IAPR/IEEE WINTER SCHOOL ON BIOMETRICS 2025*

Generative AI & Foundation Models for Biometrics

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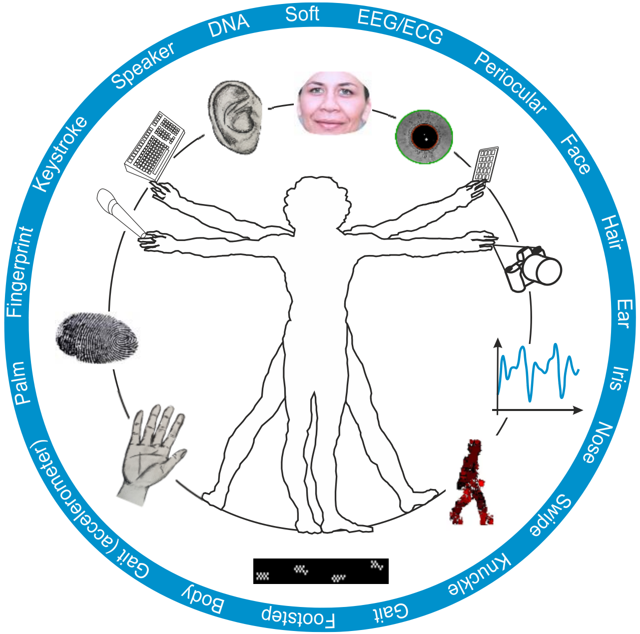
Introduction to Biometrics and Gait Biometrics



Mark Nixon

University of Southampton UK

Editor in Chief, IEEE Transactions on Biometrics, Behaviour, and Identity Science

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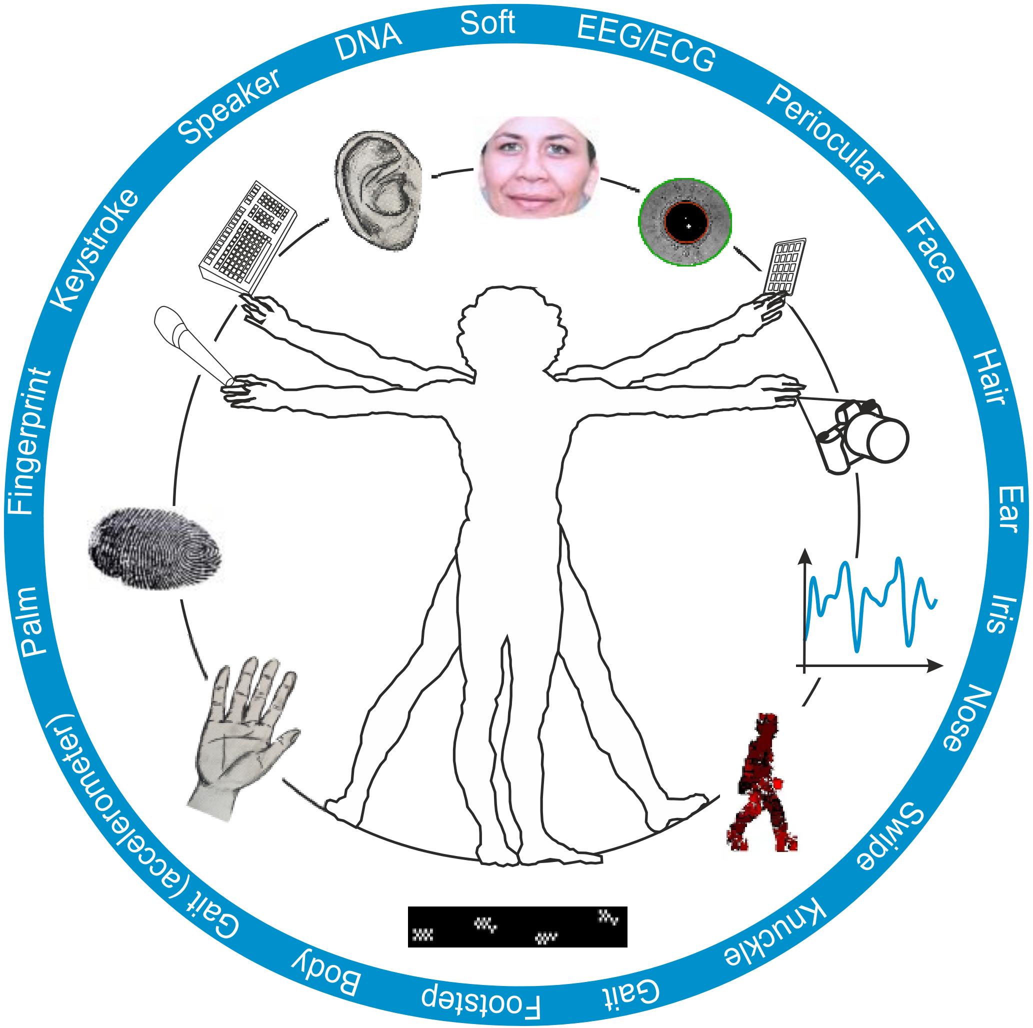

Objectives of introduction

- Cover all biometrics!
- Clarify terminology
- Define scope
- Mention IEEE TBIOM

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Assumptions

- We are unique (!!)
- Identification is central to our lifestyle
- We want it to be fast and convenient
- We want it to be secure
- We want/need to use it everywhere

Hair
Ear
Eyebrow
Ear
Iris
Periocular
Sclera
Nose
Face
Knuckle
Finger/ vein
Fingerprint
Hand
Body
Behaviour
Gait
Odour
Clothing
Soft
Footprint

Biometrics is always in the news

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Global Live Events Industry Focuses on Biometrics in 2025

BY PYMNTS | JANUARY 2, 2025

Federal joint agency report on law enforcement use of biometrics released

Room for improvement set ou...

Jan 2, 2025, 7:25 ...

CATE...

Guidance

Biometric residence permits: general information for applicants, employers and sponsors

Updated 31 December 2024

Contents

Guidance notes

Design of the biometric residence permit

Guida...

Biometric r... information...

Apple looks to compete with Google and Amazon with biometric-enabled smart home

...-listed Taiwanese company, and a ...oking to expand into the smart home ...etric-enabled products.

Quest to Revolutionize Guest Journey Drives $72 Billion Revenue for Biometric Digital Identity in Travel and Hospitality

NEWS PROVIDED BY
The Prism Project
Jan 01, 2025, 15:40 ET

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Let’s find a single person in Southampton

Characteristic – chance	Remaining population	
	300000	pop^n Southampton
>> 21 (!!) – 1/5	60000	
Male – 1/2	30000	
White (?) – 2/3	20000	
Northerner – 1/40	500	
(was) 6’ – 1/10	50	
Slim – 1/5	10	
Non-manicured hair – 1/10	1	

Let's visualise it: 7 measurements take us to a single point

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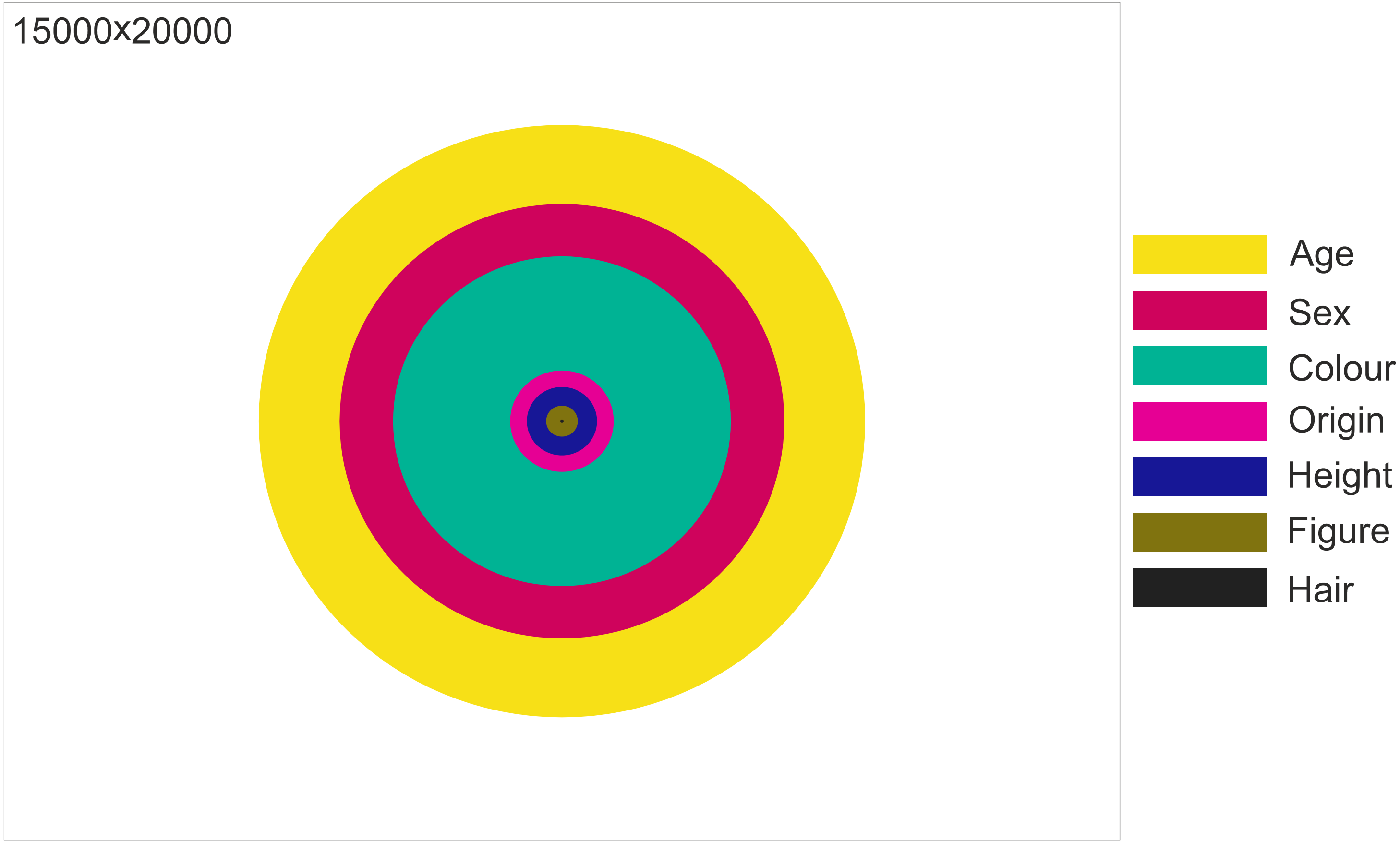
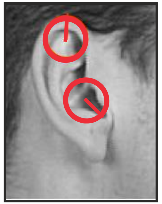


What do we do?

Image



Model-based approaches: e.g. points and features

Basis: Hand crafted and deep learning approaches

Statistical approaches: e.g. images and data

Verification and identification

Early Face Recognition (Taylor, '67)

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"The machine consists basically of a 10 x 10 input matrix of 100 photomultipliers, each connected through automatically adapting weighting units to ten output-indicating units"

"The weights, proportional to the angle through which potentiometers are turned by small driving motors,"

After 250 presentations, 100% recognition was achieved.

Fig. 1 Faces employed in the test

ELECTRONICS LETTERS September 1967 Vol. 3 No. 9

How do we do it?

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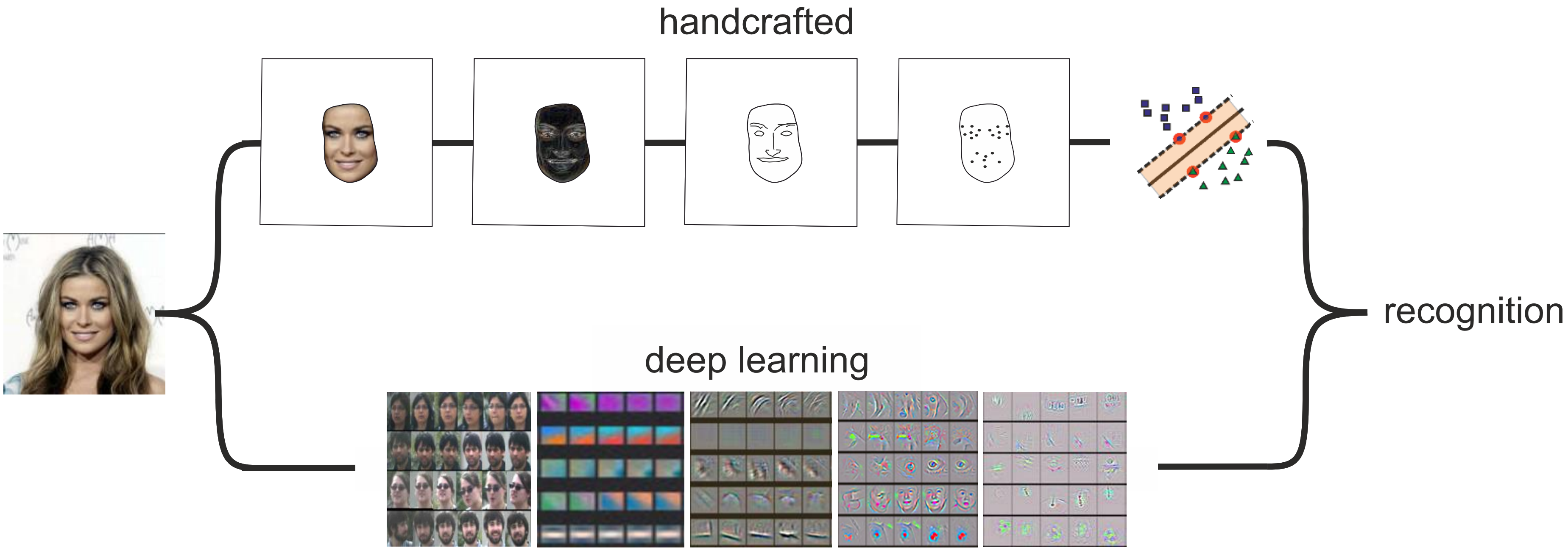
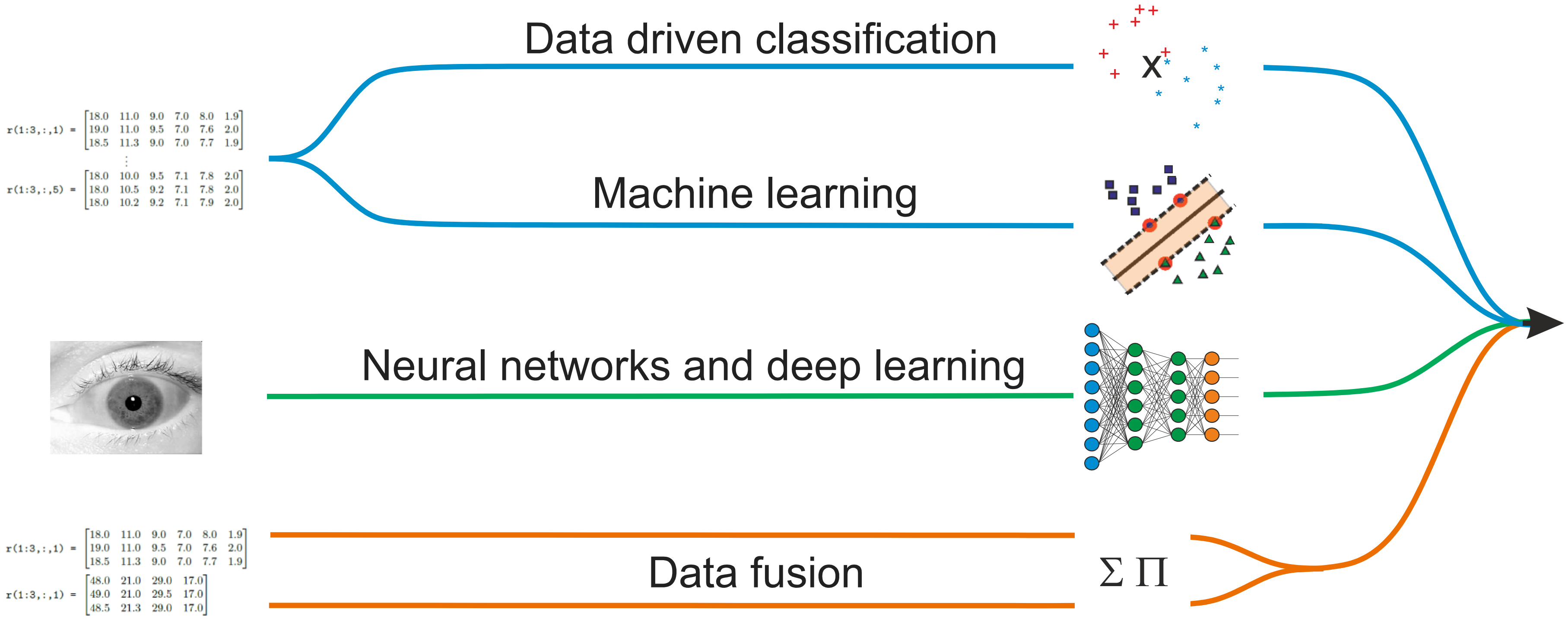


Learning approaches



History

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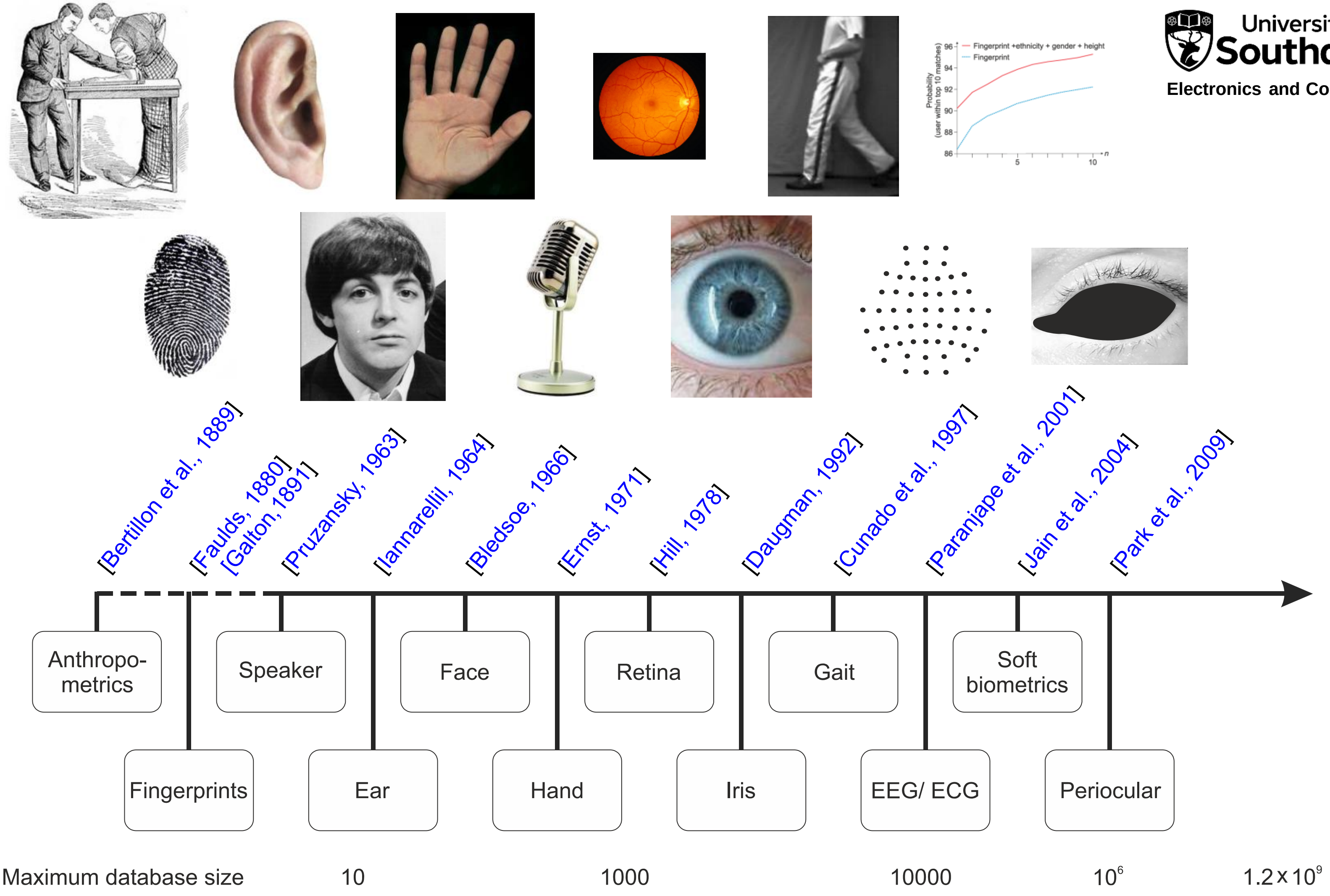

Influence of deep learning on face publications

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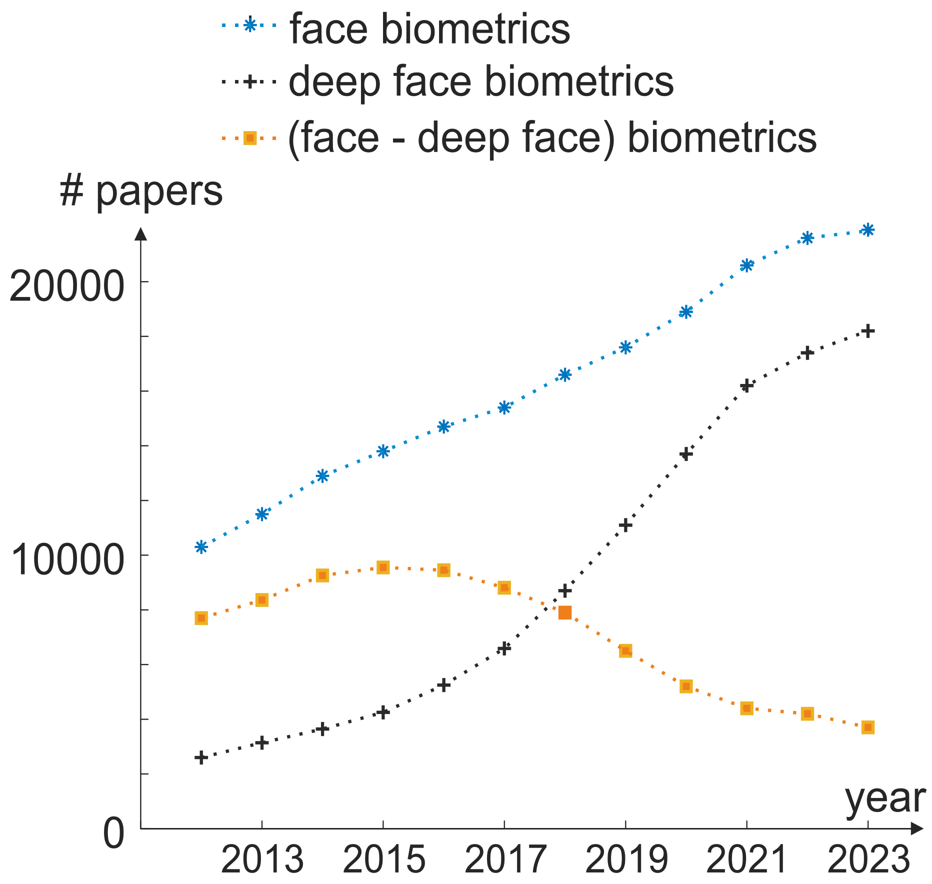

History: Bertillonage

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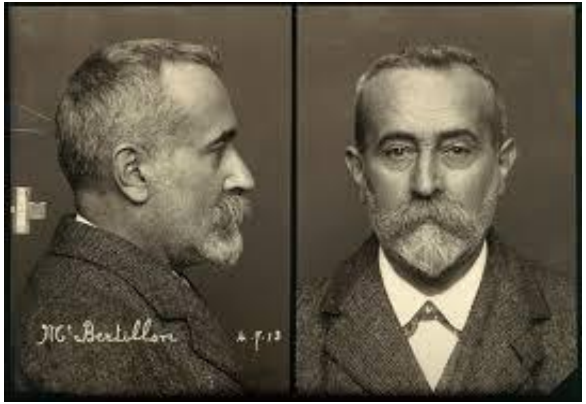

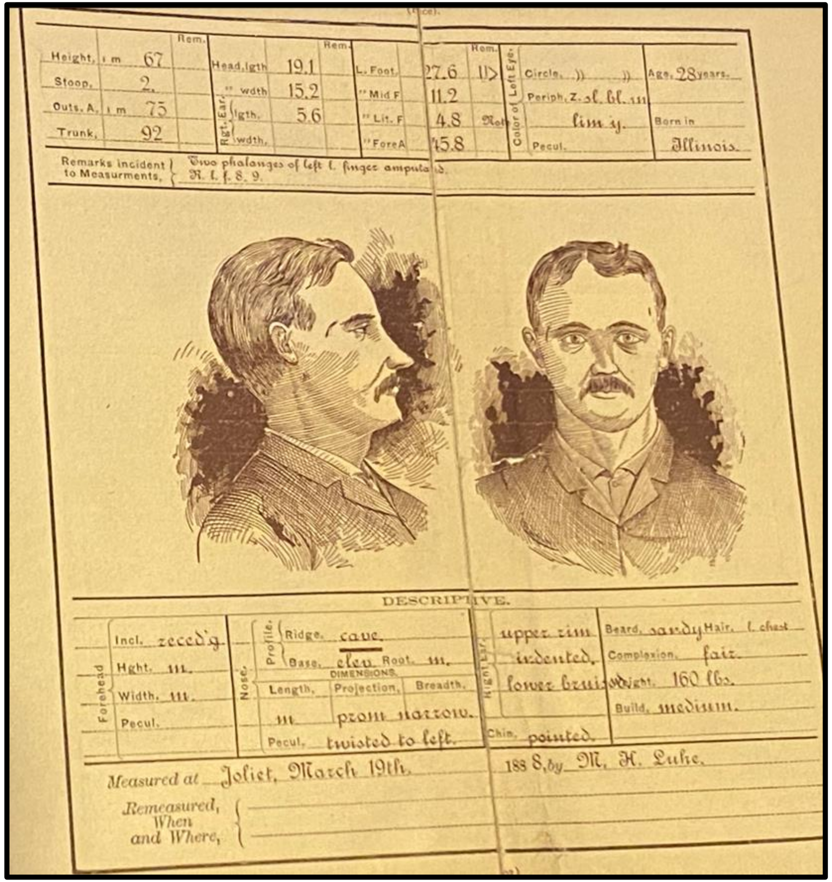

A. Bertillon, *Identification of Criminals* 1889

History: Mark!

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Eye spacing measurement for facial recognition

Fig. 3 Original image of face

Fig. 4 Gradient image of face showing gradient strength and direction

Fig. 5 Image of subject 3 showing detection of irises

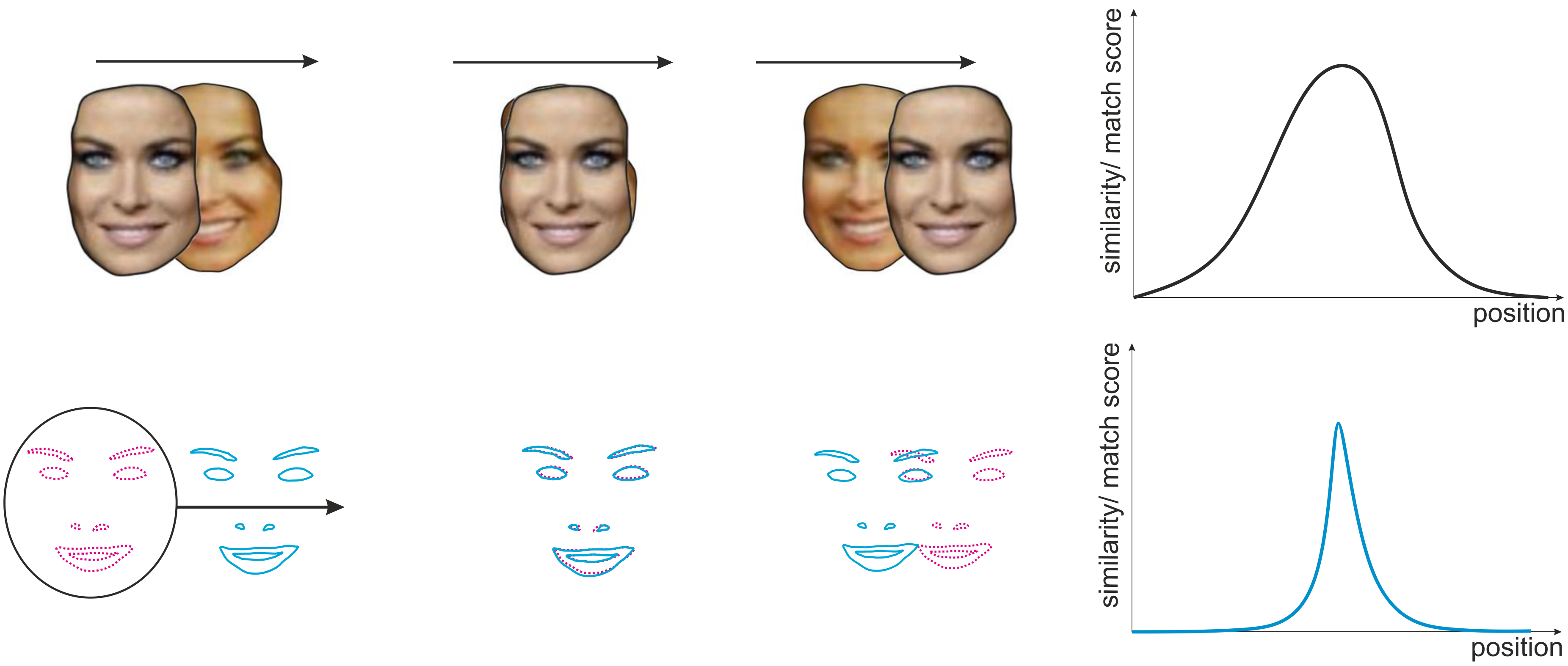
Fig. 6 Image of subject 6 showing detection of perimeter of sclera

Fig. 7 Image of subject 1 showing detection of region below eyebrows

SPIE Vol. 575 Applications of Digital Image Processing VIII (1985) / 285

M Nixon, *Proc. SPIE* 1985

Matching basis - implementation



Matching basis – result

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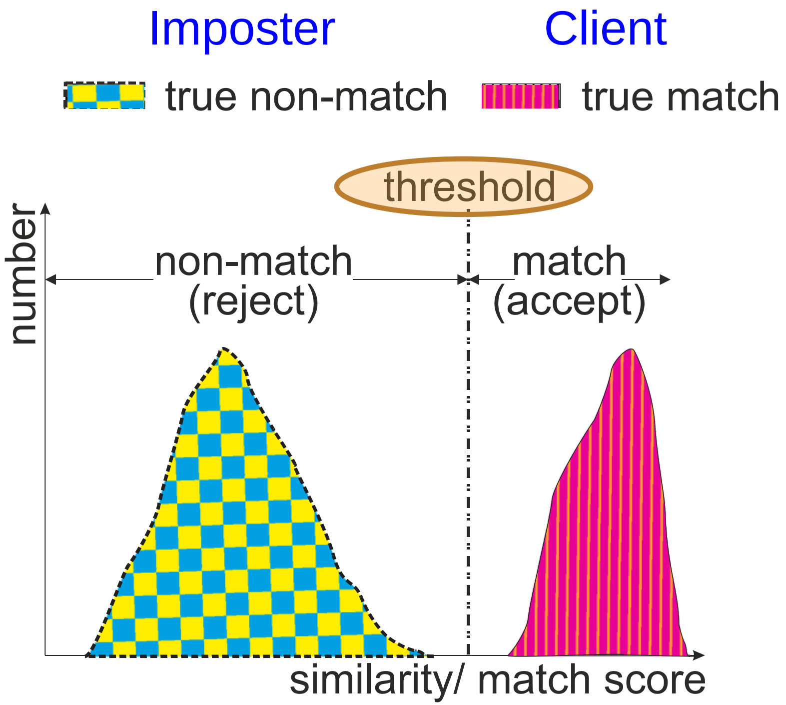

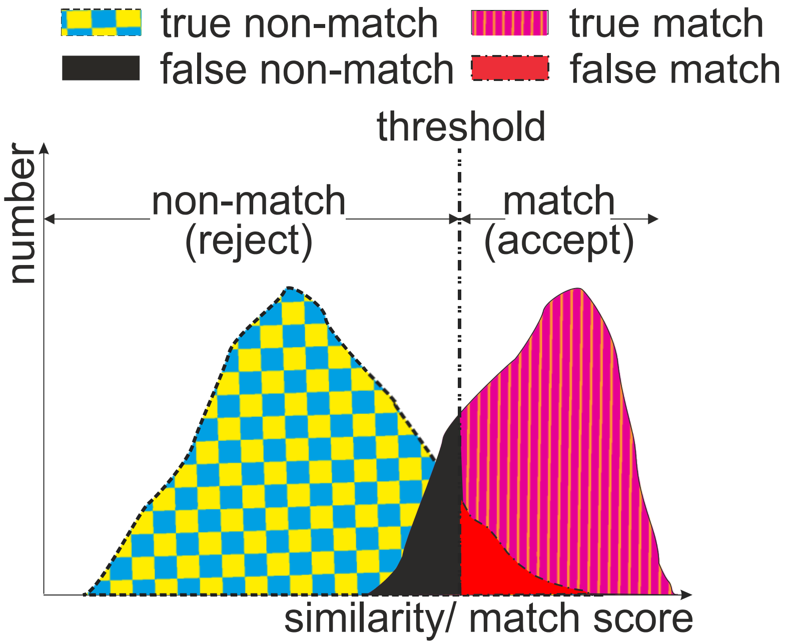

News: National Geographic 2002

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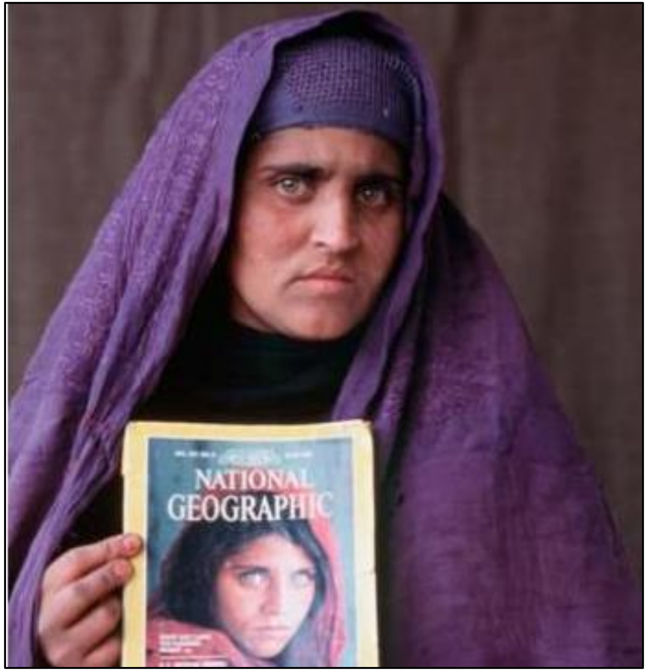
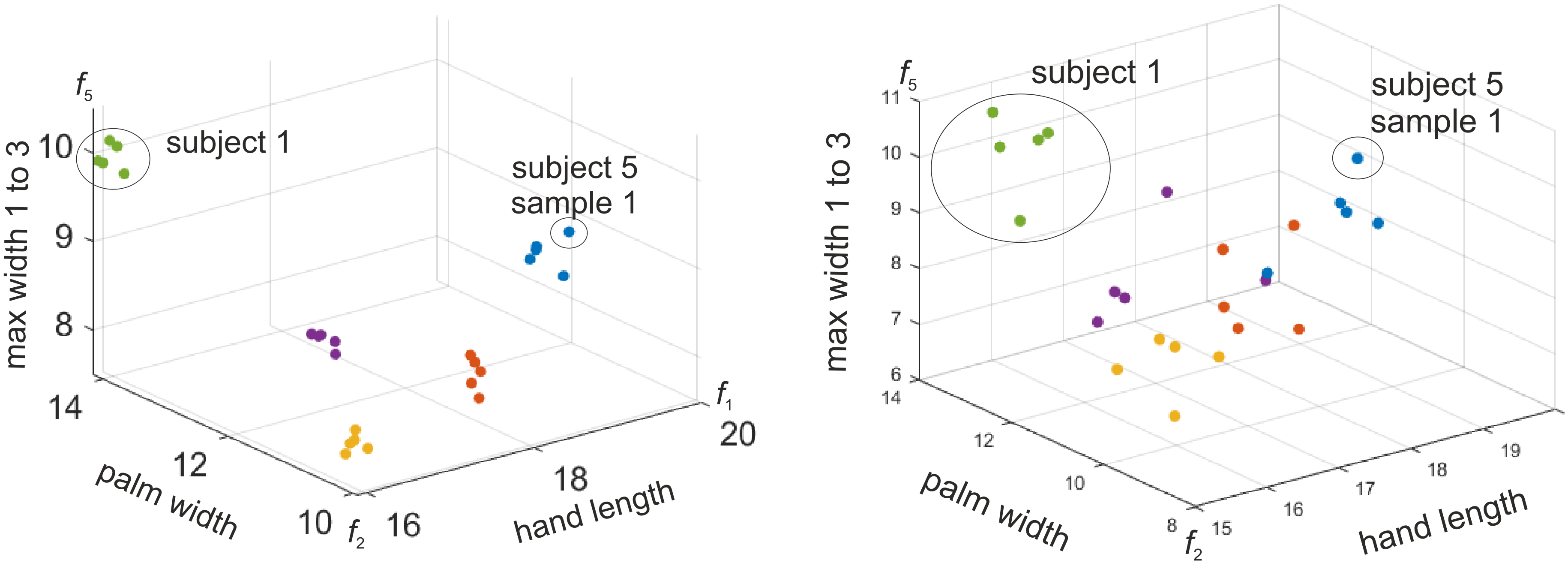
Only by biometrics…



Matching distributions (3D)



Verification terminology

Compared subjects	Prediction/ Decision: match	Prediction/ Decision: non-match
Same subject	True match	False non-match
Different subjects	False match	True non-match

Where is gender in ears?

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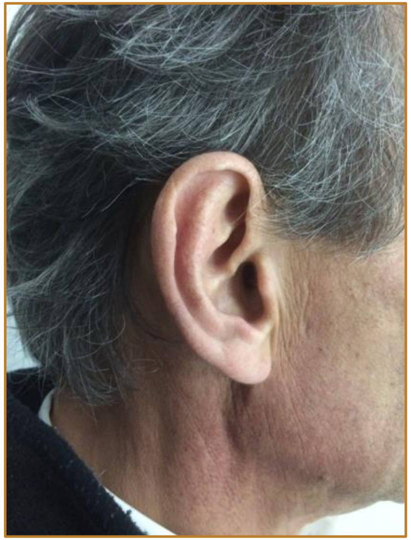
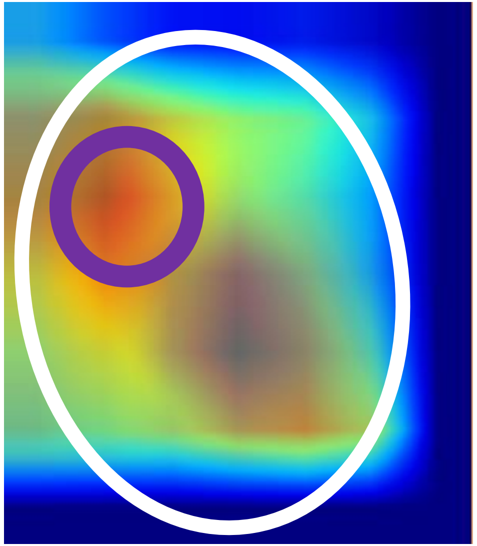
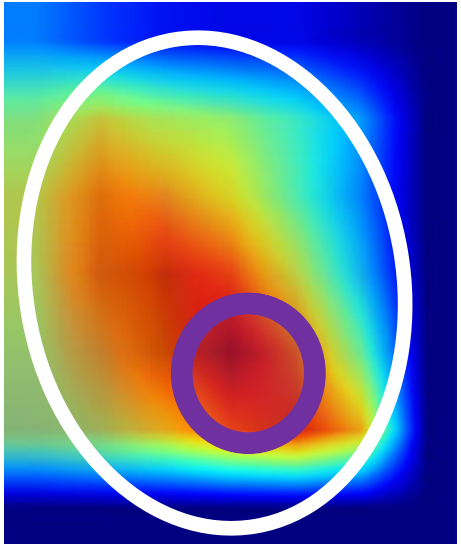
male

female







Meng, Nixon and Mahmoodi, *IEEE TBIOM*, 2021

What (and how old) is whom?

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Woman

70 40 20

Man

70 40 20

Man

70 40 20

Biometrics usage

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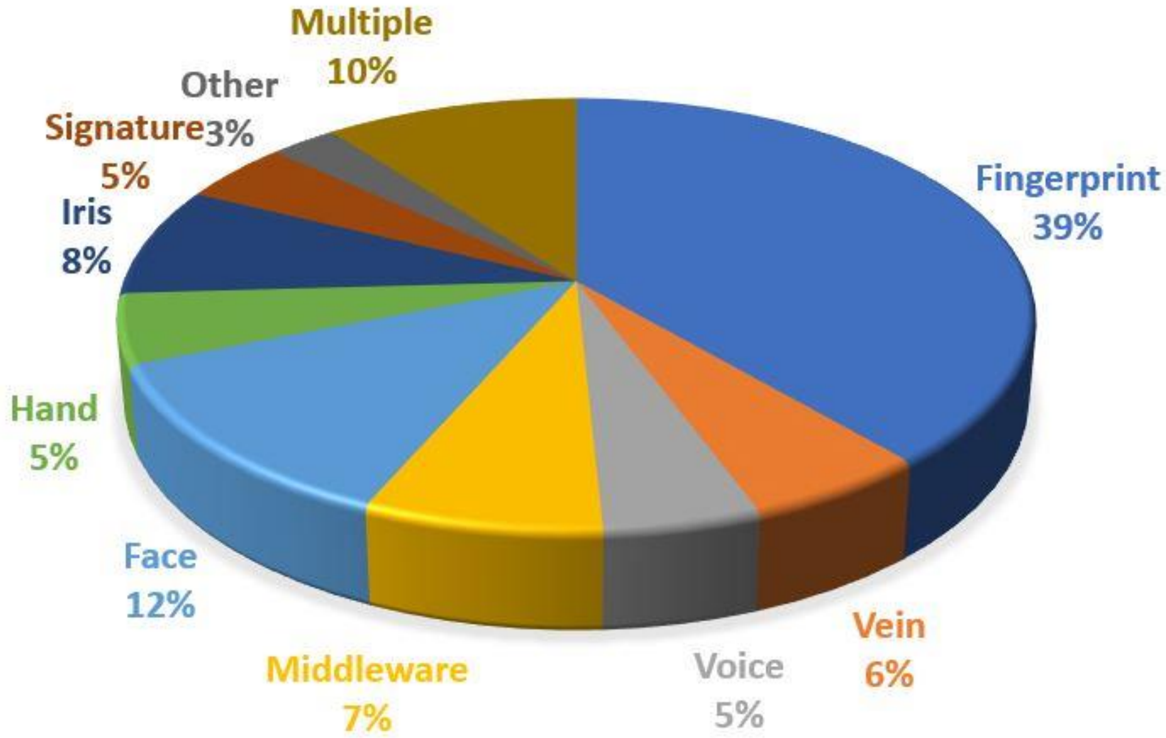
Market share (installations)



Research share

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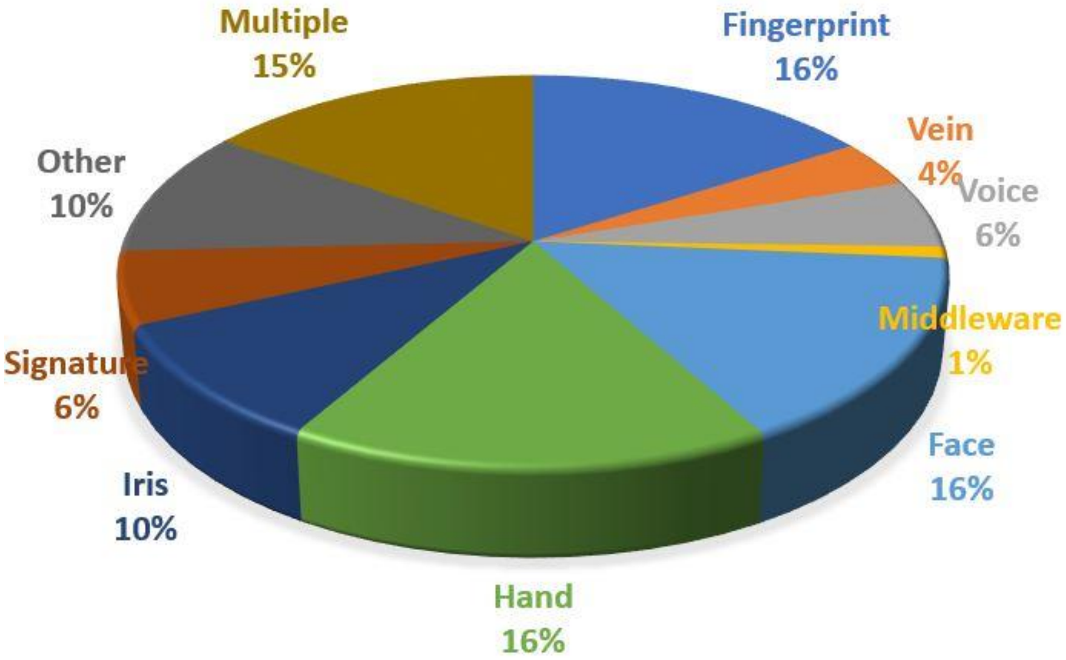

Gait as evidence – first use

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Bag snatcher, London 2008

Gait as evidence – murder case in Australia 2014

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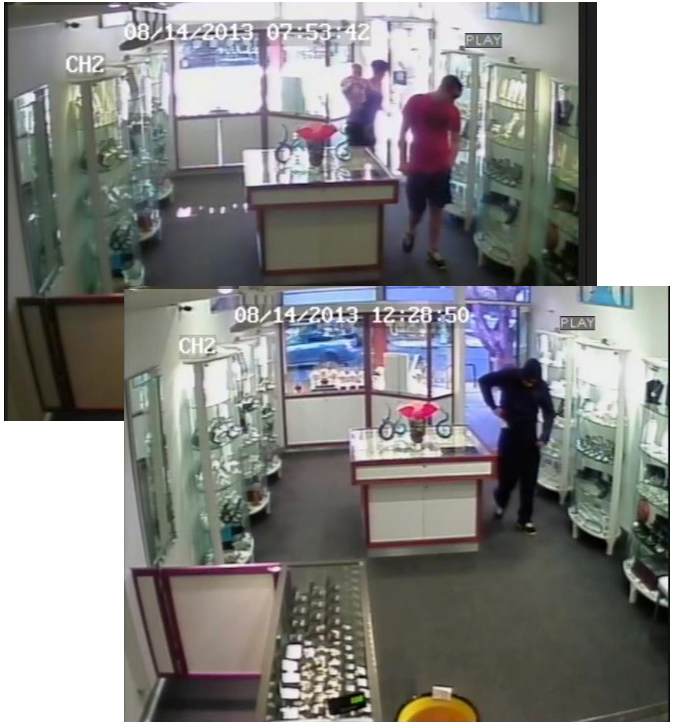

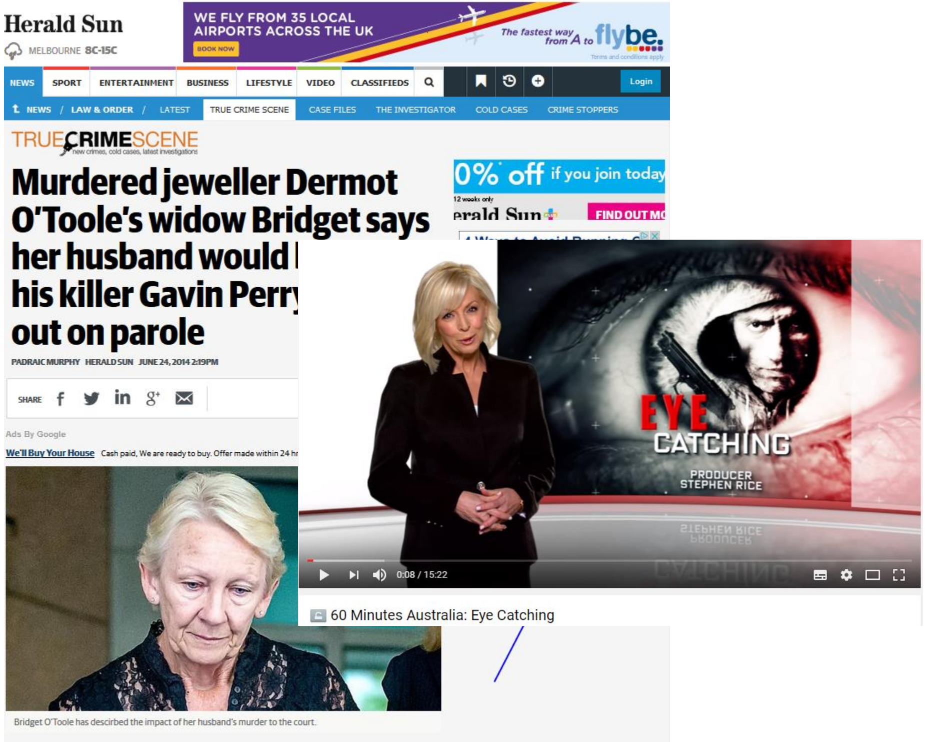

Bouchrika, Goffredo, Carter, Nixon: *J. Forensic Science* 2011, and *Eusipco* 2010

Google Scholar

forensic biometrics

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[PDF] **Biometrics** in **forensic** identification: applications and challenges — [PDF] academia.edu

M Saini, AK Kapoor - J **Forensic** Med, 2016 - academia.edu

… of **forensic biometrics** covers a wide range of applications for physical and cybercrime detection. **Forensic Biometrics** … limitations of **biometric** science in the field of **forensic** identification. …

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Forensic biometrics: From two communities to one discipline — [PDF] ieee.org

D Meuwly, R Veldhuis - … International Conference of **Biometrics** …, 2012 - ieeexplore.ieee.org

… the **forensic biometric** applications and details the role of **biometric** technology in each of them. In preamble it has to be stressed that the reliability of any **forensic biometric** application …

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On using gait in **forensic biometrics** — [PDF] wiley.com

I Bouchrika, M Goffredo, J Carter… - Journal of **forensic** …, 2011 - Wiley Online Library

Given the continuing advances in gait **biometrics**, it appears prudent to investigate the translation of these techniques for **forensic** use. We address the question as to the confidence that …

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Media

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Tom Cruise loves biometrics!

Hot topics

Without order:

- Diffusion models
- Privacy protection in biometrics
- Spoofing/ presentation attack detection and Deepfake
- Gait
- Behaviour and Identity Science

IEEE TRANSACTIONS ON

BIOMETRICS, BEHAVIOR, AND IDENTITY SCIENCE

A PUBLICATION OF THE IEEE BIOMETRICS COUNCIL

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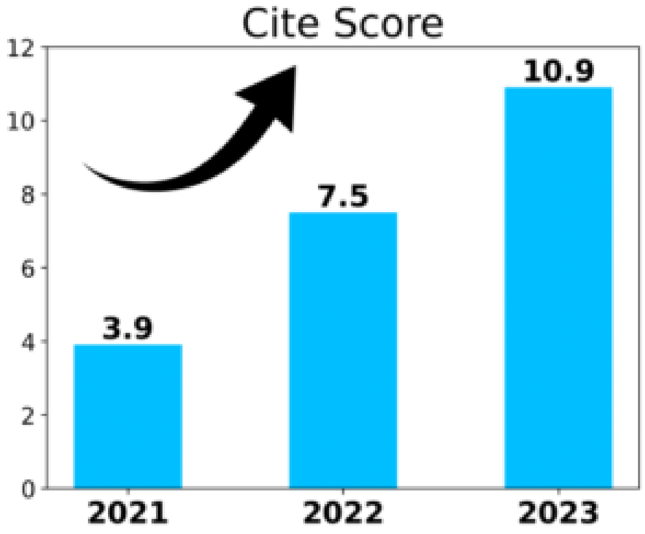
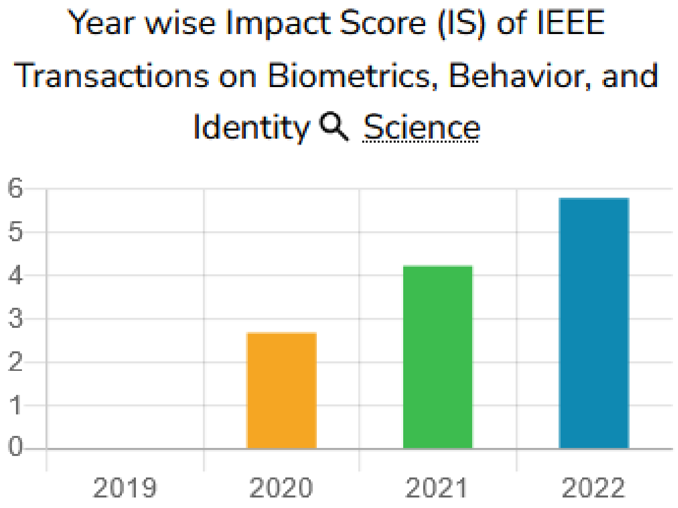


Elsevier Scopus



Resurchify

IEEE Biometrics Council

Comparison?

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https://www.scopus.com/sourceid/21101070922.

Subject Area	Percentile	RANK	Rank Out Of	Quartile
Artificial Intelligence	84	56	350	1
Computer Science Applications	89	86	817	1
Computer Vision and Pattern Recognition	88	13	106	1
Instrumentation	95	7	141	1

Source title	CiteScore 2023
IEEE Transactions on Pattern Analysis and Machine Intelligence	28.4
IEEE Transactions on Information Forensics and Security	14.4
IEEE Transactions on Biometrics, Behavior, and Identity Science	10.9
IET Biometrics	5.9
International Journal of Biometrics	1.5
Proceedings of SPIE - The International Society for Optical Engineering	0.5

Current state of journal (Jan '25)

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Journal Statistics	MTD	Prior 12 Months
Avg. days from submission to first decision	0.0	66.9
Avg. Reviewer turnaround time (days) - **Original**	0.0	27.5
Avg. Reviewer turnaround time (days) - **Resubmission**	0.0	0.0
Avg. Reviewer turnaround time (days) - **Revision**	0.0	21.6
Avg. Time to Assign Reviewer (days) - **Original**	0.0	15.7
Avg. Time to Assign Reviewer (days) - **Resubmission**	0.0	0.0
Avg. Time to Assign Reviewer (days) - **Revision**	1.0	9.7
Avg. days from submission to final decision	0.0	83.1

Other Statistics	
Accept Ratio (prior 12 months)	26 : 82 (31.7%)
Total Pending Manuscripts	63
Oldest manuscript without a decision	TBIOM-2024-07-0079 (166 days)

Gait = body shape + movement

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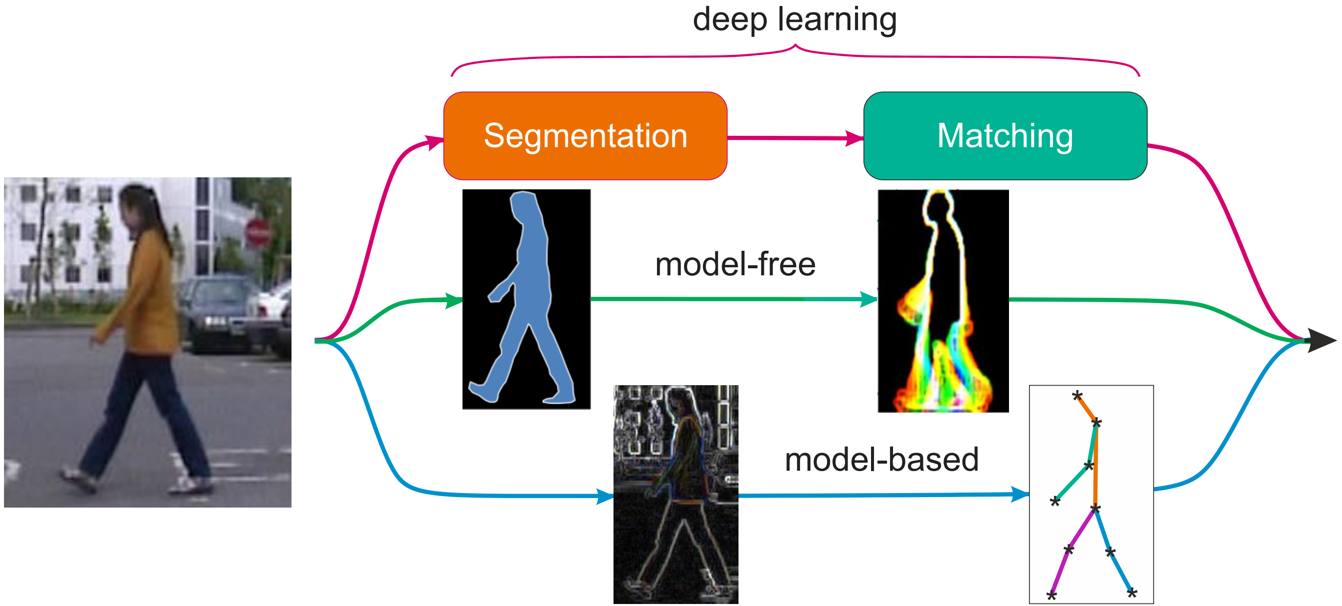


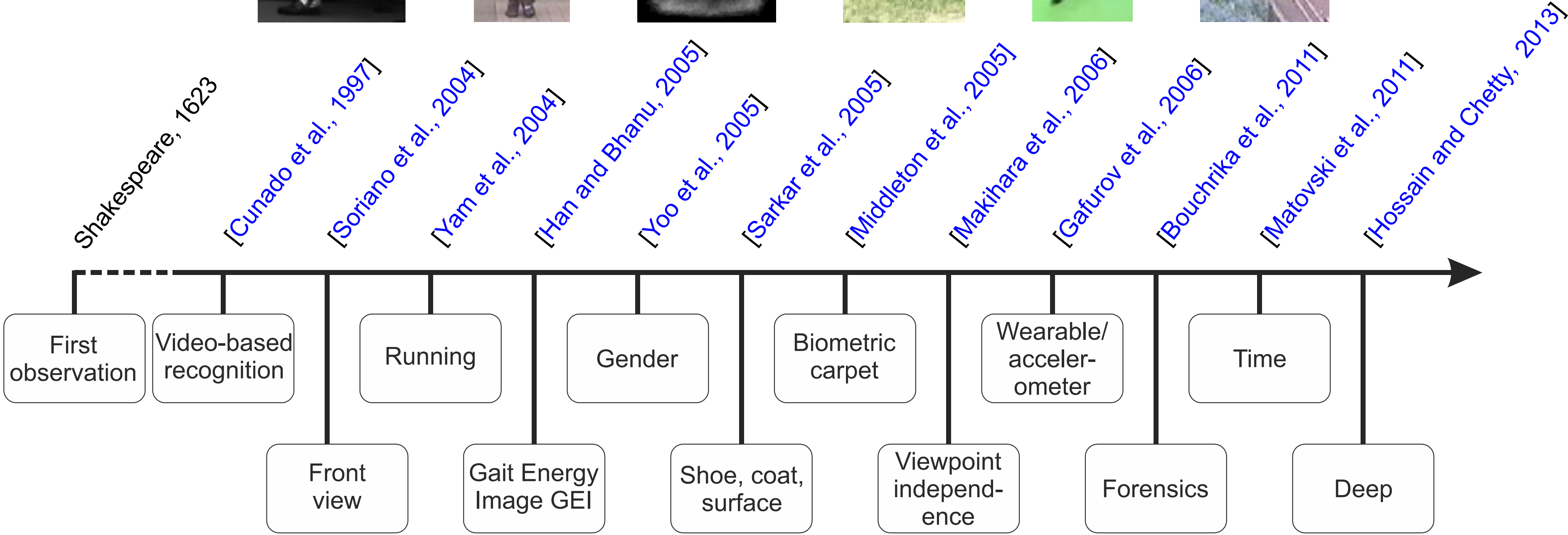
covariates: viewpoint luggage clothing shoes health gender speed

History







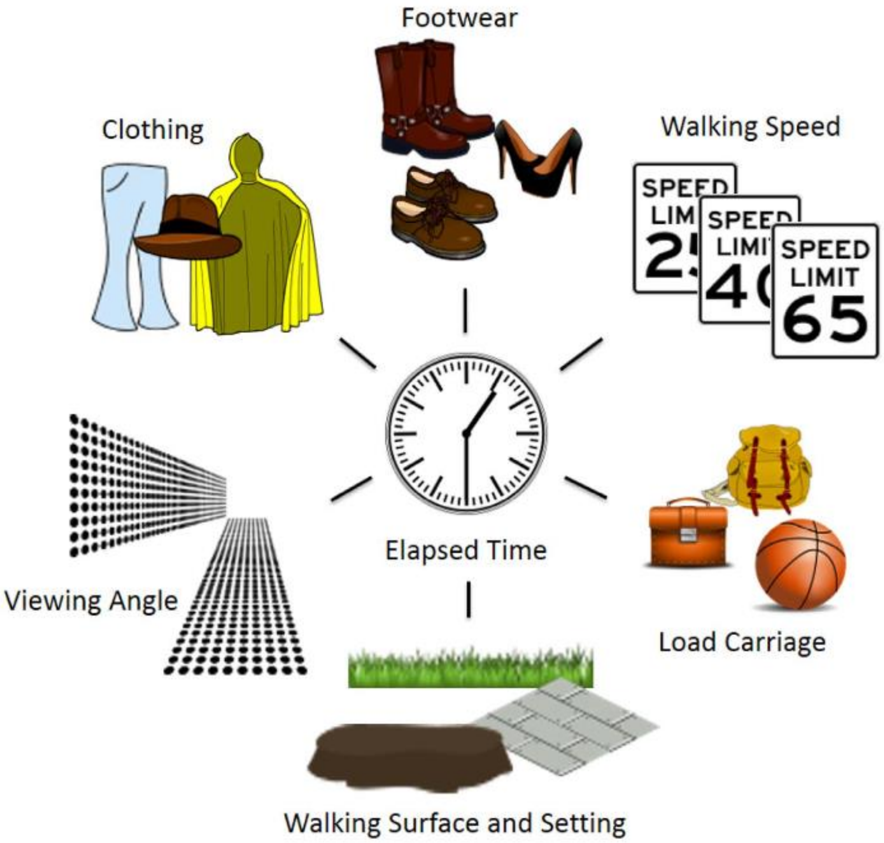

Shakespeare, 1623
[Cunado et al., 1997]
[Soriano et al., 2004]
[Yam et al., 2004]
[Han and Bhanu, 2005]
[Yoo et al., 2005]
[Sarkar et al., 2005]
[Middleton et al., 2005]
[Makihara et al., 2006]
[Gafurov et al., 2006]
[Bouchrika et al., 2011]
[Matovski et al., 2011]
[Hossain and Chetty, 2013]
First observation
Video-based recognition
Front view
Running
Gait Energy Image GEI
Gender
Shoe, coat, surface
Biometric carpet
Viewpoint independ-ence
Wearable/ acceler-ometer
Forensics
Time
Deep

What changes?

Many covariates can affect walking style

…. + health, drugs, mood,

…. but walking is a natural part of our daily lives



Gait biometrics databases

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Laboratory

- Southampton 3D and 2D
- CASIA (+ multiview, thermal)
- Osaka OU-ISIR (+ multiview)

'Real' World

- HumanID/ Southampton
- FVG
- CASIA
- Sustech (+ Lidar)

+ accelerometer, footfall, medical

M Okumura, Y Makihara, Y Yagi, IEEE TIFS 2012

C Song et al, IEEE TPAMI 2022

C Shen et al, CVPR 2023

A. Identifying people by their gait

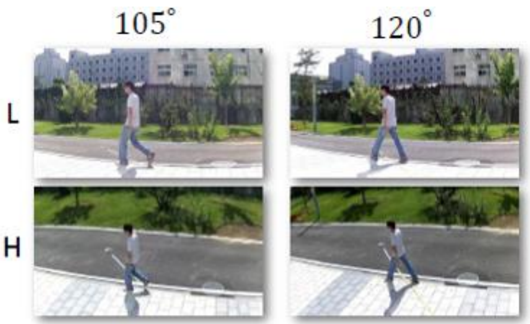
1. Where are we now?
2. How did we get here?
3. Where are we going?

Gait Recognition –state of the art

Technique: mainly deep

Data: Frontal-View Gait (FVG)
CASIA E
SUSTech
GREW
BRIAR

Applications: increasing use in crime scene analysis



Gait Recognition –state of the art

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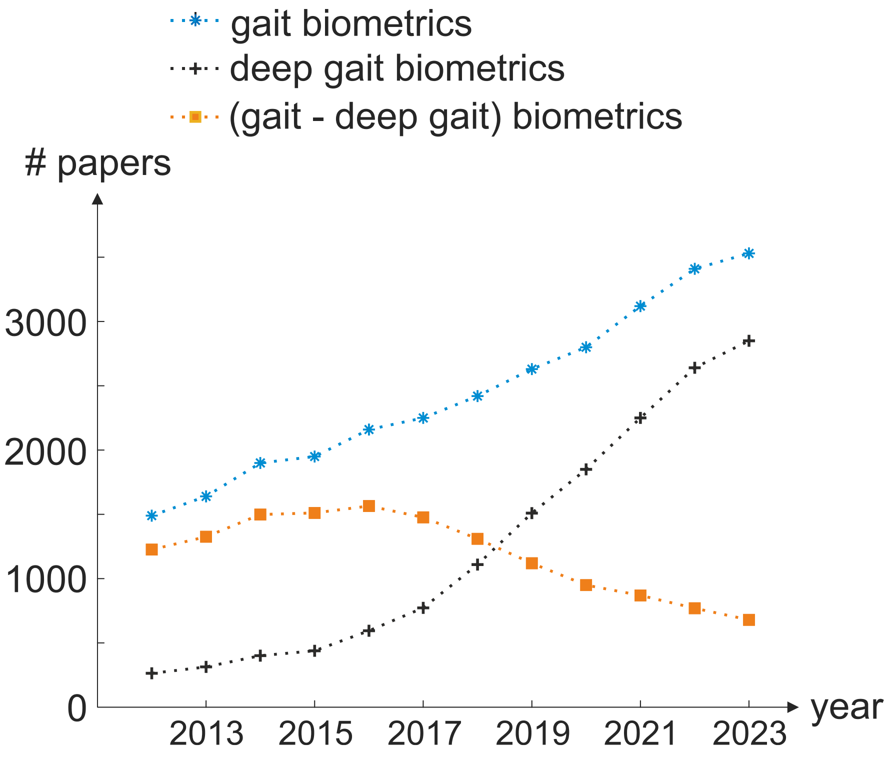
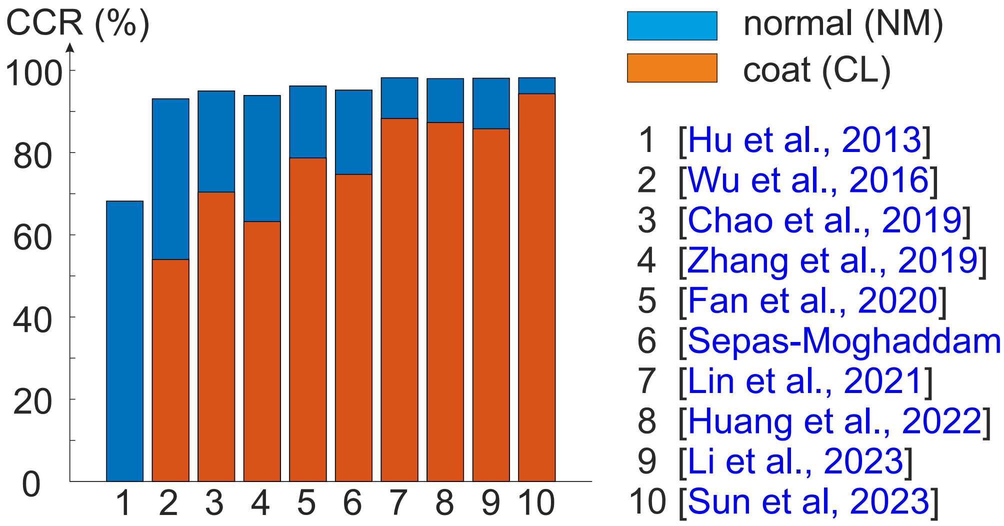


Papers on GS



Performance on CASIA B

Existing Gait Datasets

Shiqi

Table 1. Comparison of publicly available datasets for gait recognition.

Dataset	Year	Subject #	Seq #	View #	Data Type	3D	Multimodal	Outdoor
CASIA-B [50]	2006	124	13,640	11	RGB, Silhouettes	✗	✗	✗
CASIA-C [43]	2006	153	1,530	1	Infrared, Silhouettes	✗	✗	✓
KY4D [20]	2010	42	168	16	Silhouettes, RGB, 3D Volumetrics	✓	✗	✗
TUM-GAID [17]	2012	305	3,370	1	Audio, Video, Depth	✓	✓	✓
SZTAKI-LGA [3]	2016	28	11	1	3D Point Cloud	✓	✗	✓
OU-MVLP [42]	2018	10,307	288,596	14	Silhouettes	✗	✗	✗
FVG [52]	2019	226	2,856	3	RGB	✗	✗	✓
PCG [49]	2020	30	60	1	3D Point Cloud	✓	✗	✗
GREW [58]	2021	26,345	128,671	882	Silhouettes, 2D/3D Skeleton, Flow	✗	✗	✗
Gait3D [56]	2022	4,000	25,309	39	Silhouettes, 2D/3D Skeleton, 3D Mesh	✓	✗	✓
OUMVLP-Mesh [24]	2022	10,307	288,596	14	3D Mesh	✓	✗	✗
SUSTech1K	2023	**1,050**	**25,239**	**12**	**RGB, Silhouettes, 3D Point Cloud**	✓	✓	✓

Gait Recognition – the deep revolution

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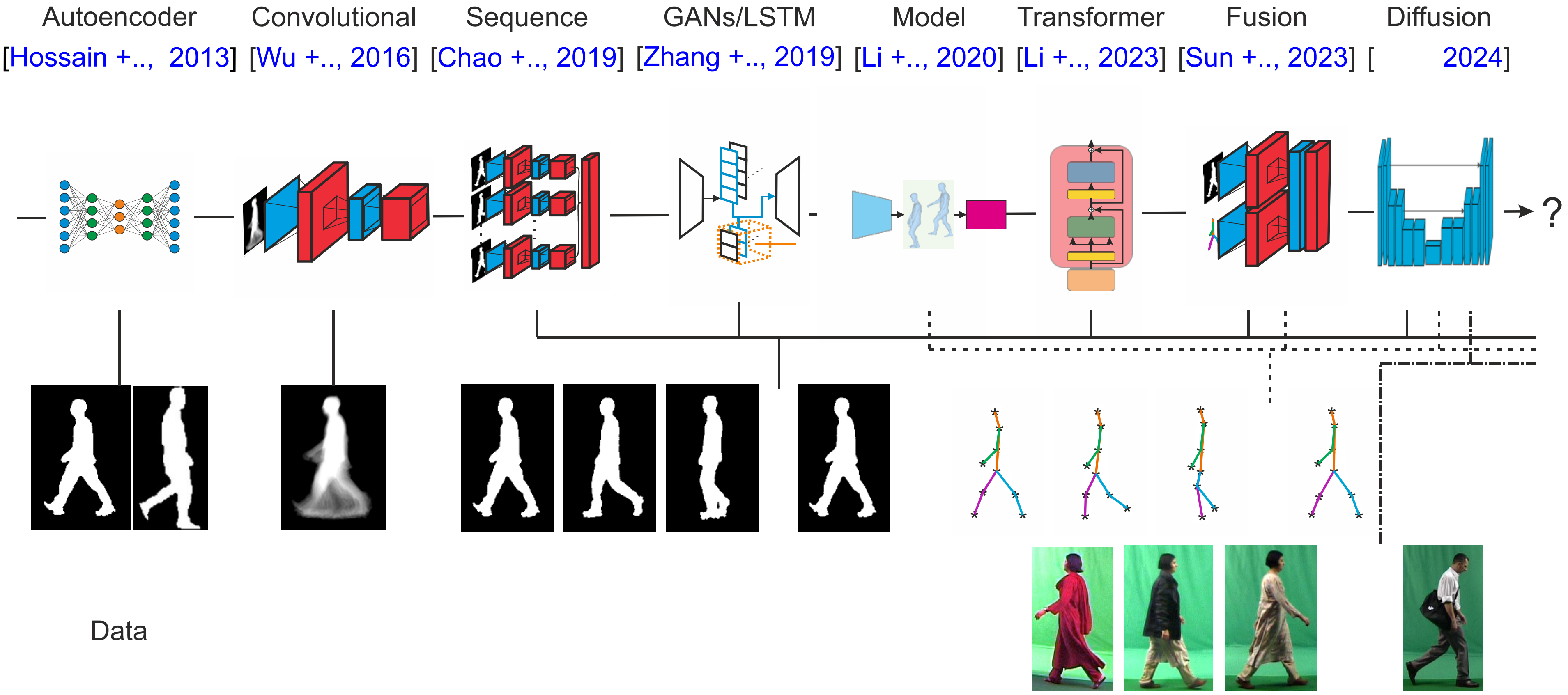
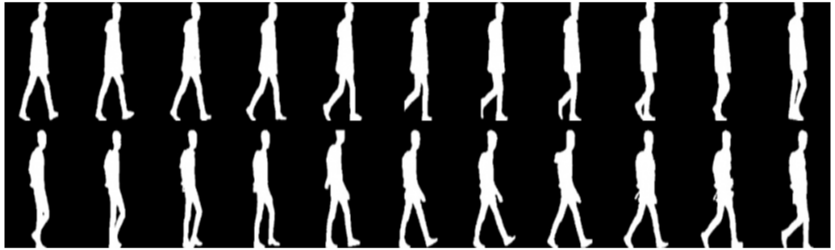
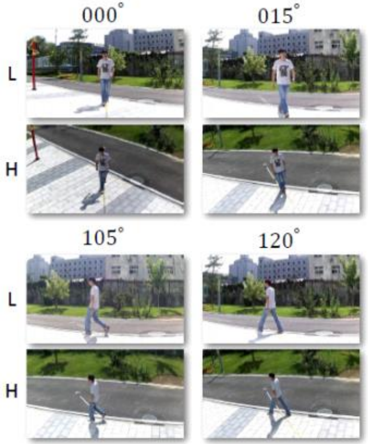


The 5th International Competition on Human Identification at a Distance 2024





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CASIA E

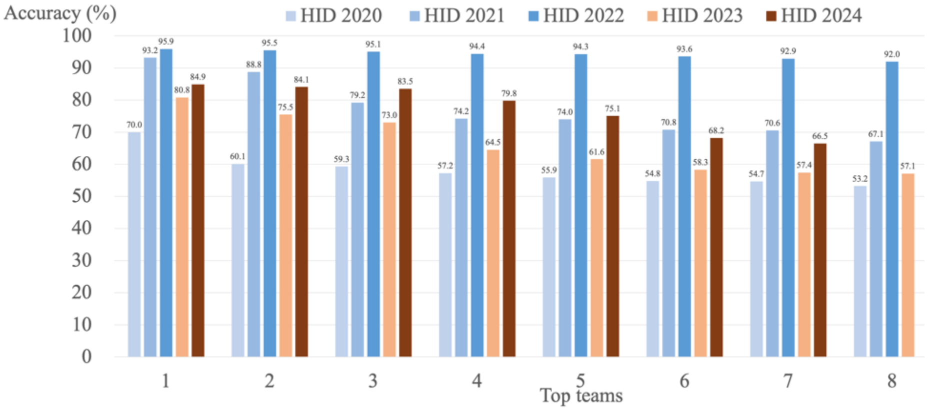
Overview

Welcome to the 5th International Competition on Human Identification at a Distance (HID 2024)! The competition will be in conjunction with IJCB 2024.

The competition focuses on human identification at a distance (HID) in videos The dataset proposed for the competition is ***SUSTech-Competition***, a new dataset collected in 2022 and has been used in HID 2023. It contains 859 subjects.

Awards

Our sponsor, Watrix Technology, will provide 6 awards (19,000 CNY in total,



https://hid.iapr-tc4.org/

ACCV 2020/ IJCB 2021/ IJCB 2022/ IJCB 2023

HID 2023-2024: A new and challenging one

Dataset for HID 2023-2024: SUSTech-Competition

- Specifically collected for HID competitions
- **Number of subjects**: 859
- **Samples**: 6 sequences / subject (1 for gallery, 5 for probe)
- **Challenges**: clothing changing, carrying condition changing, view angle changing, occlusions, etc.
- **Cross-domain**: No training set is provided
- **Data format**: Silhouettes

Shiqi

Dataset for HID 2020-2022: CASIA-E

- Number of subjects: 1005
  - 500 for training
  - 505 for test

Table 1. The technologies used by the top 7 teams and their accuracies in HID 2024.

Team rank	1	2	3	4	5	6	7
Team Name	SCUT-BIPLAB	jchu	SJTU-ICL	GRgroup	BRAVO-FJ	dashengge	HUST-MCLAB
Data cleaning	✓	×	×	✓	×	×	×
Data alignment	✓	✓	✓	✓	✓	✓	✓
Data augmentation	✓	✓	✓	✓	✓	✓	✓
Re-ranking	✓	✓	✓	✓	✓	✓	✓
Ensemble	✓	✓	✓	×	✓	×	✓
Training data	Gait3D, CASIA-B, CCPG, SUSTech1K, CASIA-E, OUMVLP, CCGR	Gait3D, CASIA-B, CCPG, SUSTech1K	CCPG, Gait3D, GREW, CASIA-B, CASIA-E, OUMVLP, SUSTech-1K	CAISA-E	GREW, HID 2022	HID2022	SUSTech1K, Gait3D
Pseudo-labelling	×	×	×	×	✓ (on HID2022 data)	×	×
Architecture	DeepGaitV2 (P3D&3D) [3]	DeepGaitV2 (3D) [3]	DeepGaitV2 (P3D) [3], SwinGait [3]	GaitGL+Gem [7]	DeepGaitV2 (P3D) [3]	DeepGaitV2 (P3D), SwinGait, GaitBase [4]	DeepGaitV2 (P3D), SwinGait [3]
GPU	RTX 3090 * 2	N/A	A100 * 4	RTX 3090 * 4	A6000*4	N/A	N/A
Accuracy(%)	84.9	84.1	83.5	79.8	75.1	68.2	66.5

S. Yu et al., *Human Identification at a Distance: Challenges, Methods and Results on the Competition HID 2024*, Proc. of IJCB 2024.

OpenGait

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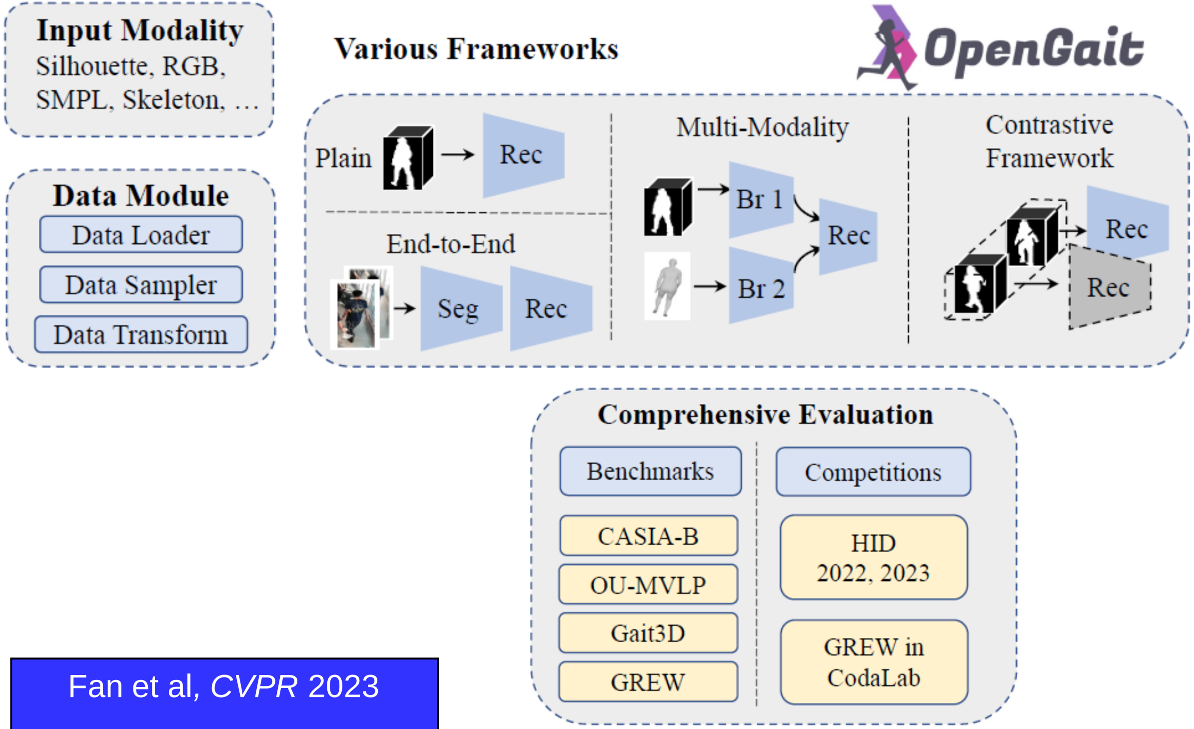
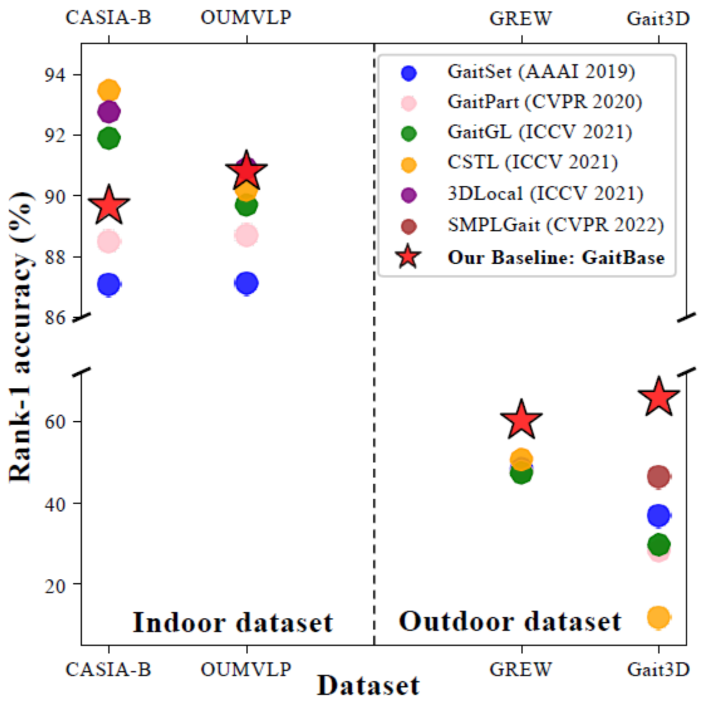
“flexible and extensible gait recognition codebase for better practicality rather than only a particular model for better performance”





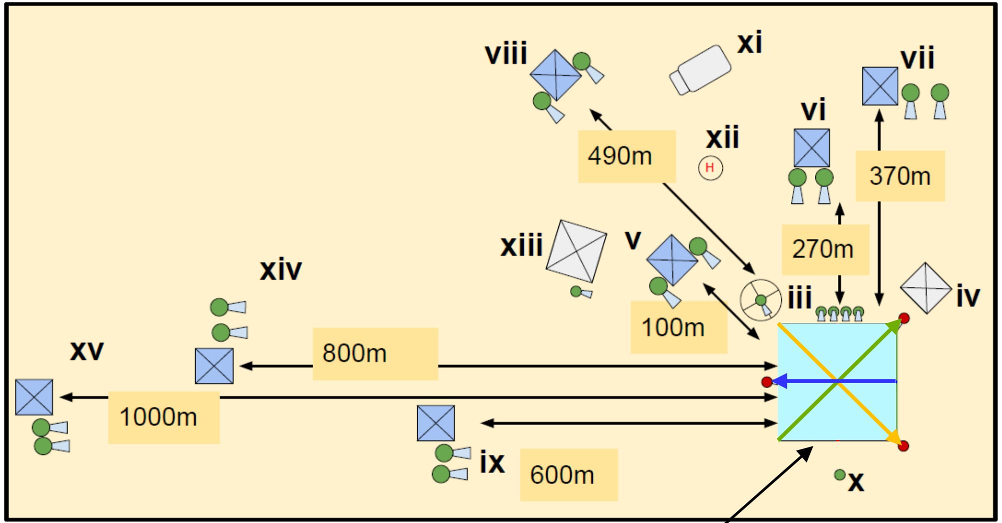
Fan et al, *CVPR* 2023

BRIAR | Office of the Director of National Intelligence IARPA | University of Southampton Electronics and Computer Science

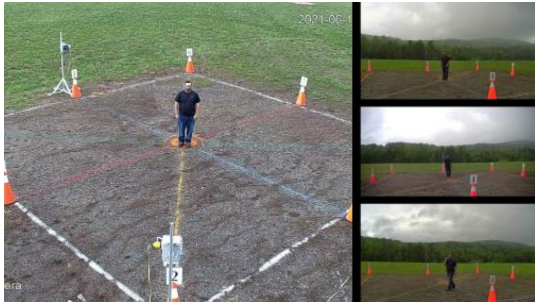
Expanding accurate person recognition to new altitudes and ranges: The briar dataset

Floorplan of collection setup for BGC2

302 subjects
Max range 1000m
Max elevation 400m
Inc. appearance change
Single subjects only



Outdoor walking arena



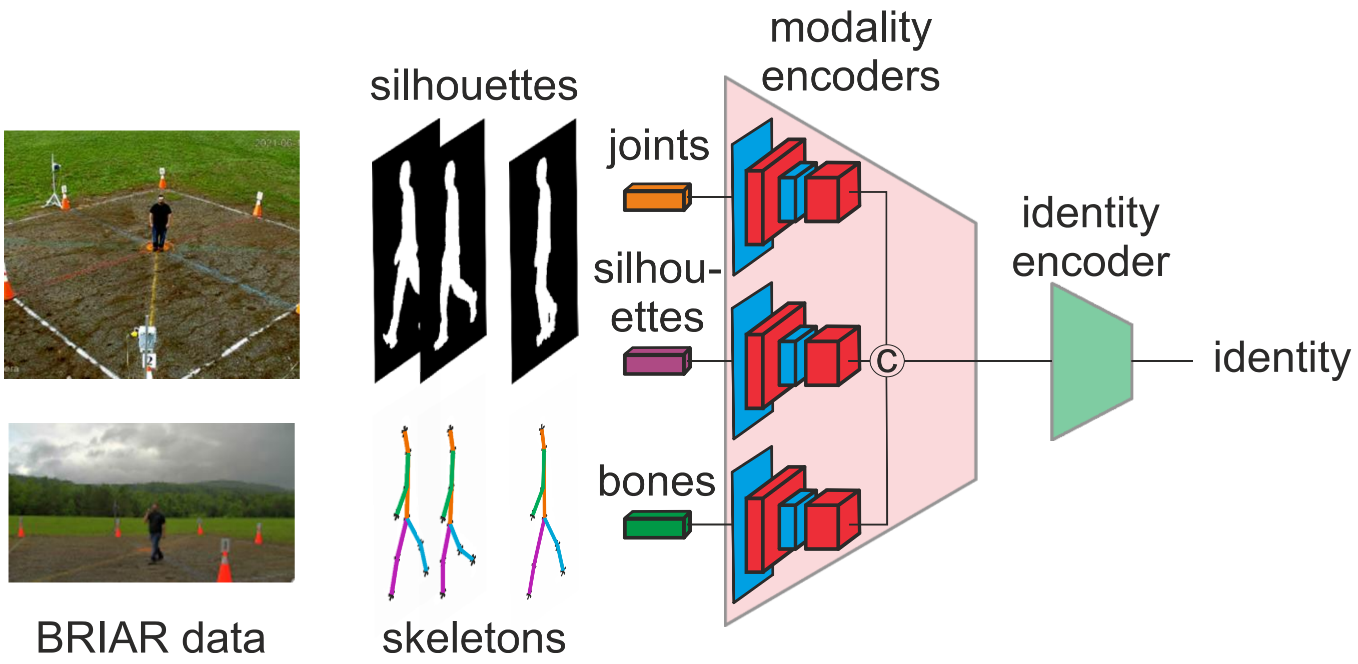
Close range BGC1 data

Left: elevated surveillance
Right: walking images

Cornett et al, *WACV* 2023

GaitSTR: Gait Recognition with Sequential Two-stream Refinement

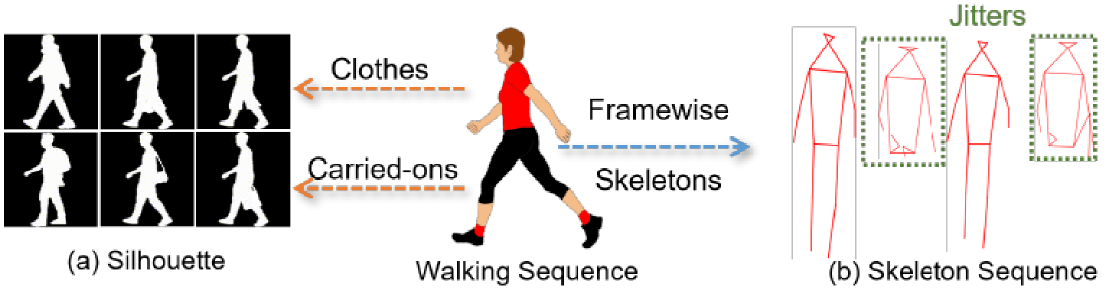
University of Southampton
Electronics and Computer Science

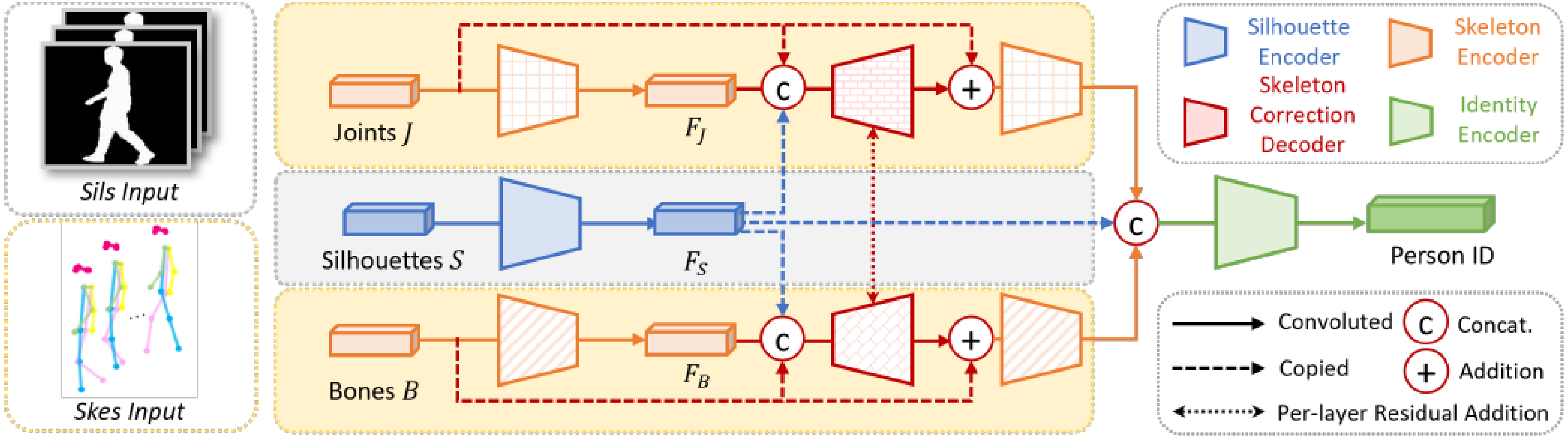


Zheng et al, *TBIOM* 2024

GaitSTR: Gait Recognition with Sequential Two-stream Refinement

University of Southampton
Electronics and Computer Science



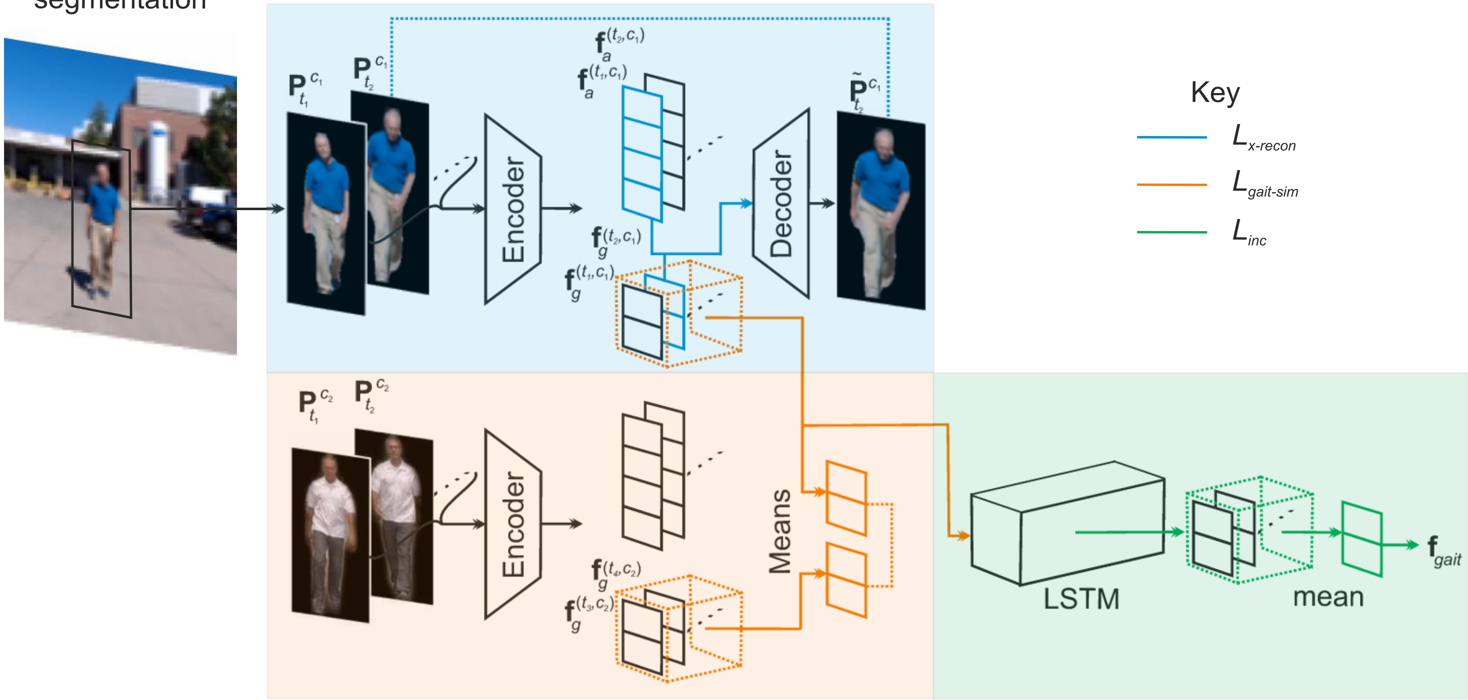


Zheng et al, *TBIOM* 2024

Gait recognition via disentangled representation learning

University of Southampton
Electronics and Computer Science

Detection and segmentation



Zhang et al, *CVPR* 2019

See also: Li, Makihara, Xu, Yagi: Gait recognition via semi-supervised disentangled representation learning to identity and covariate features, CVPR 2020

Gait recognition via disentangled representation learning

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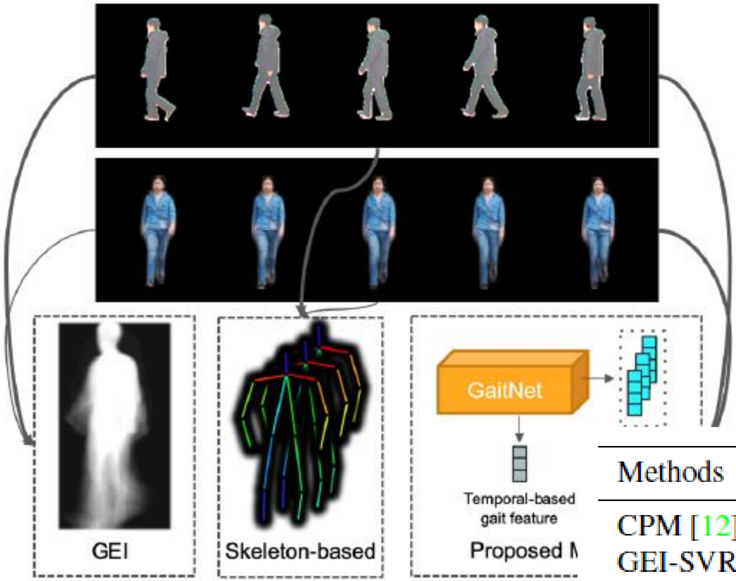


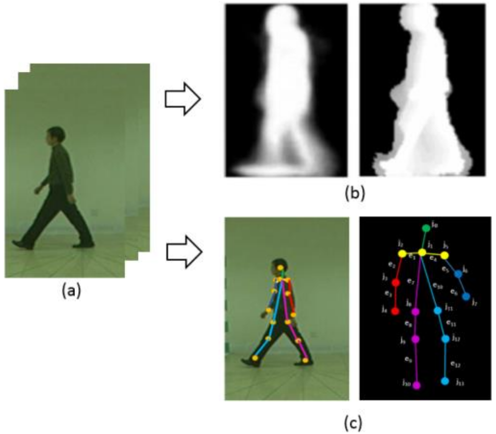
Methods	0°	18°	36°	54°	72°	108°	126°	144°	162°	180°	Average
CPM [12]	13	14	17	27	62	65	22	20	15	10	24.1
GEI-SVR [29]	16	22	35	63	95	95	65	38	20	13	42.0
CMCC [28]	18	24	41	66	96	95	68	41	21	13	43.9
ViDP [26]	8	12	45	80	**100**	**100**	81	50	15	8	45.4
STIP+NN [30]	–	–	–	–	84.0	86.4	–	–	–	–	–
LB [46]	18	36	67.5	93	99.5	99.5	92	66	36	18	56.9
L-CRF [12]	38	**75**	68	93	98	99	**93**	67	76	39	67.8
GaitNet (ours)	**68**	74	**88**	91	99	98	84	**75**	**76**	**65**	**81.8**

Generally, big(ger) numbers!!

Zhang et al, *CVPR* 2019

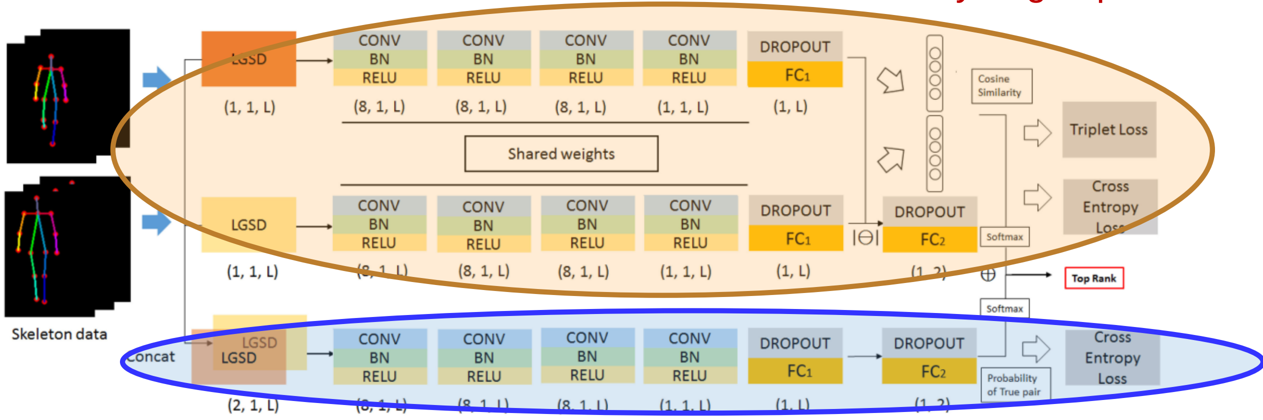
Gait Recognition based on Local Graphical Skeleton Descriptor with Pairwise Similarity Network

University of Southampton
Electronics and Computer Science



LGSD Local Graphical Skeleton Descriptor

Similarity of gait pair



Probability of gait pair

TABLE V
AVERAGED RANK-1 ACCURACIES IN PERCENT ON CASIA-B COMPARISON WITH BOTH APPEARANCE-BASED AND MODEL-BASED METHODS

Type	Methods	NM	BG	CL
Appearance-based	GaitNet[28]	91.6	85.7	58.9
	GaitSet[29]	95.0	87.2	70.4
	GaitPart[30]	96.2	91.5	78.7
Model-based	PoseGait[7]	60.5	39.6	29.8
	GaitGraph[31]	87.7	74.8	66.3
	PSN	69.8	43.5	33.2

Xu et al, *IEEE Trans on Multimedia* 2021

End-to-end model-based gait recognition

University of Southampton
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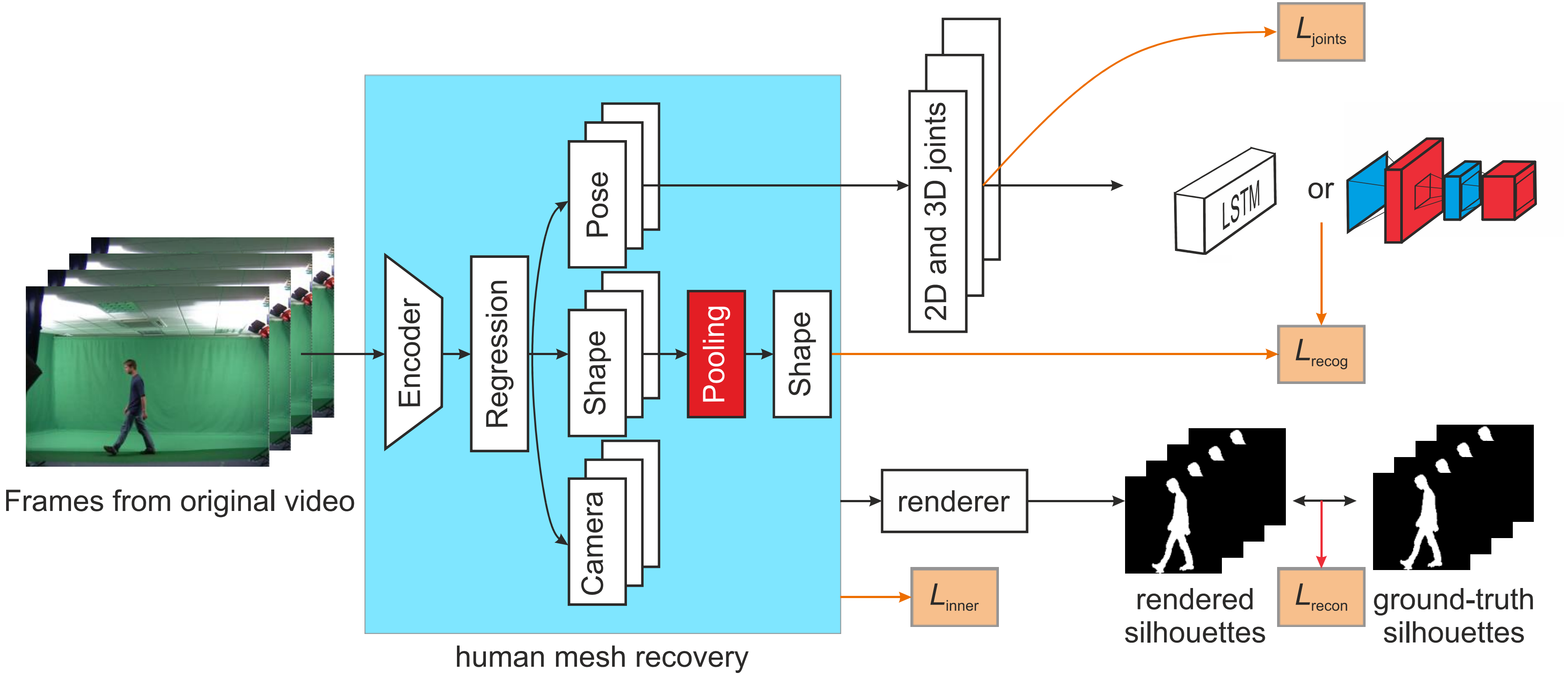

Li et al, *ACCV* 2020

GaitSet: Cross-view Gait Recognition through Utilizing Gait as a Deep Set

University of Southampton
Electronics and Computer Science

Hanqing Chao; Kun Wang; Yiwei He; Junping Zhang; Jianfeng Feng (Shanghai/ Fudan)

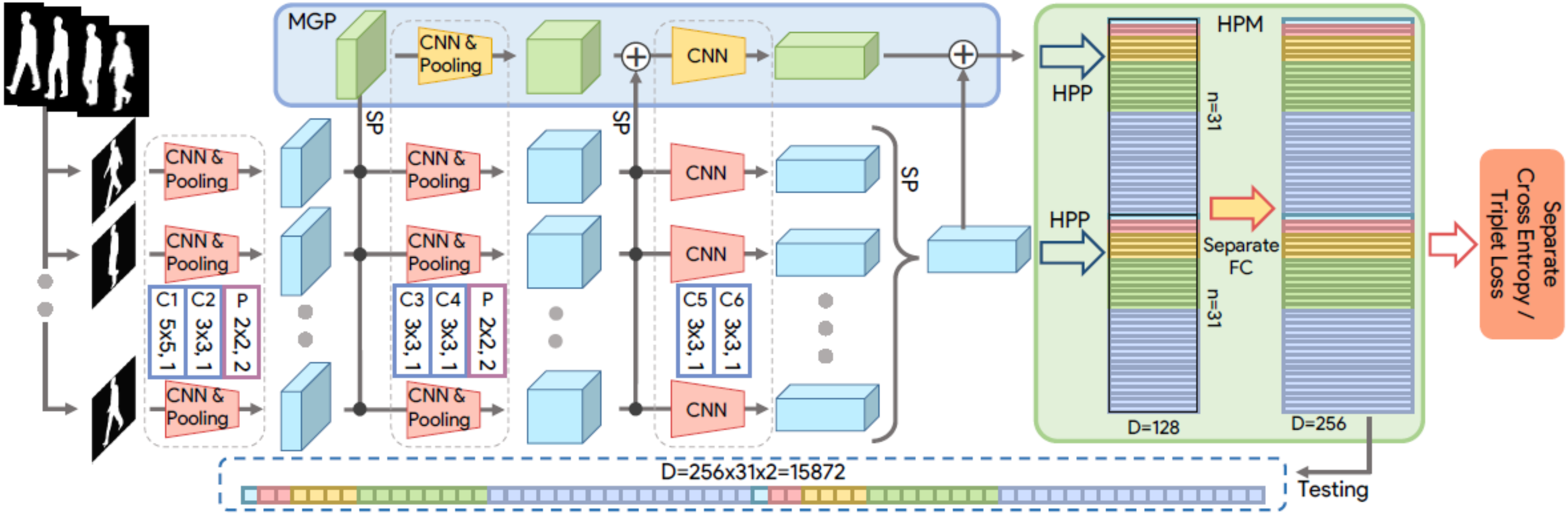

Fig. 2. The framework of GaitSet [26] . 'SP' represents set pooling. Trapezoids represent convolution and pooling blocks and those in the same column have the same configurations, as shown by the rectangles with capital letters. Note that although the blocks in MGP have the same configurations as those in the main pipeline, the parameters are shared only across blocks in the main pipeline – not with those in MGP. HPP represents horizontal pyramid pooling [27].

Chao et al, *IEEE TPAMI* 2022

GaitSet: Cross-view Gait Recognition through Utilizing Gait as a Deep Set

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TABLE 3
Averaged rank-1 accuracies on OU-MVLP, excluding identical-view cases. GEINet: [18]. 3in+2diff: [4]

Probe	Gallery All 14 Views		Gallery 0°, 30°, 60°, 90°		
	GEINet	Ours	GEINet	3in+2diff	Ours
0°	11.4	81.3	8.2	25.5	79.6
15°	29.1	88.6	-	-	87.1
30°	41.5	90.2	32.3	50.0	87.4
45°	45.5	90.7	-	-	89.8
60°	39.5	88.6	33.6	45.3	86.2
75°	41.8	89.1	-	-	88.0
90°	38.9	88.3	28.5	40.6	84.3
180°	14.9	83.1			81.8
195°	33.1	87.7			
210°	43.2	89.4			
225°	45.6	89.7			
240°	39.4	87.8			
255°	40.5	88.3			
270°	36.3	86.9			
mean	35.8	87.9			

GEINet: View-invariant gait recognition using a convolutional neural network

On input/output architectures for convolutional neural network based cross-view gait recognition

Large-Sample Training (LT)

normal (NM) walking with a bag (BG) wearing a coat or jacket (CL)

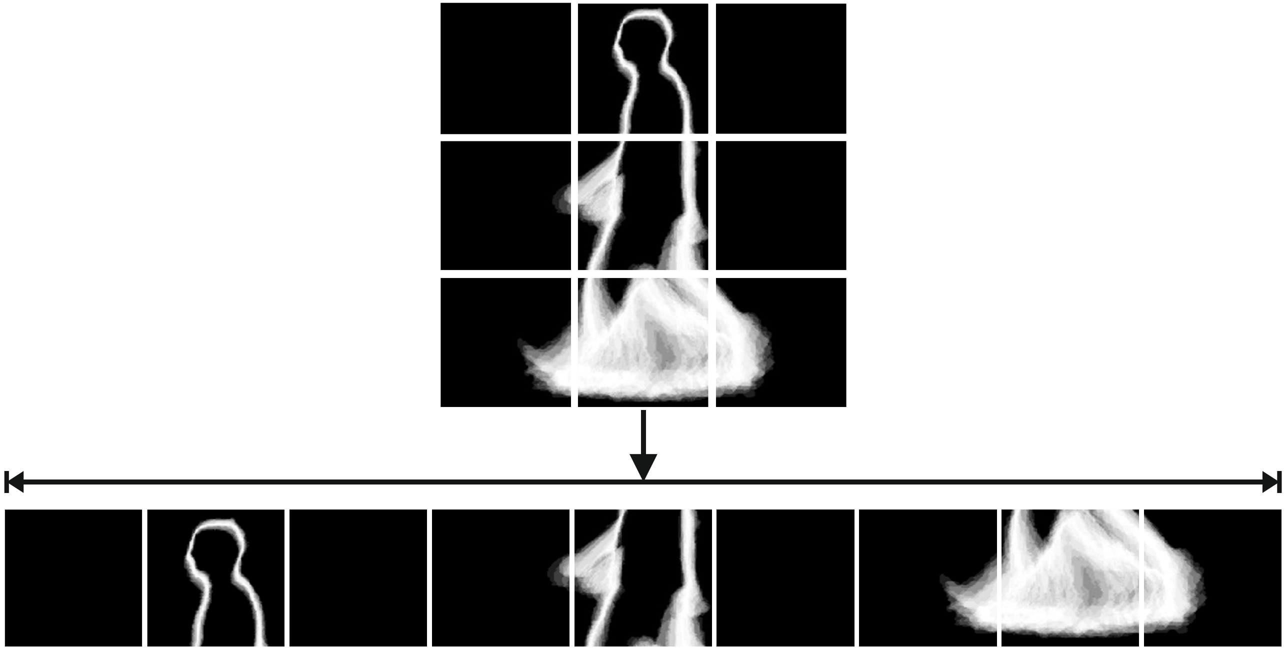
Ablation experiments conducted on **CASIA-B** using setting LT. The results are rank-1 accuracies averaged on all 11 views, excluding identical-view cases. The numbers in brackets indicate the second highest results in each column. Here ‘att’ is the abbreviation of attention.

GEI	Set	Set Pooling							MGP	NM	BG	CL
		Max	Mean	Median	Joint sum 3	Joint 1_1C 4	Pix-att	Frame att				
√										89.0	76.3	50.7
	√	√								95.4	88.7	69.9
	√		√							95.0	86.3	66.3
	√			√						94.8	84.9	63.7
	√				√					94.1	84.1	64.3
	√					√				94.9	86.9	66.8
	√						√			95.6	88.9	69.6
	√							√		95.0	85.1	65.3
	√	√							√	96.1	90.8	70.3

Chao et al, *IEEE TPAMI* 2022

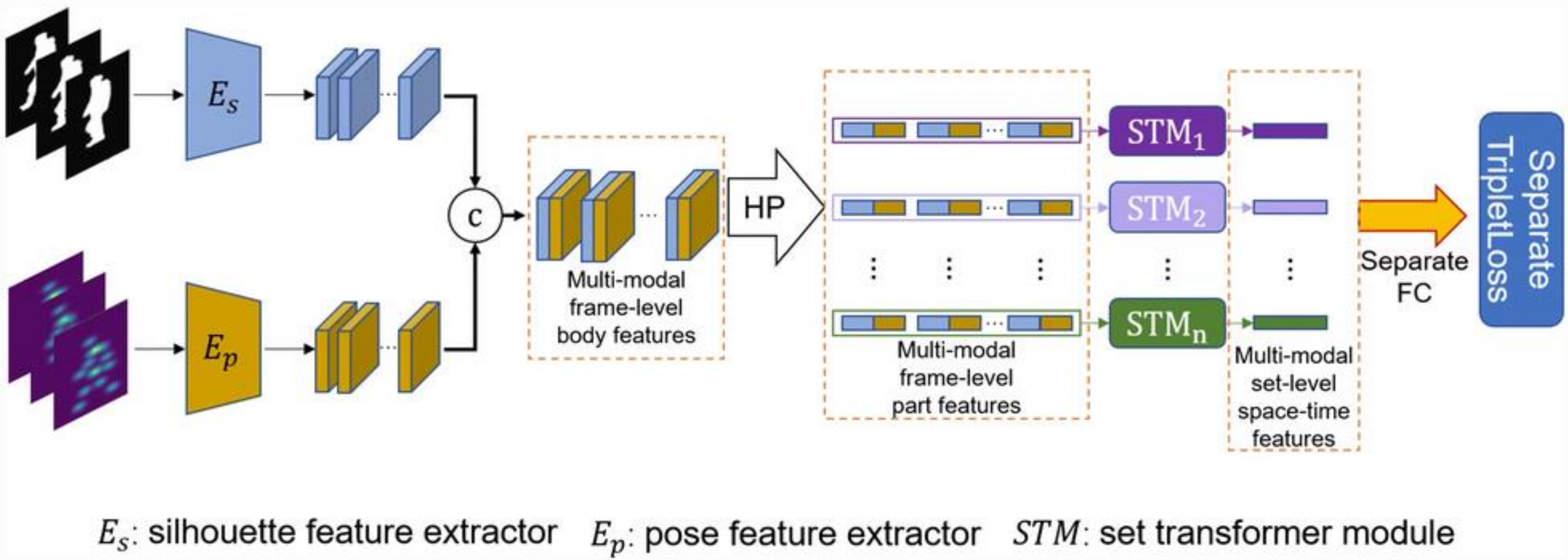
Transforming gait

Electronics and Computer Science



TransGait: Multimodal-based gait recognition with set transformer

University of Southampton
Electronics and Computer Science

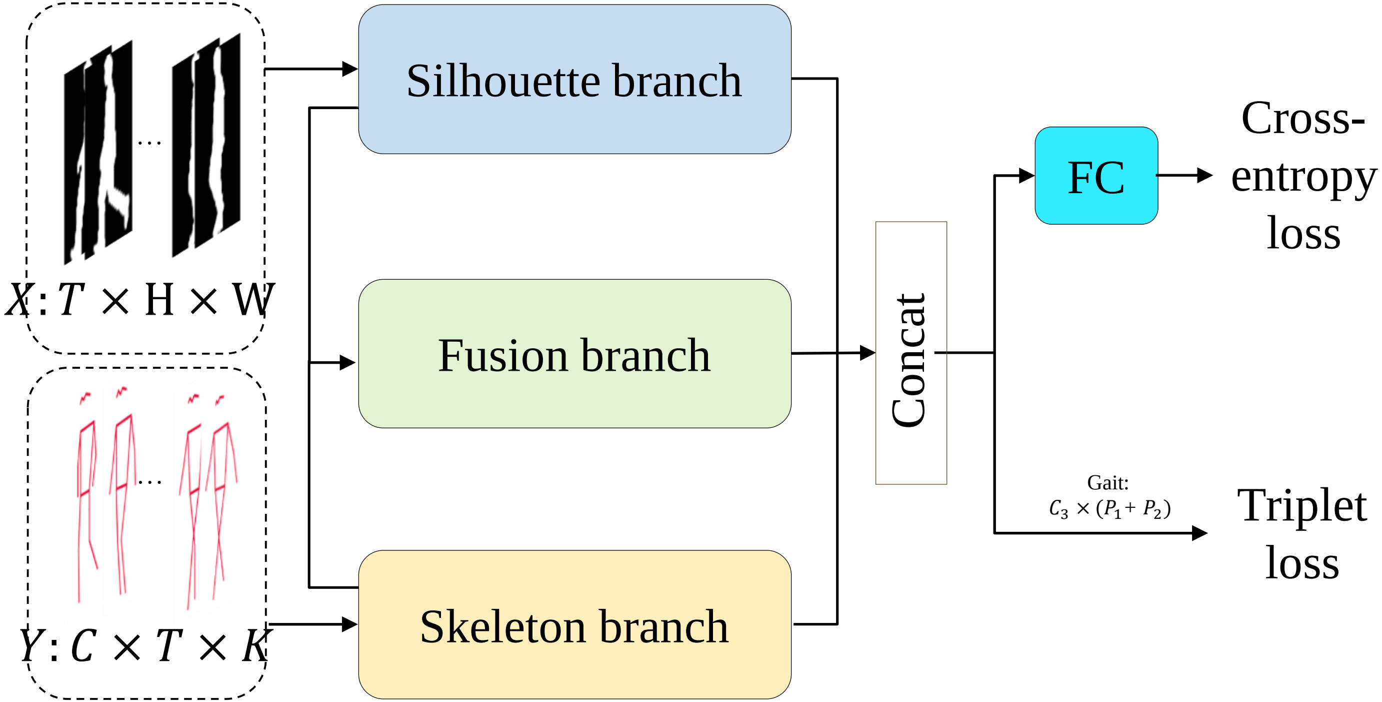


Li et al, *Applied Intelligence*, 2023

Trigait: Aligning and Fusing Skeleton and Silhouette Gait Data via a Tri-Branch Network

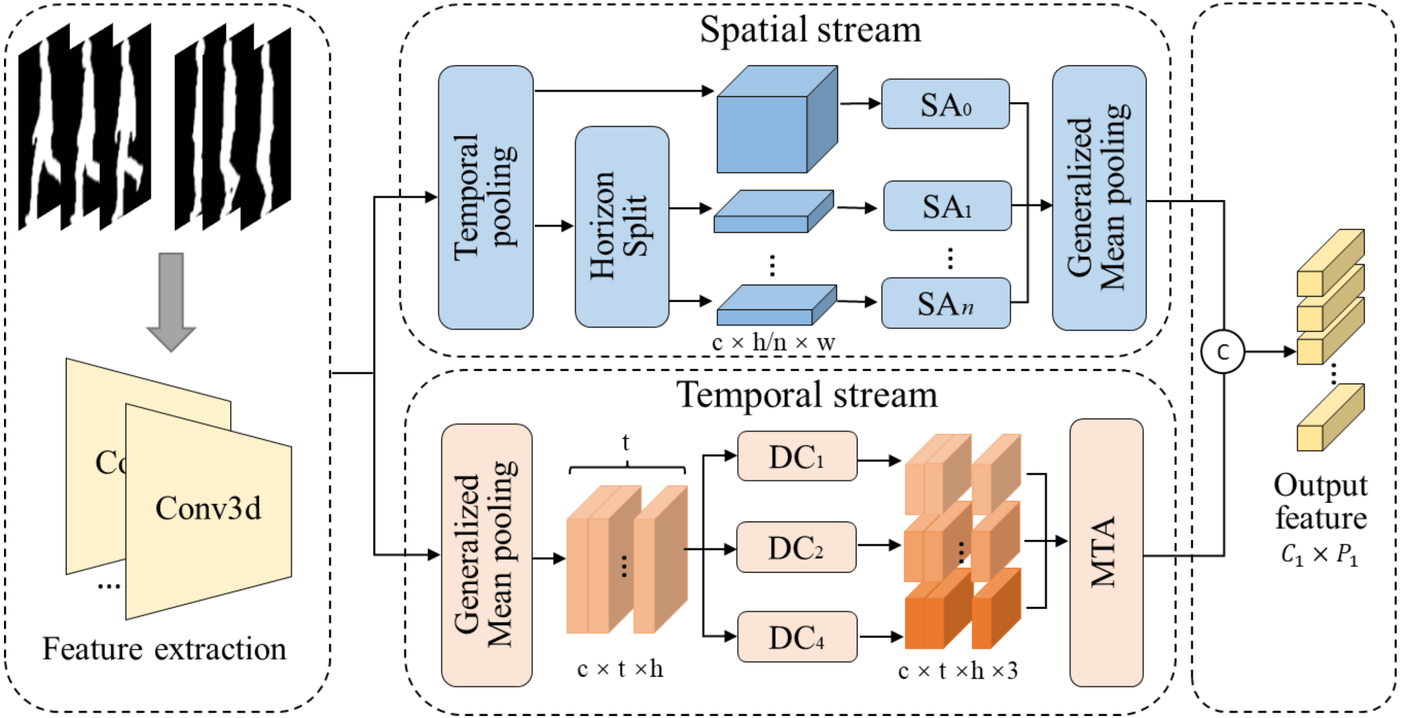
University of Southampton
Electronics and Computer Science

TriGait Network Architecture



Sun et al, *IEEE IJCB*, 2023

Trigait: silhouette branch



Sun et al, *IEEE IJCB*, 2023, *IEEE TBIOM* 2024

Trigait: NM comparison with SoTA

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Table 1. The rank-1 accuracy (%) on CASIA-B across different views, excluding the identical-view cases. TriGait stands for the proposed fusion network.

Gallery	$0^o - 180^o$											Mean
Method	0^o	18^o	36^o	54^o	72^o	90^o	108^o	126^o	144^o	162^o	180^o	
GaitGraph [7] (CVPR2022)	78.5	82.9	85.8	85.6	83.1	81.5	84.3	83.2	84.2	81.6	71.8	82.0
GaitMixer [6] (arXiv2022)	94.4	94.9	94.6	96.3	95.3	96.3	95.3	94.7	95.3	94.7	92.2	94.9
GaitSet [1] (AAAI2019)	90.8	97.9	99.4	96.9	93.6	91.7	95.0	97.8	98.9	96.8	85.8	95.0
GaitPart [2] (CVPR2020)	94.1	98.6	99.3	98.5	94.0	92.3	95.9	98.4	99.2	97.8	90.4	96.2
GaitGL [5] (arXiv2022)	96.6	**98.8**	99.1	98.1	97.0	96.8	97.9	**99.2**	99.3	98.3	95.6	98.0
GaitMSTP [3] (IJCB2022)	**98.2**	99.2	99.4	98.5	96.8	96.2	97.8	99.1	99.1	**99.5**	96.2	**98.2**
TransGait [4] (APPL INTELL2023)	97.3	99.6	**99.7**	**99.0**	97.1	95.4	97.4	99.1	**99.6**	98.9	95.8	98.1
Combine [8] (ICASSP2023)	97.0	97.9	98.4	98.3	97.2	**97.3**	98.2	98.4	98.3	98.1	96.0	97.7
TriGait (ours)	97.0	98.6	98.3	98.3	**98.4**	97.0	**98.6**	99.0	98.9	98.4	**97.4**	**98.2**

Sun et al, *IEEE IJCB, 2023*, *IEEE TBIOM* 2024 = (ours)

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Trigait: CL comparison with SoTA

Table 1. The rank-1 accuracy (%) on CASIA-B across different views, excluding the identical-view cases. TriGait stands for the proposed fusion network.

GaitGraph [7] (CVPR2022)	57.1	61.1	68.9	66.0	67.8	65.4	68.1	67.2	63.7	63.6	50.4	63.6
GaitMixer [6] (arXiv2022)	81.2	83.6	82.3	83.5	84.5	84.8	86.9	88.9	87.0	85.7	81.6	84.5
GaitSet [1] (AAAI2019)	61.4	75.4	80.7	77.3	72.1	70.1	71.5	73.5	73.5	68.4	50.0	70.4
GaitPart [2] (CVPR2020)	70.7	85.5	86.9	83.3	77.1	72.5	76.9	82.2	83.8	80.2	66.5	78.7
GaitGL [5] (arXiv2022)	82.6	92.6	94.2	91.8	86.1	81.3	87.2	90.2	90.9	88.5	75.4	87.3
GaitMSTP [3] (IJCB2022)	82.3	93.1	94.8	90.9	86.8	84.2	87.7	91.0	91.8	91.2	77.8	88.3
TransGait [4] (APPL INTELL2023)	80.1	89.3	91.0	89.1	84.7	83.3	85.6	87.5	88.2	88.8	76.6	85.8
Combine [8] (ICASSP2023)	87.4	**96.0**	**97.0**	94.6	94.0	90.1	91.5	94.1	93.8	92.6	88.5	92.7
TriGait (ours)	**91.7**	93.2	96.9	**97.0**	**95.2**	**94.0**	**94.6**	**95.3**	**94.1**	**94.1**	**90.8**	**94.3**

Sun et al, *IEEE IJCB*, 2023, *IEEE TBIOM* 2024 = (ours)

Trigait: comparison with SOTA

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Rank 1 mean accuracy (%) on CASIA-B across different conditions and viewpoints.

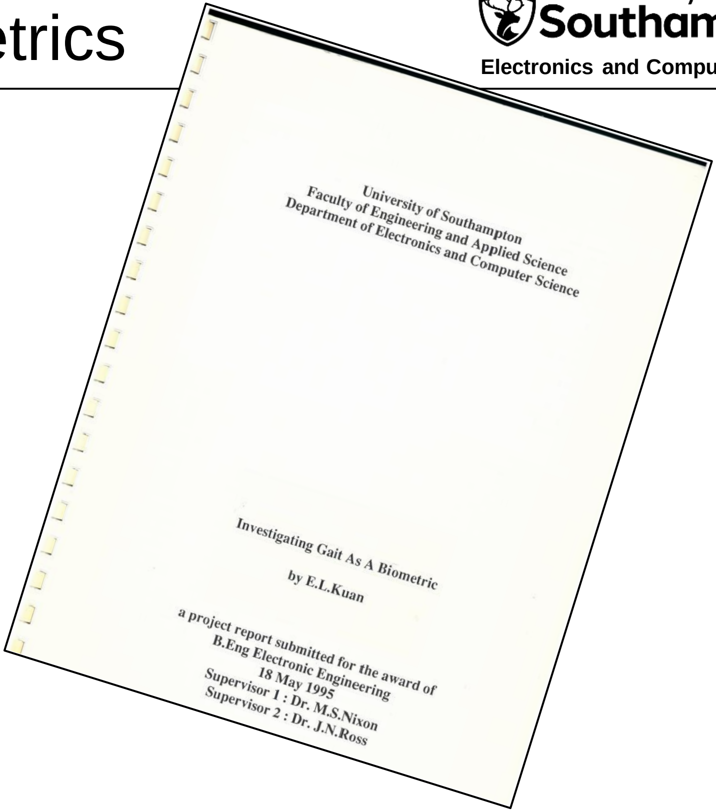
Input	Methods	NM	BG	CL	Mean
Skeleton	GaitGraph [7](CVPR2022)	82.0	73.2	63.6	72.9
	GaitMixer [6] (arXiv2022)	94.9	85.6	84.5	88.3
Silhouette	GaitSet [1](AAAI2019)	95.0	87.2	70.4	84.2
	GaitPart [2] (CVPR2020)	96.2	91.5	78.7	88.8
	GaitGL [5] (arXiv2022)	98.0	**95.4**	87.3	93.6
	GaitMSTP [3] (IJCB2022)	**98.2**	95.3	88.3	93.9
Multimodal	TransGait [4] (APPL INTELL2023)	98.1	94.9	85.8	92.9
	Combine [8] (ICASSP2023)	97.7	93.8	92.7	94.7
	TriGait (ours)	**98.2**	**95.4**	**94.3**	**96.0**

Sun et al, *IEEE IJCB*, 2023 = (ours)

A. Identifying people by their gait

1. Where are we now?
2. How did we get here?
3. Where are we going?

Gait biometrics


University of Southampton
Faculty of Engineering and Applied Science
Department of Electronics and Computer Science

Investigating Gait As A Biometric

by E.L.Kuan

a project report submitted for the award of
B.Eng Electronic Engineering
18 May 1995
Supervisor 1 : Dr. M.S.Nixon
Supervisor 2 : Dr. J.N.Ross

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

ABC News, July 13 2006

https://www.youtube.com/watch?v=6KuMe5n_jdQ

Technology in 1994

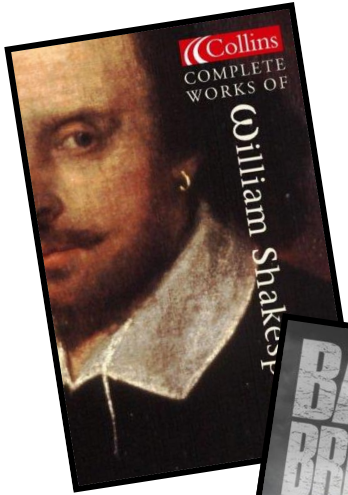
Gait and literature

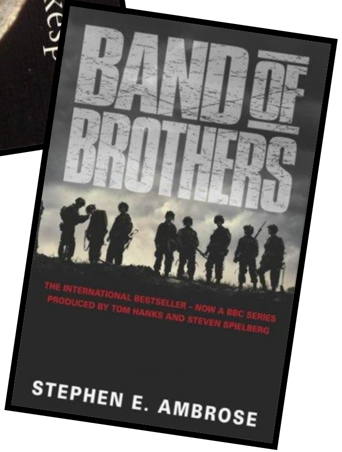
Dictionary: “manner of walking”

Shakespeare observed recognition:

> “High’st Queen of state; Great Juno comes; I know her by her gait” [The Tempest]
>
> “For that John Mortimer….in face, in gait in speech he doth resemble” [Henry IV/2]

Other literature: e.g. Band of Brothers: “I noticed this figure coming, and I realized it was John Eubanks from the way he walked”



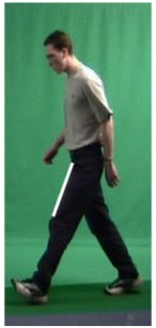


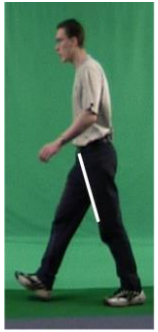
Early data

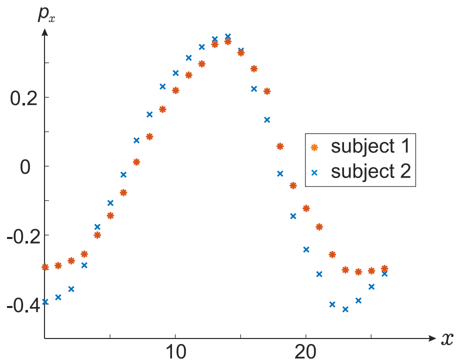



- 6 subjects; 7 sequences
- Sony Hi8 video camera
- Circular track ….exhausted subjects?
- We used a police digital video recorder

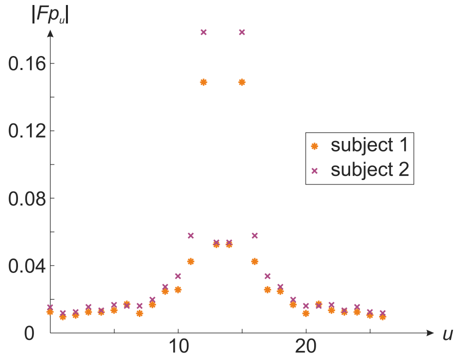
Model-based recognition



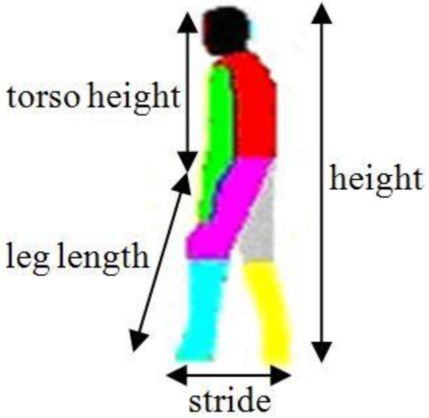




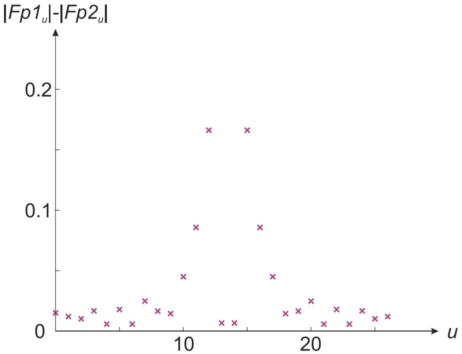
Inclination of thigh



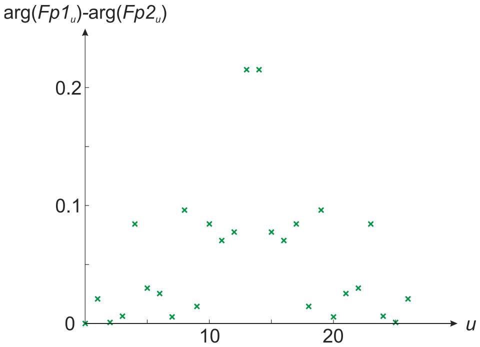
Magnitude of DFT



Other models are possible



Difference between magnitude



Difference between phase

D Cunado, MS Nixon, JN Carter, Proc. AVBPA, 1997

Using silhouettes

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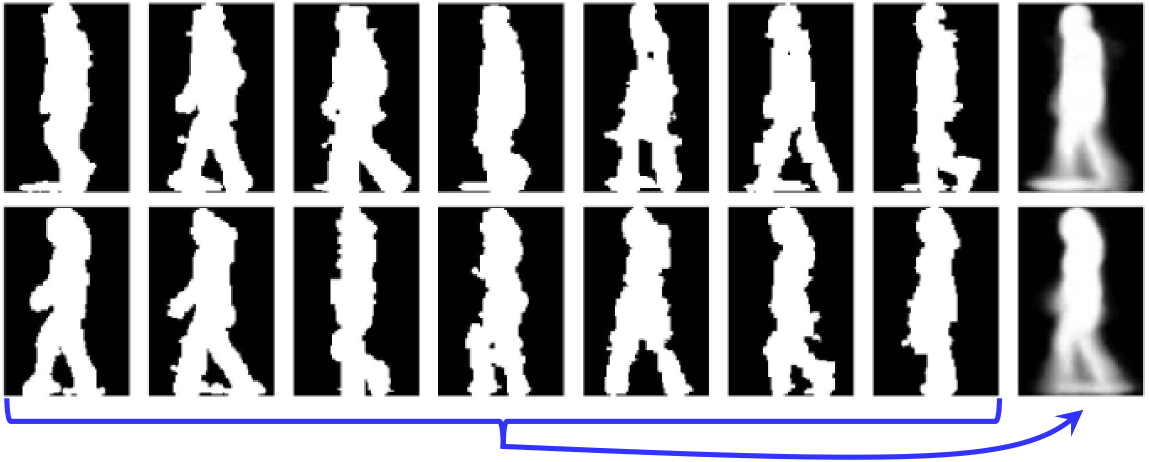
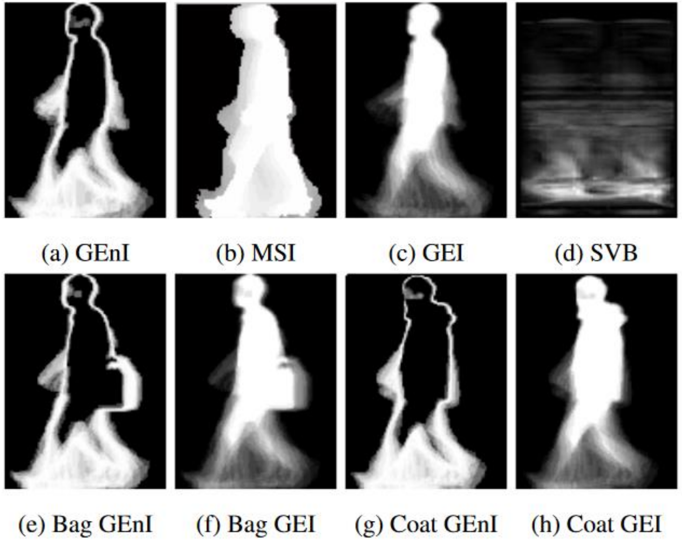
Some names: average silhouette, GEI



Gait Energy Image

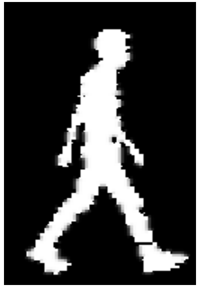


Gait Entropy Image

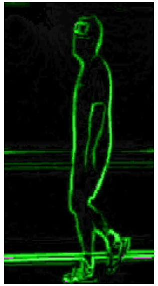
J Han, B Bhanu, *IEEE TPAMI*, 2005

Many gait representations possible

Recognising people from the motion of the whole body



silhouette

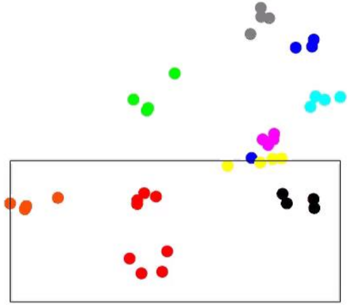


edges

flow

symmetry

acceleration



feature space

MS Nixon, T Tan, R Chellappa, Springer, 2005

DARPA's Human ID at a Distance

S Sarkar, PJ Phillips, Z Liu, IR Vega, P Grother, KW Bowyer, *IEEE TPAMI* 2005

Does gait biometrics really work?

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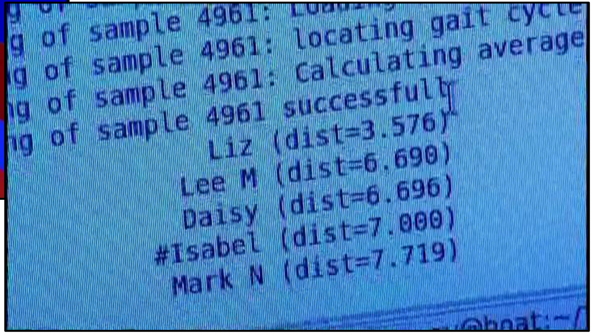

https://www.youtube.com/watch?v=PUwlNc0xAgQ

BBC1 Bang Goes the Theory Episode 1, 2009

Time for a quiz….

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Given
1. A laboratory environment; and
2. A silhouette


What is unusual about this person’s appearance

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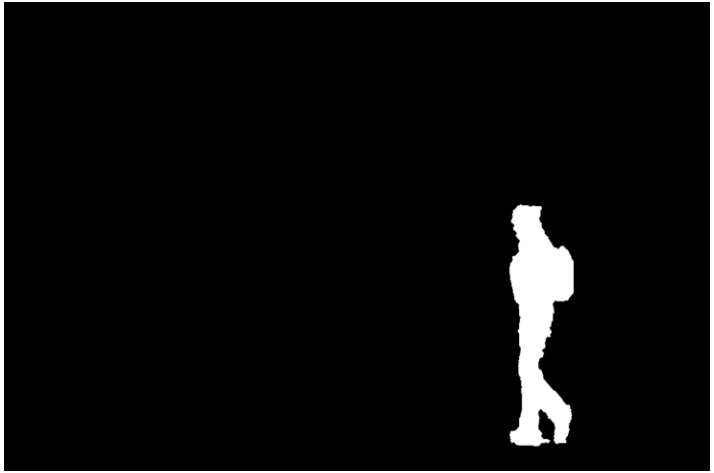
From the silhouette:
1. She was wearing Wellington boots
2. She was carrying a bag
3. She was filming for the hunchback of Notre Dame

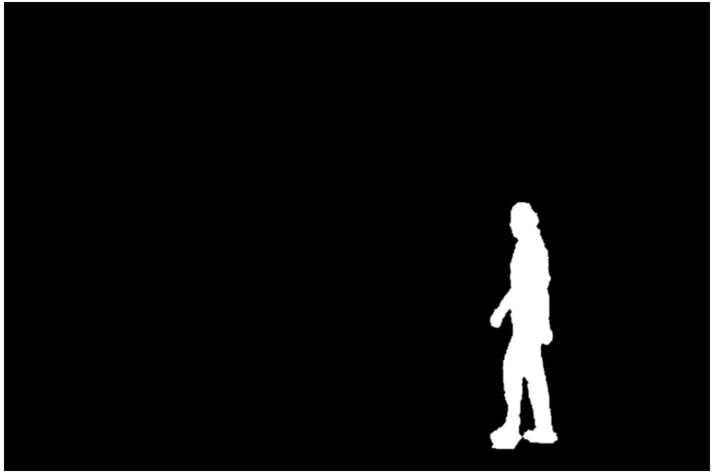


And ladies wear…

1. A rubbish bag
2. A dress
3. A coat

What is unusual this person's gait

1. The floor
2. Their footwear
3. Their clothing



Major difficulty 1 - viewpoint

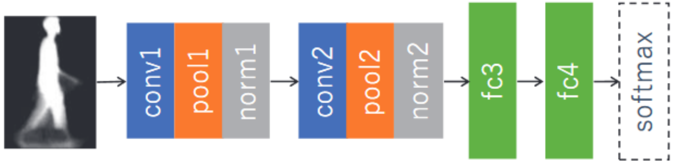
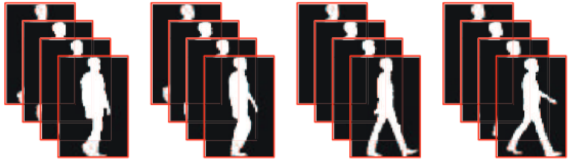


Figure 1: The structure of GEINet.

Table 1: Layer configurations for GEINet. Act. denotes the activation function.

Layer	#Kernels	Size/stride	Act.	Pooling
conv1	18	7×7×1/1	ReLU	
pool1		2×2/2		Max pooling
conv2	45	5×5×18/1	ReLU	
pool2		3×3/2		Max pooling



55 deg 65 deg 75 deg 85 deg

Figure 2: Examples of gait image sequences with four observation views in the OU-ISIR dataset

Gallery view	Method	Probe view 55	65	75	85
55	GEINet	(94.7)	**93.2**	**89.1**	***79.9***
	w/ FDF	(92.7)	***91.4***	***87.2***	**80.0**
	TCM+		79.9	70.8	54.5
	wQVTM		78.3	64.0	48.6

Shiraga, Makihara and Muramatsu ICB 2016

Major difficulty 2 - covariates

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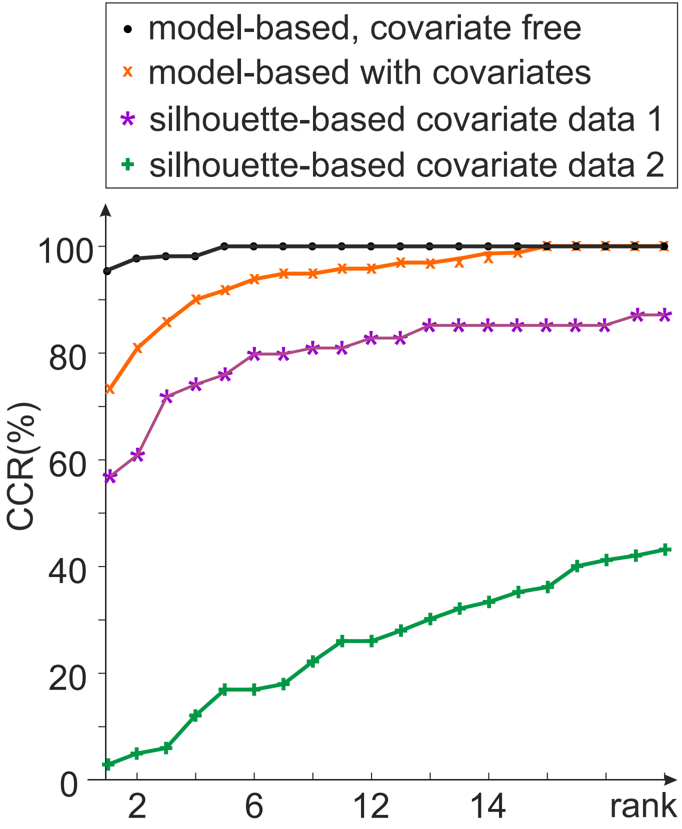

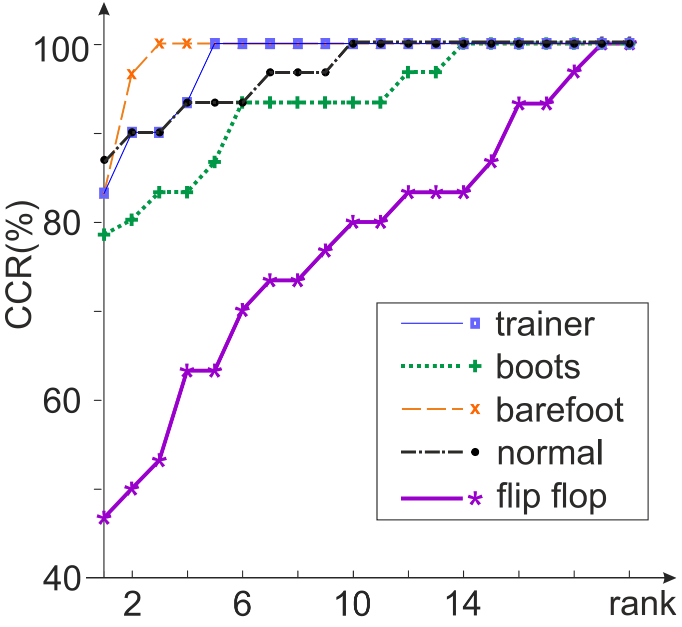

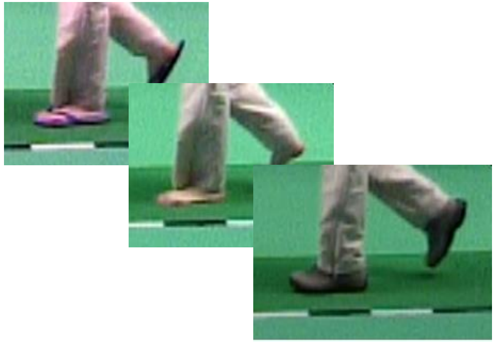

Major difficulty 3 - time

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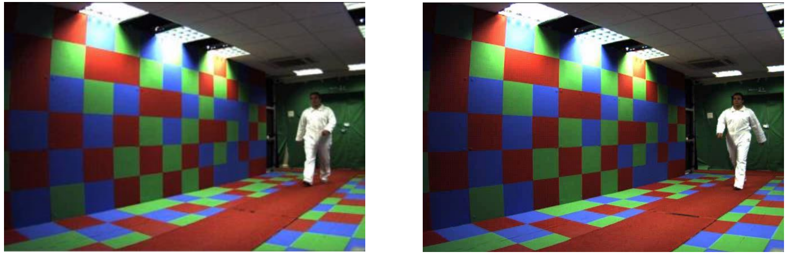
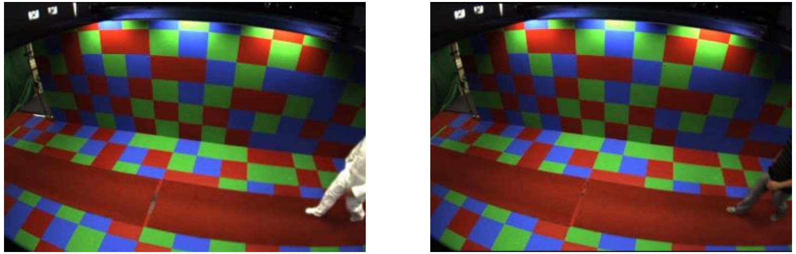
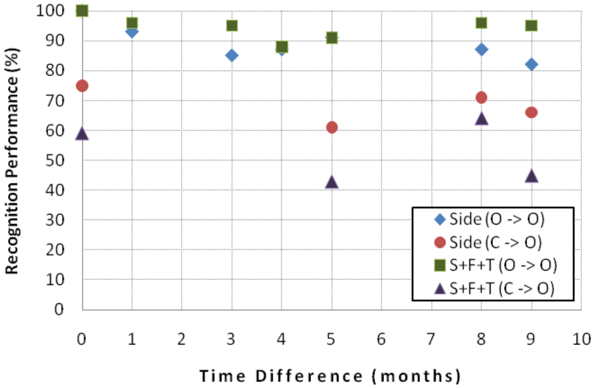


Nine months difference



Few minutes apart, different clothes



Matovski and Nixon, *Proc. IEEE BTAS 2010*, *IEEE TIFS* 2012

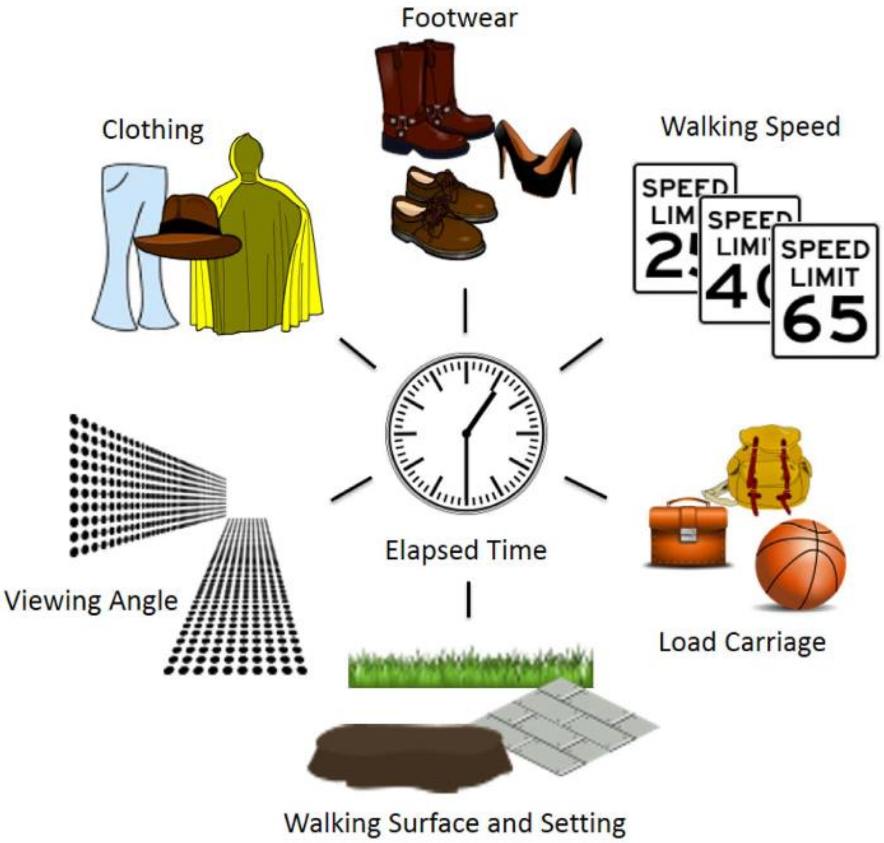
Identity science

Science/ technology

- Covariates and exploratory variables
- Soft biometrics
- Spoofing
- Deep architectures

Applications

- Medicine (dementia, balance, falls)
- Sports
- Security
- Marketing



Non video gait

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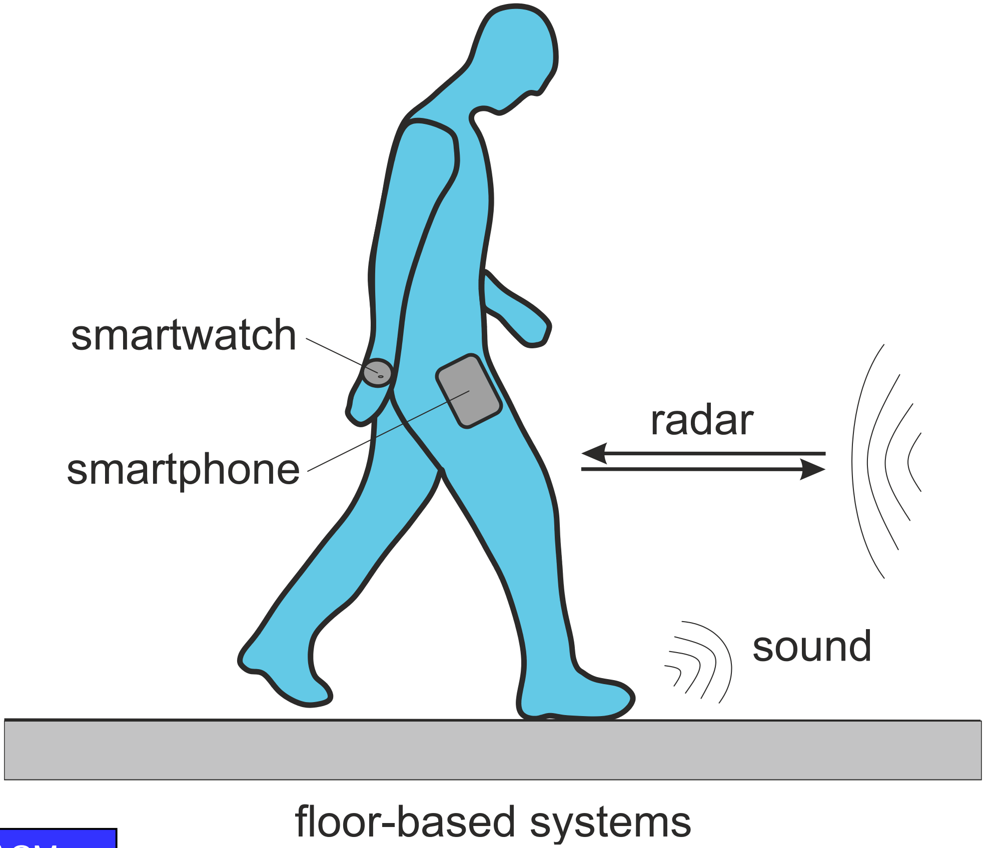
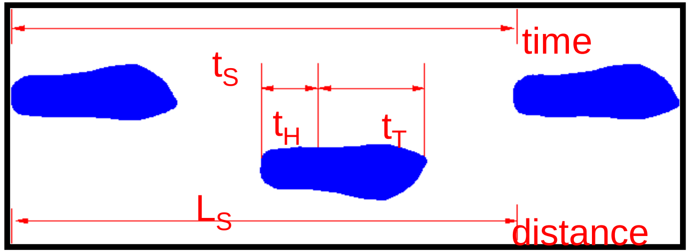
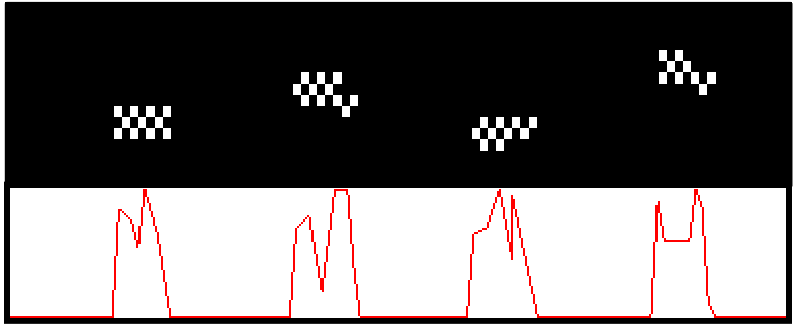


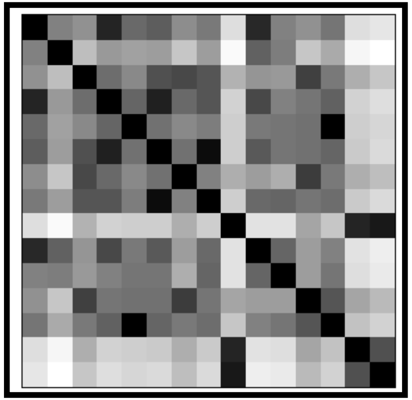
MD Marsico, A Mecca - ACM Computing Surveys (CSUR), 2019

The first intelligent carpet

192×32 binary sensor array







Middleton, Buss and Nixon, *AutoID* 2005

3D recognition – marionette based

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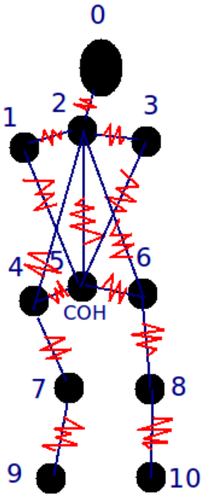
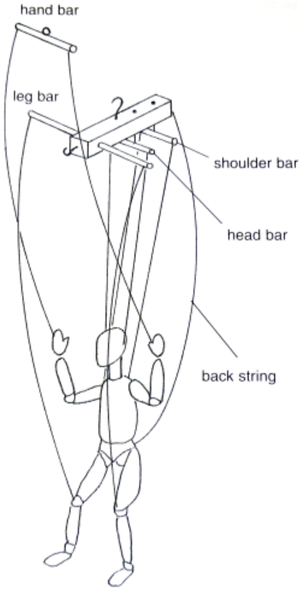
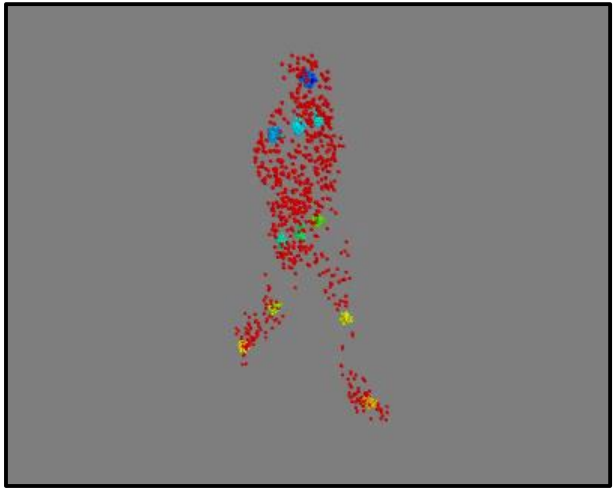






3D is completely viewpoint invariant

Ariyanto and Nixon, Proc. ICB 2013

Gait as evidence – first use

Bag snatcher, London 2008

Note controlled trajectory

Using gait as evidence -database

Use multiview gait data

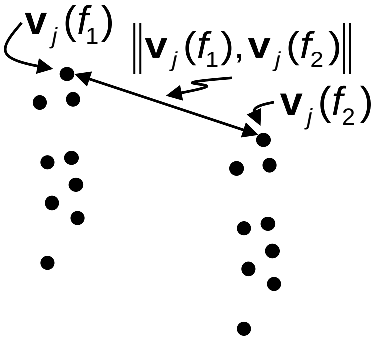
CASIA B at the time

*

with automated labelling

Wang, Ning, Hu, Tan, *Proc. ICPR* 2002

Gait as evidence -approach



Match measure for subject, *N* vertices in *W* frames

$$d = \sum_{f_1,f_2 \in W | f_1 \neq f_2} \sum_{j,k \in N} \left\|\mathbf{v}_j(f_1), \mathbf{v}_j(f_2)\right\| \Big/ (N \times W)$$

Analysis from database, *S* subjects

Within class $$d_w = \left(\sum_{s \in database} \sum_{f_1,f_2 \in W | f_1 \neq f_2} \sum_{j,k \in N} \left\|\mathbf{v}_j(f_1,s), \mathbf{v}_j(f_2,s)\right\| \Big/ (N \times W) \right) \Big/ S$$

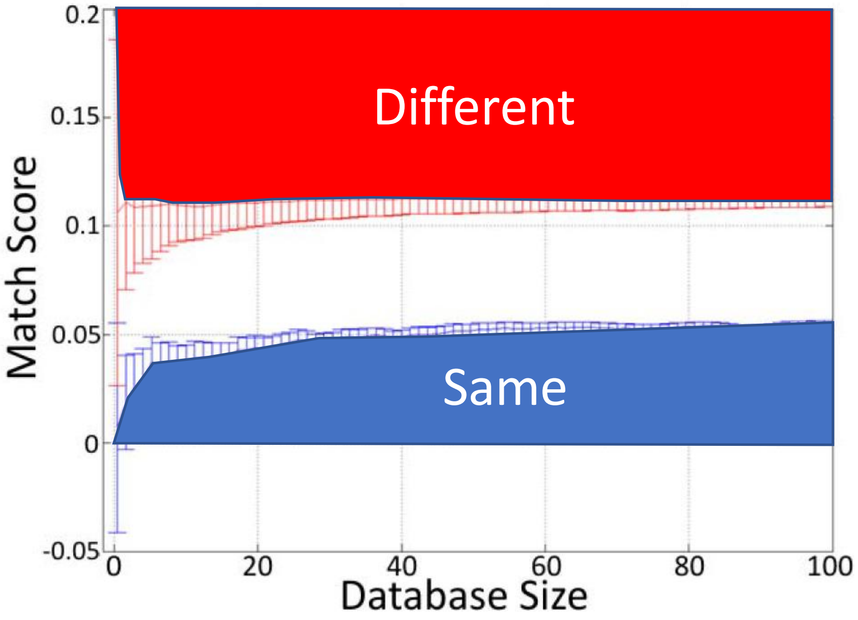
Between class $$d_b = \left(\sum_{s1,s2 \in database | s1 \neq s2} \sum_{f_1,f_2 \in W | f_1 \neq f_2} \sum_{j,k \in N} \left\|\mathbf{v}_j(f_1,s_1), \mathbf{v}_j(f_2,s_2)\right\| \Big/ (N \times W) \right) \Big/ S\text{ -1}$$

Confidence = $$\left(mean(d_b) + mean(d_w)\right) \Big/ \left(range(d_b) + range(d_w)\right)$$

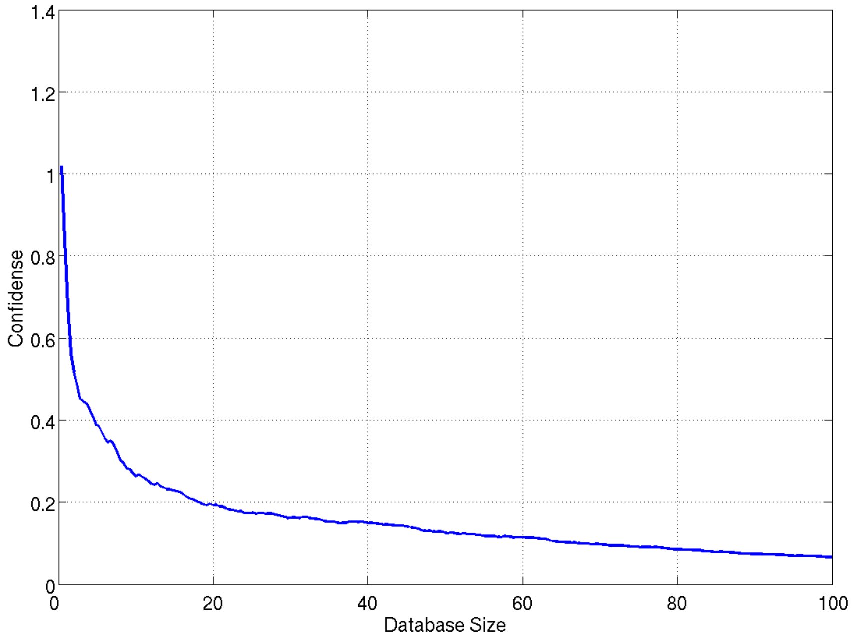
Match success = $$d \subset range(d_i)$$

Bouchrika, Nixon, Carter, *J. Forensic Science* 2011, and *Eusipco* 2010

Gait as evidence –analysis on database



Distances



Confidence

Gait as evidence: murder case in Australia 2014

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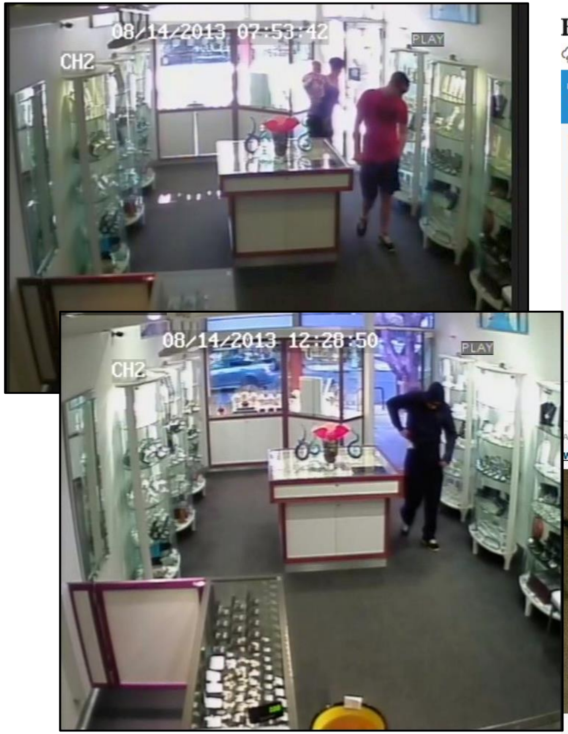
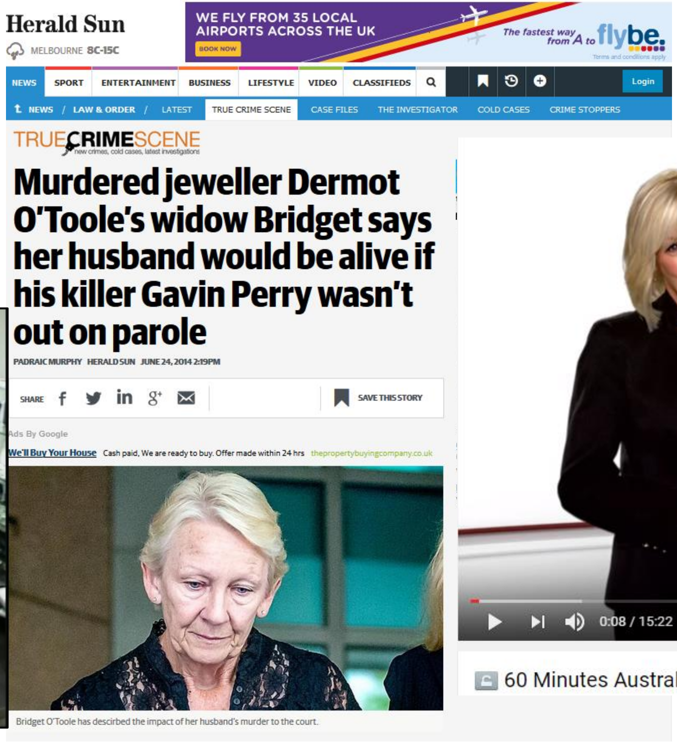



Herald Sun
MELBOURNE 8C-15C

NEWS SPORT ENTERTAINMENT BUSINESS LIFESTYLE VIDEO CLASSIFIEDS Login

NEWS / LAW & ORDER / LATEST TRUE CRIME SCENE CASE FILES THE INVESTIGATOR COLD CASES CRIME STOPPERS

TRUE CRIME SCENE

Murdered jeweller Dermot O'Toole's widow Bridget says her husband would be alive if his killer Gavin Perry wasn't out on parole

PADRAIC MURPHY HERALD SUN JUNE 24, 2014 2:19PM

SHARE SAVE THIS STORY

Bridget O'Toole has described the impact of her husband's murder to the court.

60 Minutes Australia: Eye Catching

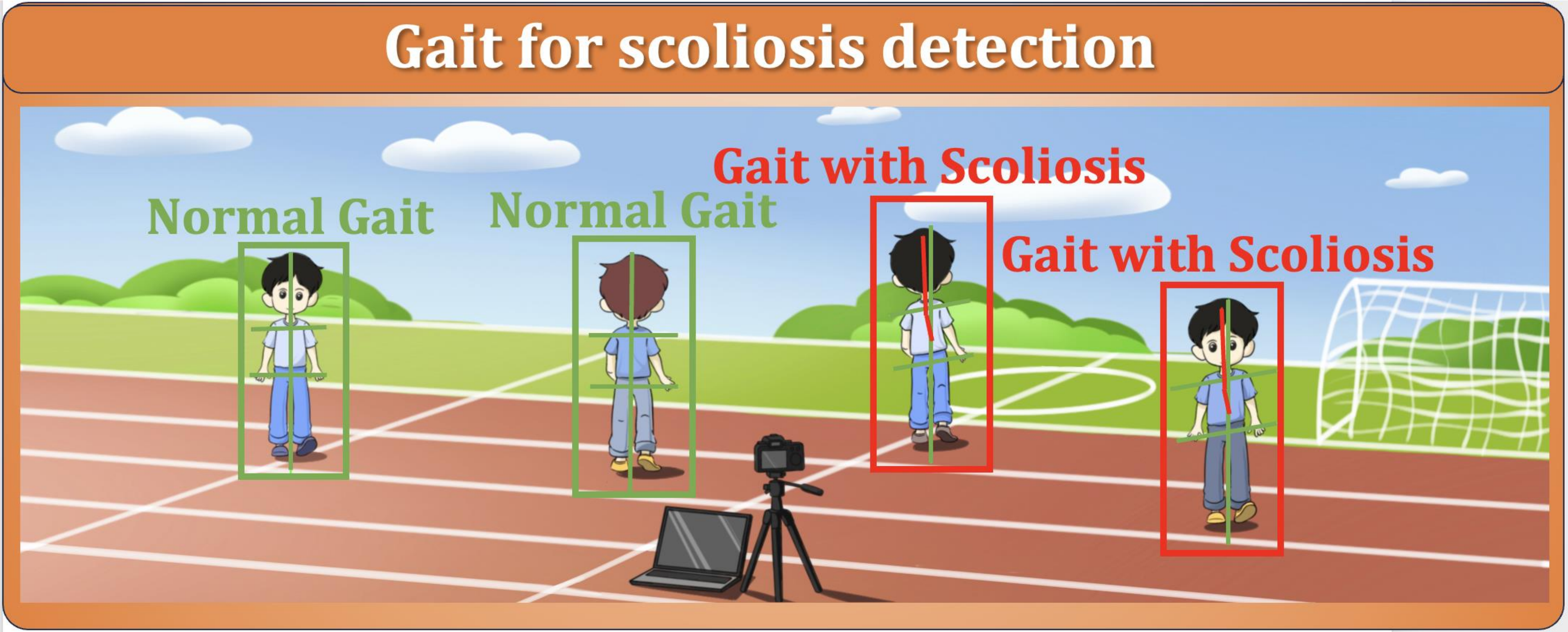
Bouchrika, Nixon, Carter, *J. Forensic Science* 2011, and *Eusipco* 2010

https://www.youtube.com/watch?v=F1b_apXjjV0&feature=youtu.be

Gait for scoliosis detection

Shiqi

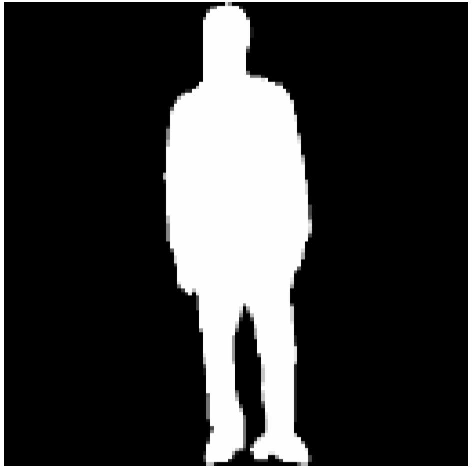
南方科技大学 SOUTHERN UNIVERSITY OF SCIENCE AND TECHNOLOGY

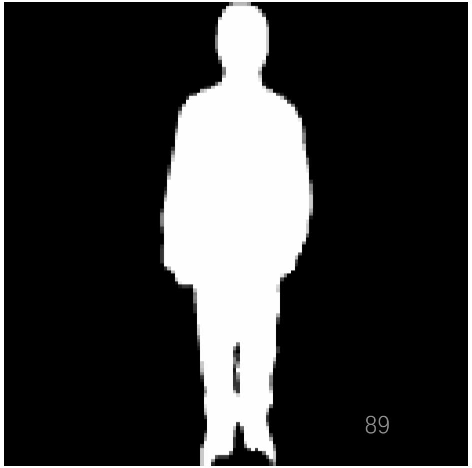


Scoliosis1K Dataset

- The first gait-based large dataset for scoliosis

Attributes	All	Positive	Neutral	Negative
Participants	**1050**	176	82	792
Sequences	1493	493	200	800
Sex (F/M)	641/409	113/63	49/33	479/313
Age (years)	15.2	14.3	14.0	15.5
Height (cm)	163.2	161.6	161.4	163.7
Weight (kg)	51.9	48.3	46.7	53.3



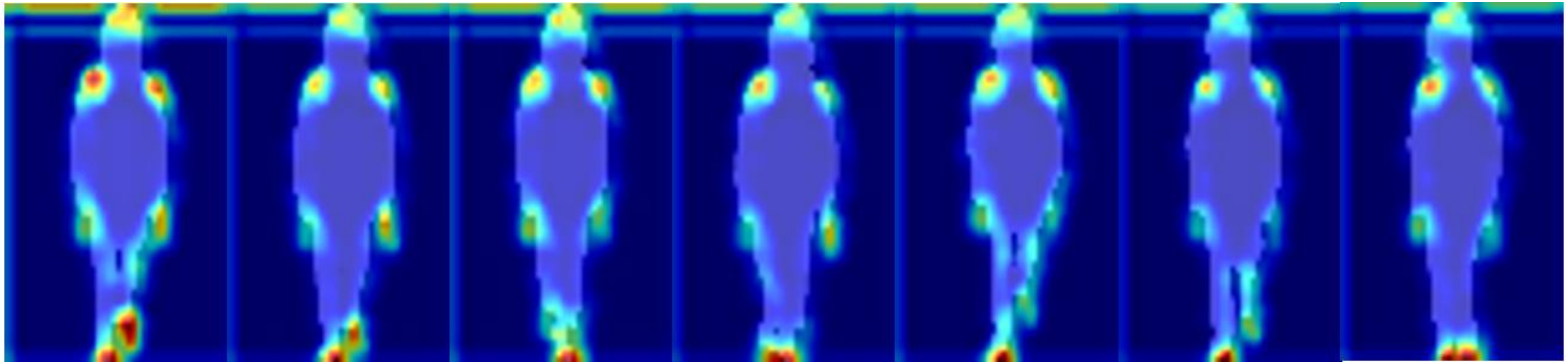


Experimental results

Shiqi

Method	Accuracy	Sensitivity	Specificity
Adams Test [3]	-	84.4%	**95.2%**
Scoliometer [3]	-	90.6%	79.8%
ScoNet (Ours)	51.3%	**100.0%**	33.2%
ScoNet-MT (Ours)	**82.0%**	99.0%	76.5%

ScoNet-MT



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Future work

- Deep and explainability
- Other covariates
- Medical issues
- Behaviour analysis
- Performance evaluation with low quality low resolution

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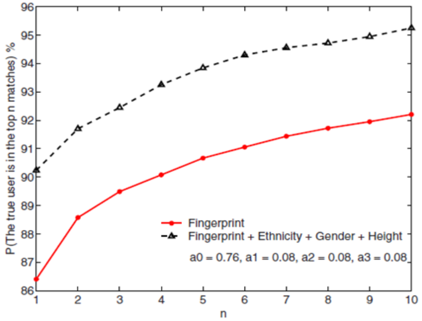
B Soft Biometrics

1. What are they?
2. How do they work?
3. Where are we going?

Soft Biometrics

Bertillonage 1890
(body, face, iris, ear, nose…)

Nandakumar and Jain 2004
(augmenting traditional biometrics



Adapted from
Ross and Nixon
Soft Biometrics
Tutorial
BTAS 2016

Face Soft
Attribute
Kumar, Klare, Zhang, Gonzalez-Sosa
Relative Attribute
[Graumann], Reid, Almudhahka,

Body Soft
Categorical
Samangooei
Comparative
Reid, Martinho-Corbishley

Other Soft
Tattoos Lee
Clothing Jaha
Makeup Dantcheva
Eyes & glasses
Mohammed
Hair Proenca

Applications: performance, identification, marketing, fashion …..

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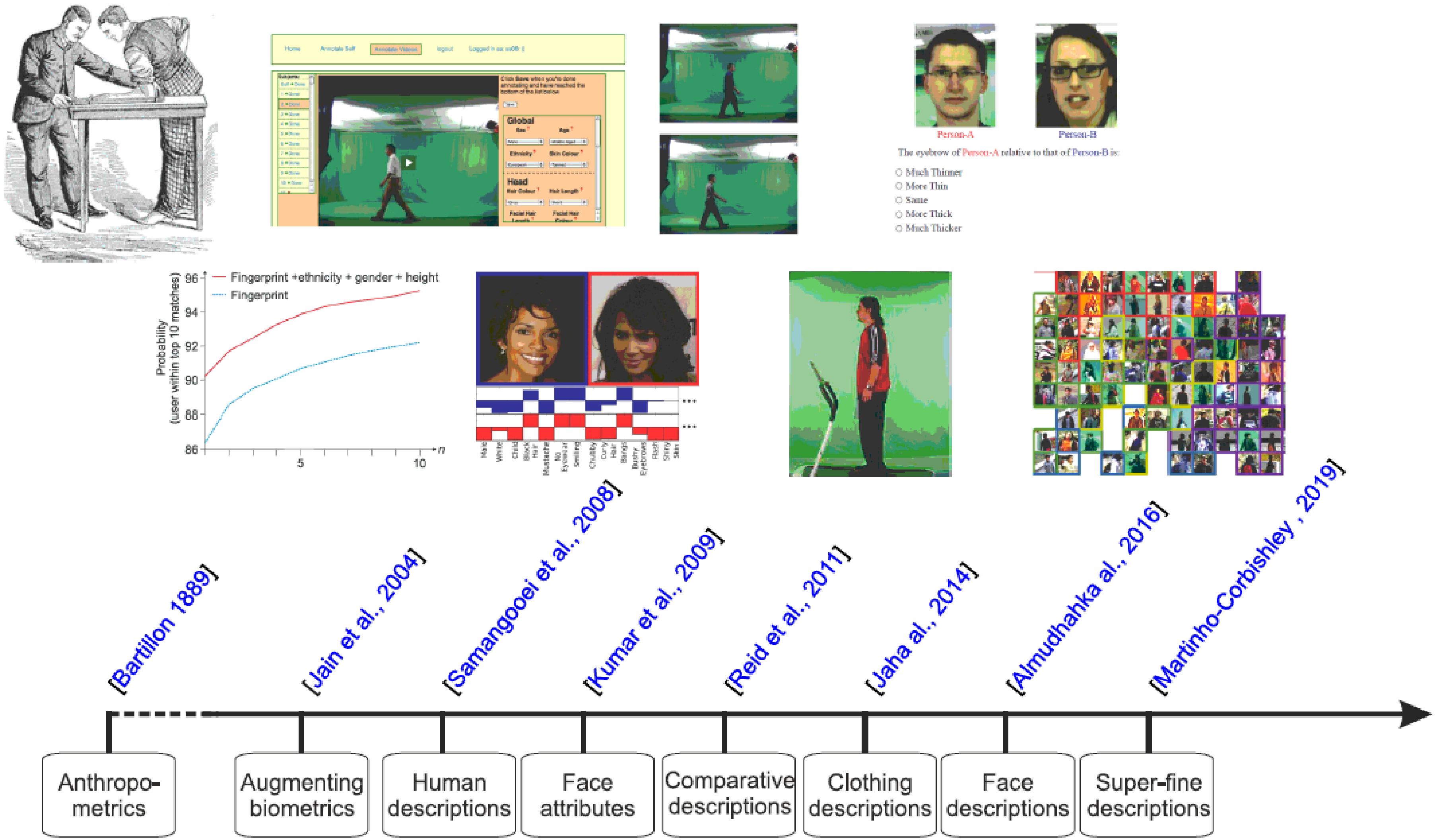


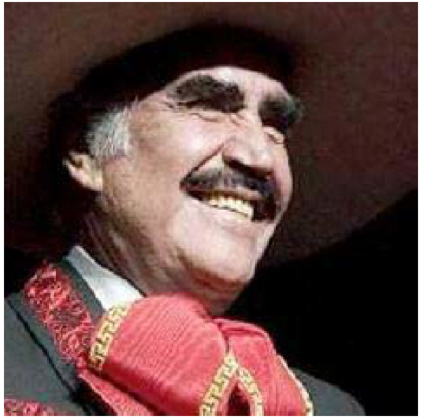
Person-A
Person-B
The eyebrow of Person-A relative to that of Person-B is:
Much Thinner
More Thin
Same
More Thick
Much Thicker
Fingerprint +ethnicity + gender + height
Fingerprint
Probability (user within top 10 matches)
96
94
92
90
88
86
5
10
n
Male
White
Child
Black Hair
Mustache
No Eyewear
Smiling
Chubby
Curly Hair
Bangs
Bushy Eyebrows
Flash
Shiny Skin
[Bartillon 1889]
[Jain et al., 2004]
[Samangooei et al., 2008]
[Kumar et al., 2009]
[Reid et al., 2011]
[Jaha al., 2014]
[Almudhahka al., 2016]
[Martinho-Corbishley , 2019]
Anthropo-metrics
Augmenting biometrics
Human descriptions
Face attributes
Comparative descriptions
Clothing descriptions
Face descriptions
Super-fine descriptions

Soft biometrics – the state of art

Technique: predominantly deep

Data: Maad-face, Annotated pedestrians

Applications: face (esp with masks), privacy, forensics?



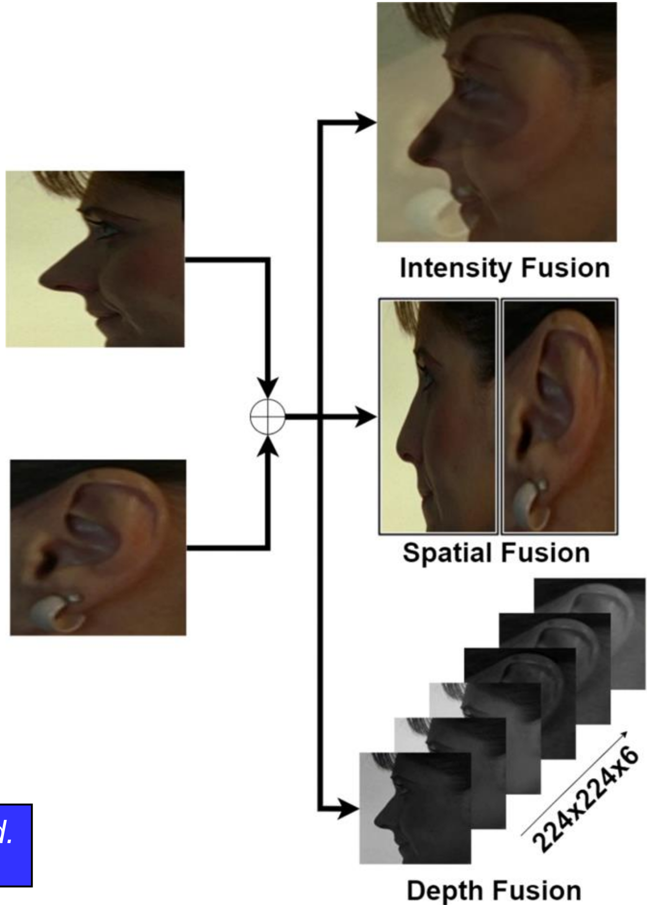
Male	1	Bangs	-1	Round Face	0	Big Lips	0
Young	-1	Sideburns	1	Double Chin	1	Big Nose	1
Middle Aged	-1	Black Hair	0	High Cheekbones	0	Pointy Nose	-1
Senior	1	Blond Hair	-1	Chubby	1	Heavy Makeup	-1
Asian	-1	Brown Hair	-1	Obstructed Forehead	1	Wearing Hat	1
White	0	Gray Hair	1	Fully Visible Forehead	-1	Wearing Earrings	-1
Black	-1	No Beard	-1	Brown Eyes	0	Wearing Necktie	-1
Rosy Cheeks	0	Mustache	1	Bags Under Eyes	0	Wearing Lipstick	-1
Shiny Skin	1	5 o Clock Shadow	-1	Bushy Eyebrows	1	No Eyewear	1
Bald	-1	Goatee	-1	Arched Eyebrows	-1	Eyeglasses	-1
Wavy Hair	-1	Oval Face	-1	Mouth Closed	0	Attractive	-1
Receding Hairline	0	Square Face	1	Smiling	0		

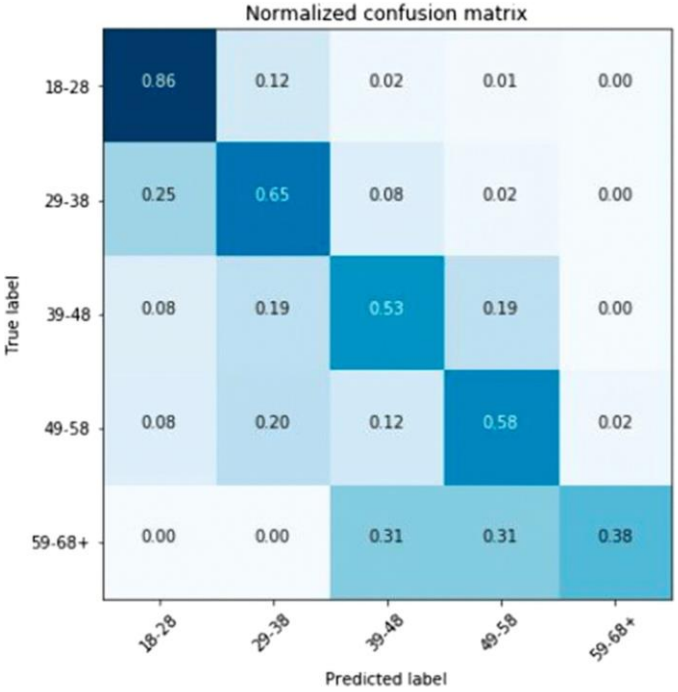
Terhörst et al, *IEEE TIFS* 2021

See also Terhörst et al. On Soft-Biometric Information Stored in Biometric Face Embeddings, *IEEE TBIOM* 2021

Multimodal soft biometrics: combining ear and face biometrics for age and gender classification

Convnet based
Age 67%
Gender 98%





Age confusion

Yaman et al, *Mult. Med. Tools. Apps* 2022

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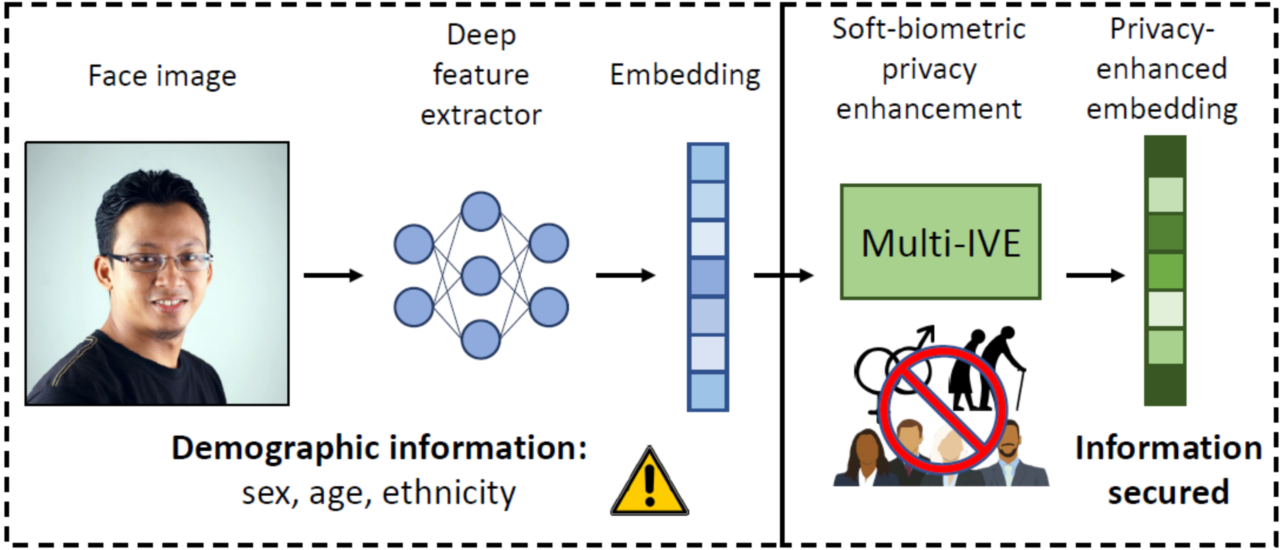
Multi-IVE: Privacy Enhancement of Multiple Soft-Biometrics in Face Embeddings

Incremental Variable Elimination to secure multiple soft biometric attributes simultaneously

Identify and discard multiple soft-biometric attributes contained in face embeddings



Melzi et al, *CVPR Workshop* 2023

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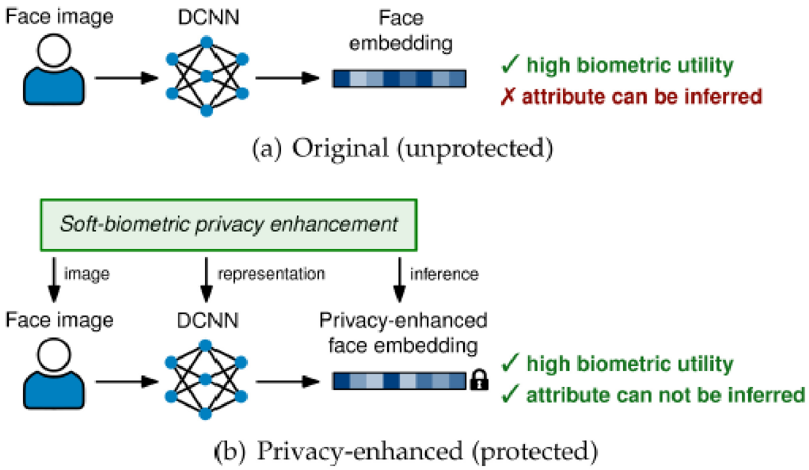
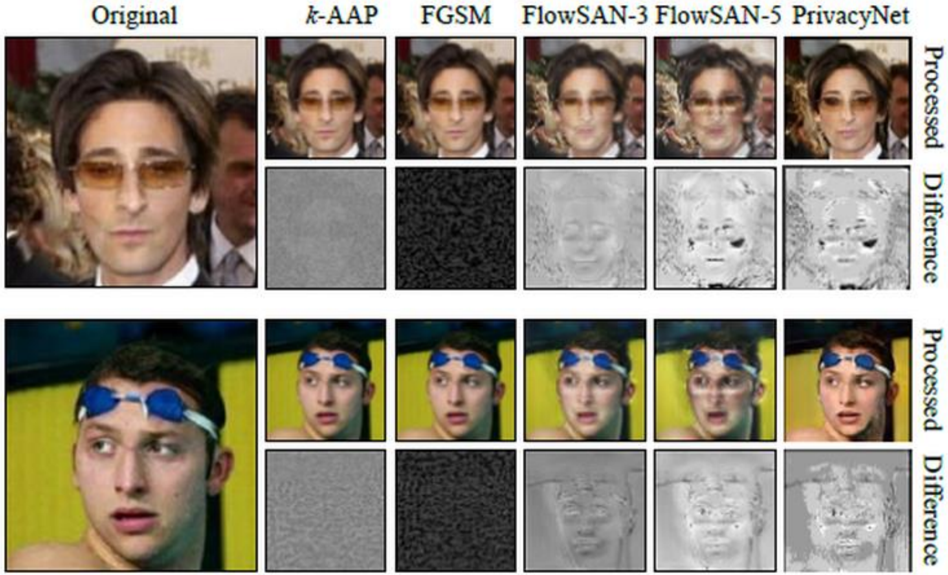
PrivacyProber: Assessment and Detection of Soft–Biometric Privacy–Enhancing Techniques





Adding privacy enhancement

Rot, Grm, and Struc, *IEEE TDSC*, 2023 +
Osoriao-Roig et al , *IEEE TBIOM* 2022

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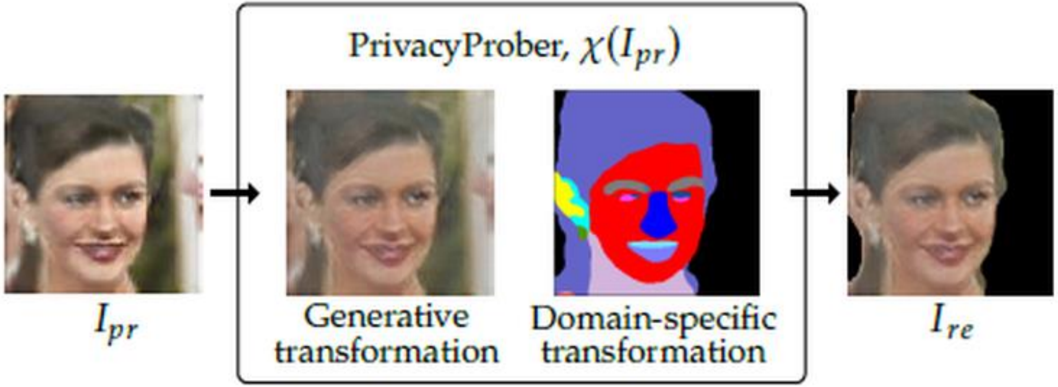
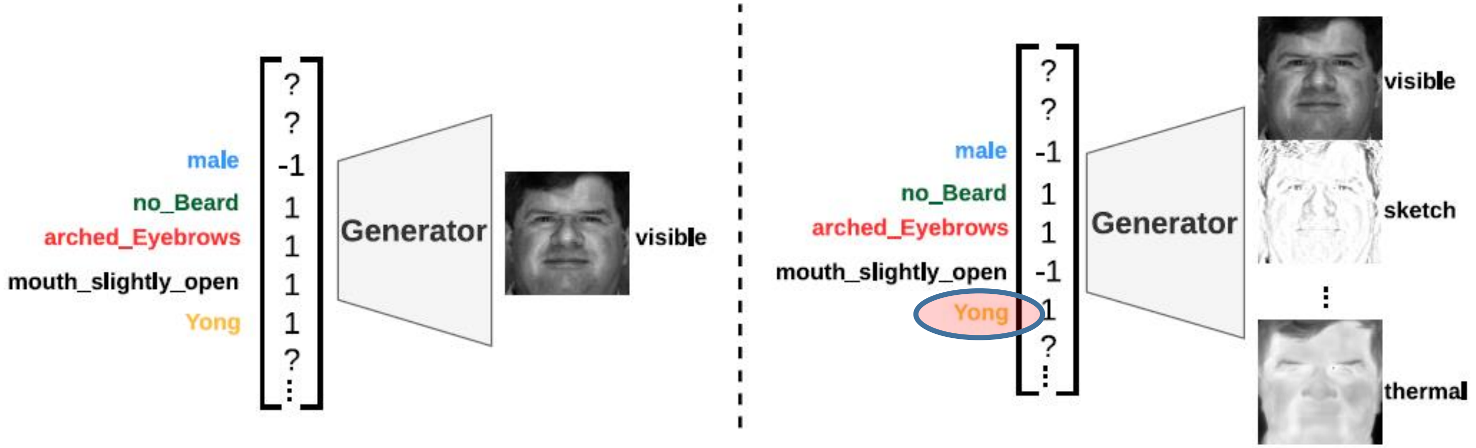
PrivacyProber: Assessment and Detection of Soft–Biometric Privacy–Enhancing Techniques



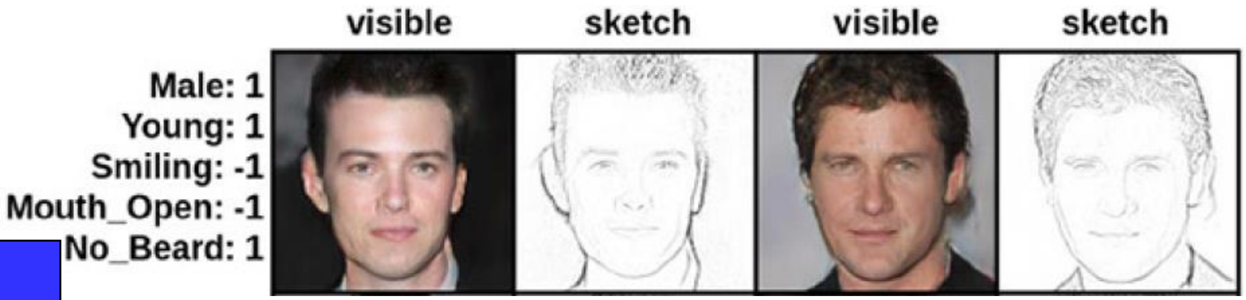
Detecting privacy enhancement

Rot, Grm, and Struc, *IEEE TDSC*, 2023 +
Osorio-Roig et al , *IEEE TBIOM* 2022

Multimodal Face Synthesis From Visual Attributes



(a) Unimodal synthesis (b) Multimodal synthesis



Di and Patel, *IEEE TBIOM*, 2021

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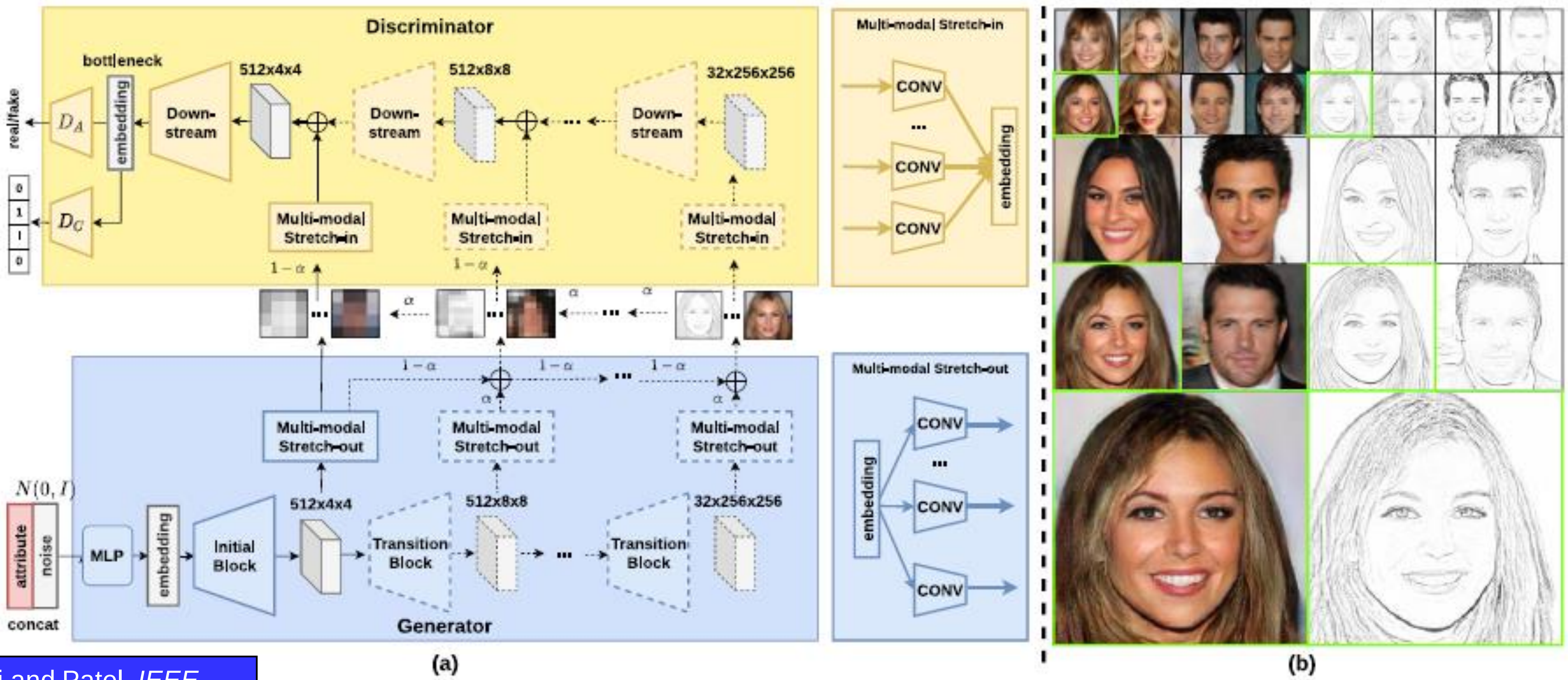
Multimodal Face Synthesis From Visual Attributes

Xing Di and Vishal M. Patel (JHU)



Di and Patel, *IEEE TBIOM*, 2021

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What can you recognise?

64×97

128×194

256×386

Recognition by fine-grained attributes

Database of images

Set of labels

Crowd sourced comparative labels

Ranking labels

Learning label structure

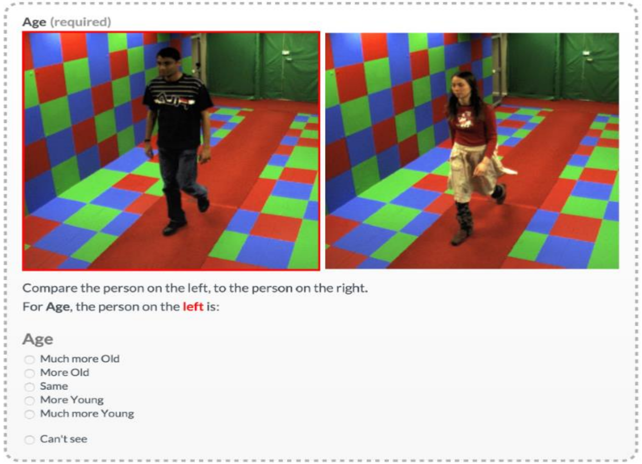
Recognise

1. Label the data

2. Turn the data into features

3. Learn how recognition can be achieved

4. Generate new labels



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Traits and terms

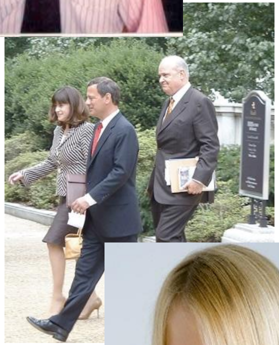
Global Features

- Features mentioned most often in witness statements
- Sex and age quite simple
- Ethnicity
  - Notoriously unstable
  - There could be anywhere between 3 and 100 ethnic groups
  - 3 "main" subgroups plus 2 extra to match UK Police force groupings

Samangooei, Guo and Nixon, *IEEE BTAS* 2008

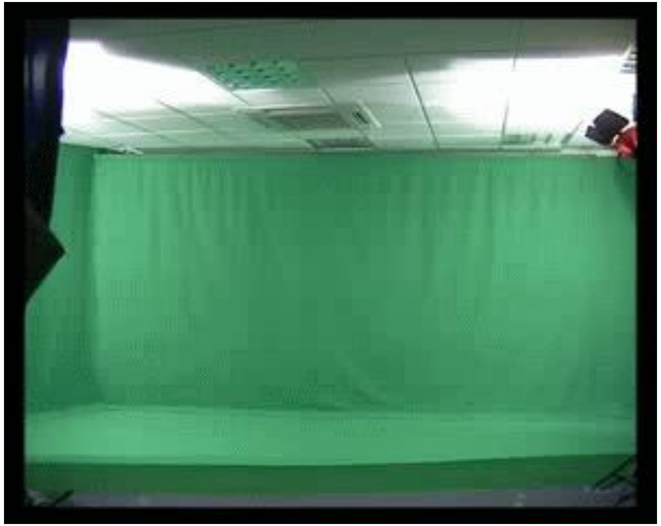
So we thought!!

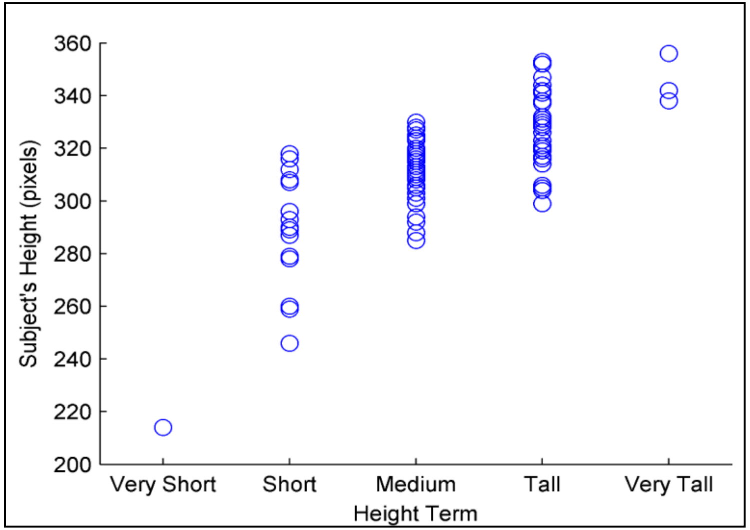
- Global
  - Sex
  - Ethnicity
  - Skin Colour
  - Age
- Body Shape
  - Figure
  - Weight
  - Muscle Build
  - Height
  - Proportions
  - Shoulder Shape
  - Chest Size
  - Hip size
  - Leg/Arm Length
  - Leg/Arm Thickness
- Head
  - Hair Colour
  - Hair Length
  - Facial Hair Colour/Length
  - Neck Length/Thickness



Problems with absolute descriptors

Subjective = unreliable; Categorical = lacks detail





Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

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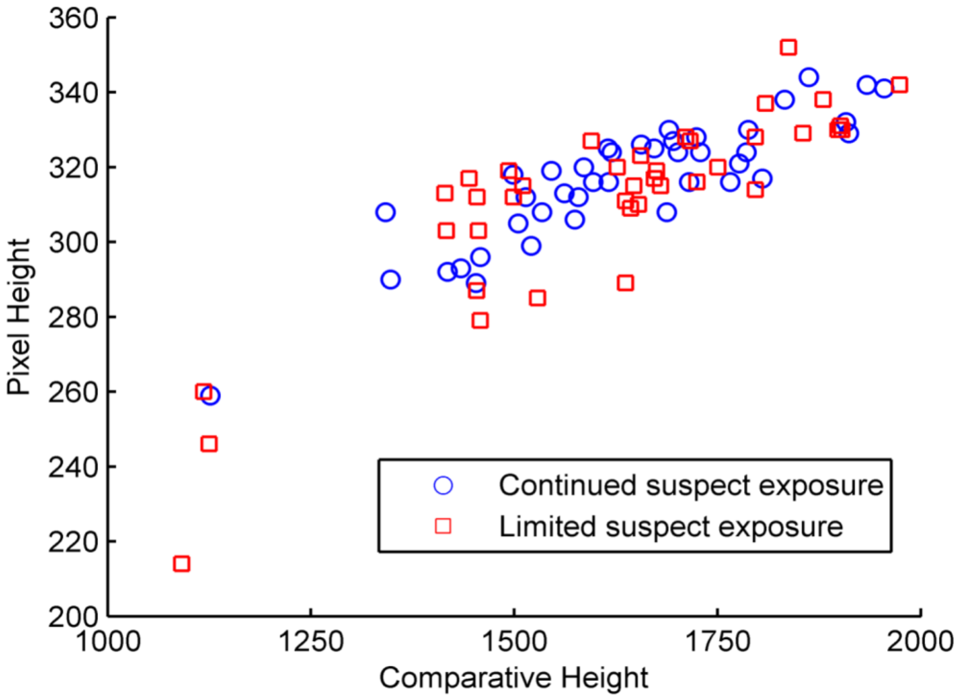
Comparative human descriptions

- Compare one subject's attribute with another's
- Infer continuous relative measurements

Reid and Nixon, IEEE
IJCB 2011; TPAMI 2015

Height correlation (with time)



Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

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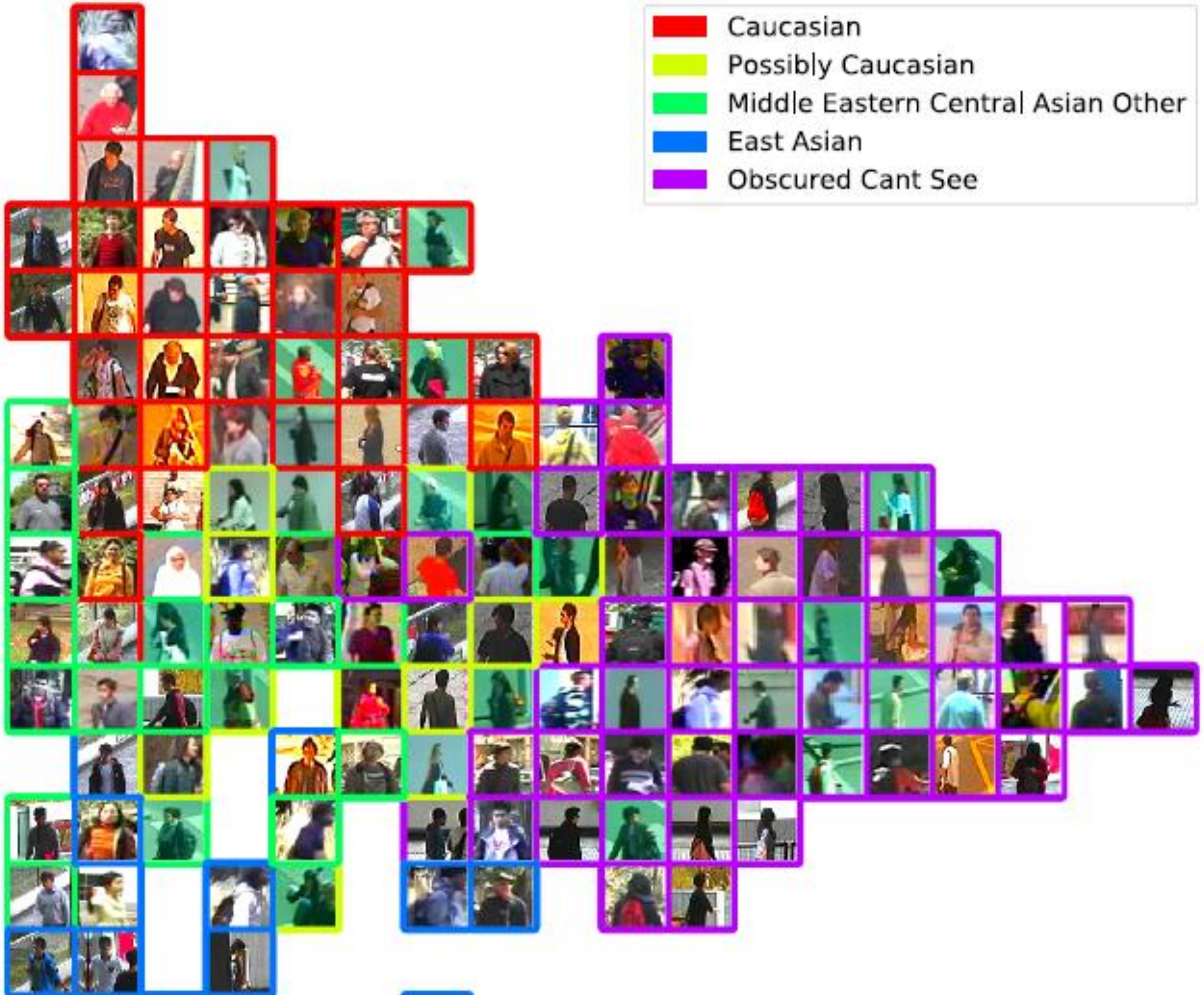
Ethnicity



Martinho-Corbishley, Nixon and Carter, *TPAMI* 2019

Gender Estimation on PETA

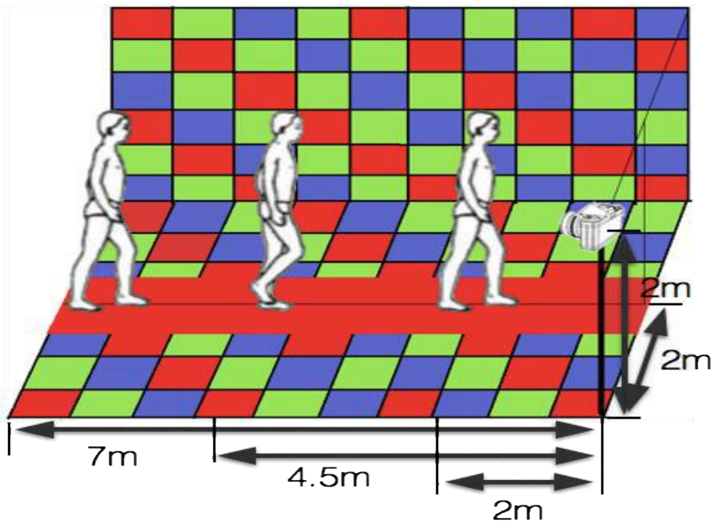
- Gender?

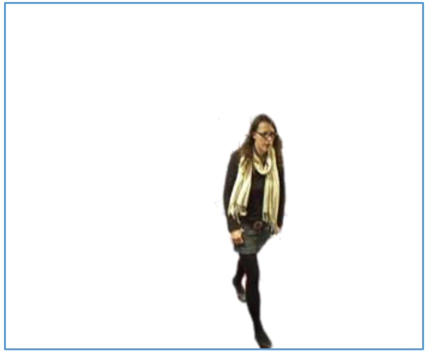
Subject	1	2	3
PETA image			
PETA label			A. Male B. Female

Martinho-Corbishley, Nixon and Carter, *Proc. BTAS 2016*

Soft biometric fusion – synthesised data

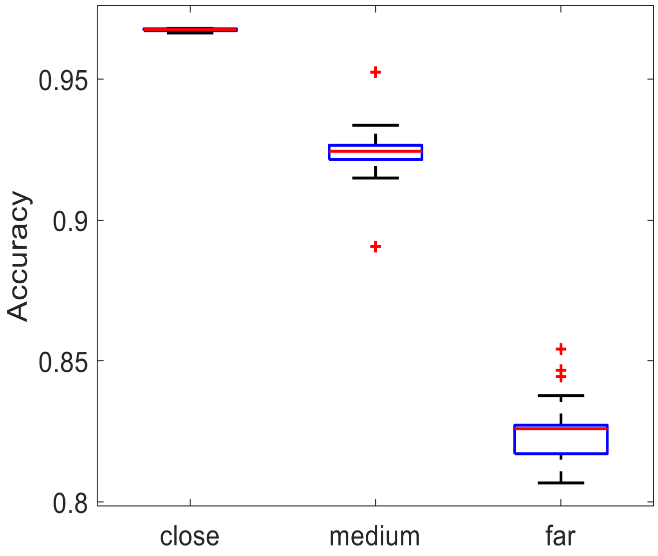
Gait tunnel

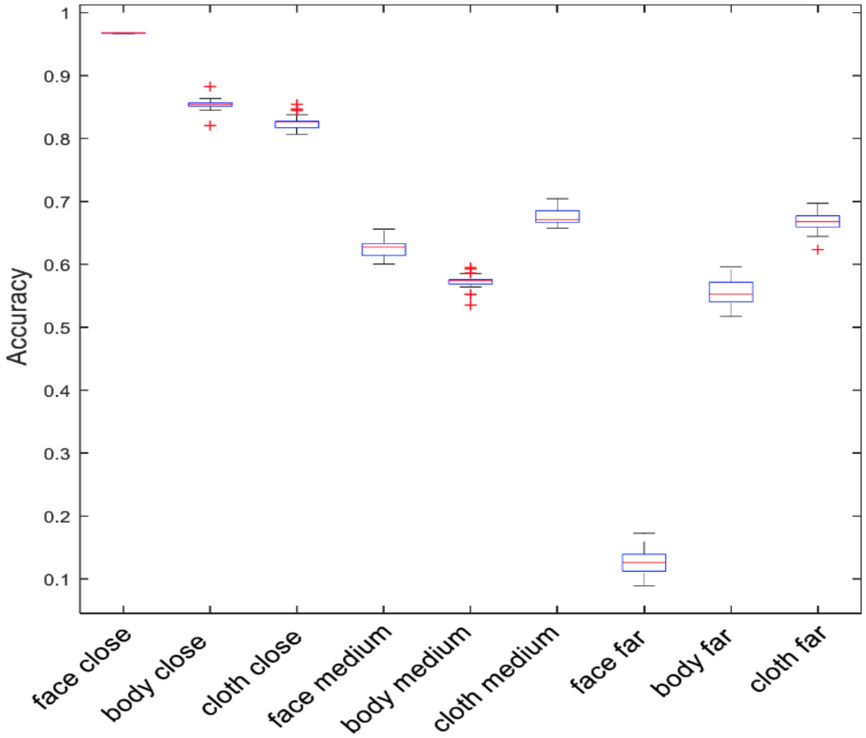




Guo, Nixon and Carter, *IEEE TBIOM* 2019

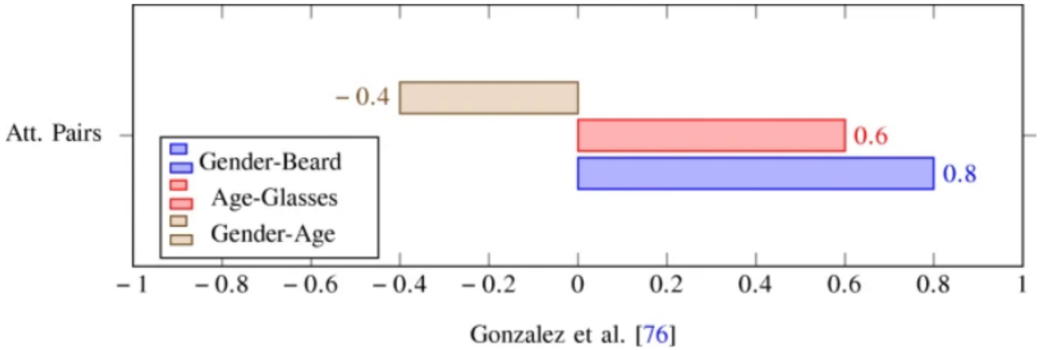
Fusion performance

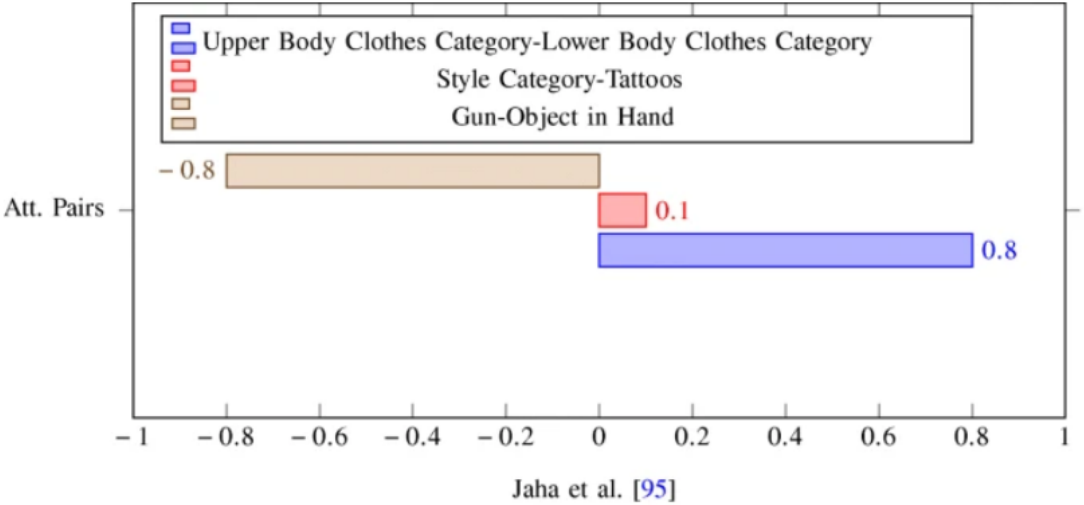




Guo, Nixon and Carter, *IEEE TBIOM* 2019

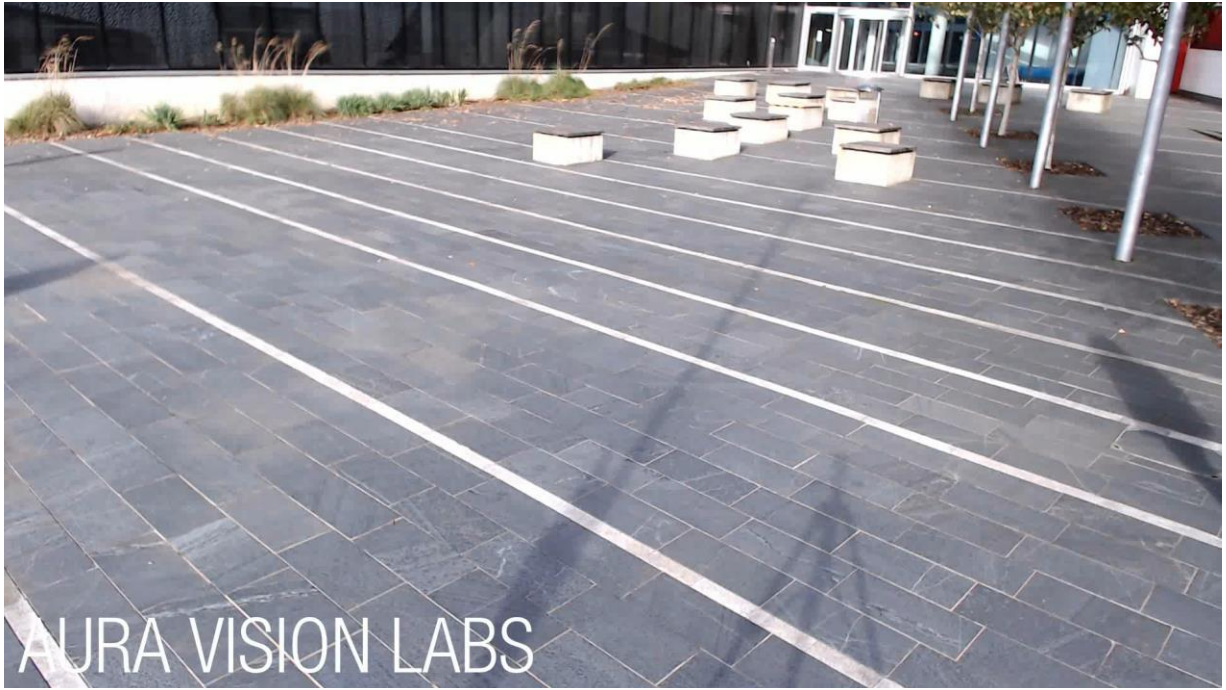
Exploiting correlation?





Hassan, Izquierdo et al MTA 2021

Biometrics and marketing …



https://vimeo.com/388480097

Conclusions

Yes, gait works, particularly with deep

Yes, we can use it in forensics?

Soft biometrics are newer, particularly human description

The technologies are grounded in science, literature, medicine + ….

Can we use deep in forensics?

We have more to learn, and learning architectures are not complete

Society still needs identification

Privacy/ ethics/ accuracy/ new technology?

And thanks to ….

University of Southampton
Electronics and Computer Science

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Selection of further reading on gait

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1. Using gait as a biometric, via phase-weighted magnitude spectra, D Cunado, MS Nixon, JN Carter, *Proc. AVBPA*, 1997
2. The humanid gait challenge problem: Data sets, performance, and analysis, S Sarkar, PJ Phillips, Z Liu, IR Vega…, *IEEE TPAMI*, 2005
3. Individual recognition using gait energy image, J Han, B Bhanu, *IEEE TPAMI*, 2005
4. Human identification based on gait, MS Nixon, T Tan, R Chellappa, Springer, 2005
5. The OU-ISIR gait database comprising the large population dataset and performance evaluation of gait recognition, M Okumura, Y Makihara, Y Yagi, *IEEE TIFS* 2012
6. Biometric recognition by gait: A survey of modalities and features, P Connor, A Ross, *Computer Vision and Image Understanding*, 2018
7. Deep gait recognition: A survey, A Sepas-Moghaddam, A Etemad , *IEEE TPAMI* 2022
8. A comprehensive survey on deep gait recognition: algorithms, datasets and challenges, C Shen, S Yu, J Wang, GQ Huang, L Wang, *arXiv* , 2023
9. TriGait: Aligning and Fusing Skeleton and Silhouette Gait Data via a Tri-Branch Network, Y Sun, X Feng, L Ma, L Hu, M Nixon, *IJCB 2023*
10. GaitSTR: Gait Recognition With Sequential Two-Stream Refinement. Zheng, W., Zhu, H., Zheng, Z. and Nevatia, R., *IEEE Transactions on Biometrics, Behavior, and Identity Science,* 2024

Apologies if your own technique is missing, or your favourite. There are many more.

Further reading -soft

1. On soft biometrics, MS Nixon, PL Correia, K Nasrollahi, TB Moeslund, A Hadid, M Tistarelli, *PRL* 2015
2. What else does your biometric data reveal? A survey on soft biometrics, A Dantcheva, P Elia, A Ross, *IEEE TIFS* 2016
3. Soft biometric traits for personal recognition systems, AK Jain, SC Dass, K Nandakumar, *ICBA* 2004
4. Demographic analysis from biometric data: Achievements, challenges, and new frontiers Y Sun, M Zhang, Z Sun, T Tan, *IEEE TPAMI* 2018
5. The use of semantic human description as a soft biometric, S Samangooei, B Guo, MS Nixon, *IEEE BTAS* 2008
6. Soft biometrics; human identification using comparative descriptions, D Reid, MS Nixon, S Stevenage, *IEEE TPAMI* 2014
7. Soft biometrics and their application in person recognition at a distance, P Tome, J Fierrez, R Vera-Rodriguez, MS Nixon, *IEEE TIFS* 2014
8. Super-fine attributes with crowd prototyping, D Martinho-Corbishley, MS Nixon, JN Carter, *IEEE TPAMI,* 2019
9. Multimodal face synthesis from visual attributes, Di, X. and Patel, V.M., *IEEE TBIOM*, 2021
10. PrivacyProber: Assessment and Detection of Soft–Biometric Privacy–Enhancing Techniques, Rot P, Grm K, Peer P, Štruc V. *IEEE TDSC*, 2023

Post Hoc Questions on Gait Biometrics

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1. The easiest way to avoid being recognised by gait is:
   A – change clothes; B – stop walking; C – put a stone in your shoe; D – run, E – hop?
2. People can recognise other people by the way they walk:
   A – always; B – only friends; C – only gender; D – never?
3. Gait biometrics requires computers and memory. How much:
   A – many GPUs and much storage; B – one GPU; C – lots of memory; D – an abacus?
4. Gait biometrics is based on video data. It should be
   A – high quality?; B – regularly sampled?; C – encoded by frame?; D – motion encoded?
5. Gait biometrics can be achieved by deploying standard computer vision techniques/ architectures:
   A – TRUE; B – FALSE; C – only on a Sunday?
6. Silhouettes can be used for recognition. Does this use
   A – body shape only; B – dynamics only; C – both shape and dynamics?
7. Gait can be modelled for recognition purposes. Does this use
   A – body shape only; B – dynamics only; C – both shape and dynamics?
8. The computational requirements are the least for
   A – model-based approaches; B – silhouette-based approaches?
9. The canonical view in gait is
   A – side view; B – front view; D – top view; D – 3D?
10. The factor which most affects gait is
    A – clothes; B – shoes; C – mood; D – time, E - alcohol?

Post Hoc Questions on Soft Biometrics

11. Soft biometrics are suitable for recognition?
    A – True; B – False
12. What is the ‘soft’ in ‘soft biometrics’?
    A – ice cream soft; B – counterpoint to traditional ‘hard’ biometrics; C – complement to traditional?
13. Makeup is a soft biometric?
    A – True; B - False
14. Which is the most discriminative: Age, Gender or Race?
    A – Age; B – Gender; C – Race
15. The ‘other race effect’ is the same as prosopagnosia?
    A – True; B - False
16. Human bias means that all observations derived from humans should be tuple, not single?
    A – True; B - False
17. When asking a person to label “is this photograph of a man or of a woman?”, should the answer include “don’t know”?
    A – Yes; B – No; C – Don’t know
18. When asking a person to label “age”, is it better to compare images or not?
    A – Yes; B – No
19. Manual search of video is the only possible way
    A – Yes, B – Yes, but only at the moment
20. The full set of practical biometrics has been explored and no new ones are possible.
    A - No

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Thank you, and for more information