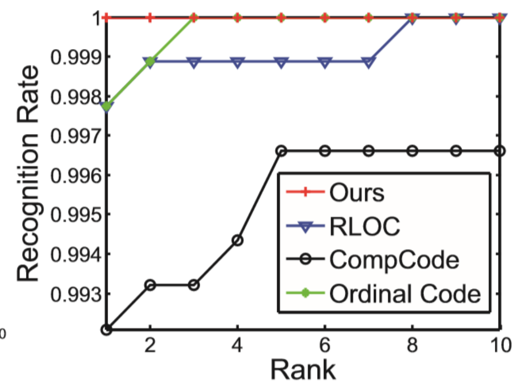
Note: The experimental environment is: Windows 8 Professional, Intel(R) Core(TM) i5-3210M CPU@2.50GHz, 8G RAM, VS 2010.

Experimental Results

➢ Comparative Performance using DoN

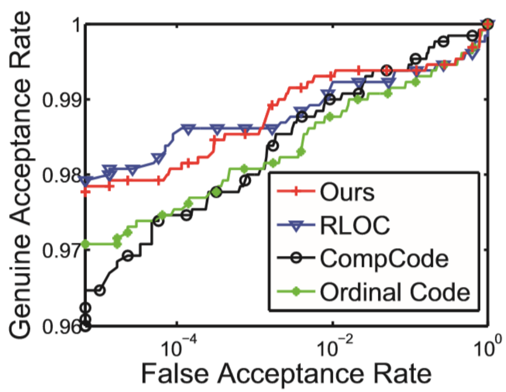
- PolyU 2D/3D Contactless Palmprint Database

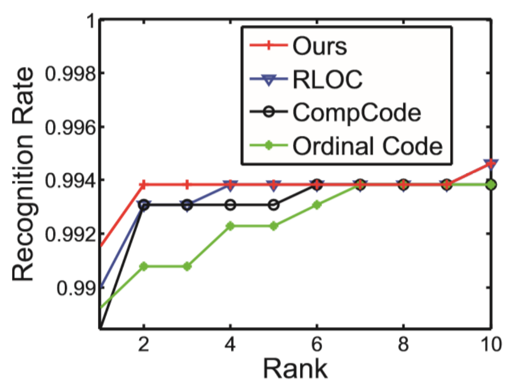




Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	**0.22**	0.64	0.68	0.33
Accuracy (%)	**100**	99.77	99.21	99.77

- IITD Palmprint Database



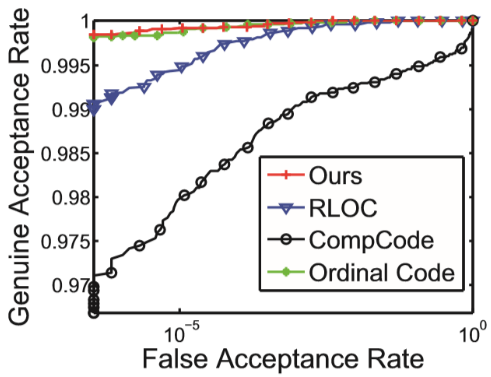


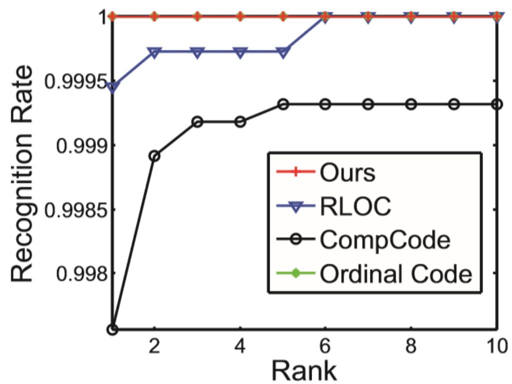
Method	Ours	RLOC	Competitive Code	Ordinal Code
EER (%)	**0.68**	0.88	1.0	1.25
Accuracy (%)	**99.15**	99.00	98.85	98.92

Experimental Results

➢ Comparative Performance using DoN

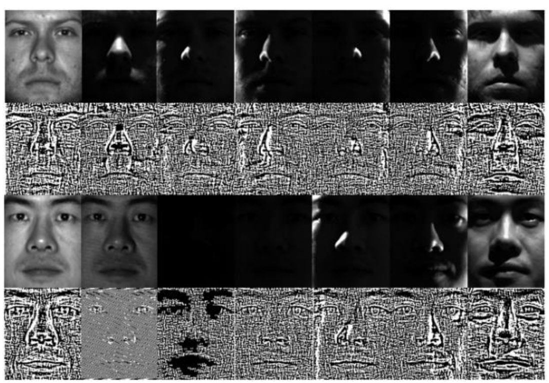
- PolyU Palmprint Database





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

- Extended Yale Face Database B



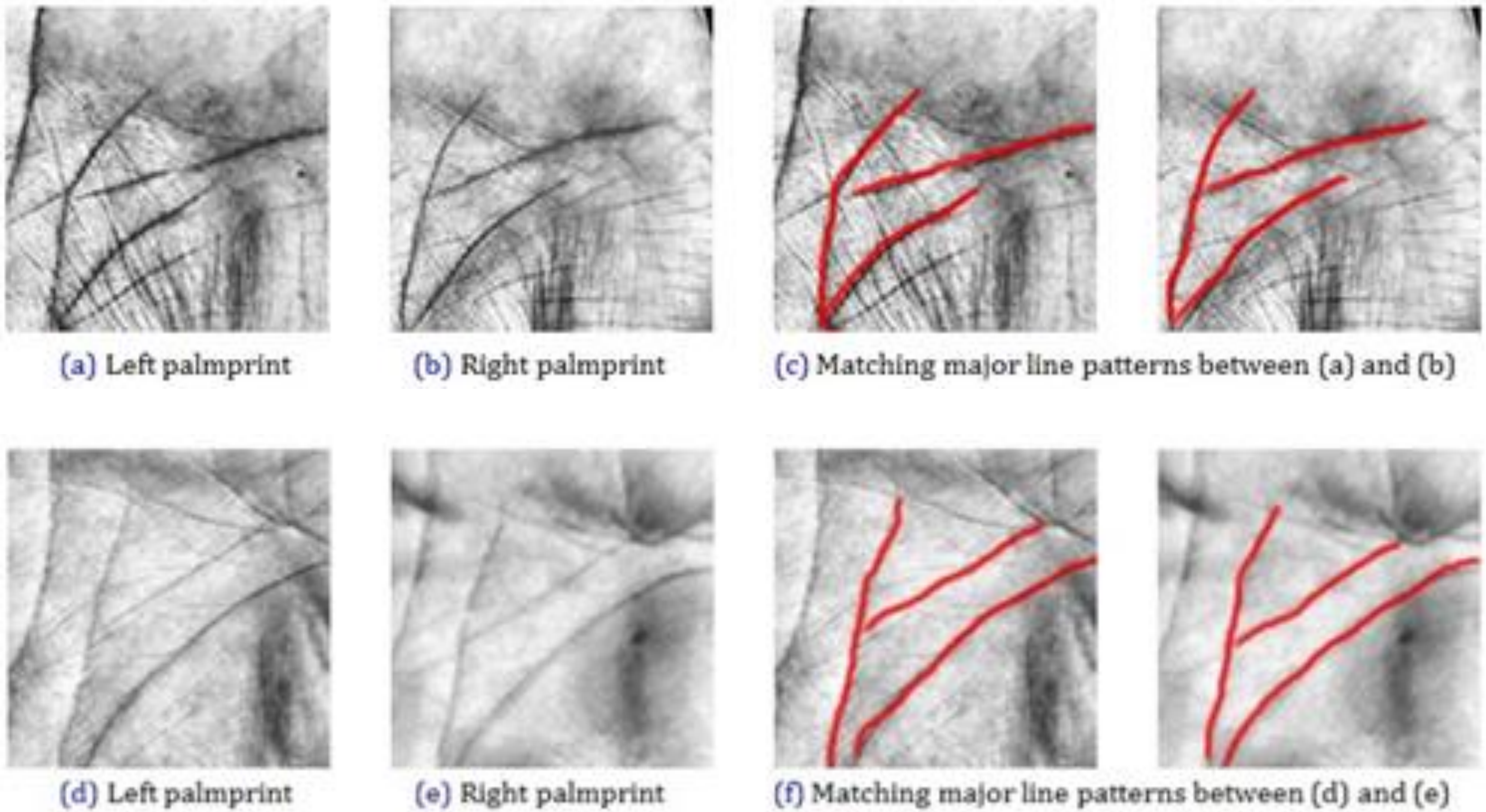
Method	Ours	PP+LTP/DT [19]	G_LDP [20]
Rank-1 rate (%)	**99.3**	99.0	97.9

Effective for a Range of Other Biometrics and Applications

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

Palmprint Similarity

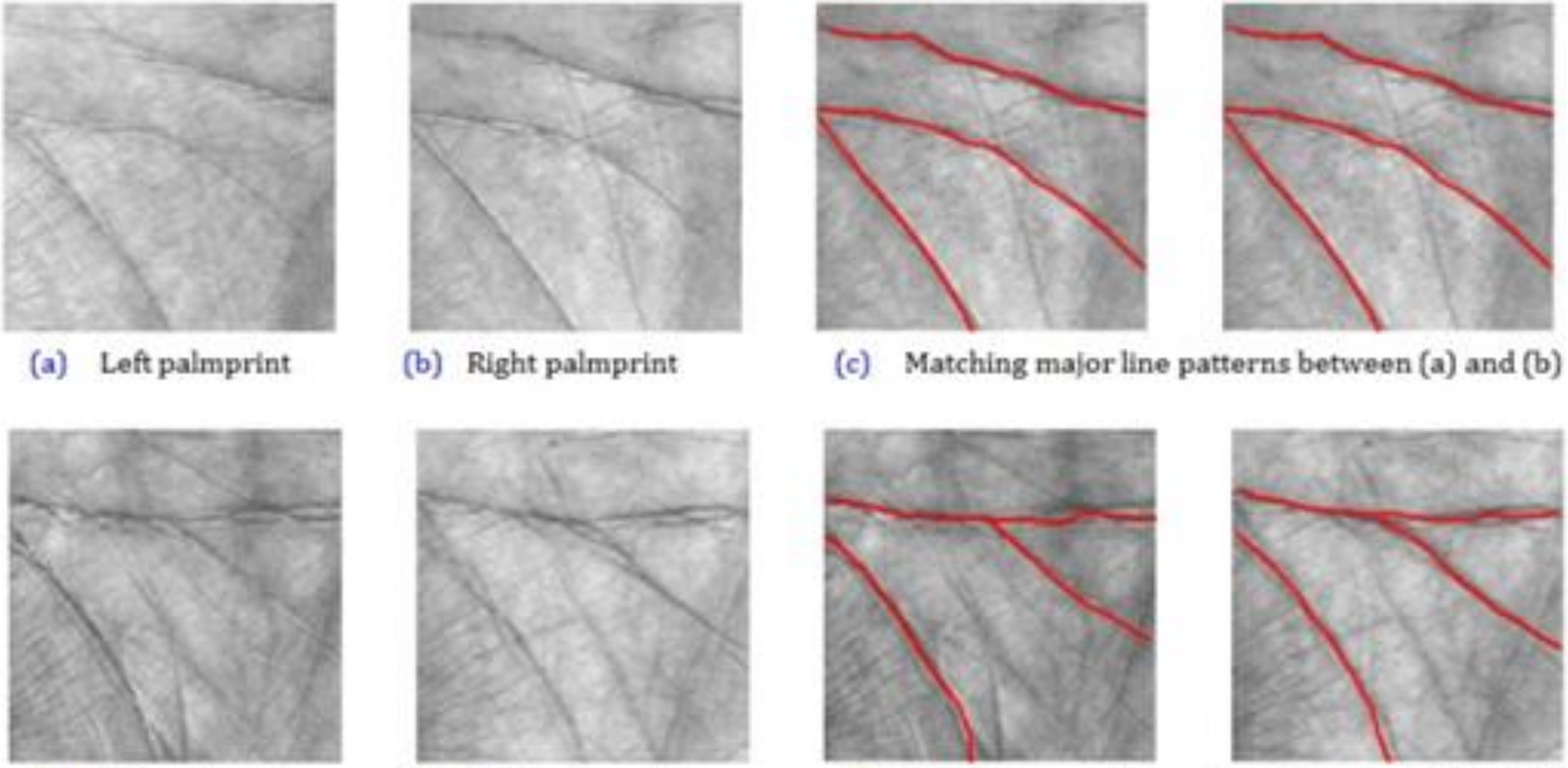
- Matching *Left* Palmprint with *Right* Palmprint
  - Samples in IITD Contactless Palmprint Database



A. Kumar, K. Wang, “Identifying humans by matching their left palmprint with right palmprint images using convolutional neural network,” *Proc. DLPR 2016*, Cancun, 2016.

Palmprint Similarity

- Matching *Left* Palmprint with *Right* Palmprint
  - Samples in IITD Contactless Palmprint Database



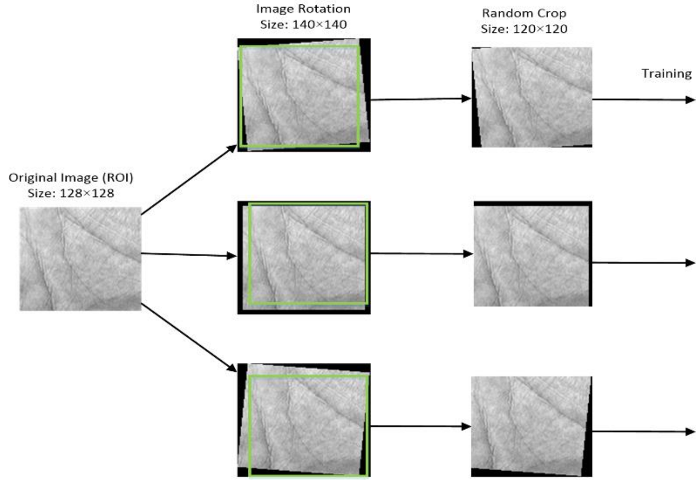
(a) Left palmprint (b) Right palmprint (c) Matching major line patterns between (a) and (b)

(d) Left palmprint (e) Right palmprint (f) Matching major line patterns between (d) and (e)

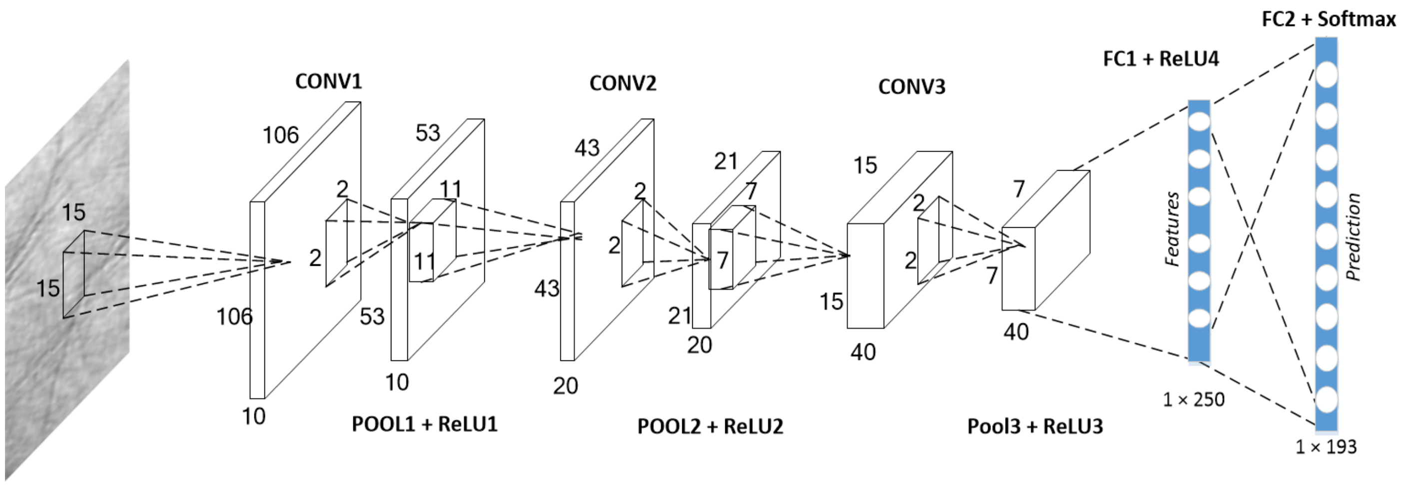
A. Kumar, K. Wang, "Identifying humans by matching their left palmprint with right palmprint images using convolutional neural network," *Proc. DLPR 2016*, Cancun, 2016.

Experiments

- Matching using a CNN



  - Network Architecture



Results

- PolyU Palmprint Database using a CNN
  - Training → First Session, Test → Second Session
  - Genuine → 19,550, Imposter → 7,497829

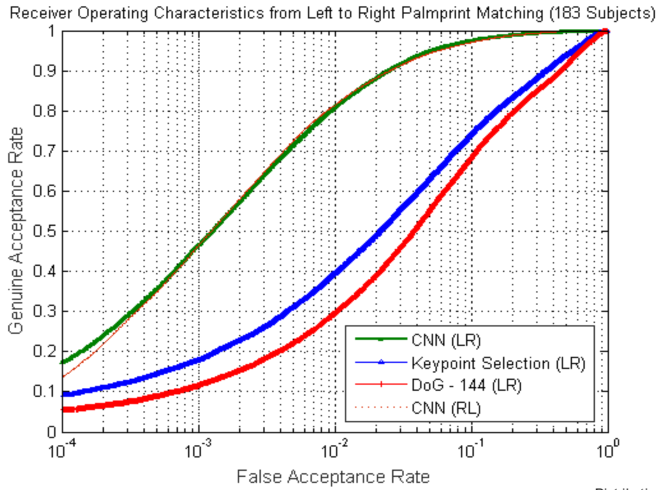
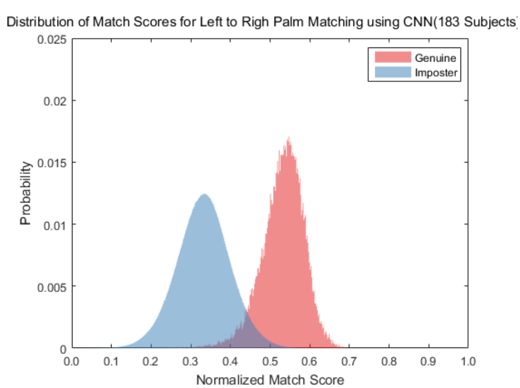
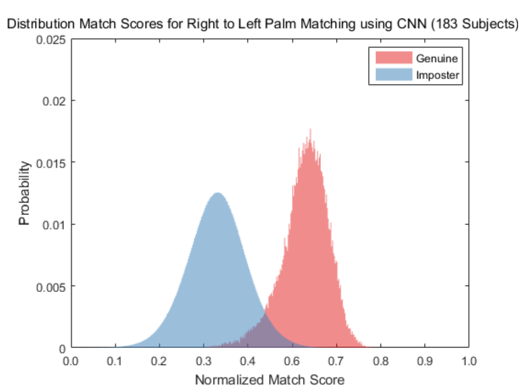


Table 2: The EER from Left-to-Right Palmprint matching.

Approach	EER
BLPOC – DoG based reference point selection	20.34%
BLPOC – Keypoint detection and selection	18.01%
Convolutional Neural Network	**9.25%**

  - Match Score Distribution

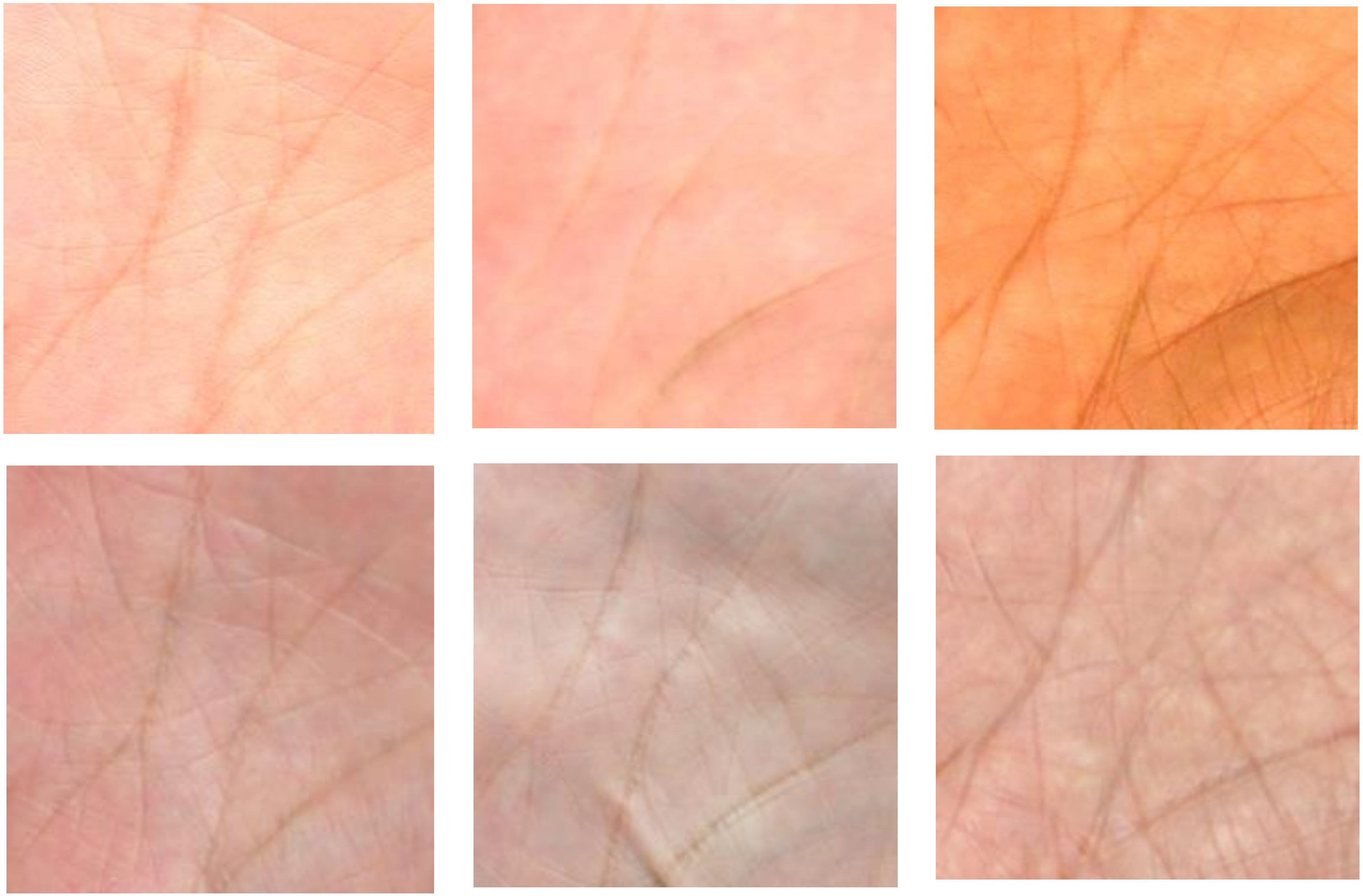




A. Kumar, K. Wang, "Identifying humans by matching their left palmprint with right palmprint images using convolutional neural network," *Proc. DLPR 2016*, Cancun, 2016.

Real World Contactless Palmprint Images

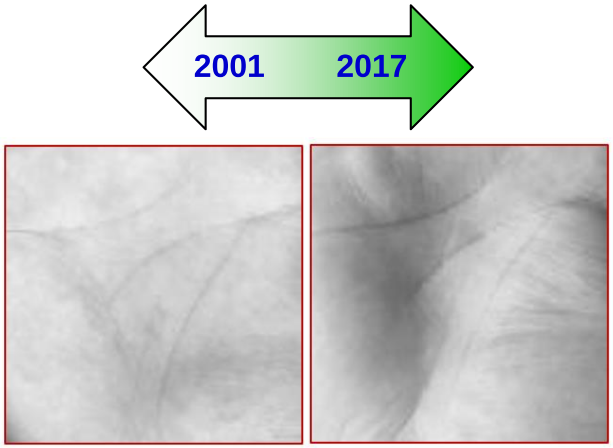
- Long Interval Palmprint (15+ Years Interval)



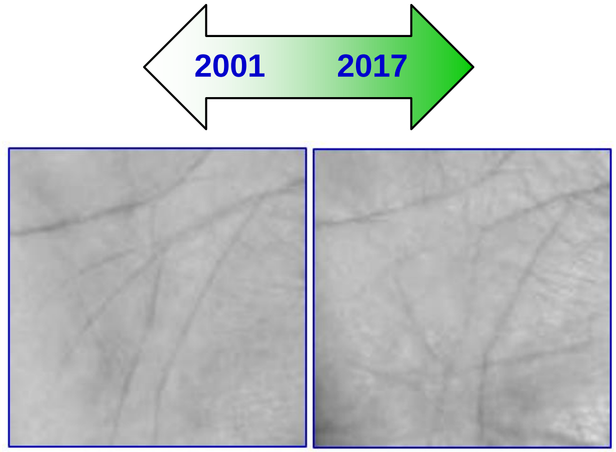
A. Kumar, "Towards accurate matching of contactless palmprint images for biometrics authentication," *IEEE Trans. IFS,* 2019.

Real World Contactless Palmprint Images

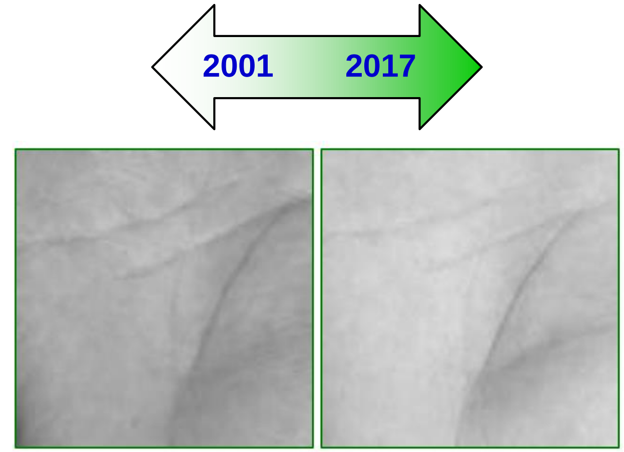
➢ Long Interval Palmprint (15+ Years Interval)



Match score: **1.1889**



Match score: **0.872**



Match score: **0.739**

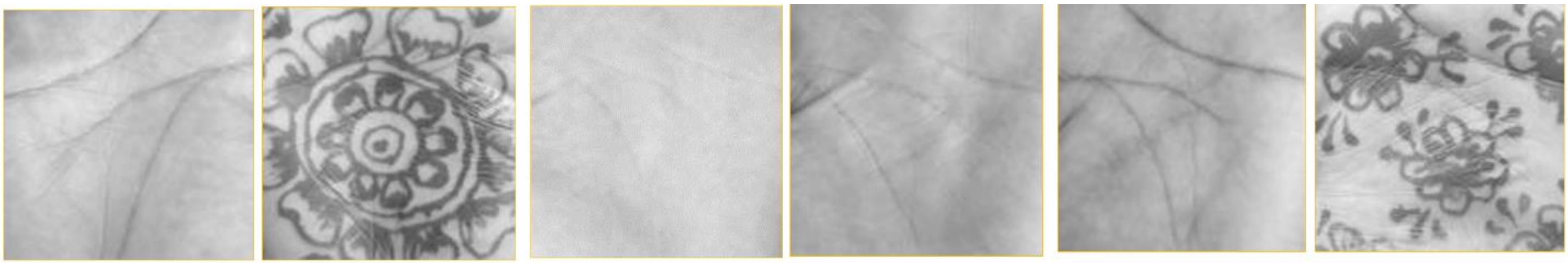
(*Decision Threshold → 1.233*)

A. Kumar, "Towards accurate matching of contactless palmprint images for biometrics authentication," *IEEE Trans. IFS,* 2019.

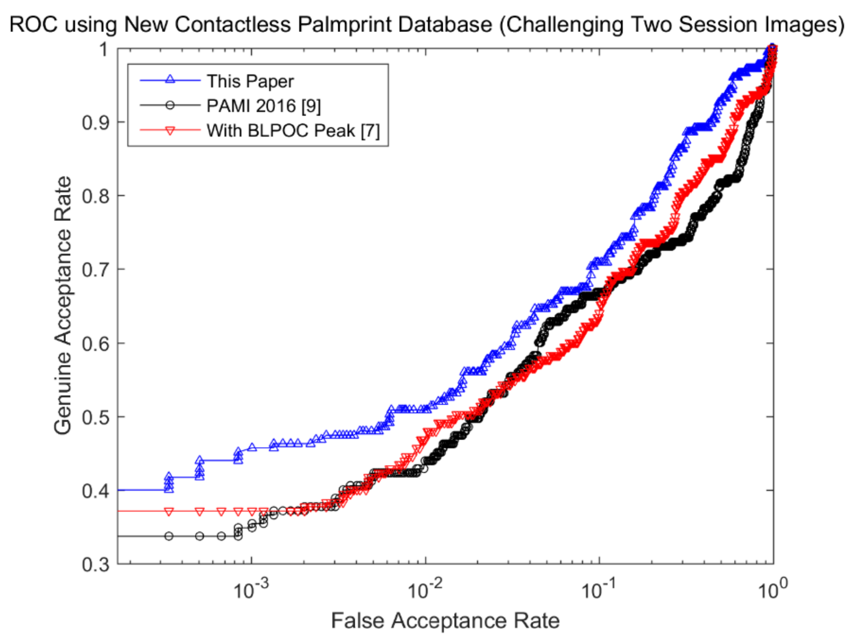
Real World Contactless Palmprint Images

Real World Contactless Palmprint Images

➢ Non-Matched Image Samples



(a) Match score: 1.454 (b) Match score: 1.347 (c) Match score: 1.408

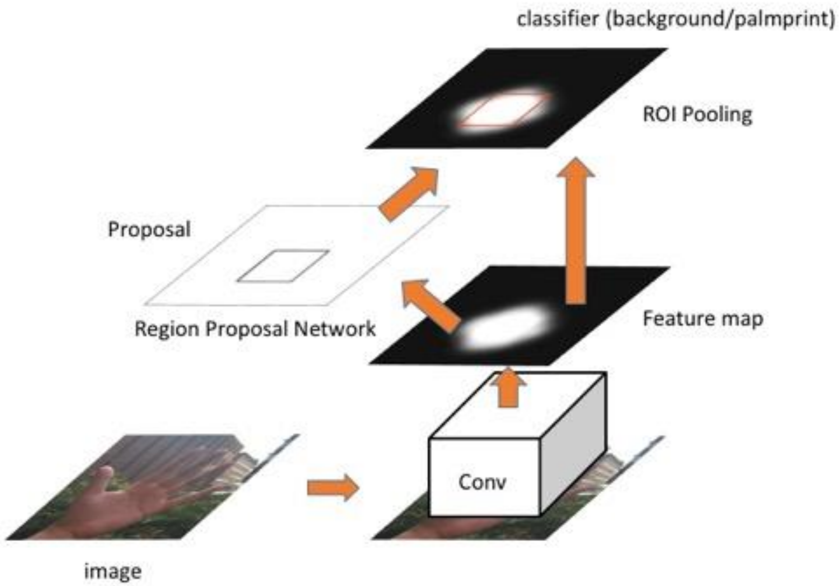


(Decision Threshold → 1.233)

A. Kumar, "Towards accurate matching of contactless palmprint images for biometrics authentication," *IEEE Trans. IFS,* 2019.

Palmprint Detection under Complex Backgrounds

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



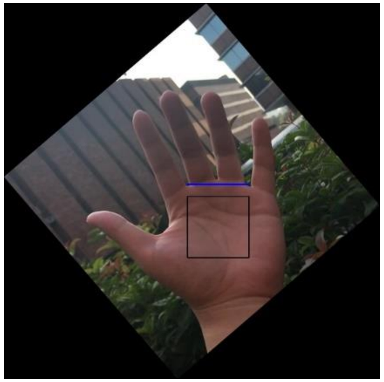
Y. Liu, A. Kumar, "A Deepl Larning Based Framework to Detect and Recognize Humans using Contactless Palmprints in the Wild," arXiv preprint arXiv:1812.11319, 2018

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

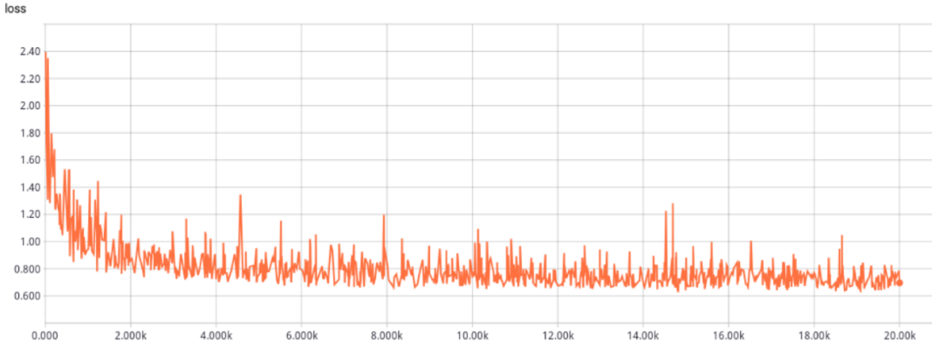
Palmprint Detection under Complex Backgrounds

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

Raw segmented frame



Aligned segmented frame



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

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*

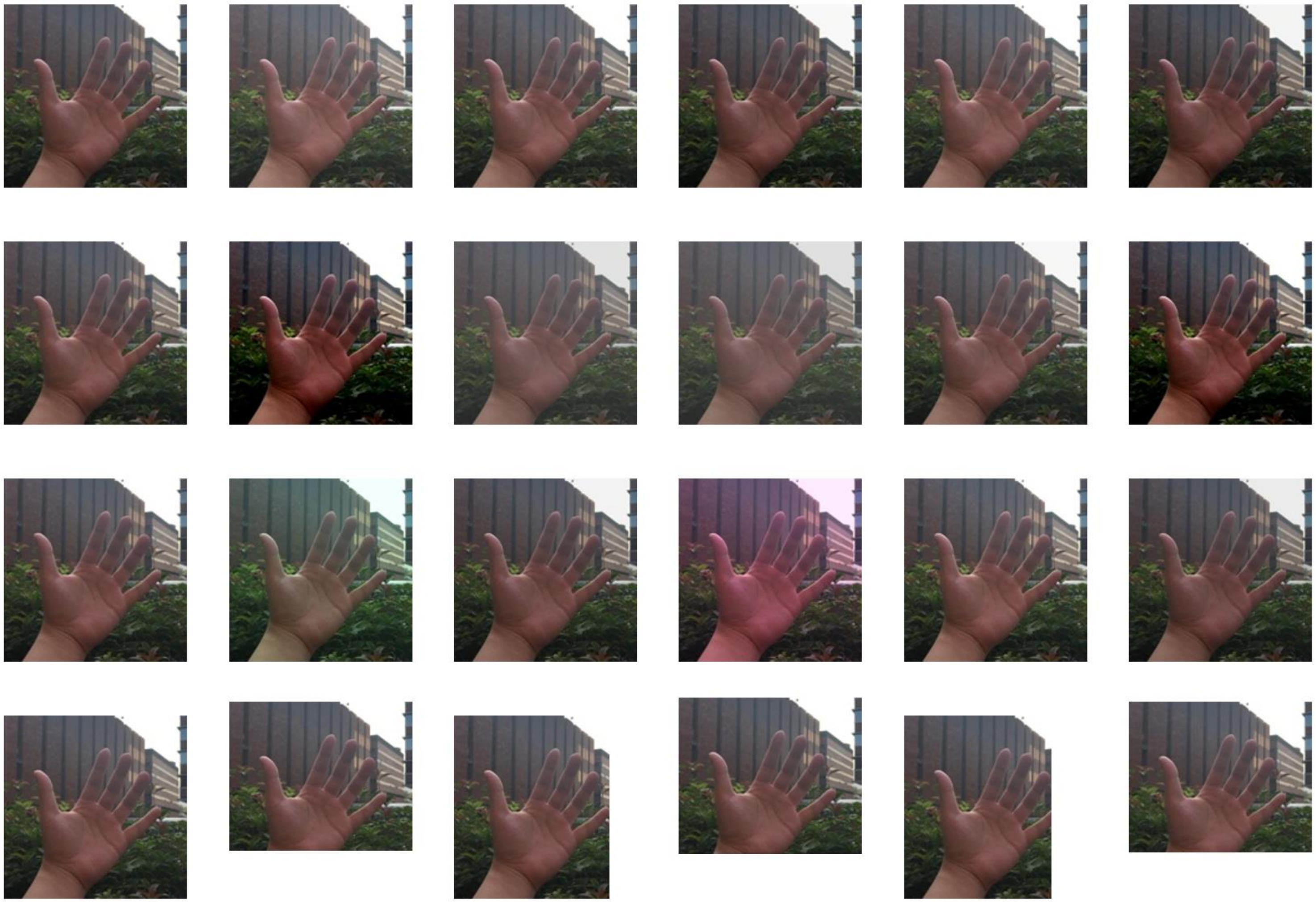
- Scale and Aspect ratio augmentation[2]
  - *Random area ratio* (a=[0.08, 1])
  - *Random aspect ratio* (s=[3/4, 4/3])
  - *Crop size*: W'=sqrt(W*H*a*s), H'=sqrt(W*H*a/s)

- 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



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

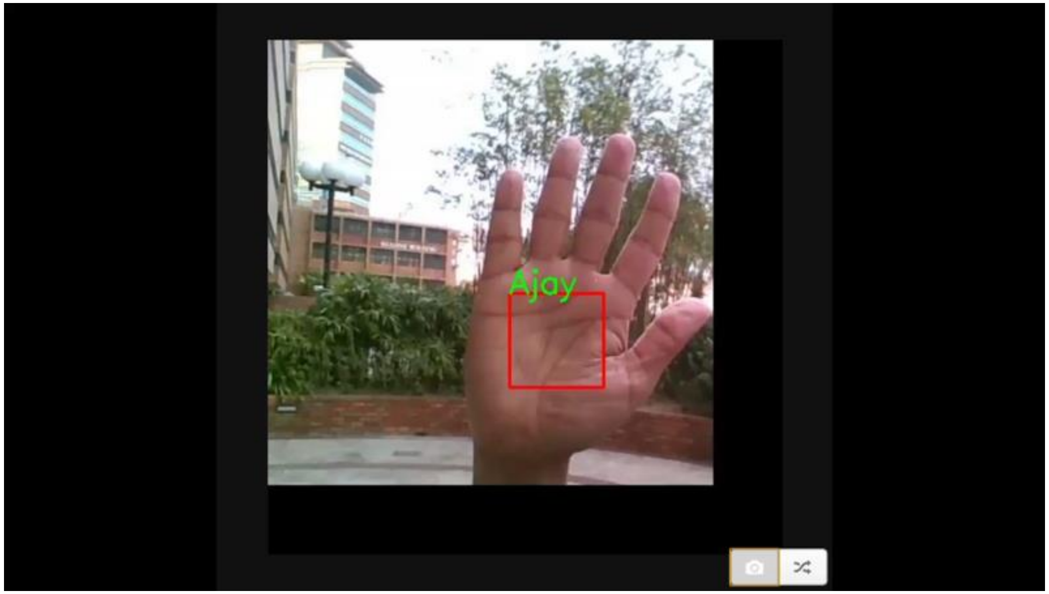
Palmprint Detection under Complex Backgrounds

➢ Results

- Trained Model → 0.0101 sec. (300 RPN outputs)

The mAP and recall value at different (IOU) threshold.

Experiments	mAP			recall		
	Overlap IOU threshold			Overlap IOU threshold		
	0.35	0.5	0.6	0.35	0.5	0.6
strategy(a)	100.0	99.89	98.20	100.0	99.84	98.97
strategy(b)	100.0	98.44	86.45	100.0	98.78	90.50



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

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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  - Yang Liu
  - Qian Zheng
  - Vivek Kanhangad
  - Kuo Wang

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Thank You !