



Department of Computer Science and Engineering



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Biometrics: Progress, Problems and Prospects

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(Thanks to Wang Yunlong, SUN Zhenan, LI Qi and ZHANG Kunbo for their help in preparing this talk)

Nanjing University Institute of Automation, Chinese Academy of Sciences

January 15, 2025

Outline

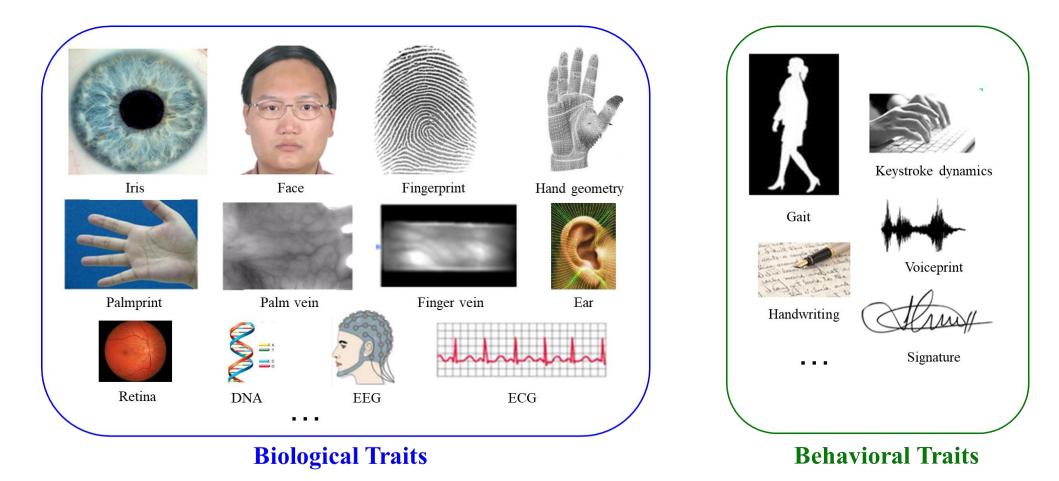
- Preamble
- Recent Progress
- Remaining Challenges
- Future Directions and Prospects
- Conclusions

Outline

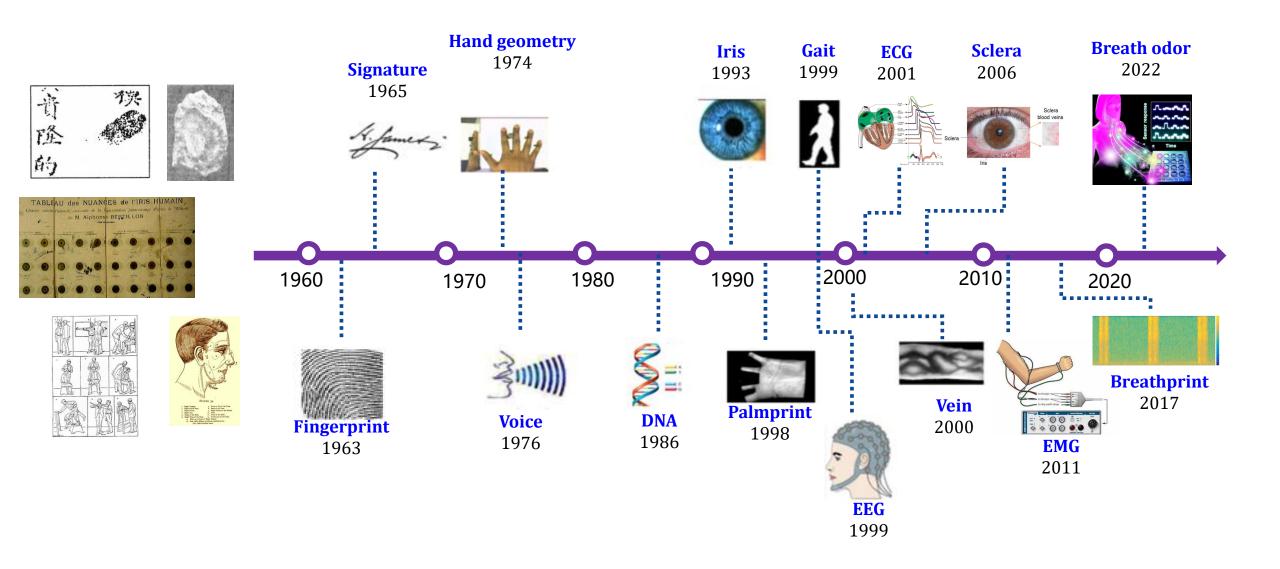
- Preamble
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- Future Directions and Prospects
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Biometrics

Automated recognition of individuals based on their behavioral and biological characteristics [ISO/IEC 2382-37:2022]



Timeline of Biometrics History



Applications of Biometrics



Fingerprint recognition for mobile authentication



Face recognition for border control



Iris recognition for coal miner identification





Gait recognition for criminal identification



Finger vein recognition for ATM authentication



Voiceprint recognition for payment



Signature verification for credit card security



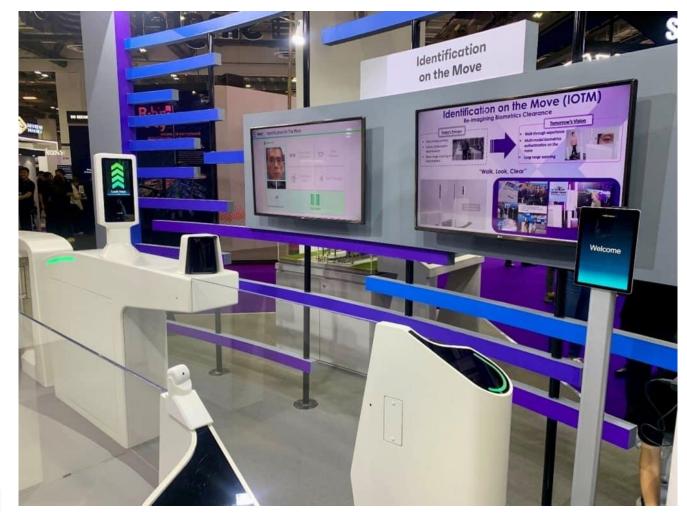
Palmprint recognition for transportation

Travel without Passports



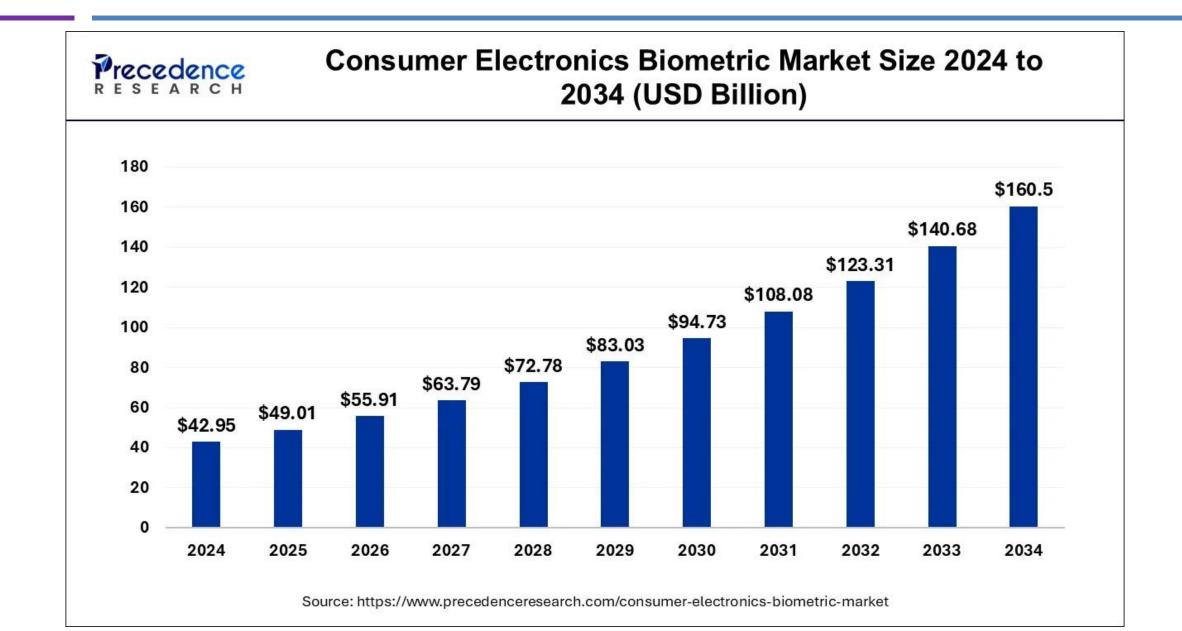
Arriving and departing Singapore residents can clear immigration without the need to present their passports. All foreign visitors can also enjoy the convenience of passport-less clearance when they depart Singapore.





For example, on-the-move facial and iris recognition technology facilitates passport-less clearance in Changi Airport, Singapore.

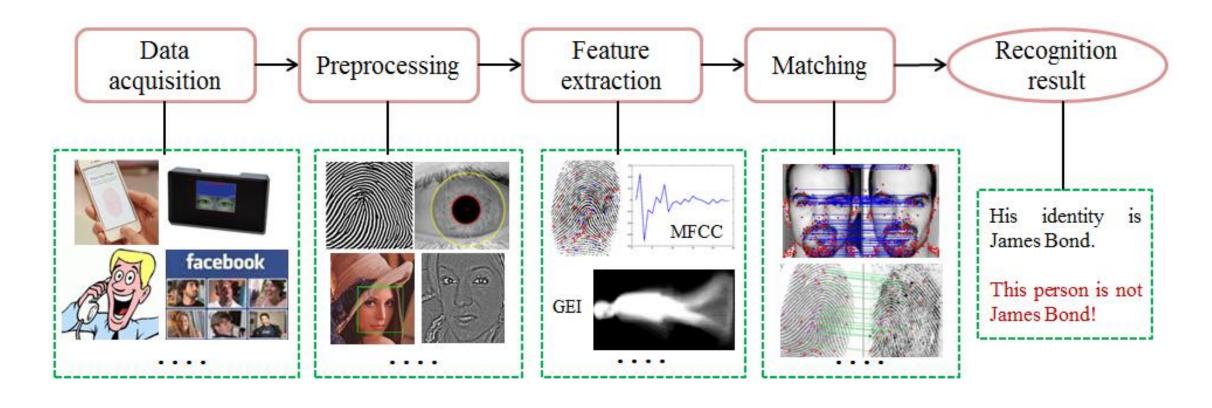
Market Potential of Biometrics



Outline

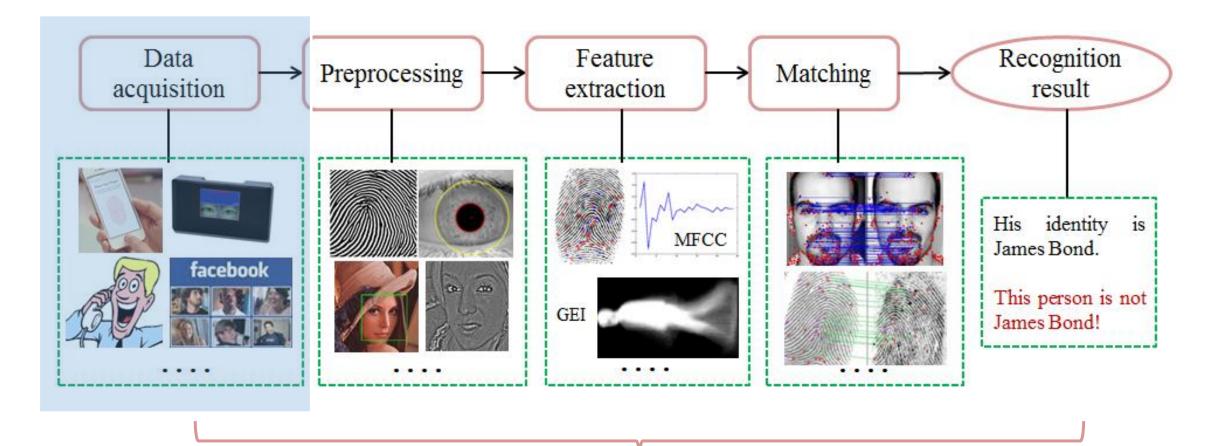
- Preamble
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Recent Progress



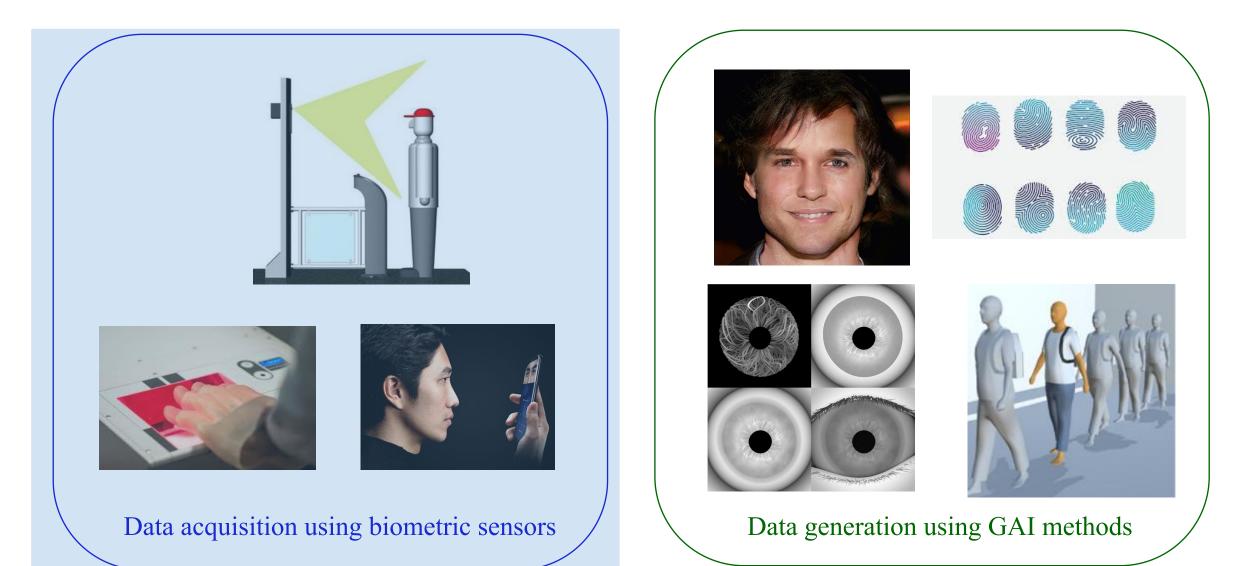
- $\checkmark\,$ Security and privacy
- ✓ Fairness
- ✓ Explainability

Recent Progress



- ✓ Security and privacy
- ✓ Fairness
- ✓ Explainability

Biometric Data Acquisition



Biometric Sensor Design

More user-friendly sensor



Touchless 3D fingerprint recognition



Far-field voiceprint recognition

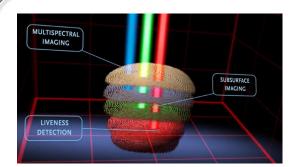


Noncontact palm vein Recognition

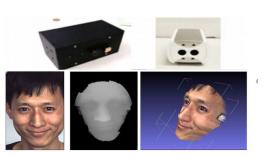


Iris recognition at a distance

Higher dimensional information



Multispectral imaging for fingerprint



ToF camera for 3D face recognition



Polarized face camera for anti-spoofing



Mircolens-based light field camera

Our Journey in Iris Camera Development















CASIA 10m Prototype Now



2005



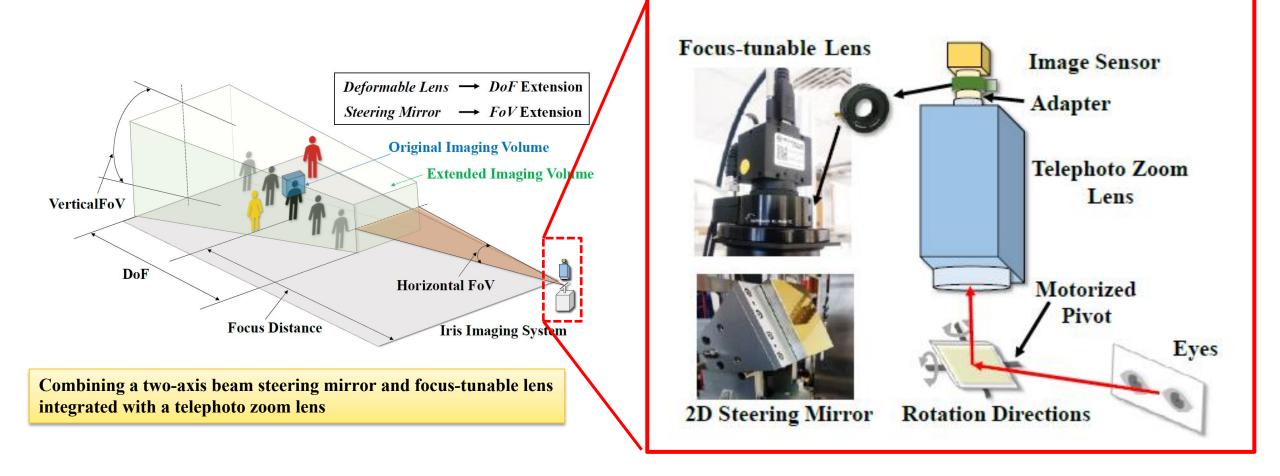


2008



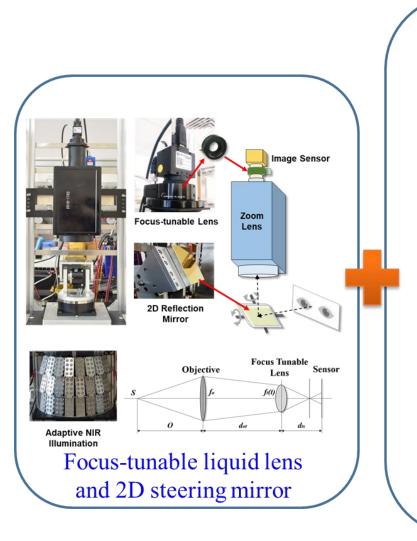
2014

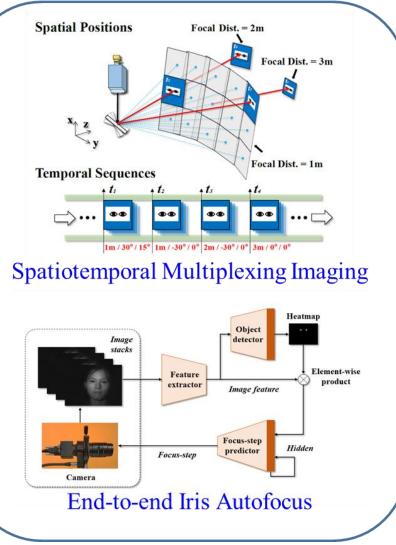
Iris Imaging With Expanded Capture Volume



Zhang K, Shen Z, Wang Y, et al. All-in-focus iris camera with a great capture volume[C]//IEEE International Joint Conference on Biometrics (*IJCB*), 2020. (*IJCB* 2020 Google Best Paper Award Runner-Up)

CASIA Long-range (10m) Iris Prototype

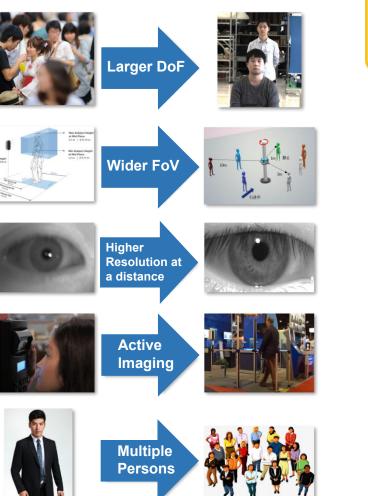






[1] Zhang K, Shen Z, Wang Y, et al. All-in-focus iris camera with a great capture volume[C]//IEEE International Joint Conference on Biometrics (*IJCB*), 2020. [2] Wang L, Zhang K, Wang Y, et al. An end-to-end autofocus camera for iris on the move[C]//IEEE International Joint Conference on Biometrics (*IJCB*), 2021.

CASIA Long-range (10m) Iris Prototype



Small DoF 20cm	Narrow FoV <10° (no PTZ)			le FoV Multiple 60° (≥3)
Model	Distance	Performance	Person	User cooperation
IOM, Sarnoff	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	3-6 m	3 m x 2 m x 3 m, double cameras	1	Standstill
CASIA	2.4-3 m	0.15 m x 0.15 m x 0.1 m, PTZ camera	1	Standstill
CMU	12 m	0.97 m x 0.73 m @1 m	1	Standstill, walk (0.6m/s)
SRI	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	0.5-1 m	0.2 m x 0.5 m x 0.5 m, vertical moving camera (50 mm)	1	Standstill
S200P, Iristar	1-1.2 m	Height 1.3-1.95 m, DoF 30 cm, 2 s recognition	1	Standstill
Versa F Max, Irisian	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	≥3	Standstill, walk (1m/s@1-10 m)

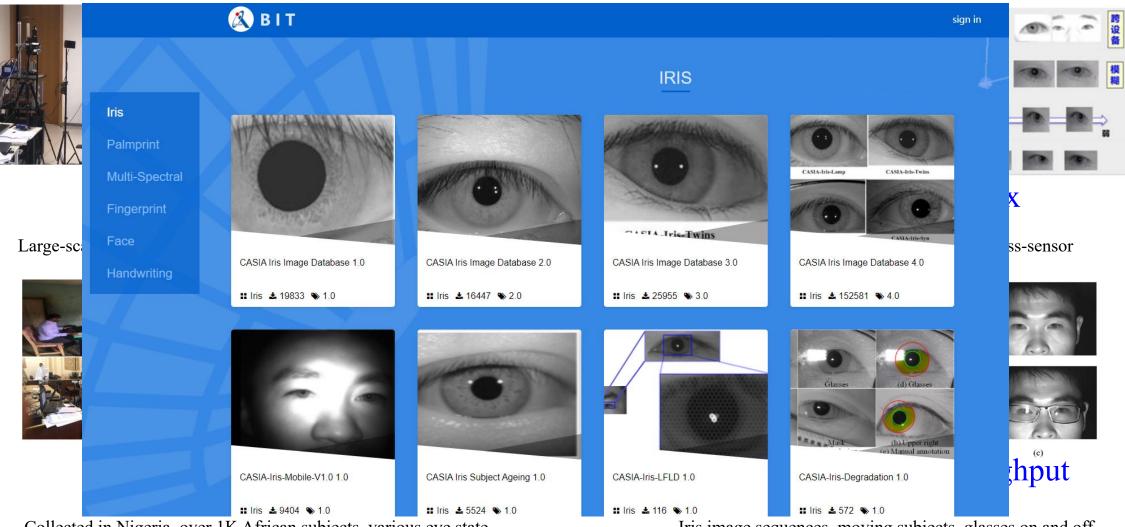
CASIA Long-range (10m) Iris Prototype



Iris recognition process of multiple persons

CASIA Iris Image Database V5.0-pre

BIT website: http://www.idealtest.org/

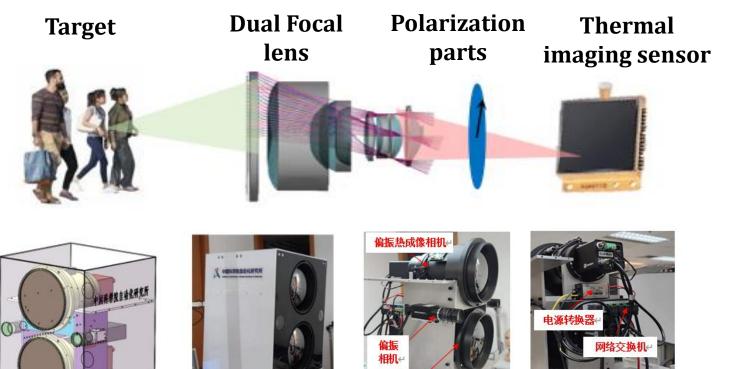


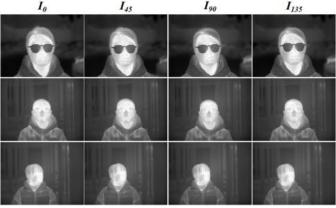
Collected in Nigeria, over 1K African subjects, various eye state

Iris image sequences, moving subjects, glasses on and off

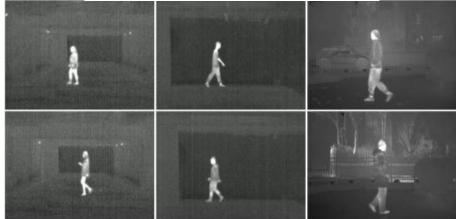
CASIA Thermal and Polarization Integrated Imaging Device

We integrate infrared thermography and polarization imaging technologies to construct a multimodal biometric imaging device specifically designed for ultralong-range low-illumination scenarios. $I_0 = I_{ss} = I_{ss}$



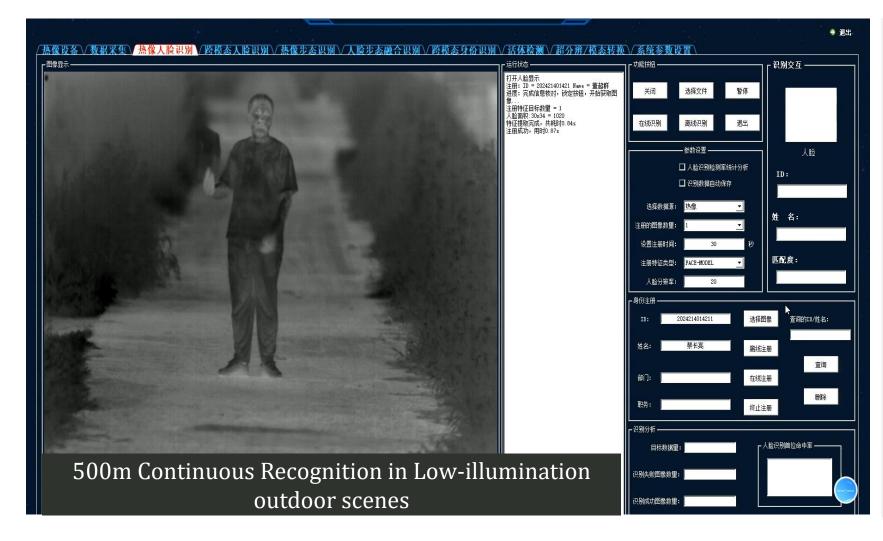


Captured Face Instances



Captured Gait Sequences

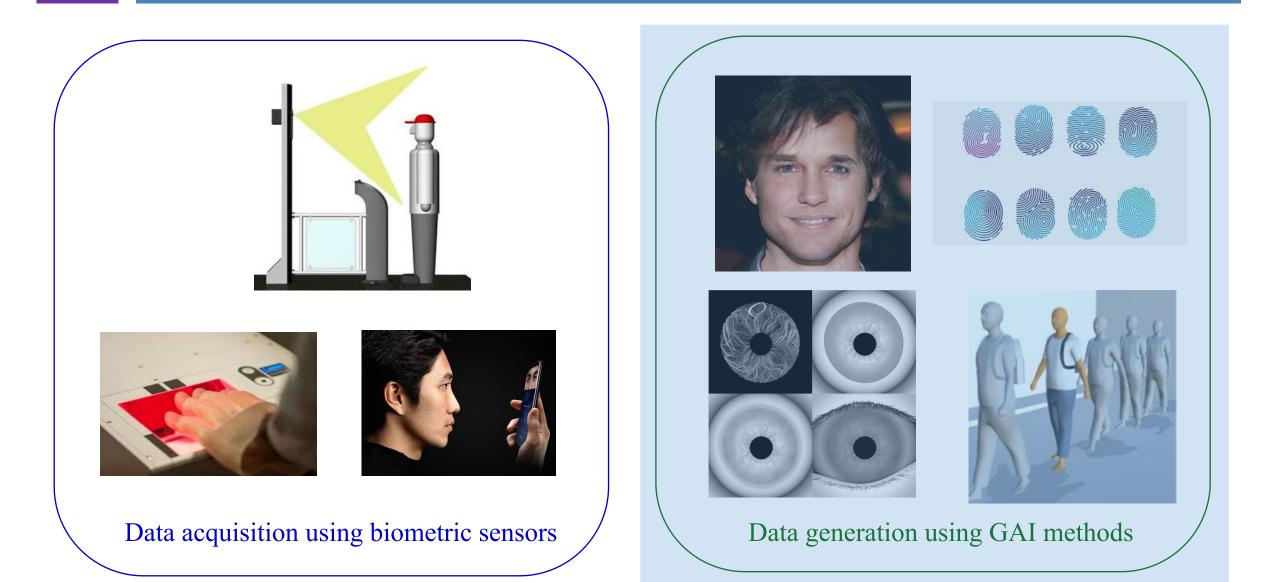
CASIA Thermal and Polarization Integrated Imaging Device



<u>Highlights</u>

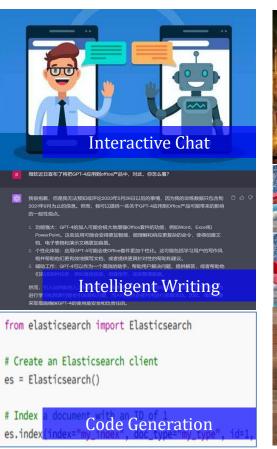
- > 500 meters multi-modal biometric (e.g., face and gait) data acquisition and continuous recognition
- Extremely low-illumination outdoor scenarios
- Active imaging, requiring no cooperation from targets
- High frame rate (50fps)

Biometric Data Acquisition



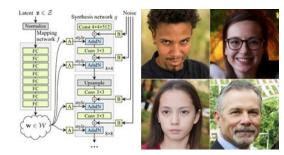
Generative AI (GAI)





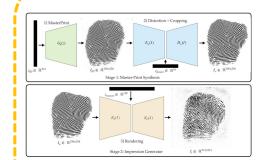


Biometric Data Generation using GAN



A style-based generator is proposed for high fidelity face generation.

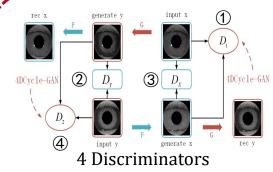
Face StyleGAN [Karras et al., CVPR'19]



Capable of generating more realistic fingerprints. 512K fingerprints are synthesized.

Fingerprint

PrintsGAN [Engelsma et al., TPAMI'23]



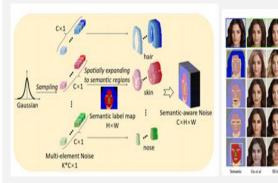
A novel 4DCycle-GAN with is proposed to synthesize fake iris images.

Iris 4DCycleGAN [Zou et al., ICPR'18] Encoder ← → Decoder

A GAN model is taken as a regressor to generate gait images.

Gait GaitGAN [Yu et al., CVPR'17]

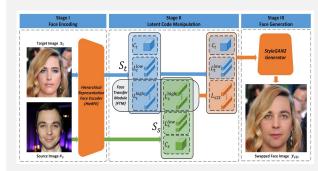
Our Work on Face Image Generation



3D semantic noise is proposed for semantic portrait synthesis and manipulation.

Generation from noise

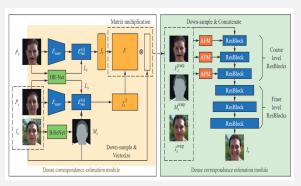
Deng et al. Semantic-aware noise driven portrait synthesis and manipulation[J]. IEEE Transactions on Multimedia (*TMM*), 2022, 25: 2799-2811



Capable of conducting one shot face swapping at megapixel level.

Face Swapping

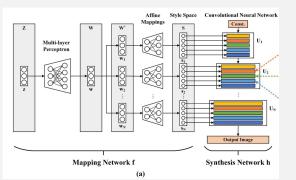
Zhu et al. One-shot face swapping on megapixels[c]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (*CVPR*),2021, 4834-4844



A 3D Morphable is used for explicit facial semantic segmentation and identity disentanglement.

Face Reenactment

Liu et al. One-shot face reenactment with dense correspondence estimation[J]. Machine Intelligence Research (*MIR*), 2024, 21:941-953



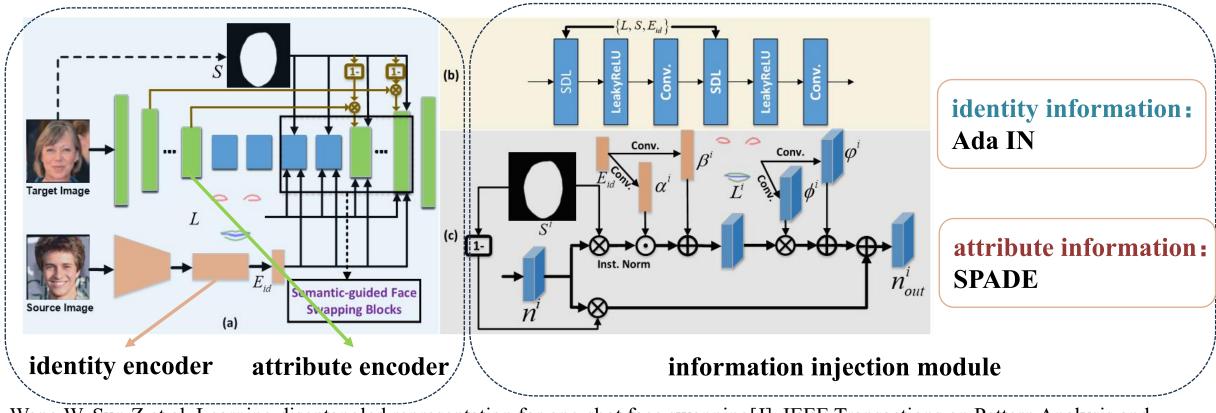
Spatially disentangled manipulation of highresolution images with a pre-trained StyleGAN generator.

Facial Attribute Manipulation

Liu et al. Towards spatially disentangled manipulation of face images with pre-trained stylegans [J]. IEEE Transactions on Circuits and Systems for Video Technology (*TCSVT*), 2023, 33: 1725-1739

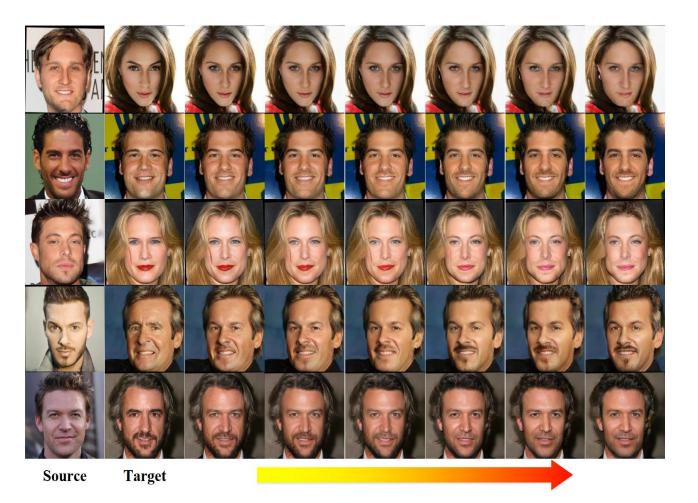
Disentangled Representation for Face Swapping

We designed identity and attribute encoders to separate facial features and embedded semantic information into the generator, enabling efficient and accurate progressive face swapping with low computational cost.

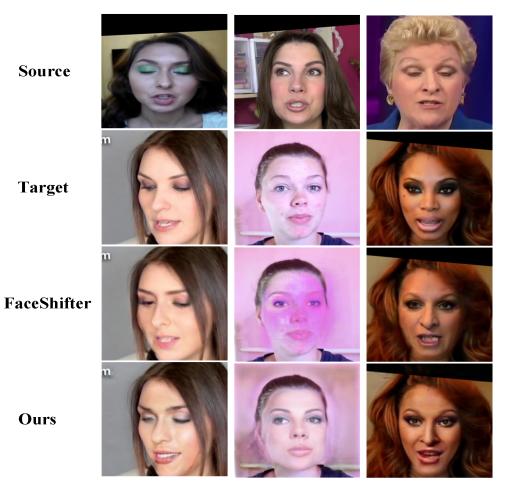


Li Q, Wang W, Sun Z et al. Learning disentangled representation for one-shot face swapping[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence (*TPAMI*), 2024, 46: 8348-8364.

Disentangled Representation for Face Swapping



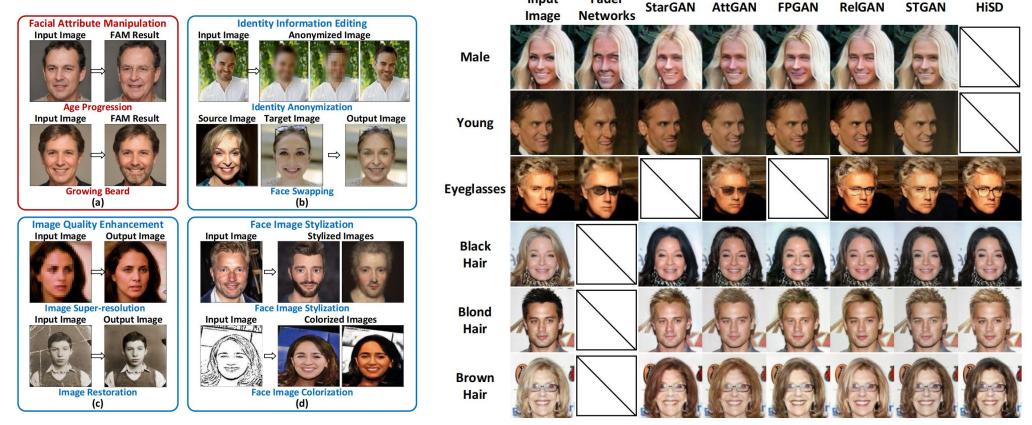
Progressive face swapping results



Face swapping results under large poses, drastic lighting changes, and exaggerated facial expressions.

GAN-based Facial Attribute Manipulation

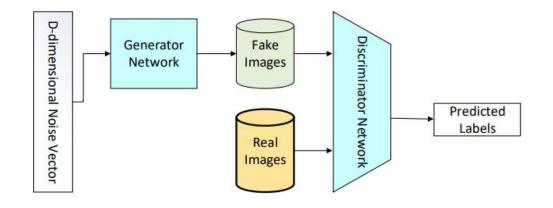
We have made a comprehensive review on GAN-based facial attribute manipulation (FAM) methods and an in-depth discussion of important properties of FAM methods, open issues, and future research directions.

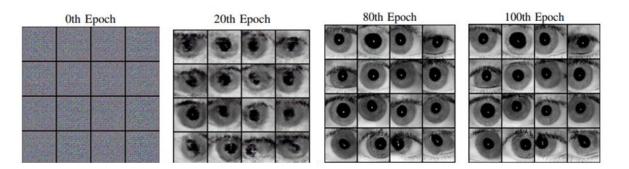


Li Q, Deng Q, et al. Gan-based facial attribute manipulation[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence (*TPAMI*), 2023.

Iris Generation and Synthesis with GAN

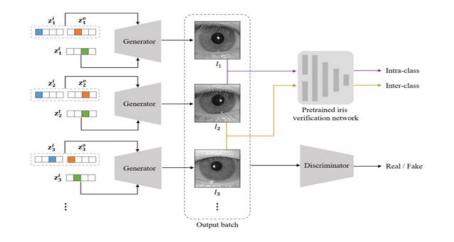
• Unconditional iris generation

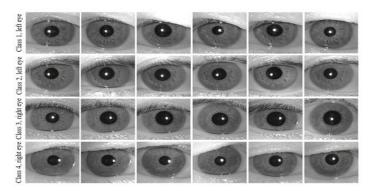




Iris-GAN [Minaee and Abdolrashidi, *Arxiv'18*]

• Conditional iris generation

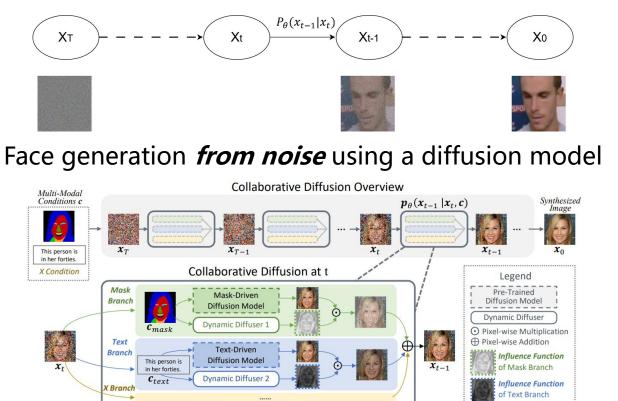




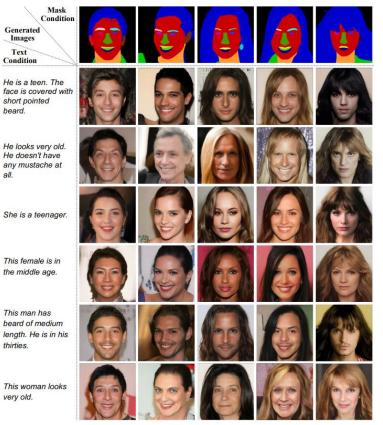
Identity control [Wang et al., IJCB'22]

Biometric Data Generation with Diffusion Models

• Multimodal conditioned diffusion model



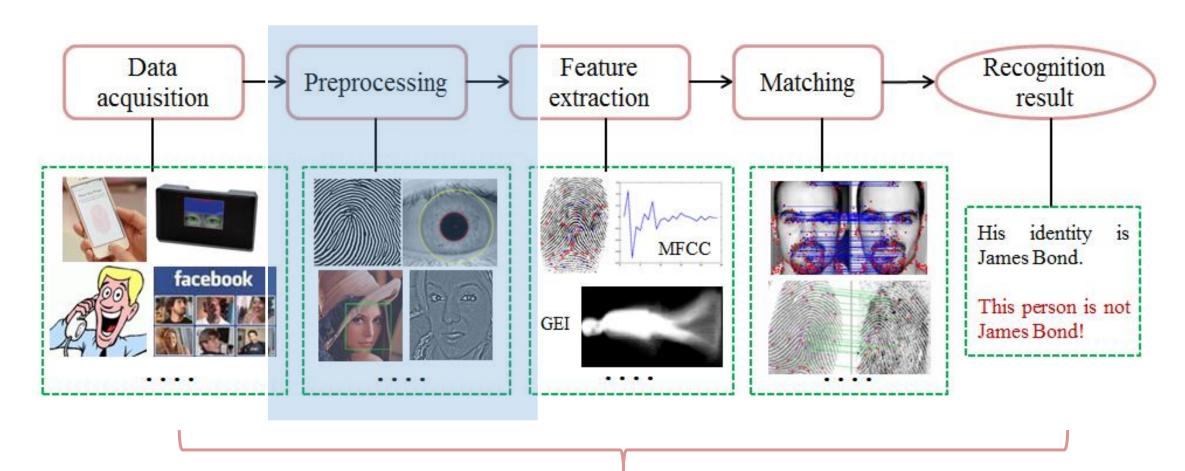
Multimodal (semantic mask, text, ...) conditioned diffusion model for face generation



high-quality synthesized facial images consistent with the input conditions

Huang Z, Chan K C K, Jiang Y, et al. Collaborative diffusion for multi-modal face generation and editing[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2023: 6080-6090.

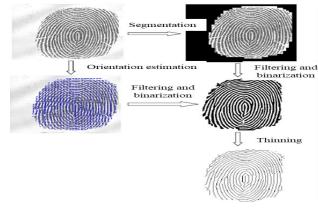
Recent Progress



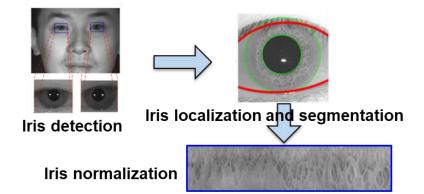
- ✓ Security and privacy
- ✓ Fairness
- ✓ Explainability

Preprocessing of Biometric Data

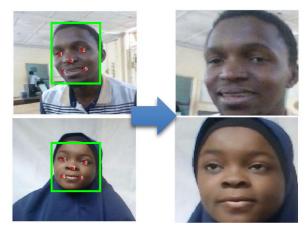
The preprocessing of biometric data aims to detect and segment out the target subject, align or normalize ROI to attenuate variations in scale, pose, illumination, etc.



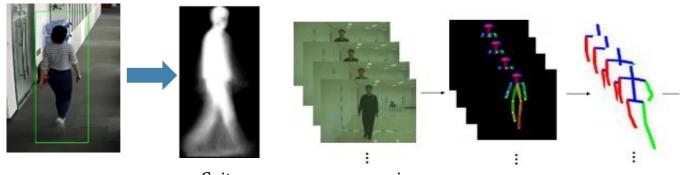
Fingerprint image preprocessing



Iris image preprocessing



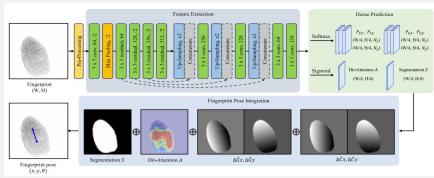
Face image preprocessing



Gait sequence preprocessing

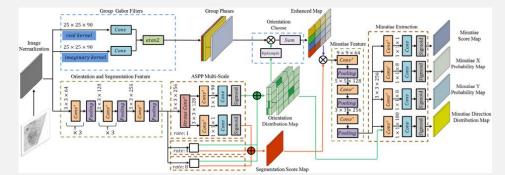
Progress in Fingerprint Preprocessing

• Fingerprint Pose Estimation



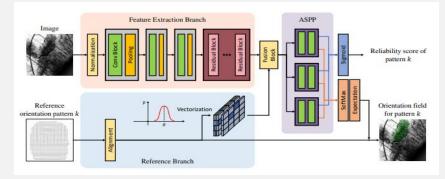
Voting strategy and deep network are fused to estimate fingerprint center and direction. [Duan et al. *TIFS'23*]

• 2D Minutiae Extraction



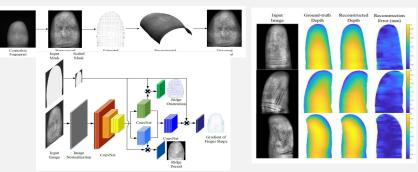
Domain knowledge and the representation ability of deep learning are combined for minutiae extraction. [Tang et al. *IJCB'17*]

Orientation Field Estimation



Residual orientation fields and reliability scores are estimated using a deep network. [Duan et al. *IJCB'21*]

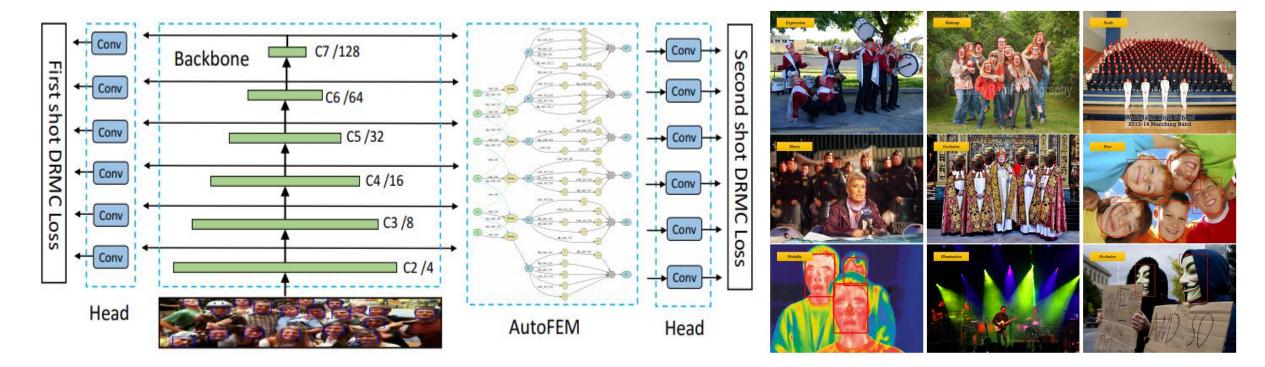
• 3D Finger Reconstruction



A 3D finger shape from a single image is reconstructed and the raw image is unwarped to suppress the perspective distortion. [Cui et al. *TPAMI'23*]

Face Preprocessing: Face Detection

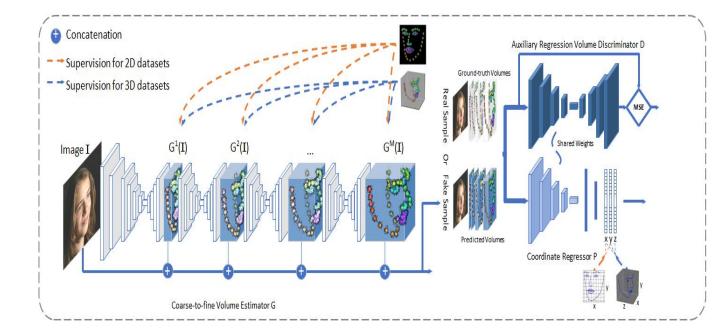
Feature aggregation and enhancement (FAE) modules are proven to be pivotal in deep learning based face detection frameworks. For instance, Automatic and Scalable Face Detector (ASFD) is able to automatically search an effective FAE architecture.



Li J, Zhang B, Wang Y, et al. ASFD: Automatic and scalable face detector[C]//Proceedings of the 29th ACM International Conference on Multimedia (*ACM MM*). 2021: 2139-2147.

Face Preprocessing: 2D/3D Facial Landmark Detection

We have proposed an adversarial voxel and coordinate regression framework for 2D and 3D facial landmark localization in real-world scenarios, in which an end-to-end pipeline is designed to jointly regress the proposed volumetric representation and the coordinate vector.

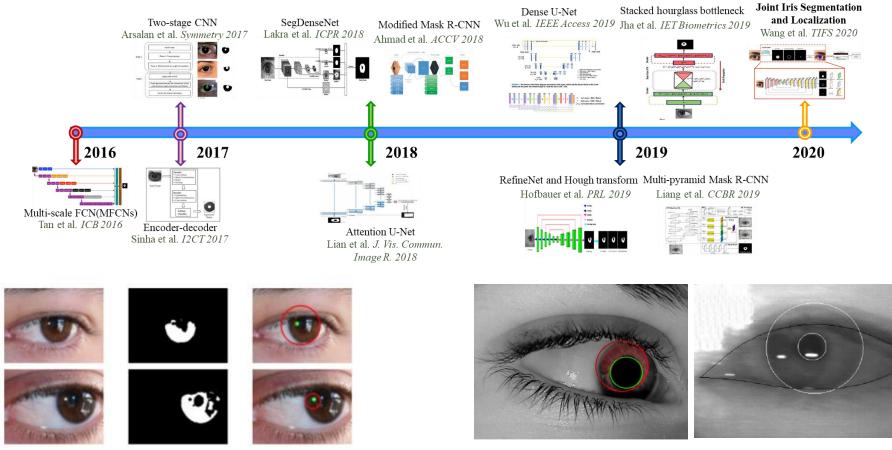




Zhang H, Li Q, Sun Z. Adversarial learning semantic volume for 2d/3d face shape regression in the wild[J]. IEEE Transactions on Image Processing (*TIP*), 2019, 28(9): 4526-4540.

Progress in Iris Preprocessing

The majority of current methods focus on predicting accurate iris masks by following popular semantic segmentation frameworks, but ignore the parameterized boundary for iris localization.

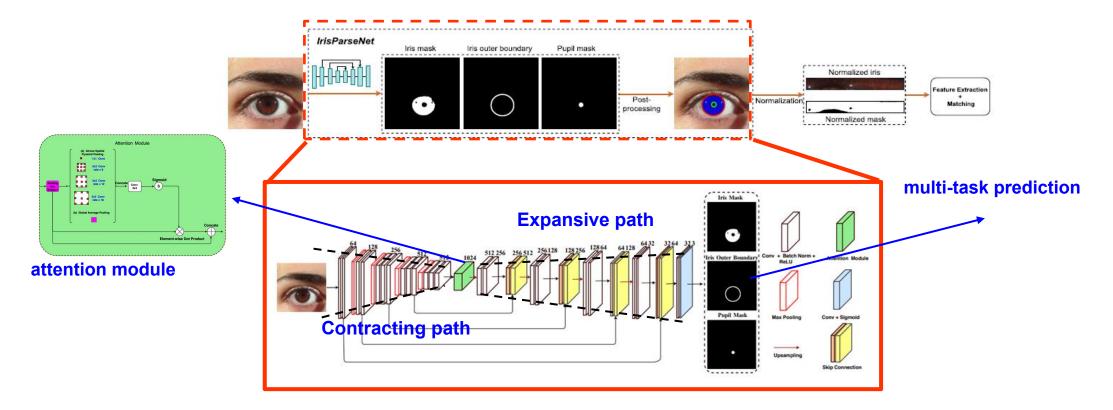


No boundary information for normalization

Dependent on training data and label quality

Our Solution: Simultaneous Iris Segmentation and Localization

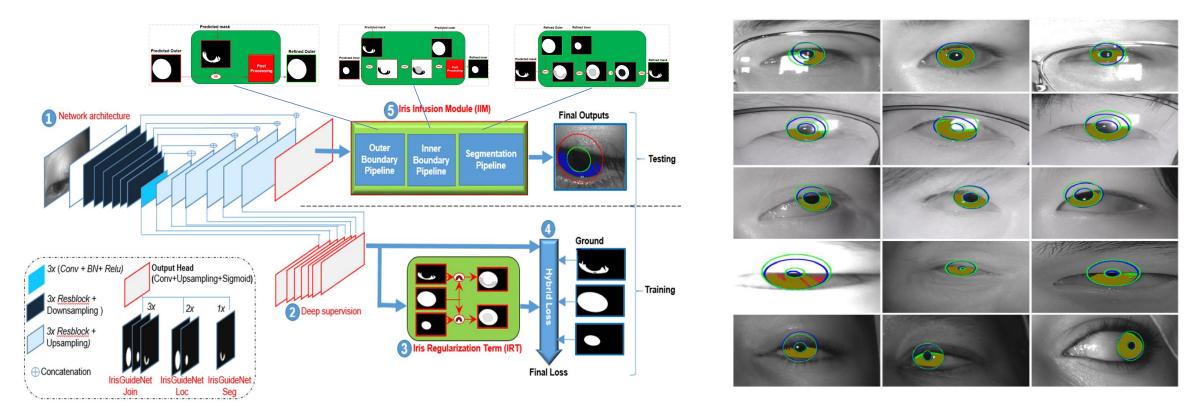
We proposed a unified framework for simultaneously learning segmentation mask and inner/outer iris boundaries, followed by simple yet efficient post-processing operations for complete iris segmentation.



Wang C, Muhammad J, Wang Y, et al. Towards complete and accurate iris segmentation using deep multi-task attention network for non-cooperative iris recognition[J]. IEEE Transactions on information forensics and security (*TIFS*), 2020, 15: 2944-2959.

One Step Further: Iris Prior Guided Network

An iris prior infusion module and a prior regularization term are incorporated in deep learning models to reduce its dependence on training data, guide the model to converge better and faster, significantly enhance the localization and segmentation of low-quality iris images.



Jawad Muhammad, Caiyong Wang, Yunlong Wang, Kunbo Zhang, Zhenan Sun. "IrisGuideNet: Guided Localization and Segmentation Network for Unconstrained Iris Biometrics", IEEE Transactions on Information Forensics and Security (*TIFS*), vol. 18, pp. 2723-2736, 2023.

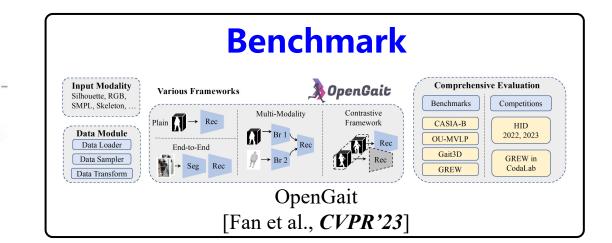
Progress in Gait Preprocessing





Popular ways for gait sequence preprocessing

- Pedestrian detection: YOLO series or variants
- Pedestrian segmentation: U-Net or variants
- Pedestrian pose: HRNet, OpenPose, ...



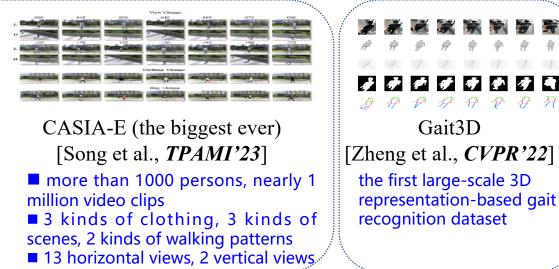
1 1

Database

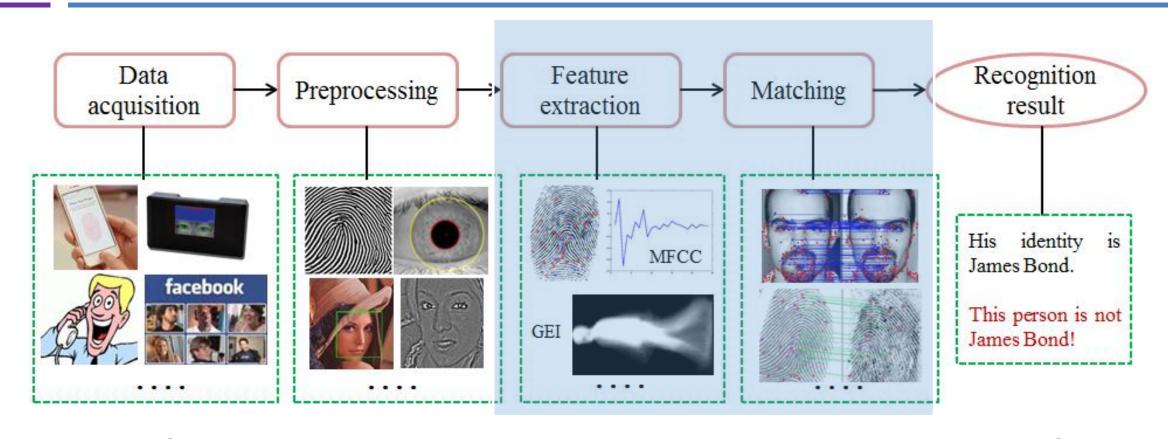


CASIA-B (cross-view) [Yu et al., *ICPR'06*] The first cross-view and crossdressing database in the world 124 people, 11 views per person covering backpack and clothing changes

OU-MVLP [Takemura et al., *CVA'18*] Multi-view large population dataset



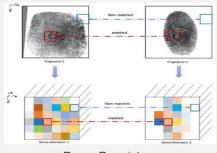
Recent Progress

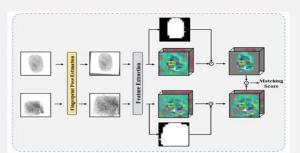


- ✓ Security and privacy
- ✓ Fairness
- ✓ Explainability

Progress in Fingerprint Feature Extraction and Matching

• Fixed-length Dense Descriptor



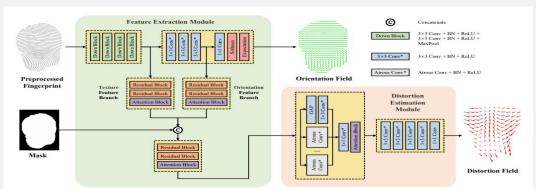


Dense Descriptor

The fingerprint matching using FDD

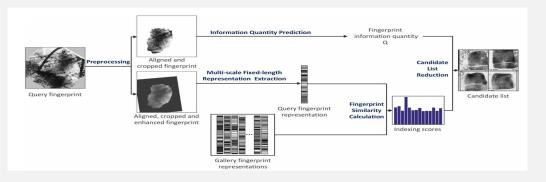
A three-dimensional representation Fixed length Dense Descriptor (FDD) for efficient fingerprint matching [Pan et al., *WIFS'24*]

• Fingerprint distortion rectification



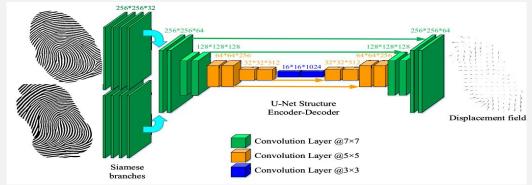
A self-reference based network is utilized to directly estimate the dense distortion field of distorted fingerprint [Guan et al., *TIFS'23*]

• Latent fingerprint matching



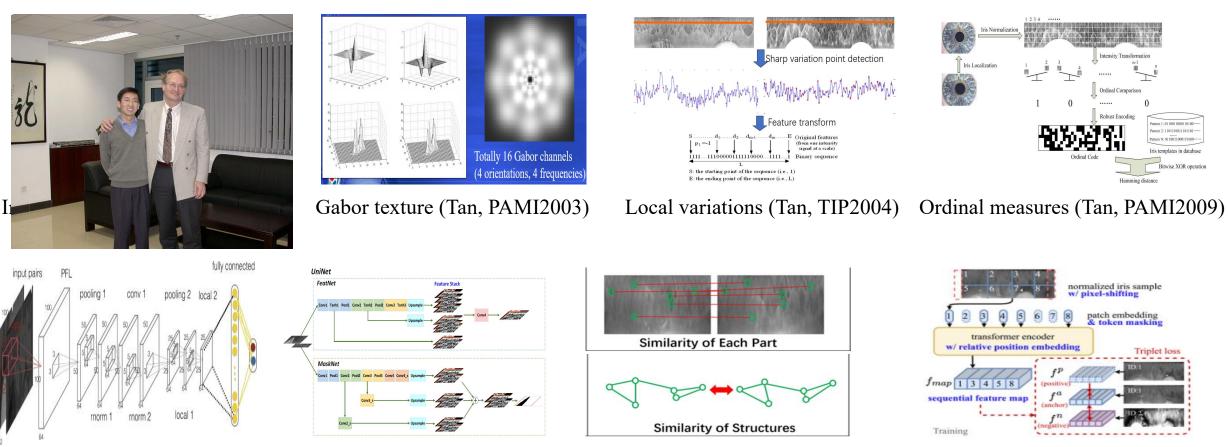
A multi-scale fixed-length representation approach for latent fingerprint indexing [Gu et al., *TIFS'22*]

• Fingerprint dense registration



An end-to-end network to directly output pixel-wise displacement field between two fingerprints [Cui et al., *TIFS'21*]

Progress in Iris Feature Extraction and Matching



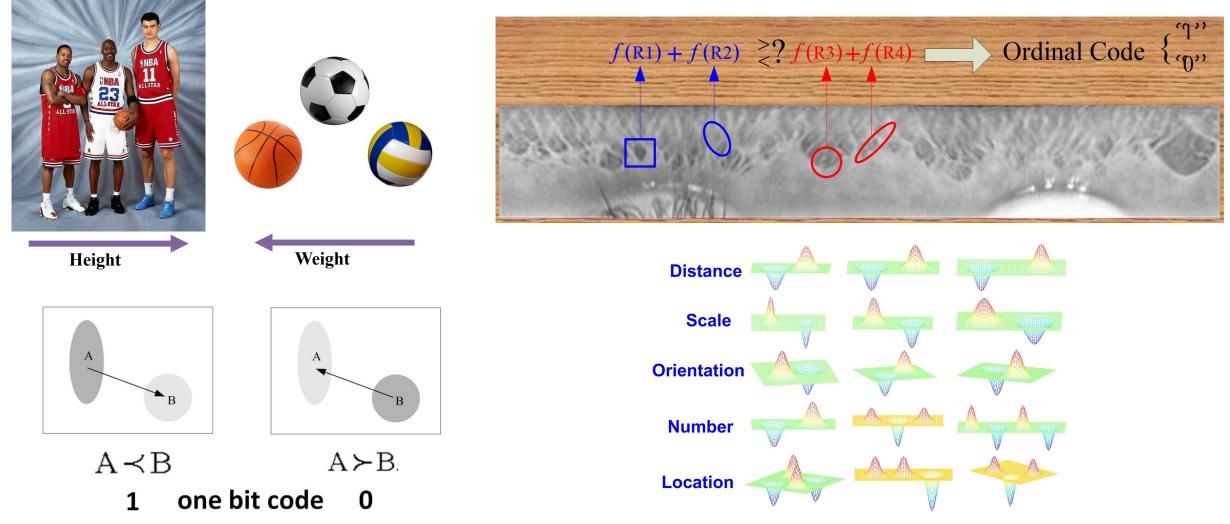
DeepIris (Tan, PRL2016)

UniNet (Kumar, ICCV2017)

DGR (Tan, AAAI2020, TPAMI 2023)

IrisFormer (Sun, SPL2024)

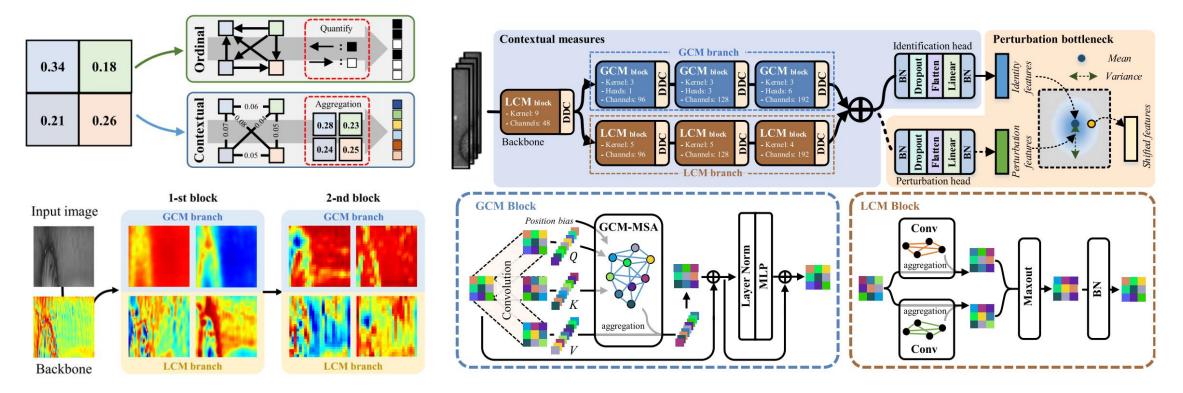
Ordinal Measures for Iris Pattern Recognition



Zhenan Sun and Tieniu Tan, "Ordinal Measures for Iris Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence (*T-PAMI*), Vol. 31, No. 12, 2009, pp. 2211 - 2226.

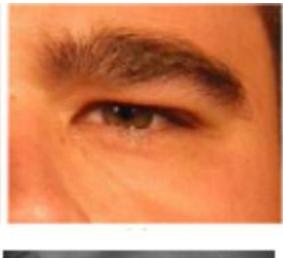
Contextual Measures for Iris Recognition

Estimate quantitative relationships between different regions and aggregate features from a global contextual measure (GCM) branch and a local contextual measure (LCM) branch for iris recognition



Jianze Wei, Yunlong Wang*, Huaibo Huang, Ran He, Zhenan Sun, Xingyu Gao*. "Contextual Measures for Iris Recognition", IEEE Transactions on Information Forensics and Security (*TIFS*), vol. 18, pp. 57-70, 2023.

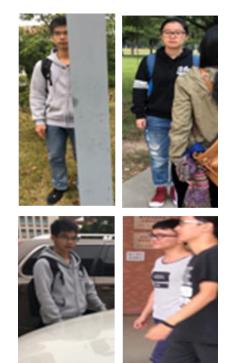
Occlusion in Biometrics











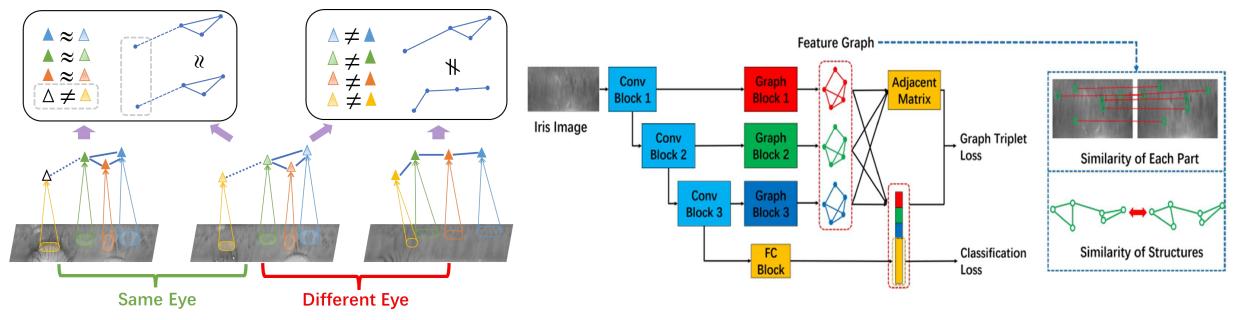
Iris

Face

Re-ID

Dynamic Graph Representation for Iris Recognition

- Modelling both local features and geometric relationships between local regions using deep graphical models
- The nodes of the occluded parts are removed during matching
- Robust against occlusions in iris recognition, face recognition and person ReID tasks

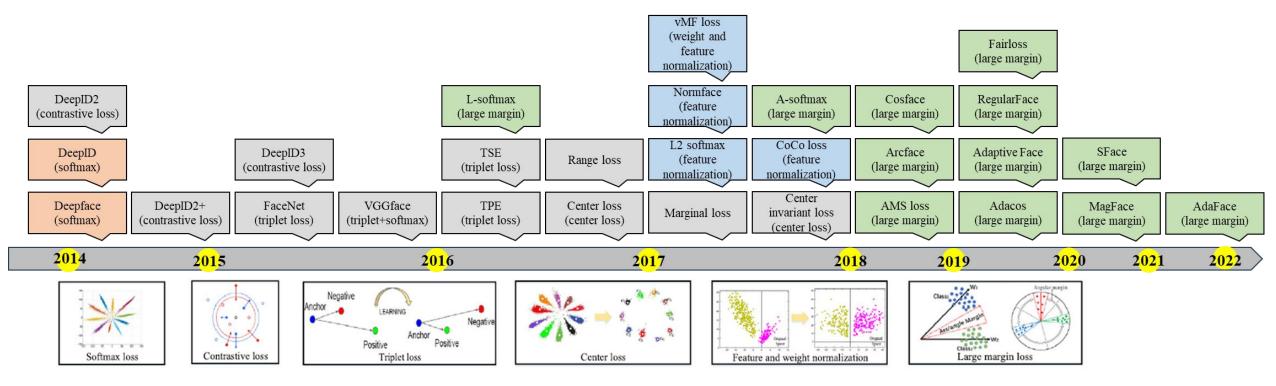


[1] Ren M, Wang Y, Sun Z, et al. Dynamic graph representation for occlusion handling in biometrics[C]//Proceedings of the AAAI Conference on Artificial Intelligence (*AAAI*). 2020, 34(07): 11940-11947.

[2] Ren M, Wang Y, Zhu Y, et al. Multiscale Dynamic Graph Representation for Biometric Recognition with Occlusions[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence (**TPAMI**), 2023.

Progress in Deep Facial Feature Extraction

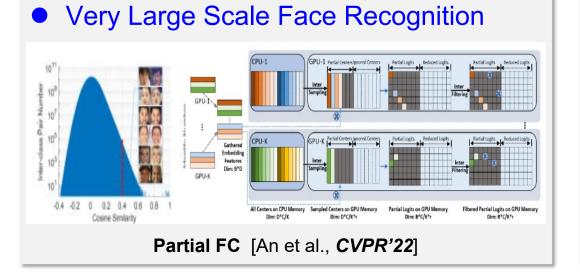
Deep learning has become the mainstream method for facial feature extraction and the main development centres around network architecture and loss function design.



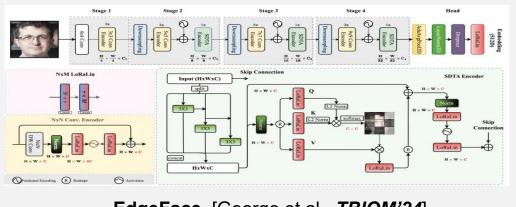
The development of loss functions for facial feature extraction

Mostly from Wang et al. Deep face recognition: A survey[J]. Neurocomputing, 2021, 429: 215-244.

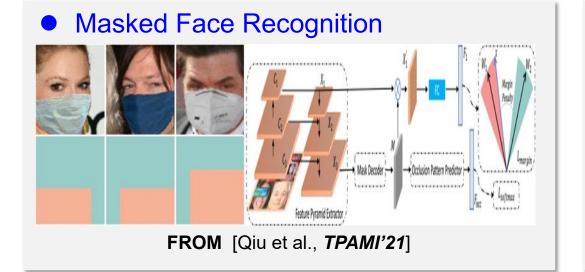
Progress in Deep Facial Feature Extraction

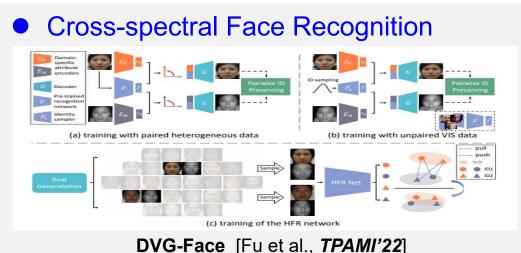


• Extremely Efficient Face Recognition

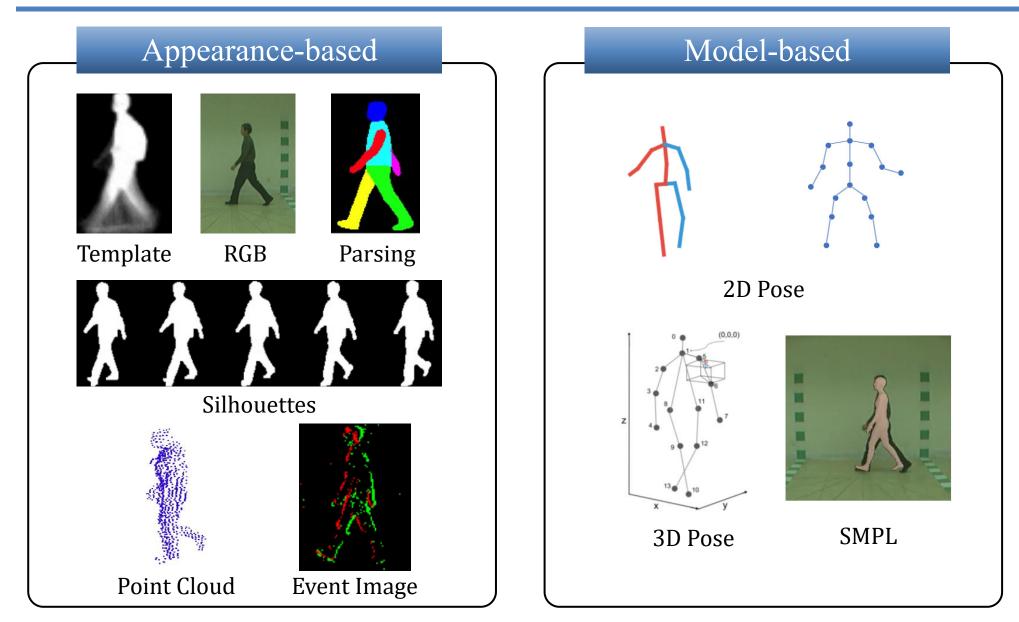


EdgeFace [George et al., TBIOM'24]

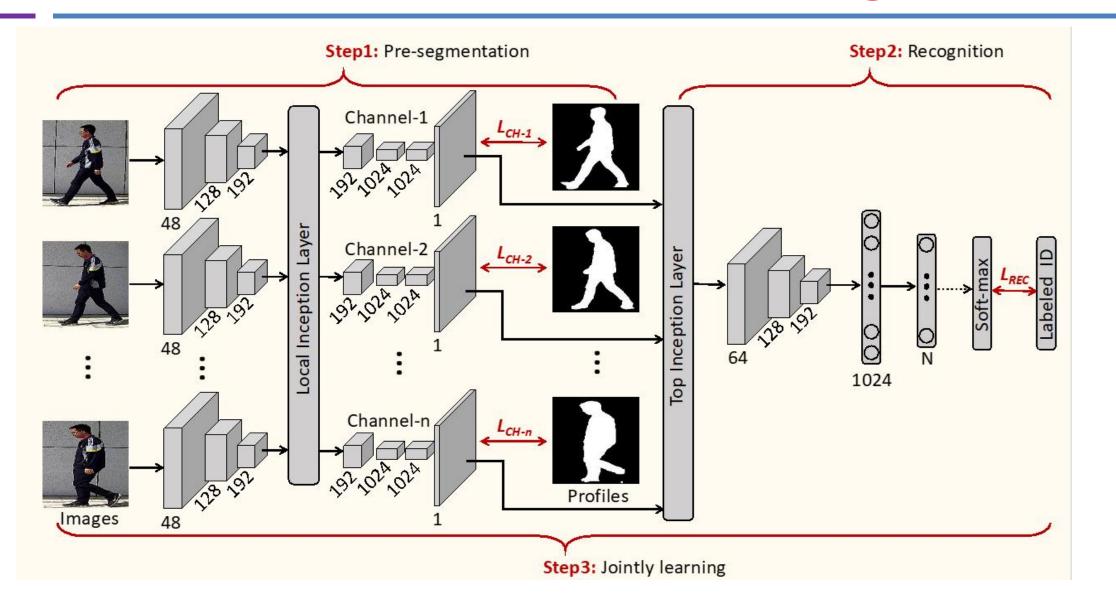




Progress in Gait Recognition



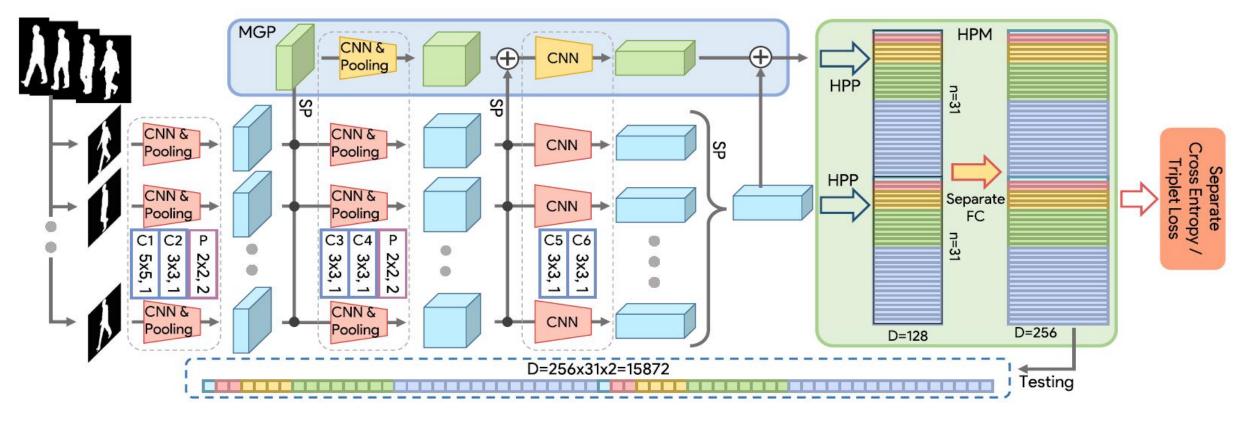
GaitNet: End-to-end Gait Recognition



Song C, Huang Y, Huang Y, et al. GaitNet: An end-to-end network for gait based human identification[J]. Pattern recognition, 2019.

GaitSet: Regarding Gait as a Deep Set

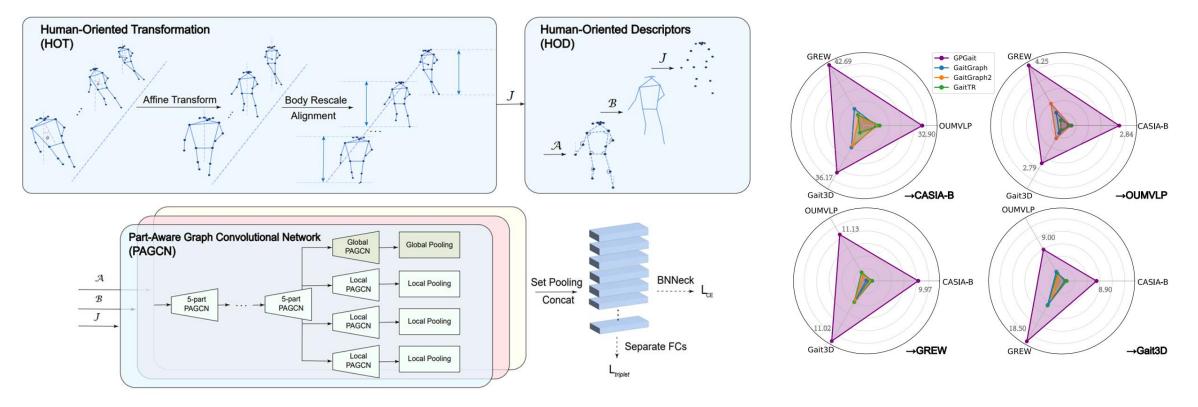
A set of gait frames are integrated by a global-local fused deep network. The advantages are that GaitSet is immune to frame permutations, and can naturally integrate frames from different videos that have been acquired under different scenarios.



Chao H, Wang K, He Y, et al. GaitSet: Cross-view gait recognition through utilizing gait as a deep set[J]. IEEE transactions on pattern analysis and machine intelligence (*TPAMI*), 2021, 44(7): 3467-3478.

GPGait: Generalized Pose-based Gait Recognition

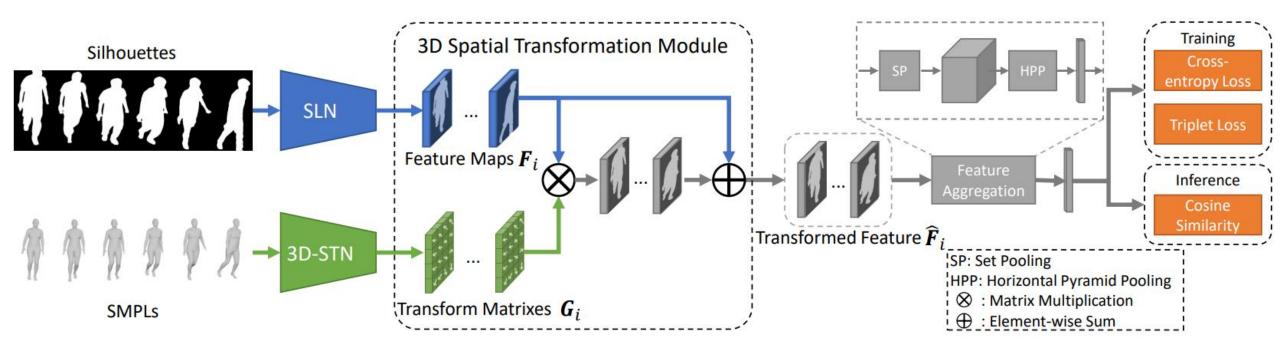
A series of human-oriented operations are proposed to facilitate a uniform pose input that overcomes problems caused by various environmental covariances, and a part-aware GCN is proposed to achieve efficient graph partition and local-global feature relation extraction.



Fu Y, Meng S, Hou S, et al. GPGait: Generalized pose-based gait recognition[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision (*CVPR*). 2023: 19595-19604.

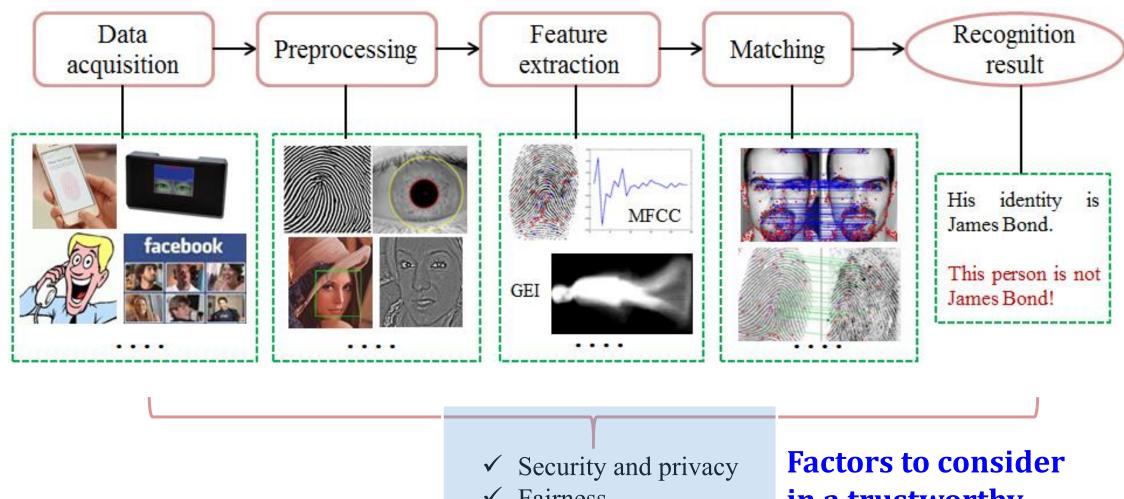
SMPLGait: Leverage SMPL Model

The 3D Skinned Multi-Person Linear (SMPL) model of the human body is explored for gait recognition. 3D gait representations are learnt by combining appearance features from silhouettes and knowledge learnt from 3D viewpoints and shapes of SMPL model.



Zheng J, Liu X, Liu W, et al. Gait recognition in the wild with dense 3d representations and a benchmark[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (*CVPR*). 2022: 20228-20237.

Recent Progress



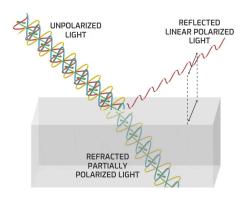
- ✓ Fairness
- ✓ Explainability

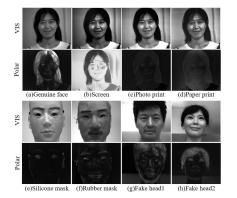
in a trustworthy biometric system

Polarized Image Translation for Face Anti-spoofing

Polarized Image Translation from Nonpolarized Cameras for Multimodal Face Anti-spoofing

The polarization characteristics of reflected light are closely related to the target's material, texture, and roughness.

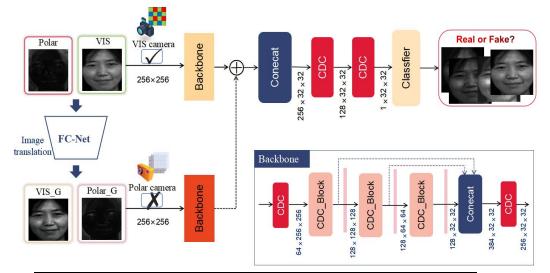




Polarized Face Dataset (CASIA-Polar)

- > Polarized Face
- 121 subjects, 22,174 images, 3 types of images
- RGB Face 2,104 images
- Five Categories of spoofing photo/paper print, replay, 3D mask, dummy head
- > Multi-Illumination

VIS, polarized VIS, NIR, and polarized NIR

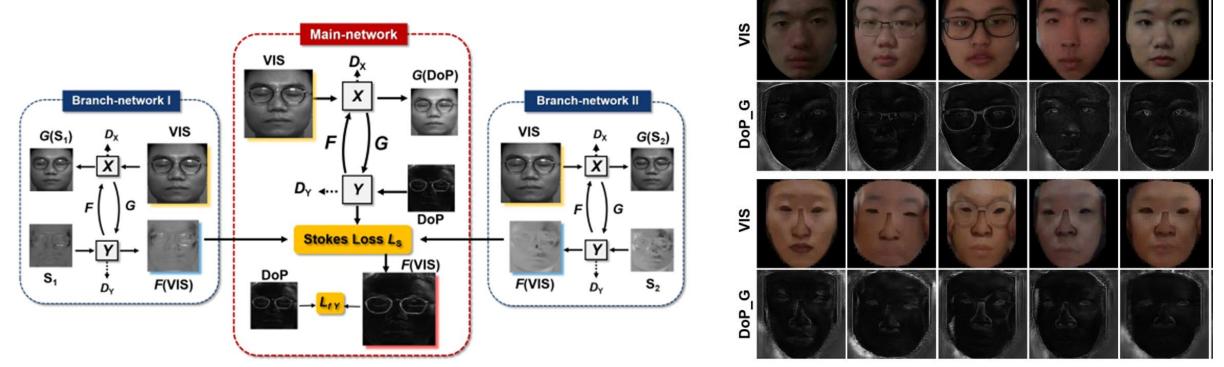




Tian Y, Huang Y, Zhang K, et al. Polarized Image Translation from Nonpolarized Cameras for Multimodal Face Anti-spoofing[J]. IEEE Transactions on Information Forensics and Security (*TIFS*), 2023.

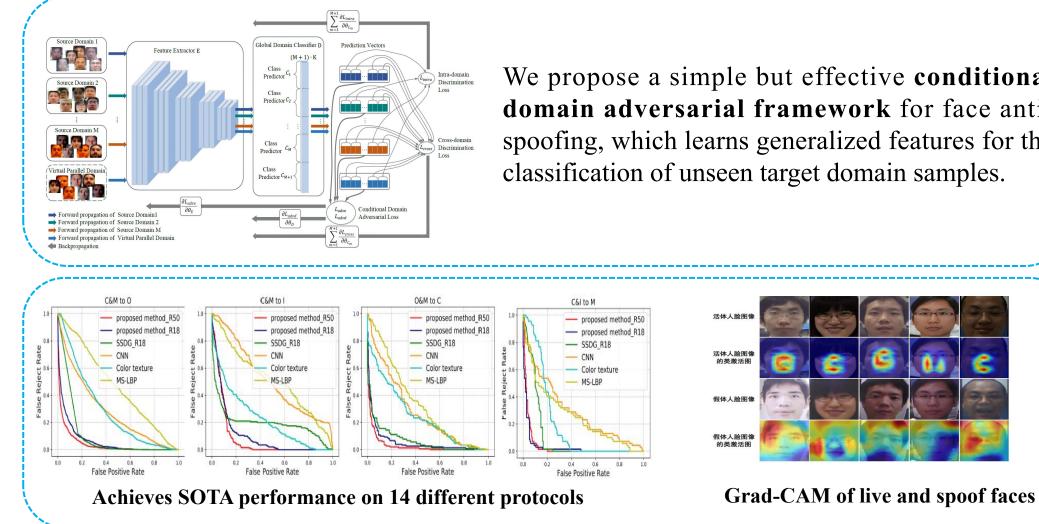
Polarized Image Translation for Face Anti-spoofing

We further translate VIS images into degree of polarization (DoP) images and Stokes polarization parameters, and employ frequency domain loss and the Stokes loss conforming to objective physical laws.



Yu Tian, Kunbo Zhang, Yalin Huang, Leyuan Wang, Yue Liu, Zhenan Sun.Cross-Optical Property Image Translation for Face Anti-Spoofing: From Visible to Polarization. IEEE Transactions on Information Forensics and Security (*TIFS*), 2024.

Improvement of Robustness of Face Anti-spoofing via Domain Generalization

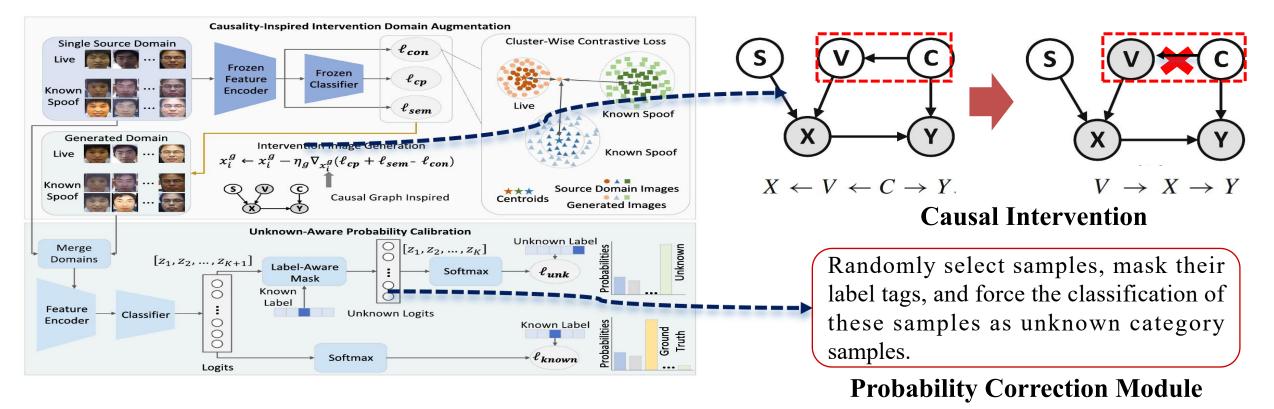


We propose a simple but effective **conditional** domain adversarial framework for face antispoofing, which learns generalized features for the classification of unseen target domain samples.

Jiang F, Li Q, Liu P, et al. Adversarial learning domain-invariant conditional features for robust face anti-spoofing[J]. International Journal of Computer Vision (*IJCV*), 2023, 131: 1680-1703.

Causality-based Face Anti-spoofing

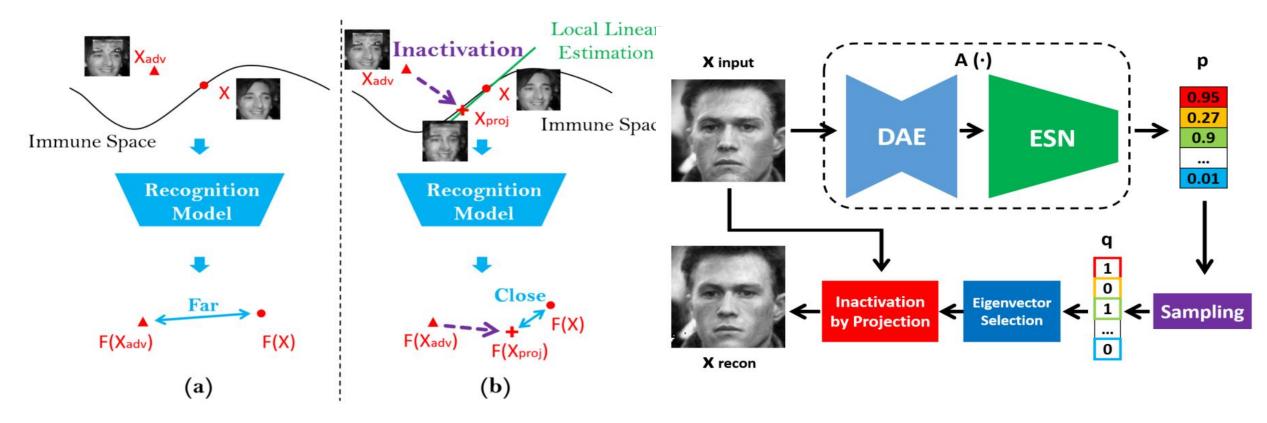
We propose a causal inference-based face anti-spoofing method. This method enhances the diversity of training samples in the source domain through visual intervention while preserving semantic consistency.



Jiang F, Li Q, Sun Z, et al. Open-set single-domain generalization for robust face anti-spoofing[J]. International Journal of Computer Vision (*IJCV*), 2024, 132: 5151-5172.

Perturbation Inactivation based Adversarial Defense

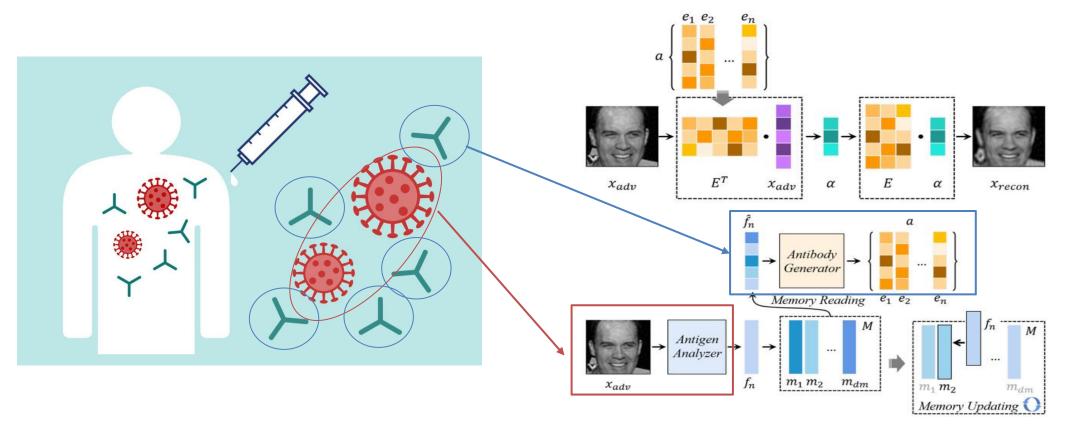
We propose to solve the unknown adversarial noises problem by estimating the immune space and inactivate the adversarial perturbations by restricting them to this subspace.



Ren M, Zhu Y, Wang Y, et al. Perturbation Inactivation Based Adversarial Defense for Face Recognition[J]. IEEE Transactions on Information Forensics and Security (*TIFS*), 2022, 17: 2947-2962.

Artificial Immune System for Adversarial Defense in Face Recognition

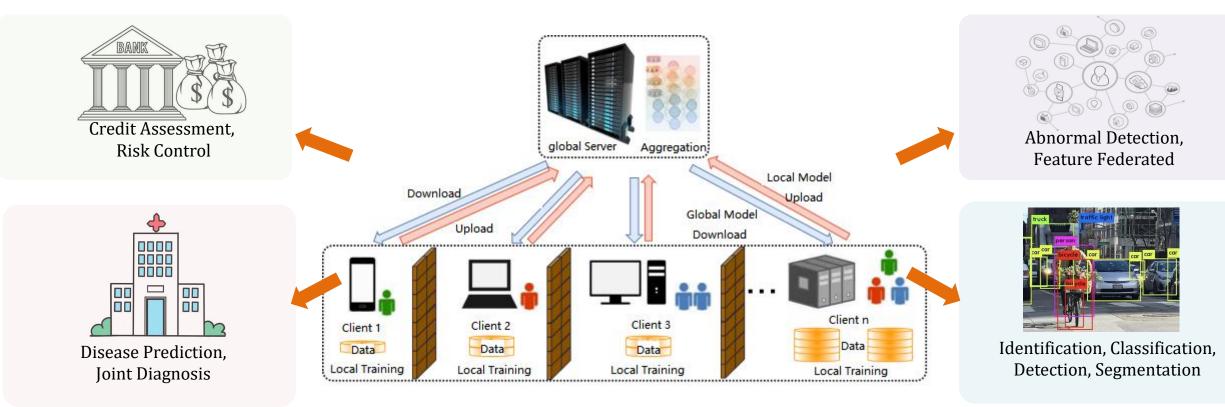
Inspired by biological immune system, an artificial immune system is proposed to provide adversarial defense for face recognition. It incorporates the principles of antibody cloning, mutation, selection, and memory mechanisms to generate a distinct "antibody" for each sample



Min Ren[#], Yunlong Wang[#], Yuhao Zhu, Yongzhen Huang, Zhenan Sun, Qi Li, Tieniu Tan. "Artificial Immune System of Secure Face Recognition Against Adversarial Attacks", International Journal of Computer Vision (*IJCV*), Vol. 132, 2024, pp. 5718-5740.

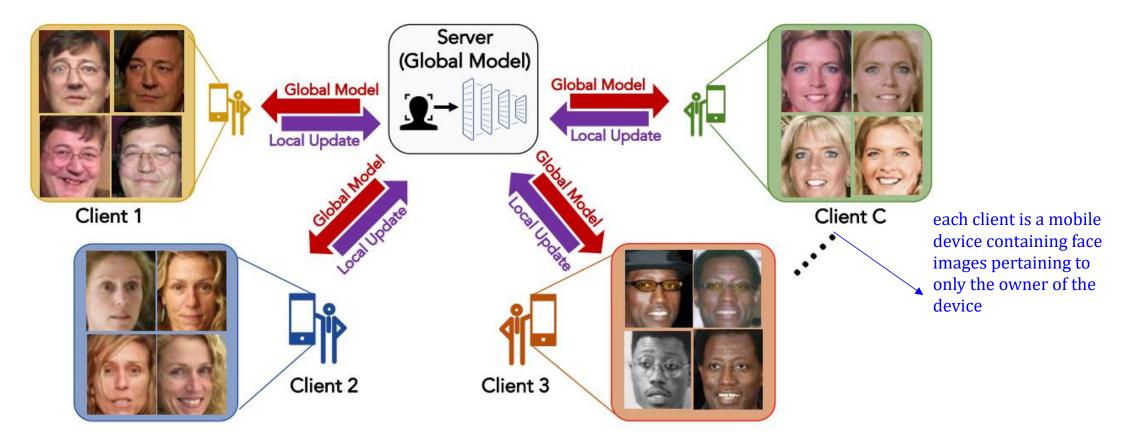
Privacy-preserving Biometrics

Federated learning (FL) framework is suitable for privacy-preserving biometrics, which collaboratively trains biometric recognition models without sharing each client's source biometric data with the server or with other clients.



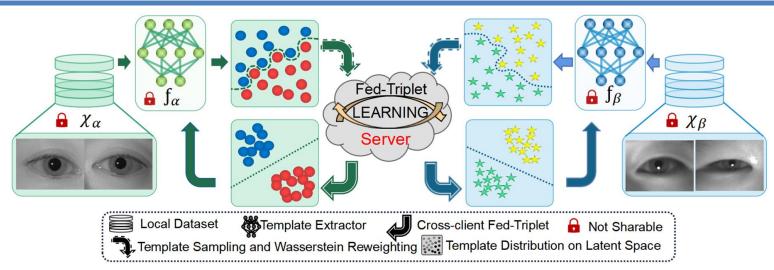
Federated Learning for Face Recognition

A federated learning (FL) framework can be applied for collaborative learning of face recognition models in a privacy-aware manner.



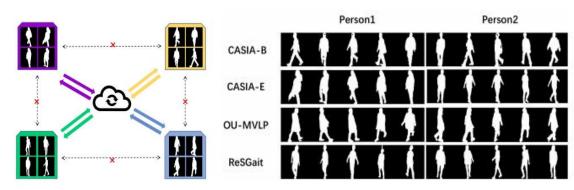
Aggarwal D, Zhou J, Jain A K. Fedface: Collaborative learning of face recognition model[C]//2021 IEEE International Joint Conference on Biometrics (*IJCB*), 2021.

Federated Learning for Other Biometric Modalities

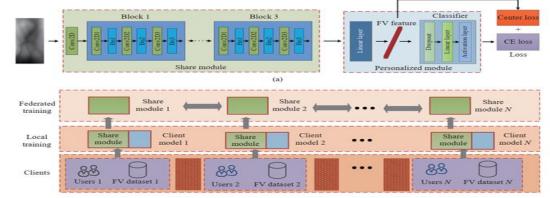


Federated Iris Template Communication

FedIris [Tan et al., CVPRW'22]



Distributed gait data on multiple clients

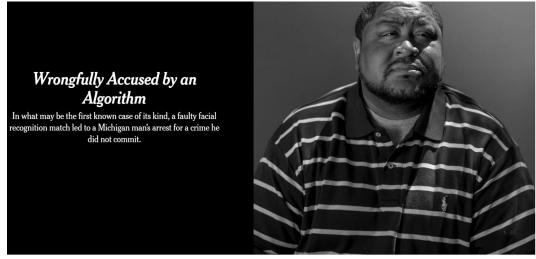


Personalized federated finger vein authentication framework

FedGait [Yu et al., ICPR'22]

FedFV [Kang et al., MIR'23]

Fair Biometrics



[&]quot;This is not me," Robert Julian-Borchak Williams told investigators. "You think all Black men look alike?" Sylvia Jarrus for The New York Times

The majority of the 106 face recognition algorithms have **relatively higher false positive rates on subjects from African and Asian countries** than those of other races

-- NIST report "Face Recognition Vendor Test Part 3: Demographic Effects", https://www.nist.gov/publications/face-recognition-vendor-testpart-3-demographic-effects

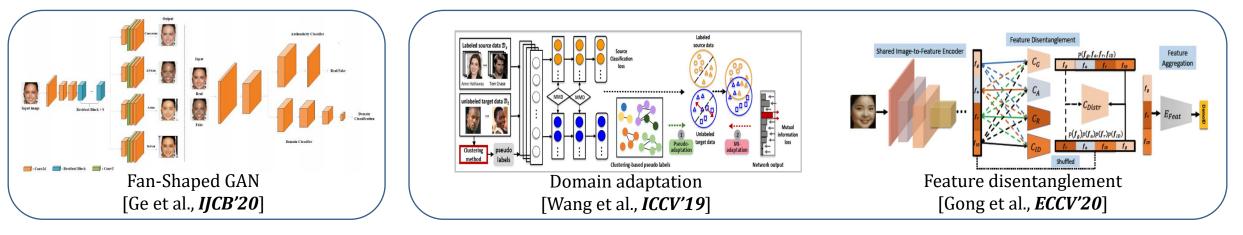
A faulty facial recognition match led to a Michigan man's arrest for a crime he did not commit.

--New York Times, https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html

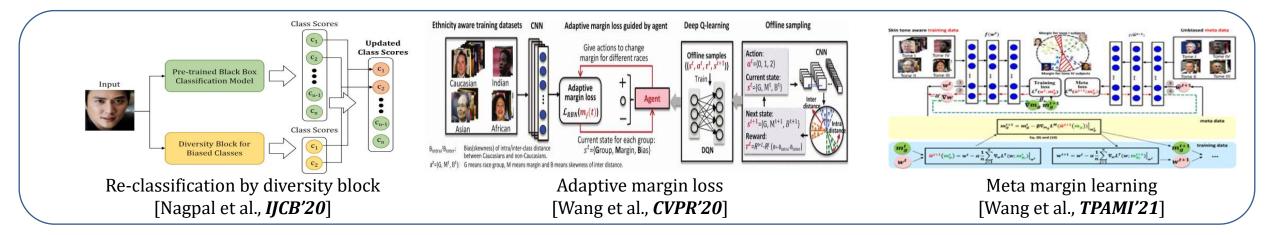
		Algorith	m: imp	erial_0	02 Th	reshok	1.38	1120 0	Dataset	t Application														
				Vomina	FMR	0.000	030 Se	ax: M	log10 l	FMR			unesaw.	-6	-5	-4	-	-3	-2	-1	0			
7_Vietnam =	-6.00	-6.62	-6.00	-4.49	-4.64	-4.64	-5.99	-5.64	-5.74	-6.56	-5.30	-5.65	-5.49	-5.67	-5.40	-6.00	-6.00	-6.00	-3.22	-3.70	-3.67	-3.23	-3.13	-2.83
7_Thailand =	-6.00	-5.65	-6.87	-4.51	-4.60	-4.55	-0.55	-6.00	-5.78	-5.56	-5.32	-5.42	-5.55	-5.42	-5.33	-6.00	-6.00	-5.81	-3.35	-3.66	-3.66	-3.24	-3.14	-3.13
7_Phillippines -	-6.00	-5.64	-6.00	-4.34	-4.46	-4.39	-5.90	-6.00	-5.70	-9.56	-5.45	-5.53	-5.67	-5.43	-4.99	-6.00	-6.00	-5.78	-3.61	-3.95	-3.99	-2.89	-3.24	-3.21
7_Korea =	-6.00	-5.16	-6.00	-5.28	-5.30	-5.77	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-5.60	-6.00	-6.00	-6.00	-3.27	-3.24	-2.97	~4.00	-3.63	-3.68
7_Japan =	-6.00	-5.20	-6.00	-5.01	-5.03	-5.48	-6.00	-5.56	-6.00	-6.91	-5.71	-5.93	-6.00	-6.00	-5.41	-6.00	-6.00	-6.00	-3.44	-3.05	-3.27	-3.94	-3.67	-3.73
7_China =	-8.00	-5.37	-5.96	-4.87	-4.94	-5.12	-6.00	-6.00	-6.00	-6.00	-5.99	-6.00	-6.00	-6.00	-5.46	-6.00	-6.00	-6.00	-2.99	-3.39	-3.22	-3.62	-3.35	-3.20
6_Pakistan -	-6.00	-5.76	-5.66	-4.91	-4.95	-4.81	-6.00	-6.00	-6.00	-6.00	-5.95	-5.23	-5.33	-5.55	-3.90	-4.32	-4.30	-3.79	-5.85	-6.00	-6.00	-5.50	-5.50	-6.80
6_traq =	-6.37	-5.10	-5.14	-4.89	-4.73	~4.94	-6.00	-6.00	-6.00	-6.00	-6.00	-5.30	-6.00	-5.43	-4.79	-4.11	-3.77	-4.38	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00
6_tran -	~5.68	-5.18	-6.22	-6.12	-5.05	-5.17	-6.00	-0.00	-6.00	-6.00	-6.00	-5.84	-5.98	-6.00	-4.04	-3.86	~4.08	-4.25	-6.00	-5.77	-5.79	-6.00	-6.00	-6.00
6_India -	-6.00	-5.68	-5.94	-4.98	-5.15	-4.87				-					3.58	~4.63	-4.70	-3.90	-5.42	-5.68	-5.72	-5.23	-6.33	-5.50
5_Somalia -	-6.00	-5.65	~6.00	-5.44	-5.36	-5.30	-4.49	~4.23	~4.34	-4.19	-4.30	-2.96	-3.57	-2.17	4.90	-6.00	-5.62	-5.40	-6.00	-6.00	-6.00	-5.86	-5.50	-5.56
5_Kenya -	-6.00	-6.00	-6.00	-6.75	-5.91	-6.00	-3.88	-3.91	-3.88	-4.01	-4.12	-4.01	-3.40	-3.48	4.90	-5.85	-6.00	-5.25	-6.00	-6.00	-6.00	-5.87	-6.00	-6.00
5_Ethiopia -	~6.00	-5.95	-6.00	-5.08	-5.03	-5.02	-4.97	-4.74	~4.85	-4.51	-4.59	-2.88	-4.00	-2.91	4.07	-5.79	-5.43	-8.21	-6.00	-6.00	-6.00	-5.52	-5.45	-5.63
4_Jamaica -	-6.00	-6.00	-6.00	-5.64	-5.75	-5.21	-3.94	-4.05	-3.94	-3.91	-3.93	-4.59	-4.19	-4.34	-5.51	-6.00	-5.99	-5.69	-5.94	-5.92	-6.00	-5.22	-5.32	-5.24
4_Halti -	-6.00	-6.00	-6.00	-5.60	-5.99	-5.65	-3.67	-3.70	-3.73	-3.64	-3.91	-4.00	-3.96	-4.28	6.00	-6.00	-6.00	-6.00	-5.81	-6.00	-6.00	-5.44	-0.51	-6.37
3_Nigeria -	-6.00	-6.00	-6.00	-6.00	-6.00	-5.00	-3.37	-3.47	-3.33	-3.69	-3.94	~4.83	-3.86	-4.49	5.98	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-5.87	-5.51	-6.71
3_Liberia -	-6.00	-6.00	-6.00	-5.82	-6.00	-5.00	-3.45	-3.36	-3.49	-3.72	-3.96	~4.84	-3.82	-4.41	6.00	~5.50	-5.74	-6.00	-6.00	-6.00	-6.00	-5.97	-5.67	-5.67
3_Ghana =	-6.00	-6.00	-6.00	-6.00	-6.00	-5.85	-3.21	-3.43	-3.38	-3.67	-3.94	~4.91	-3.90	-4.60	6.00	-6.00	-6.00	-6.00	-6.00	-5.74	-5.81	-5.83	-5.68	-5.86
2_Nicaragua =	-5.84	-5.18	-5.86	-3.61	-3.65	-2.04		1.1.1				-			4.77	-5.18	-4.99	-4.89	-5.02	-5.40	-5.62	-4.37	-4.66	-4.56
2_Mexico =	-5.89	-0.36	-5.50	-3.41	-3.15	-3.64	-6.00	-6.00	-6.00	-6.00	-5.67	-5.12	-6.00	-6.61	-5.06	-4.95	-4.70	-4.94	-4.92	-4.98	-5.39	-4.35	-4.64	-4.59
2 El Salvador -	-5.09	-5.44	-5.44	-3.40	-3.45	-3.61	-6.00	-6.00	-6.00	-6.00	-5.00	-5.05	-6.00	-5.37	-4.08	-5.08	-4.97	-4.88	-4.94	-5.01	-5.34	-4.27	-4.52	-4.50
1_Ukraine -	-4.55	-4.68	-4.44	-5.00	-5.46	-5.78	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-5.32	-6.22	-5.83	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00
1_Russia	-4.64	-4.67	-4.68	-0.47	-5.44	-5.20	-6.00	-0.00	-6.00	-6.00	-6.00	-6.00	-6.00	-5.77	-5.73	~4.99	~4.91	-6.42	-4.96	-5.07	-5.19	-5.61	-6.21	-6.20
1_Poland =	-4.47	~4.71	-4.52	-5.64	-5.84	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00	-5.48	-5.58	-5.74	-6.00	-6.00	-6.00	-6.00	-6.00	-6.00
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Racial Bias Mitigation

Data: transfer the facial images of one race to other faces with generative models (GAN, etc.) **Model:** mimic the model paradigm in transfer learning or disentanglement learning to bridge the domain gap and transfer knowledge between races



Result generation: impose constraints (biased class scores, margin loss, etc.) on the model's output to perform fairly across different races



Racial Bias Mitigation through Database Balancing



CASIA-Face-Africa is the first large-scale African face image database. The proposed database along with its annotations, evaluation protocols and preliminary results forms **a good benchmark to study face racial bias problem for African subjects**.

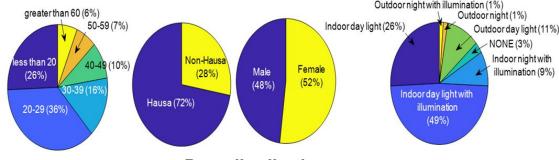


Capture setup



Facial expressions

1183 African subjects, 38546 face images





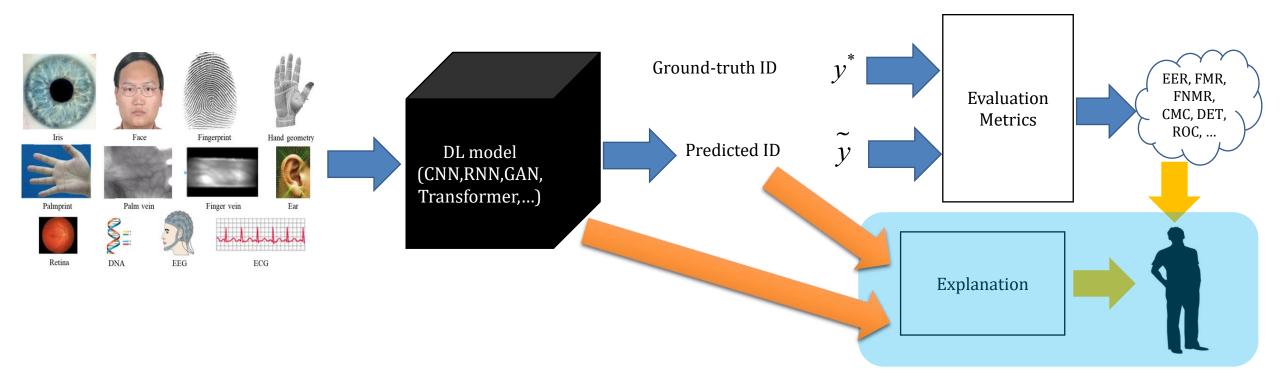


Lighting conditions

Muhammad J, Wang Y, Wang C, et al. CASIA-Face-Africa: A large-scale African face image database[J]. IEEE Transactions on Information Forensics and Security (*TIFS*), 2021, 16: 3634-3646.

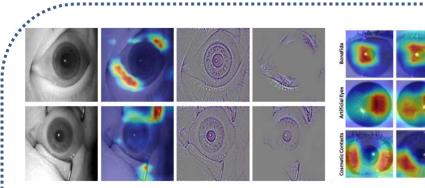
Explainability

Due to the **lack of transparency and explainability of DL models**, it is difficult to understand the reasons that lead to an ID prediction, which reduces trust from users and hinders the ability to verify their decisions and behavior.

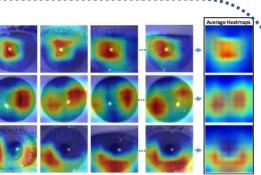


Progress in Explainable Biometrics

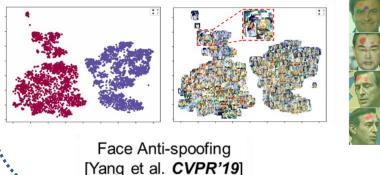
Visualizations

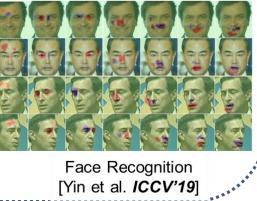


Cadaver Iris PAD [Trokielewicz et al. *BTAS'2018*]



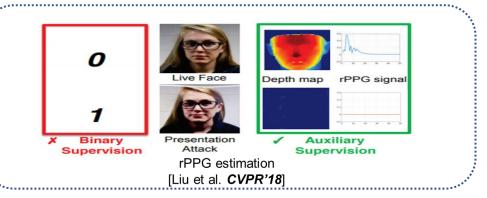
D-NetPAD [Sharma and Ross, *IJCB'20*]





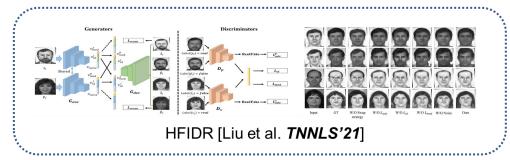
t-SNE: make a visualization of ID predictions in a smaller latent space **Grad-CAM**: generate a heatmap to spatially highlight the most relevant areas for ID predictions

Auxiliary Supervision



Attaining explainable decisions through auxiliary supervision, e.g., rPPG estimation in face anti-spoofing

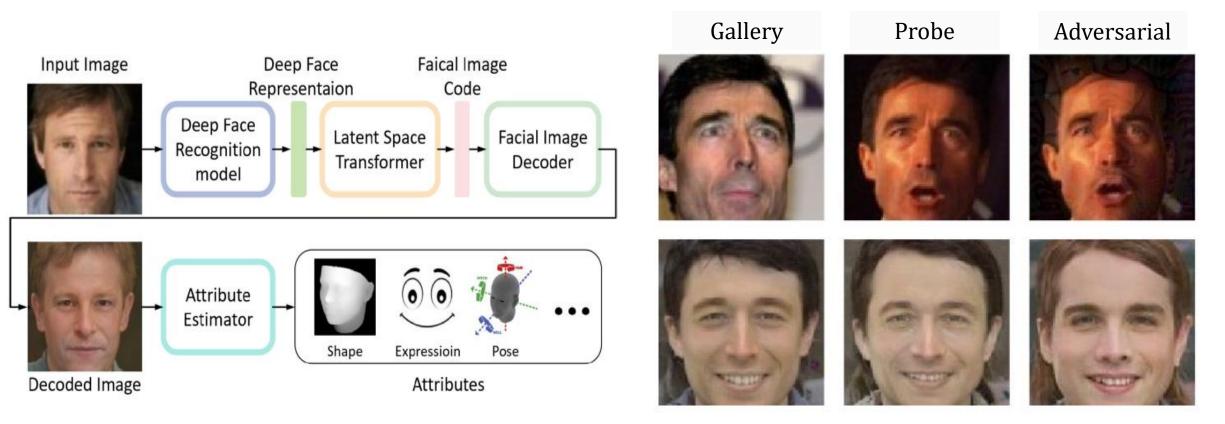
Interpretable Feature Disentanglement



Disentangling the biometric features into semantic components for interpretable disentangled representation

Understanding Deep Face Representation via Attribute Recovery

By utilizing attributes as an interpretable interface, we are able to acquire a deeper understanding of how the recognition model conceptualizes the notion of "identity" and understand the reasons behind the error decisions made by the deep models.

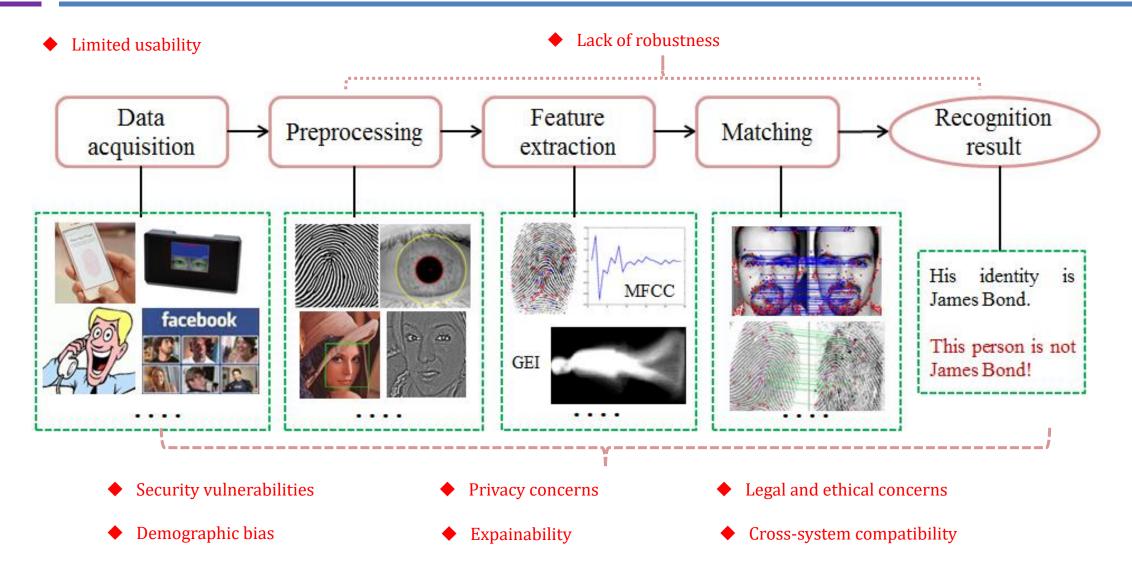


Min Ren, Yuhao Zhu, Yunlong Wang, Yongzhen Huang, Zhenan Sun. "Understanding Deep Face Representation via Attribute Recovery," IEEE Transactions on Information Forensics and Security (*TIFS*), vol. 19, pp. 6949-6961, 2024.

Outline

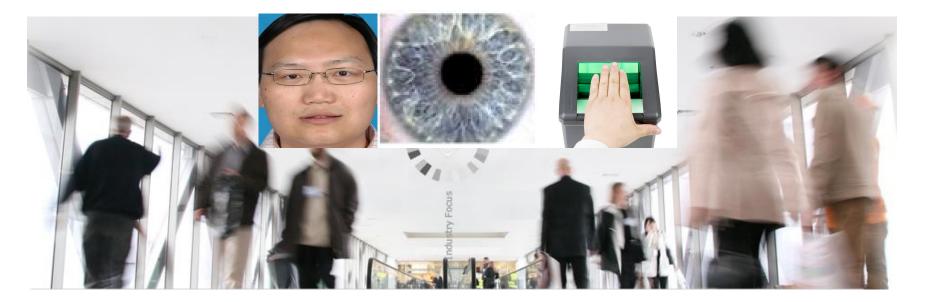
- Preamble
- Recent Progress
- Remaining Challenges
- Future Directions and Prospects
- Conclusions

Remaining Challenges



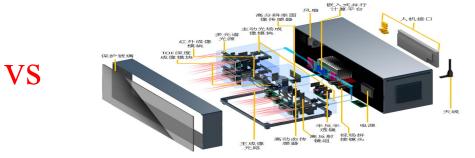
Remaining Challenges

• High level of requirements on user cooperation



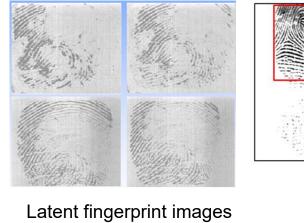


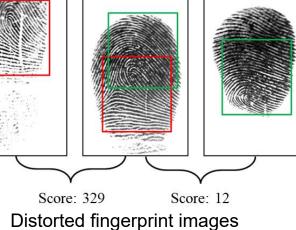
Varying real-world scenarios (user, occlusions, etc.)



Fixed optics settings of biometric sensors

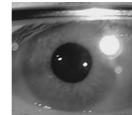
• Deteriorated performance on degraded or non-ideal biometric data







Eyelid obscuration

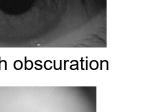


Specular Reflection



Eyelash obscuration







Motion blur



Iris Deformation

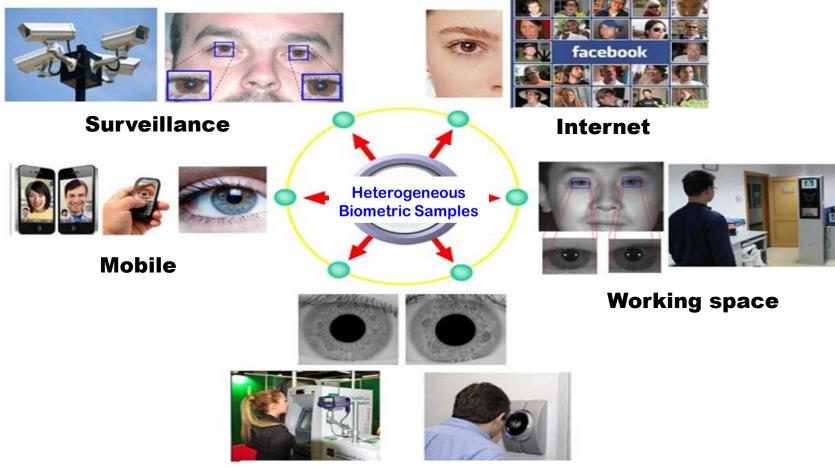


Face images in surveillance Masked Face Images

PIE (Pose, Illumination, Expression)

Blurred, Low-resolution, Side-view gait sequences

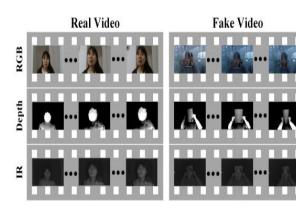
• Poor generalization ability on heterogenous biometric samples



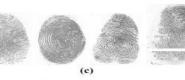
Public spots

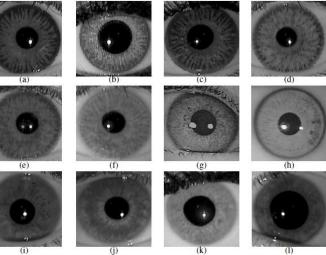
VS

• Security vulnerabilities to unpredictable attacks

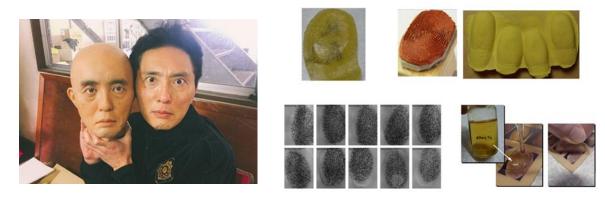








Limited training data



Well-made eye model
Synthetic iris

Well-made eye model
Synthetic iris

Well-made eye model
Contact lens

Well-made eye model
Contact

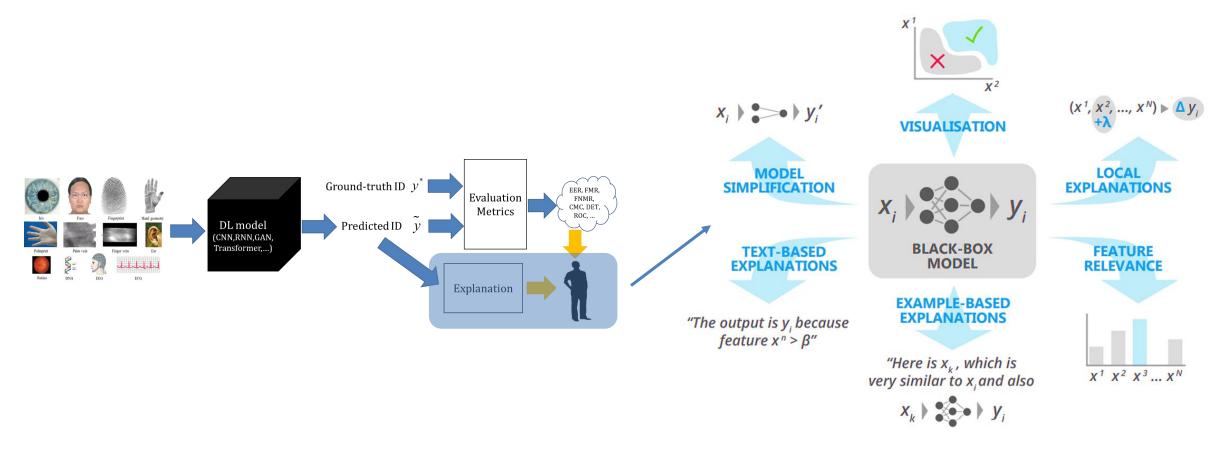
Unpredictable spoof attacks

• Security vulnerabilities to unpredictable attacks - AIGC



Finance worker pays out \$25 million after video call with "deepfake CFO"

• Very limited explainability



Neto P C, Gonçalves T, Pinto J R, et al. Explainable biometrics in the age of deep learning[J]. arXiv preprint arXiv:2208.09500, 2022.

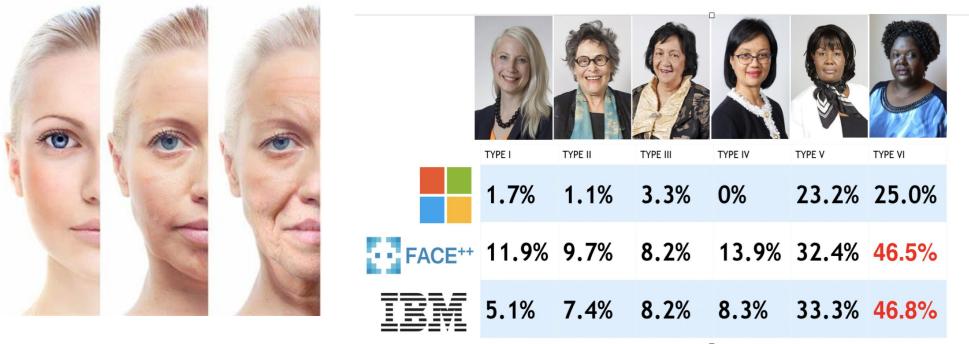
• Privacy concerns



"Iris Photography" threatens customers' biometric data privacy

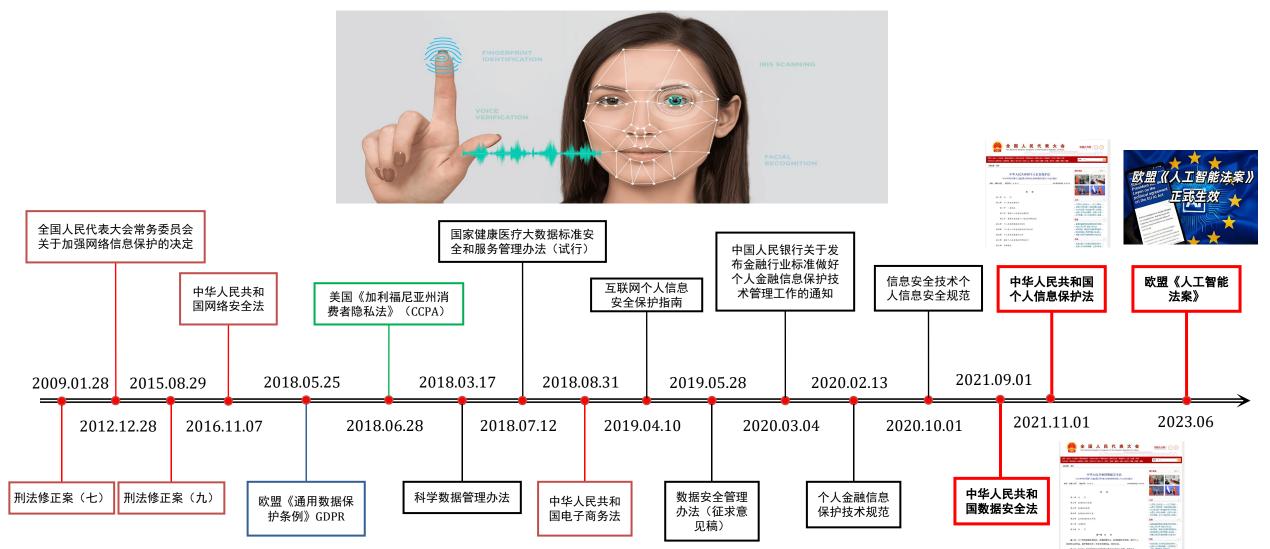
• Demographic bias

Error Rate(1-PPV) By Female x Skin Type



Not only racial bias, but also bias in other demographic attributes such as age, gender, hair color, etc. (*Gender shades projects*, http://gendershades.org/)

• Legislation and standards lag behind technology innovation



Outline

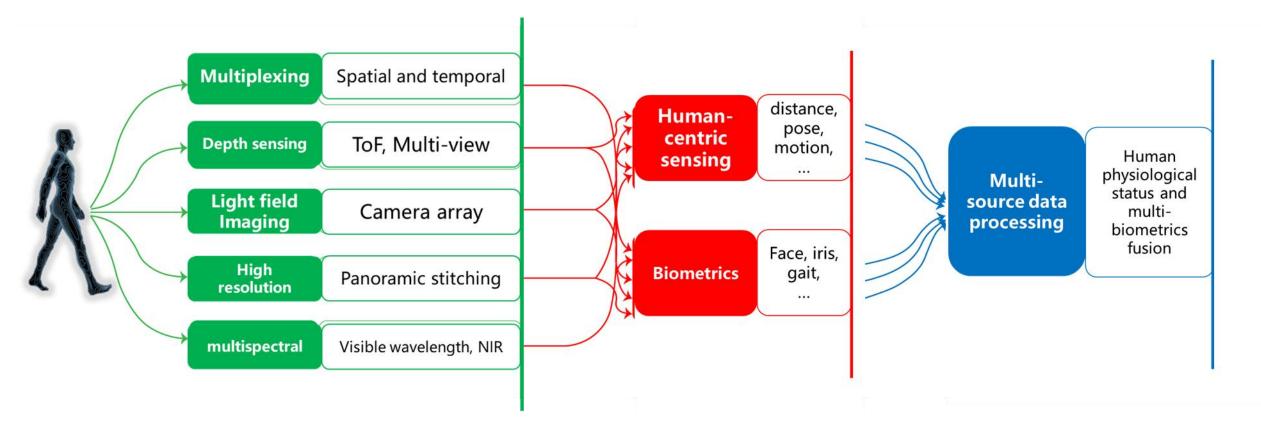
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• Human-centric biometrics

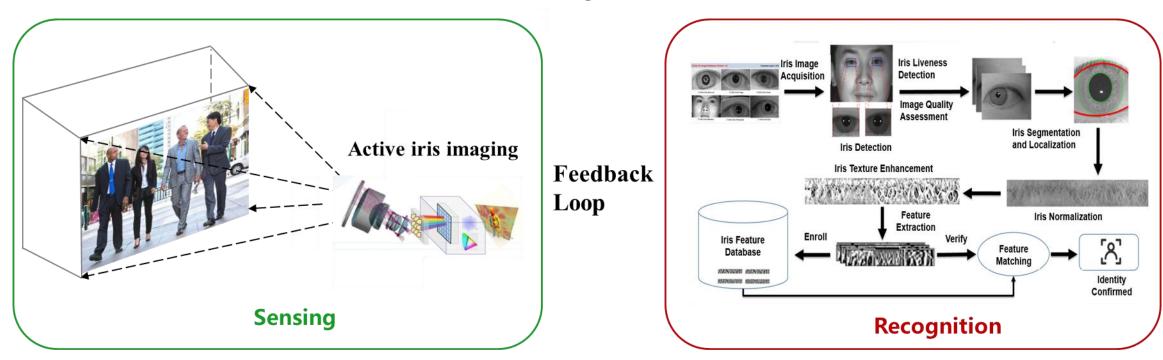


- Prioritizing user experience in the design of biometric systems is essential for user acceptance, ease of use, efficiency, etc.
- Biometric sensors and algorithms should be codesigned for better adaptation to user situations
- Biometric data should be captured and recognized successfully under various conditions and scenarios while accommodating the needs and preferences of the user

• Multi-modal biometrics and adaptive spatial-temporal fusion



• Co-design and coordination of biometric sensing and recognition



Streaming iris data

Imaging control signal (focal lens, aperture, exposure...)

Hardware-software co-design

Acquisition and processing coordination

• Lightweight biometrics



Smartwatch with iris recognition

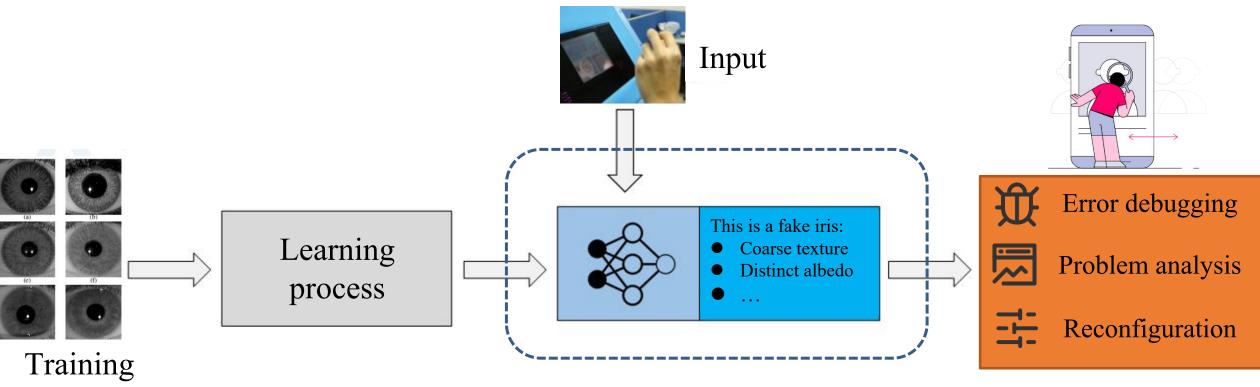


Iris sensor on an embedded device (from Irisking)



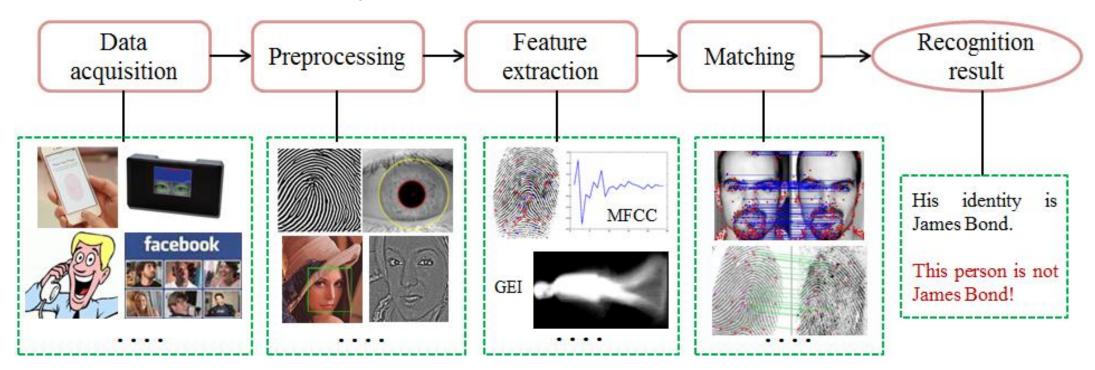
All-in-one gait recognition device (from Watrix.ai)

• Explainable biometrics



data

• Secure and trustworthy biometrics



- Biometric data security (template security)
- Liveness detection (anti-spoofing)

•

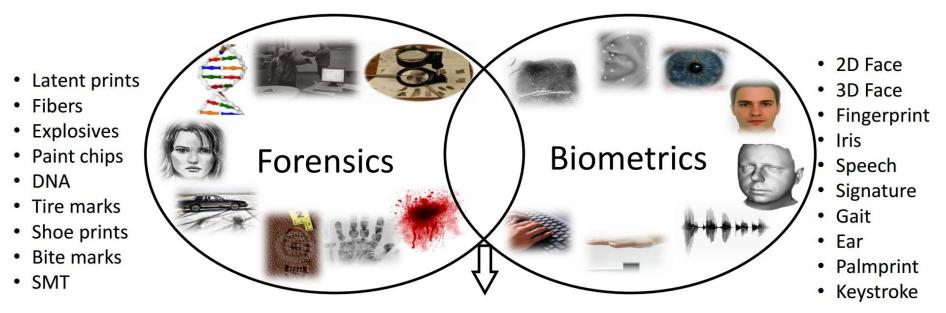
- Secure and trustworthy biometrics
 - Growing importance of AIGC detection
 - AIGC detection based on LLM



@From Internet

• Biometrics for forensic applications

Forensics & Biometrics: Shared Goals



Forensics: Identify suspects from crime scene evidence

Biometrics: Automated person recognition from *body traits*

• Biometrics in Internet of Everything (IoE) applications





Outline

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Conclusions

- Significant progress has been made in biometrics. Innovations in sensor design and GAI algorithms have collectively contributed to improved usability, reliability and security.
- Many challenges and concerns remain to be resolved such as privacy issues, security vulnerabilities, robustness, fairness, explainability, etc.
- Future efforts should focus on human-centric biometrics, trustworthy biometrics, multimodal biometrics, lightweight biometrics, fair and just biometrics, etc.
- Good balance between the benefits of biometrics and the protection of individuals' rights and ethics is crucial to the sustainable and widespread deployment of biometrics.







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Thanks!

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