IAPR IEEE Biometrics Council

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Biometric Identification of Human Individuals: Recent Advances and Future Directions

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January 13, 2019

Outline

- Preamble
- Overview of Recent Progress on Biometrics
  - ✓ Fingerprint Recognition
  - ✓ Iris Recognition
  - ✓ Face Recognition
  - ✓ Gait Recognition
  - ✓ Others
- Future Directions and Conclusions

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Personal identification is required by a wide variety of applications

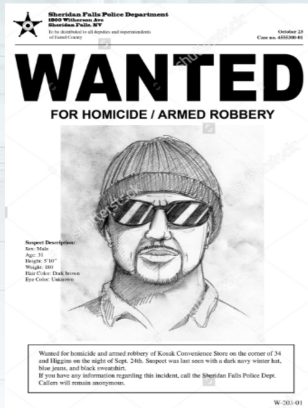
Access control

Bank

Email login

Border control

Unlock mobile phone



Forensics

Traditional methods of personal identification

ID Card

Password

Card+PW

- Passwords and cards can be shared and thus cannot provide non-repudiation
- Passwords may be forgotten or cracked
- Cards may be lost, stolen or forged

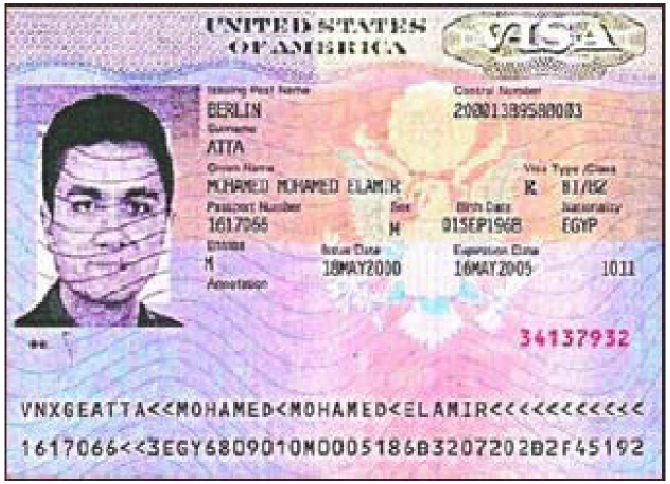
Too Many Passwords to Remember!

"Sorry about the odor. I have all my passwords tattooed between my toes."

- Heavy web users have an **average of 21 passwords**; 81% of users select a common password (e.g., PASSWORD) and 30% write their passwords down or store them in a file. *(2002 NTA Monitor Password Survey)*

Security threats of identity theft

On September 11, 2001, 19 terrorists boarded aircraft in Boston, Mass., and Dulles, Va., and changed our world. All had successfully passed through security screening prior to boarding the aircraft and, previously, had also successfully passed through immigration screening while entering the country. A suspected 20th terrorist had been refused entry by a suspicious immigration inspector at Florida's Orlando International Airport the previous month. Of the remaining 19 terrorists, 18 had been issued U.S. identification documents. The global war on terror had reached American soil, and the terrorists had already realized how important identity was to be in this fight.



"Sources of identification are the last opportunity to ensure that people are who they say they are and to check whether they are terrorists."

"For terrorists, travel documents are as important as weapons."

--The 9/11 Commission Report

Security threats of identity theft

The Marriott data breach reported on November 30, 2018 indicates that everyone is at risk of identity theft and passport and credit card are not reliable identifiers.

Security

Identity stolen because of the Marriott breach? Come and claim your new passport

It's the least they could do. Really. The bare minimum

By Shaun Nichols in San Francisco 7 Dec 2018 at 23:35 14 SHARE ▼

Marriott customers should change credit card numbers, be alert for identity theft

by Special on November 30, 2018 in NEWS

The names, addresses, contact information and passport numbers of over 300 million people who stayed at a Starwoods hotel property may have been accessed in a major data hack, Marriott hotels reported Friday. Marriott's data team confirmed that the Starwood guest reservation database — which contains up to 500 million accounts — had been compromised, and the hacking may have been ongoing since

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Biometrics

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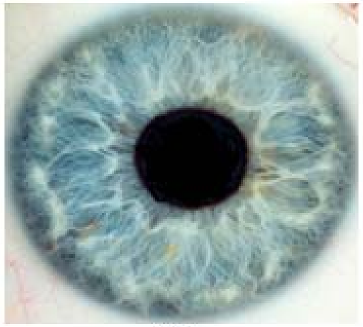
Automated recognition of individuals based on their behavioral and biological characteristics [ISO/IEC JTC1 2382-37:2012]

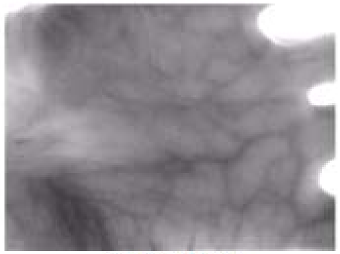
Physiological Modalities

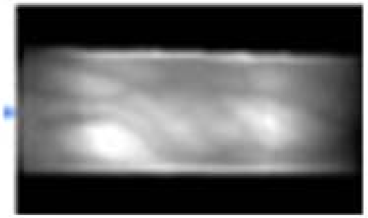

Iris


Face


Fingerprint

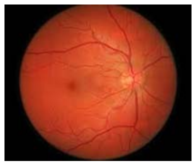

Palmprint


Palm vein


Finger vein


Hand geometry

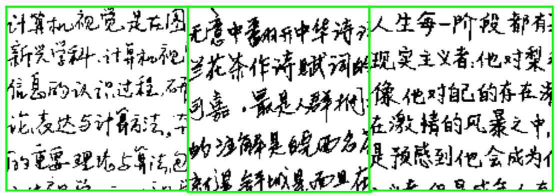

Ear

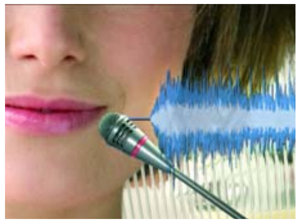

Retina


DNA

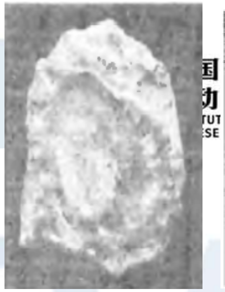
Behavioral Modalities

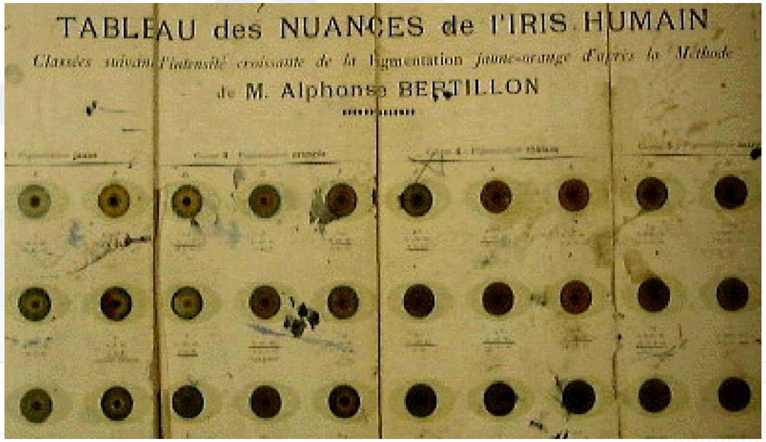

Gait

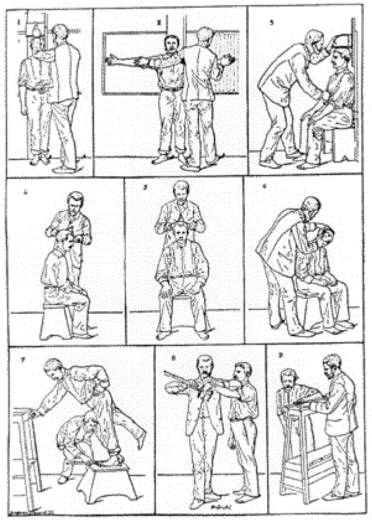

Handwriting

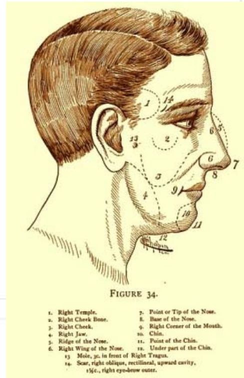

Voiceprint

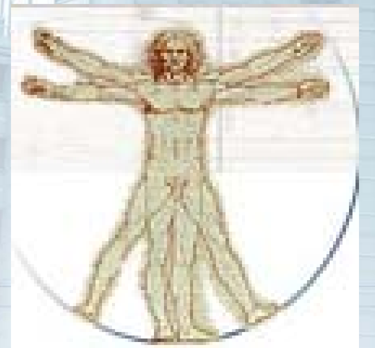
The history of biometrics

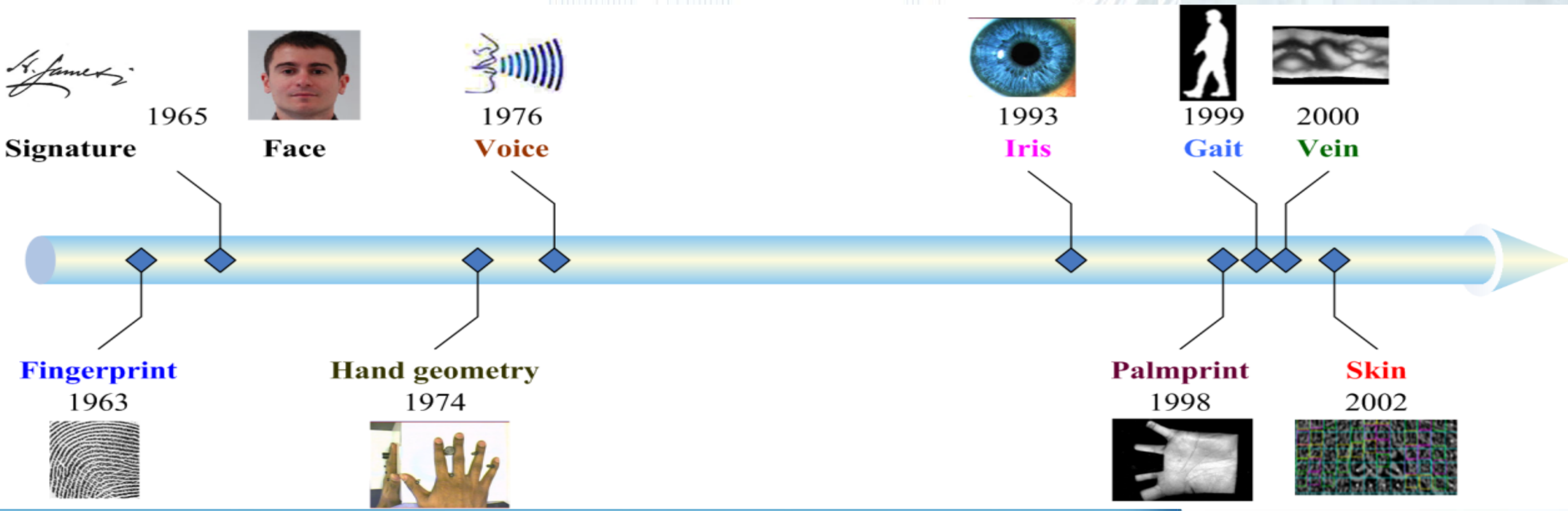




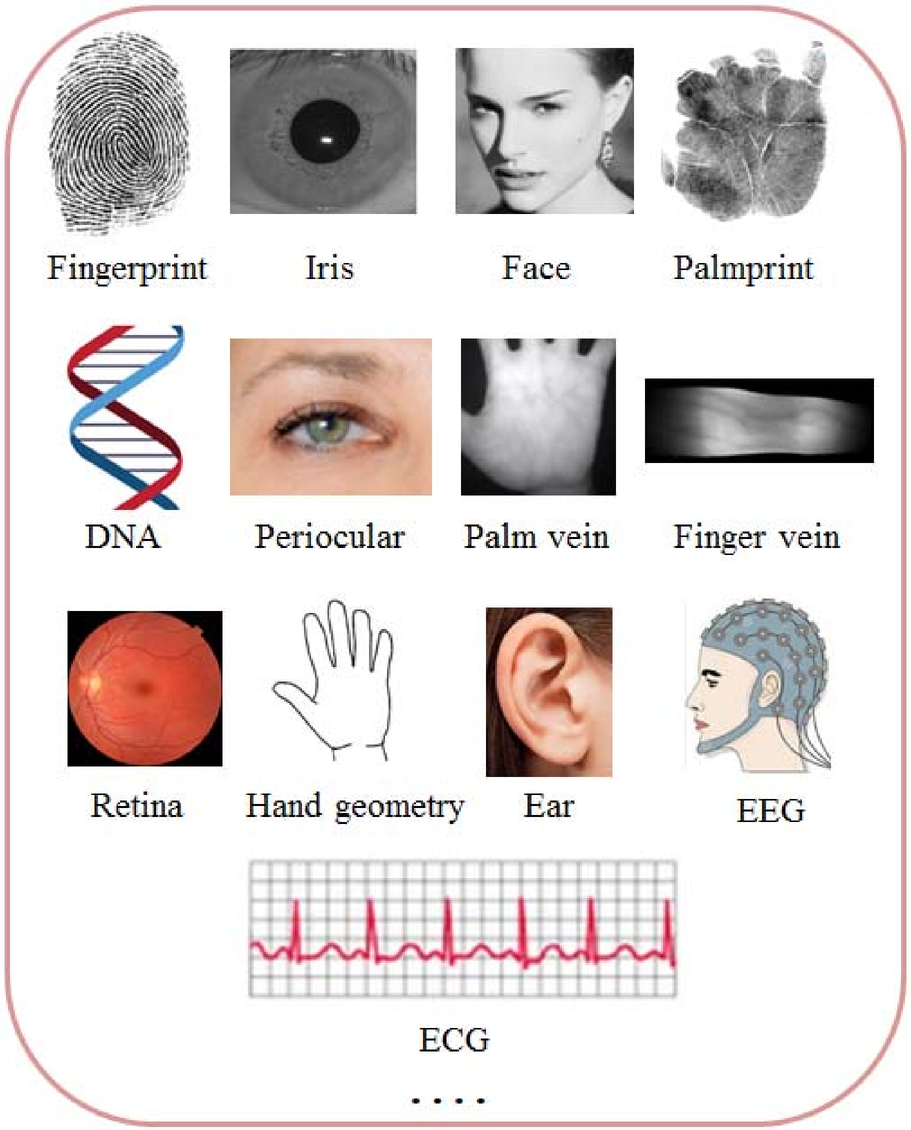








Main biometric modalities



Physiological Traits

Behavioral Traits

Applications of Biometrics

Fingerprint recognition for mobile authentication

Face recognition for border control

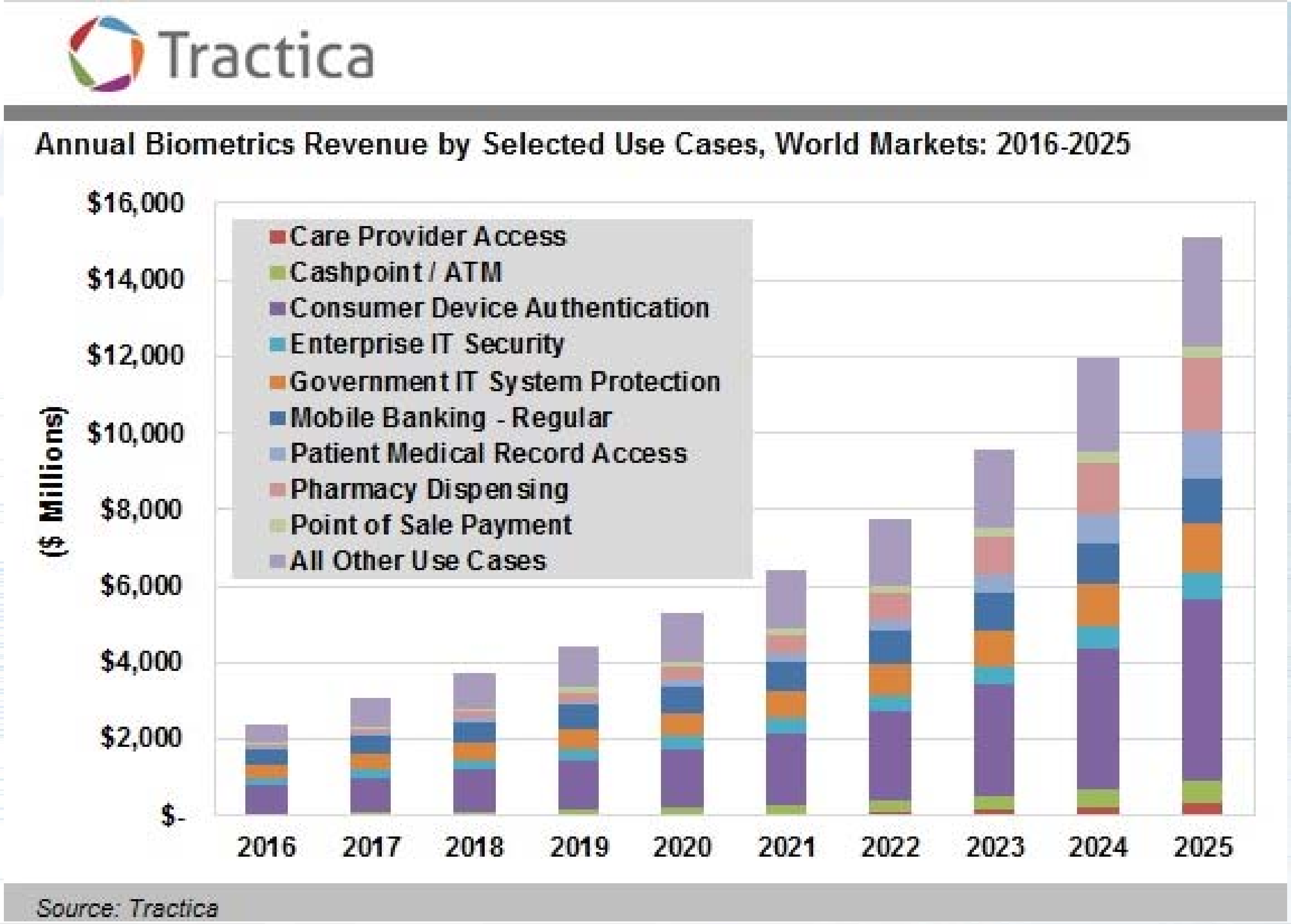
Iris recognition for coal miner identification

Finger vein recognition for ATM authentication

Voiceprint recognition for payment

Signature verification for credit card security

Fast Growing Market of Biometric Recognition



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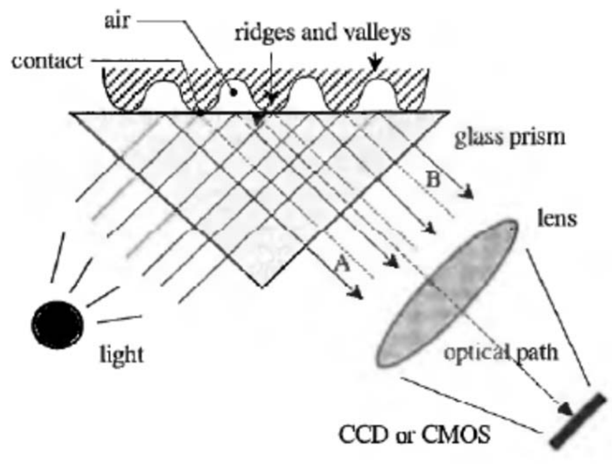
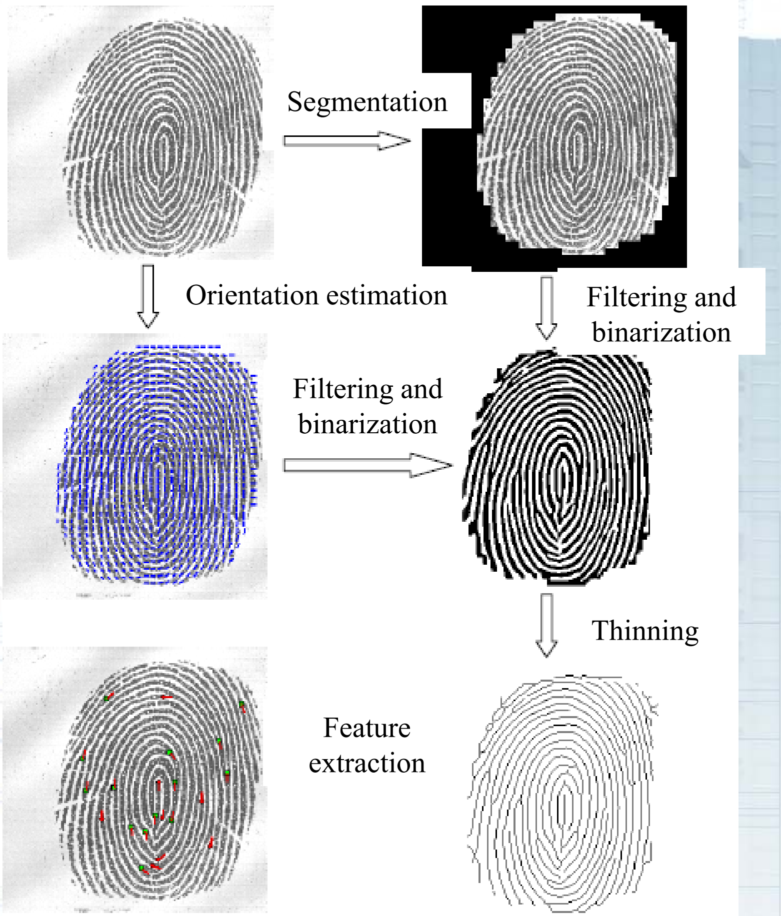
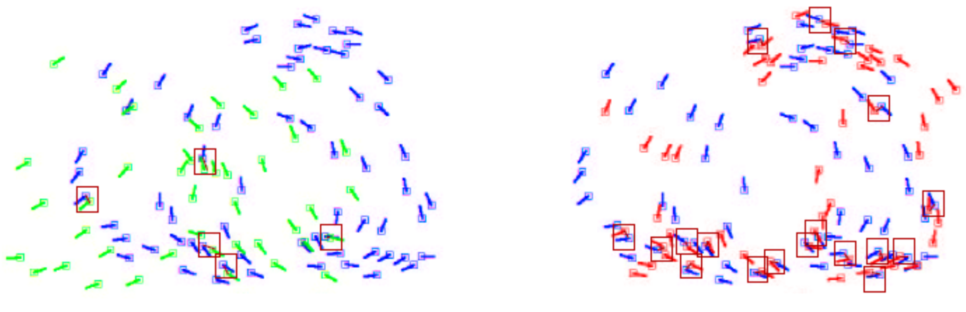
Fingerprint Recognition



Imaging



Preprocessing and feature extraction

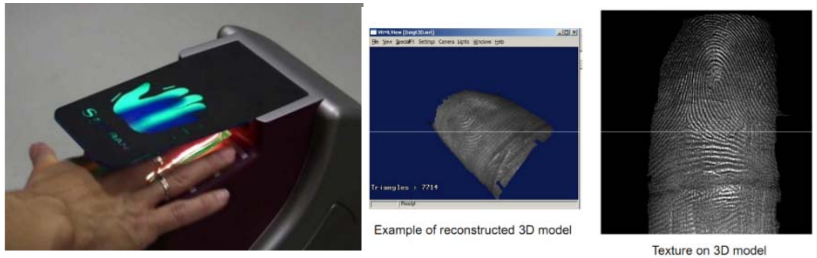


Minutiae matching

Recent Progress of Fingerprint Recognition

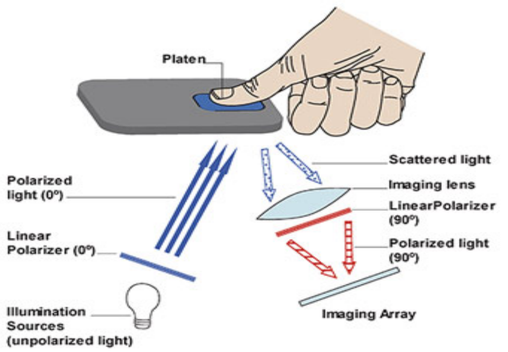
Better user experience

Under-Display Fingerprint Sensor Technology (Qualcomm-Vivo)

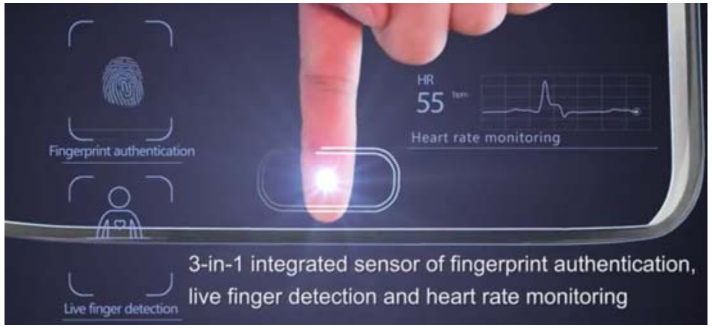


Touchless 3D fingerprint (SAFRAN Morph)

More secure



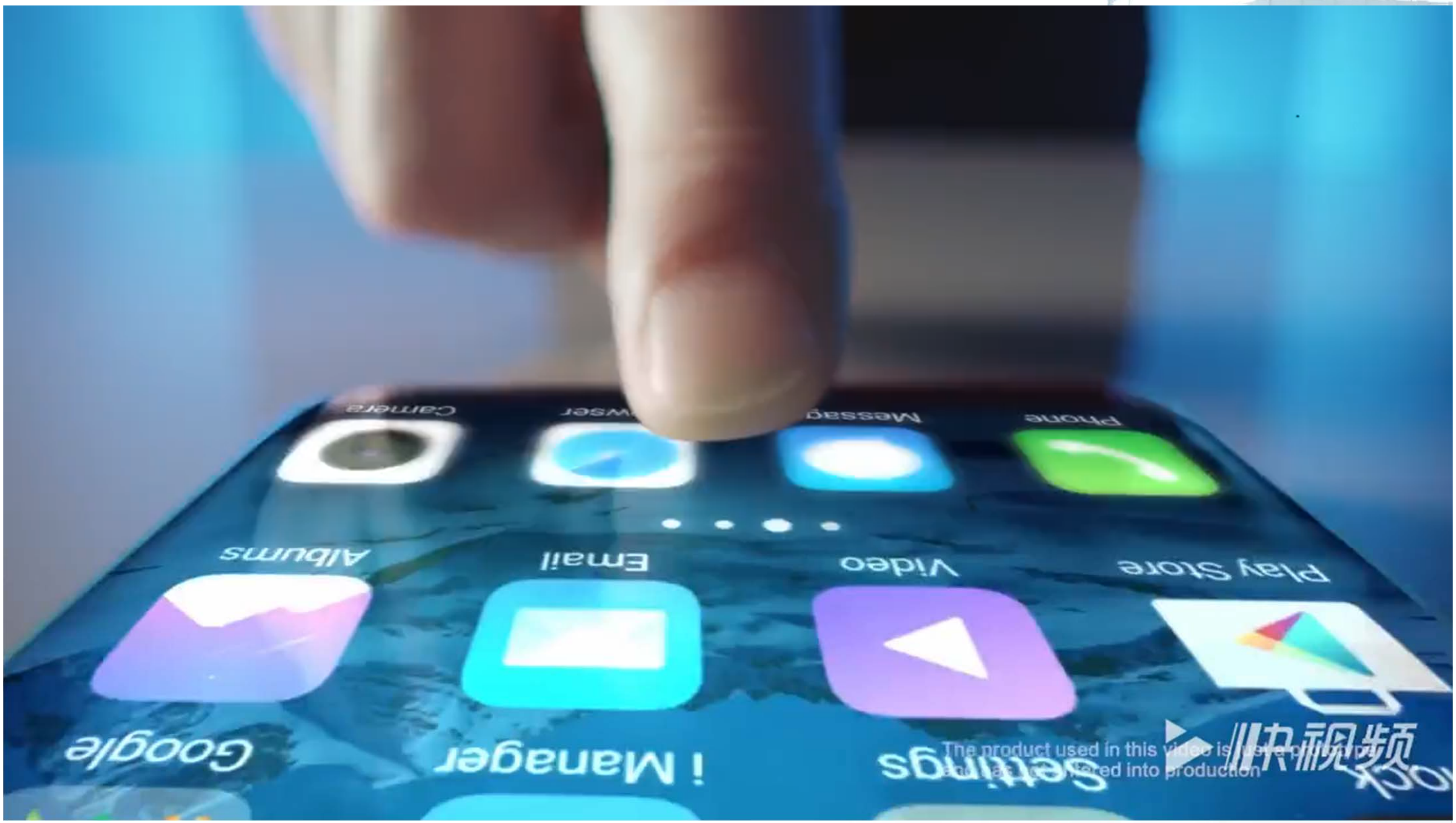
Multispectral imaging for anti-spoofing (Lumidigm)



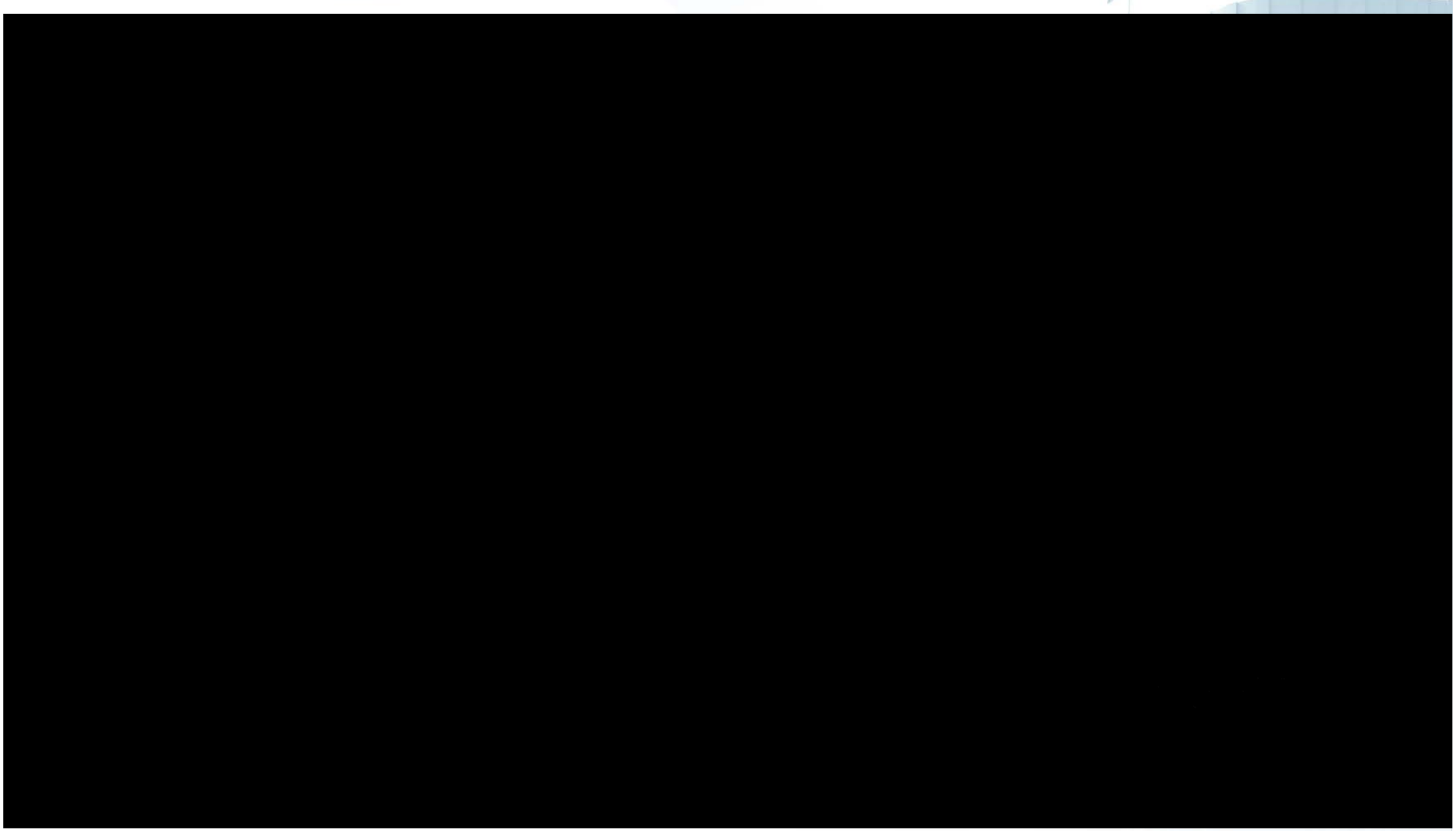
IC solution of blood flow detection (Goodix)

Under Display Fingerprint Scanning

(Qualcomm-Vivo, ultrasonic fingerprint solution, MWC2017)



Touchless 3D Fingerprint Recognition (SAFRAN Morph)



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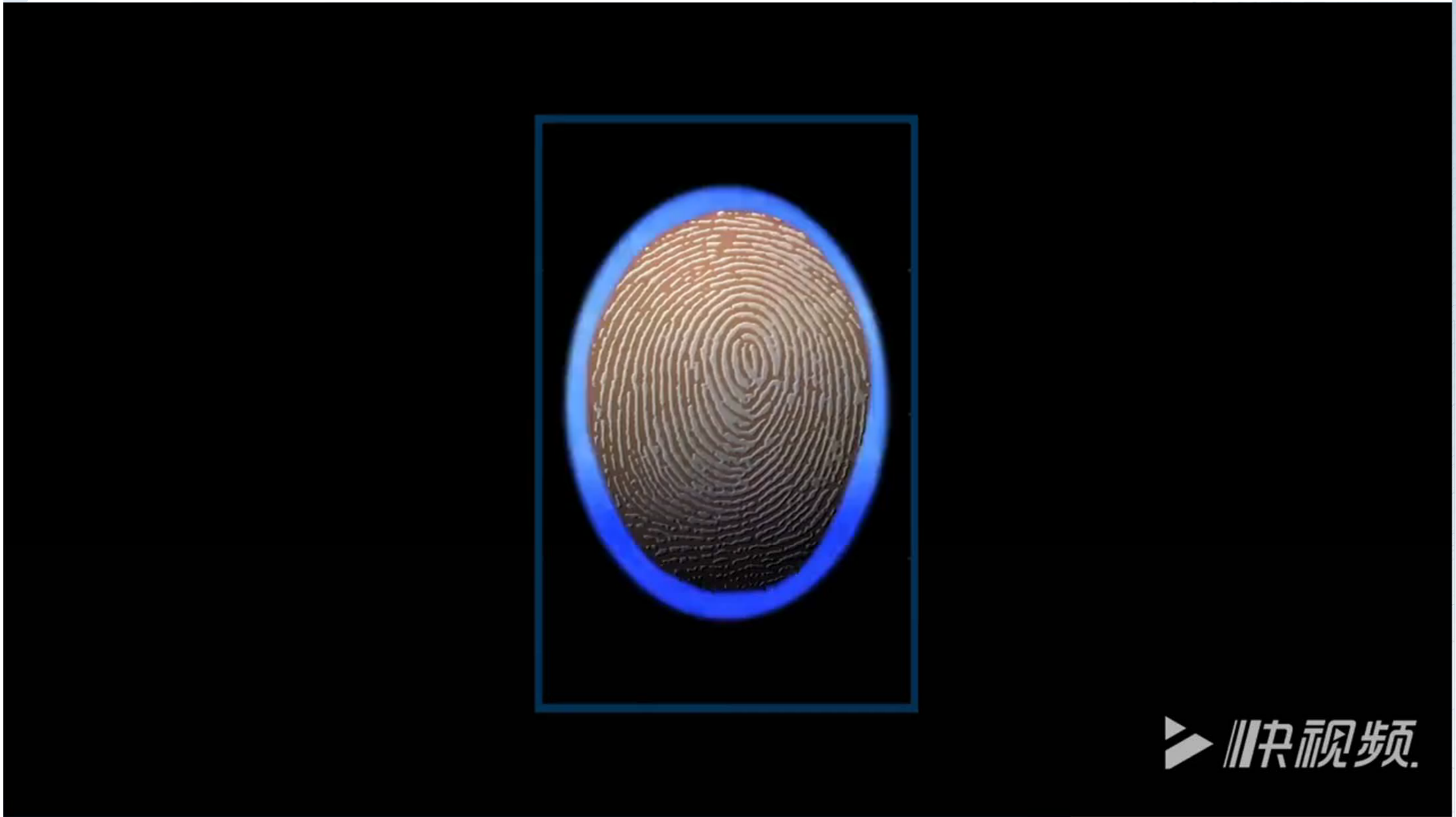
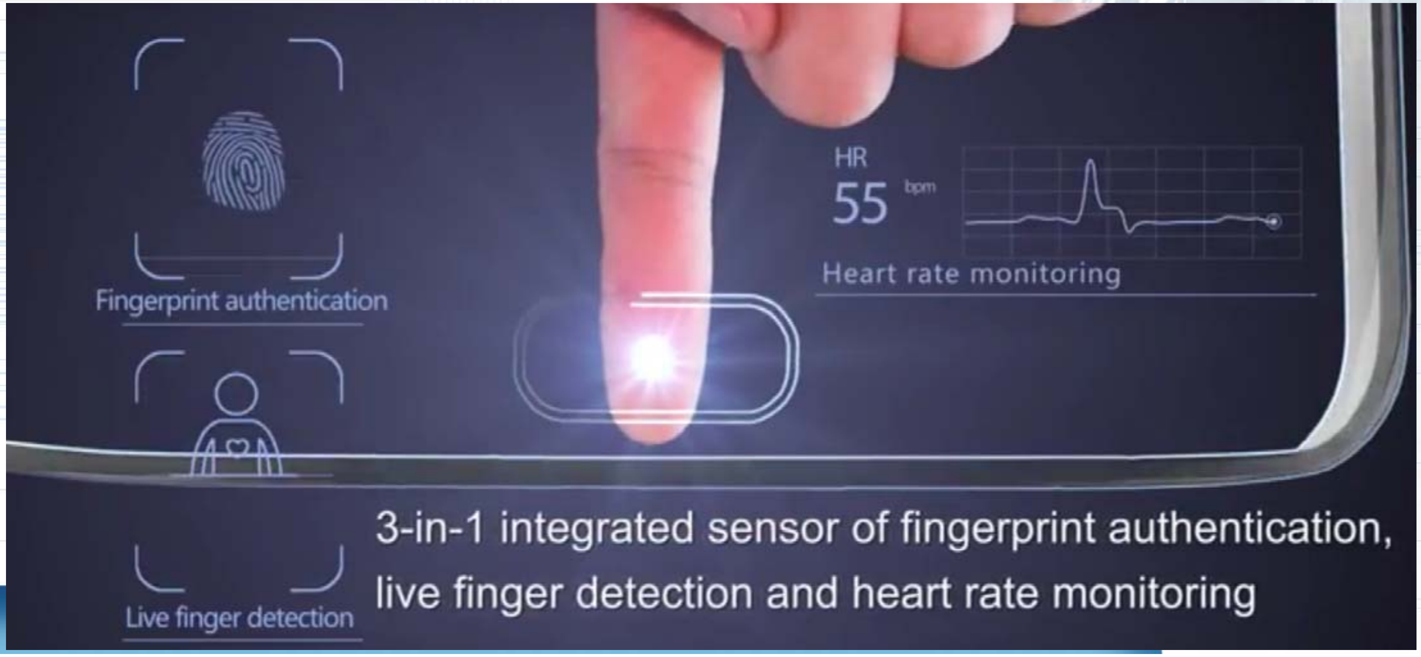
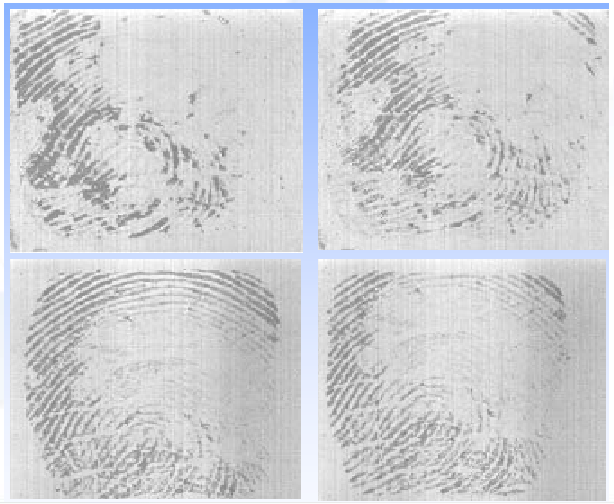


IC Solution for Live Finger Detection

IC designer Goodix developed Live Finger Detection™ technology on mobile devices, which allows a capacitive sensor and an optical sensor to be seamlessly combined into one. Through the detection of fingerprint, blood flow and infrared signals, this cutting-edge technology embedded within the sensor is able to authenticate the user's identity and reject faked fingerprints.

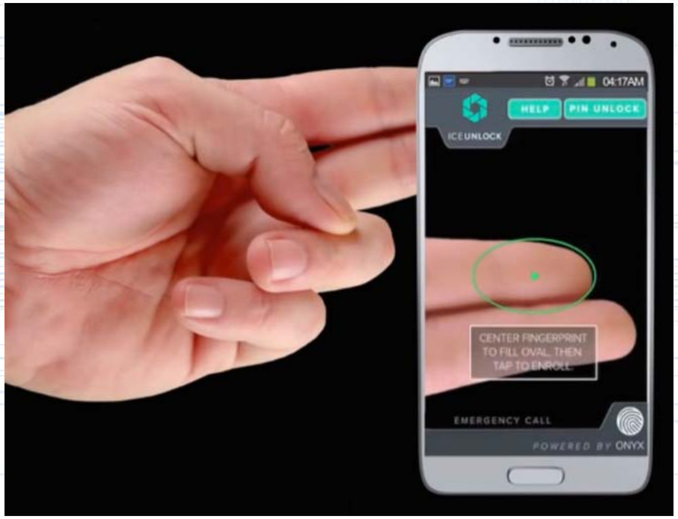


Open Problems of Fingerprint Recognition

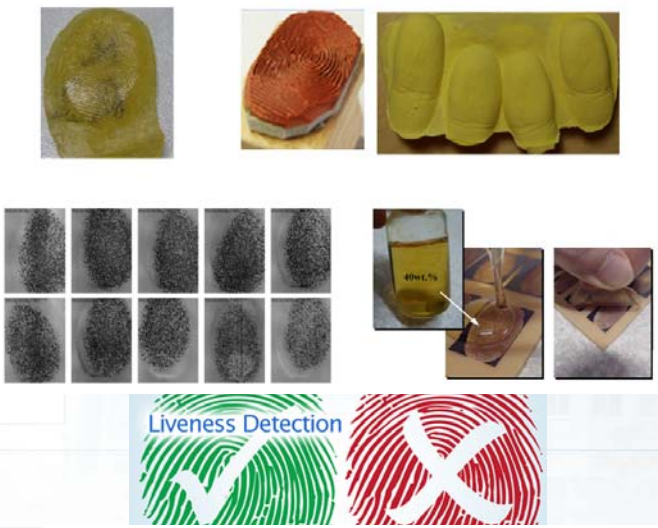


Latent fingerprint images

Distorted fingerprint images



Touchless fingerprint recognition

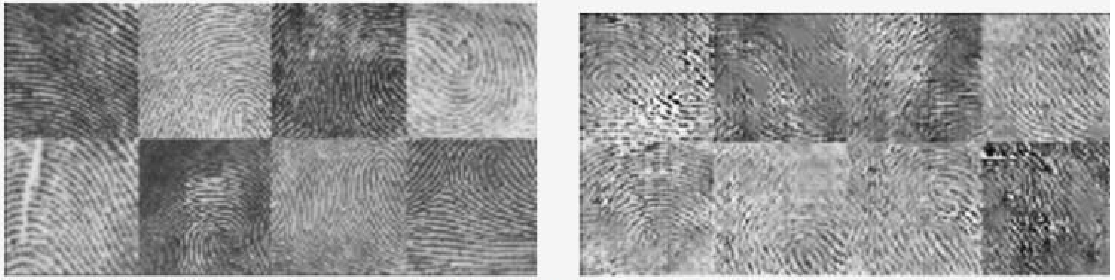


Fingerprint liveness detection

Open Problems of Fingerprint Recognition

By AstroJane

Posted on November 19, 2018



(a) Real (left) and generated (right) samples for the NIST dataset.

(b) Real (left) and generated (right) samples for the FingerPass capacitive dataset.

Computer scientists at New York University and Michigan State University have trained an artificial neural network to create fake digital fingerprints that can bypass locks on cell phones. The fakes are called "DeepMasterPrints", and they present a significant security flaw for any device relying on this type of biometric data authentication. After exploiting the weaknesses inherent in the ergonomic needs of cellular devices, DeepMasterPrints were able to imitate over 70% of the fingerprints in a testing database.

Philip Bontrager, Aditi Roy, Julian Togelius, Nasir Memon, Arun Ross, DeepMasterPrints: Generating MasterPrints for Dictionary Attacks via Latent Variable Evolution，IEEE BTAS 2018.

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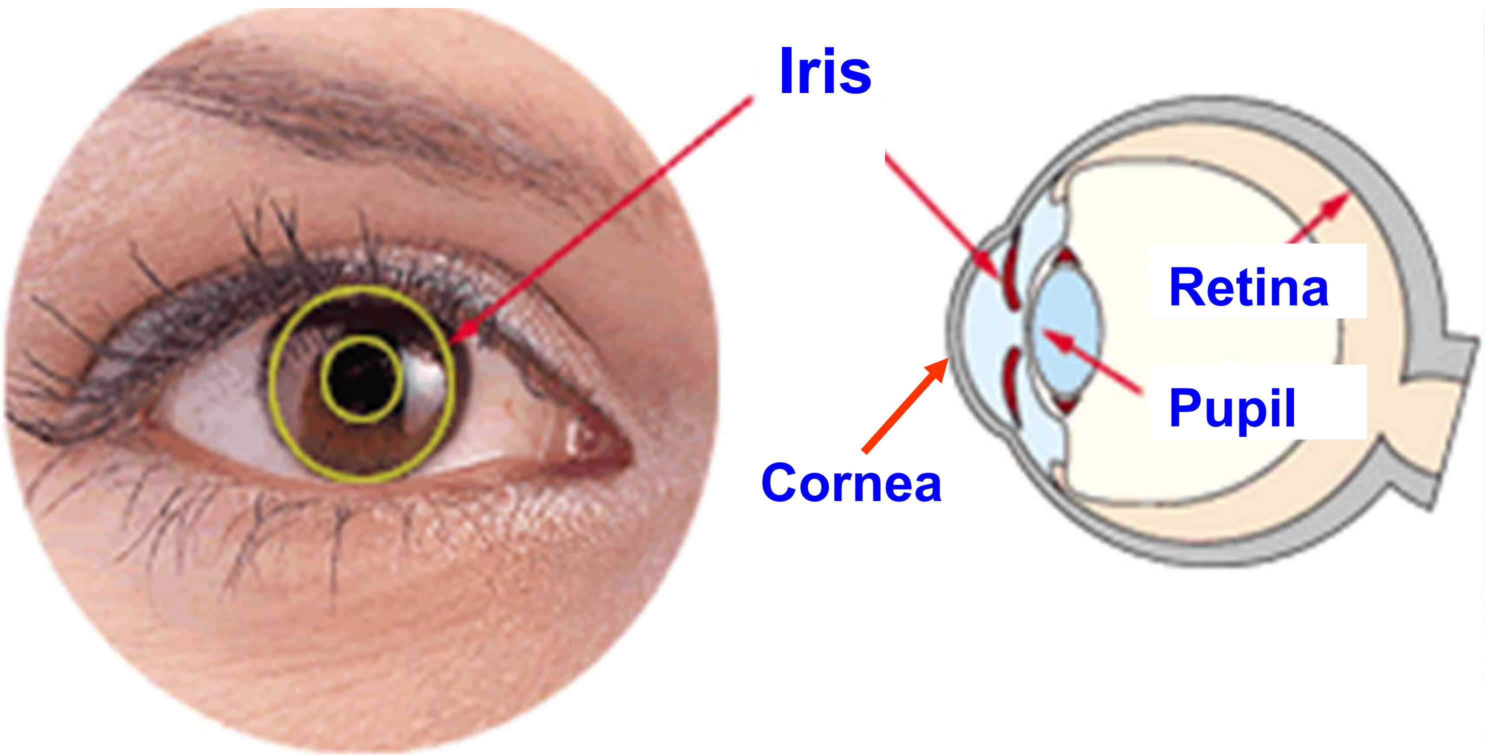
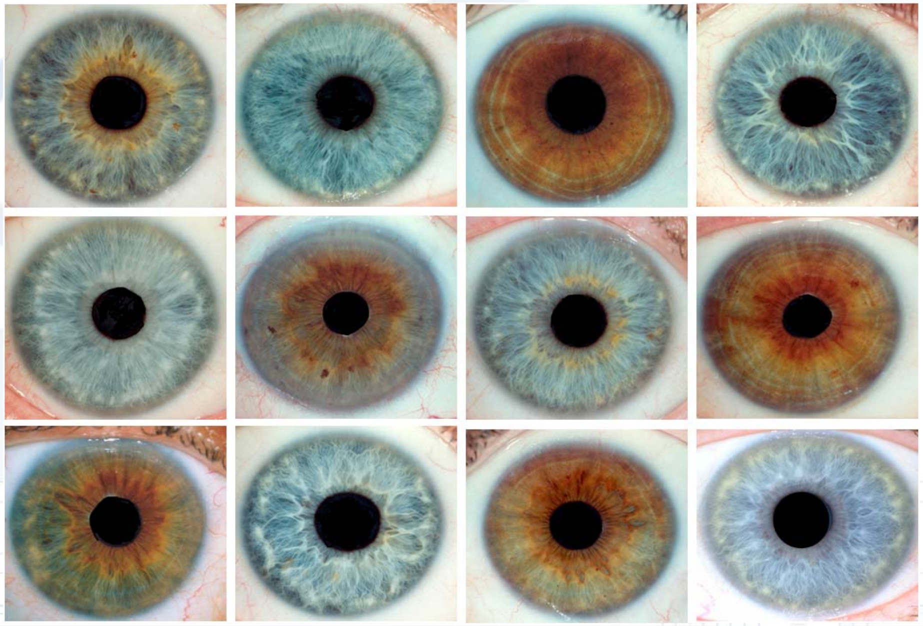
Human Iris

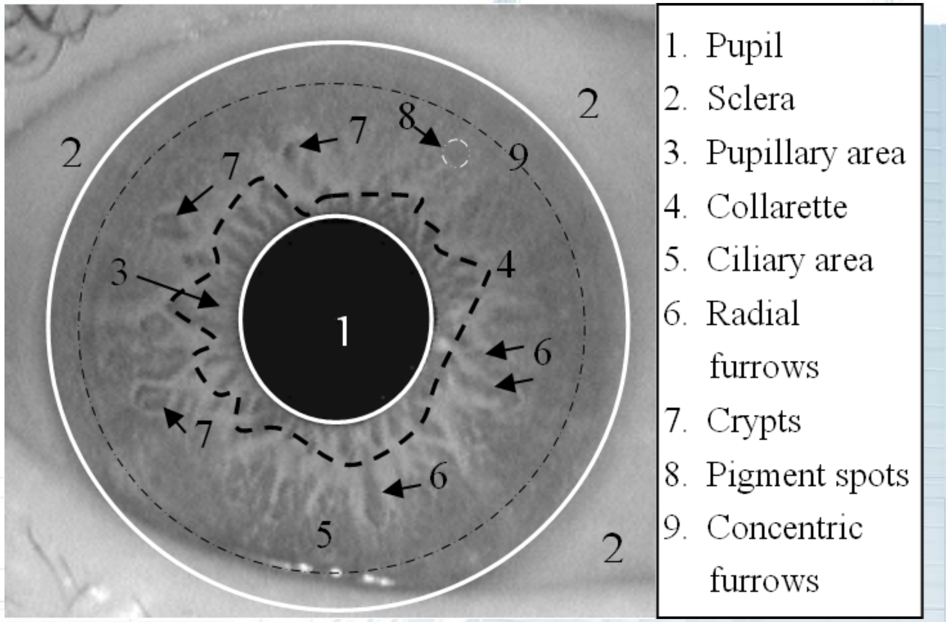
- The iris of your eye is the circular, colored membrane that surrounds the pupil.
- It controls light levels inside the eye similar to the aperture on a camera.
- Highly protected by cornea but externally visible at a distance



Human iris is unique for personal identification



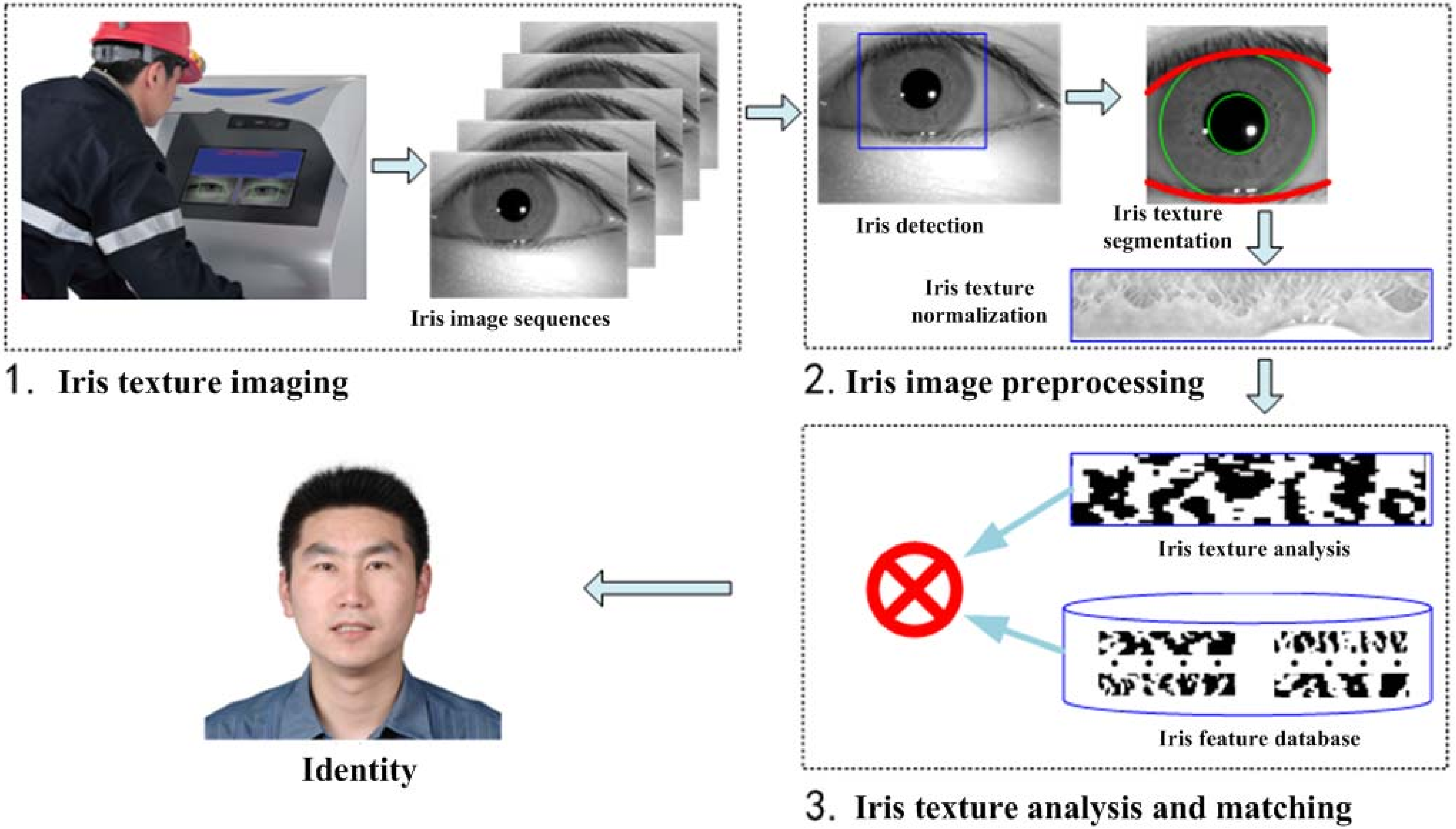
Visible illumination



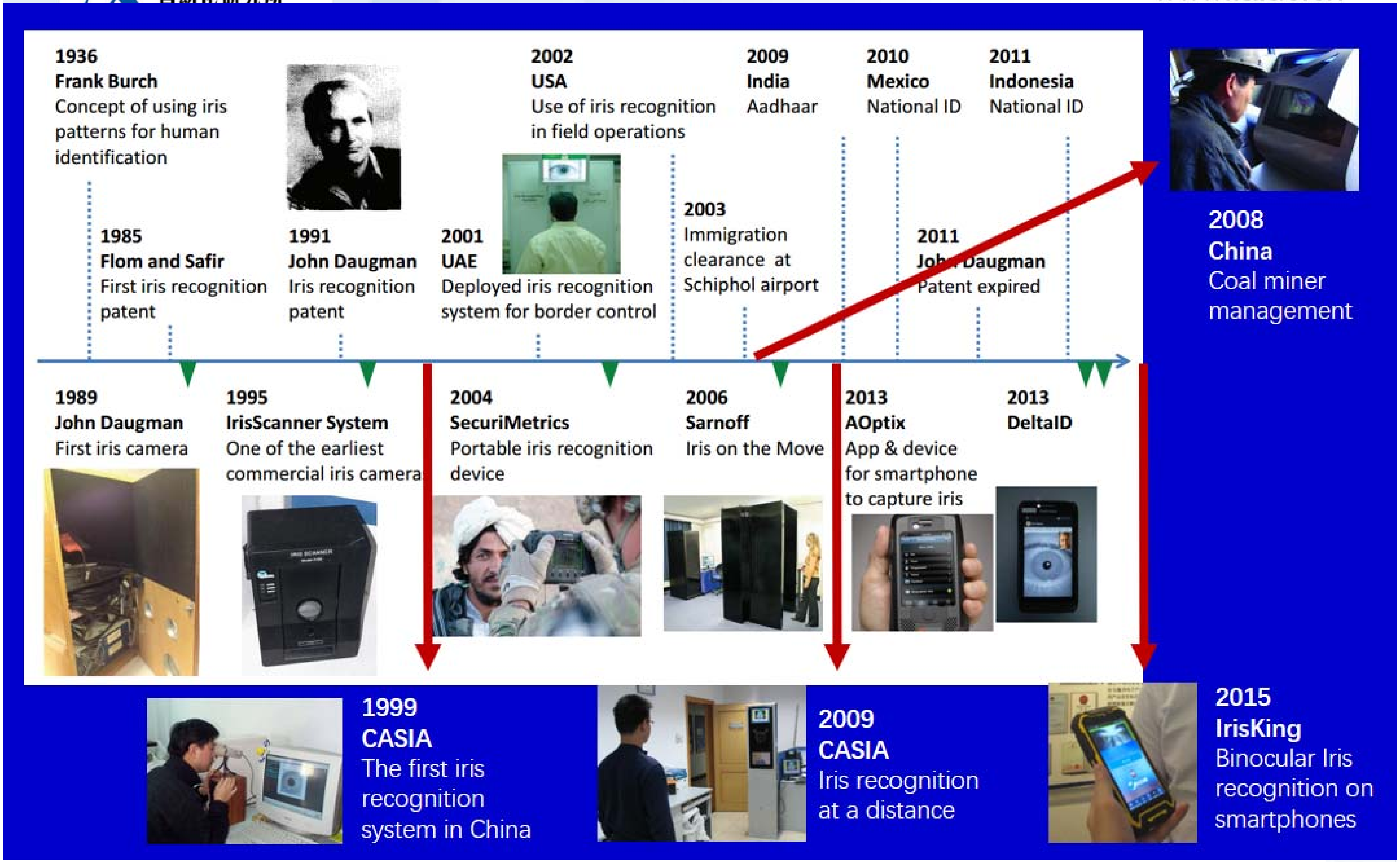
Near infrared illumination

- The uniqueness of iris texture comes from the random and complex structures such as furrows, ridges, crypts, rings, corona, freckles etc. which are formed during gestation
- The epigenetic iris texture remains stable after 1.5 years old or so

Iris Recognition



History of Iris Recognition



A.K. Jain, K. Nandakumar and A. Ross, 50 Years of Biometric Research: Accomplishments, Challenges, and Opportunities. Pattern Recognition Letters, 2015

Close-range iris devices


OKI IrisPass-H


OKI IrisPass-M


IrisID iCAM T10


IrisID iCAM 7000


Panasonic BM-ET300


Panasonic BM-ET500


IrisGuard IG-H100


IrisGuard IG-AD100


SecuriMetrics PIER 2.3

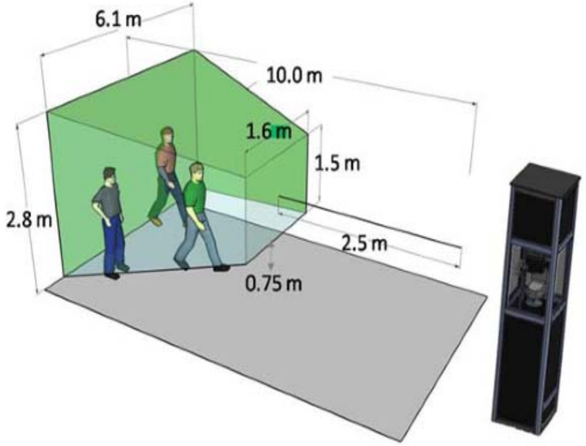

Crossmatch I SCAN2


IrisKing IKEMB-110

Long-range iris devices

Aoptix InSight

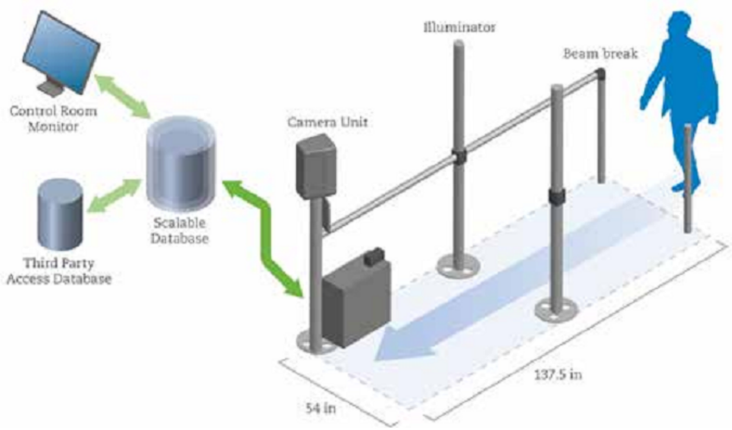
EyeLock HBOX



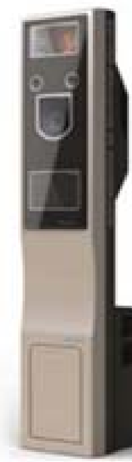
Eagle-eyes

IOM PassThru

System Diagram
IOM PassPort SL with floor kit assembly
IOM PassPort



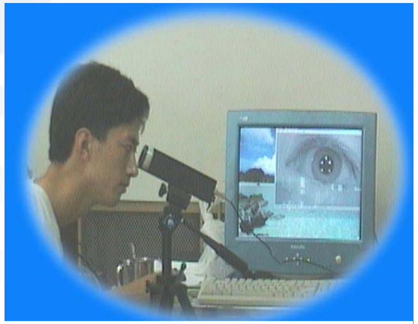
IrisID iCAM D1000



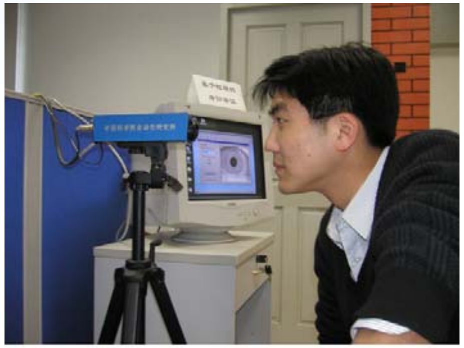
CASIA

Iris Recognition at CASIA

1999



2000



2001

2004

2005

2007

2008

2009

2014

2015

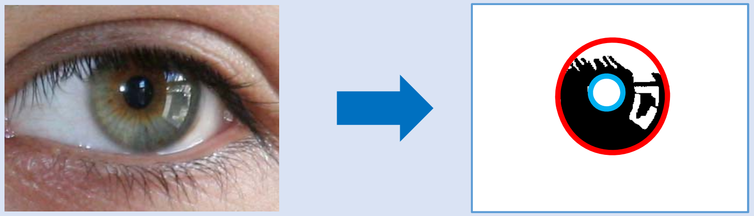
2016

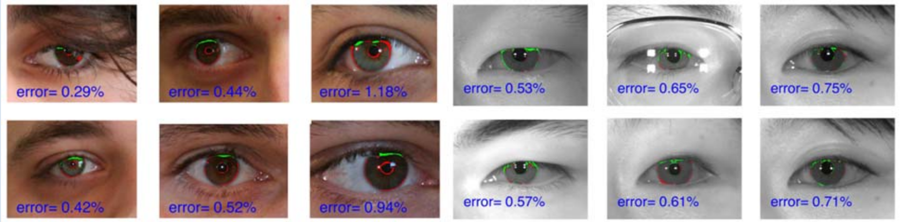
Recent work of iris recognition

www.ia.ac.cn

Acquisition

Segmentation

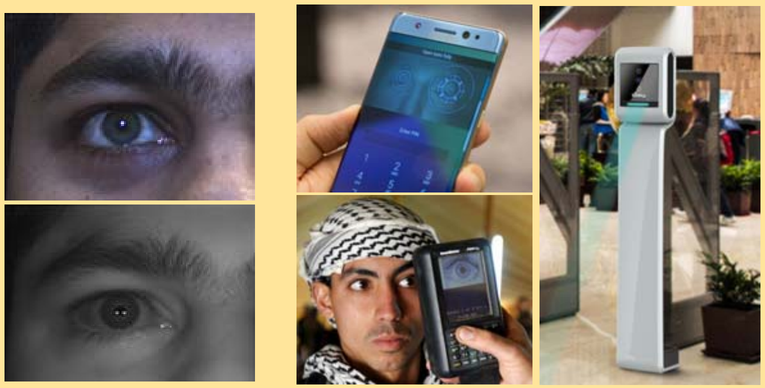




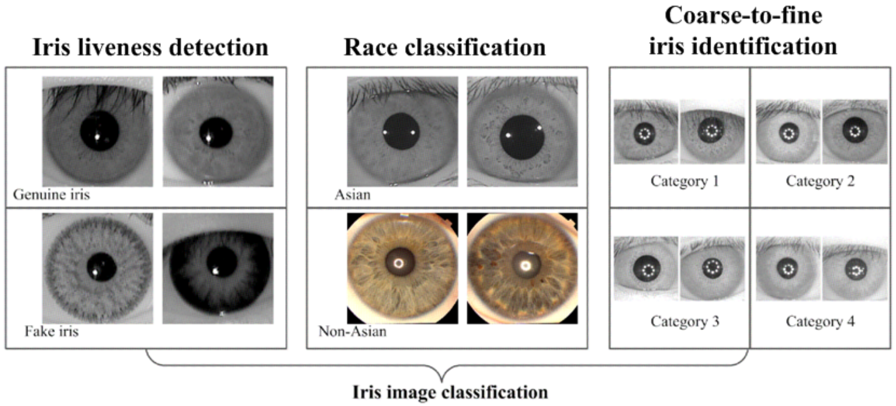
Red： false accept green: false reject

Recognition

Heterogeneous Iris Recognition



Classification

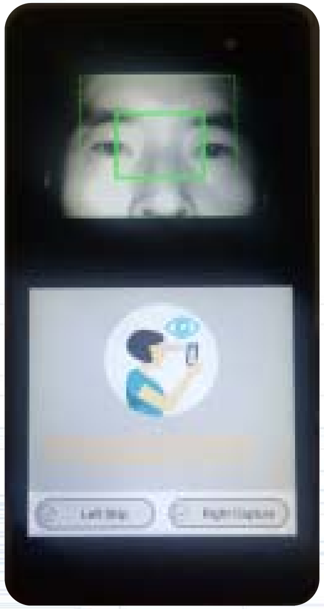


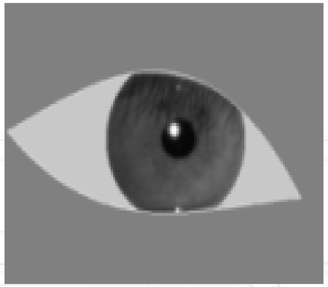
Iris recognition on mobile devices

- Chip level solution of iris imaging
- Iris image acquisition under complex conditions
- Iris image quality assessment and enhancement
- Improvement of usability with friendly interface and advanced algorithms
- Secure processing and storage of iris information in mobile operating systems

Successful applications of iris recognition on mobile devices

The first Chinese mobile phone with iris recognition

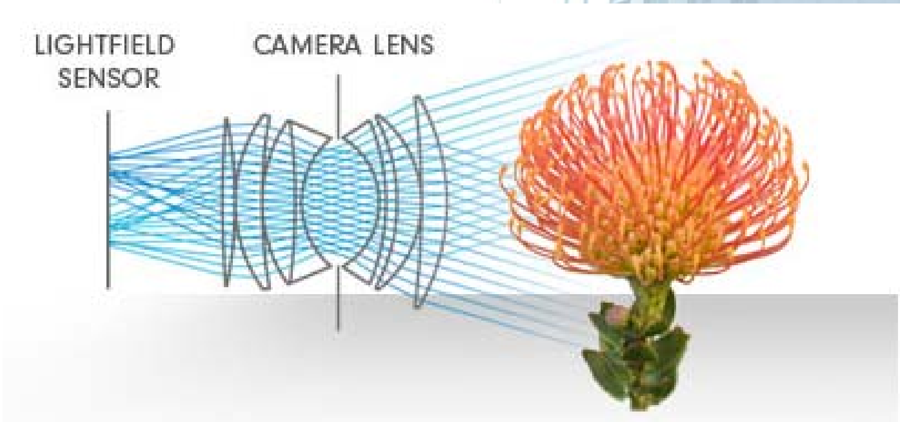


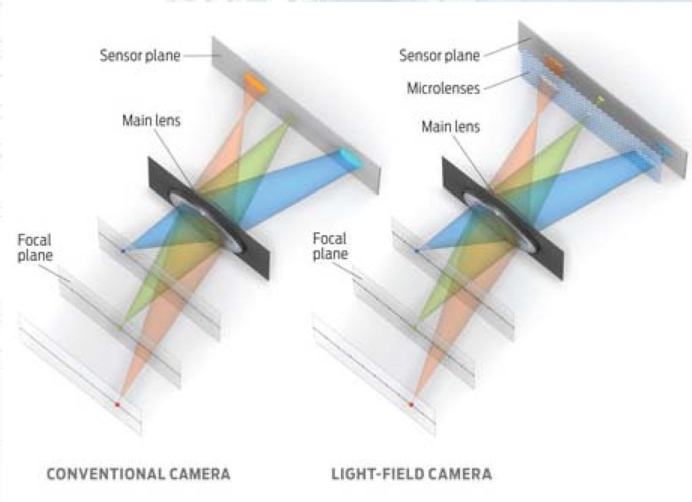


AadHaar Authentication in India

Banking applications

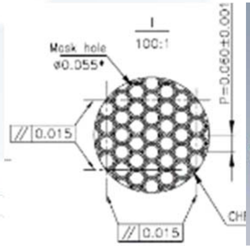
Light field photography for iris image acquisition

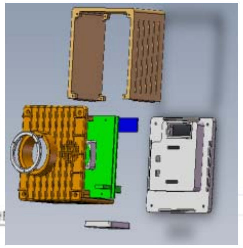




Development of light field cameras

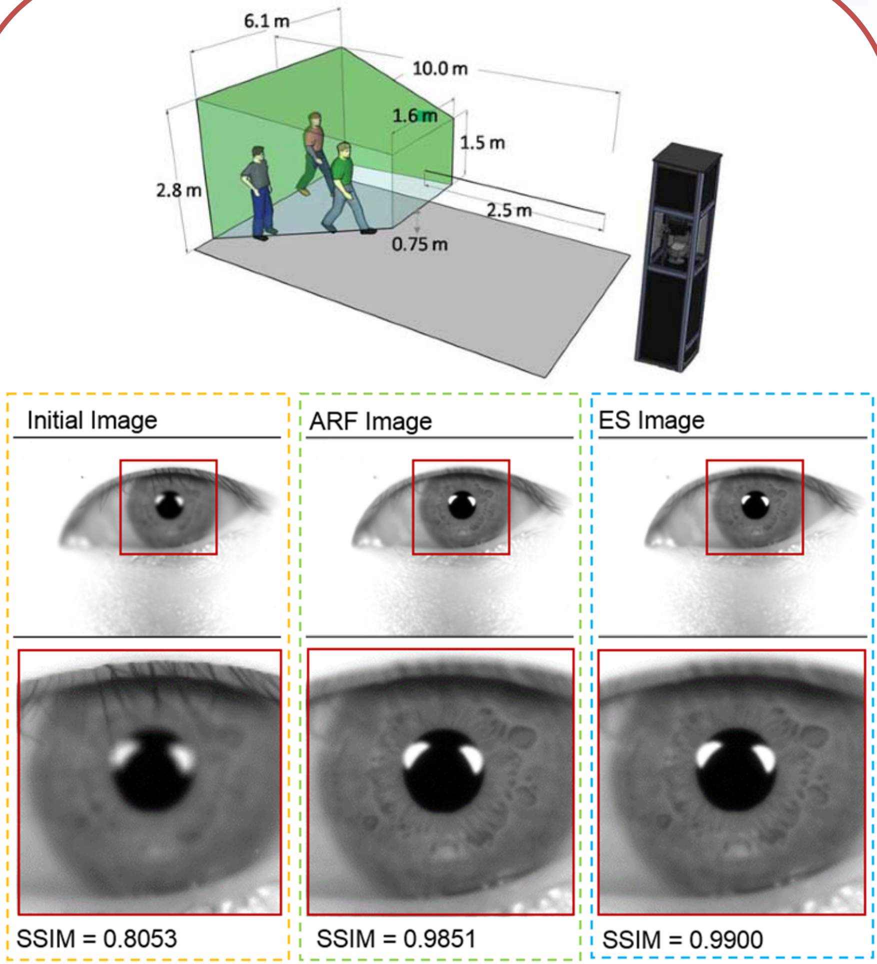
- High-resolution cameras with micro-optical lenslets
- Computational imaging algorithms (refocusing, depth estimation)



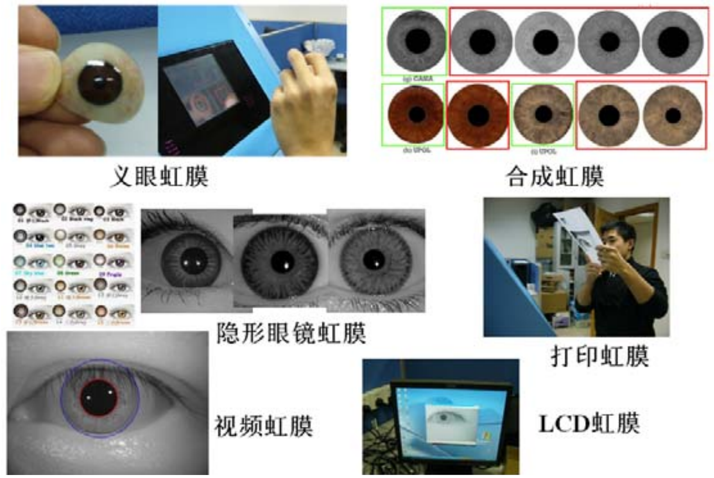



1. Yunlong Wang, Fei Liu, Kunbo Zhang, Guangqi Hou, Zhenan Sun, Tieniu Tan, LFNet: A Novel Bidirectional Recurrent Convolutional Neural Network for Light-Field Image Super-Resolution, IEEE Transactions on Image Processing, Vol. 27, No. 9, 2018, pp.4274-4286.
2. Chi Zhang, Guangqi Hou, Zhaoxiang Zhang, Zhenan Sun, Tieniu Tan, Efficient auto-refocusing for light field camera, Pattern Recognition, Vol.81, 2018, pp.176-189.
3. Fei Liu, Guangqi Hou, Zhenan Sun, Tieniu Tan, High quality depth map estimation of object surface from light-field images, Neurocomputing, Vol.252, 2017, pp.3-16.

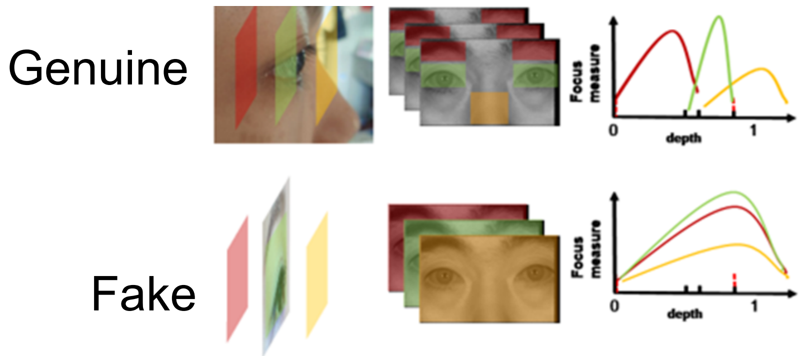
Promising applications of light field imaging in iris recognition



Extending depth-of-field (6X)

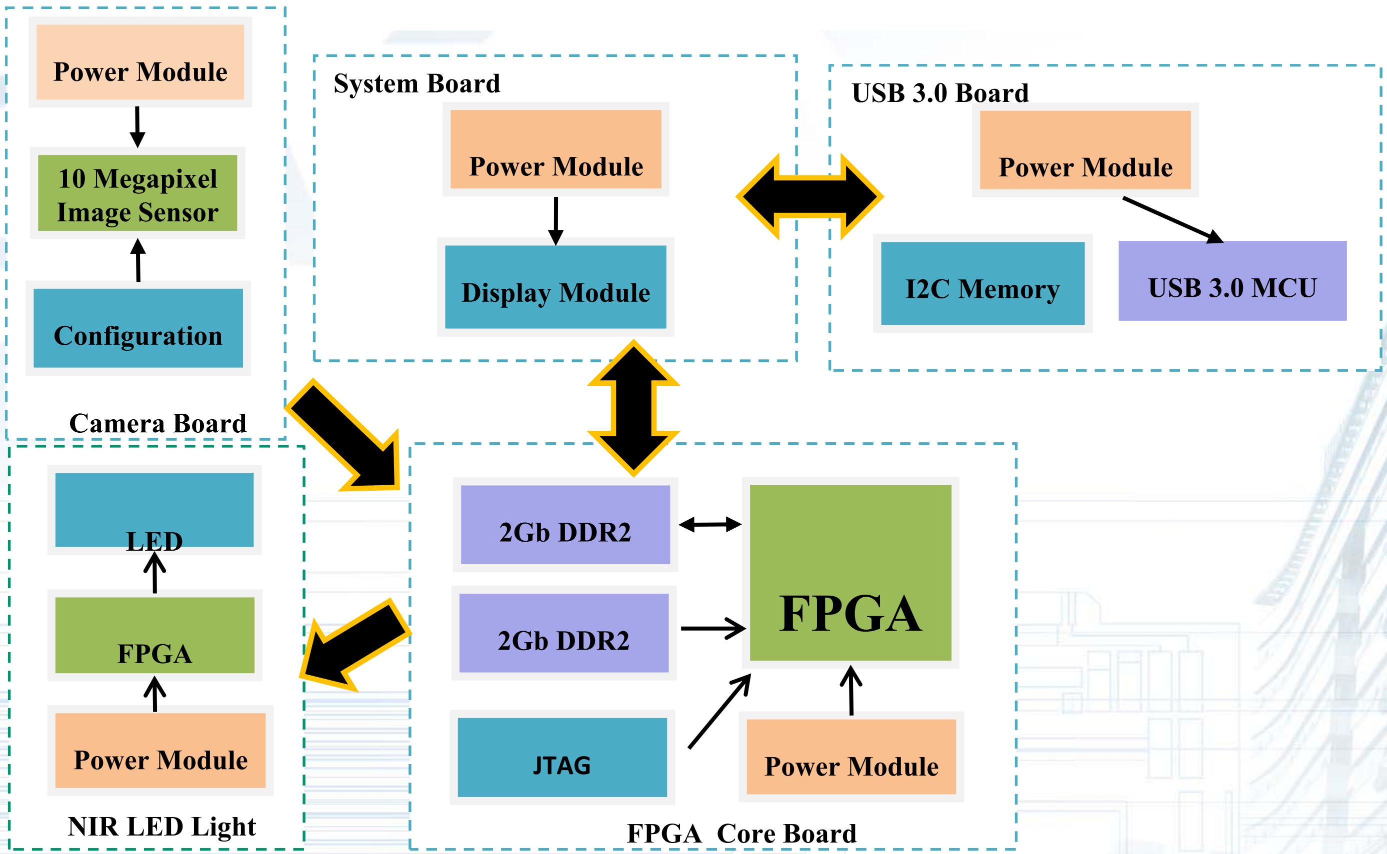


Focus value variations of refocused image regions around human eyes



Liveness detection

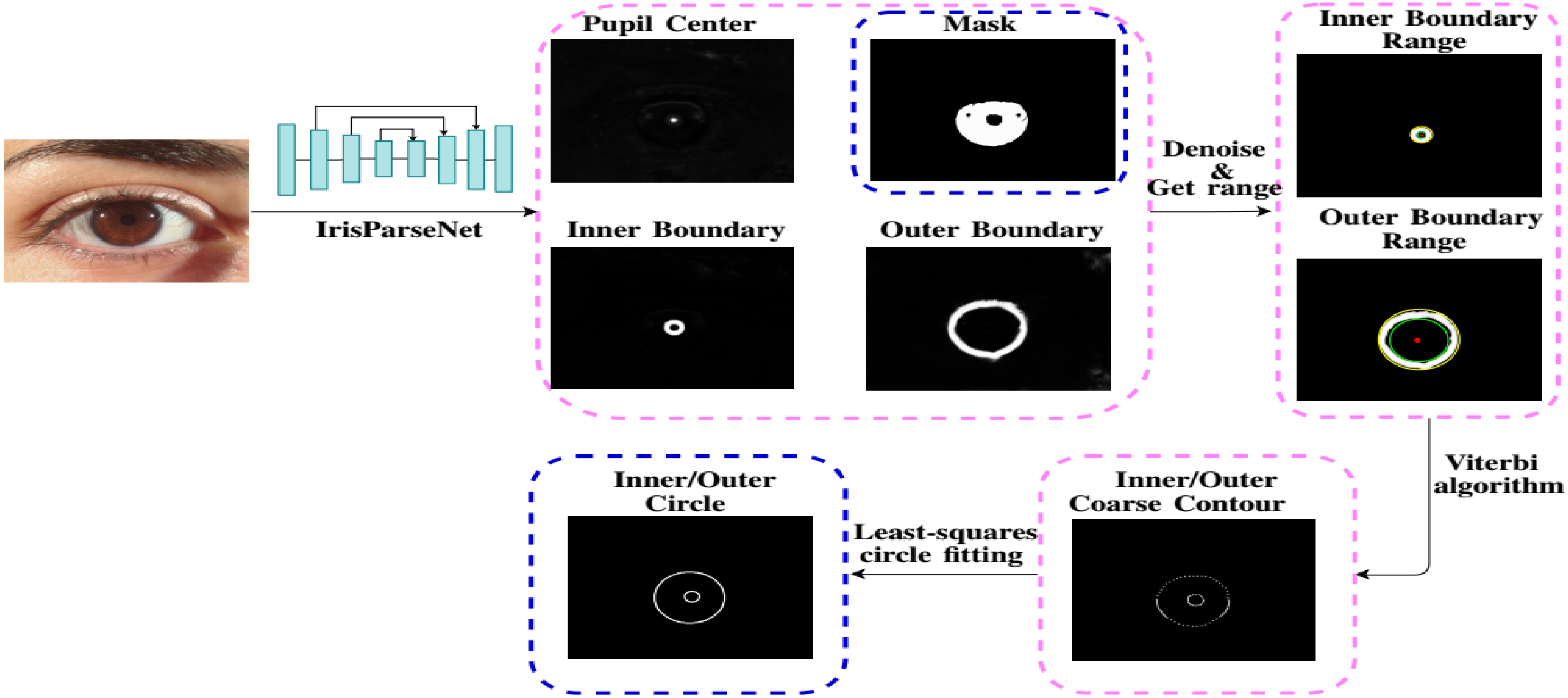
Long-range Iris/Face Recognition System



- High Resolution Iris Camera
- High-Speed Iris Image Acquisition
- NIR Illumination Optimization
- Fast Recognition Procedure

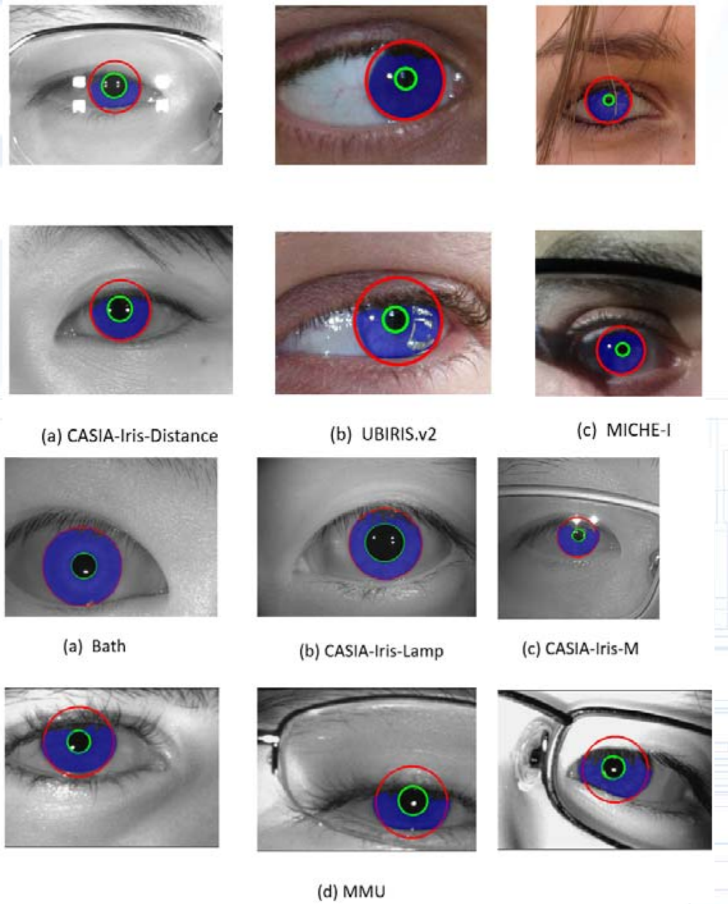
Multi-task Neural Network for Iris Segmentation and Localization

A multi-task deep neural network is proposed for iris region segmentation and iris boundary localization and they both are important for iris image preprocessing.



Caiyong Wang et al., Joint Iris Segmentation and Localization Using Deep Multi-task Learning Framework, Submitted to IEEE Trans. IFS.

Multi-task Neural Network for Iris Segmentation and Localization

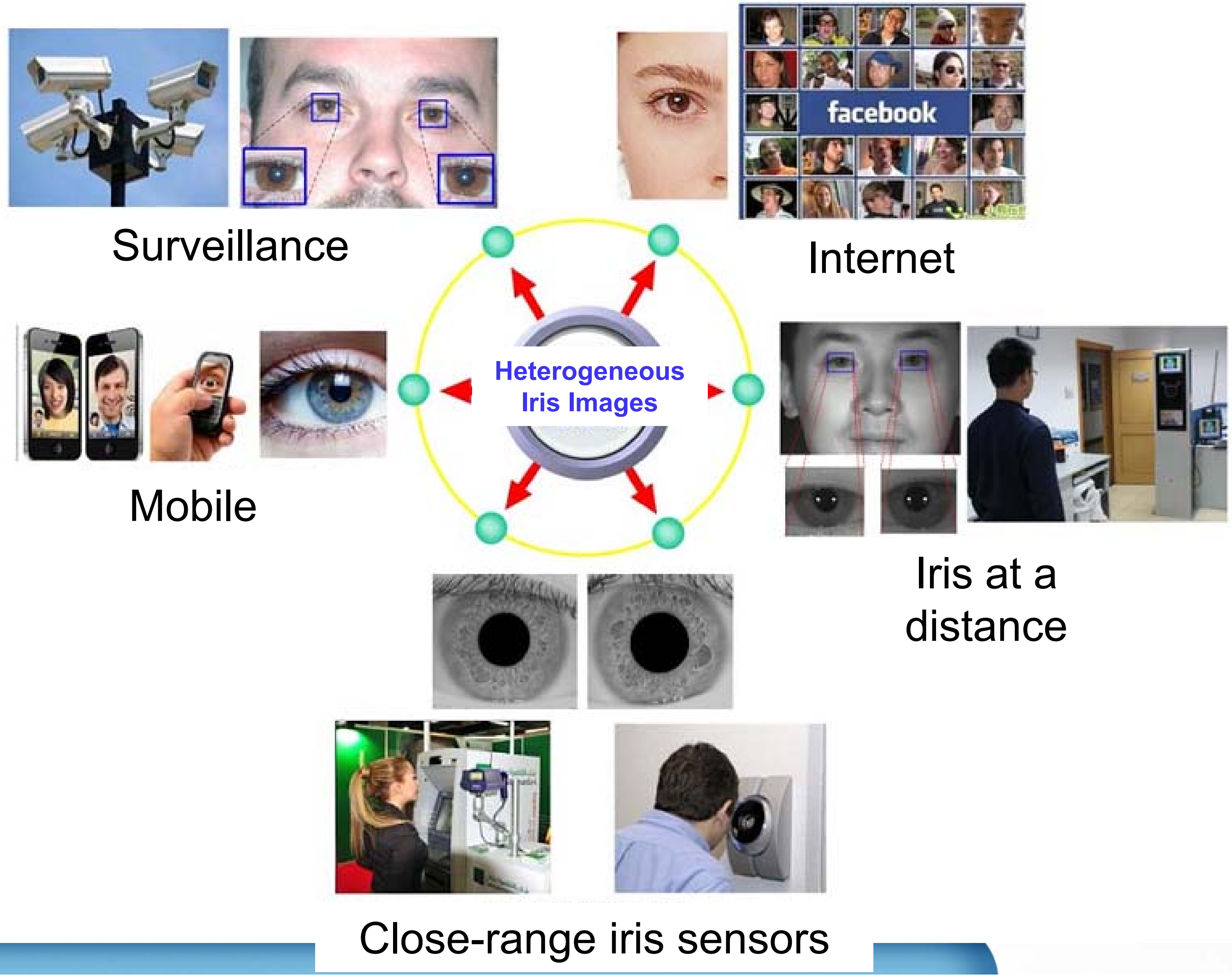


Method	Dataset	E1 (%)	E2 (%)	F1 $\mu(\%)$	F1 $\sigma(\%)$	mIOU (%)	Average Runtime(s)
T. Tan *et. al.* [65]	UBIRIS	1.31	N/A	N/A	N/A	N/A	N/A
RTV-L^1 [13]	CASIA	0.68	0.44	87.55	4.58	78.11	2.46
	UBIRIS	1.21	0.83	85.97	8.72	74.01	1.07
	MICHE	2.27	1.13	77.10	14.71	64.21	1.58
Haindl and Krupička [24]	UBIRIS	3.24	1.62	77.03	20.67	65.08	14.33
	MICHE	5.08	2.54	62.19	25.28	49.79	21.94
MFCNs [1]	CASIA	0.50	0.25	93.14	2.97	87.30	0.47†
	UBIRIS	0.92	0.46	90.78	4.70	81.92	0.32†
	MICHE	0.96	0.48	88.70	8.98	80.63	0.38†
IrisParseNet (ASPP)	CASIA	**0.40**	**0.20**	**94.30**	**3.70**	**89.40**	**0.25†**
	UBIRIS	**0.84**	**0.42**	**91.82**	**4.26**	**85.39**	**0.11†**
	MICHE	0.82	**0.41**	91.33	8.04	84.79	**0.13†**
IrisParseNet (PSP)	CASIA	0.41	0.21	94.20	3.16	89.19	0.30†
	UBIRIS	0.85	**0.42**	91.63	4.06	85.07	**0.11†**
	MICHE	**0.81**	**0.41**	**91.50**	**8.01**	**85.07**	**0.13†**

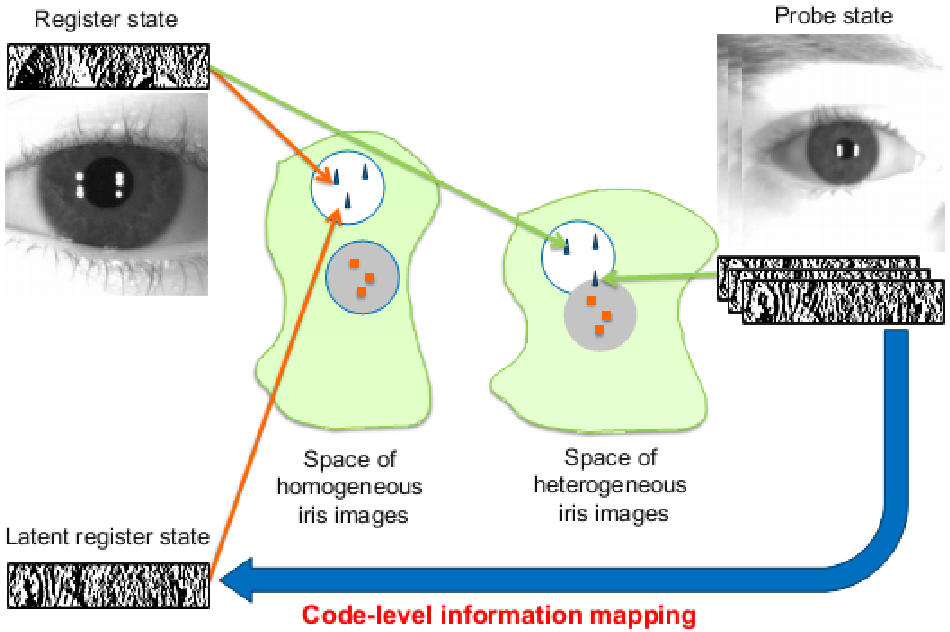
† GPU time.

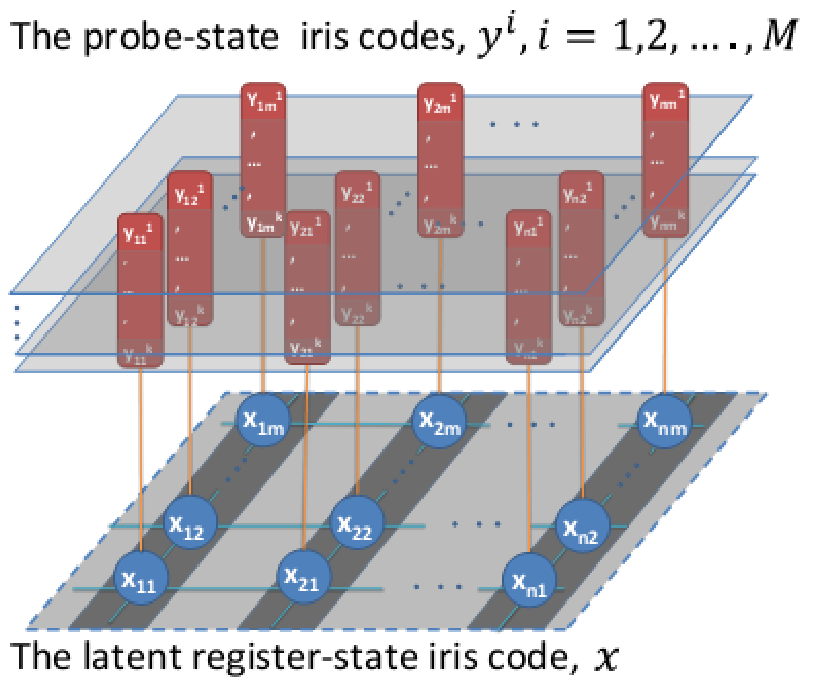
Caiyong Wang et al., Joint Iris Segmentation and Localization Using Deep Multi-task Learning Framework, Submitted to IEEE Trans. IFS.

Recognition of Heterogeneous Iris Images



A Code-Level Approach to Heterogeneous Iris Recognition

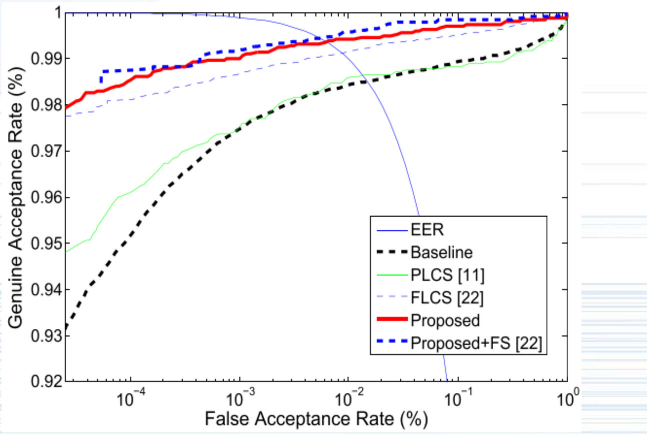




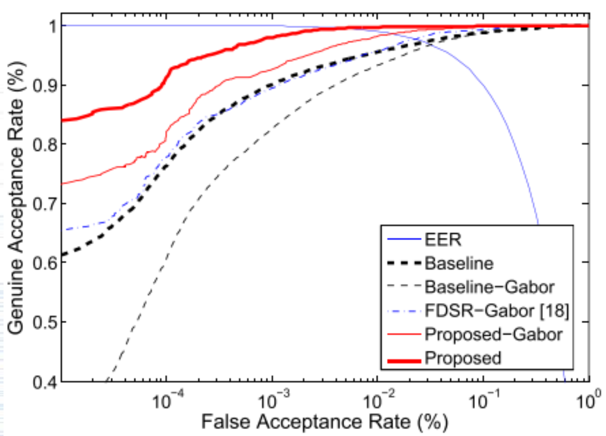
Nianfeng Liu, Jing Liu, Zhenan Sun, Tieniu Tan, A Code-level Approach to Heterogeneous Iris Recognition, IEEE Transactions on Information Forensics and Security, vol. 12, no.10, 2017, pp. 2373-2386.

A Code-Level Approach to Heterogeneous Iris Recognition

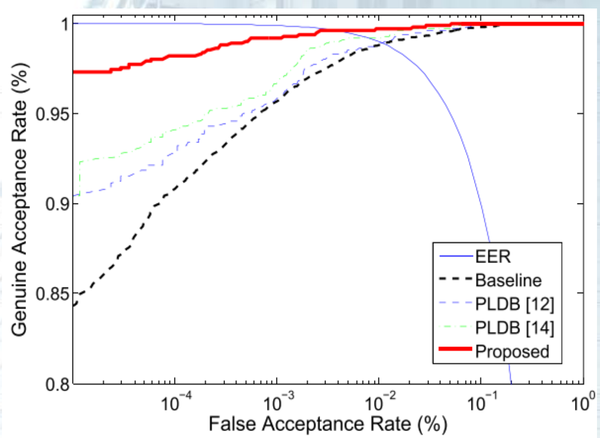
Experimental results of matching cross-sensor, high-resolution versus low-resolution and, clear versus blurred iris images.



Cross-sensor iris recognition.
PLCS: pixel-level cross-sensor solution.
FLCS: feature-level cross-sensor solution.

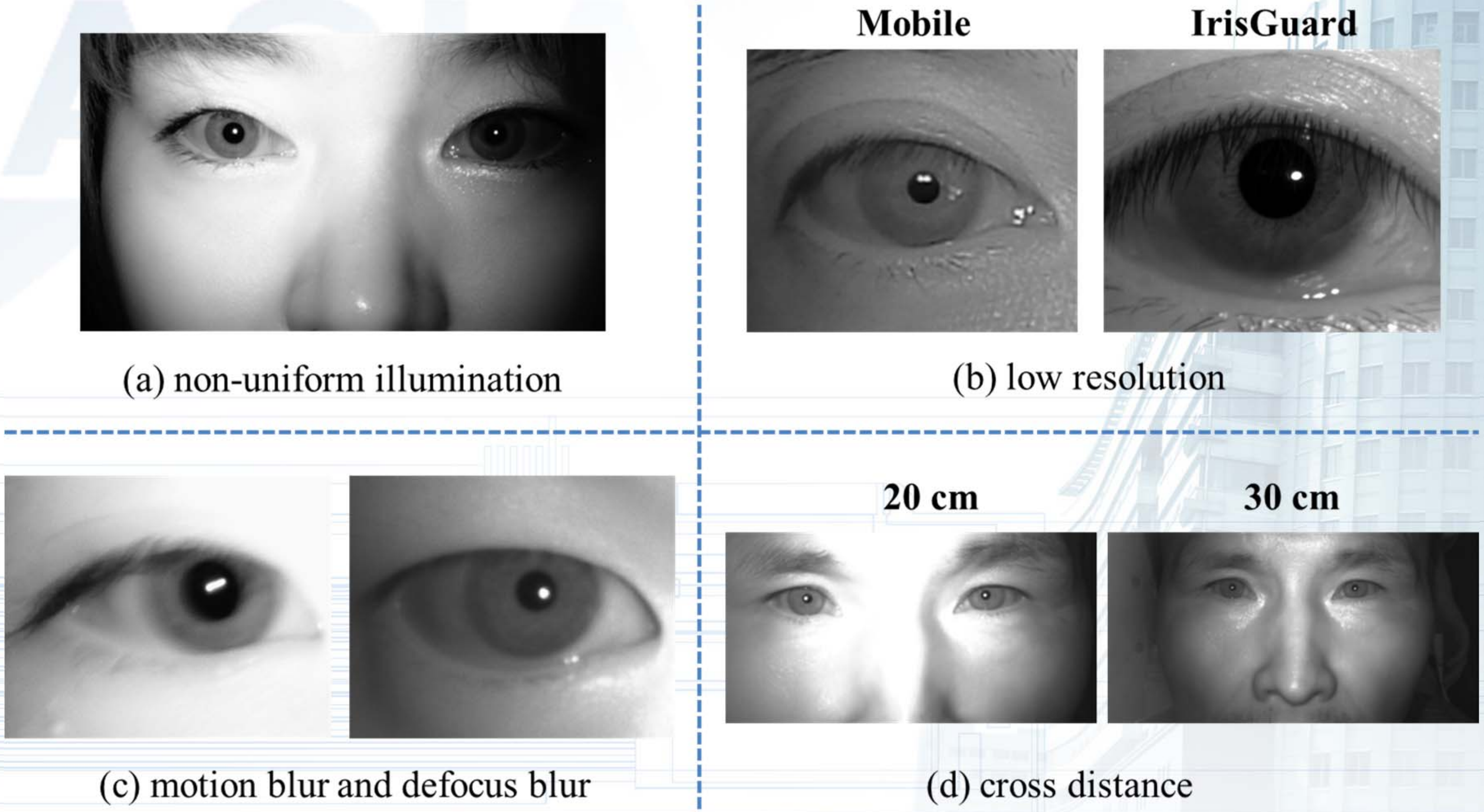


Low-resolution iris recognition.
FDSR: feature-level super-resolution solution.



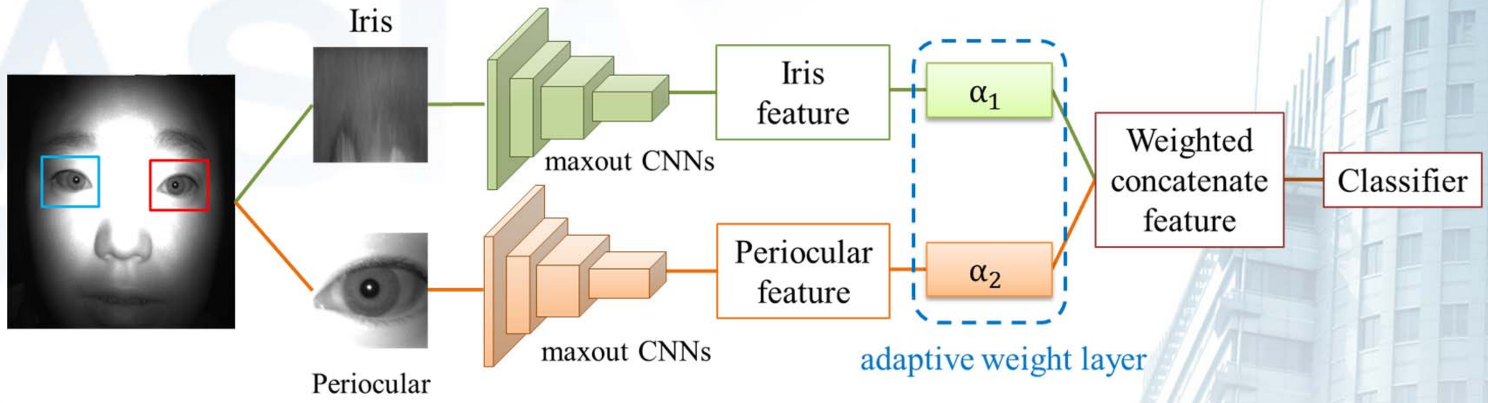
Defocus blurred iris recognition.
PLDB: pixel-level deblurring method.

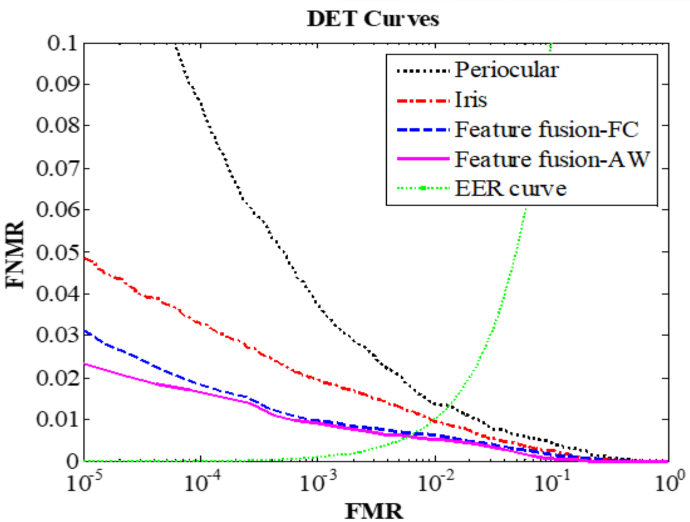
Deep Feature Fusion for Iris and Periocular Biometrics on Mobile Devices



- It is a challenging problem to recognize iris images on mobile devices.
- So a deep feature fusion network is proposed to exploit the complementary information presented in iris and periocular regions.

Deep Feature Fusion for Iris and Periocular Biometrics



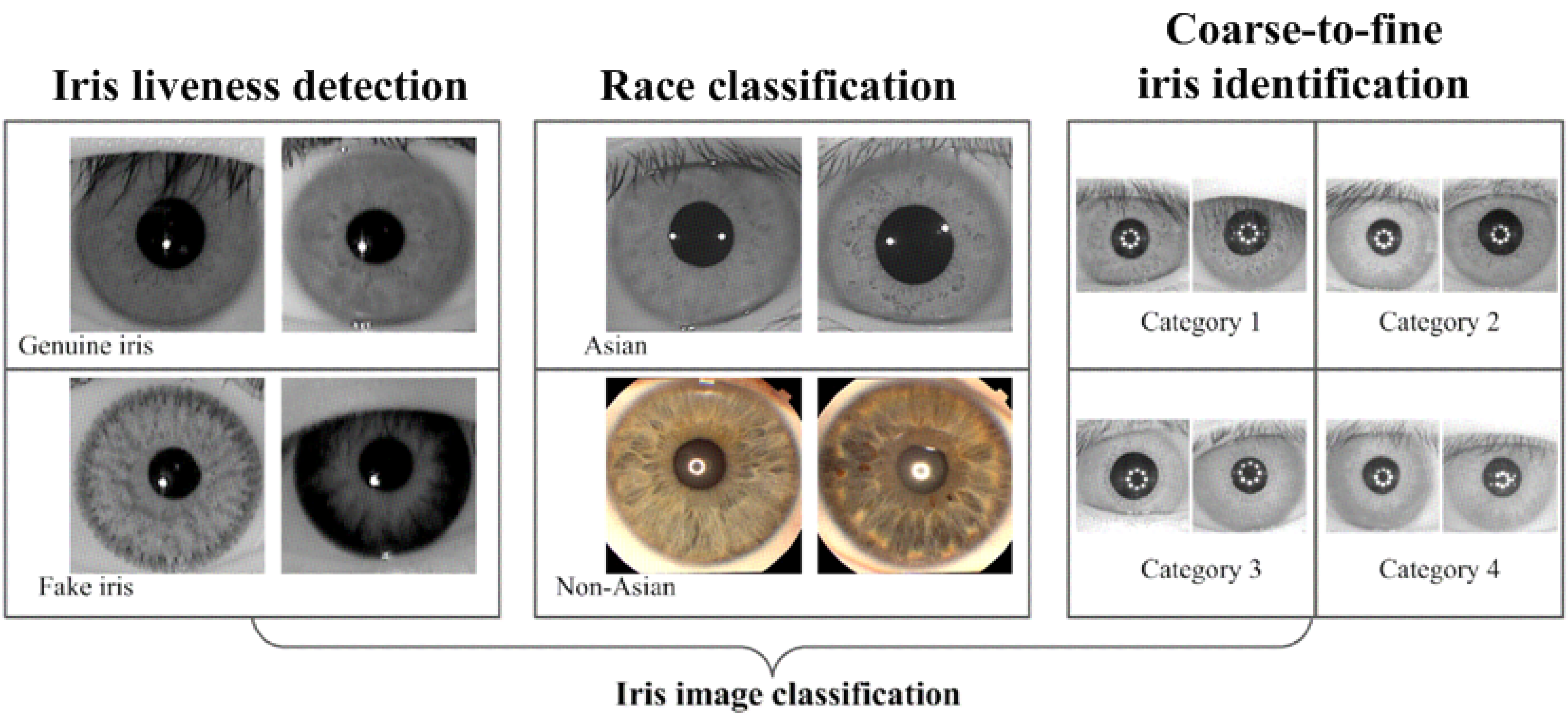


Method	EER	FNMR@FMR=10^{-5}	DI
Periocular	1.31%	12.7%	5.35
Iris	0.96%	4.83%	5.80
Feature fusion–FC	0.67%	3.10%	6.37
Feature fusion–AW	**0.60%**	**2.32%**	**6.50**

Qi Zhang, Haiqing Li, Zhenan Sun, Tieniu Tan, Deep Feature Fusion for Iris and Periocular Biometrics on Mobile Devices, IEEE Transactions on Information Forensics and Security, Vol.13, No.11, 2018, pp.2897-2912.

Iris Classification

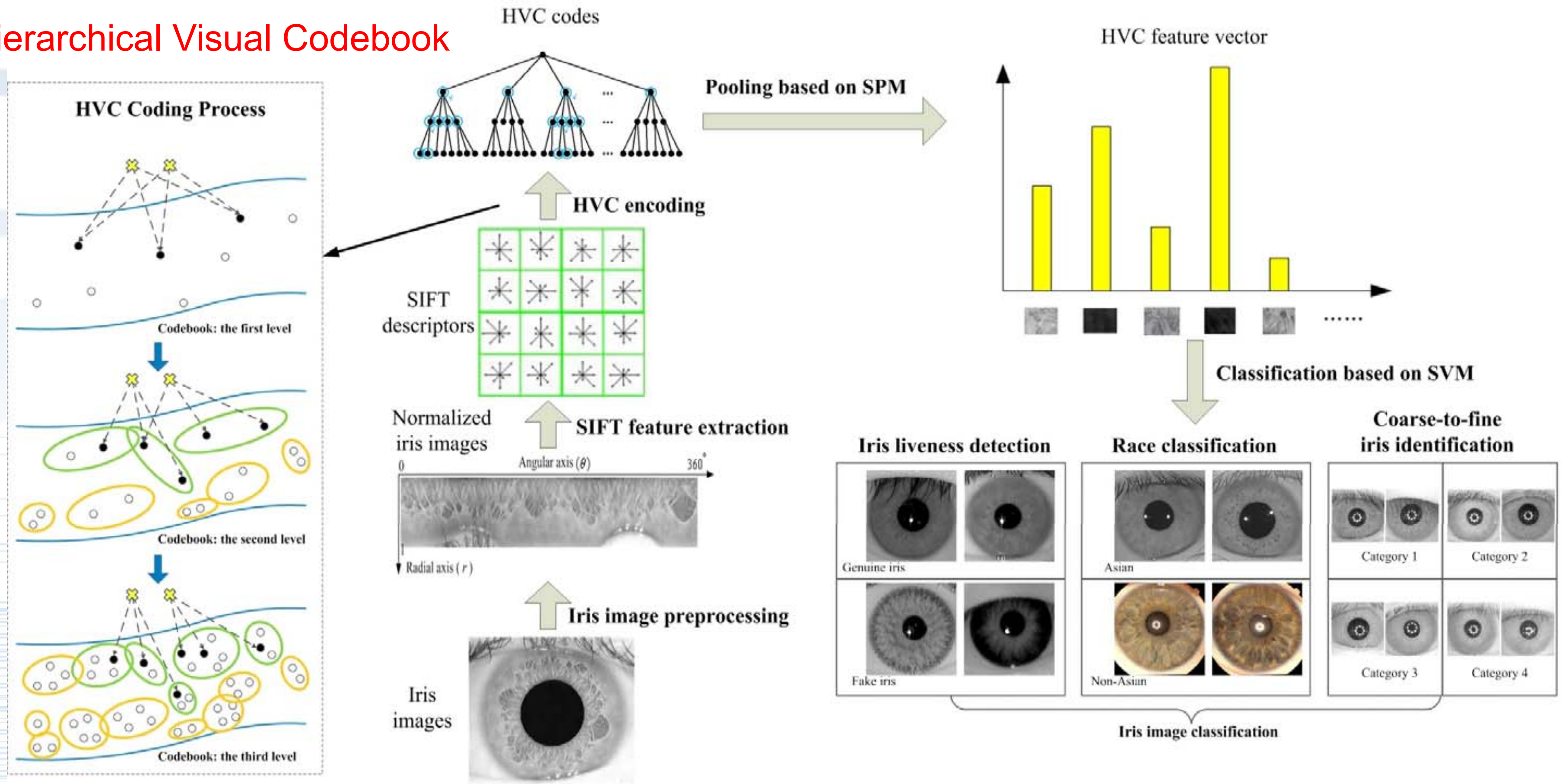
One solution to multiple problems



Iris image classification:
- Classify iris image into application specific category
- Different from iris recognition

Iris Classification

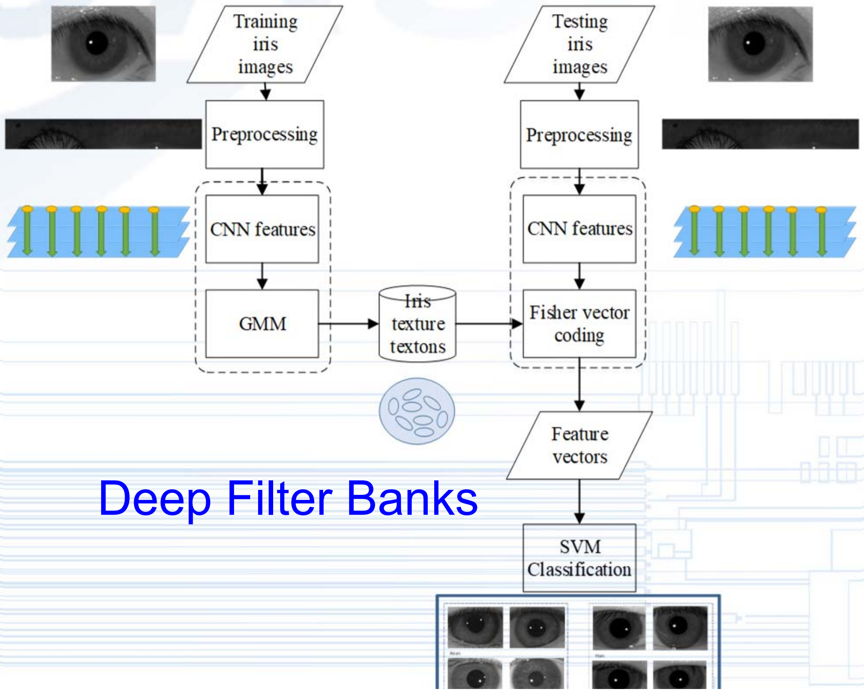
Hierarchical Visual Codebook



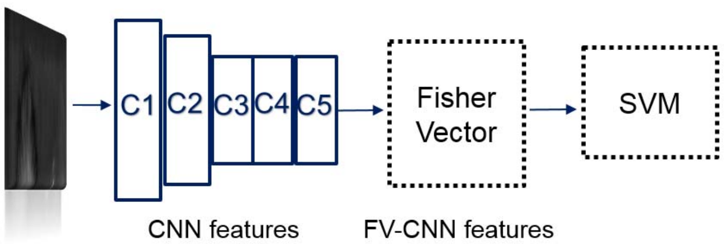
Zhenan Sun, Hui Zhang, Tieniu Tan, and Jianyu Wang, "Iris Image Classification Based on Hierarchical Visual Codebook," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 36, No. 6, pp.1120-1133, 2014.

Iris Classification based on CNN features and Fisher vector coding

- Recent research results show that orderless pooling of convolutional neural network features is a remarkably good texture descriptor for iris classification



Deep Filter Banks



Coarse classification

Method	CCR (%)
Gabor and K-means[10]	63.88
SIFT and LLC[11]	83.72
SIFT and HVC[12]	85.21
FC-CNN	91.18
FV-CNN(ours)	**91.94**

Liveness Detection

Databases	FV-CNN	MCNN	HVC	HVC with SPM
ND-Contact	100%	100%	100%	100%
CASIA-Iris-Fake	99.92%	100%	99.51%	99.79%
Syn_real	100%	99.87%	-	-
Warsaw	100%	98.15%	-	-
ATVS	99.91%	100%	-	-

Applications of Iris Recognition

Syrian refugees identification

Miss children identification

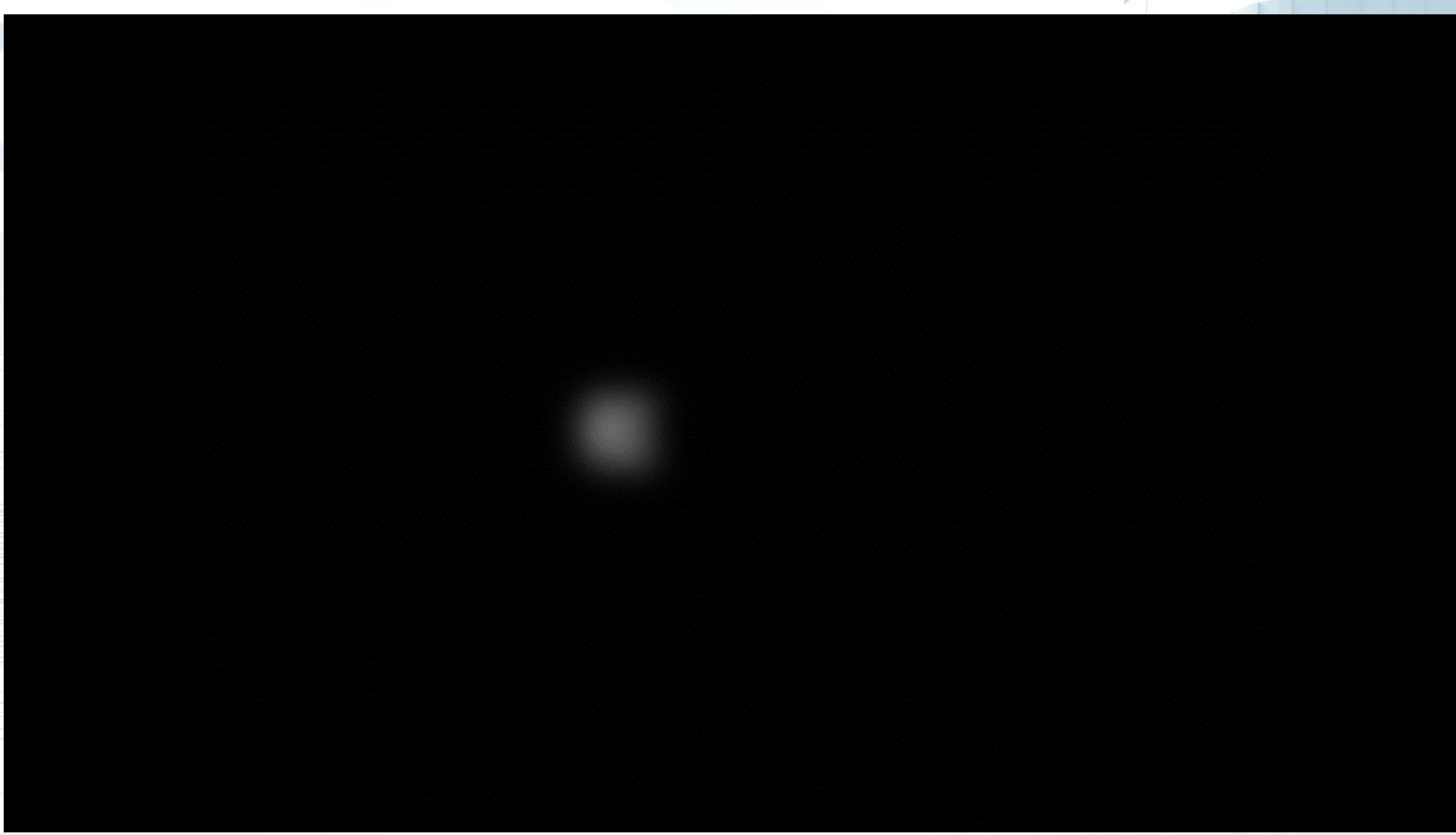
Anti-terrorism

Prisoners identification

Coal miner identification

Banking

Demo of Iris Recognition



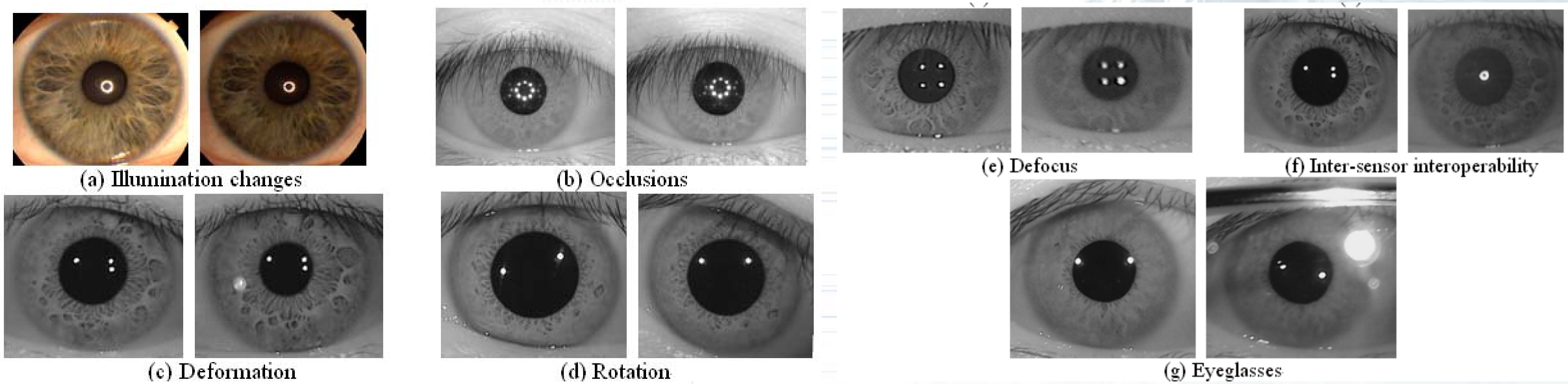
Iris Recognition of Refugees

We have cooperated with IrisGuard to use iris recognition for identity management of refugees.

Open Problems of Iris Recognition

Less or unconstrained iris image acquisition

Forensic applications

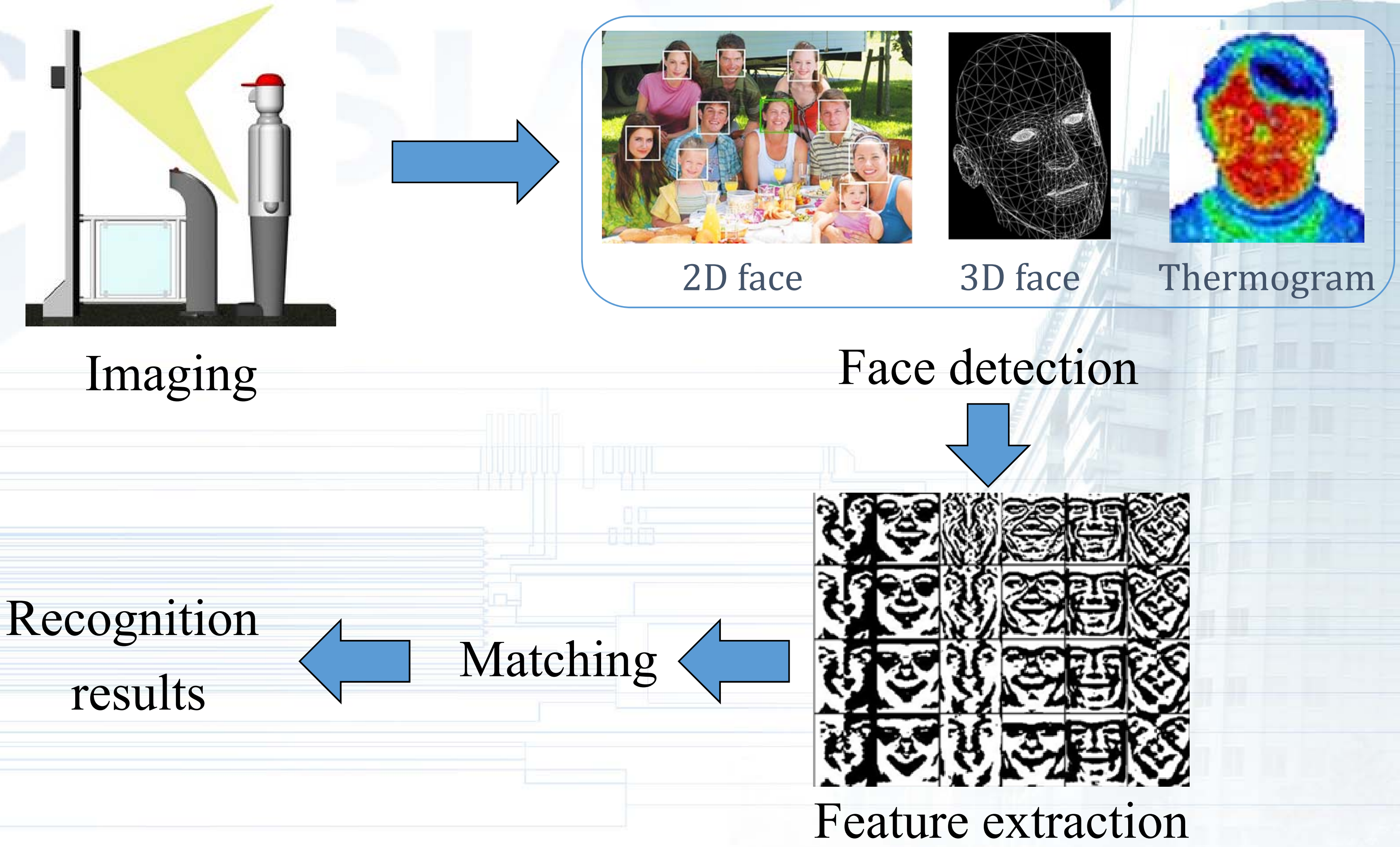


Poor quality iris images

Outline

- Preamble
- Overview of Recent Progress on Biometrics
  - ✓ Fingerprint Recognition
  - ✓ Iris Recognition
  - ✓ Face Recognition
  - ✓ Gait Recognition
  - ✓ Others
- Future Directions and Conclusions

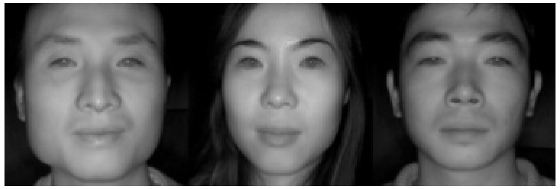
Face Recognition



Popular methods: Gabor/LBP/Ordinal measures/Sparse representations/Deep learning

Recent Work on Face Recognition

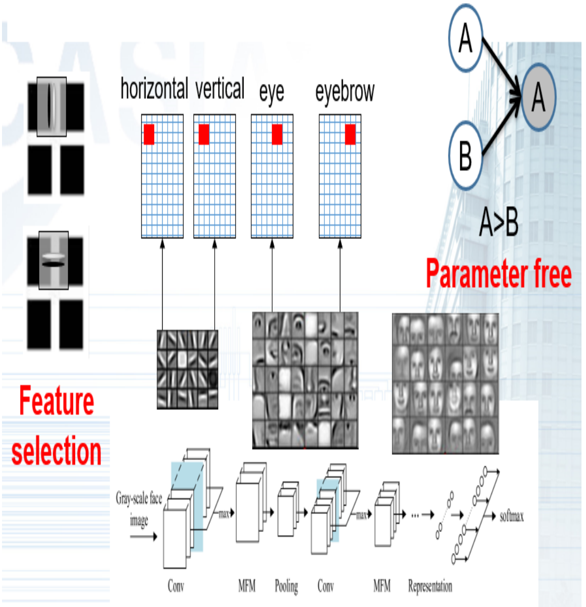
Heterogeneous Face Recognition



NIR vs VIS Face Images

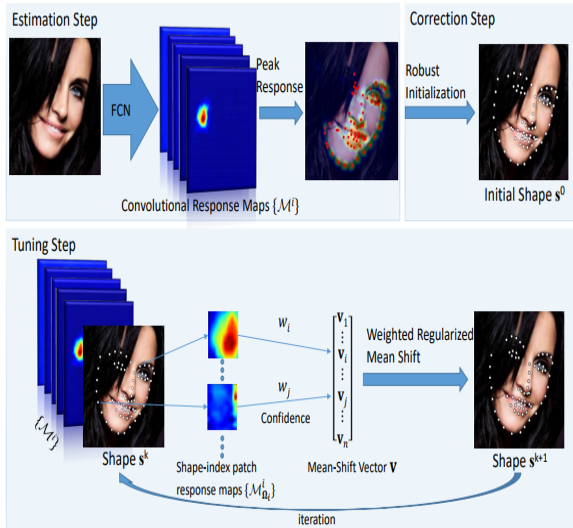
PAMI 2018
Wasserstein CNN

Efficient Face Recognition



TIFS 2018
Light CNN

Accurate Facial Landmark Localization



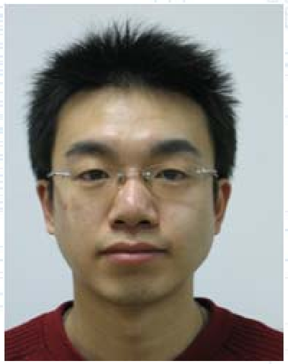
TIFS 2018
Combining Data-driven and Model-driven Methods

Heterogeneous Face Recognition

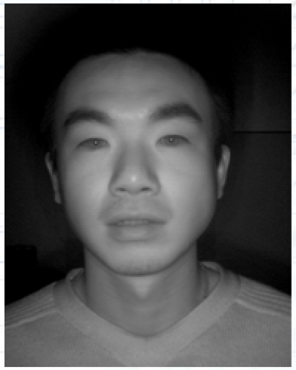
Heterogeneous face recognition (HFR) aims to match facial images acquired from different sensing modalities.

Two problems：

- large intra-class variations of heterogeneous face images
- limited training samples of cross-modality face image pairs

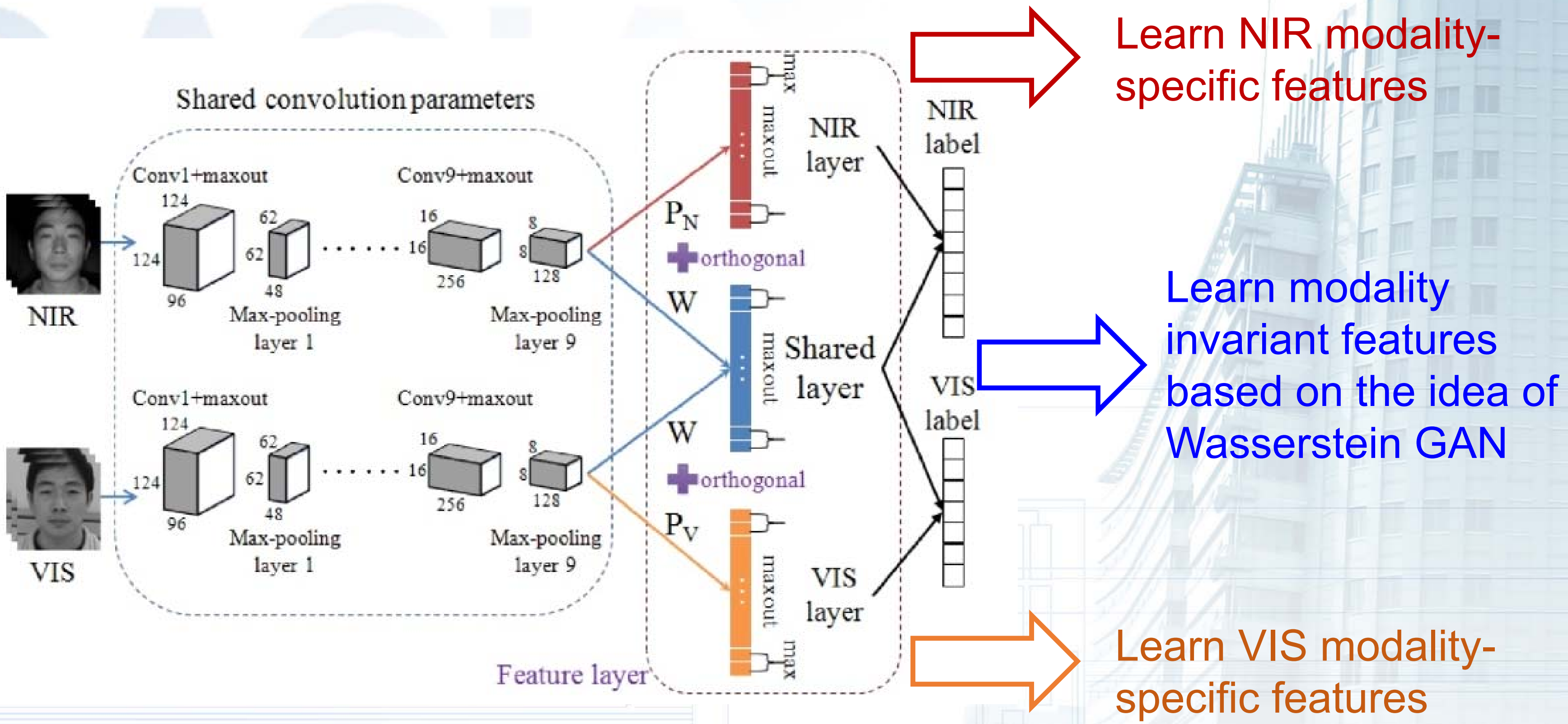


VIS



NIR

Wasserstein CNN: Learning Invariant Features for NIR-VIS Face Recognition



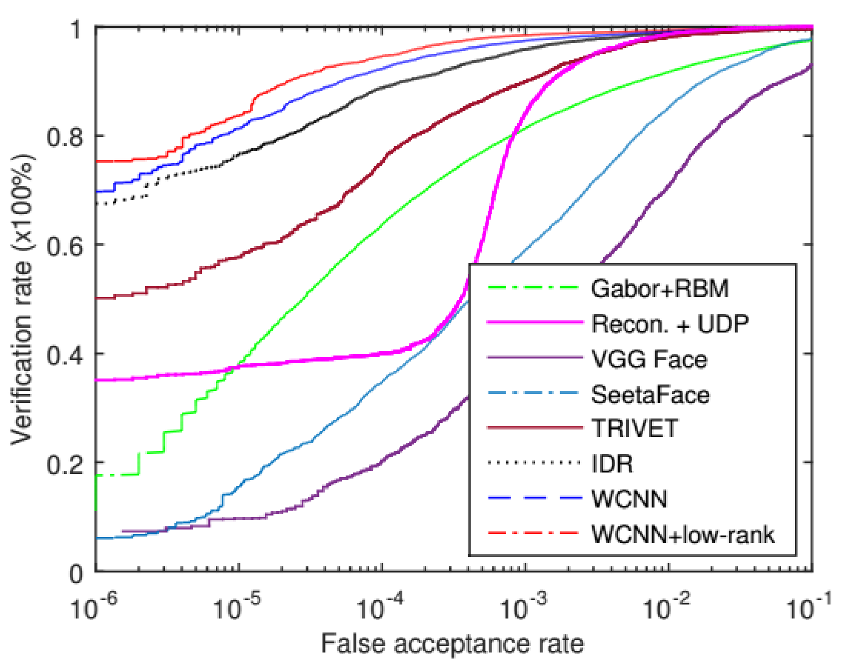
- Ran He, Xiang Wu, Zhenan Sun, Tieniu Tan. Learning Invariant Deep Representation for NIR-VIS Face Recognition. In Proc. AAAI Conference on Artificial Intelligence, 2017.
- Ran He, Xiang Wu, Zhenan Sun, Tieniu Tan. Wasserstein CNN: Learning Invariant Features for NIR-VIS Face Recognition. PAMI, 2018.

Experimental results

CASIA 2.0 NIR-VIS face database

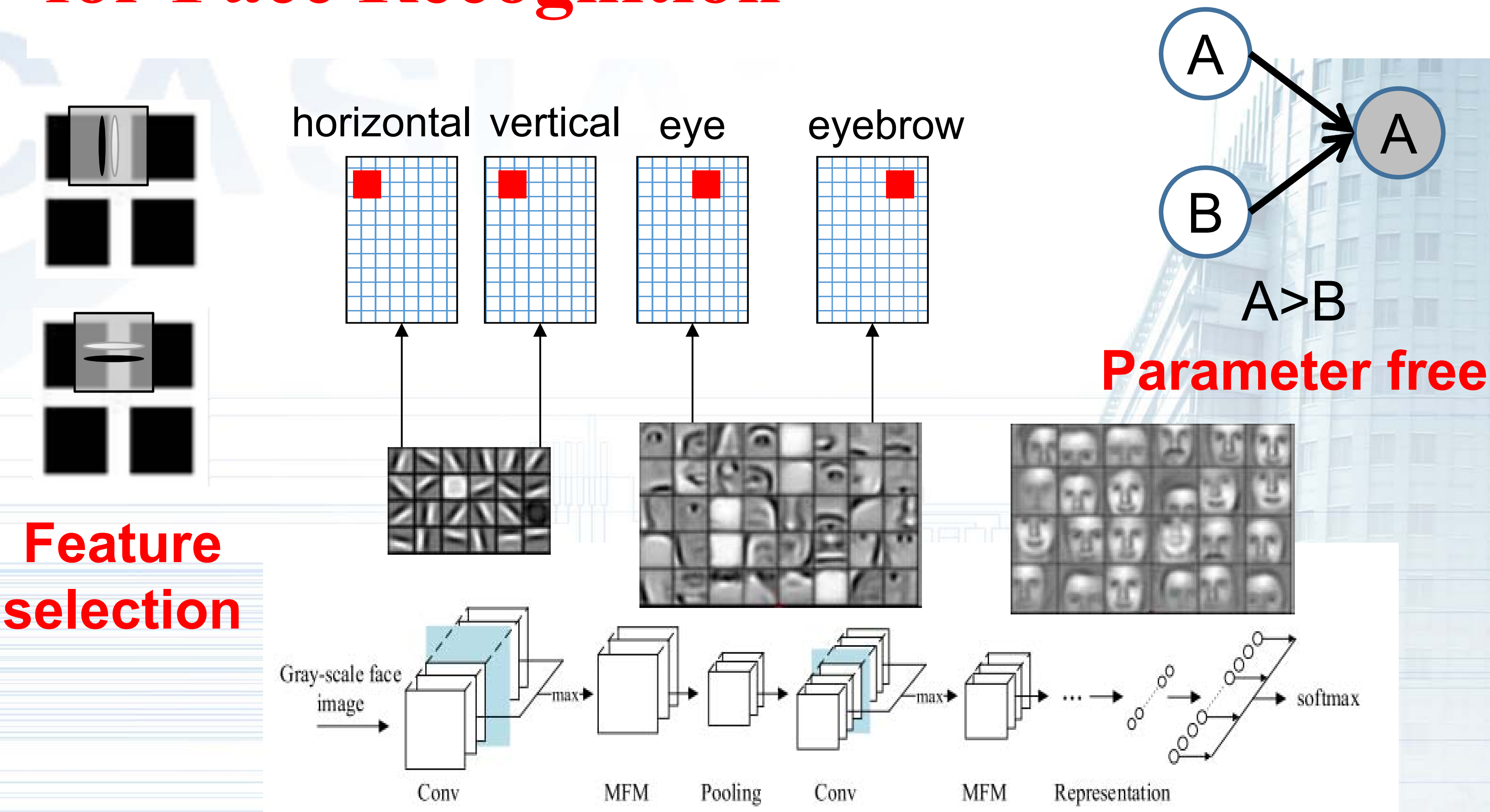
Methods	Rank-1	FAR=1%	FAR=0.1%	Dim
KCSR [53]	33.8	28.5	7.6	-
KPS [43]	28.2	17.4	3.7	-
KDSR [41]	37.5	33.0	9.3	-
PCA+Sym+HCA [4]	23.7	-	19.3	-
LCFS [42] [11]	35.4	35.7	16.7	-
H2(LBP3) [38]	43.8	36.5	10.1	-
C-DFD [54] [11]	65.8	61.9	46.2	-
DSIFT [55]	73.3	-	-	-
CDFL [11]	71.5	67.7	55.1	1000
Gabor+RBM [18]	86.2	-	81.3	-
Recon.+UDP [31]	78.5	-	85.8	1024
CEFD [3]	85.6	-	-	-
VGG [56]	62.1	70.9	39.7	4096
SeetaFace [23]	68.0	85.2	58.8	2048
TRIVET [15]	95.7	98.1	91.0	512
HFR-CNNs [16]	85.9	-	78.0	-
IDNet [8]	87.1	-	74.5	320
IDR [47] AAAI 2017	97.3	98.9	95.7	128
WCNN PAMI 2018	98.4	99.4	97.6	128
WCNN + low-rank	**98.7**	**99.5**	**98.4**	128

PAMI 2018



Significant improvement of NIR-VIS face identification and verification

Light CNN Based on Ordinal Measures for Face Recognition

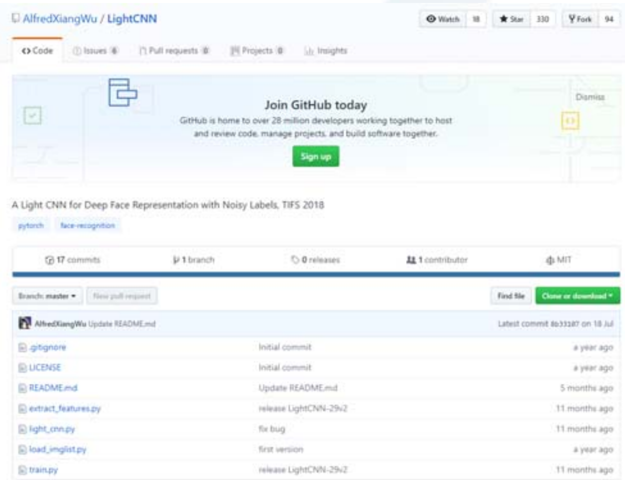


Xiang Wu, Ran He, Zhenan Sun, Tieniu Tan. A Light CNN for Deep Face Representation with Noisy Labels. IEEE TIFS, 2018.

State-of-the-art Performance of Light CNN on the LFW, BLUFR and MegaFace

Method	Acc on LFW	BLUFR		MegaFace		Performance	
		VR@0.1%	DIR@1%	Rank-1	VR@1e-6	Speed	Size
DeepID2+ [37]	99.47	-	-	-	-	-	-
WebFace [38]	97.73	80.26	28.90	-	-	-	-
FaceNet [24]	99.63	-	-	70.49	86.47	-	-
CenterLoss [25]	99.28	-	-	65.23	76.51	-	-
SphereFace [27]	99.42	-	-	72.73	85.56	-	-
Light CNN [20]	99.40	98.88	92.29	73.75	85.13	121 ms	50.30 MB
VGG Face* [39]	97.27	73.34	36.56	-	-	581 ms	524 MB
CenterLoss*	98.70	94.64	70.66	63.10	74.66	160 ms	76.54 MB

Light CNN has become a popular face recognition model with hundreds of citations



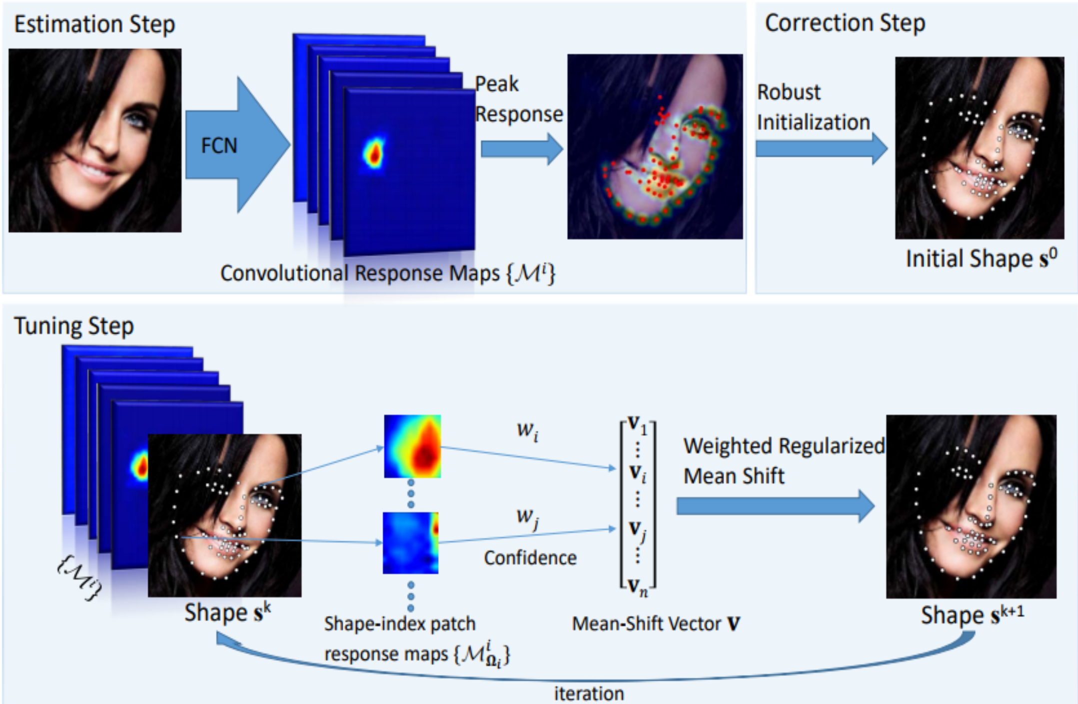
Winner on the competition of MS-Celeb-1M
(Light CNN used by the Shuicheng Yan's Group)

Network	Training ID	TPR@FPR=0.01	Top-1	Scheme
ResNet-18 [6]	10k	0.201	-	None
ResNet-18 [6]	10k	0.343	-	At
ResNet-50 [6]	10k	0.315	-	None
ResNet-50 [6]	10k	**0.437**	-	At
ResNet-50 [6]	50k	0.686	-	None
ResNet-50 [6]	50k	0.758	-	At
ResNet-50 [6]	50k	0.857	-	L2
ResNet-50 [6]	50k	**0.896**	0.9908	At+L2
ResNet-50 [6]	80k	0.824	-	At
ResNet-50 [6]	80k	**0.903**	0.9913	At+L2
Light-CNN-29 [23]	80k	0.889	-	None
Light-CNN-29 [23]	80k	**0.929**	0.993	At
Light-CNN-29 [23]	80k	0.917	-	At+L2

- Open source
  - **Caffe**: https://github.com/AlfredXiangWu/face_verification_experiment
  - **Pytorch**: https://github.com/AlfredXiangWu/LightCNN
  - **Mxnet**: https://github.com/tornadomeet/mxnet-face
  - **Tensorflow**: https://github.com/yxu0611/Tensorflow-implementation-of-LCNN
- Performance on LFW:
  - LightCNN-9: Caffe (98.80%); Pytorch (98.70%) ; MXNet (98.13%);
  - LightCNN-29: Pytorch (99.43%); Tensorflow (99.43%)

Robust Facial Landmark Detection

Prior knowledge on geometric distribution of facial landmarks is integrated into deep learning process, with enhanced robustness in facial landmark detection.



Results on the 300W

Hongwen Zhang, Qi Li, Zhenan Sun, and Yunfan Liu, "Combining Data-driven and Model-driven Methods for Robust Facial Landmark Detection," IEEE Transactions on Information Forensics and Security (TIFS), 2018.

Recent Work on Face Image Generation

Photo-realistic Face Image Generation

Unconditional Generation	IntroVAE [NIPS 2018]
Rotation	• TP-GAN [ICCV 2017] • CAPG-GAN [CVPR2018] • HF-PIM [NIPS 2018]
Super-resolution	• Wavelet-SRNet [ICCV 2017]
Make-up	• BLAN [AAAI 2018]
Cross-spectral	• AD-HFR [AAAI 2018]
Completion	• FCENet [AAAI 2019]
Expression synthesis	• G2-GAN [ACM MM 2018] • CAFP-GAN [ACM MM 2018]
Aging	• GLCA-GAN [ICPR 2018]

The theory of face image generation

Generative adversarial networks (GANs) have been successfully applied in image/video/music/art generation, computer vision and pattern recognition.

MIT Technology Review

10 BREAKTHROUGH TECHNOLOGIES 2018

Dueling Neural Networks

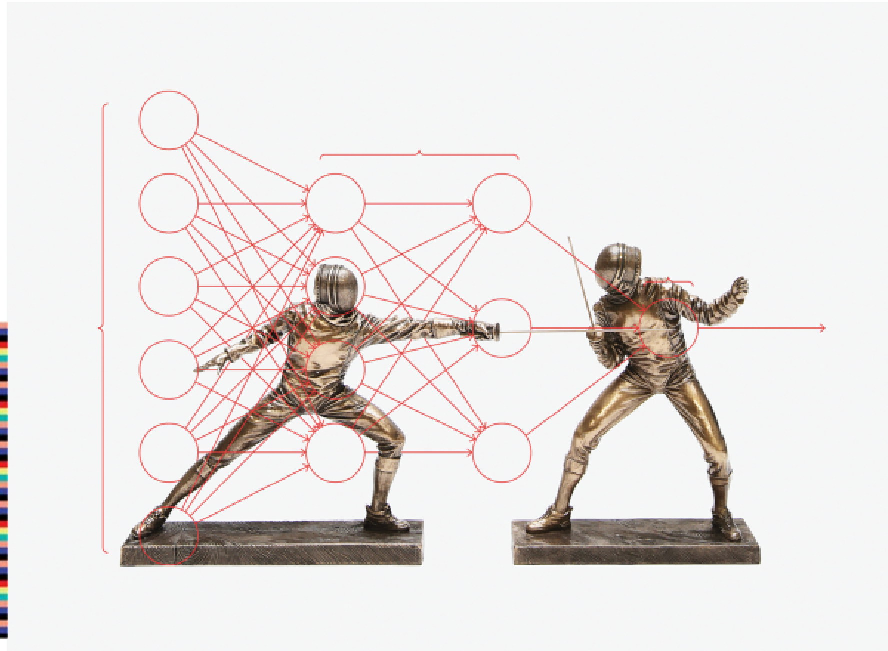


ILLUSTRATION BY DEREK BRAHNEY | DIAGRAM COURTESY OF MICHAEL NIELSEN, "NEURAL NETWORKS AND DEEP LEARNING", DETERMINATION PRESS, 2015

Dueling Neural Networks

Breakthrough
Two AI systems can spar with each other to create ultra-realistic original images or sounds, something machines have never been able to do before.

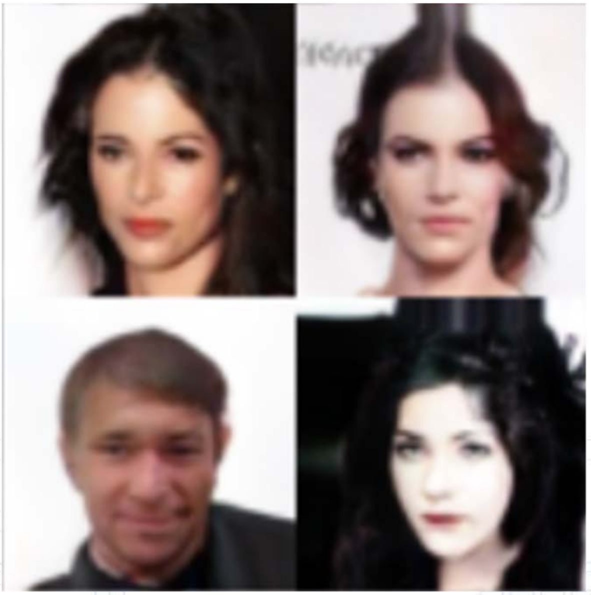
Why It Matters
This gives machines something akin to a sense of imagination, which may help them become less reliant on humans—but also turns them into alarmingly powerful tools for digital fakery.

Key Players
Google Brain, DeepMind, Nvidia

Availability
Now

Generating face images from white noise

[Goodfellow et al., 2014]
University of Montreal



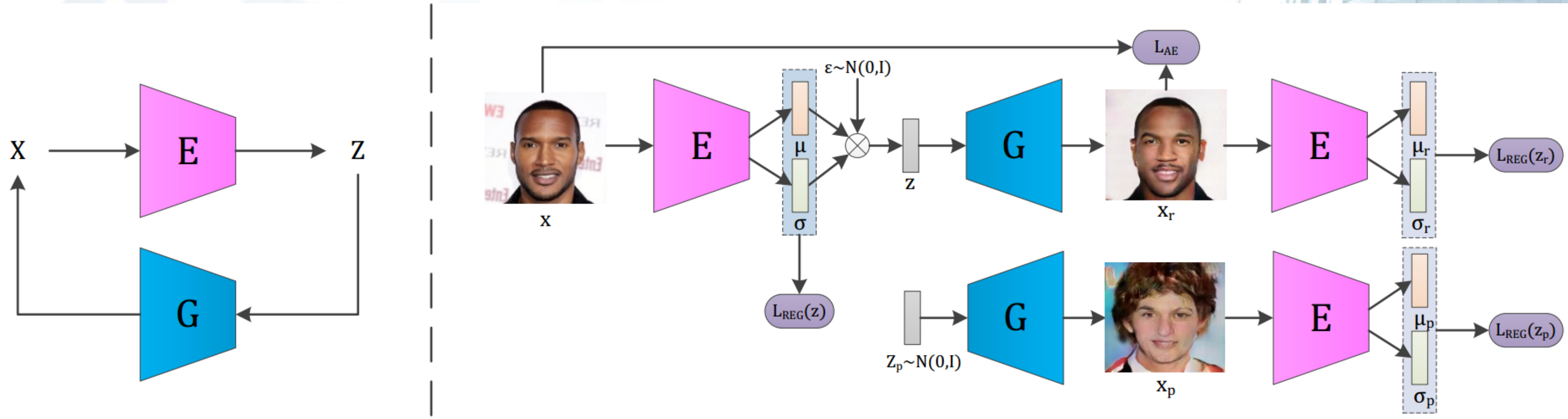
[Roth et al., 2017]
Microsoft and ETHZ

[Karras et al., 2018]
NVIDIA

- Problem: Existing high-resolution image synthesis methods mainly contains multiple stages, facing challenges in training stability and complex network architecture.

Introspective VAEs

A novel introspective variational autoencoder (IntroVAE) model is proposed for synthesizing high-resolution photographic images



$$L_E(x,z) = \boxed{E(x) + [m - E(G(z))]^+} + \boxed{L_{AE}(x)}$$

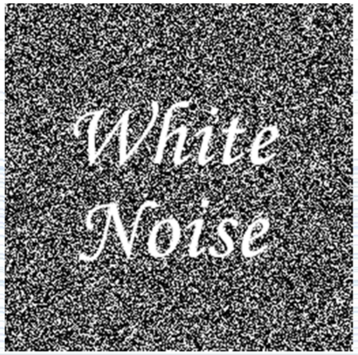
$$L_G(z) = \boxed{E(G(z))} + \boxed{L_{AE}(x)}$$

Adversarial ***Reconstruction***

Huaibo Huang, Zhihang Li, Ran He, Zhenan Sun, Tieniu Tan. IntroVAE: Introspective Variational Autoencoders for Photographic Image Synthesis. NIPS, 2018.

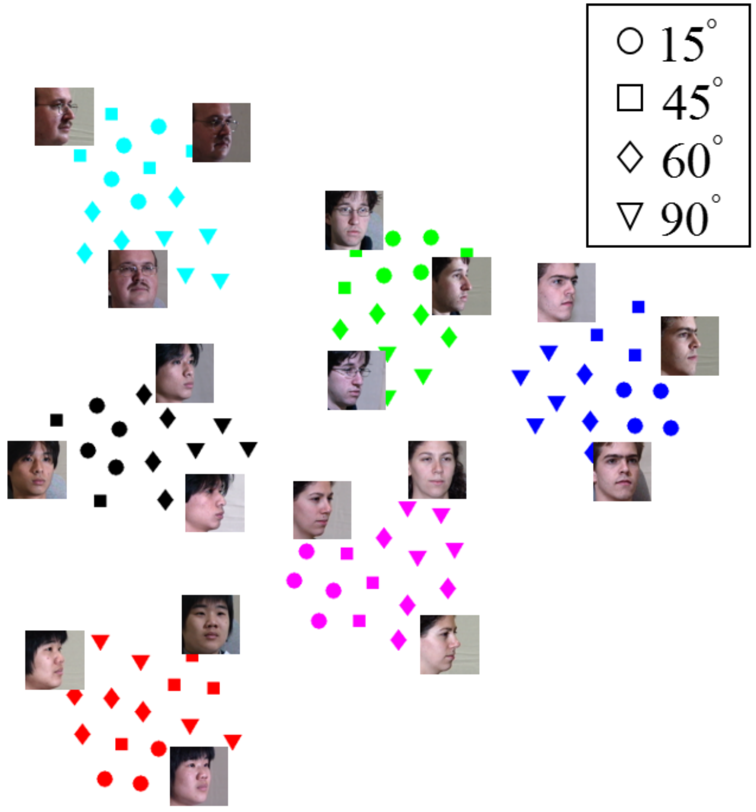
Introspective VAEs

1024*1024

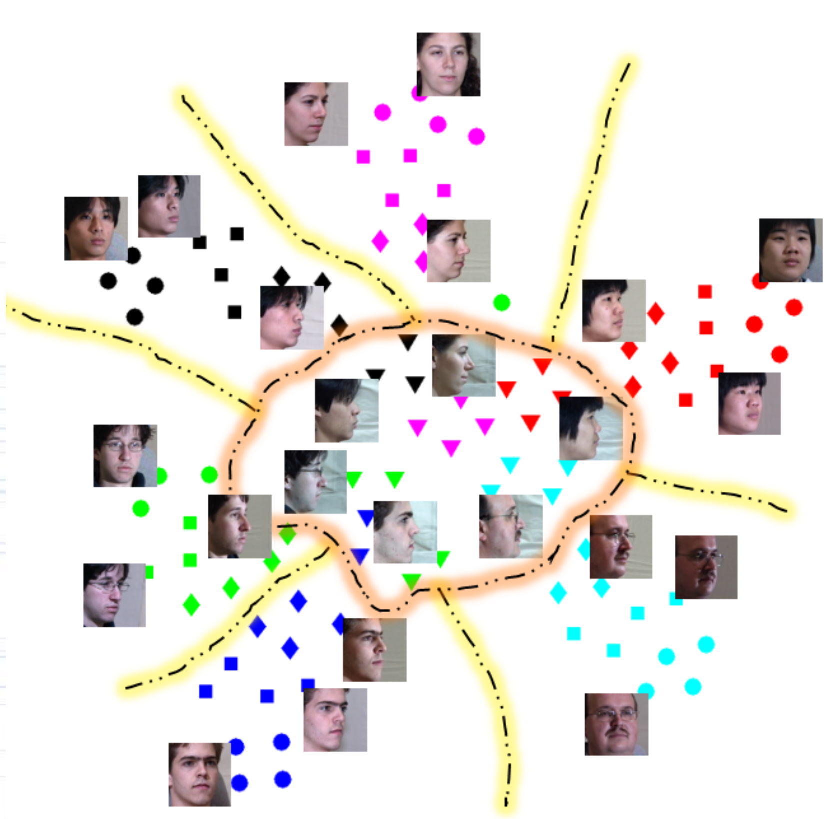


Large pose variations greatly degrade face recognition performance

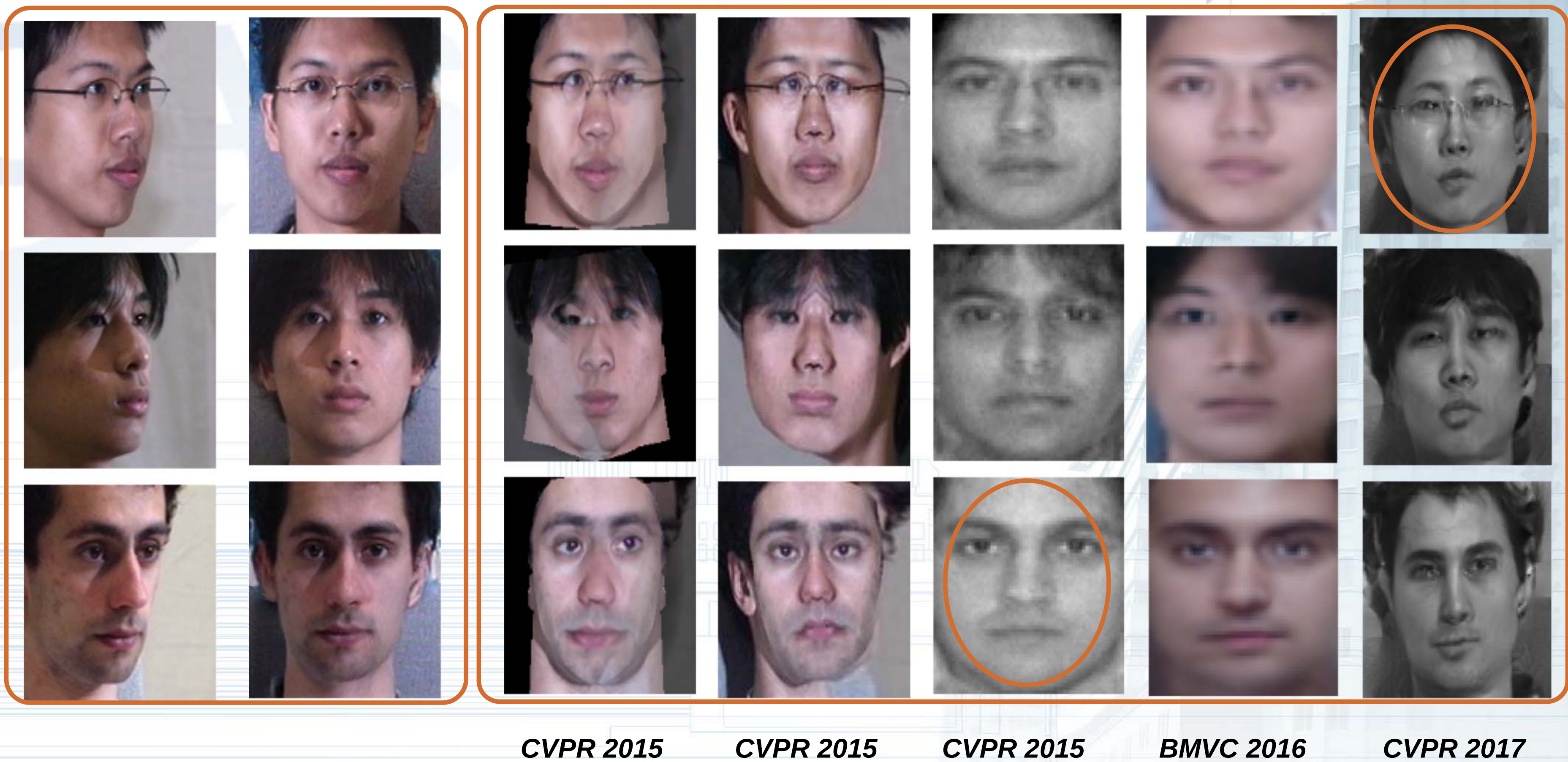
What we'd like to have:



What we've really got:



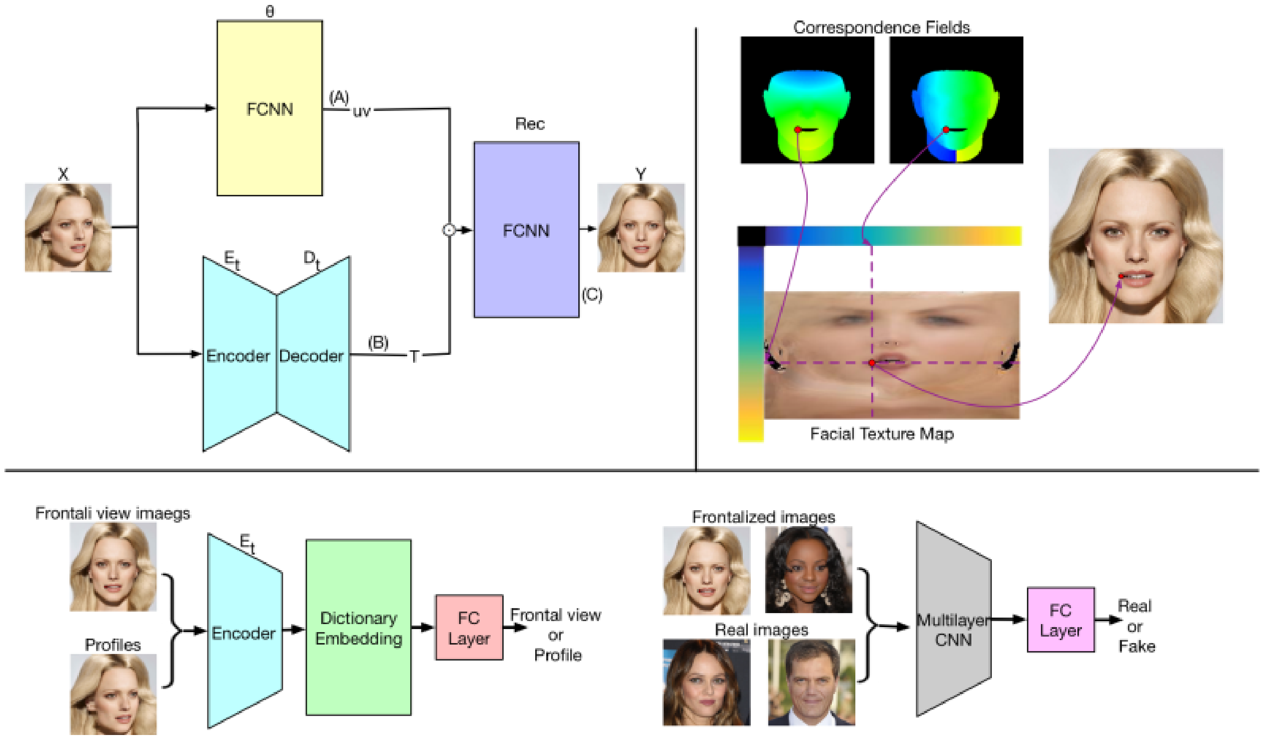
Main problems of current frontalization methods



Appearance: limited resolution, fail to preserve global structure, local details lost
Recognition: useless in face recognition performance improvement

High-resolution Face Frontalization

High Fidelity Pose Invariant Model (HF-PIM) is proposed to produce realistic and identity-preserving frontalized face images with the highest resolution (256*256) in the literature .



Jie Cao, Yibo Hu, Hongwen Zhang, Ran He, Zhenan Sun. Learning a High Fidelity Pose Invariant Model for High-resolution Face Frontalization, NIPS, 2018

High Fidelity Pose Invariant Model

256*256

High Fidelity Pose Invariant Model

Face recognition accuracy is significantly improved via face frontalization

Table 2: Face recognition performance (%) comparisons for in-the-wild datasets. The left part is compared on LFW and the right side is on IJB-A. The results on IJB-A are averaged over 10 testing splits. "-" means the result is not reported.

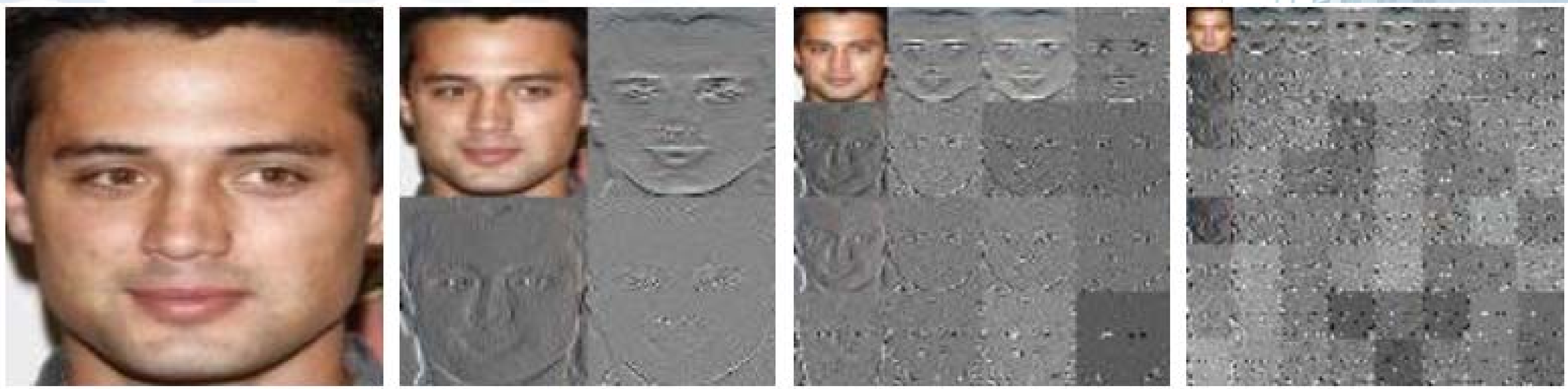
Method	LFW		Method	IJB-A			
	Verification			Verification		Recognition	
	ACC	AUC		FAR=0.01	FAR=0.001	Rank-1	Rank-5
LFW-3D [14]	93.62	88.36	DR-GAN [30]	77.4±2.7	53.9±4.3	85.5±1.5	94.7±1.1
Ferrari [8]	-	94.29	VGG-Face [25]	80.5±3.0	-	91.3±1.1	-
LFW-HPEN [36]	96.25	99.39	FF-GAN [33]	85.2±1.0	66.3±3.3	90.2±0.6	95.4±0.5
FF-GAN [33]	96.42	99.45	LightCNN [15]	91.5±1.0	84.3±2.4	93.0±1.0	-
CAPG-GAN [32]	99.37	99.90	PIM [35]	93.3±1.1	87.5±1.8	94.4±1.1	-
HF-PIM(Ours)	**99.41**	**99.92**	HF-PIM(Ours)	**95.15±0.74**	**89.72±1.4**	**96.1±0.5**	**97.9±0.2**

The problem of current methods for face super resolution

(a) LR (b) HR (c) Bicubic (d) WaveletIP (e) SRCNN (f) URDGN (g) CBN

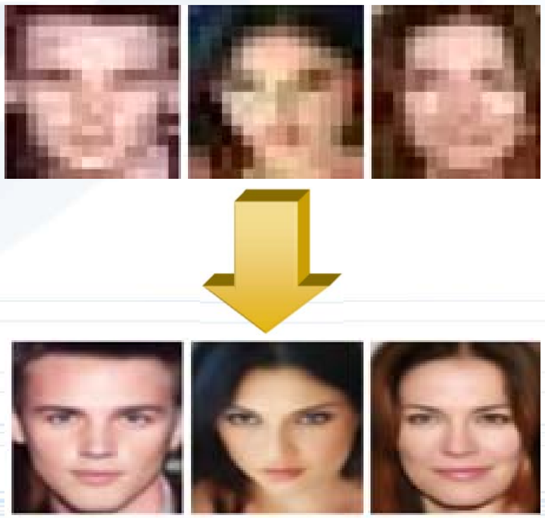
- Reconstruction of high resolution face images from very low resolution (LR) images is a challenging task for current methods.
- Problem: Image level super resolution may produce over smoothed outputs and miss some textual details.

Learning wavelet information for face super resolution



- Global and local face information is shown in approximation coefficients and detail coefficients of different-level wavelet packet decomposition respectively.
- So face super resolution is transformed to accurately predict a series of wavelet coefficients using deep learning.

Face Super Resolution



- The first wavelet domain CNN (convolutional neural networks) solution to face super resolution
- Special design of loss functions to capture both global topology information and local textual details

Huaibo Huang, Ran He, Zhenan Sun, and Tieniu Tan, Wavelet-SRNet: A Wavelet-based CNN for Multi-scale Face Super Resolution, International Conference on Computer Vision, 2017.

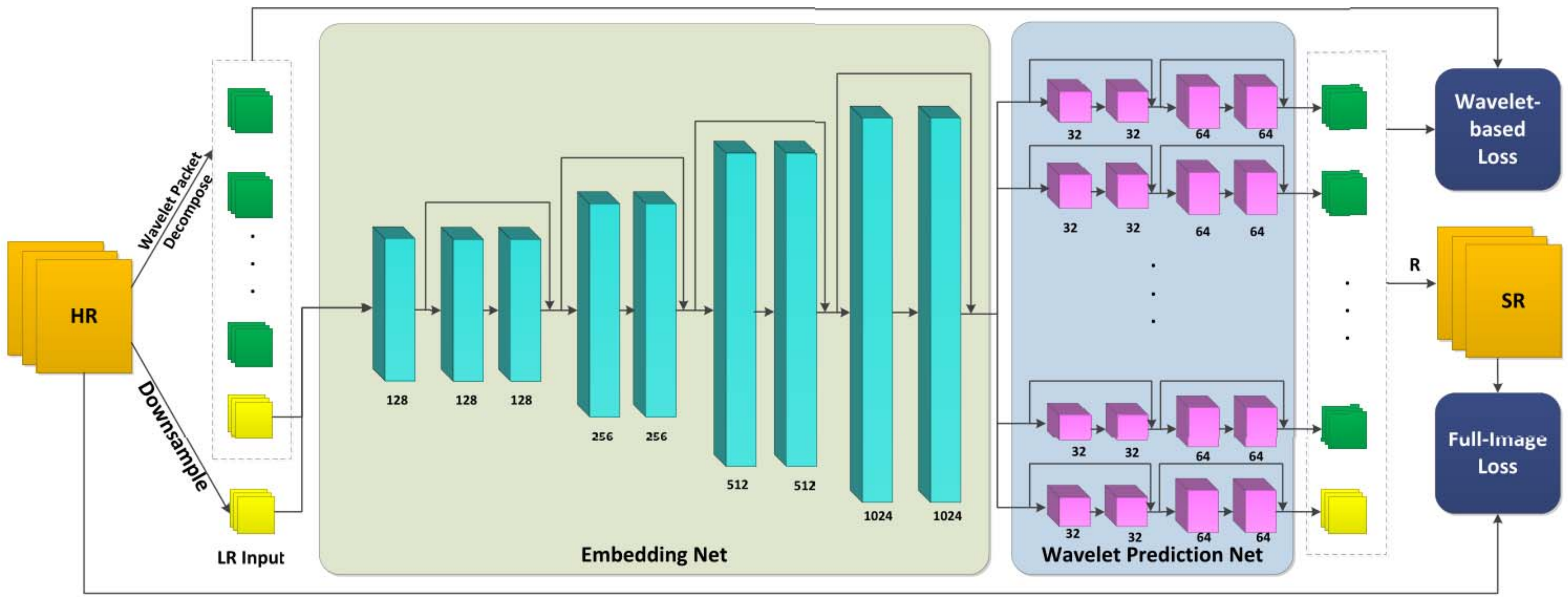
Wavelet-SRNet

Object Function:

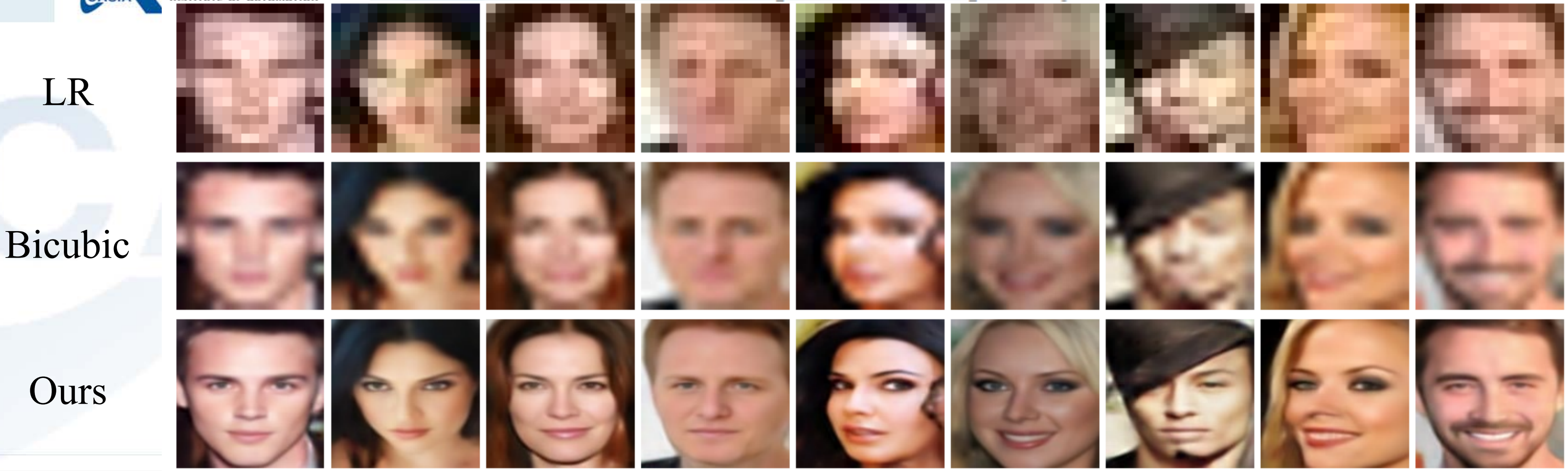
$$l_{wavelet}(\hat{C}, C) = \|W^{1/2} \odot (\hat{C} - C)\|_F^2 = \sum_{i=1}^{N_w} \lambda_i \|\hat{c}_i - c_i\|_F^2$$

$W = (\lambda_1, \lambda_2, \cdots, \lambda_{N_w})$ is the weight matrix to balance the importance of different band wavelet coefficients.

Network Architecture:



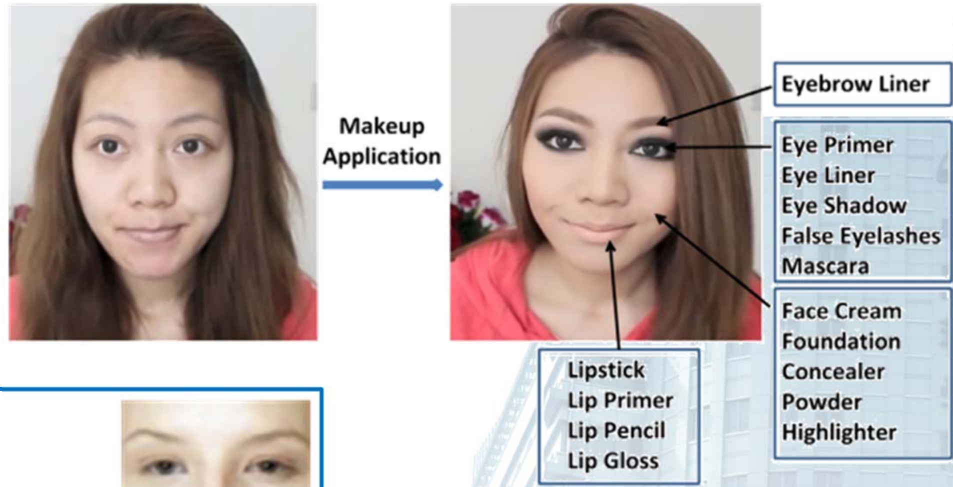
Face Super Resolution

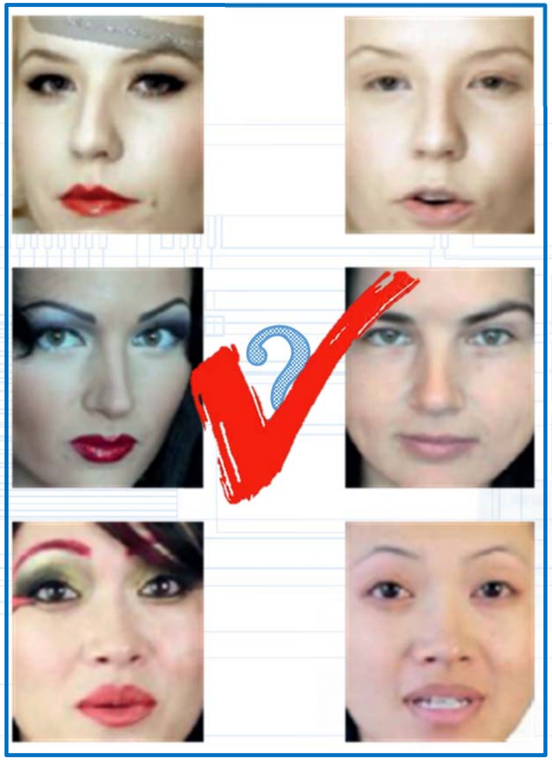


16 × 16 input-size, 8× upscaling

8 × 8 input-size, 16× upscaling

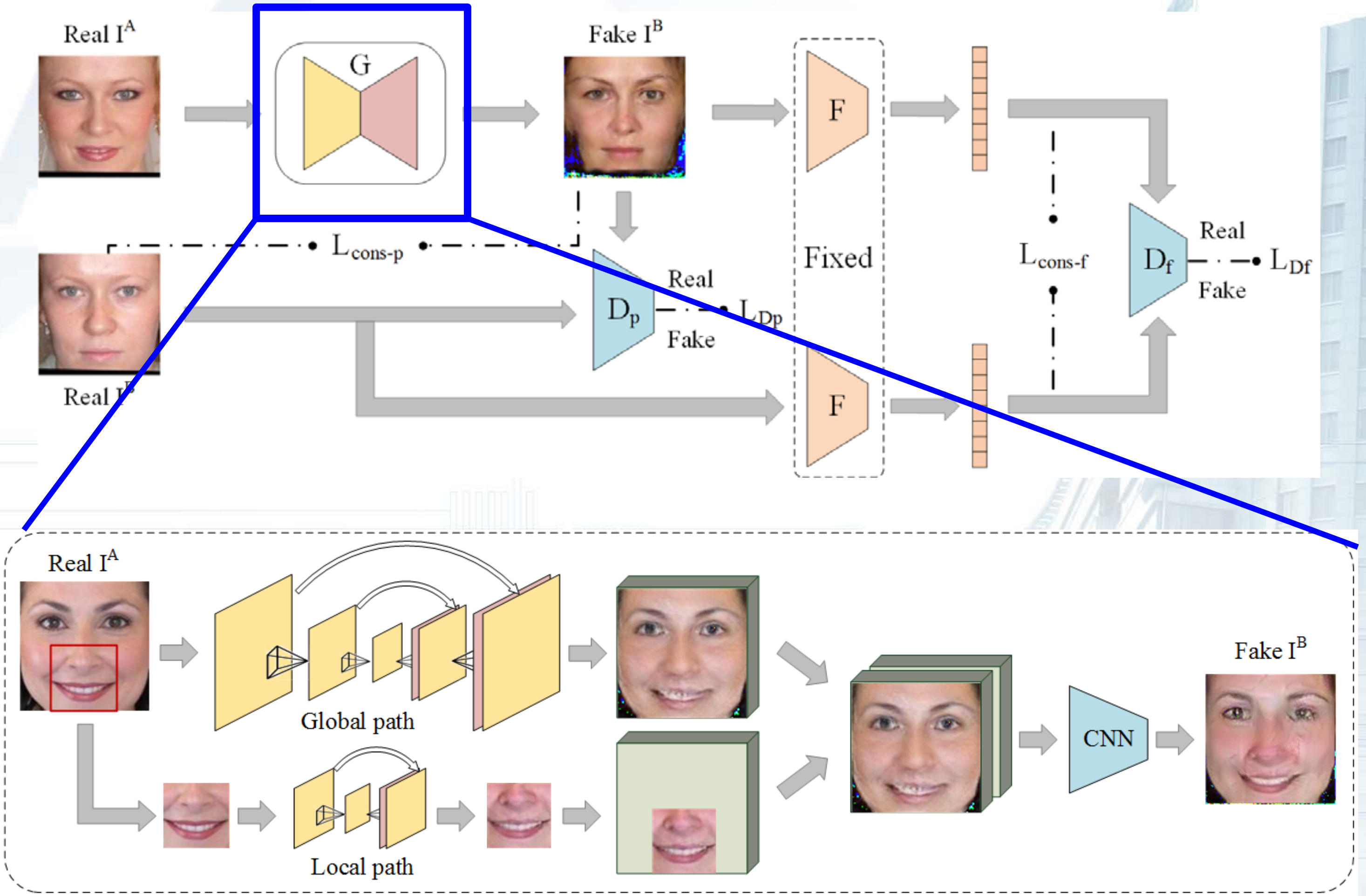
Makeup changes the overall facial appearance





The recognition accuracy of existing face recognition methods can be reduced by up to 76.21% due to makeup.

Anti-Makeup Using BLAN (Bi-Level Adversarial Network)



Yi Li, Lingxiao Song, Xiang Wu, Ran He, Tieniu Tan. Anti-Makeup: Learning A Bi-Level Adversarial Network for Makeup-Invariant Face Verification. AAAI, 2018.

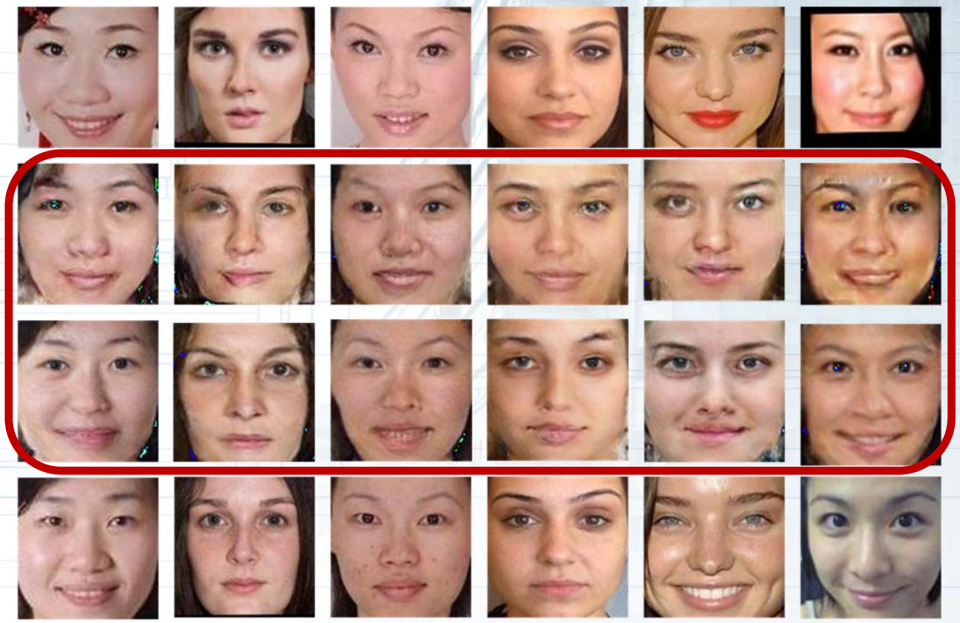
BLAN (Bi-Level Adversarial Network)

Table 2. Rank-1 accuracy (%) on three makeup datasets.

Dataset	Method	Accuracy
Dataset 1	Guo et al. (2014)	80.5
	Sun et al. (2017)	82.4
	VGG	89.4
	Light CNN	92.4
	BLAN	94.8
	BLAN-2	95.5
Dataset 2	Sun et al. (2017)	68.0
	VGG	86.0
	Light CNN	91.5
	BLAN	92.3
	BLAN-2	93.4
FAM	Nguyen and Bai (2010)	59.6
	Hu et al. (2013)	62.4
	VGG	81.6
	Light CNN	86.3
	BLAN	88.1
	BLAN-2	90.0

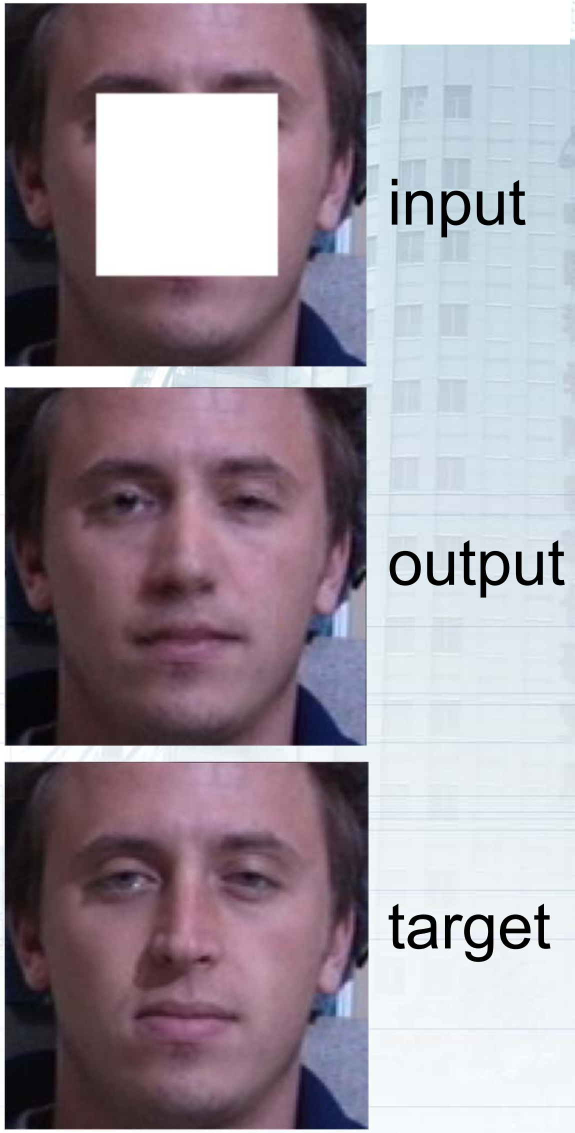
Table 3. True Positive Rate (%) on three makeup datasets.

Method	Dataset	TPR@FPR=0.1%	TPR@FPR=1%
BLAN	Dataset 1	65.9	99.8
	Dataset 2	38.9	82.7
	FAM	52.6	97.0
BLAN-2	Dataset 1	68.2	99.5
	Dataset 2	44.6	84.2
	FAM	53.8	94.9

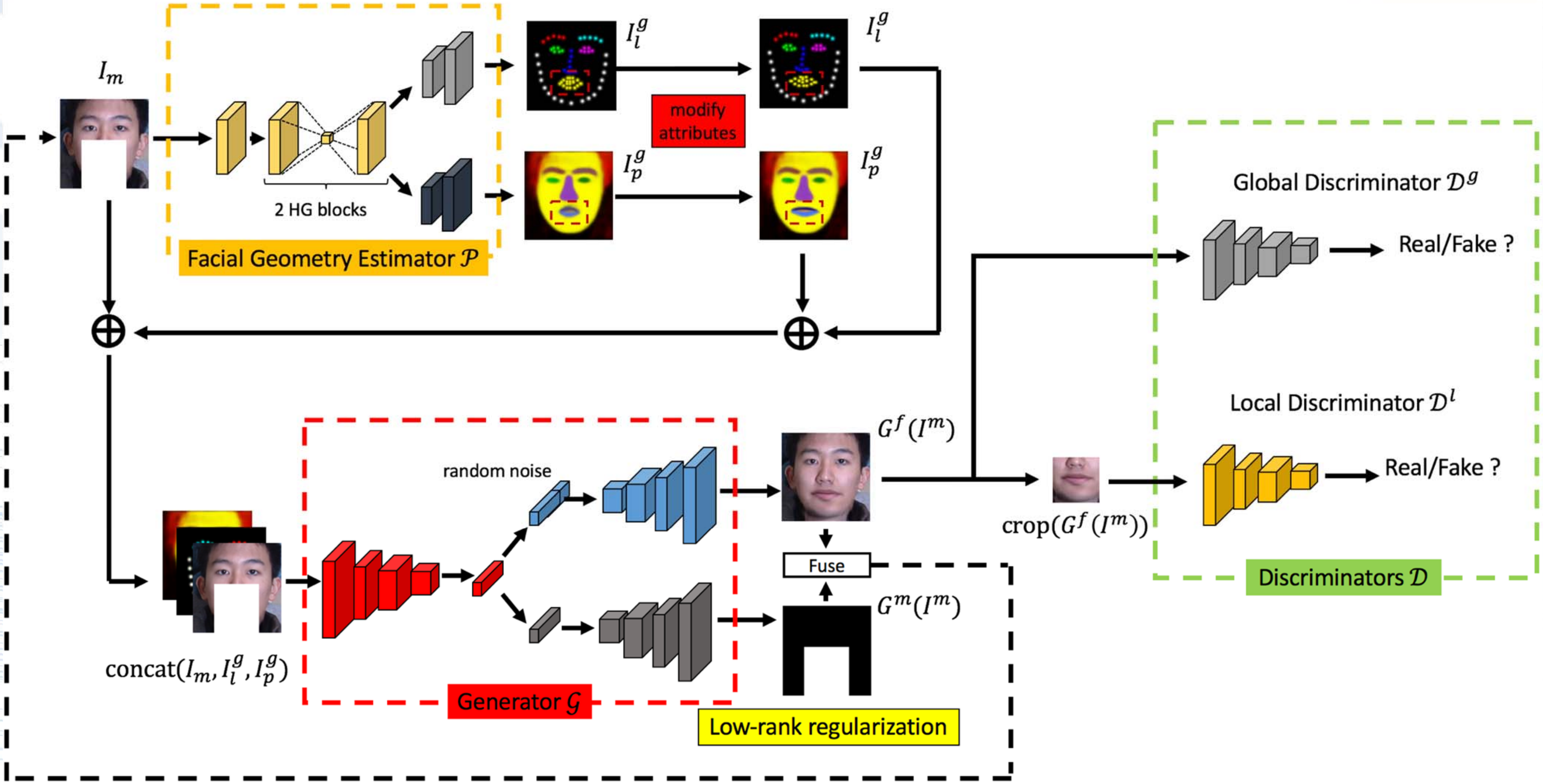


Main problems of existing face completion methods

- Different from general objects, human faces have distinct geometry distribution. Most of the existing methods don’t well utilize this prior knowledge.
- Existing methods are incapable of modifying the face attributes of the filled region.

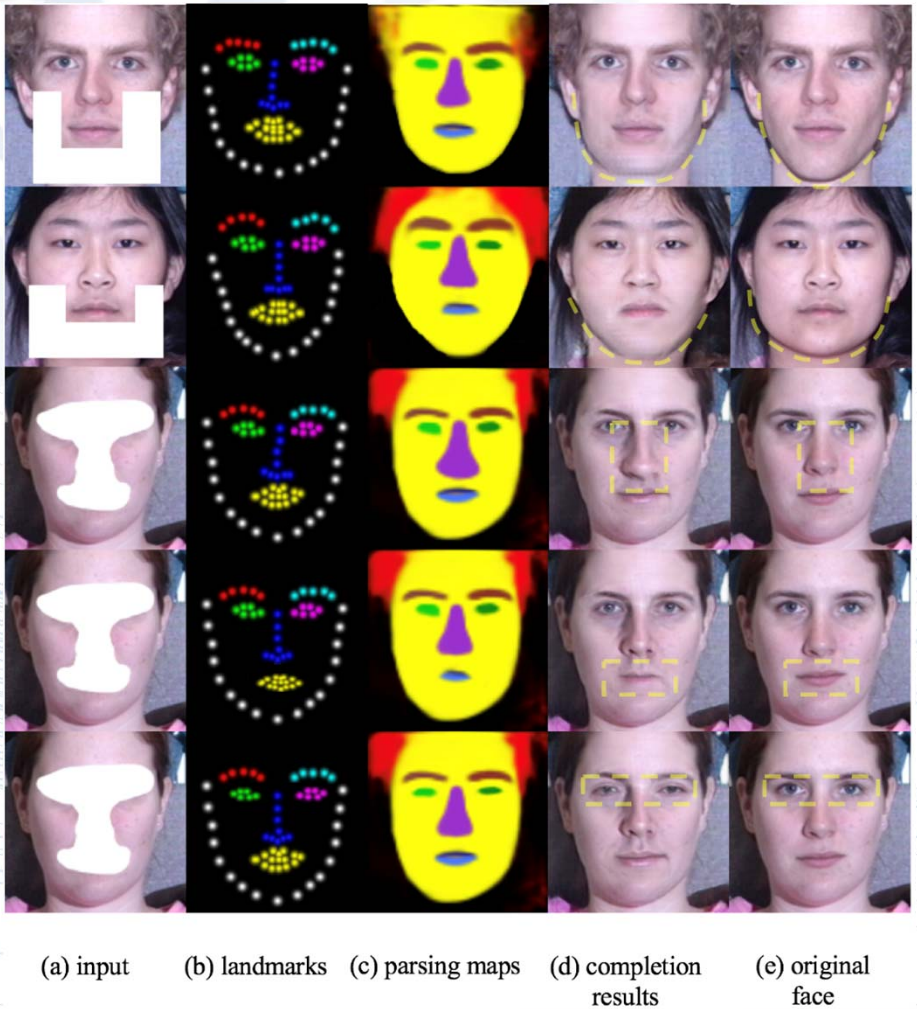


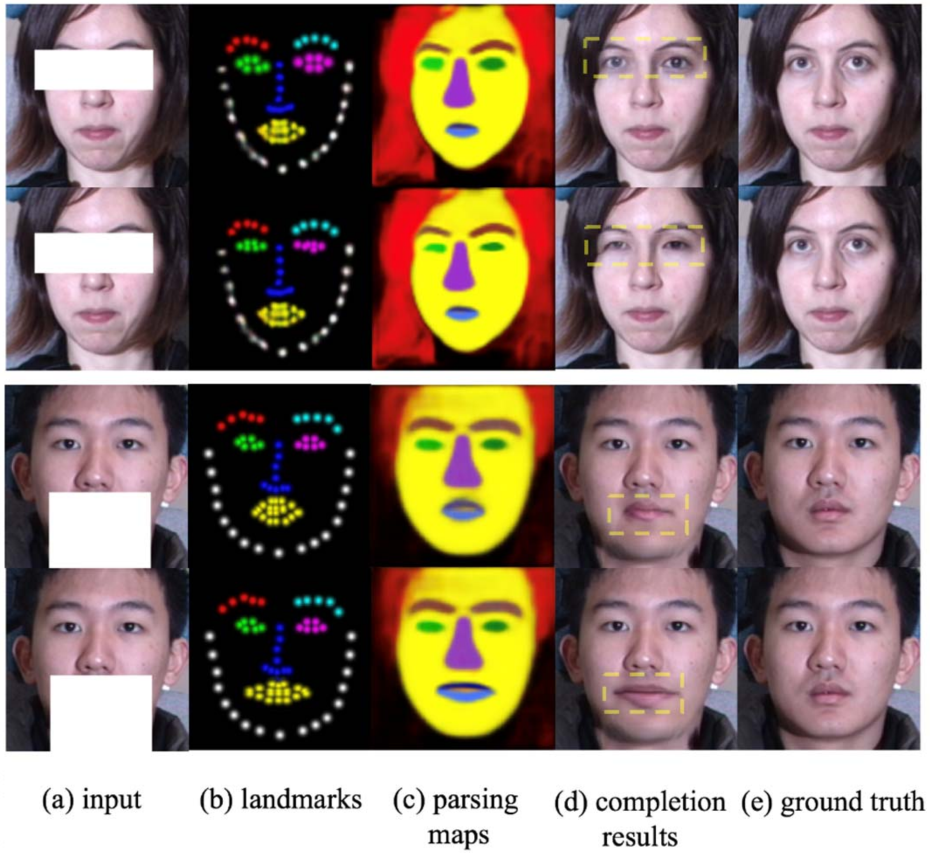
Geometry-Aware Face Completion and Editing



Linsen Song, Jie Cao, Lingxiao Song, Yibo Hu and Ran He. Geometry-Aware Face Completion and Editing. AAAI, 2019.

Geometry-Aware Face Completion and Editing



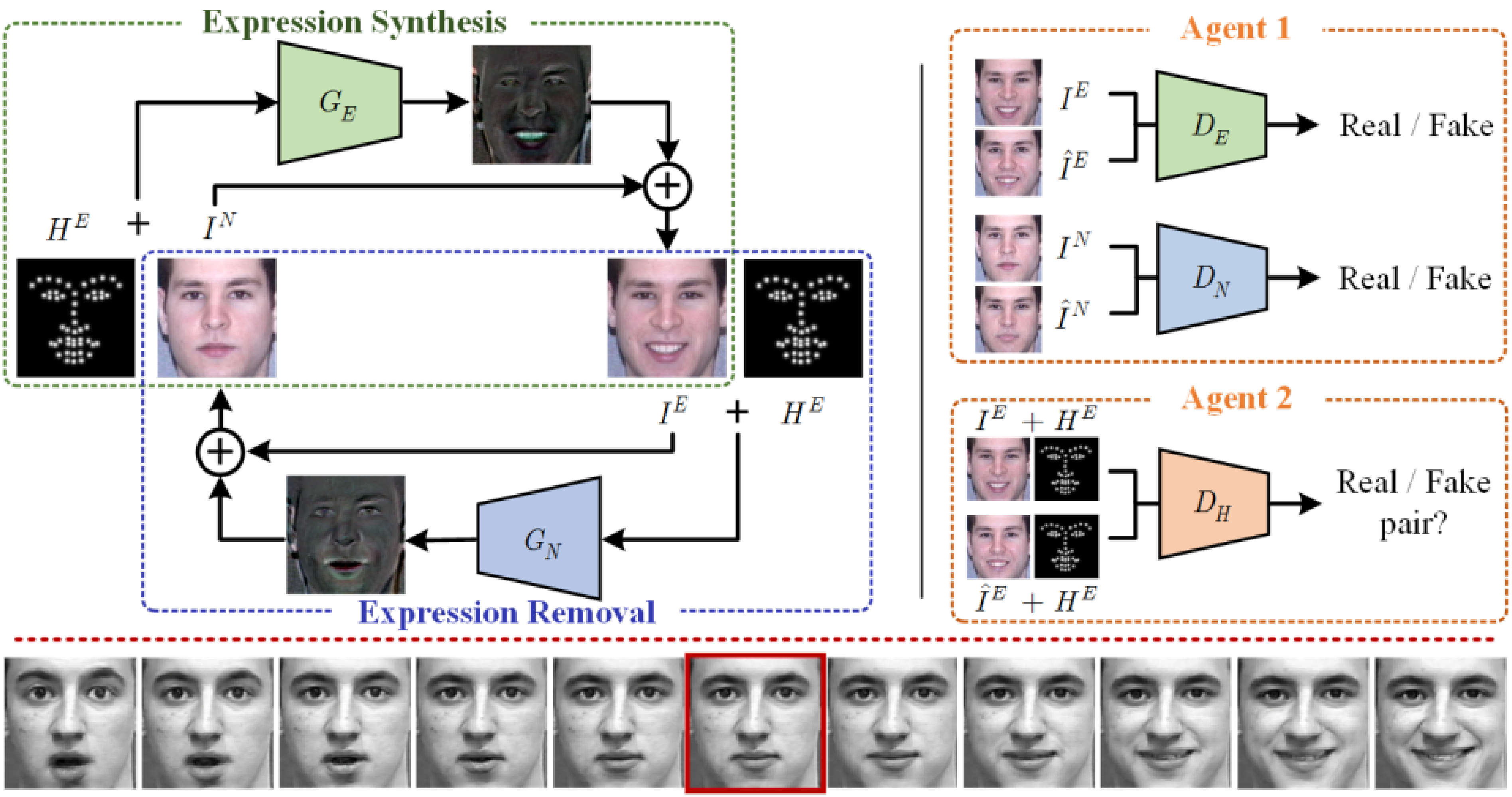


Facial Expression Editing

- Problem Definition:
  - Change the expression without affecting the identity
  - Key points: expression, reality, identity
- Existing methods:

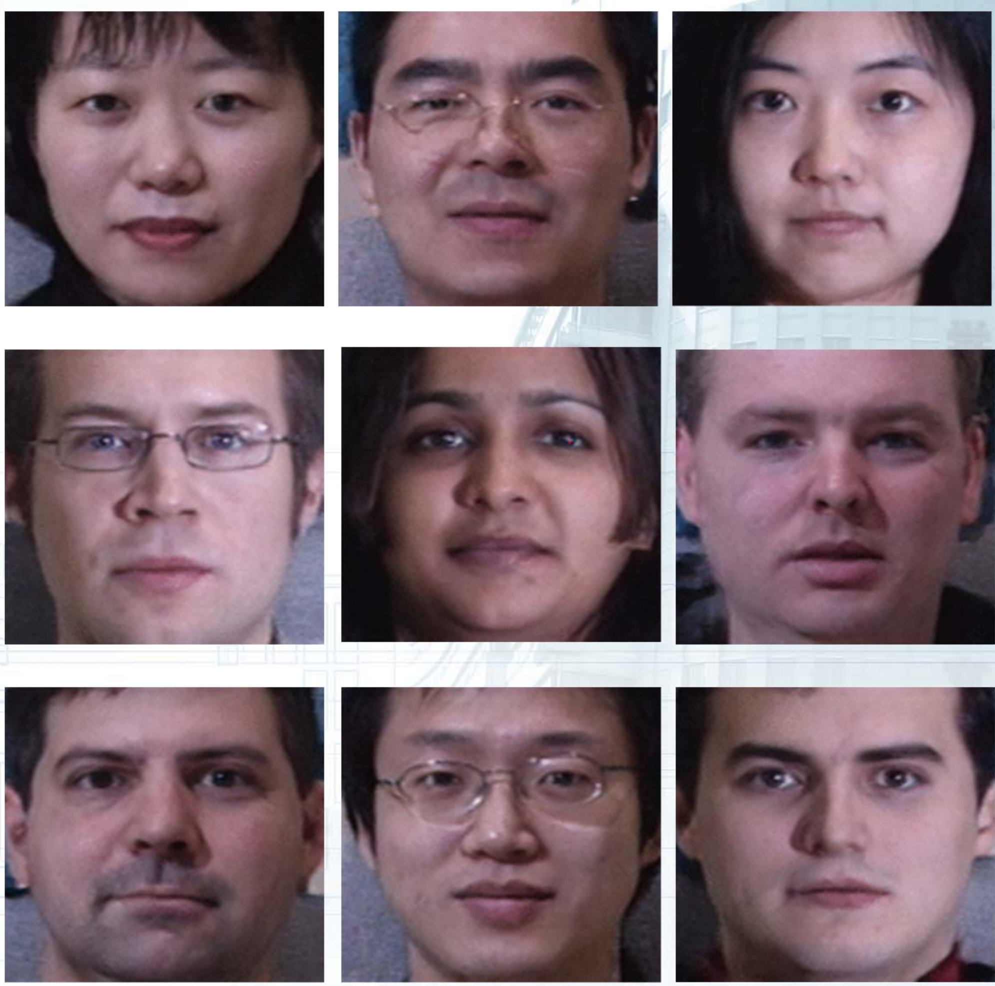
Methods		expression	reality	identity
Traditional methods	images reordering	√	×	×
	flow- based	√	×	√
	3D-based	√	√	×
Generative models	VAE-based	√	×	×
	GAN based	√	√	×

Geometry-Guided Generative Adversarial Network (G2-GAN)

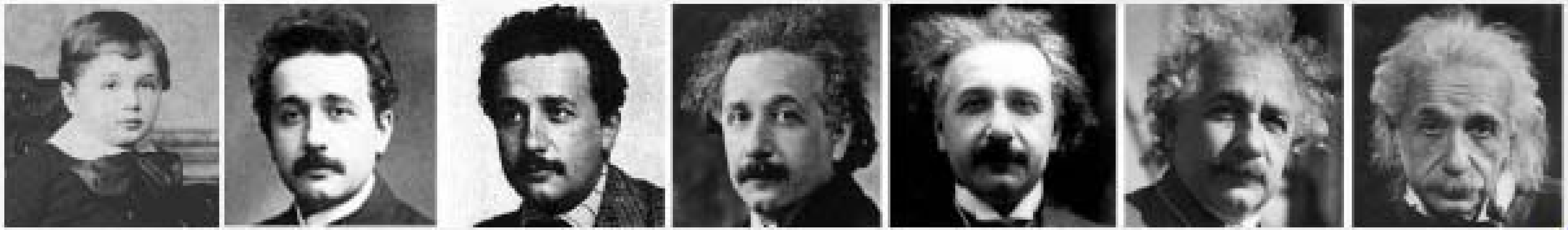


Lingxiao Song, Zhihe Lu, Ran He, Zhenan Sun, Tieniu Tan. Geometry Guided Adversarial Facial Expression Synthesis. ACM MM, 2018.

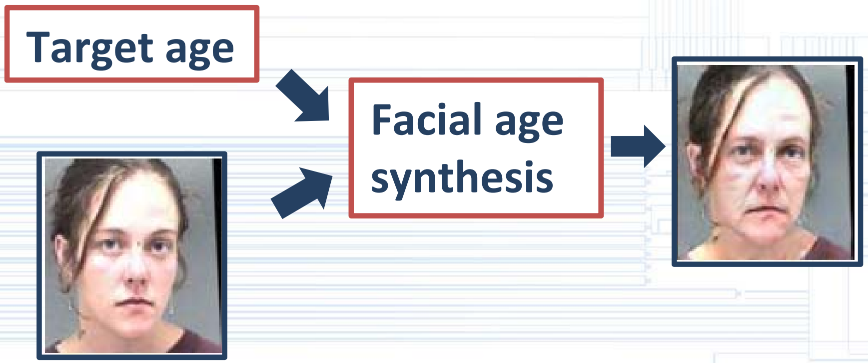
Geometry-Guided Generative Adversarial Network (G2-GAN)



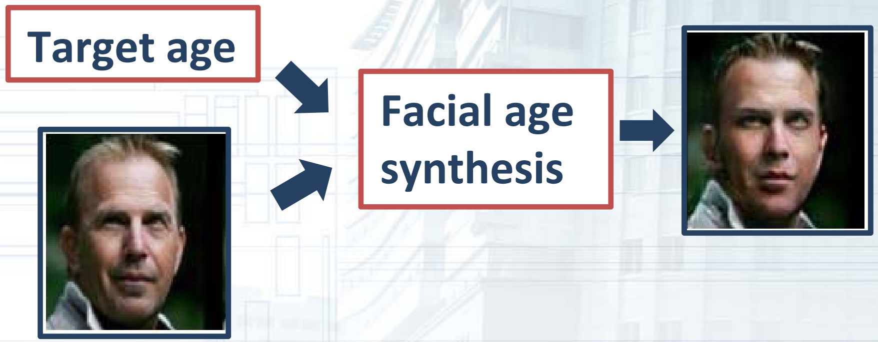
Human Facial Aging



Facial aging of Albert Einstein



Facial Aging

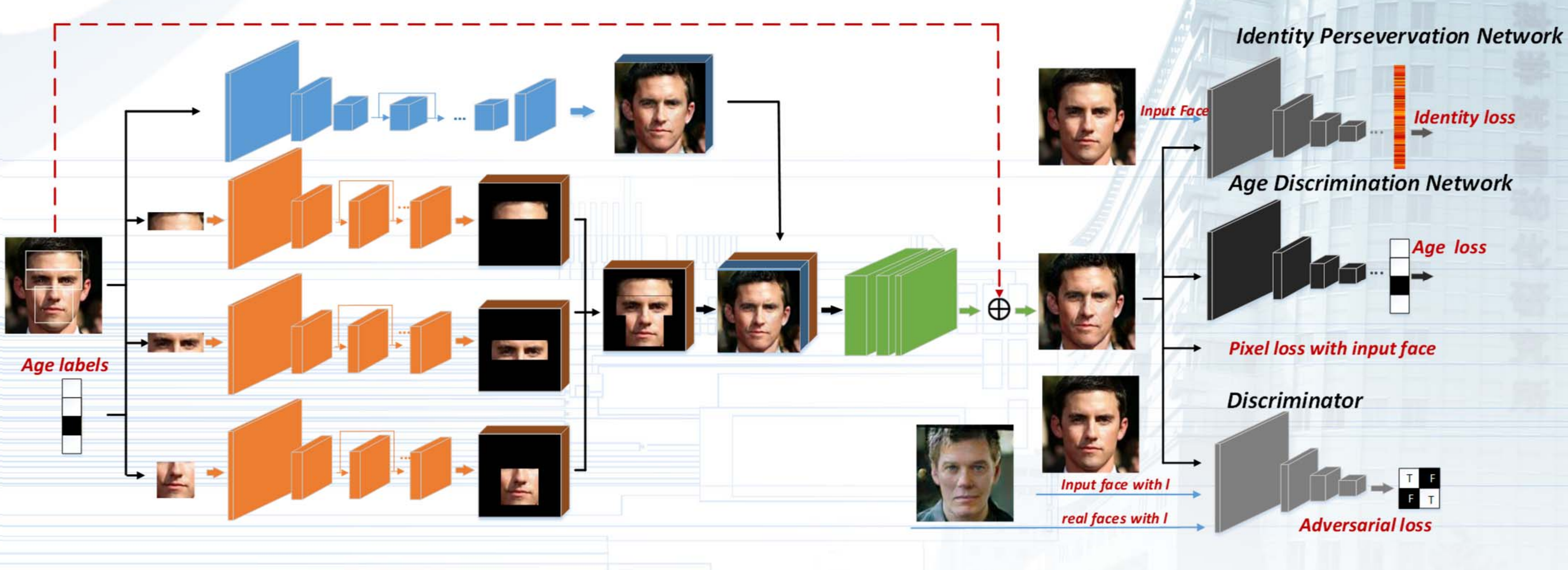


Facial Rejuvenation

Global and Local Consistent Age GANs

Unpaired vs. Paired
Direct vs. Step by step

Whole vs. Cropped
Single vs. Multi



Peipei Li, Yibo Hu, Qi Li, Ran He, Zhenan Sun. Global and Local Consistent Age Generative Adversarial Networks. ICPR, 2018.

Global and Local Consistent Age GANs

Testing face 50-41 40-31 30-

61 years

55 years

60 years

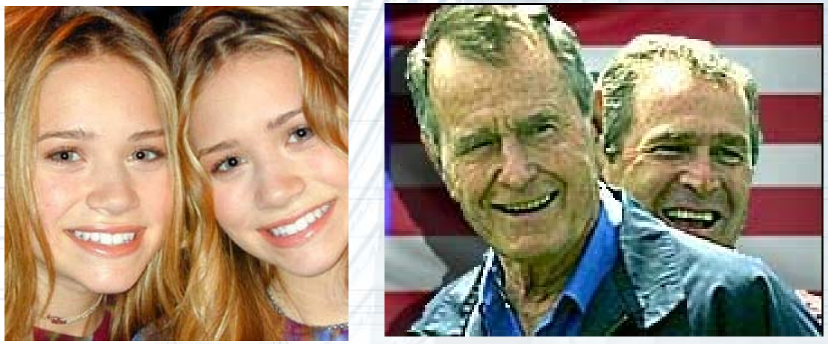
55 years

Open Problems of Face Recognition

PIE (Pose, Illumination, Expression)

Face recognition in surveillance

Spoof-attack



Face recognition of twins

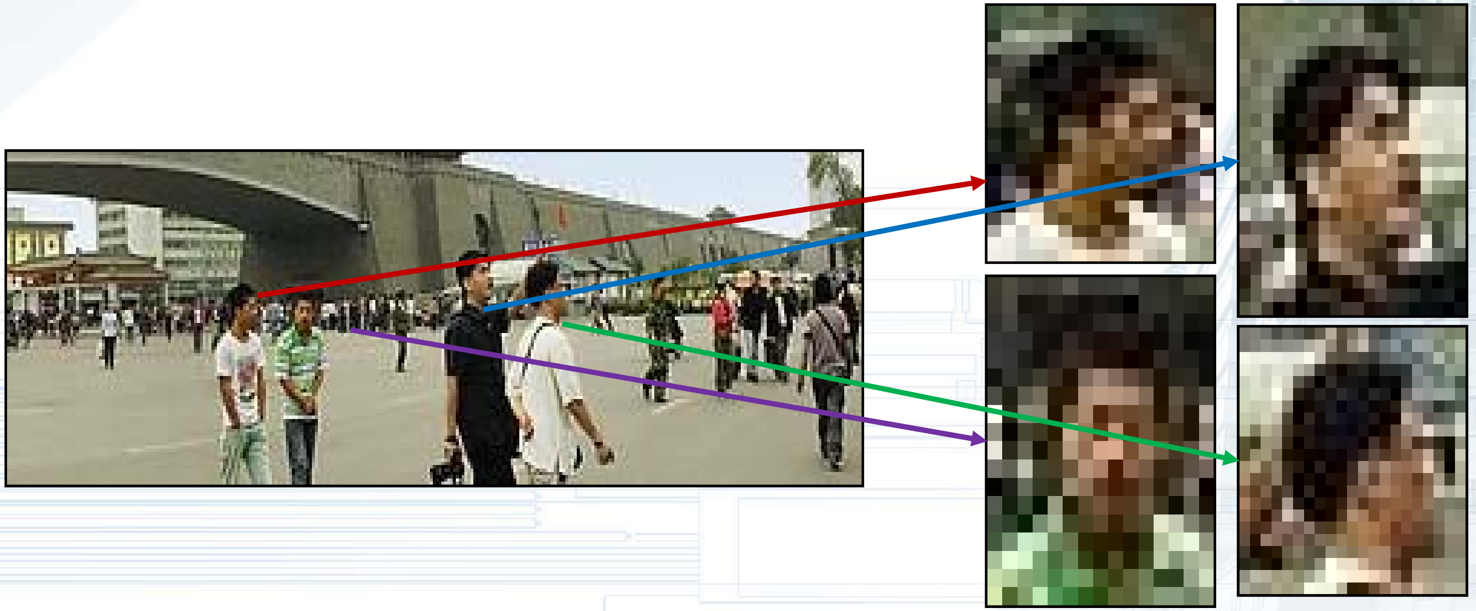
Facial disguise

Outline

- Preamble
- Overview of Recent Progress on Biometrics
  - ✓ Fingerprint Recognition
  - ✓ Iris Recognition
  - ✓ Face Recognition
  - ✓ Gait Recognition
  - ✓ Others
- Future Directions and Conclusions

Advantages of gait recognition

As a biometric, gait is still available at a distance when other biometrics are obscured or at too low resolution.



Advantages: robust against imaging distance, resolution, view, illumination

History of gait recognition

1997 — First gait biometrics paper - Cunado, Nixon and Carter (AVBPA 1997) - 90% CCR

2000 — DARPA Program: Human ID at a distance

2015 — Learning Representative Deep Features for Image Set Analysis， TMM

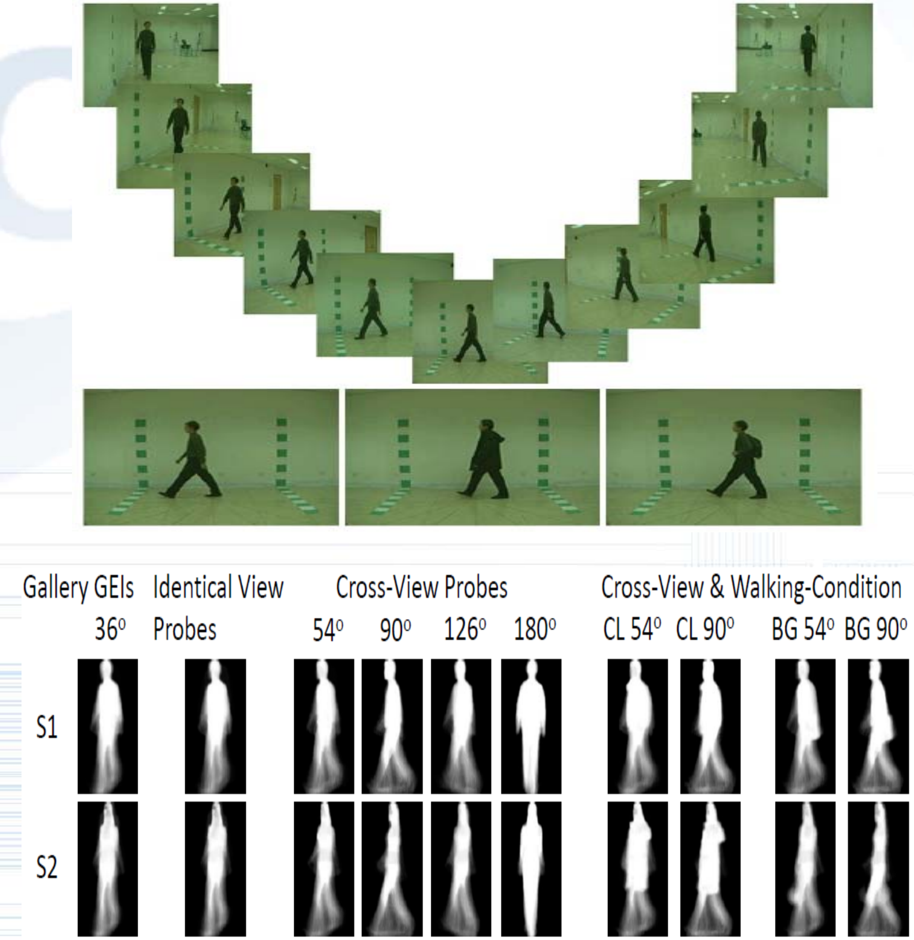
2016 — Cross-view gait based human identification with deep CNNs， TPAMI

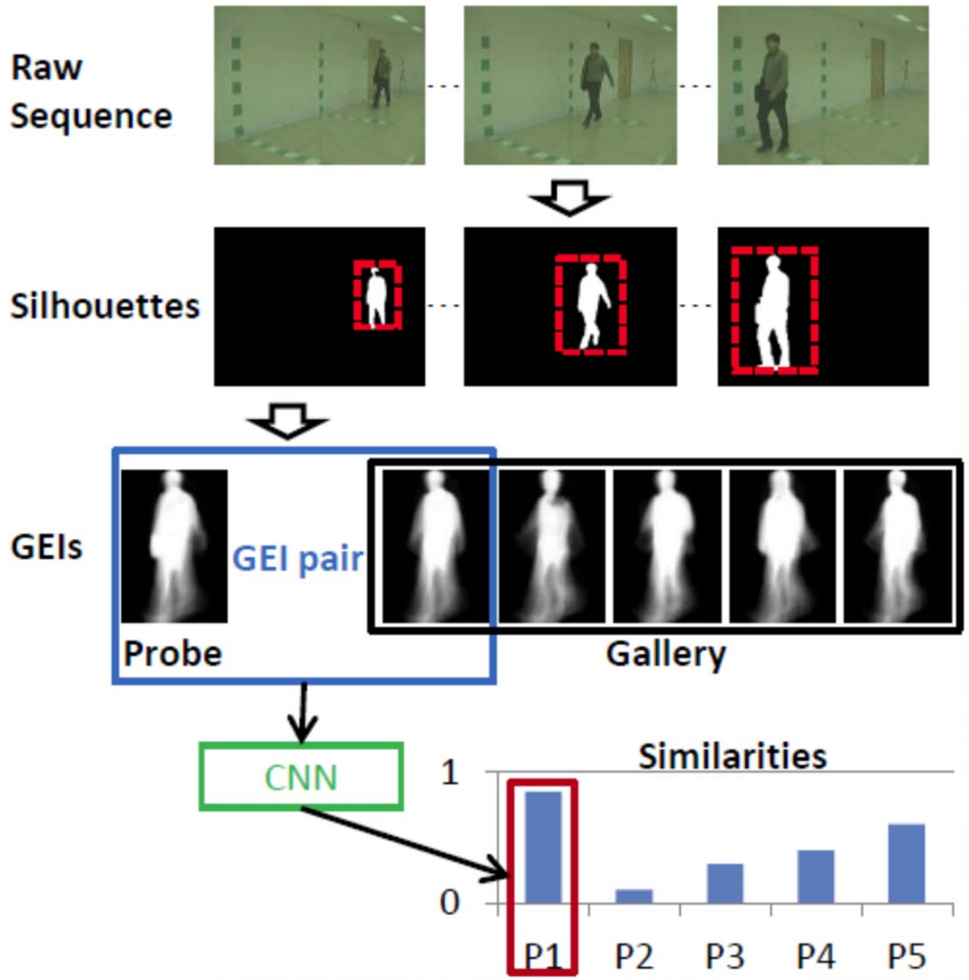
GEINET: view-invariant gait recognition, ICB

1997–2015: Design hand-crafted features for gait recognition

2015–2016: Deep learning for gait recognition

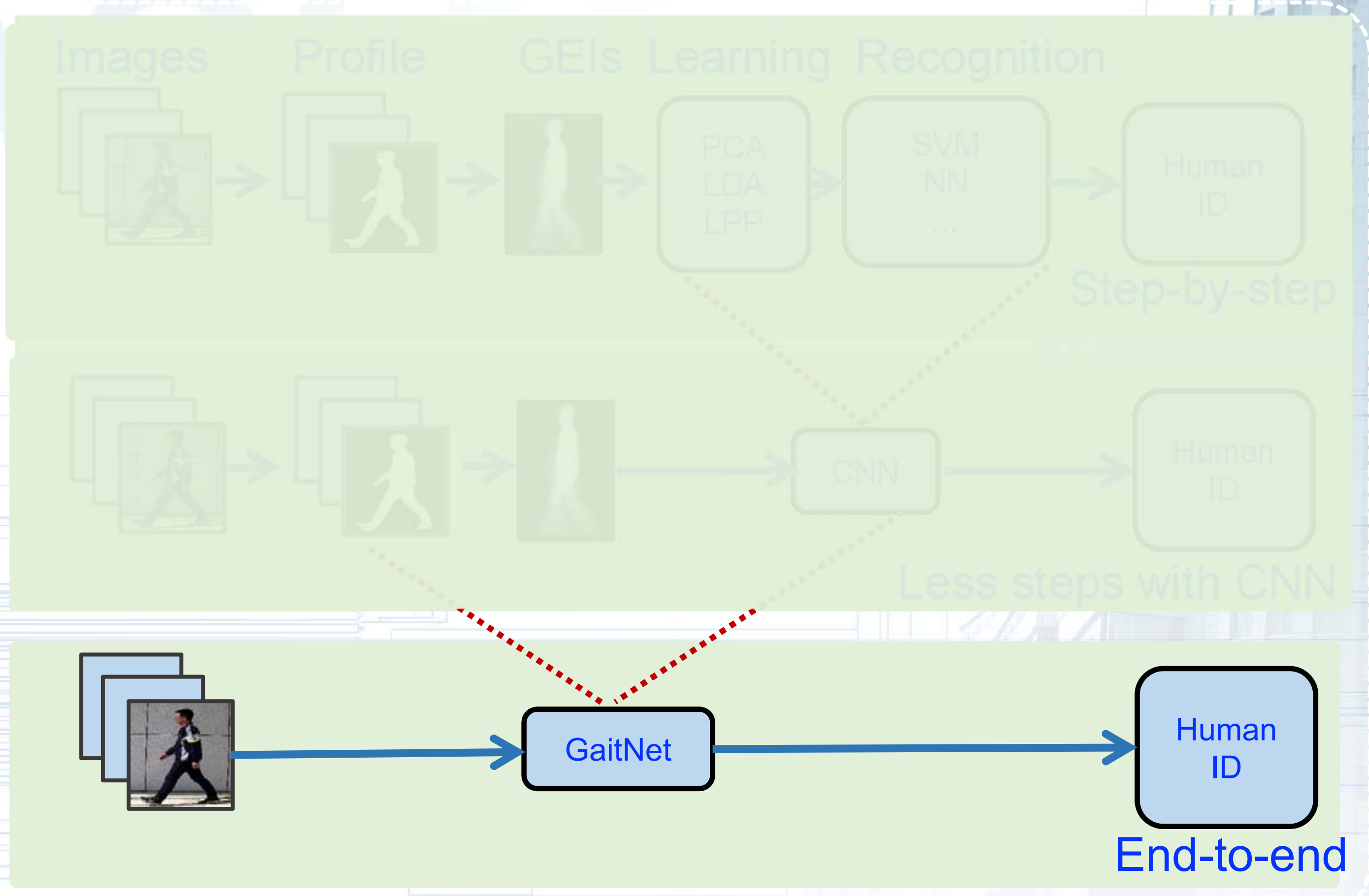
Multi-view Gait Recognition



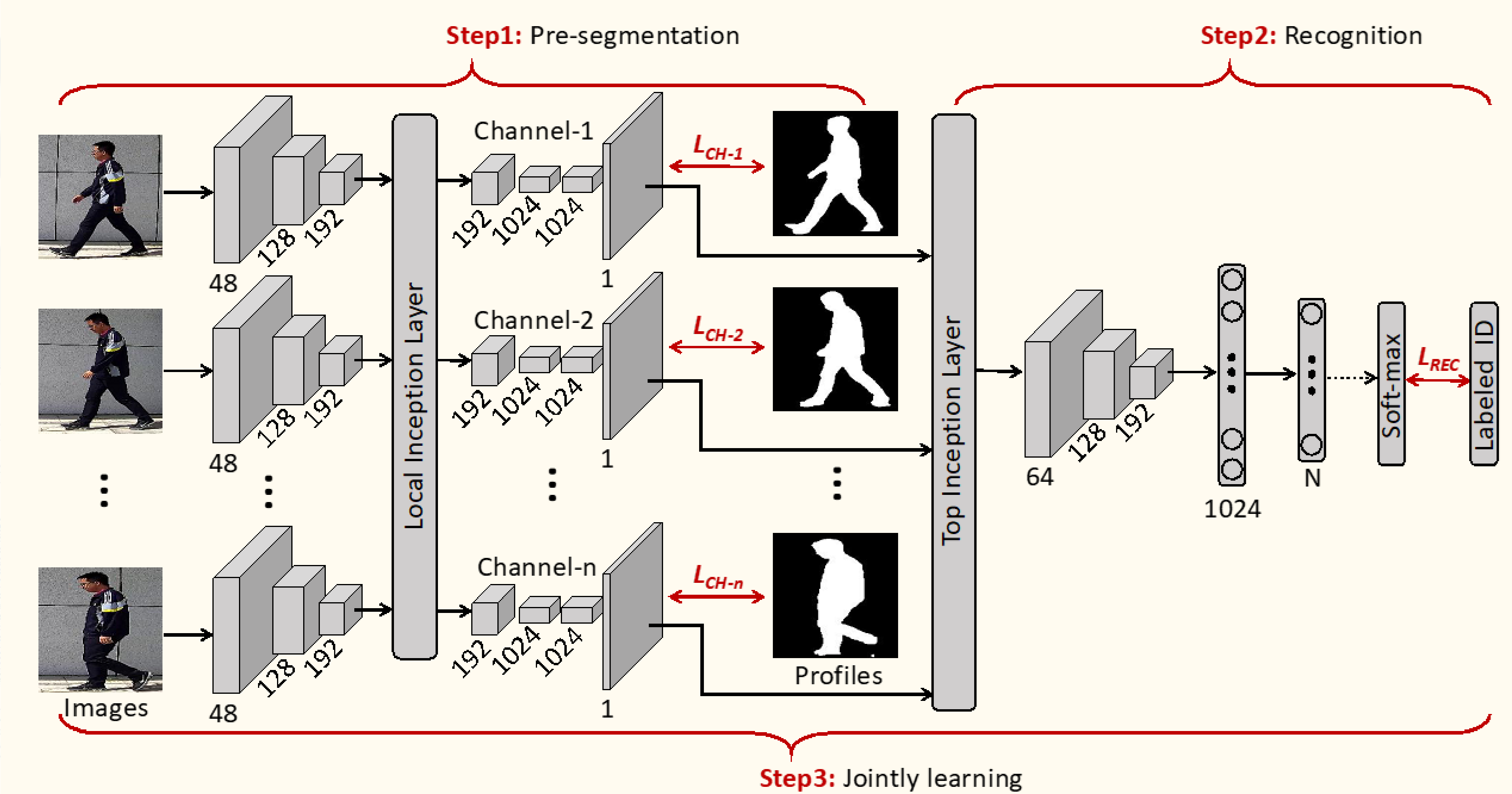


Zifeng Wu, Yongzhen Huang, Liang Wang, Xiaogang Wang, and Tieniu Tan, A comprehensive study on cross-view gait based human identification with deep CNNs, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2017.

An end to end gait recognition system



Flowchart of end-to-end gait recognition



C. Song, Y. Huang L. Wang, et al, GaitNet: An End-to-end Network for Video-based Human Identification, submitted to PR.

Experiments-Results on Outdoor-Gait

Methods		SCENE-1			SCENE-2			SCENE-3			Mean
		NM	CL	BG	NM	CL	BG	NM	CL	BG	
GEI[9]	PCA	79.71	84.56	86.23	97.83	93.48	96.38	65.22	66.42	72.26	82.45
	LDA	88.41	87.50	86.23	97.10	94.93	97.10	60.87	61.94	71.53	82.85
	LPP	86.96	87.50	89.13	93.48	92.03	97.10	60.87	59.70	76.64	82.60
GEnI[3]	PCA	79.71	78.68	78.26	98.55	92.75	96.38	57.25	51.49	65.69	77.64
	LDA	82.61	86.03	84.78	97.10	92.75	95.65	58.70	57.46	69.34	80.49
	LPP	86.23	86.03	85.51	93.48	95.65	95.65	55.80	58.21	71.53	80.90
GFI[17]	PCA	81.16	83.82	87.68	95.65	91.30	94.93	66.67	58.96	72.26	81.38
	LDA	79.71	68.38	81.88	88.41	86.96	91.30	46.38	43.28	57.66	71.55
	LPP	66.67	69.85	78.26	81.88	86.23	86.96	44.93	50.75	53.29	68.76
CGI[28]	PCA	71.01	72.99	80.44	86.96	89.13	91.30	39.86	41.05	51.83	69.40
	LDA	71.01	68.61	78.99	84.78	88.41	90.58	31.88	39.55	50.37	67.13
	LPP	71.01	68.61	74.64	84.06	84.06	86.96	38.41	44.78	48.91	66.83
GEI-CNN[23]		86.23	90.55	93.48	96.01	95.65	96.74	70.65	70.55	76.81	86.30
GaitNet	Non-Joint	95.59	95.22	**99.26**	98.16	98.9	**100.0**	92.28	92.28	97.06	96.53
	Joint	**100.0**	**100.0**	98.9	**100.0**	**100.0**	99.63	**99.26**	**98.16**	**100.0**	**99.55**

Applications of Gait Recognition

- **Public Security**

Gait Retrieval System

Shanghai/Beijing - Sample test

- **Commercial Security**

PetroChina - field drilling platform

Gait recognition for white list

- **Smart Home**

Midea(Fortune 500) air conditioner

Family member gait recognition

中国科学院
自动化研究所
INSTITUTE OF AUTOMATION
CHINESE ACADEMY OF SCIENCES

Gait Retrieval - Field Test

www.ia.ac.cn

△ Crime scene (lateral side, shadow on face）

△ Retrieval result: similarity 0.97

Gait Retrieval - CCTV

Demo of Gait Recognition

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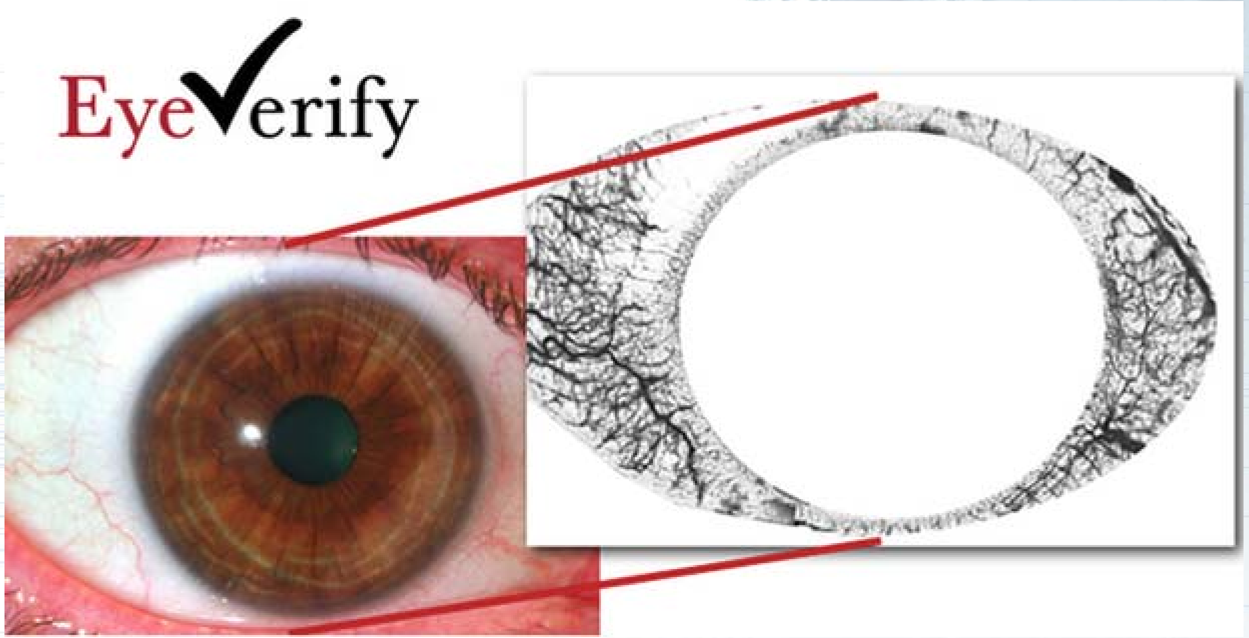
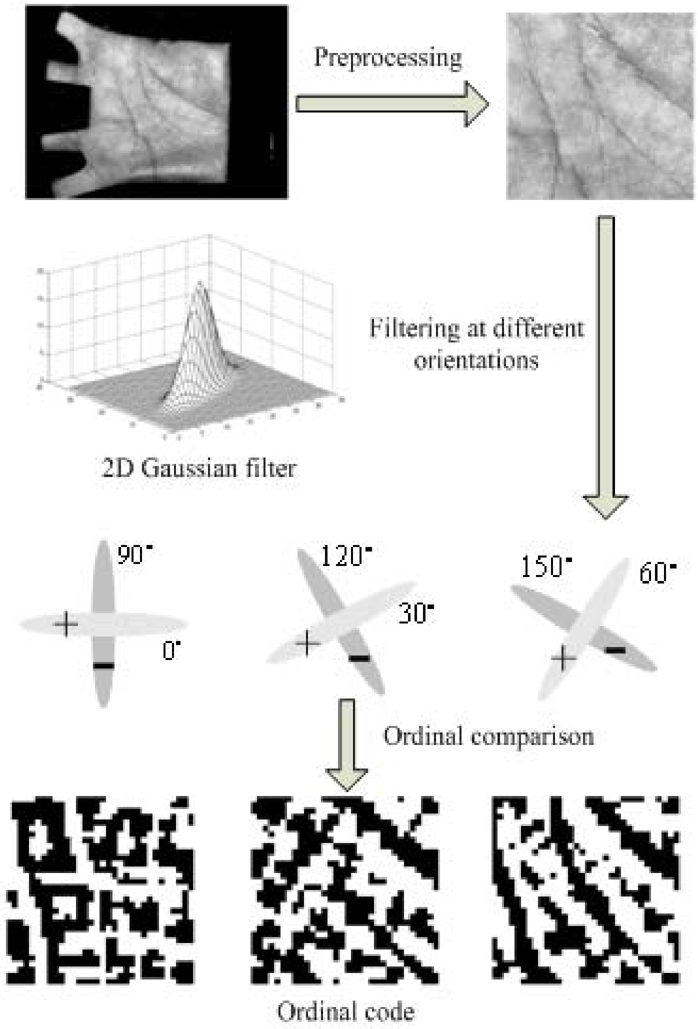
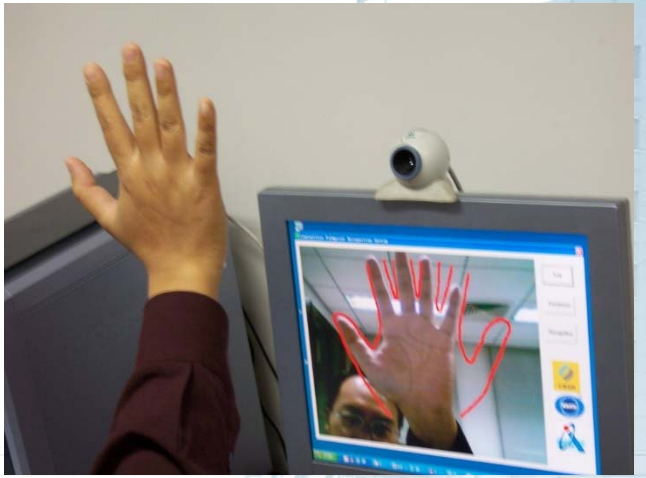
Eyeprint Recognition

Regular front-facing smartphone cameras can create an cryptographic key used to authenticate users based on the micro features in and around their eyes, the most important of which are the blood vessels visible in the whites of the eyes.



Ordinal Measure-based Palmprint Recognition



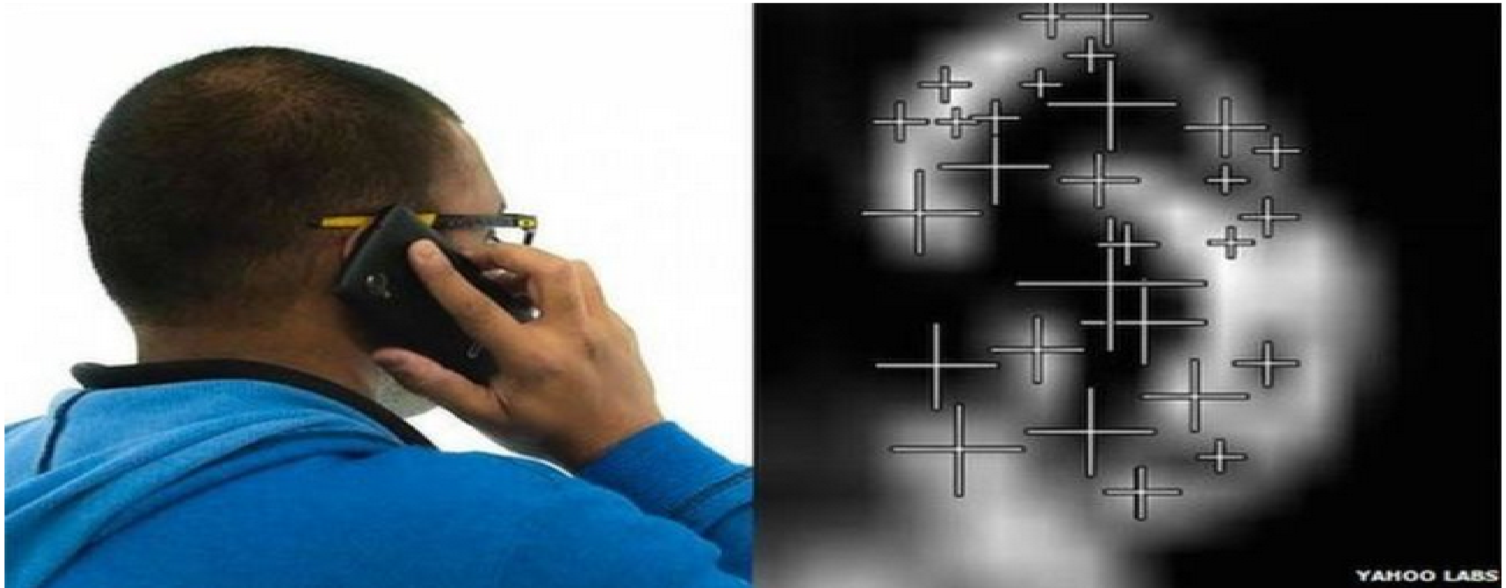


Ear Biometrics

Technology

Yahoo tests ear-based smartphone identification system

28 April 2015 | Technology



The system identifies users based on the shape of their ears

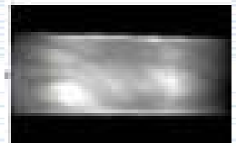
Hand Vein Patterns for Biometric Recognition

Unique, stable and secure biometric patterns underneath the skin surface

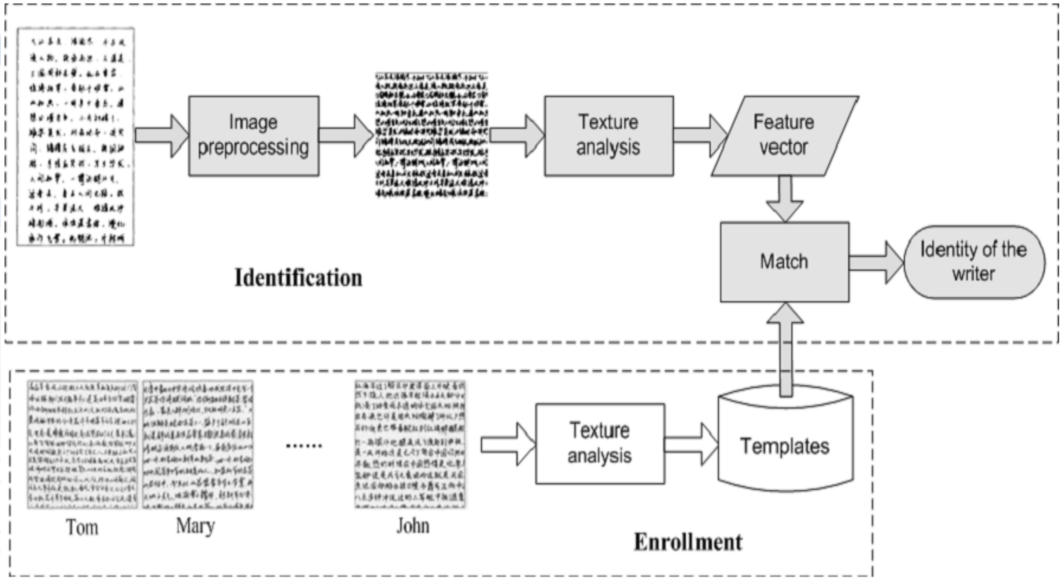
Finger vein

Palm vein

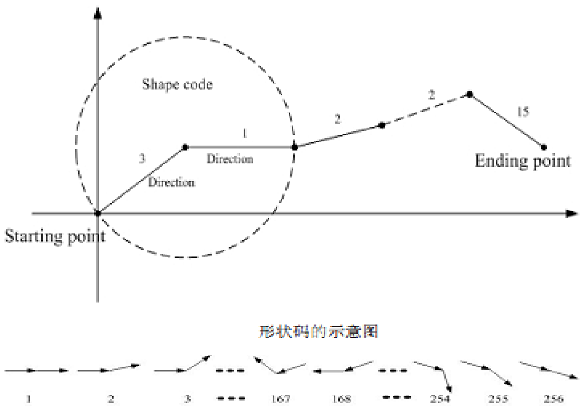
Hand vascular pattern



Handwriting Biometrics

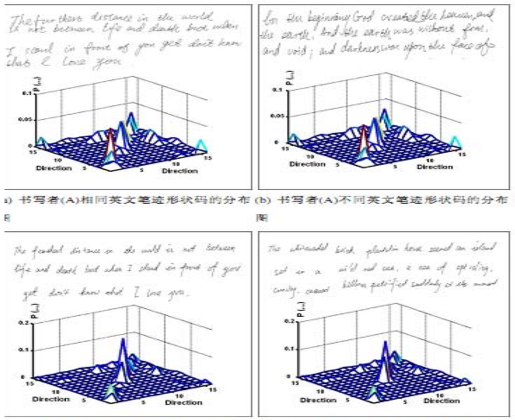


Handwriting texture analysis for writer identification



形状码的示意图

形状码类型的示意图



(a) 书写者(A)相同英文笔迹形状码的分布图 (b) 书写者(A)不同英文笔迹形状码的分布图

(c) 书写者(B)相同英文笔迹形状码的分布图 (d) 书写者(B)不同英文笔迹形状码的分布图

Statistical analysis of stroke shape features for writer identification

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Challenges of Biometric Recognition

From Solved to Unsolved

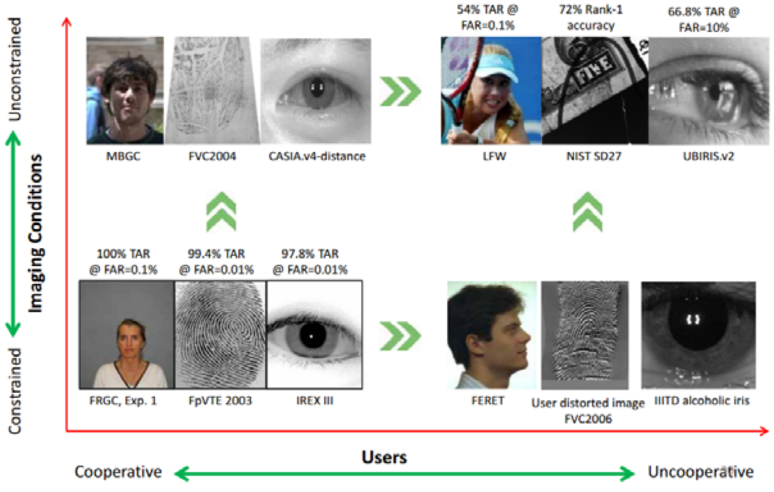
50 Years of Biometric Research:

Almost ~~The~~ Solved, The Unsolved, and The Unexplored

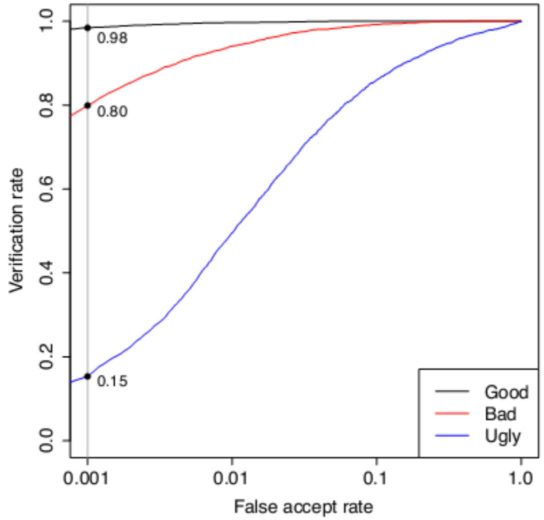
Anil Jain
Michigan State University

June 5, 2013

Keynote Talk Delivered at the International Conf. on Biometrics, Madrid, Spain, June 5, 2013



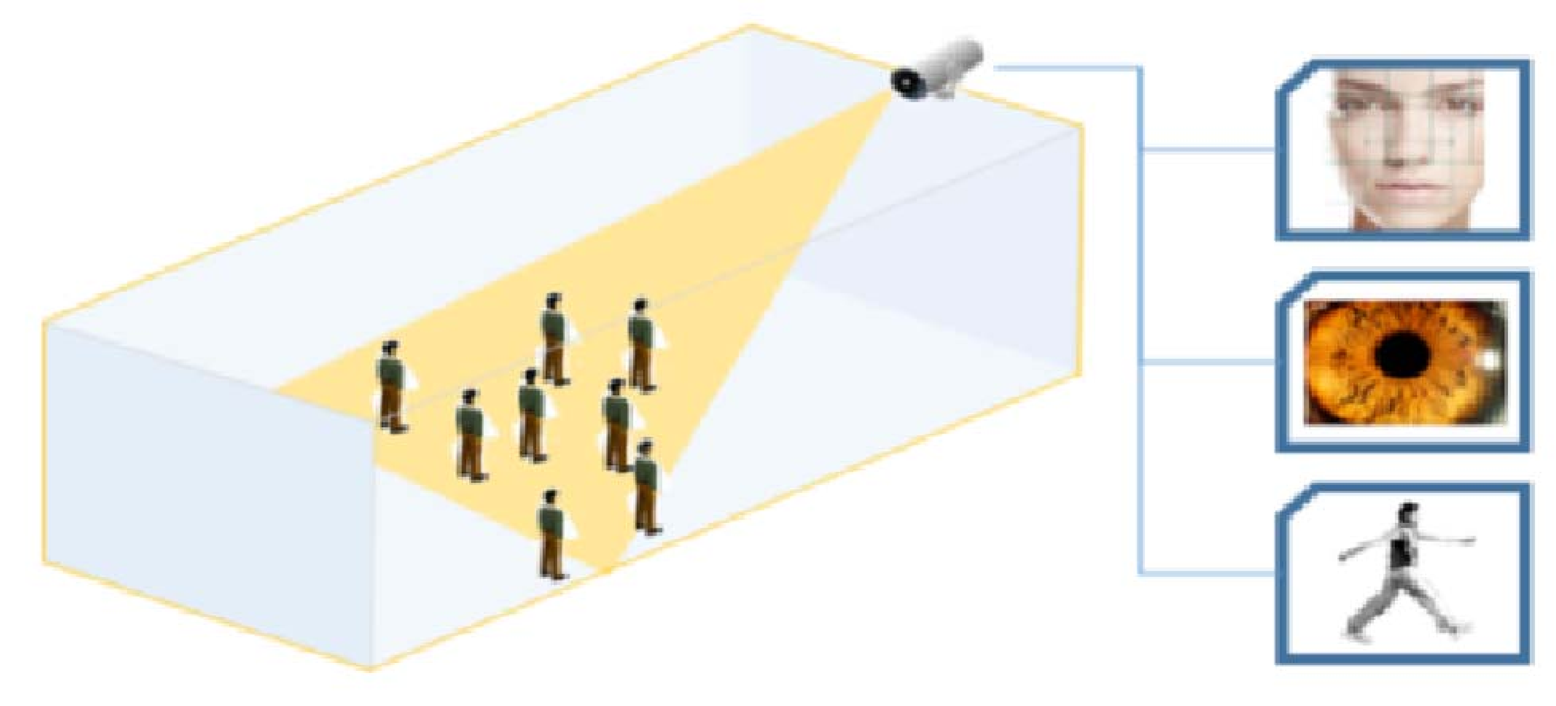
Jonathon Phillips
NIST



An Introduction to the Good, the Bad, & the Ugly Face Recognition Challenge Problem (FG2011)

Future Directions

- Multi-biometrics at a distance



Future Directions

- Multi-biometrics for mobile devices

Fingerprint

Face

Iris

Eyeprint

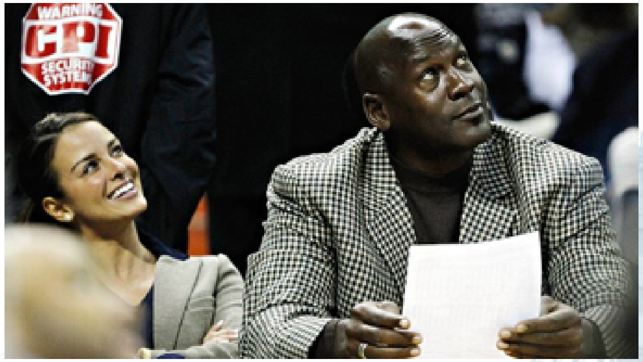
Palmprint

Voiceprint

Future Directions

- Demographic Analysis from Biometric Data

What demographic and affective information can be derived from this face image?



Identity	Rose	Jordan
Gender	Female	Male
Ethnicity	White	Black
Age	27	45
Affect	Happy	Surprised

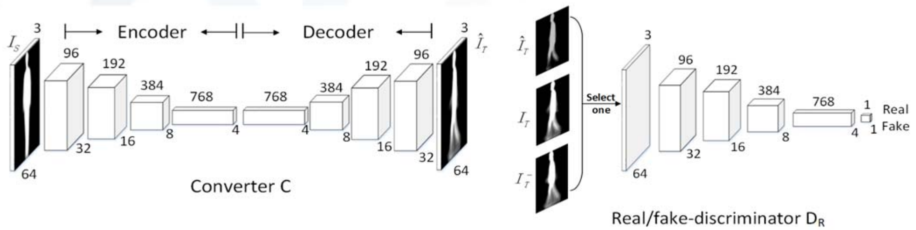
How to determine such information from biometric data?

Yunlin Sun, Man Zhang, Zhenan Sun, Tieniu Tan, Demographic Analysis from Biometric Data: Achievements, Challenges, and New Frontiers, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2018.

Future Directions

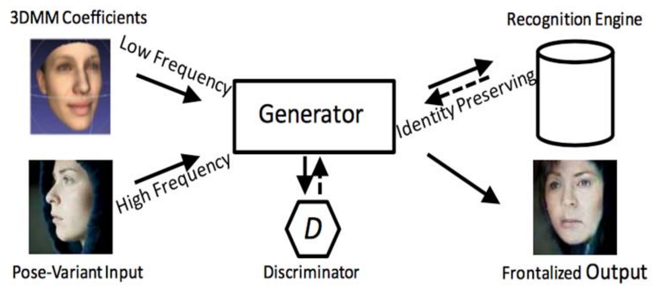
- GAN for biometrics

Gait

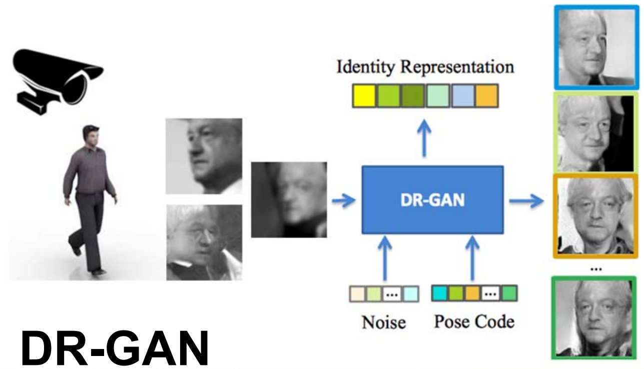


GaitGAN (ICCV 2017 workshop**)**

Face

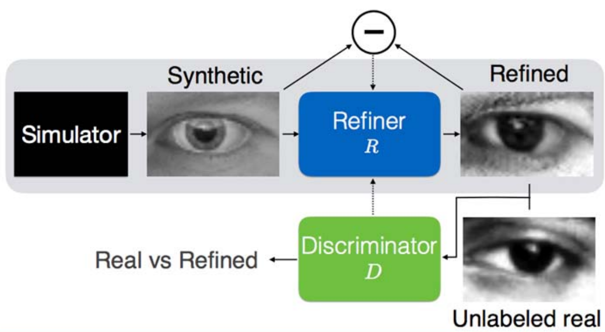


FF-GAN (ICCV 2017)



DR-GAN (CVPR 2017)

Gaze & Hand pose



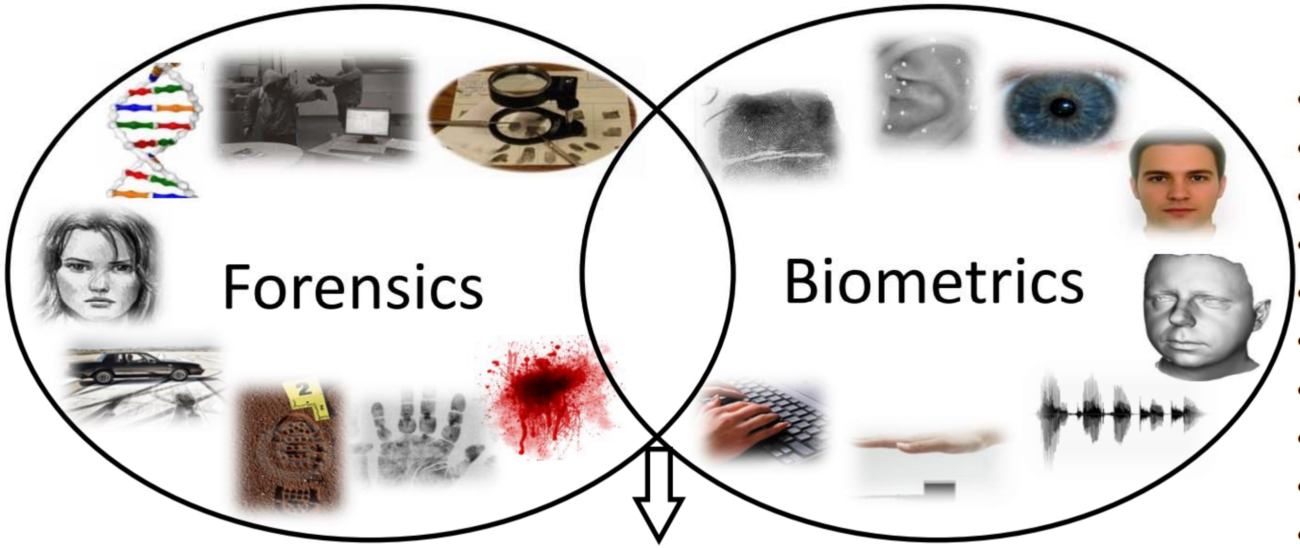
Sim-GAN (CVPR 2017)

Future Directions

- Biometrics for forensic applications

Forensics & Biometrics: Shared Goals

- Latent prints
- Fibers
- Explosives
- Paint chips
- DNA
- Tire marks
- Shoe prints
- Bite marks
- SMT



- 2D Face
- 3D Face
- Fingerprint
- Iris
- Speech
- Signature
- Gait
- Ear
- Palmprint
- Keystroke

Forensics: Identify suspects from crime scene evidence

Biometrics: Automated person recognition from *body traits*

Anil K. Jain, Forensics: The Next Frontier for Biometrics, Iowa State University, Ames, Iowa, October 27, 2015.

Conclusions

- Great progress on biometric recognition has been achieved using novel sensors (biometrics-on-the-fly, light field camera) and algorithms (CNN, GAN).
- State-of-the-art biometric methods are accurate and fast enough for many practical applications.
- Many open problems remain to be resolved to make biometric recognition more user-friendly, robust and secure.

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Thank you!

Q & A