Fundamentals and Recent Progress of Biometrics

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Outline

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

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Personal identification is required by a wide variety of applications

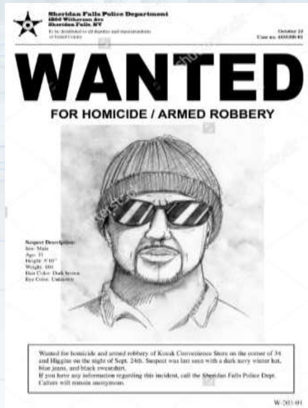
Access control

Bank

Email login

Border control

Unlock mobile phone



Forensics

Traditional methods of personal identification

ID Card

Password

Card+PW

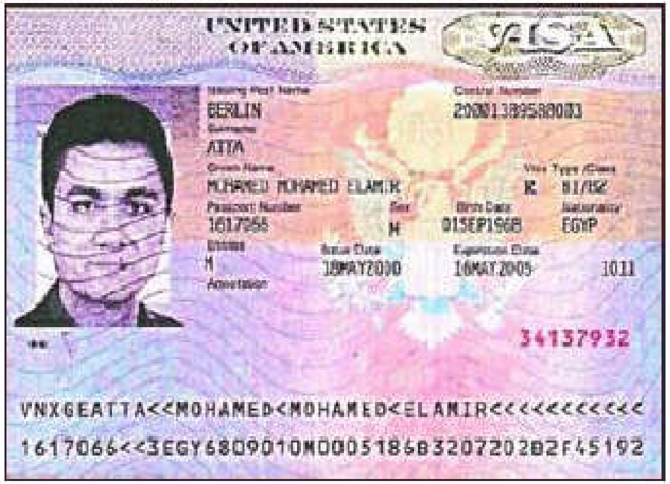
- Passwords and cards can be shared and thus cannot provide non-repudiation
- Passwords may be forgotten or cracked
- Cards may be lost, stolen or forged

Too Many Passwords to Remember!

- 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

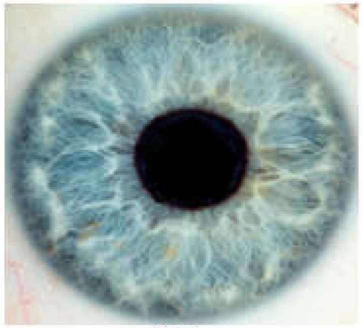
by Special on November 30, 2018 in NEWS

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

Biometrics

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

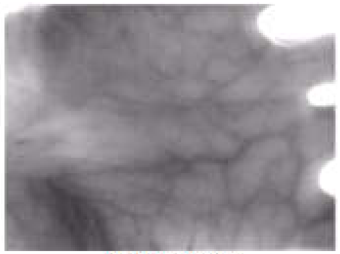
Physiological Modalities

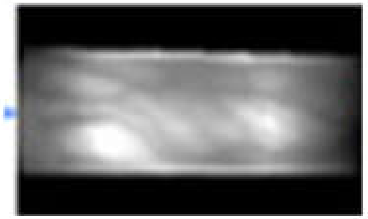

Iris


Face


Fingerprint

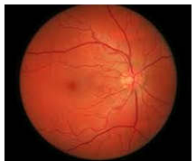

Palmprint

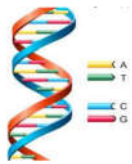

Palm vein


Finger vein


Hand geometry

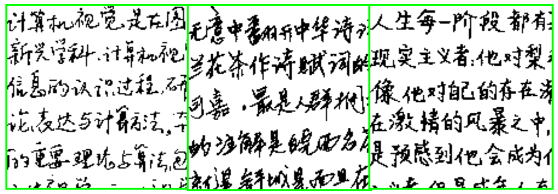

Ear

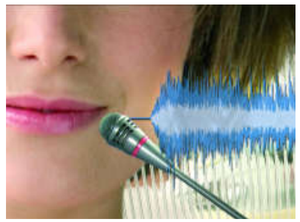

Retina


DNA

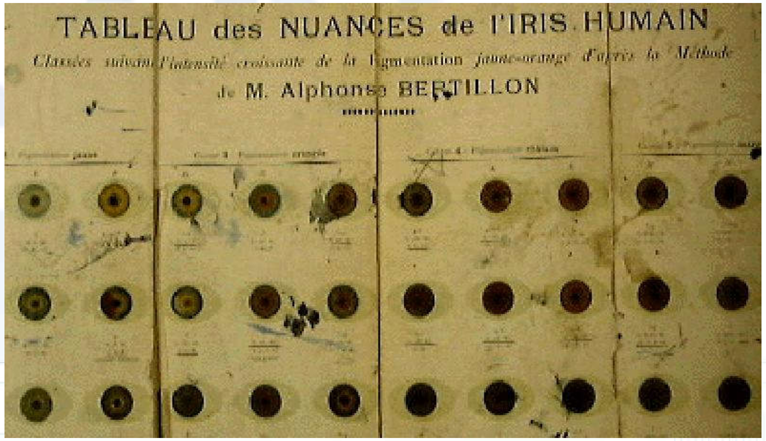
Behavioral Modalities

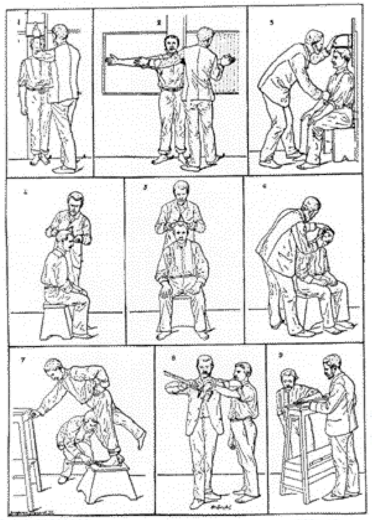

Gait

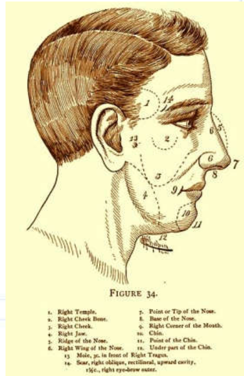

Handwriting

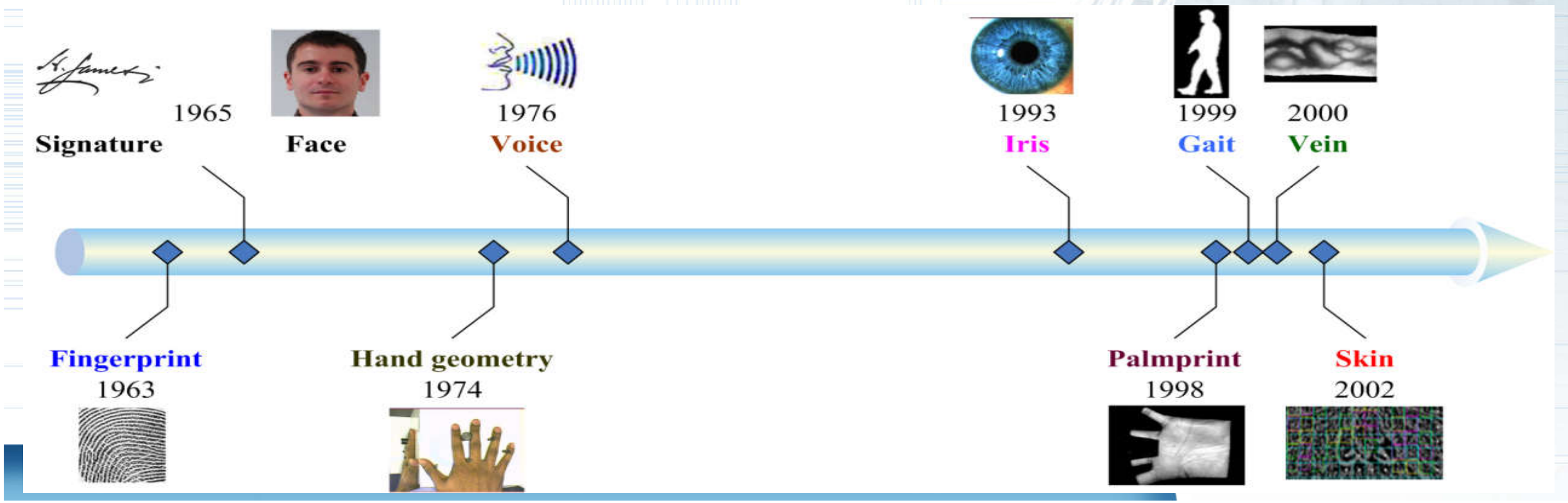

Voiceprint

The history of biometrics

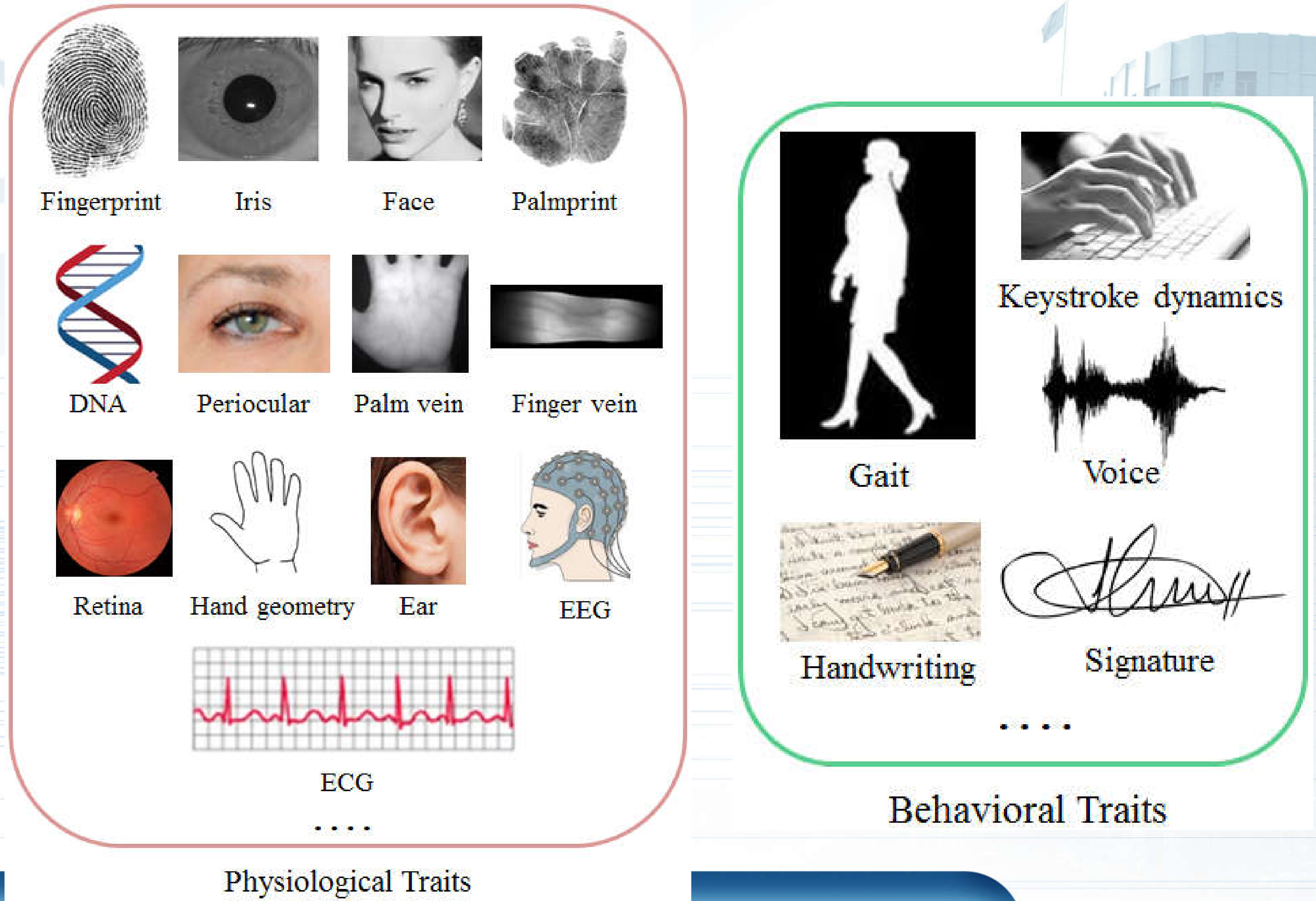








Main biometric modalities



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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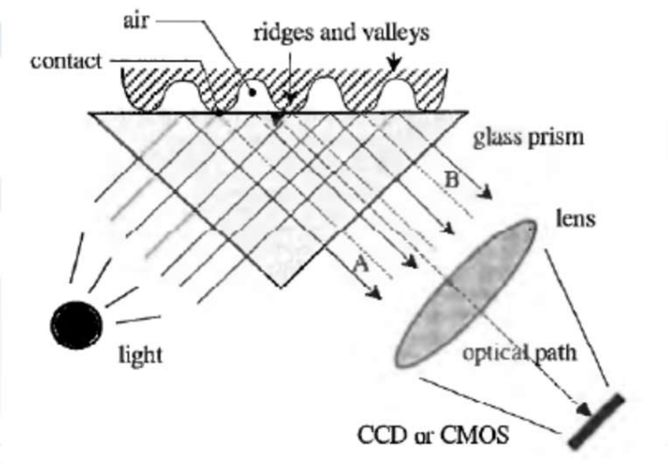
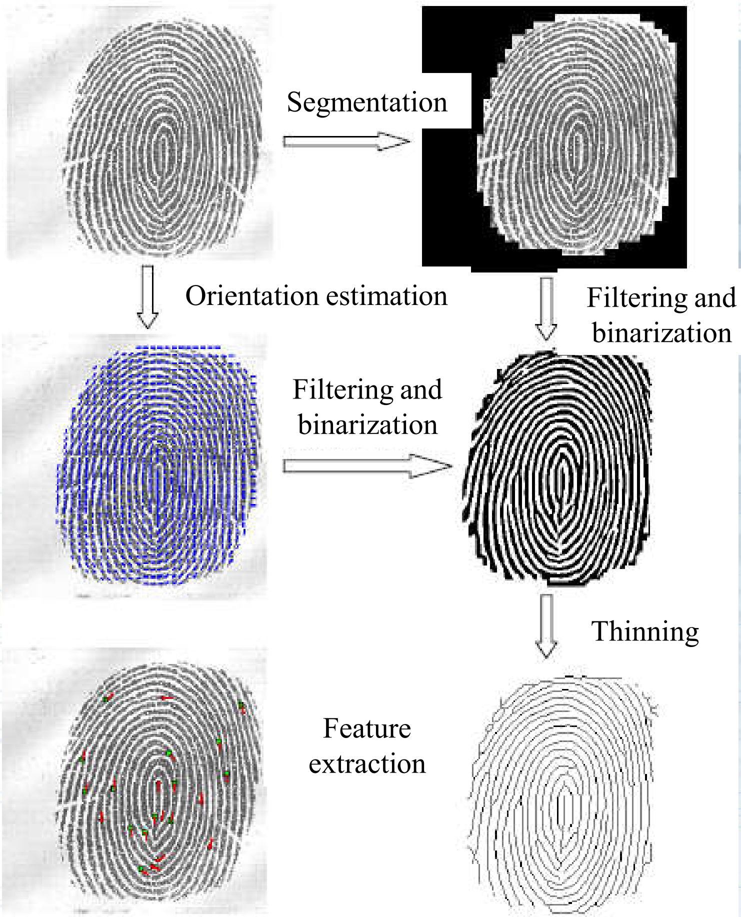
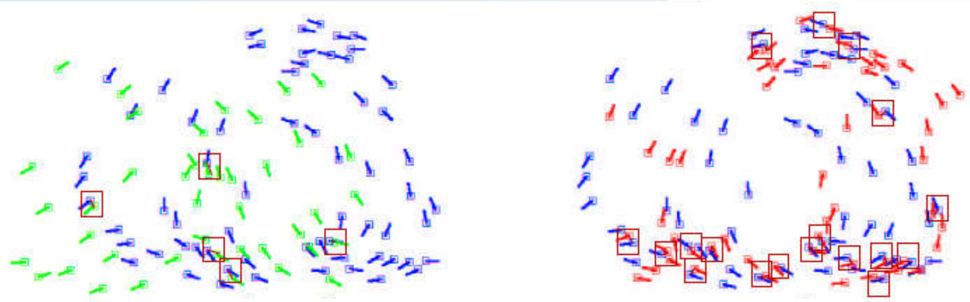
Fingerprint Recognition



Imaging



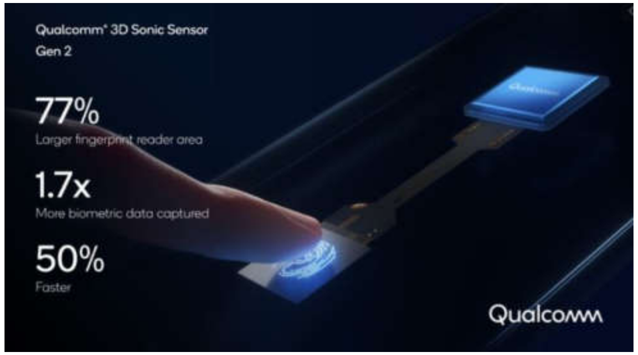
Preprocessing and feature extraction



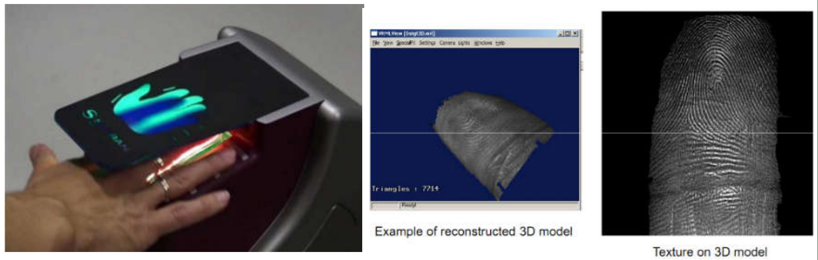
Minutiae matching

Recent Progress of Fingerprint Recognition

Better user experience

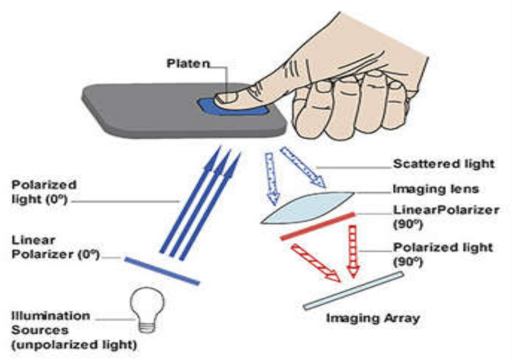


3D Sonic Sensor 2th Generation (Qualcomm)

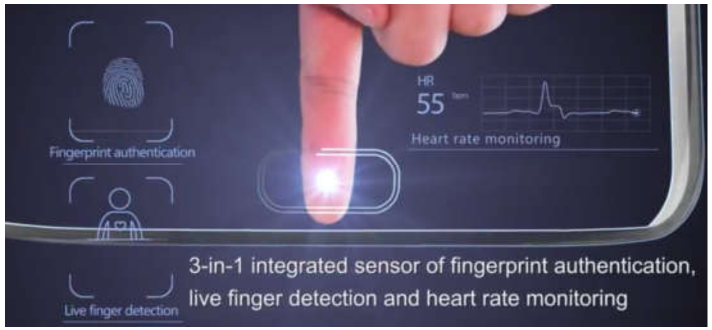


Touchless 3D fingerprint (SAFRAN Morph)

More secure



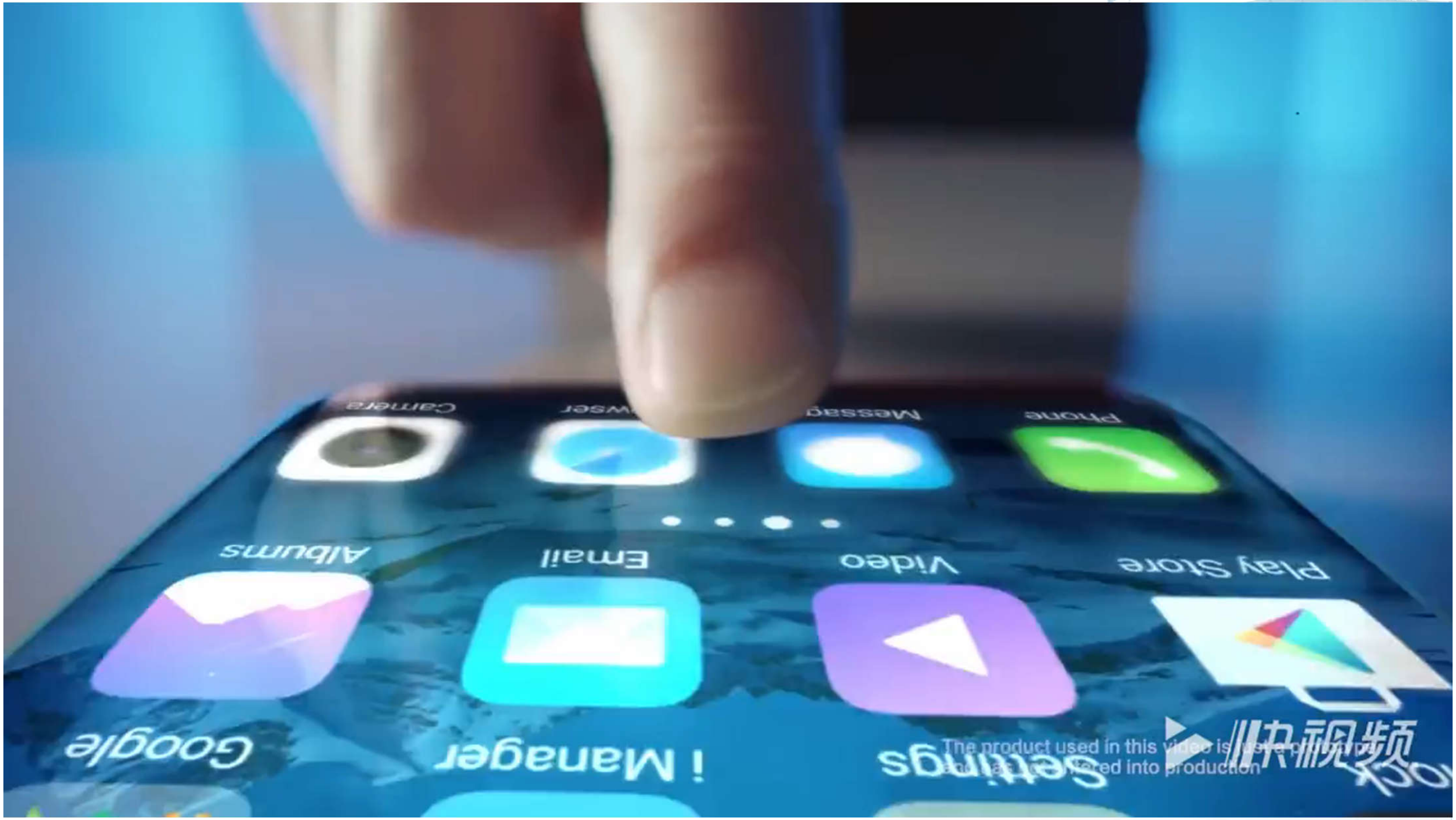
Multispectral imaging for anti-spoofing (Lumidigm)



IC solution of blood flow detection (Goodix)

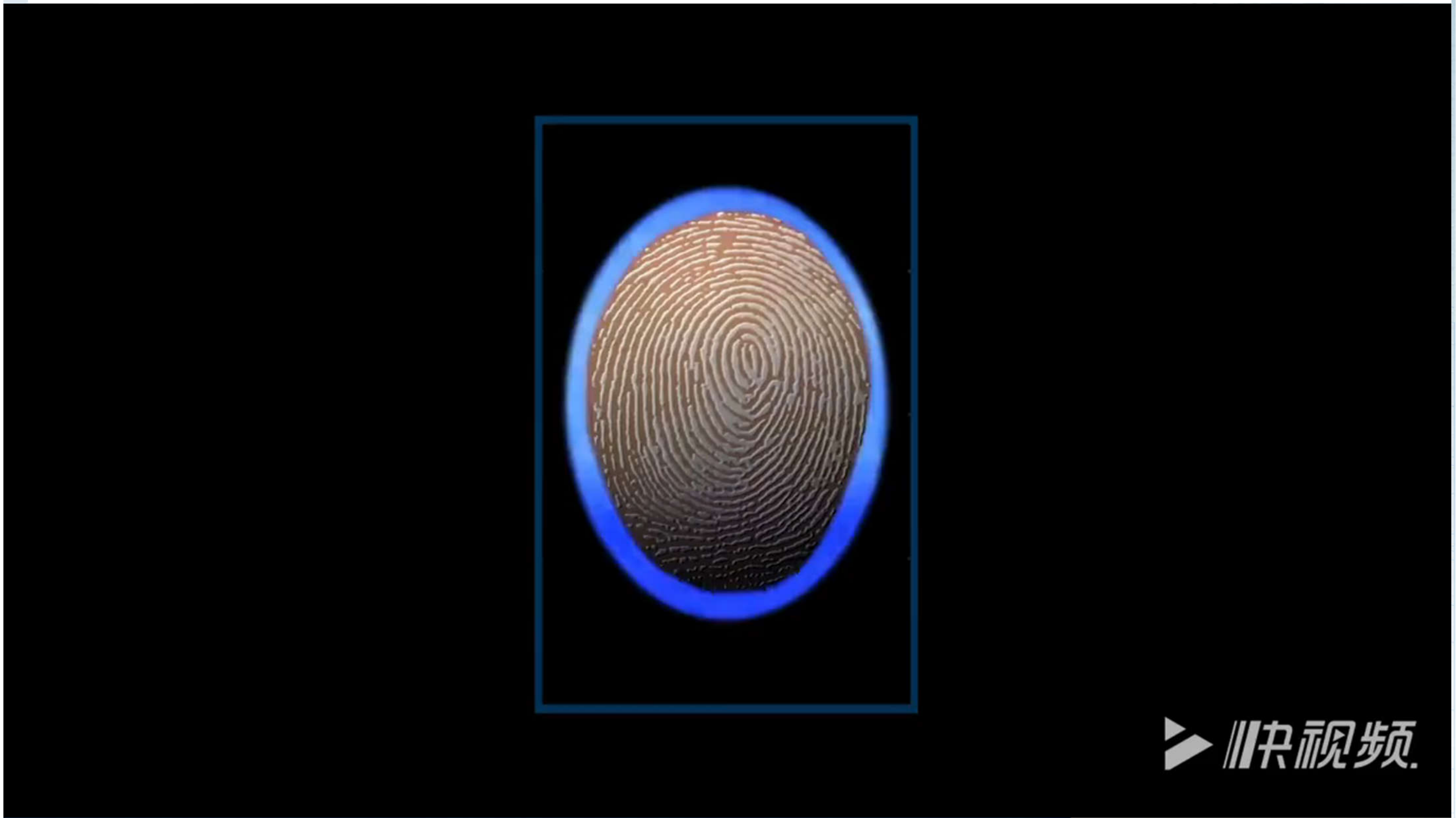
Under Display Fingerprint Scanning

(Qualcomm-Vivo, ultrasonic fingerprint solution, MWC2017)



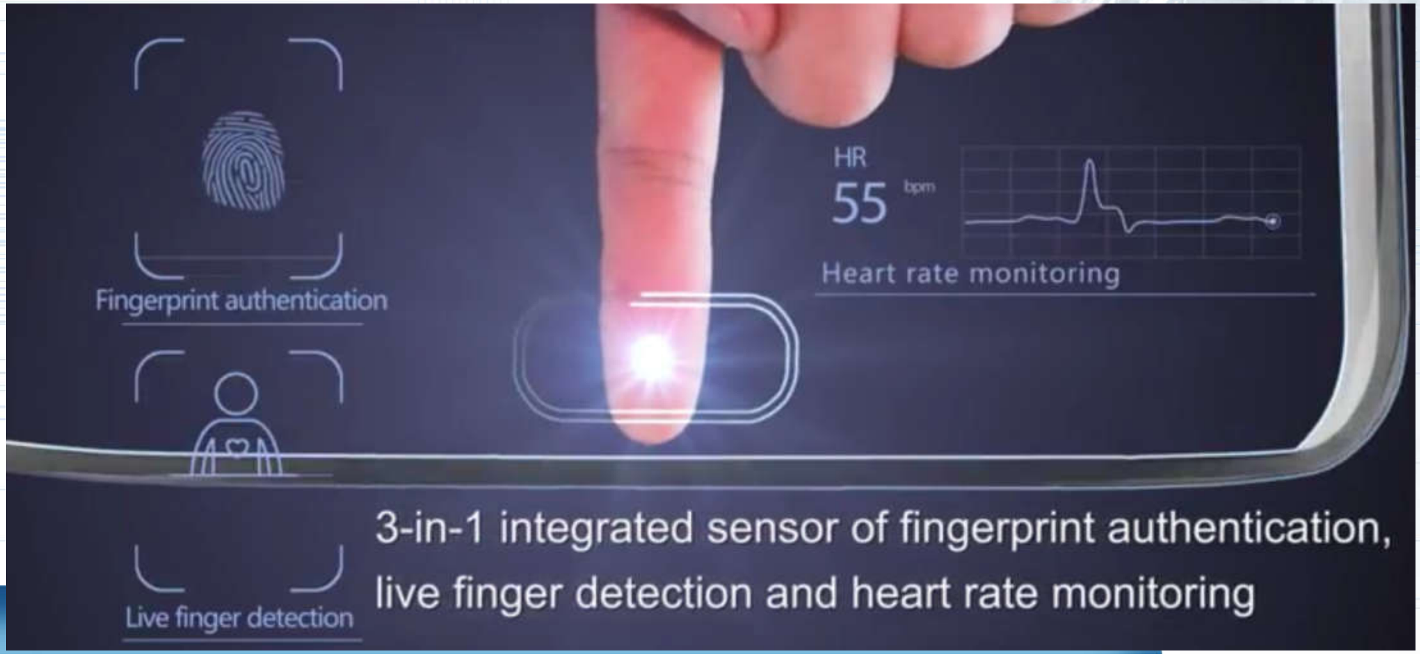
Touchless 3D Fingerprint Recognition (SAFRAN Morph)

Multispectral imaging for anti-spoofing (Lumidigm)

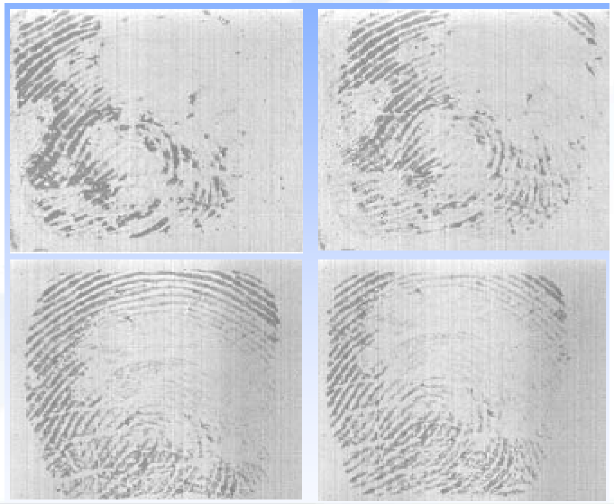


IC Solution for Live Finger Detection

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.

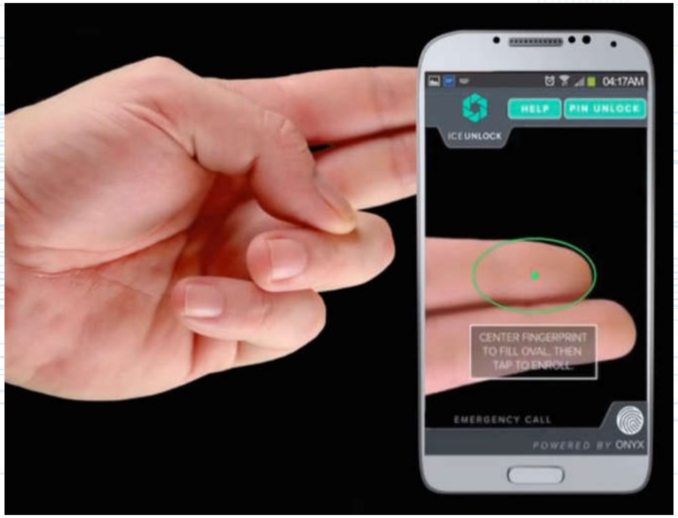


Open Problems of Fingerprint Recognition

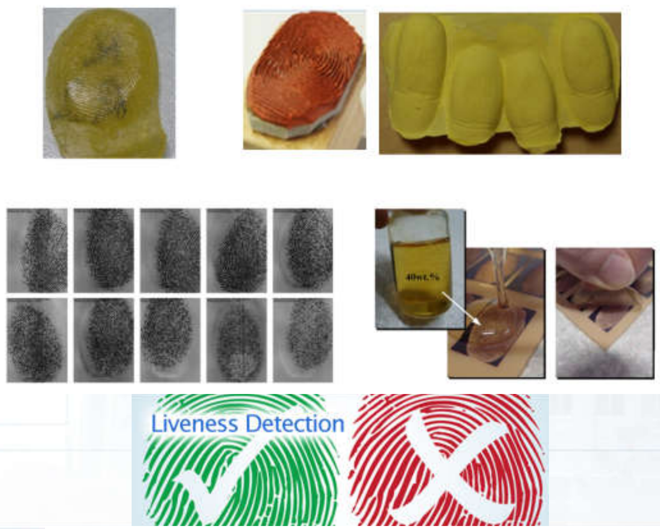


Latent fingerprint images

Distorted fingerprint images



Touchless fingerprint recognition

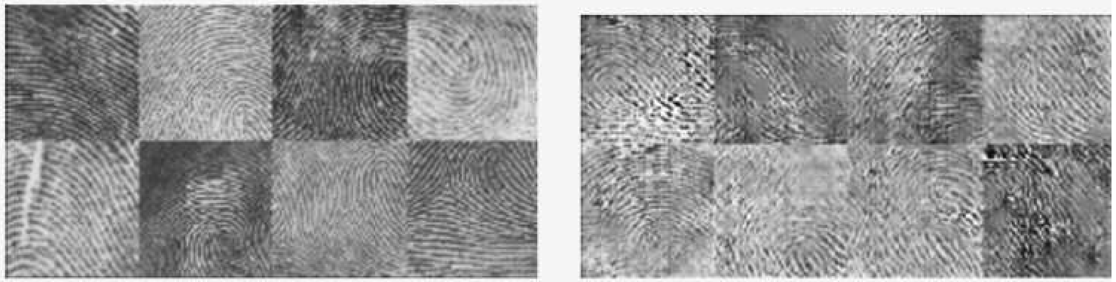


Fingerprint liveness detection

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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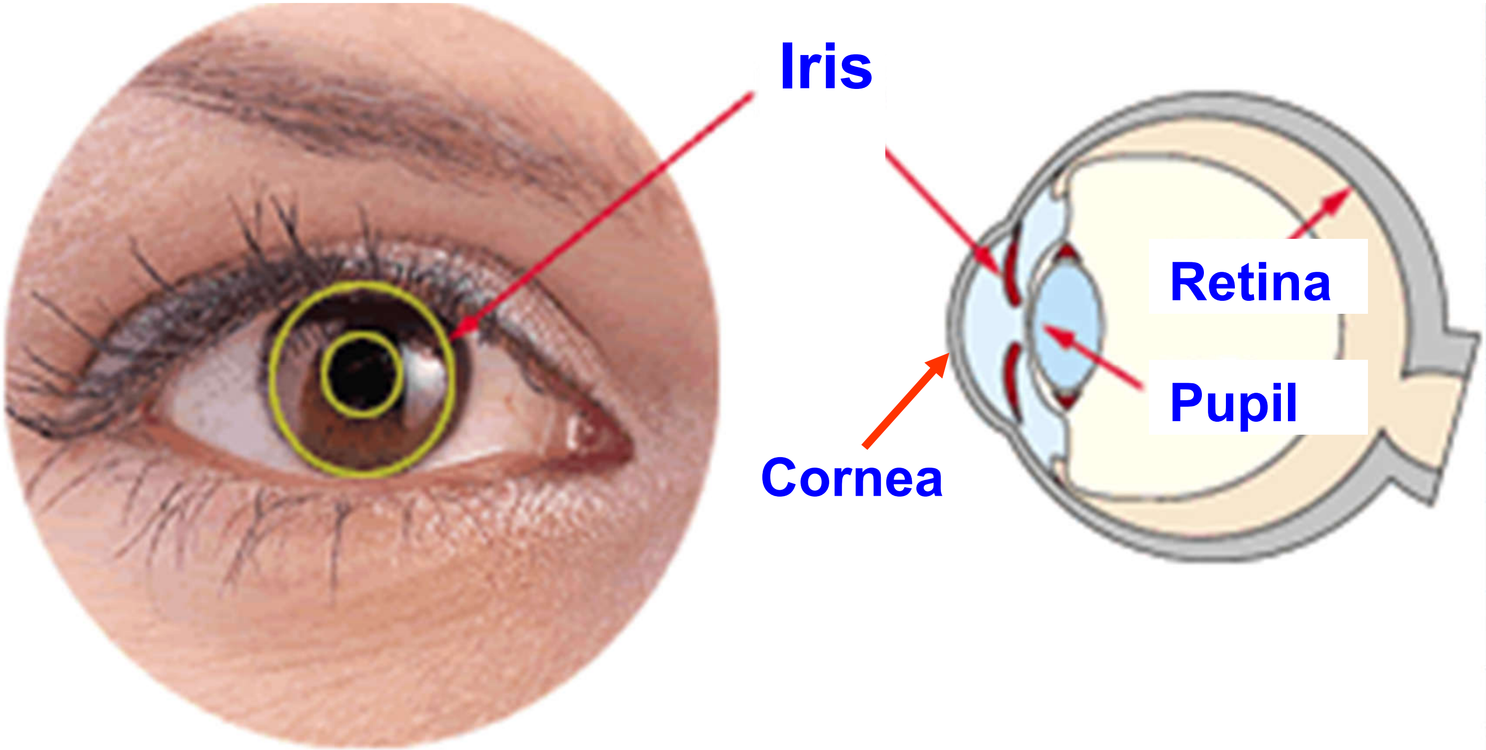
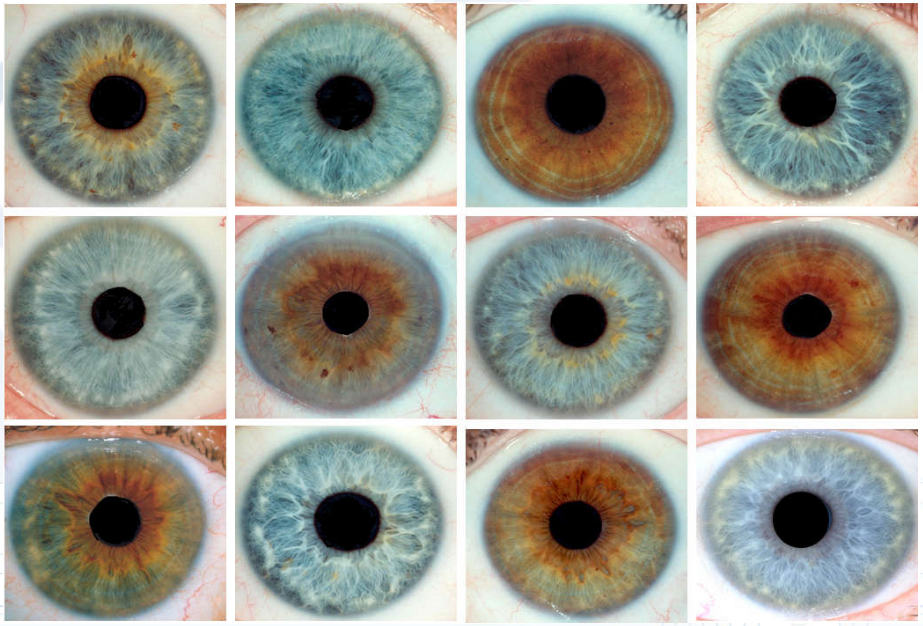
Human Iris

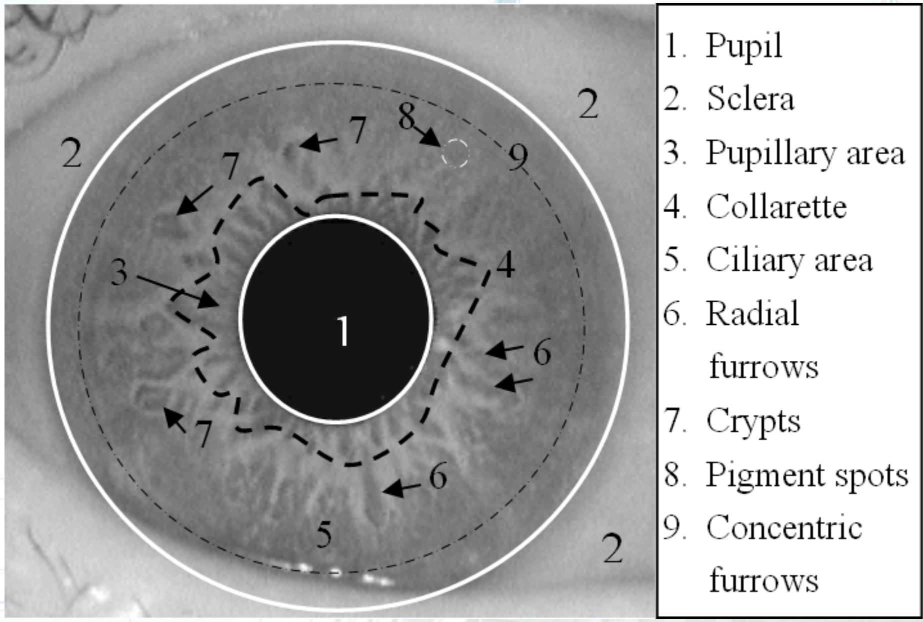
- The iris of your eye is the circular, colored membrane that surrounds the pupil.
- It controls light levels inside the eye similar to the aperture on a camera.
- Highly protected by cornea but externally visible at a distance



Human iris is unique for personal identification



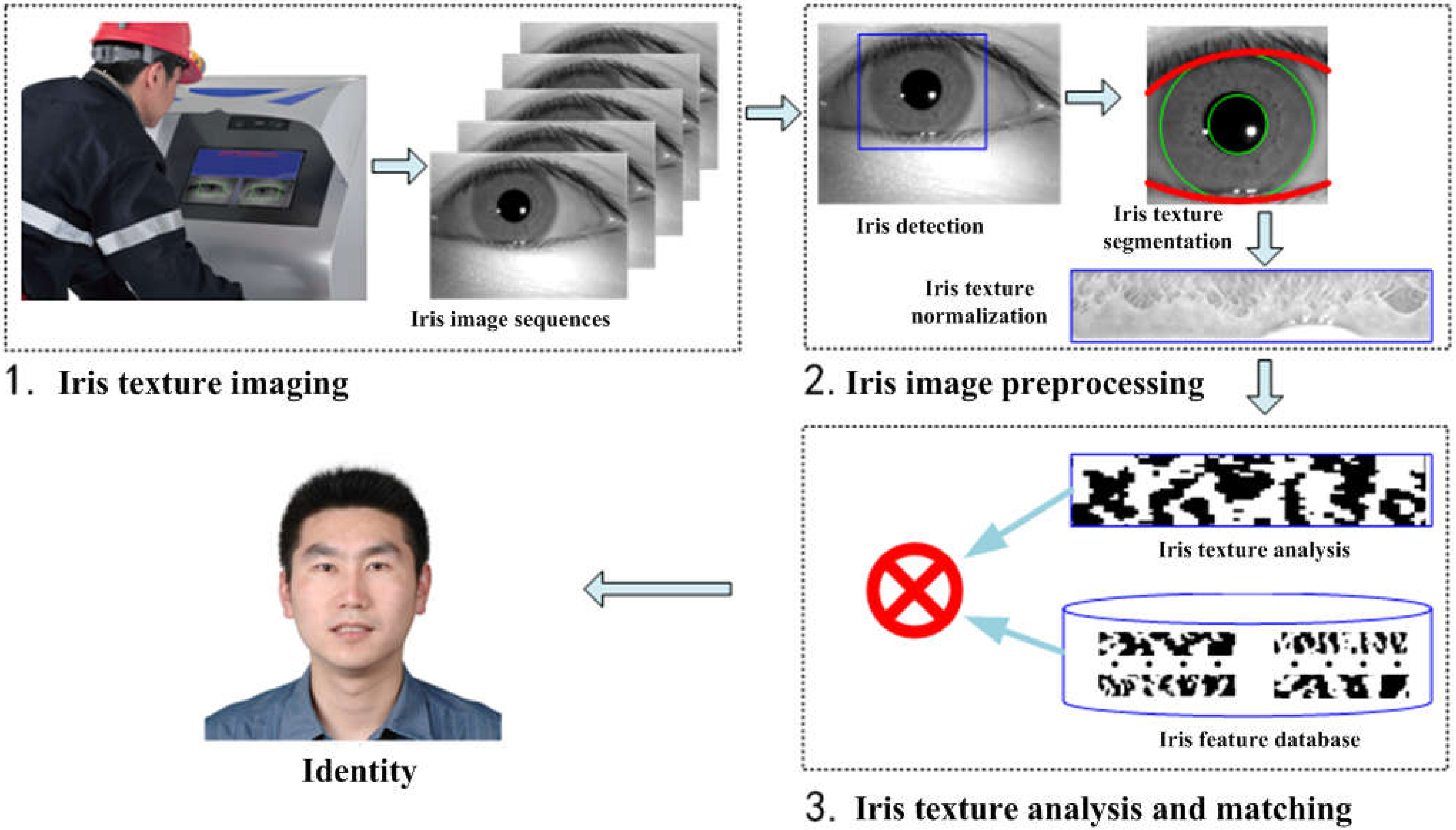
Visible illumination



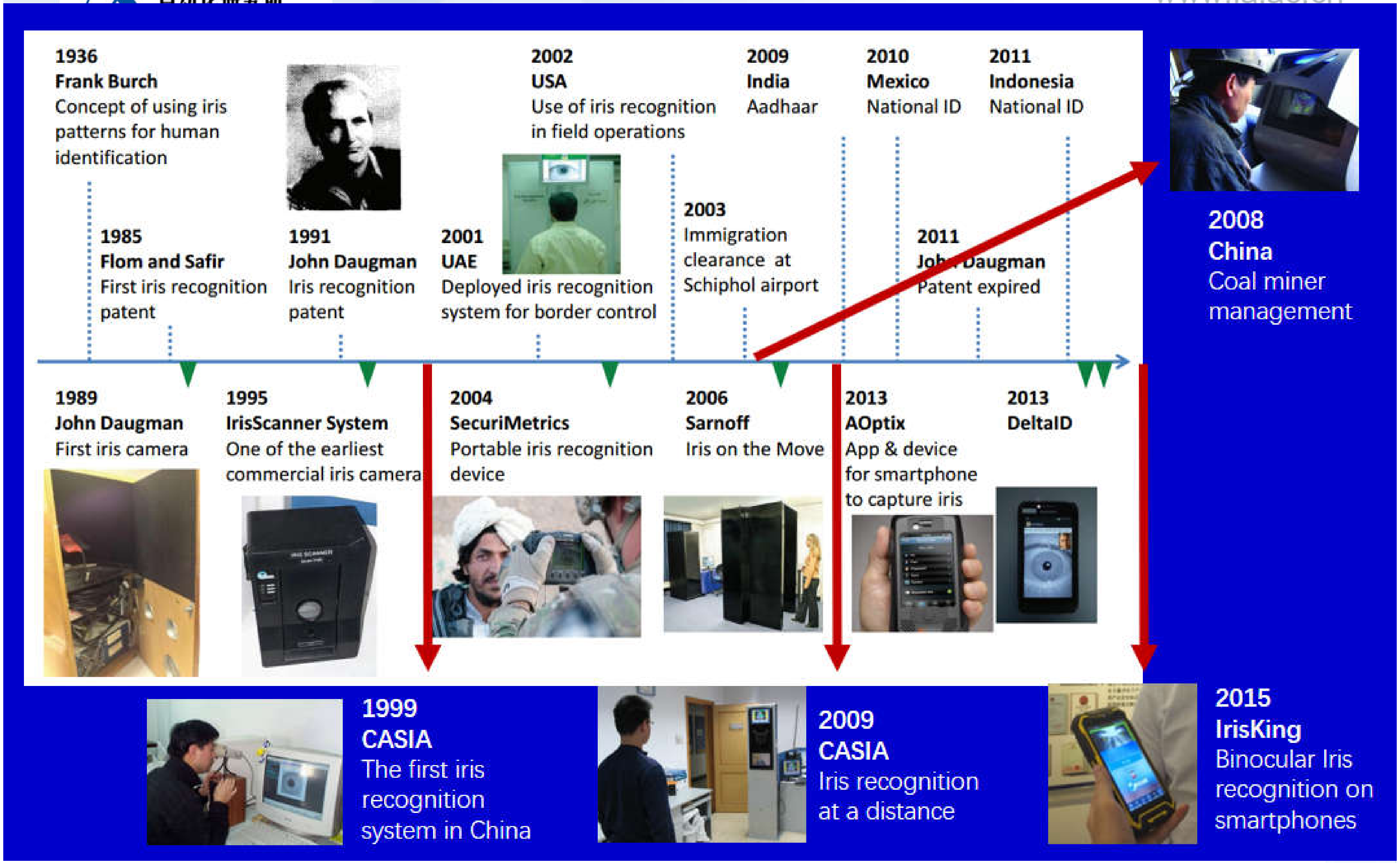
Near infrared illumination

- 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

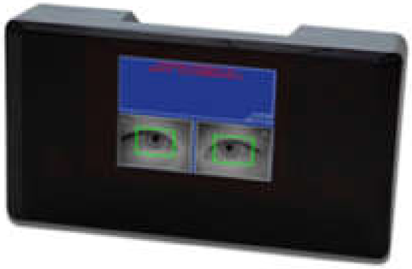

Panasonic BM-ET500


IrisGuard IG-H100


IrisGuard IG-AD100


SecuriMetrics PIER 2.3

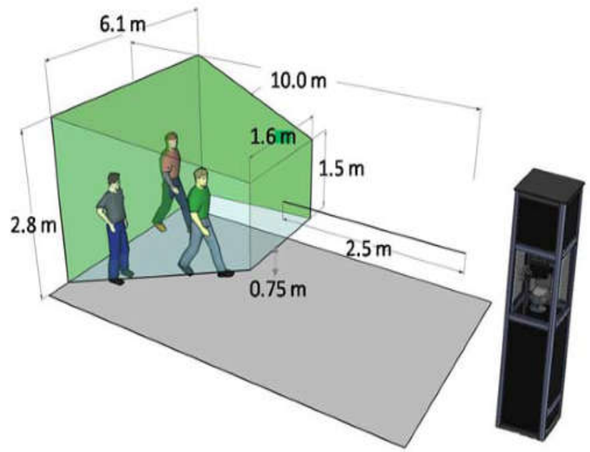

Crossmatch I SCAN2


IrisKing IKEMB-110

Long-range iris devices


Aoptix InSight

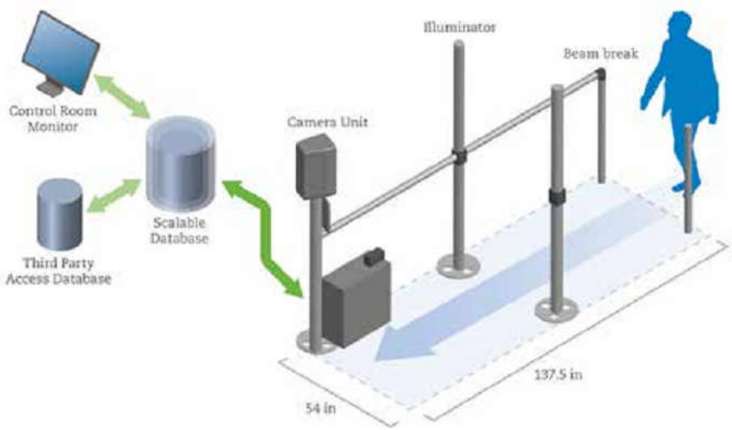

EyeLock HBOX



Eagle-eyes


IOM PassThru

System Diagram
IOM PassPort SL with floor kit assembly
IOM PassPort




IrisID iCAM D1000


CASIA

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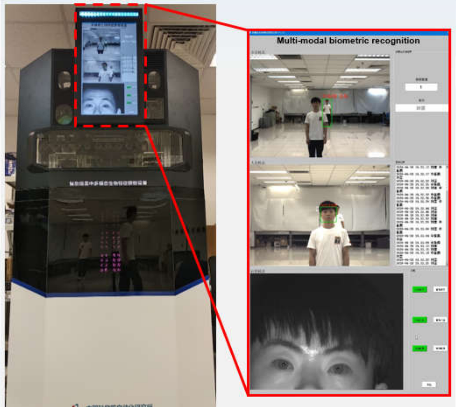
All-in-Focus Iris Camera

www.ia.ac.cn



Interaction HMI

IJCB 2020 Google Best Paper Award Runner-Up

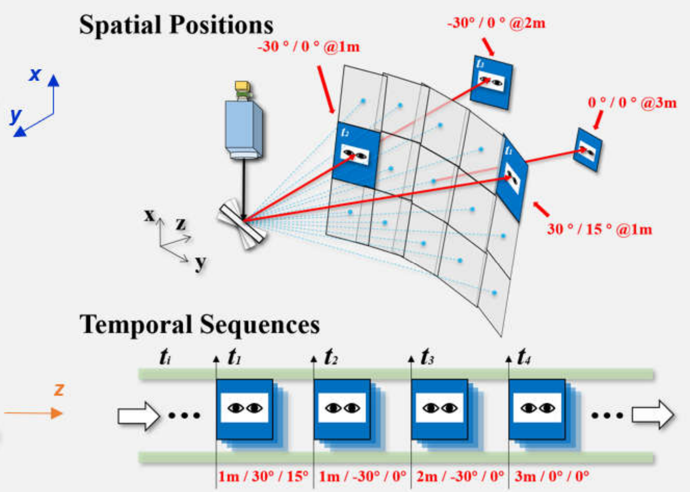
Kunbo Zhang, Zhenteng Shen, Yunlong Wang, Zhenan Sun: All-in-Focus Iris Camera With a Great Capture Volume

Multi-view multiplexing

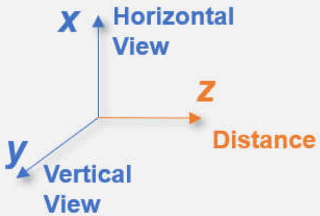
(FoV extension)

Multi-focus multiplexing

(DoF extension)



Spatial-temporal multiplexing imaging



Omni all-in-focus high spatial-temporal resolution imaging

- Multi-person iris
- Iris on-the-move
- Large DoF
- Omnidirectional

All-in-Focus Iris Camera

Small DoF	Narrow FoV	Single
20cm	<10° (no PTZ)	person

→

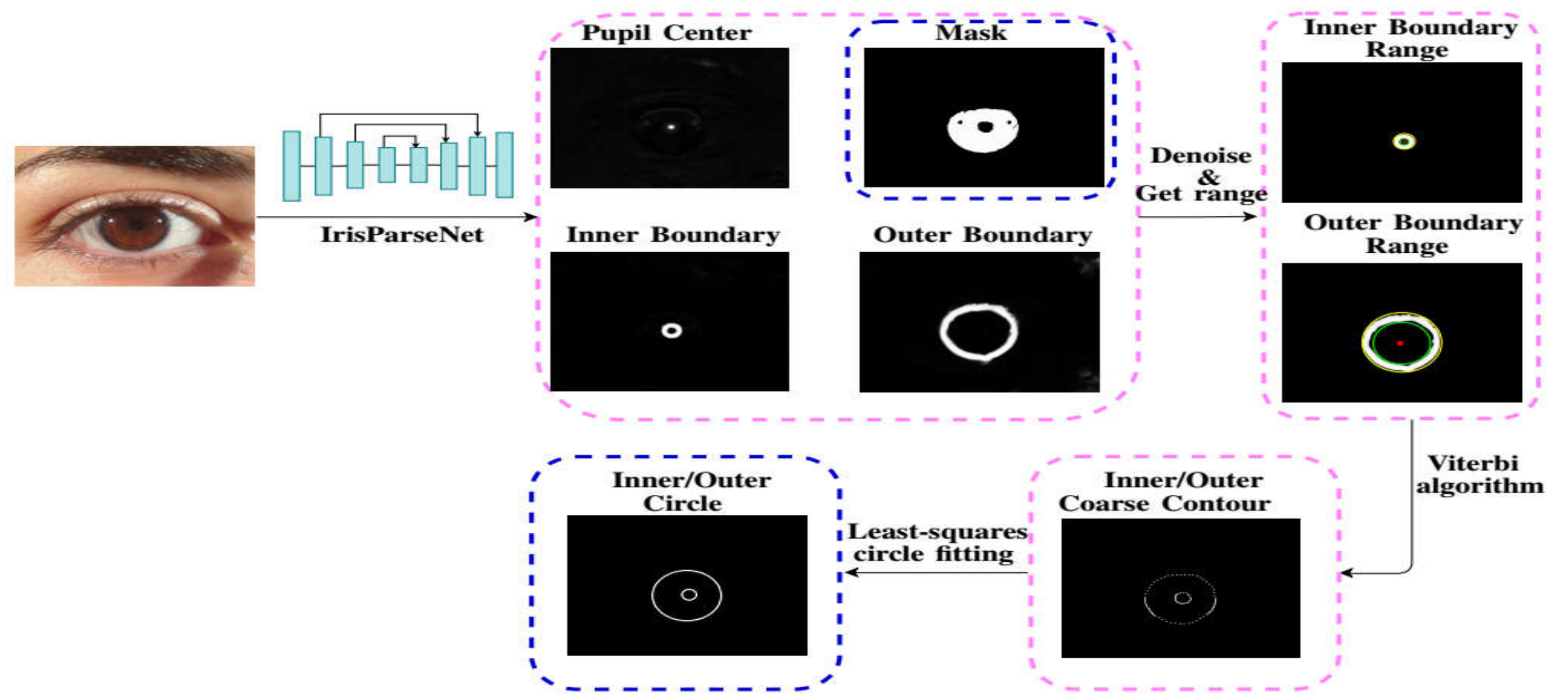
Large DoF	Wide FoV	Multiple
3.9 m@5m	360°	(≥5)

Model	Distance	Performance	Person	User cooperation
IOM, Sarnoff [3]	2.4-3 m	0.2m x 0.4 m x 0.1 m, two cameras, 0.5 s/person	1	Standstill, walk (1m/s@5m)
Eagle-Eyes, Retica [4]	3-6 m	3 m x 2 m x 3 m, double cameras	1	Standstill
CASIA [5]	2.4-3 m	0.15 m x 0.15 m x 0.1 m, PTZ camera	1	Standstill
CMU [6]	12 m	0.97 m x 0.73 m @1 m	1	Standstill, walk (0.6m/s)
SRI [7]	25 m	0.305 m x 0.405 m@25 m, long focal zoom lens, O.D. 254 mm	1	Standstill
iCAM D1000, Iris ID [8]	0.5-1 m	0.2 m x 0.5 m x 0.5 m, vertical moving camera (50 mm)	1	Standstill
S200P, Iristar [9]	1-1.2 m	Height 1.3-1.95 m, DoF 30 cm, 2 s recognition	1	Standstill
Versa F Max, Irisian [10]	0.8-2 m	Height 1.2-2 m, PTZ camera, 1 s eye tracking, 3 s recognition	1	Standstill
Ours	**1–10 m**	**Height 0.8-2 m, 360° , single camera**	**≥5**	**Standstill, walk (1m/s@1-10 m)**

Demo of All-in-Focus Iris Camera

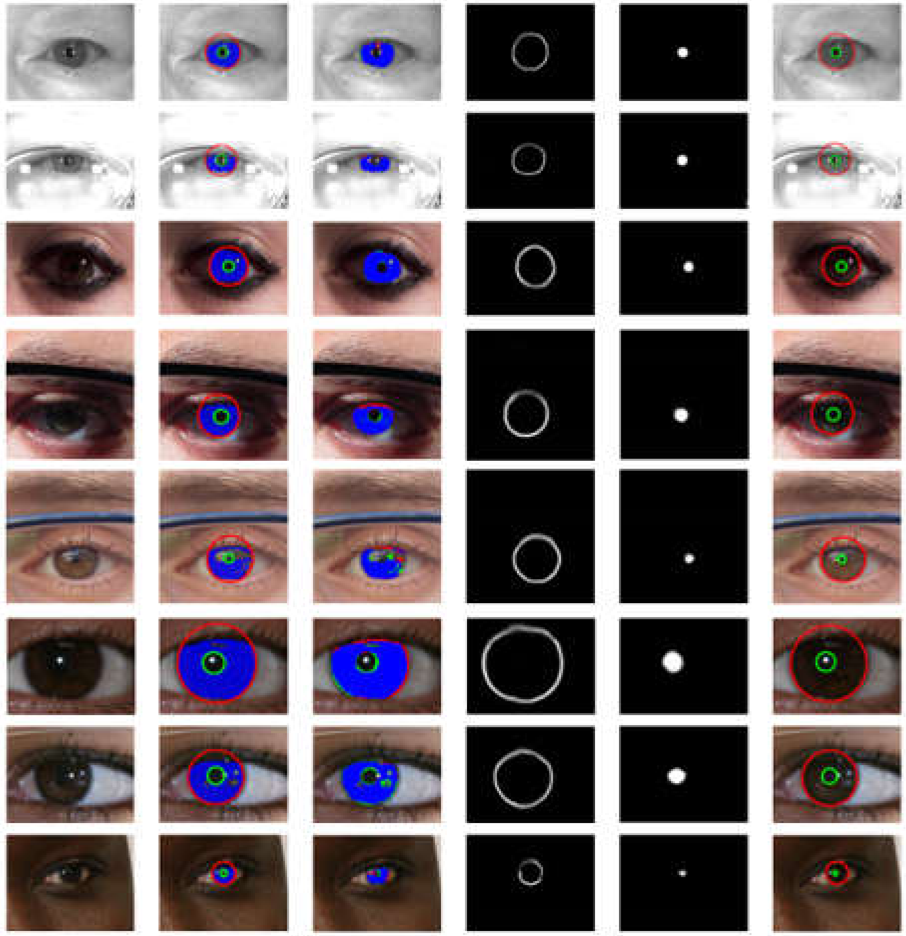
Multi-task Neural Network for Iris Segmentation and Localization

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, Jawad Muhammad, Yunlong Wang, Zhaofeng He, Zhenan Sun. “Towards Complete and Accurate Iris Segmentation Using Deep Multi-task Attention Network for Non-Cooperative Iris Recognition ”. IEEE Trans IFS, 2020,15(1): 2944-2959.

Multi-task Neural Network for Iris Segmentation and Localization



(a) (b) (c) (d) (e) (f)

Method	Database	$E1$ (%)	$E2$ (%)	$F1$ (%)
T. Tan *et al.* [90]	UBIRIS.v2 (NICE.I)	1.31	N/A	N/A
RTV-L^1 [92]	CASIA.v4-distance	0.68	0.44	87.55
	UBIRIS.v2 (NICE.I)	1.21	0.83	85.97
	MICHE-I	2.42	1.21	79.24
Haindl and Krupička [93]	UBIRIS.v2 (NICE.I)	3.24	1.62	77.03
	MICHE-I	3.86	1.93	70.17
MFCNs [101]	CASIA.v4-distance	0.59	0.24	93.09
	UBIRIS.v2 (NICE.I)	0.90	0.49	91.04
	MICHE-I	0.74	0.37	92.01
CNNHT [2] (RefineNet)	CASIA.v4-distance	0.56	0.28	92.27
	UBIRIS.v2 (NICE.I)	0.97	0.48	90.34
	MICHE-I	0.80	0.40	91.41
IrisParseNet	CASIA.v4-distance	**0.41**	**0.20**	**94.25**
	UBIRIS.v2 (NICE.I)	**0.84**	**0.42**	**91.78**
	MICHE-I	**0.66**	**0.33**	**93.05**

Applications of Iris Recognition

Syrian refugees identification

Miss children identification

Anti-terrorism

Prisoners identification

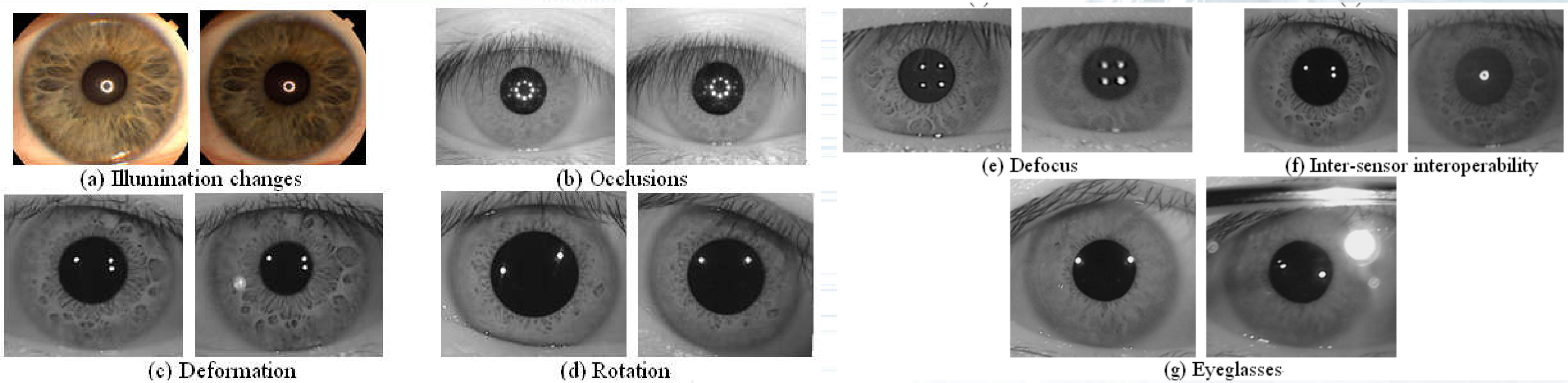
Coal miner identification

Banking

Open Problems of Iris Recognition

Less or unconstrained iris image acquisition

Forensic applications



Poor quality iris images

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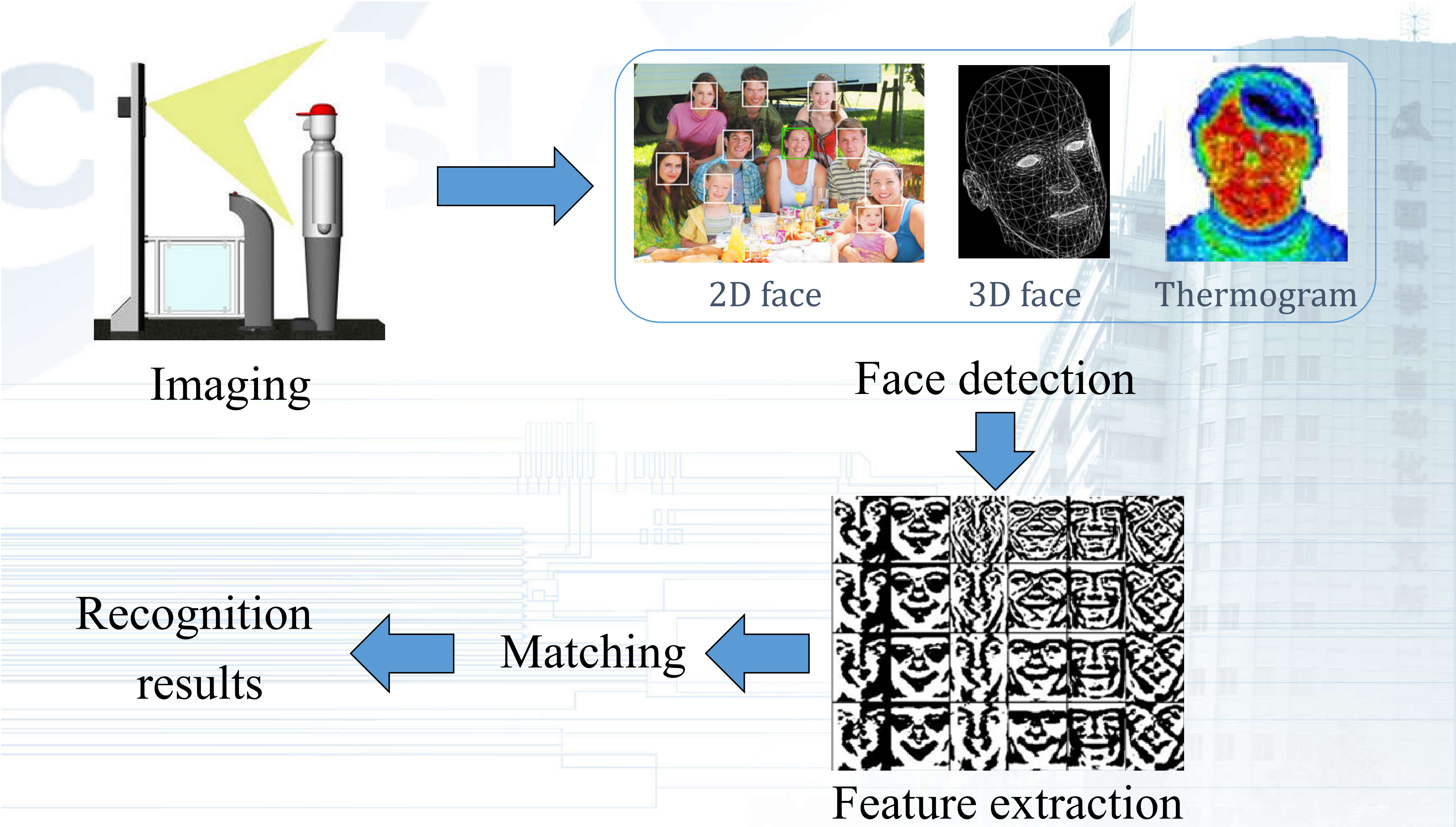
Face Recognition



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

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 [IJCV 2019, NIPS 2018]
Super-resolution	• Wavelet-SRNet [IJCV 2019, ICCV 2017]
Make-up	• BLAN [AAAI 2018]
Cross-spectral	• AD-HFR [AAAI 2018][PAMI 2020]
Completion	• FCENet [AAAI 2019][ACM MM2020]
Expression synthesis	• G2-GAN [ACM MM 2018] • CAFP-GAN [ACM MM 2018]
Aging	• Attribute-aware Face Aging [CVPR 2019][ECCV 2020]

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

Dueling Neural Networks

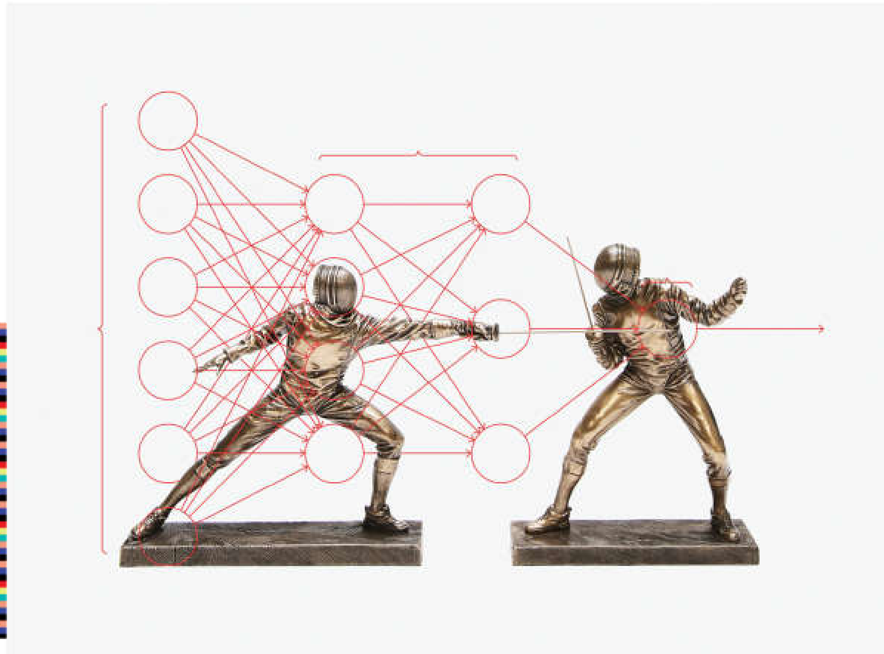


ILLUSTRATION BY DEREK BRAHNEY | DIAGRAM COURTESY OF MICHAEL NIELSEN, "NEURAL NETWORKS AND DEEP LEARNING", DETERMINATION PRESS, 2015

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

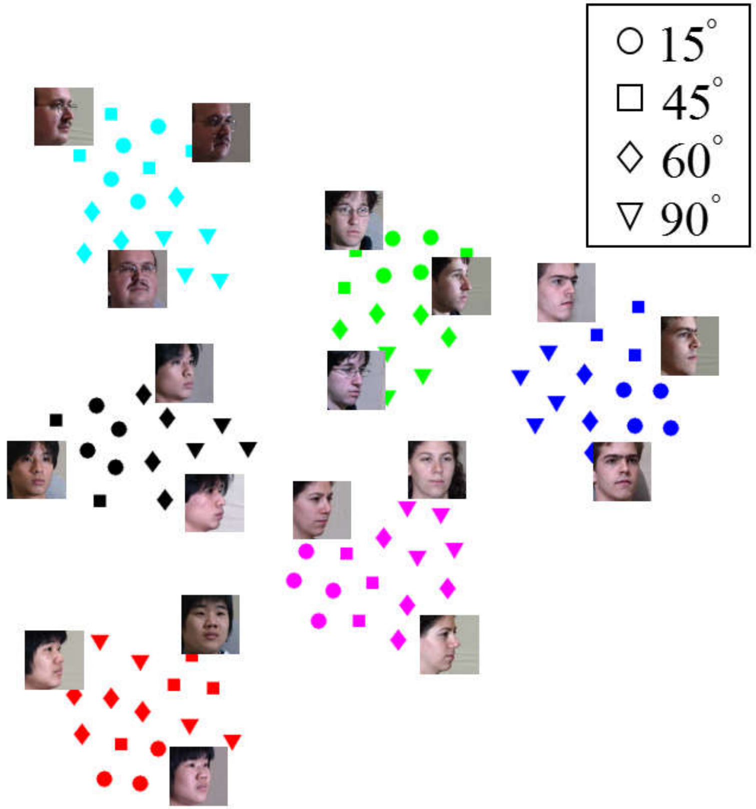
Google Brain, DeepMind, Nvidia

Availability

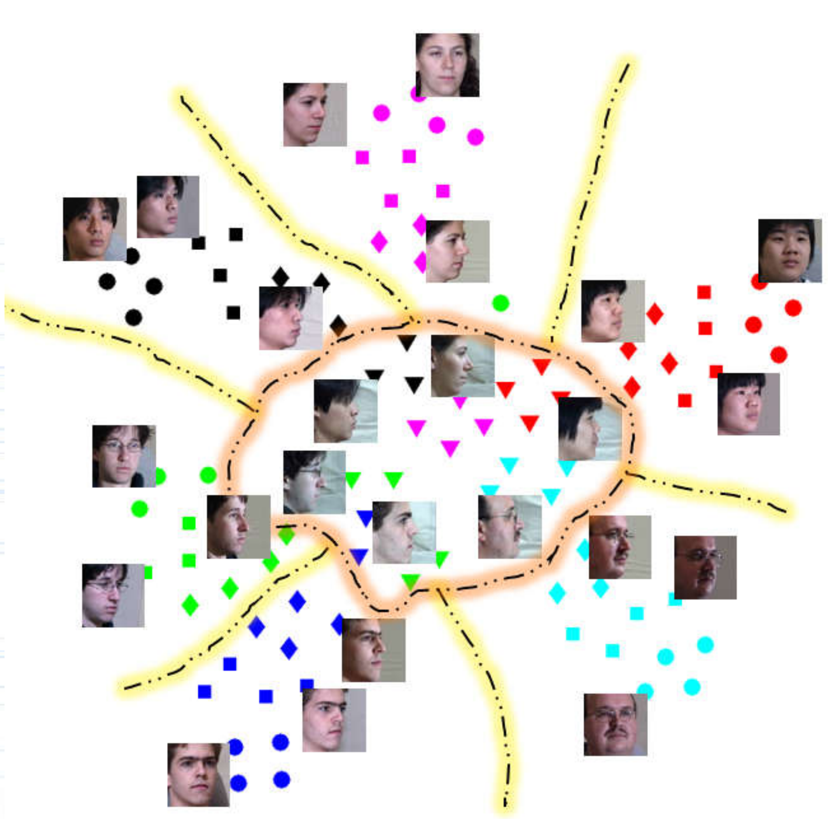
Now

Large pose variations greatly degrade face recognition performance

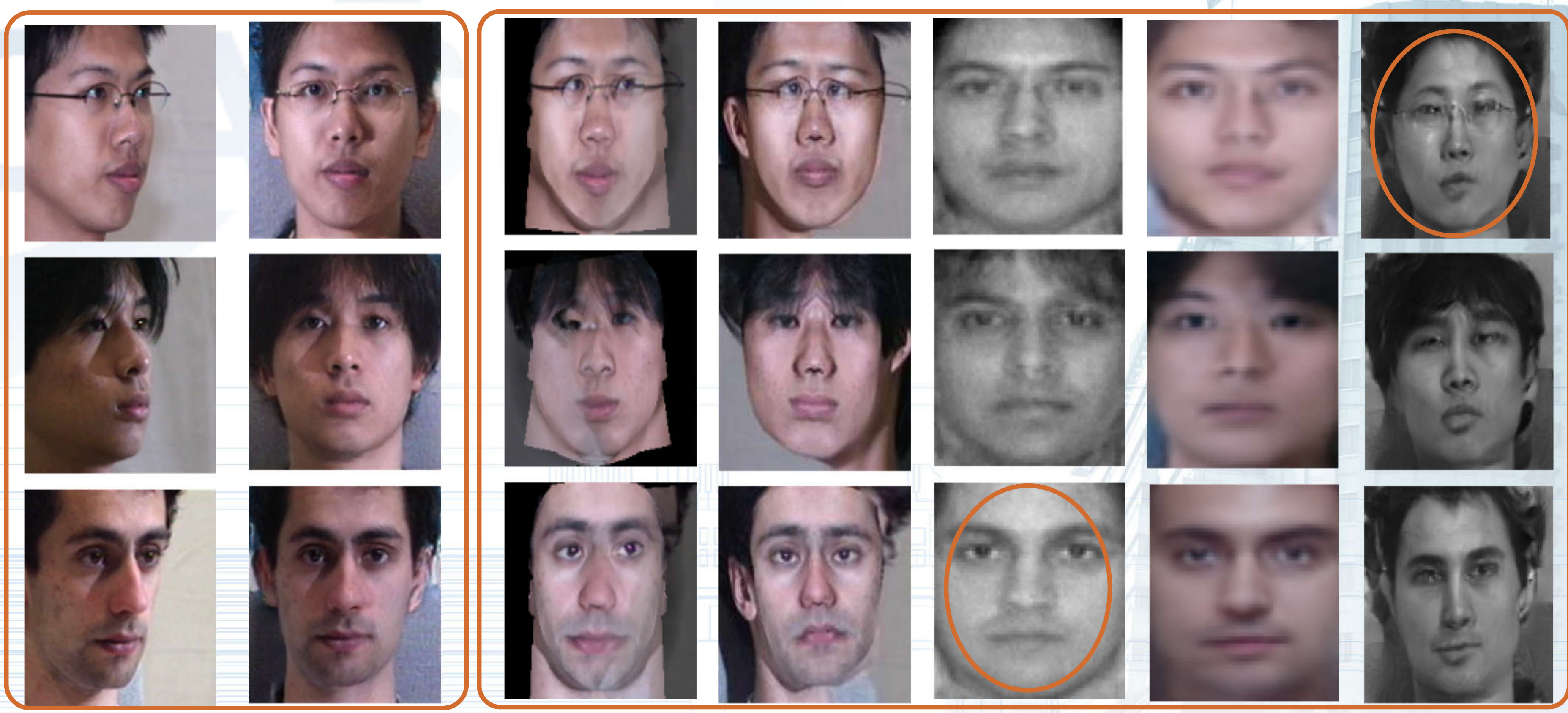
What we'd like to have:



What we've really got:



Main problems of current frontalization methods

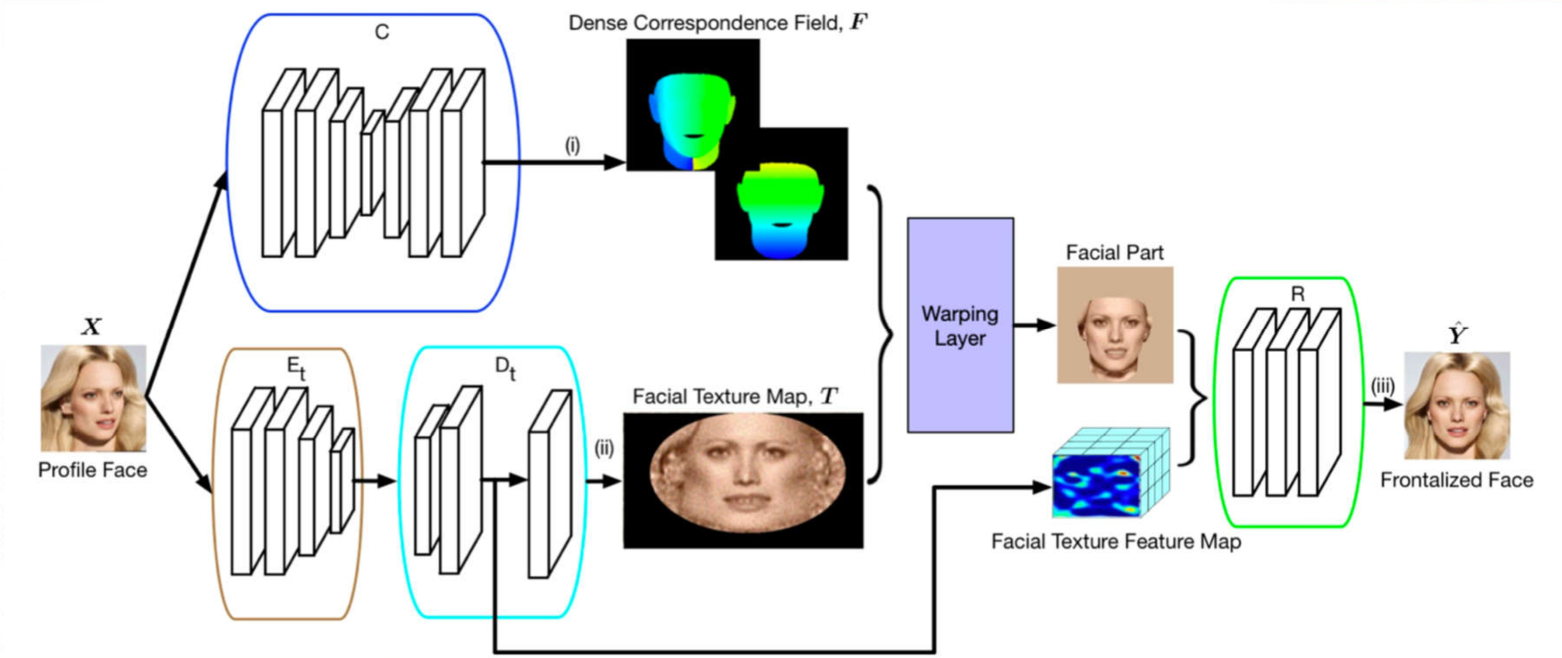


CVPR 2015 CVPR 2015 CVPR 2015 BMVC 2016 CVPR 2017

Appearance: limited resolution, distorted global structure, unable to preserve identity
Recognition: useless in face recognition performance improvement

Towards High Fidelity Face Frontalization in the Wild

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. Towards High Fidelity Face Frontalization in the Wild, IJCV, 2019.

High Fidelity Pose Invariant Model (HF-PIM)

High-resolution face frontalization

High Fidelity Pose Invariant Model (HF-PIM)

Face frontalization on extreme poses in the unconstrained condition

High Fidelity Pose Invariant Model

Face recognition accuracy is significantly improved via face frontalization

Table 4: Face recognition/verification performance (%) comparisons on IJB-A. The results are averaged over 10 testing splits. "-" means the result is not reported.

Method	Verification		Recognition	
	FAR=0.01	FAR=0.001	Rank-1	Rank-5
DR-GAN [53]	77.4±2.7	53.9±4.3	85.5±1.5	94.7±1.1
FF-GAN [60]	85.2±1.0	66.3±3.3	90.2±0.6	95.4±0.5
PIM [61]	93.3±1.1	87.5±1.8	94.4±1.1	-
Light CNN [56]	91.5±1.0	84.3±2.4	93.0±1.0	-
HF-PIM(Ours)	**95.3±0.7**	**89.9±1.3**	**96.4±0.5**	**98.1±0.2**

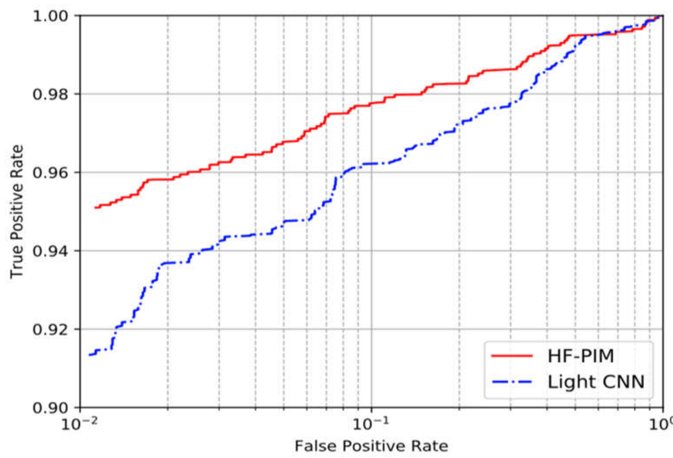
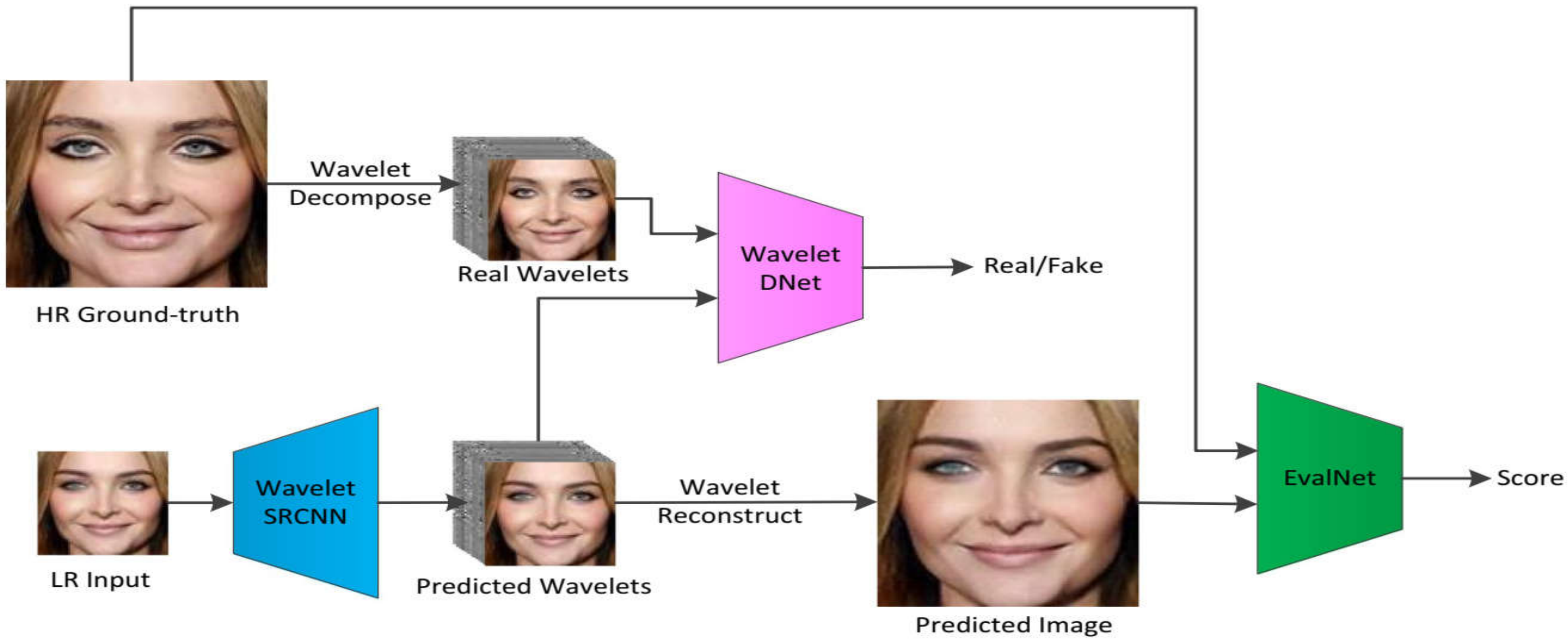


Fig. 5: ROC curves on the IJB-A verification protocol.

Face Super Resolution



- Wavelet domain CNN [1] and GAN [2] solutions to face super resolution
- Special design of loss functions to capture both global topology information and local textual details

[1] Huaibo Huang, Ran He, Zhenan Sun, and Tieniu Tan, Wavelet-SRNet: A Wavelet-based CNN for Multi-scale Face Super Resolution, ICCV, 2017.

[2] Huaibo Huang, Ran He, Zhenan Sun, Tieniu Tan, Wavelet Domain Generative Adversarial Network for Multi-scale Face Hallucination, International Journal of Computer Vision, Volume 127, Issue 6–7, pp.763–784, 2019.

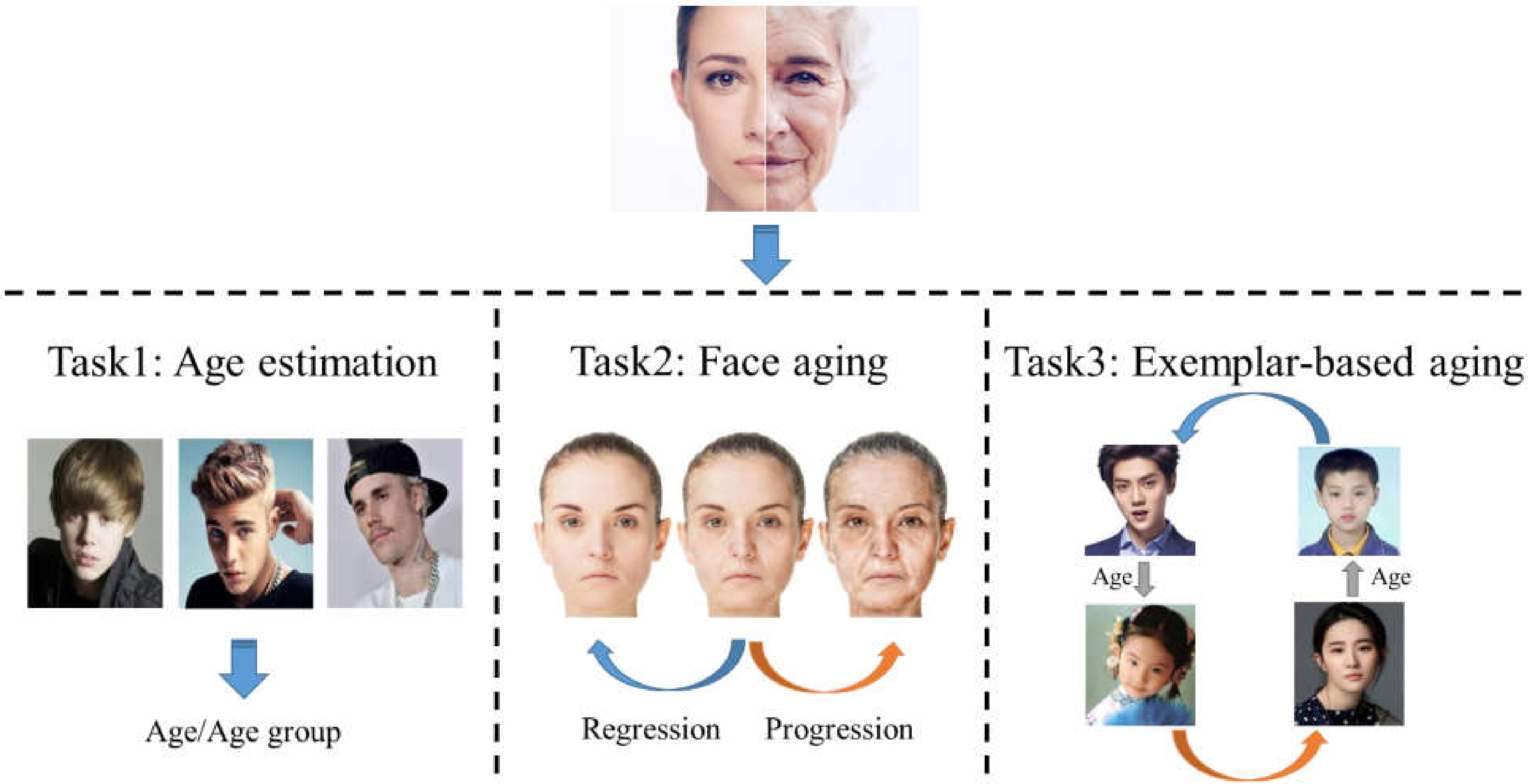
Table 3 Face verification results on the LFW dataset

Model	Settings	Metric	Original	Bicubic	WTIP	SRCNN	SRGAN	URDGN	SRDense	CBN	Our-CNN	Ours
LightCNN	$32 \times 32, 4\times$	AUC	99.31	99.16	99.04	99.17	99.22	–	99.21	90.80	99.25	**99.28**
		FAR = 1%	97.77	96.10	95.83	96.23	96.93	–	96.90	46.77	**97.40**	97.03
		FAR = 0.1%	96.23	91.90	91.70	92.87	94.07	–	94.97	32.53	95.73	**96.10**
	$16 \times 16, 8\times$	AUC	99.31	90.68	89.97	91.42	96.77	93.60	96.35	89.98	97.92	**98.48**
		FAR = 1%	97.77	45.50	40.53	48.70	78.83	53.57	77.50	46.90	87.97	**90.86**
		FAR = 0.1%	96.23	21.17	24.47	23.50	56.60	27.10	57.03	31.13	68.33	**81.20**
	$8 \times 8, 16\times$	AUC	99.31	60.89	59.40	61.47	77.10	–	74.30	63.00	87.29	**89.40**
		FAR= = 1%	97.77	3.17	2.90	2.83	16.40	–	12.67	4.57	38.43	**42.87**
		FAR= = 0.1%	96.23	0.27	0.47	0.30	4.23	–	3.73	1.30	12.93	**22.83**

Multi-task facial age analysis in a unified framework

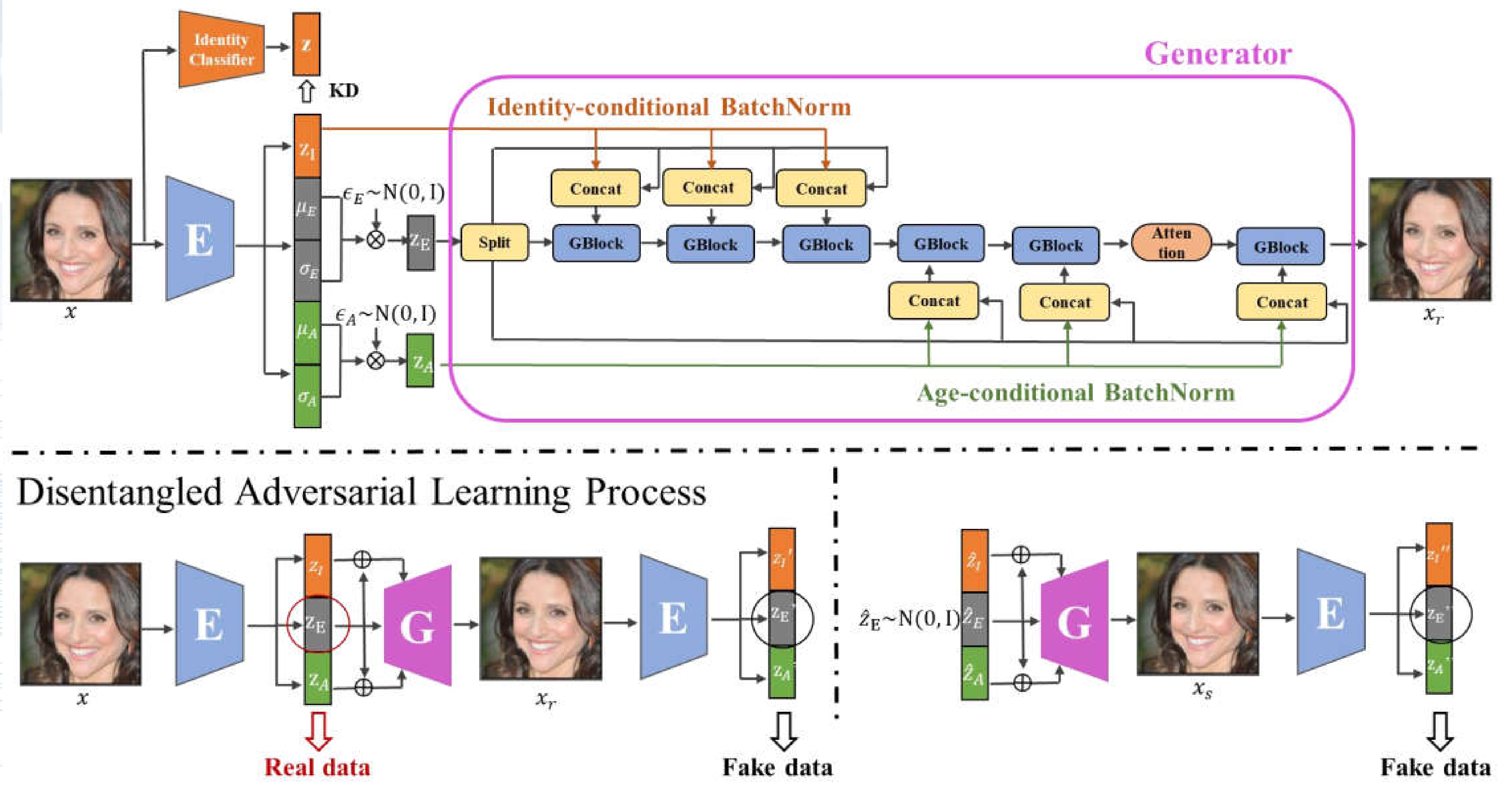
Disentangled Adversarial Autoencoder (DAAE)

- DAAE is the first attempt to achieve facial age analysis tasks in a universal framework.



Peipei Li, Huaibo Huang, Yibo Hu, Xiang Wu, Ran He, Zhenan Sun. "Hierarchical Face Aging through Disentangled Latent Characteristics." **ECCV** 2020 (Oral).

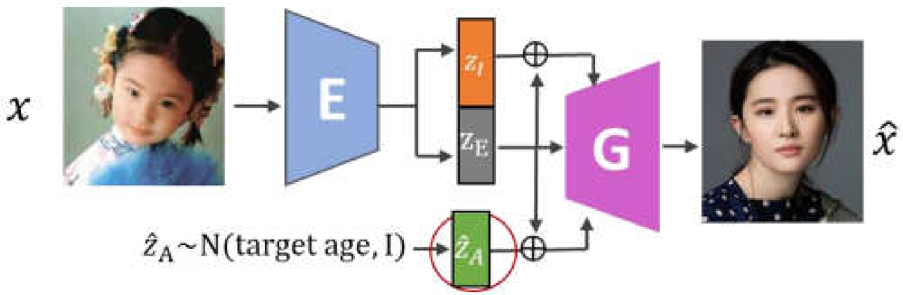
Multi-task facial age analysis in a unified framework



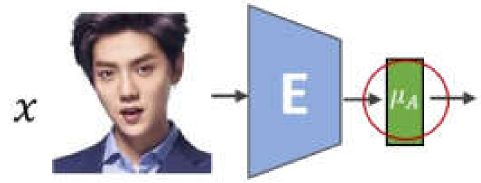
Multi-task facial age analysis in a unified framework

Inference and Sampling

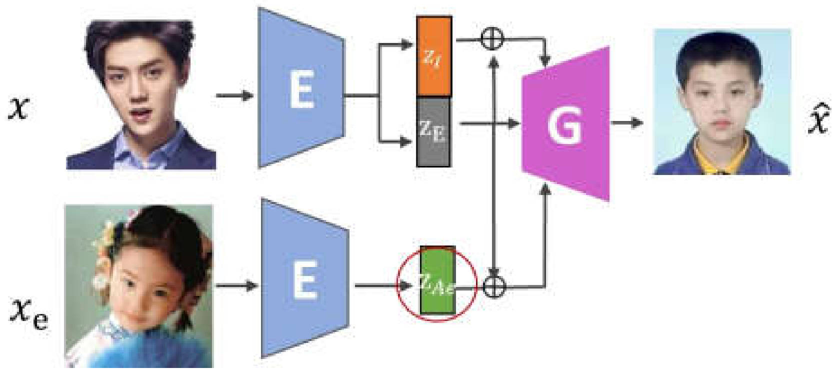
1) Face aging $\hat{x} = G\left(\hat{z}_A, z_I, z_E\right)$



3) Age estimation $\hat{y} = \frac{1}{C}\sum_{i=1}^{C} \mu_A^i$



2) Exemplar-based face aging $\hat{x} = G\left(z_{A\_e}, z_I, z_E\right)$

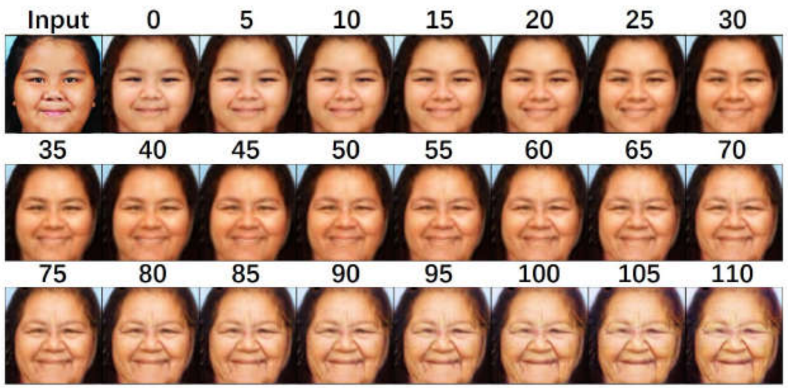


Multi-task facial age analysis in a unified framework

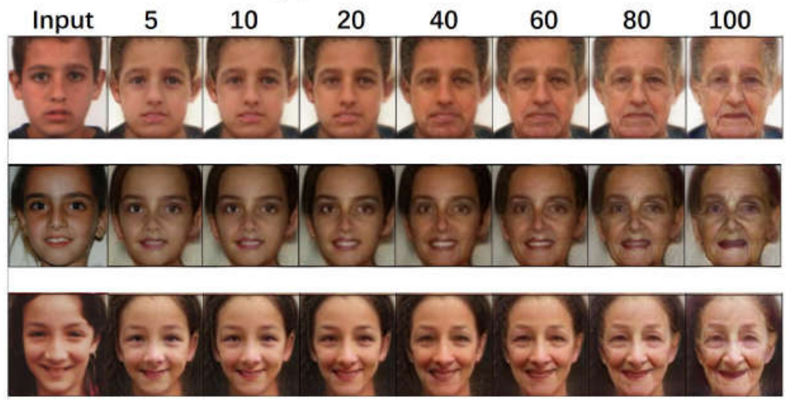
Lifespan Age Synthesis

Generating age images from 1 to 100

(a) On UTKFace



(b) On FG-NET



	(a) on Morph				(b) on CACD2000			
Method	Input	AG1	AG2	AG3	Input	AG1	AG2	AG3
CAAE [40]	-	15.07	12.02	8.22	-	4.66	3.41	2.40
Yang et al. [35]	-	100.00	98.91	93.09	-	99.99	99.81	98.28
GLCA-GAN [18]	-	97.66	96.67	91.85	-	97.72	94.18	92.29
Liu et al. [20]	-	100.00	100.00	98.26	-	99.76	98.74	98.44
Ours	-	99.48	99.36	99.36	-	99.24	99.19	99.19

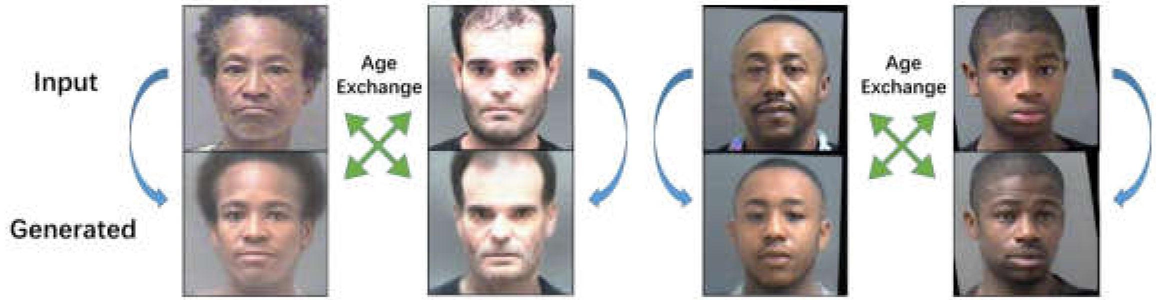
Face verification results on Morph and CACD2000

	(a) on Morph				(b) on CACD2000			
Method	Input	AG1	AG2	AG3	Input	AG1	AG2	AG3
CAAE [40]	-	28.13	32.50	36.83	-	31.32	34.94	36.91
Yang et.al [35]	-	42.84	50.78	59.91	-	44.29	48.34	52.02
GLCA-GAN [18]	-	43.00	49.03	54.60	-	37.09	44.92	48.03
Liu et al. [20]	-	38.47	47.55	56.57	-	38.88	47.42	54.05
Ours	-	37.46	49.40	59.67	-	39.21	46.38	51.66
Real Data	28.19	38.89	48.10	58.22	30.73	39.08	47.06	53.68

Aging accuracy results on Morph and CACD2000

Multi-task facial age analysis in a unified framework

- Exemplar-based face aging



- Age estimation

Methods	Pre-trained	Morph
OR-CNN[23]	-	3.34
DEX[27]	IMDB-WIKI	2.68
Ranking [4]	Audience	2.96
Posterior[39]	-	2.87
SSR-Net[36]	IMDB-WIKI	2.52
M-V Loss[24]	-	2.51
ThinAgeNet [7]	MS-Celeb-1M	2.35
Ours	-	$\boxed{2.23}$

Large-scale Image Database Generation for Face Parsing

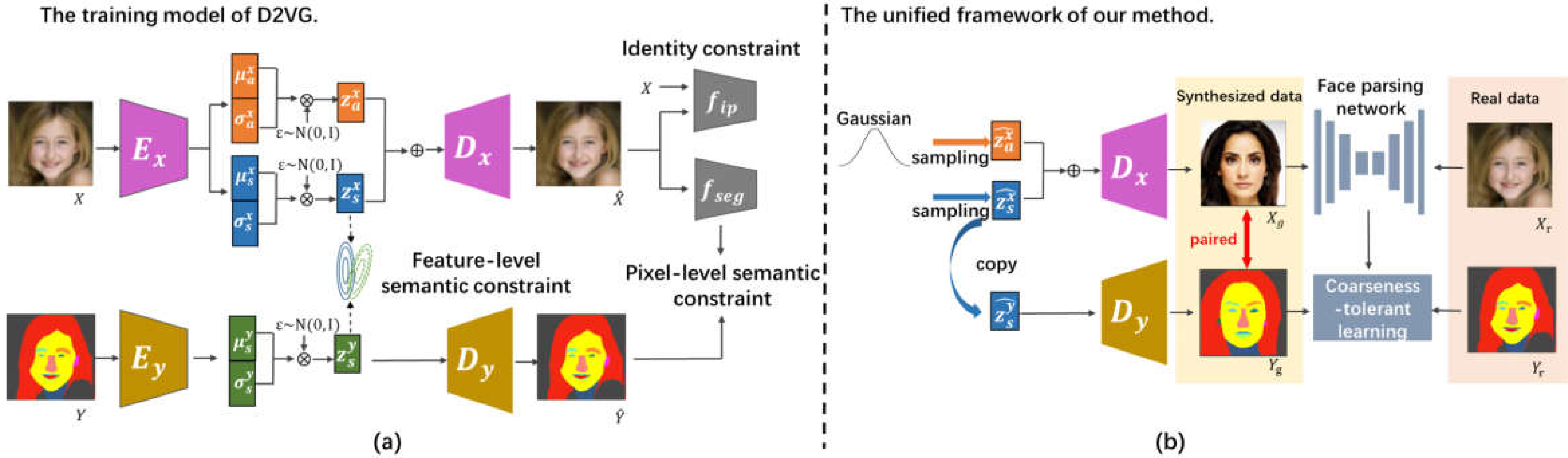
Motivation

- It is expensive and time-consuming to construct a large-scale pixel-level manually annotated dataset for face parsing.
- We propose a D2VG, which can synthesize large-scale paired face images and parsing maps from a stand Gaussian distribution.

Peipei Li, Yinglu Liu, Hailin Shi, Xiang Wu, Yibo Hu, Ran He, Zhenan Sun. "Dual-structure Disentangling Variational Generation for Data-limited Face Parsing." **ACM MM**(Oral), 2020.

Large-scale Image Database Generation for Face Parsing

Overall of the architecture and training flow



$$L_{seg_f} = \frac{1}{2}\left(\|\mu_s^x - \mu_s^y\|_2^2 + \|\sigma_s^x - \sigma_s^y\|_2^2\right).$$

$$L_{ip} = \left\|f_{ip}(\hat{x}) - f_{ip}(x)\right\|_2^2,$$

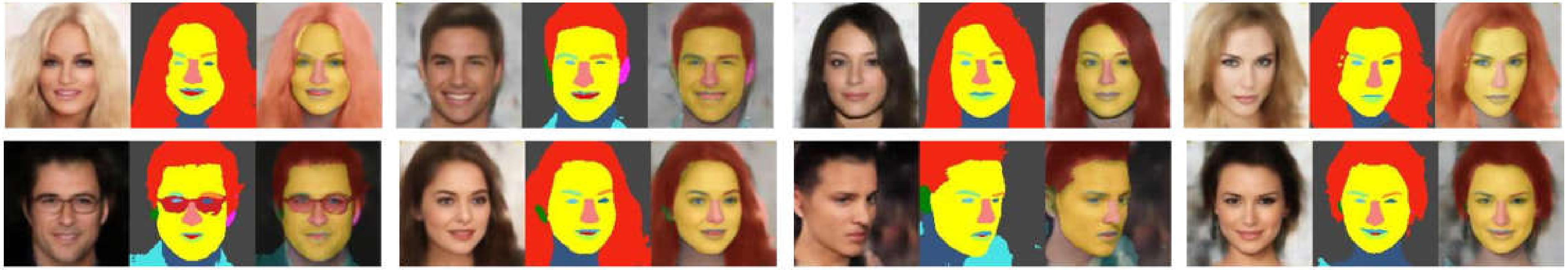
$$L_{seg_p} = -\frac{1}{M}\sum_{m=1}^{M}\sum_{c=1}^{C}\hat{y}_{m,c}\log\left(f_{seg}\left(\hat{x}_{m,c}\right)\right),$$

$$L = L_{rec} + L_{kl} + \lambda_1 L_{seg_f} + \lambda_2 L_{seg_p} + \lambda_3 L_{ip},$$

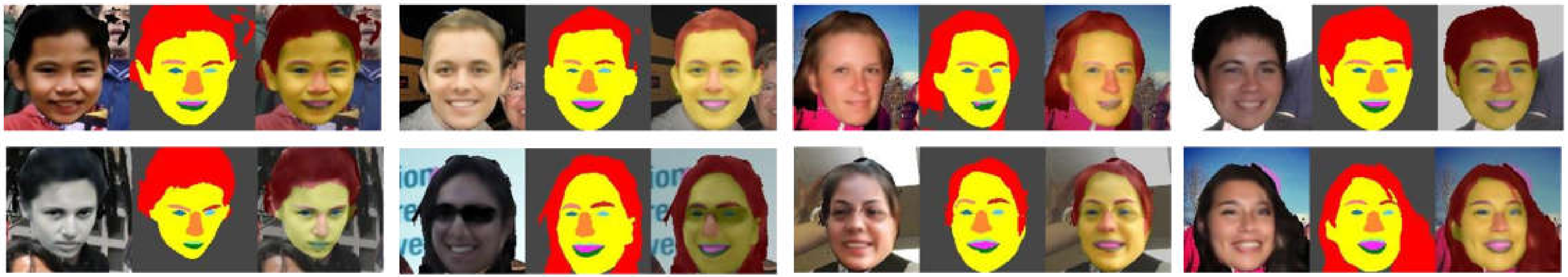
Large-scale Image Database Generation for Face Parsing

Experiments

a) The synthesized paired data by D2VG trained with CelebAMask-HQ and LaPa, respectively.



a) on CelebAMask-HQ



b) on LaPa

Large-scale Image Database Generation for Face Parsing

Experiments

b) Comparisons with state-of-the-art methods CelebAMask-HQ and LaPa.

Table 1: Comparisons with state-of-the-art methods on CelebAMask-HQ. mF1 is a mean F1-Score over the 13 categories.

Methods	skin	nose	glasses	eyes	brows	ears	ear_r	mouth	hair	hat	neck_l	neck	cloth	mF1	mIoU	mAcc
Lee *et al.* [13]	95.8	93.1	87.9	86.2	85.2	86.2	88.5	93.9	73.8	58.6	0.0	87.6	77.6	78.4	71.9	80.3
PSPNet	96.3	93.6	91.0	88.5	84.8	87.8	90.9	95.1	87.6	65.9	1.9	90.2	86.0	81.5	75.6	82.6
PSPNet + D2VG	96.4	93.7	91.7	89.5	85.7	88.5	92.0	95.3	88.4	69.3	10.1	90.6	86.8	82.9	77.0	84.4
PSPNet + D2VG + GCE	96.4	93.9	91.9	89.5	85.8	88.6	92.0	95.3	87.7	68.9	15.2	90.4	86.6	83.2	77.2	84.1
PSPNet + DV2G + MG-GCE	96.6	93.9	92.4	89.5	86.3	88.8	92.1	95.4	88.3	70.3	45.7	90.8	86.2	85.9	78.7	85.8

Table 2: Comparisons with state-of-the-art methods on LaPa. mF1 is a mean F1-Score over the 10 foreground categories.

Methods	hair	skin	left eyebrow	right eyebrow	left eye	right eye	nose	upper lip	inner mouth	lower lip	background	mF1
Liu *et al.* [18]	96.3	97.2	87.7	87.6	88.1	87.9	95.5	84.4	87.6	85.7	99.2	89.8
PSPNet	95.4	97.1	87.0	87.3	88.5	87.7	96.1	84.6	87.1	86.9	98.9	89.8
PSPNet+D2VG	95.5	97.1	88.9	87.8	88.9	88.9	96.3	84.8	88.3	87.2	99.0	90.3
PSPNet + D2VG + GCE	95.9	97.3	88.8	88.5	89.1	89.3	96.6	86.0	88.7	88.1	99.2	90.8
PSPNet + DV2G + MG-GCE	96.4	97.5	89.6	89.6	89.5	89.9	96.7	86.7	89.5	88.5	99.3	91.4

AI enables face manipulation easier and has caused security risks

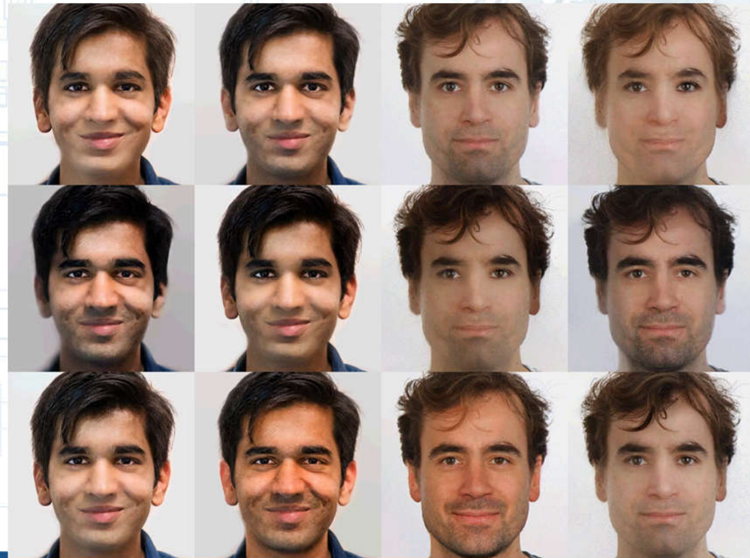

Fraudster Dimitri de Angelis Jailed for Fake Celebrity Friend Photoshop Scam

Conman scammed investors out of $8.5m by pretending to be friends with Queen, Pope, Bush and Clinton

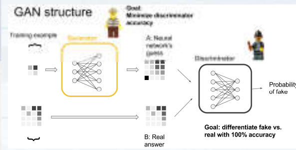
By Hannah Osborne
March 1, 2013 16:47 GMT

Dimitri de Angelis with Bill Clinton

Experts



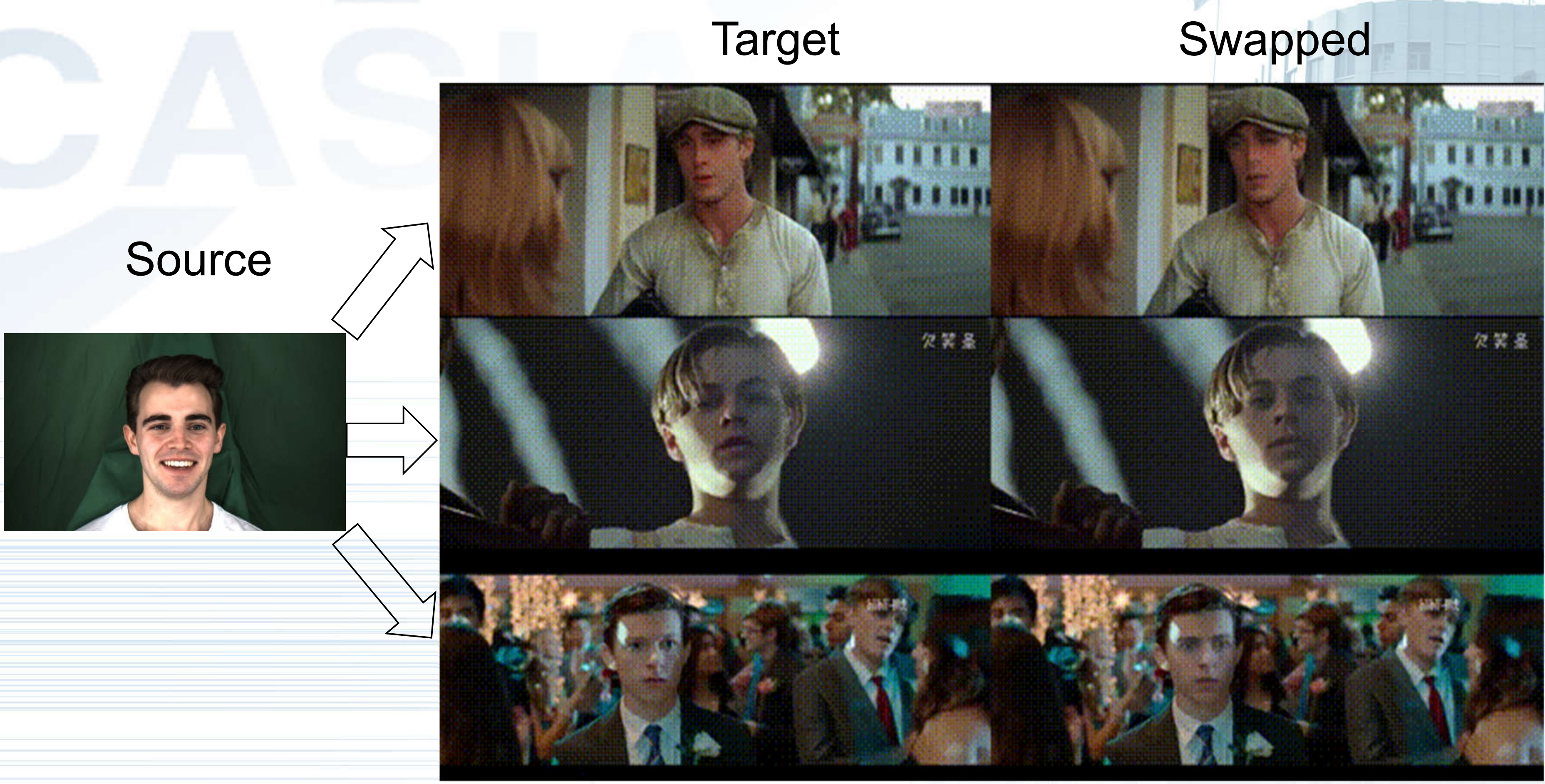
AI Enabled



from Internet

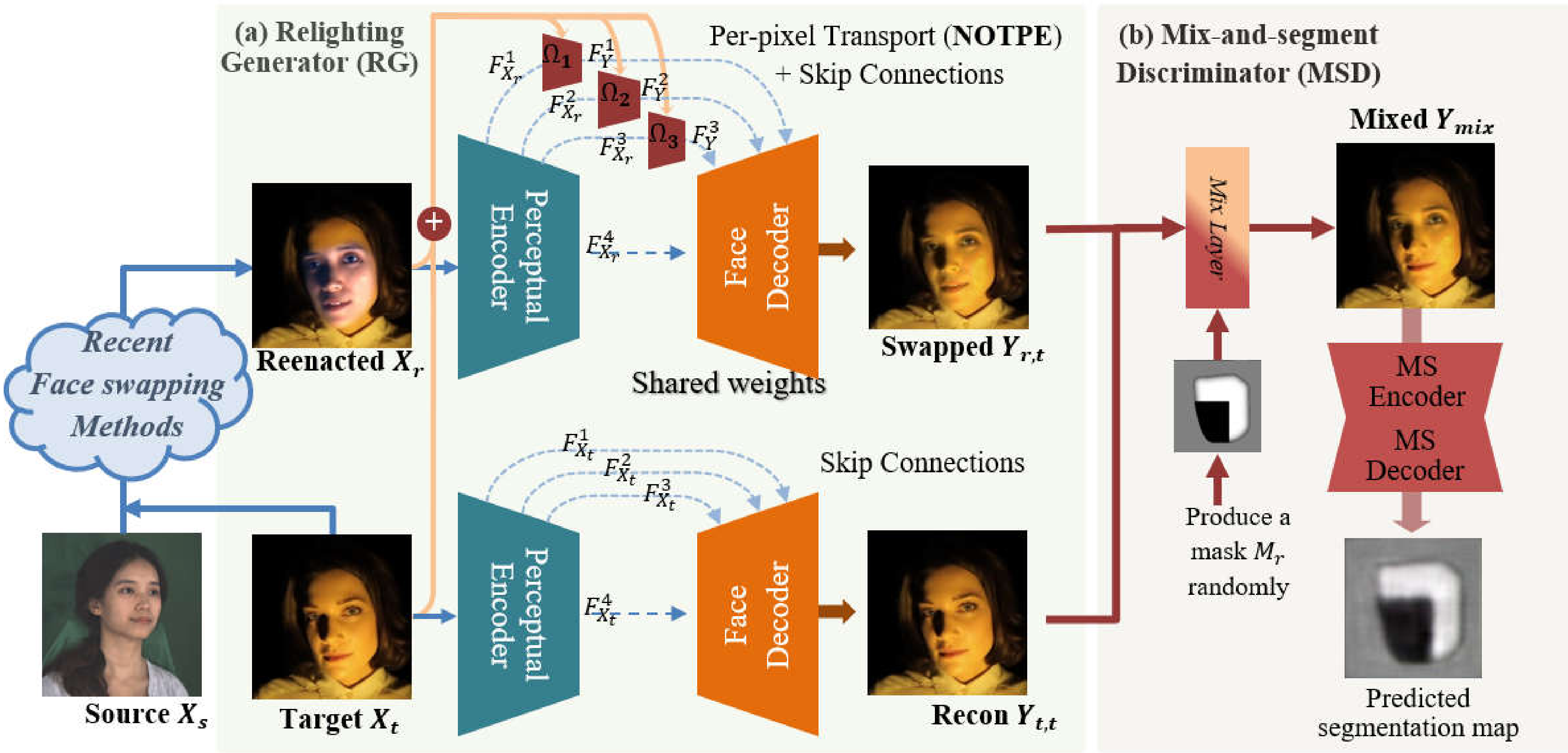
中国科学院自动化研究所
INSTITUTE OF AUTOMATION CHINESE ACADEMY OF SCIENCES
CASIA
www.ia.ac.cn

High-quality Identity Swap



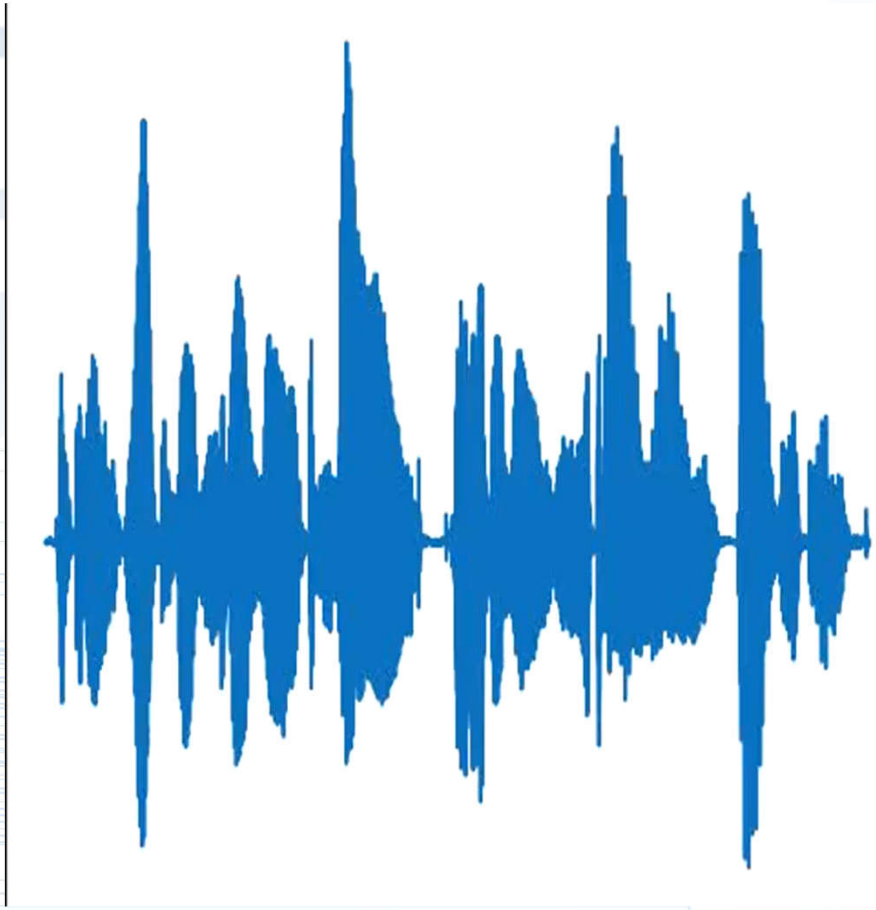
Hao Zhu, Ran He et al. AOT: Appearance Optimal Transport Model for Face Swapping. NeurIPS 2020.

High-quality Identity Swap



Hao Zhu, Ran He et al. AOT: Appearance Optimal Transport Model for Face Swapping. NeurIPS 2020.

Talking Face Video Generation



Kaisiyuan Wang, Ran He, et al. MEAD: A Large-scale Audio-visual Dataset for Emotional Talking Face Generation. ECCV, 2020.
Hao Zhu, Ran He, et al. Arbitrary Talking Face Generation via Attentional Audio-Visual Coherence Learning. IJCAI, 2020.

Possible features for fake detection

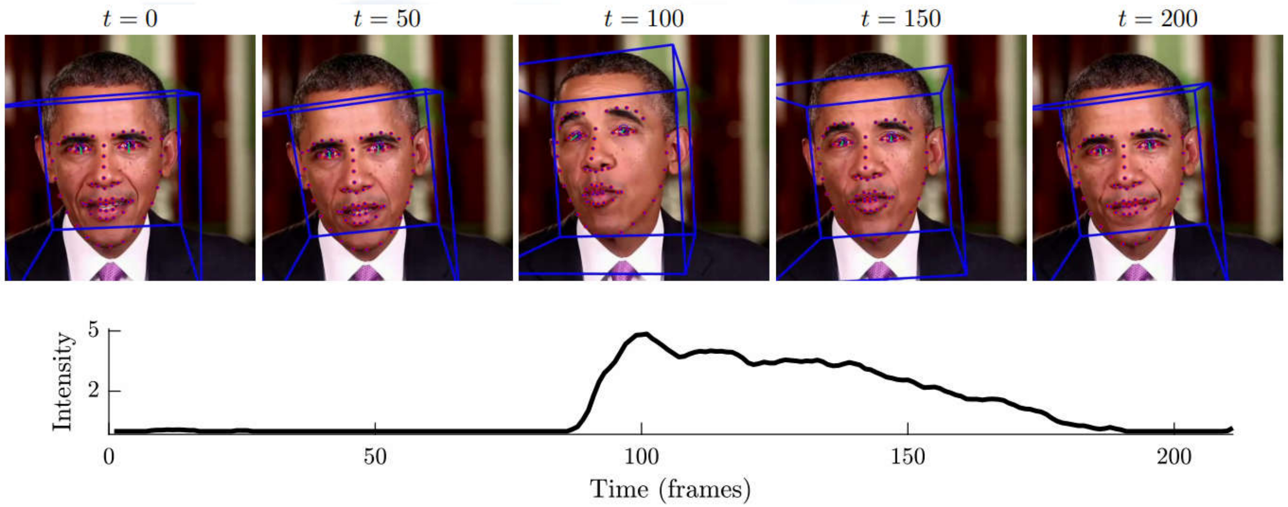
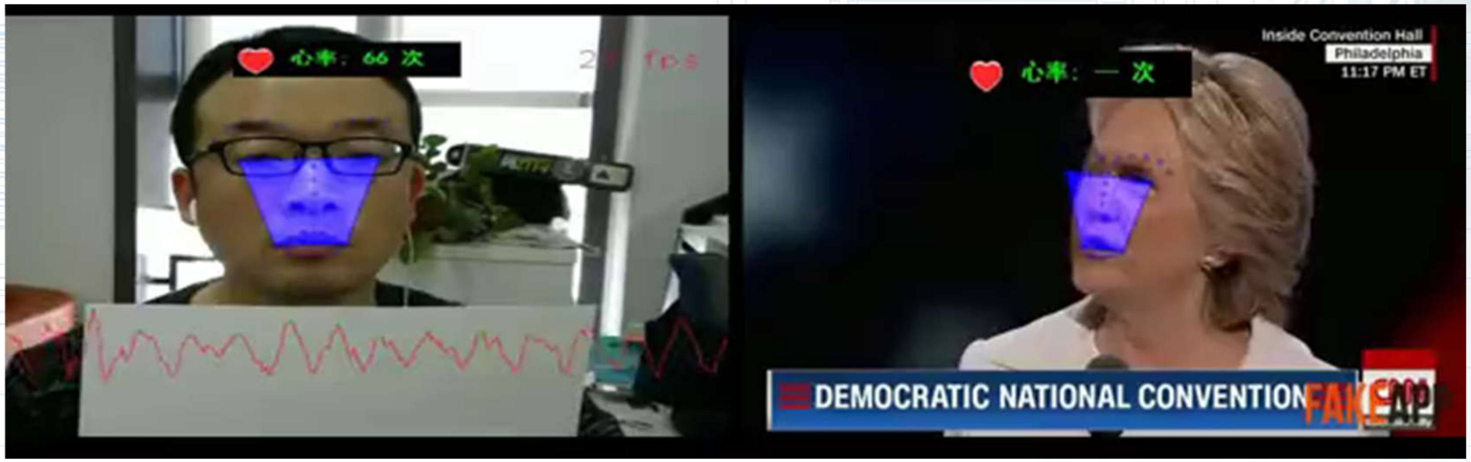


Figure 1. Shown above are five equally spaced frames from a 250-frame clip annotated with the results of OpenFace tracking. Shown below is the intensity of one action unit AU01 (eye brow lift) measured over this video clip.

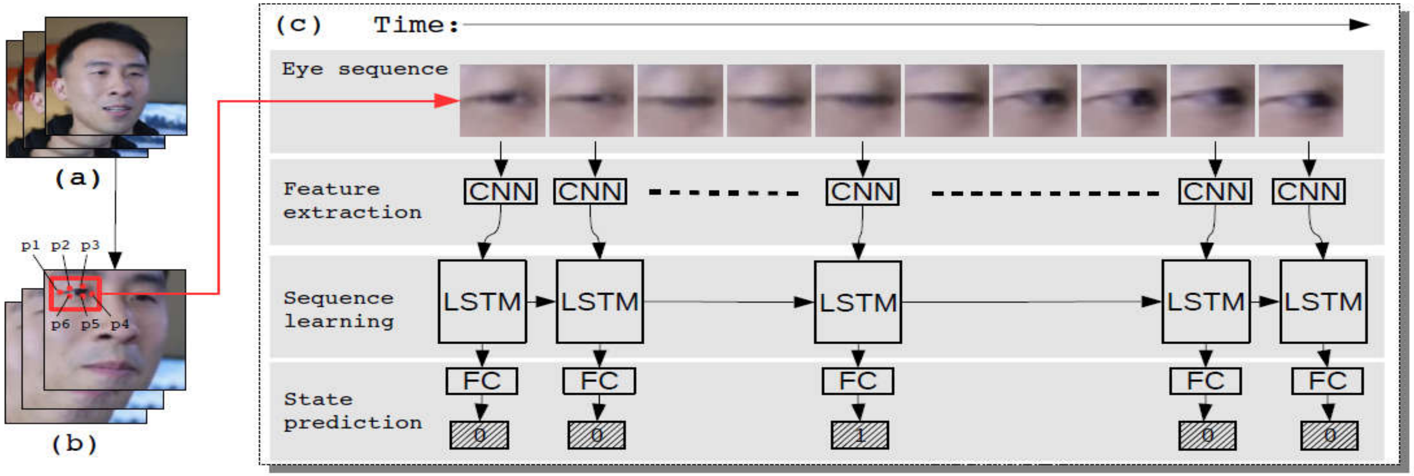
Facial Behavior Modeling



Physiological Indicator

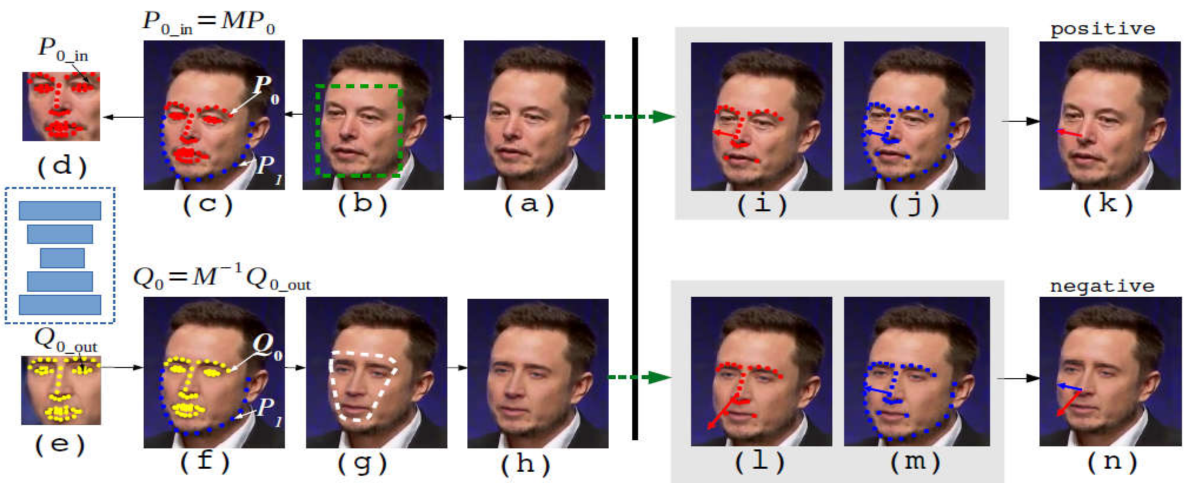
Agarwal, Shruti, Hany Farid, et. al. "Protecting World Leaders Against Deep Fakes." CVPR 2019.

Possible features for fake detection



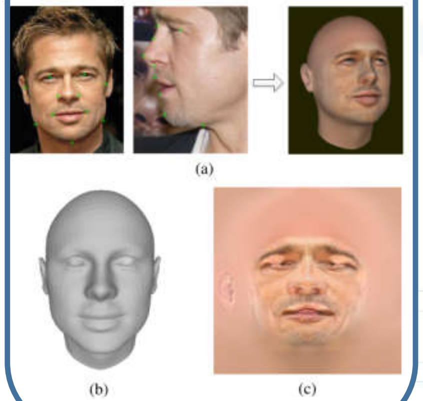
Eye-blinking clue

Head pose consistency



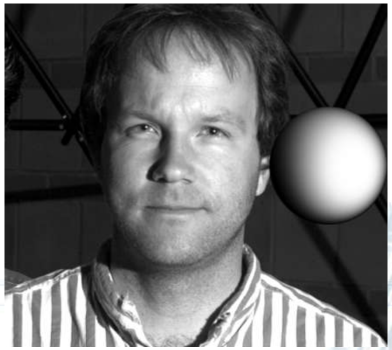
Inconsistency of lighting conditions

3D Face Fitting

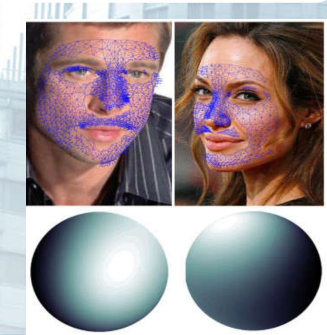


Face Model Alignment

Optimized Lighting Estimation



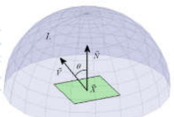
Inconsistency Measure

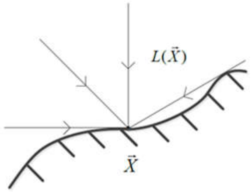


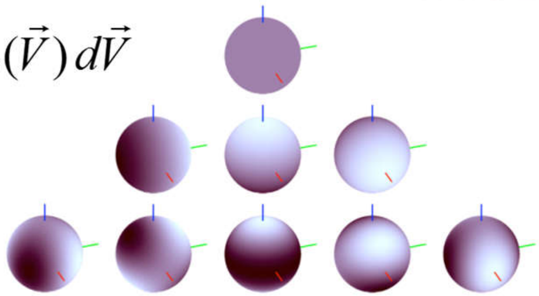
$$Dist(L_1, L_2) > T\,?$$

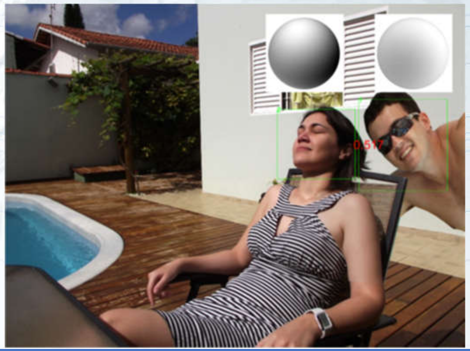
RELAXATION !

$$I(\vec{x}) = \int_{\Omega} \underbrace{\rho(\vec{X})}_{\text{Texture}} \underbrace{G(\vec{X},\vec{V})}_{\text{Occlusion}} R(\vec{V},\vec{N}(\vec{X}))L(\vec{V})\,d\vec{V}$$





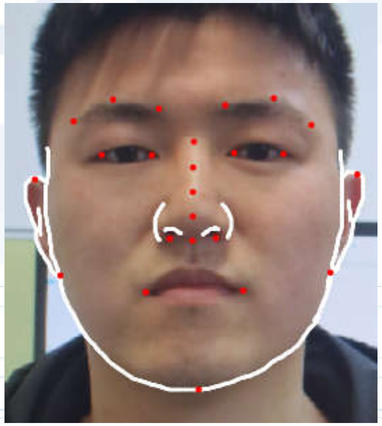




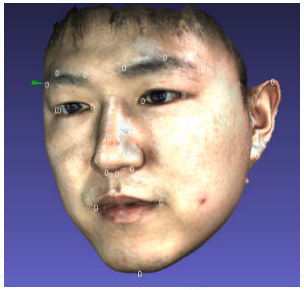
- Bo Peng, **Wei Wang**, Jing Dong, and Tieniu Tan, "Optimized 3D Lighting Environment Estimation for Image Forgery Detection," IEEE Transactions on Information Forensics and Security, 2016.
- Bo Peng, **Wei Wang**, Jing Dong, and Tieniu Tan, "Automatic detection of 3D lighting inconsistencies via a facial landmark based morphable model," IEEE International Conference on Image Processing (ICIP), 2016, pp. 3932-3936.
- Bo Peng, **Wei Wang**, Jing Dong, and Tieniu Tan, "Improved 3D lighting environment estimation for image forgery detection," IEEE International Workshop on Information Forensics and Security (WIFS), 2015, pp. 1-6.

Invalidation of projective geometry laws

S1: Landmark & Contour Obervation



S2: Estimation by Landmark Correspondence



- Minimize projection error of landmarks
- Gold Standard Method

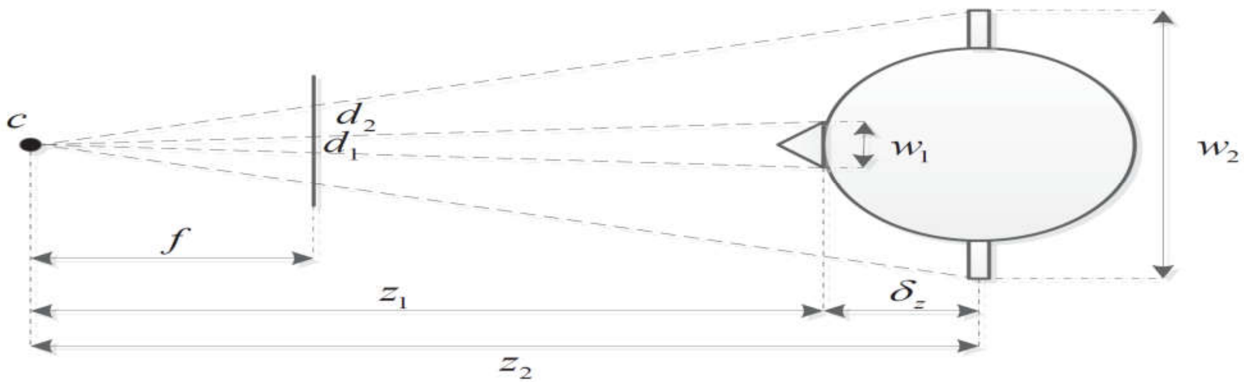
S3: Fine Tune using Contour

- Minimize projection error of contours
- ICP algorithm

S4: Consistency between Intrinsic paras

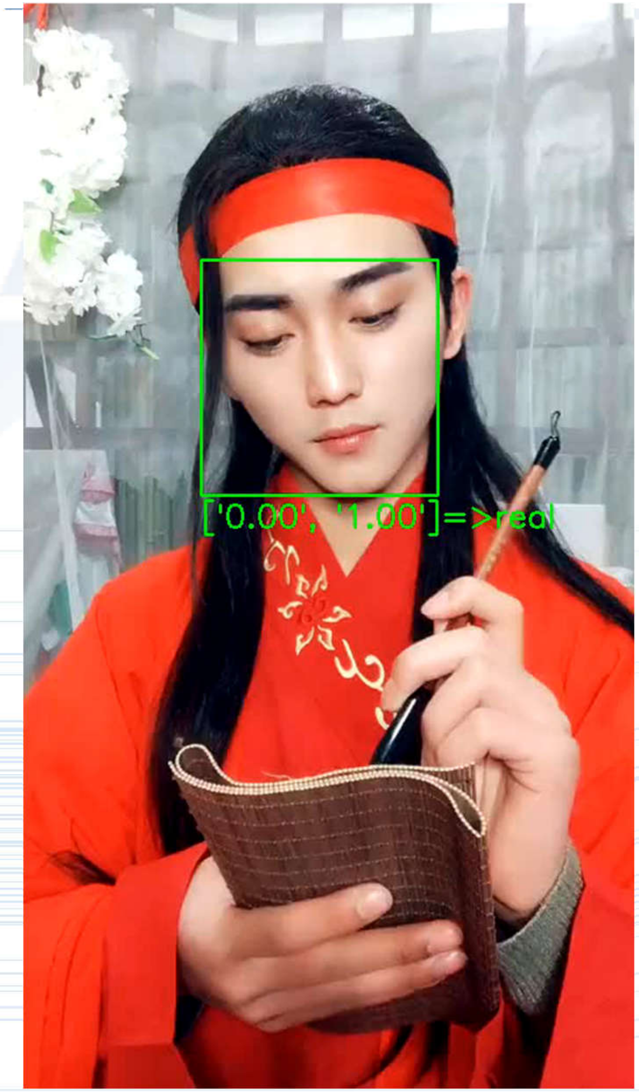
$$Dist(\theta,\{\hat{\theta}\}) > T\ ?$$

- Random perturbation
- Mahalanobis distance

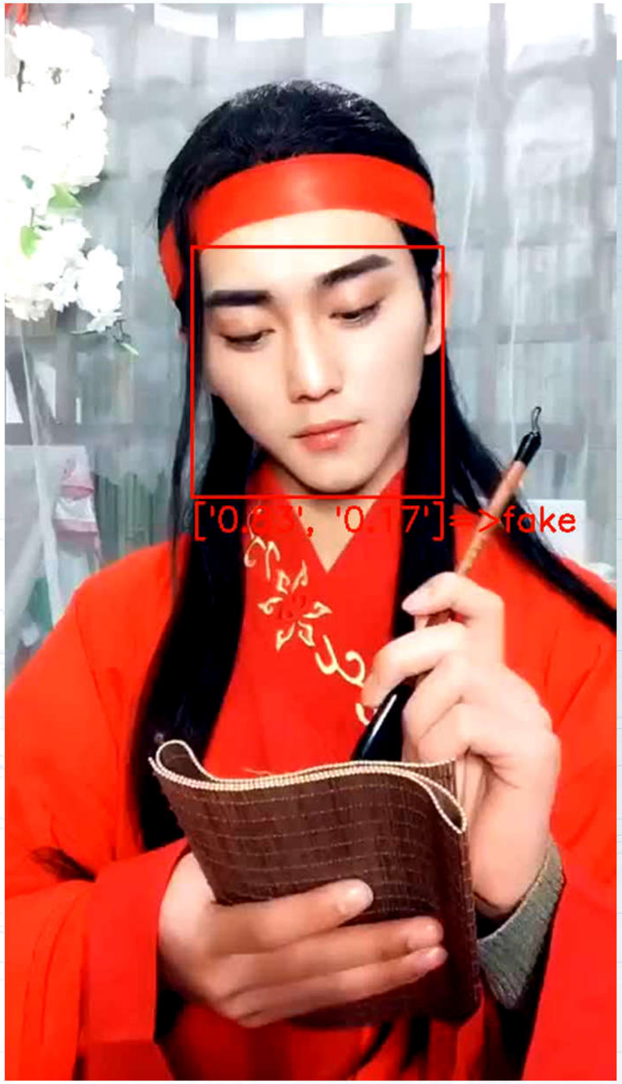


Bo Peng, Wei Wang, Jing Dong, and Tieniu Tan, "Position Determines Perspective: Investigating Perspective Distortion for Image Forensics of Faces," CVPR Workshop on Media Forensics 2017.

Fake Detection of Face Videos Generated by ZAO

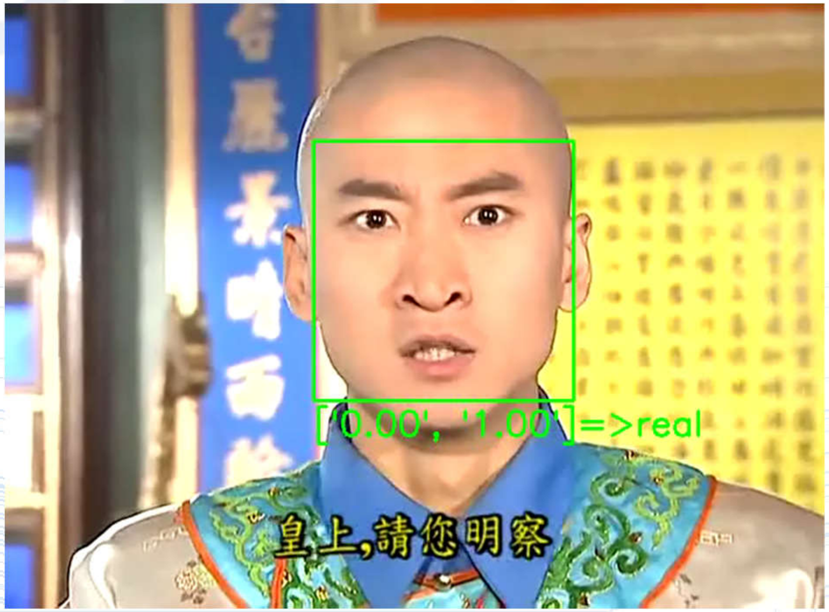


原始视频



ZAO视频

Fake Detection of Face Videos Generated by ZAO



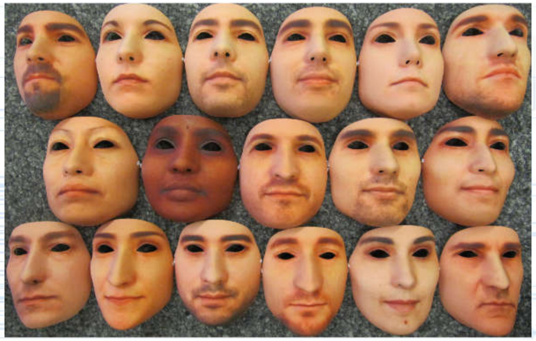
原始视频

ZAO视频

Open Problems of Face Recognition

PIE (Pose, Illumination, Expression)

Face recognition in surveillance



Spoof-attack

Face recognition of twins

Facial disguise

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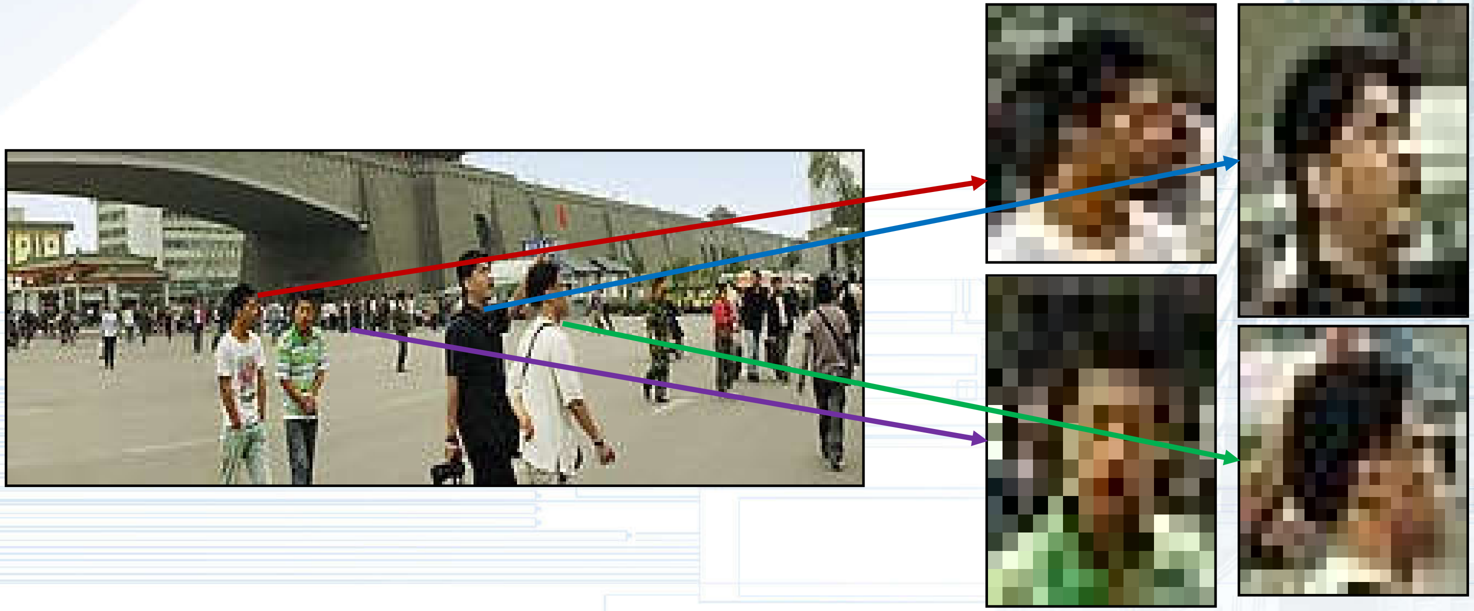
Advantages of gait recognition

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

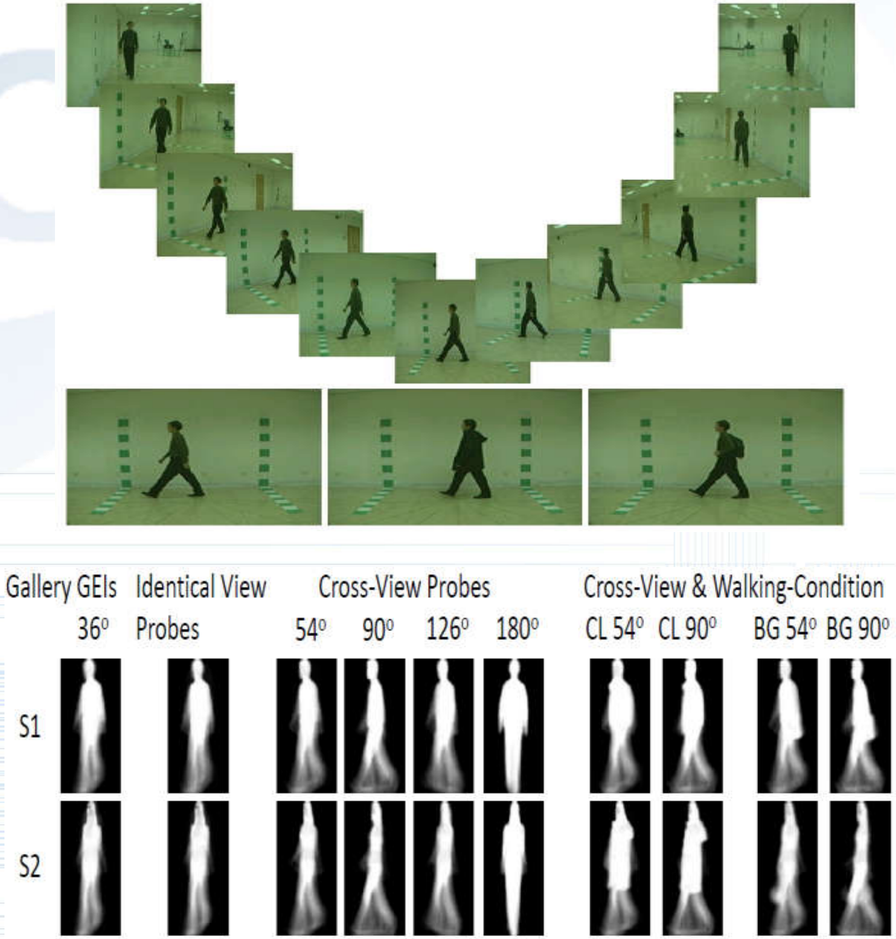
2016 — Cross-view gait based human identification with deep CNNs，TPAMI

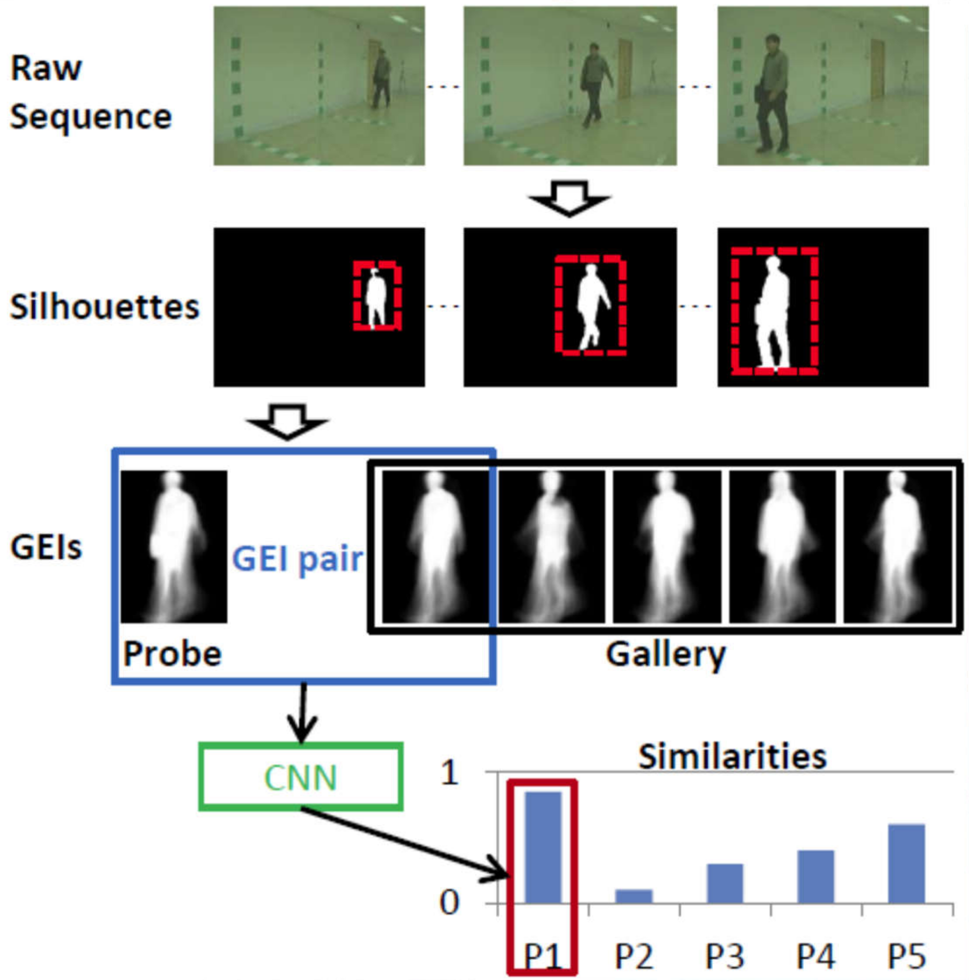
GEINET: view-invariant gait recognition, ICB

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

2015–2016: Deep learning for gait recognition

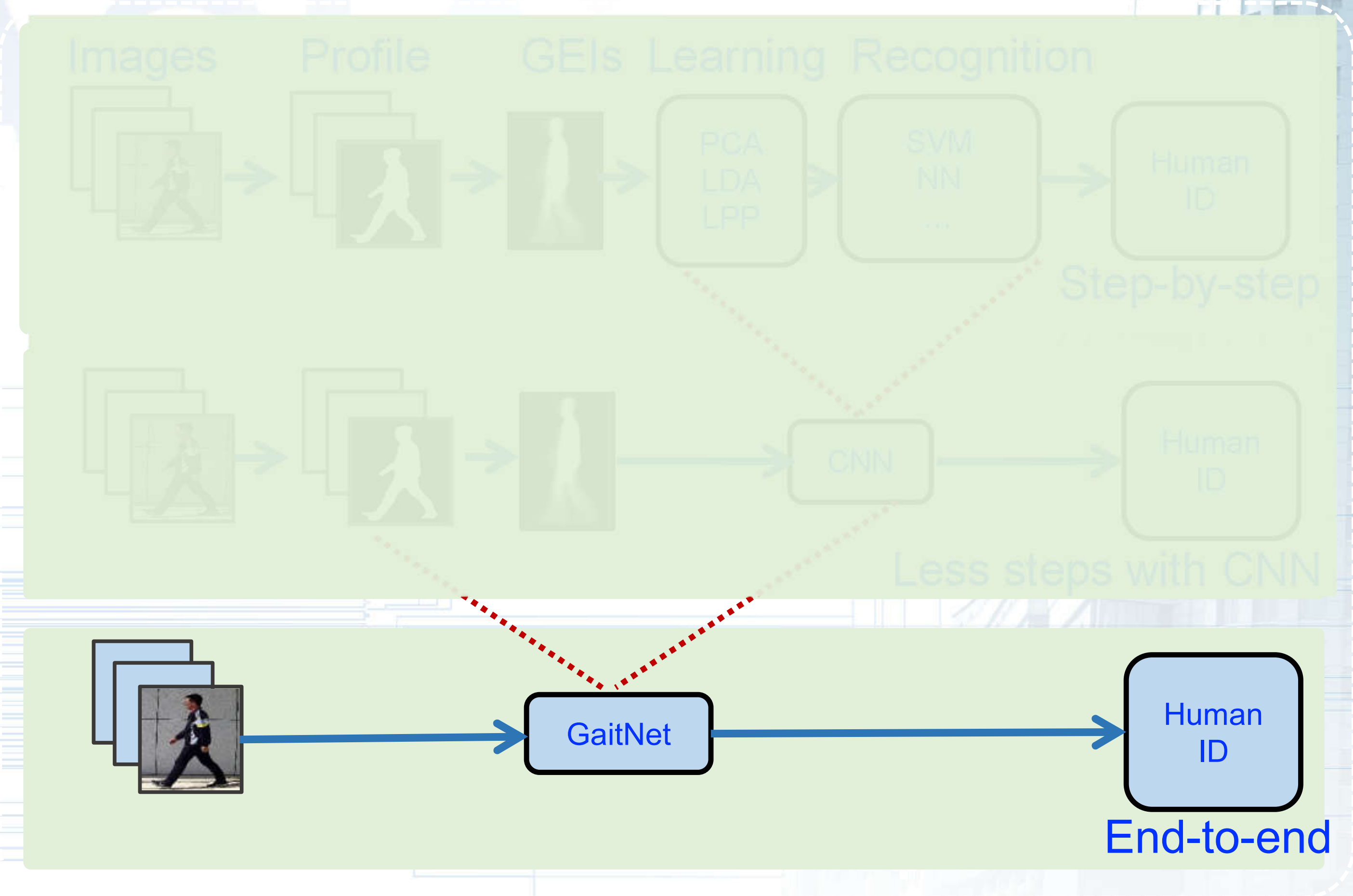
Multi-view Gait Recognition



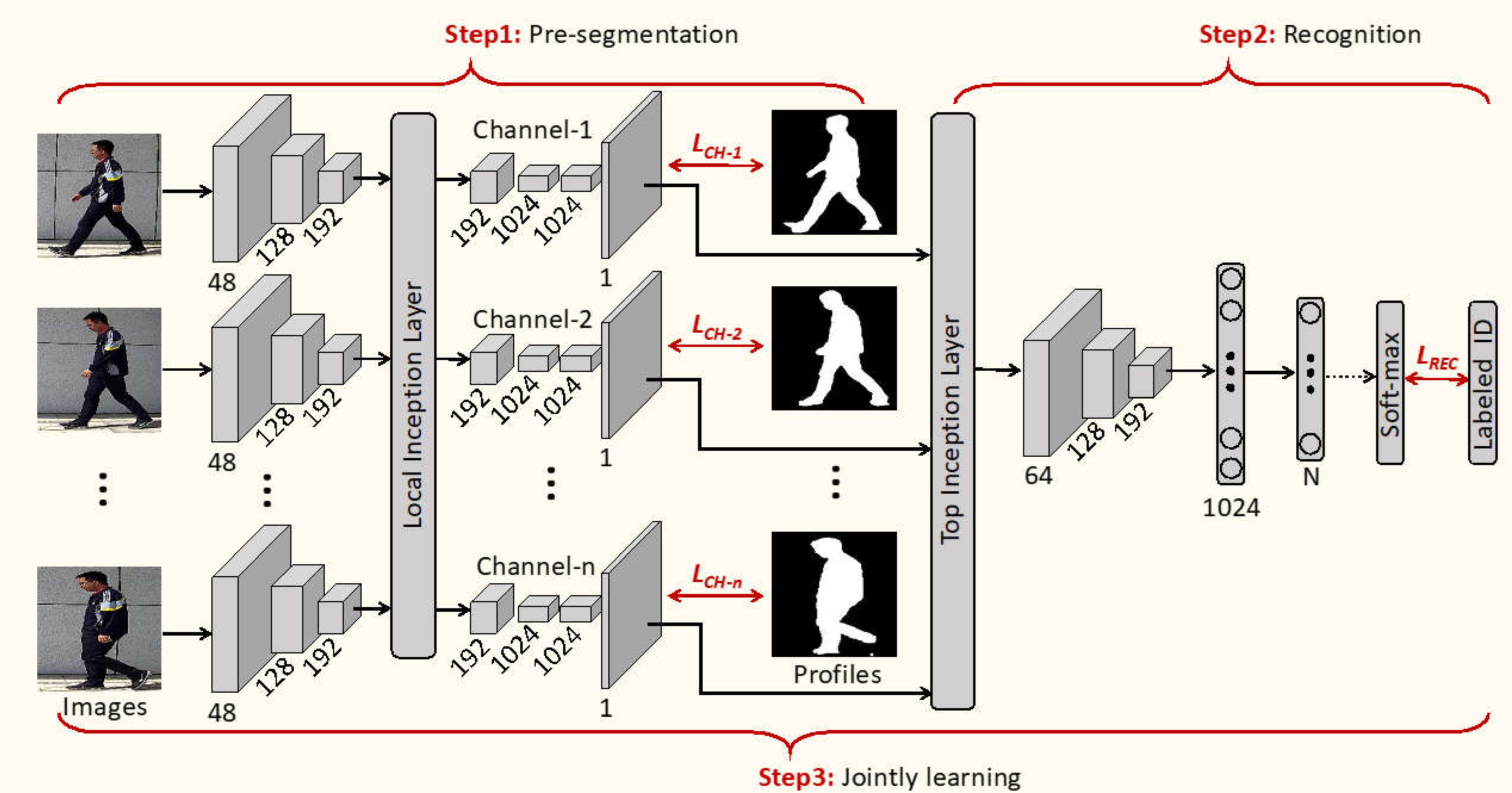


Zifeng Wu, Yongzhen Huang, Liang Wang, Xiaogang Wang, and Tieniu Tan, A comprehensive study on cross-view gait based human identification with deep CNNs, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2017.

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, PR 2019.

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**

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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

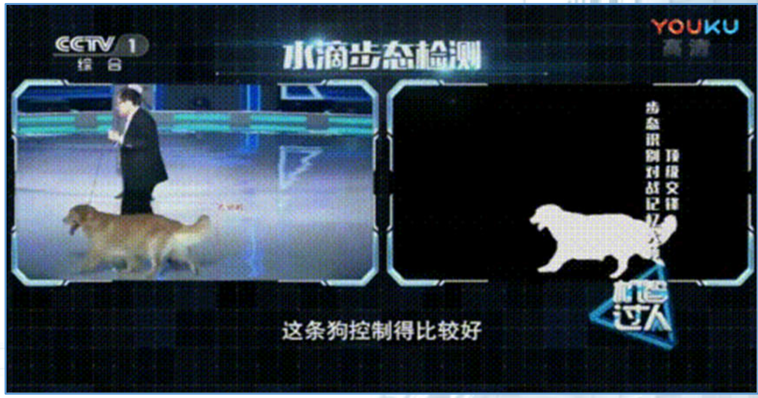
Family member gait recognition

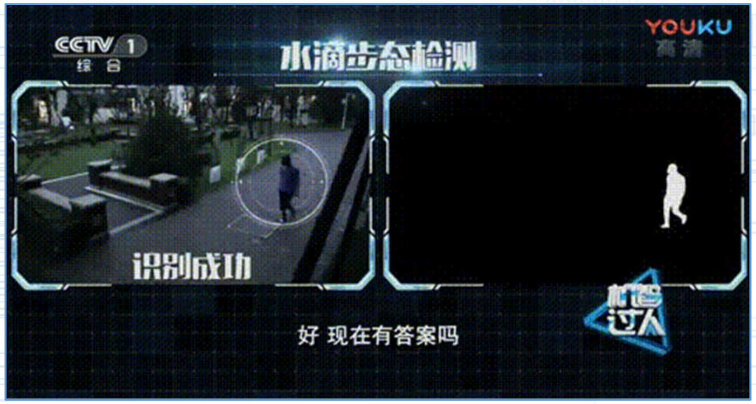
Gait Retrieval - Field Test

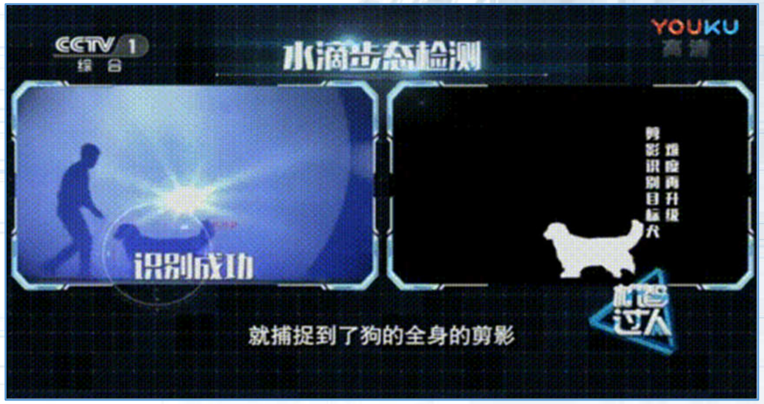
△ Crime scene (lateral side, shadow on face）

△ Retrieval result: similarity 0.97

Gait Retrieval - CCTV







Demo of Gait Recognition

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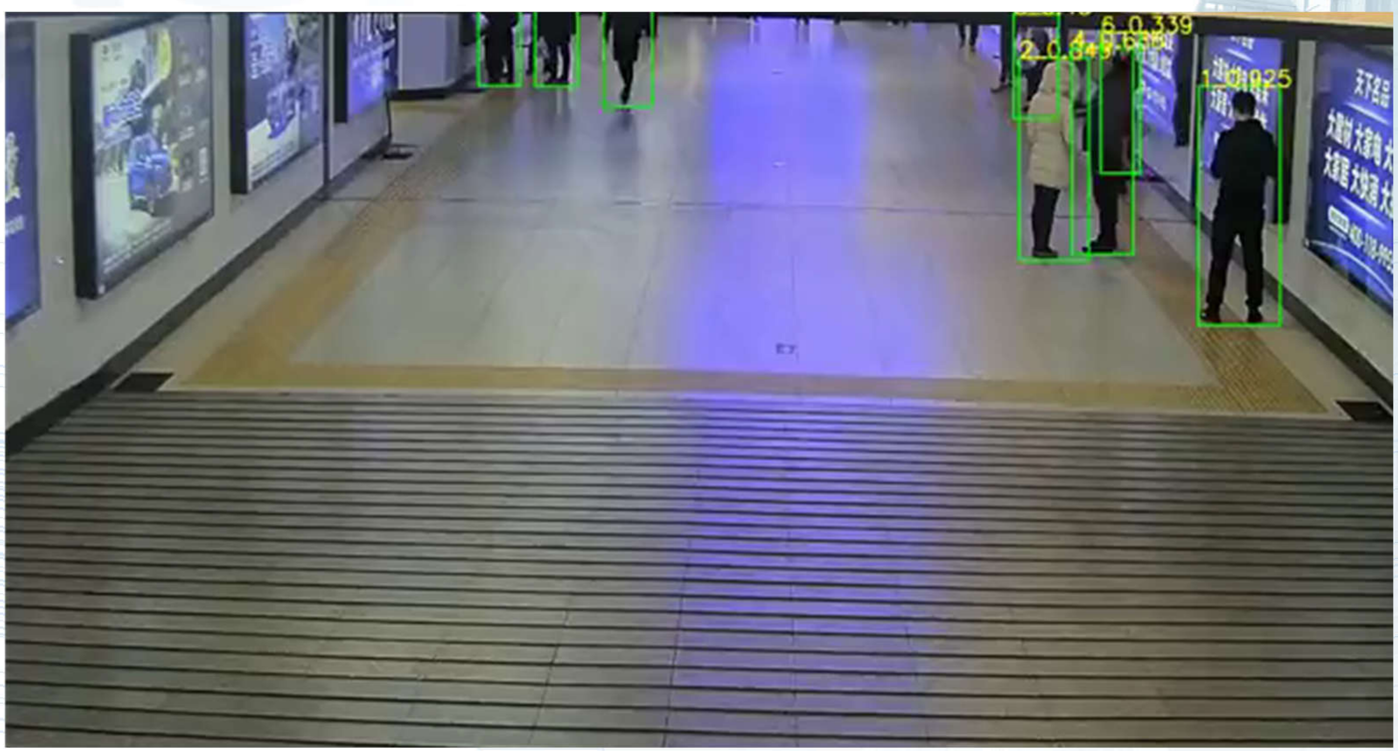
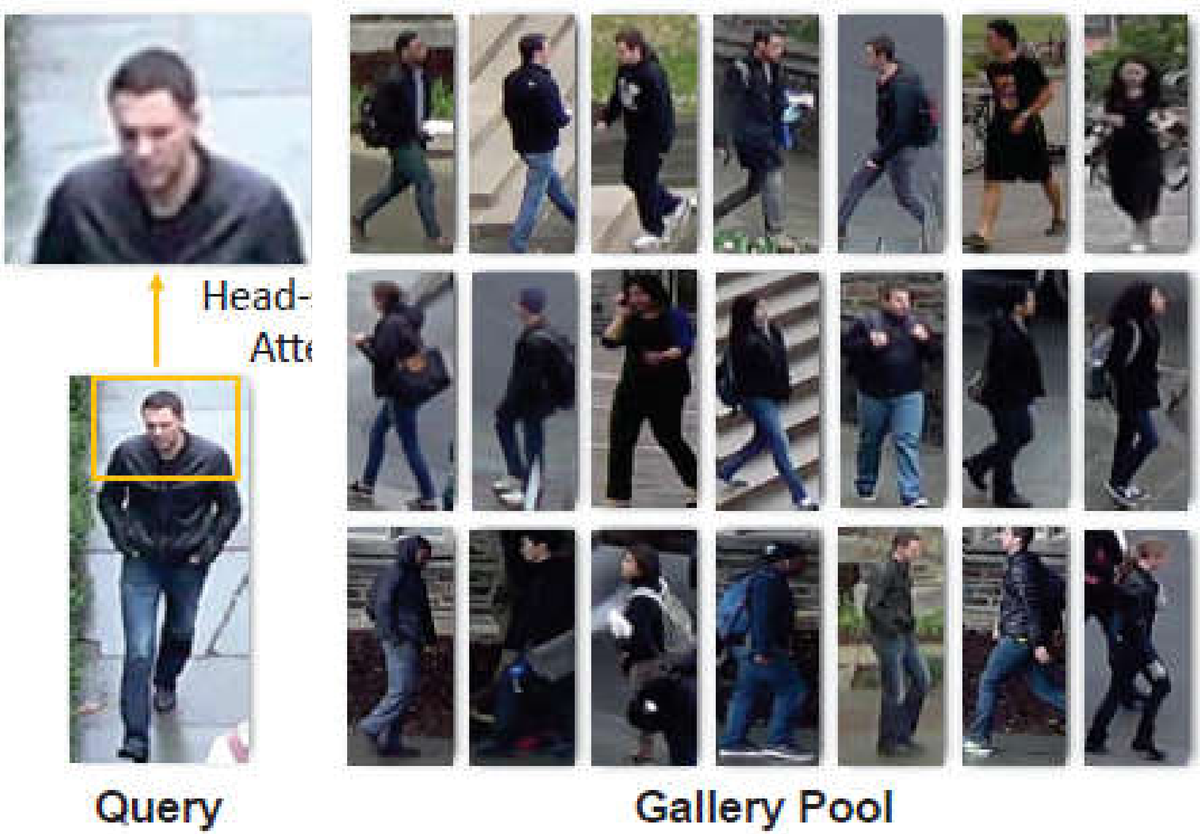
Black Re-ID

Black Re-ID problem: When people wear black clothes or they are captured by surveillance systems in low light illumination, the attributes of the clothing are severely missing.



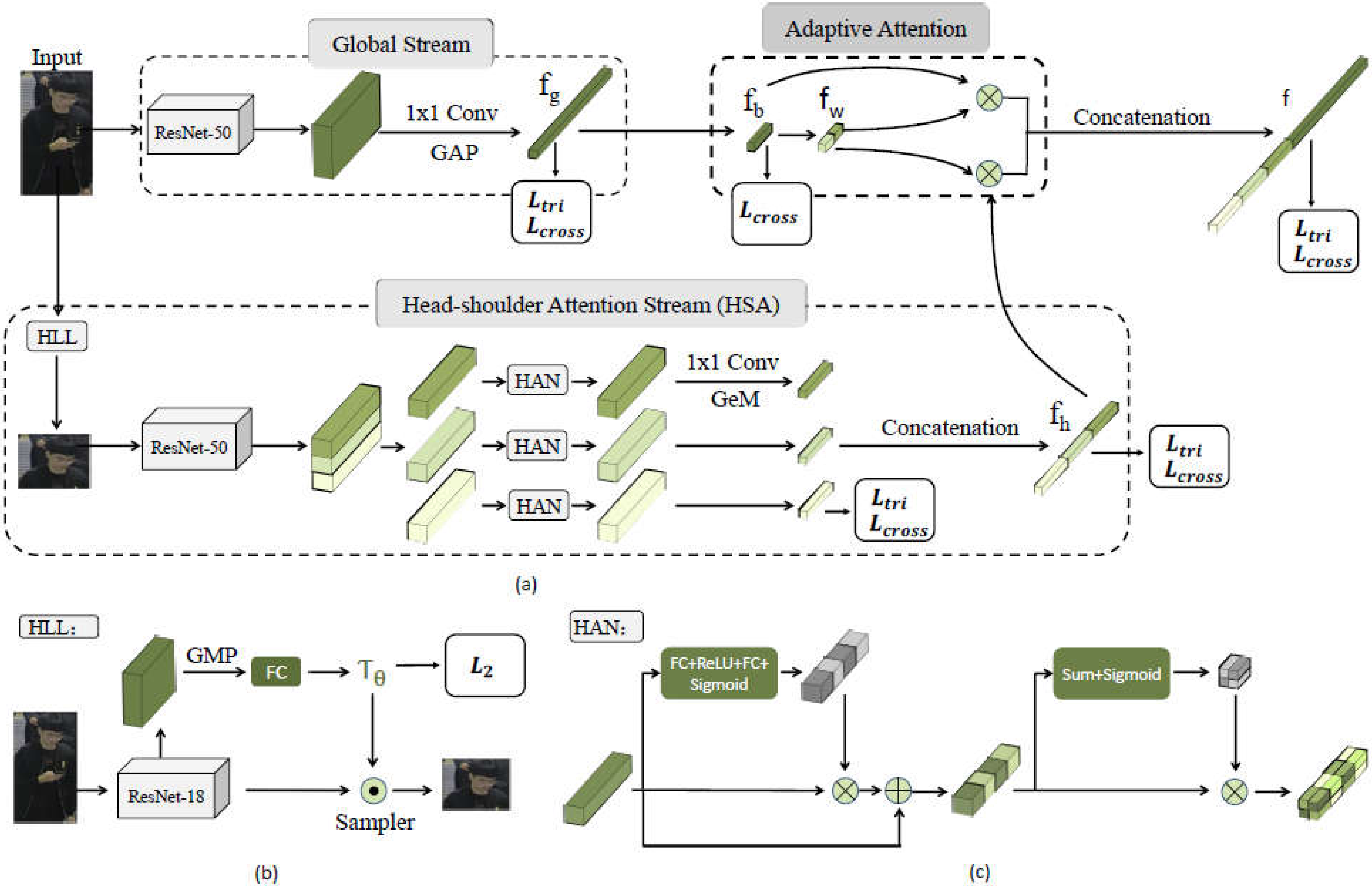
Boqiang Xu, Lingxiao He, Xingyu Liao, Wu Liu, Zhenan Sun, Tao Mei. "Black Re-ID: A Head-shoulder Descriptor for the Challenging Problem of Person Re-Identification." ACM MM. 2020 (Oral).

Black Re-ID



We exploit the head-shoulder feature to assist solving the Black Re-ID problem.

Black Re-ID


Input
Global Stream
ResNet-50
1x1 Conv
GAP
f_g
L_{tri} L_{cross}
Adaptive Attention
f_b
f_w
L_{cross}
Concatenation
f
L_{tri} L_{cross}
Head-shoulder Attention Stream (HSA)
HLL
ResNet-50
HAN
HAN
HAN
1x1 Conv
GeM
Concatenation
f_h
L_{tri} L_{cross}
L_{tri} L_{cross}
(a)
HLL:
GMP
FC
T_θ
L_2
ResNet-18
Sampler
(b)
HAN:
FC+ReLU+FC+ Sigmoid
Sum+Sigmoid
(c)

Black Re-ID

Table 2: Quantitative comparison with the state-of-the-art methods in person re-id on Black-reID dataset. Bold number denote the best performance. We denote HAA (ResNet50) and HAA (MGN) by the method selecting ResNet50 and MGN as the backbone respectively.

Method	Black Group		White Group	
	mAP	Rank-1	mAP	Rank-1
ResNet50 [4]	70.8	80.9	75.8	89.5
PCB [29]	73.4	83.2	78.2	90.8
AlignedReID [34]	75.5	83.5	80.5	91.3
MGN [31]	79.1	86.7	85.8	94.3
HAA (ResNet50)	79.0	86.7	84.4	93.5
HAA (MGN)	**83.8**	**91.0**	**88.1**	**95.3**

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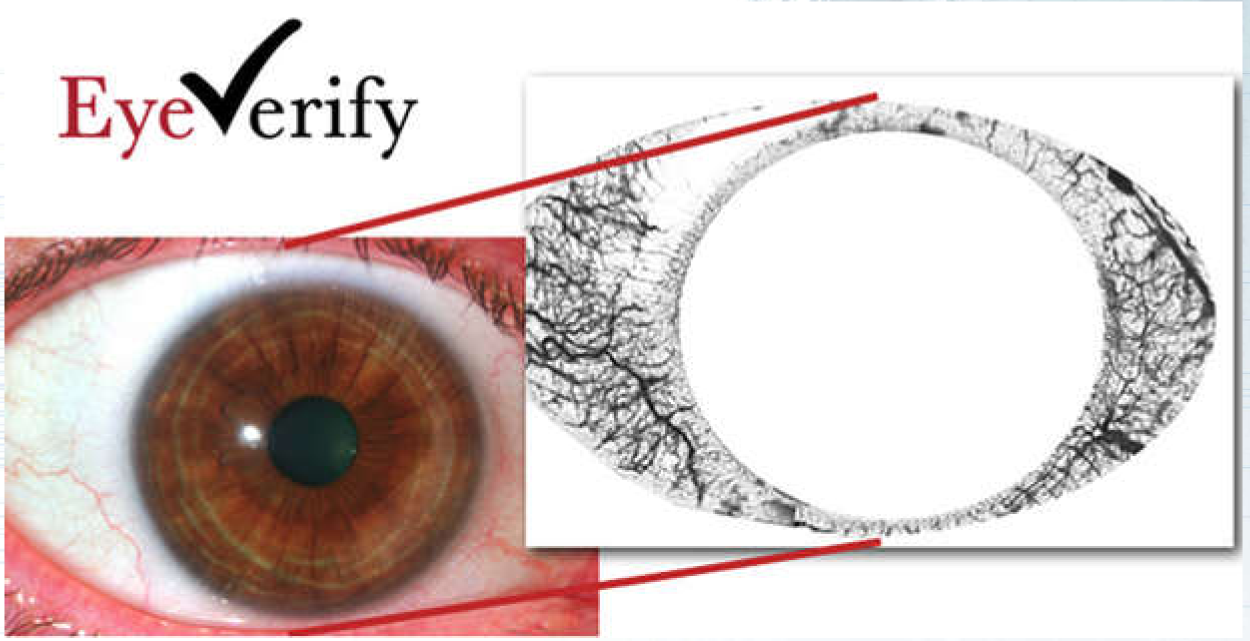
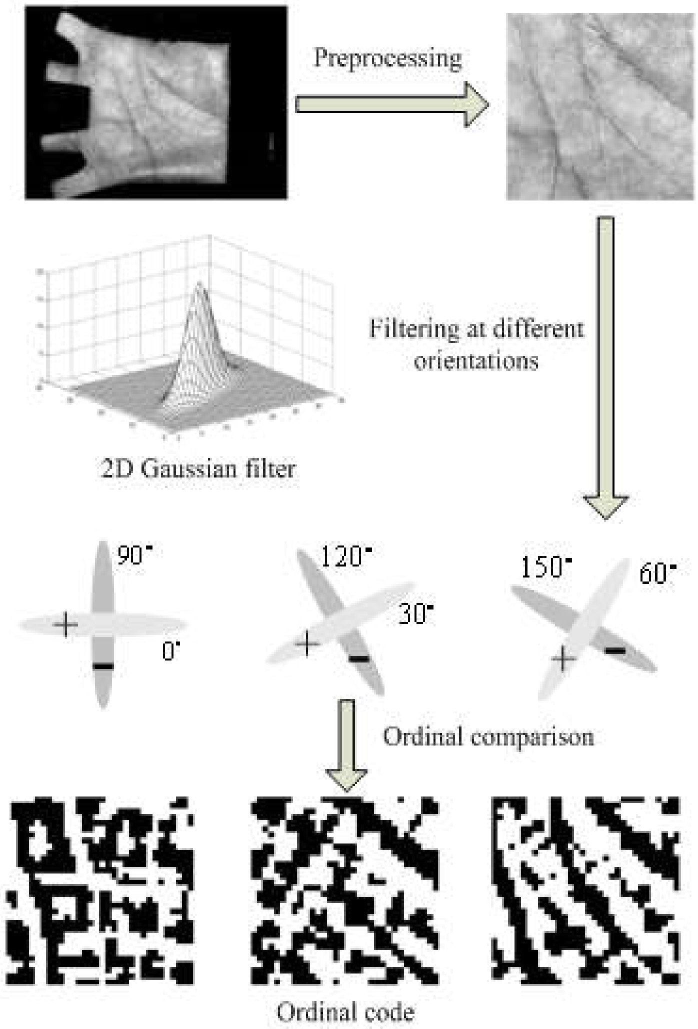
Eyeprint Recognition

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

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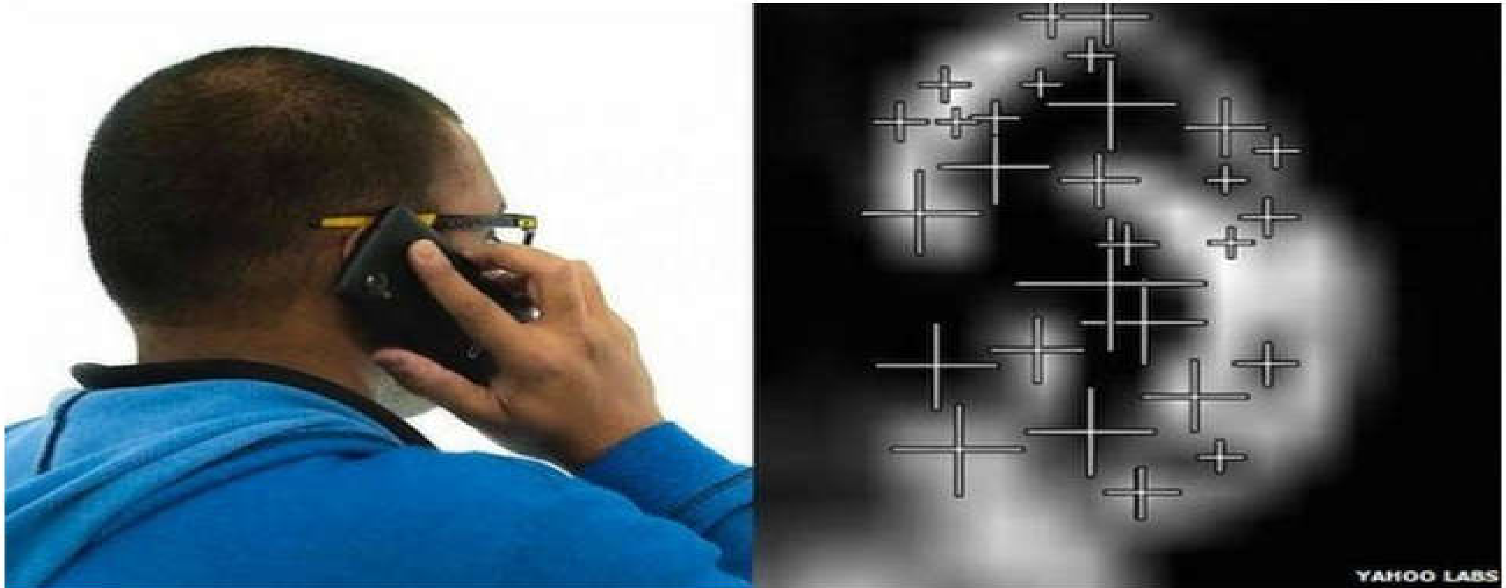
Technology

Yahoo tests ear-based smartphone identification system

28 April 2015 | Technology



The system identifies users based on the shape of their ears

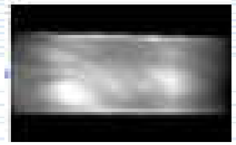
Hand Vein Patterns for Biometric Recognition

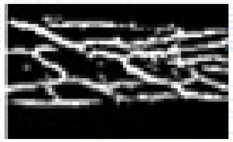
Unique, stable and secure biometric patterns underneath the skin surface

Finger vein

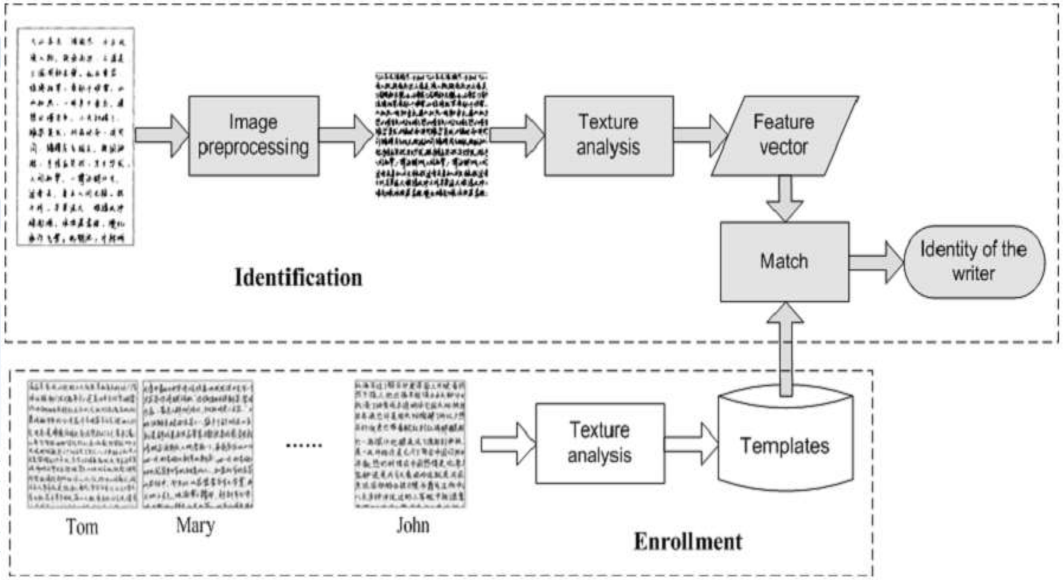
Palm vein

Hand vascular pattern

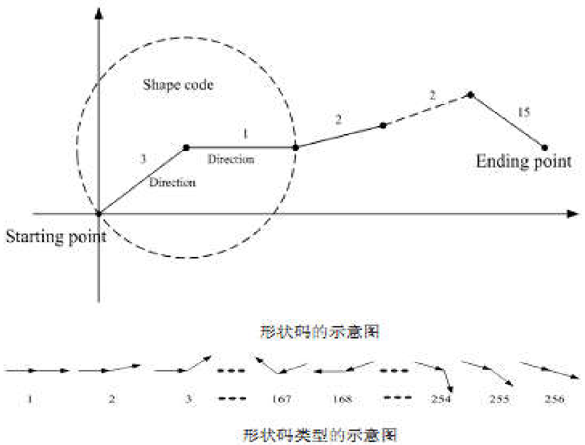


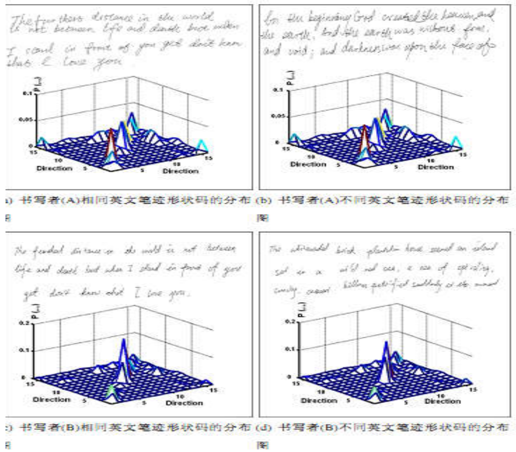


Handwriting Biometrics



Handwriting texture analysis for writer identification





Statistical analysis of stroke shape features for writer identification

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Challenges of Biometric Recognition

50 Years of Biometric Research:

Almost

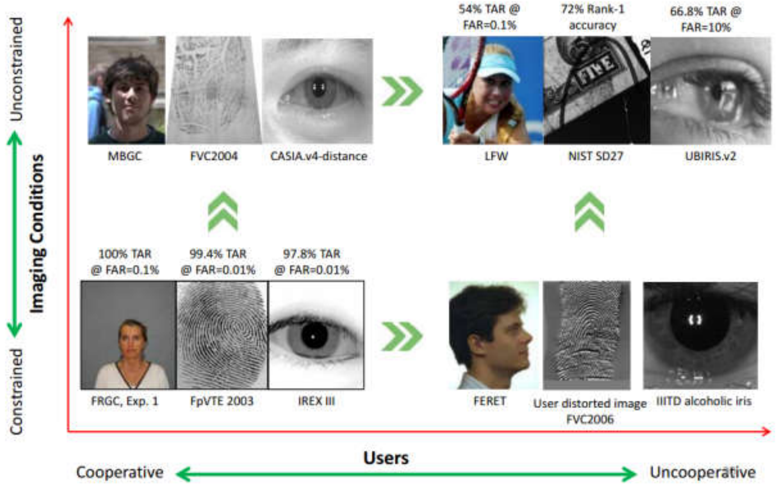
~~The~~ Solved, The Unsolved, and The Unexplored

Anil Jain
Michigan State University

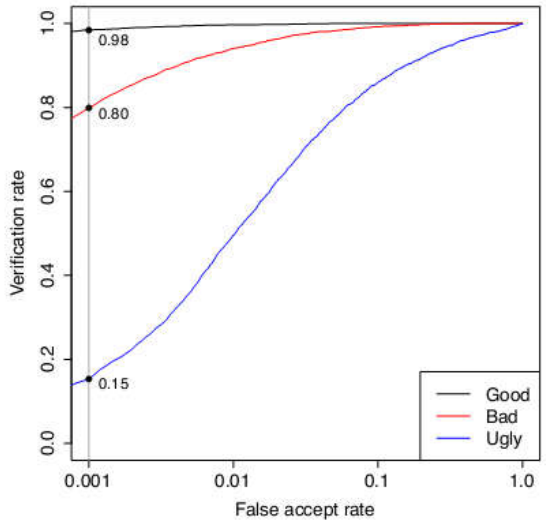
June 5, 2013

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

From Solved to Unsolved



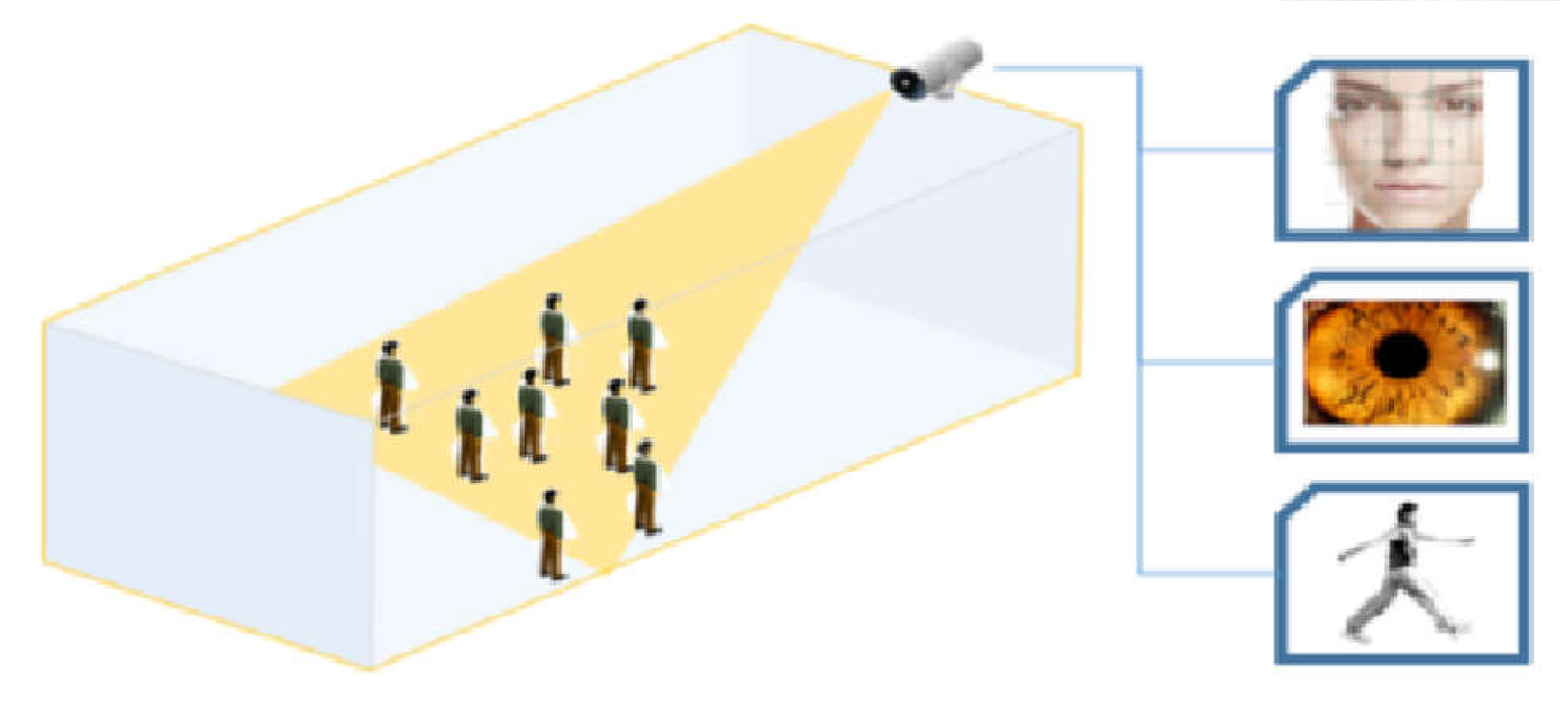
Jonathon Phillips
NIST



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

Future Directions

- Multi-biometrics at a distance



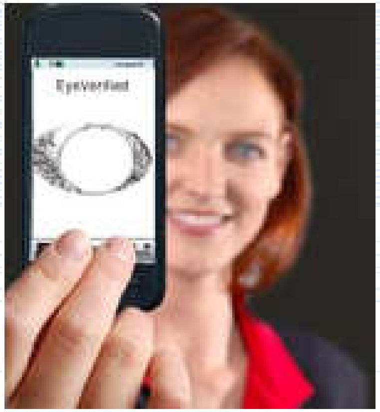
Future Directions

- Multi-biometrics for mobile devices

Fingerprint

Face

Iris



Eyeprint

Palmprint

Voiceprint

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Future Directions

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- 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

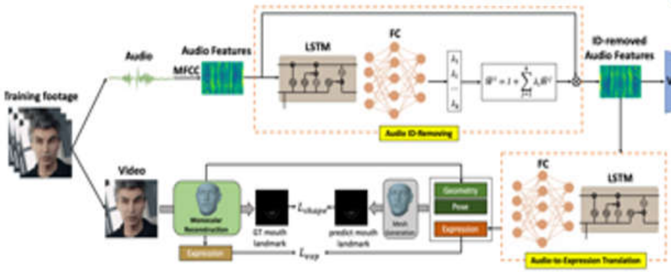
How to determine such information from biometric data?

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.

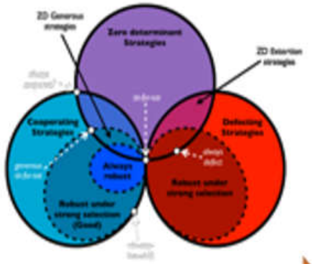
Future Directions

- Deepfake and Anti-Deepfake

Deepfake



Game Theory



Endless War

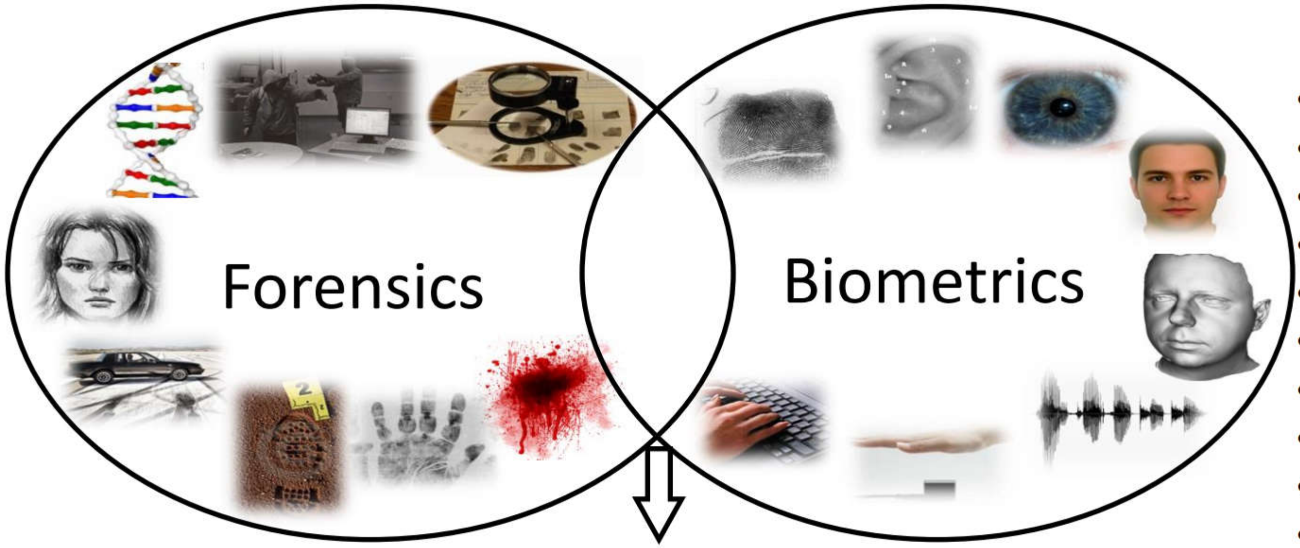
Anti-Deepfake

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