University of Southampton
Electronics and Computer Science

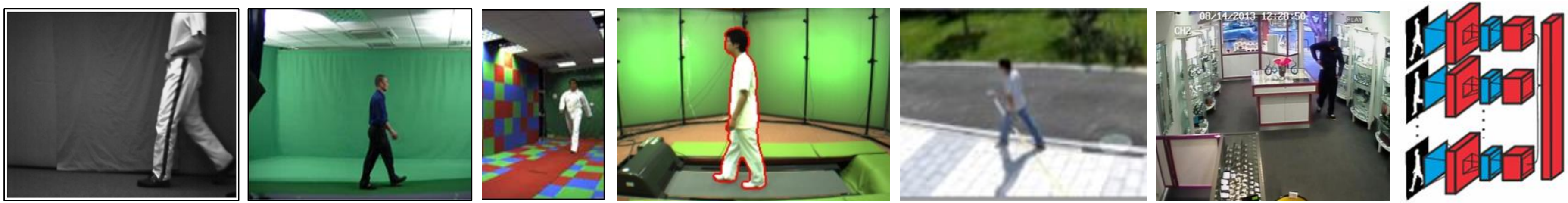
Biometrics Winter School 2024

Gait Biometrics, Forensics and Soft Biometrics:

Mark Nixon

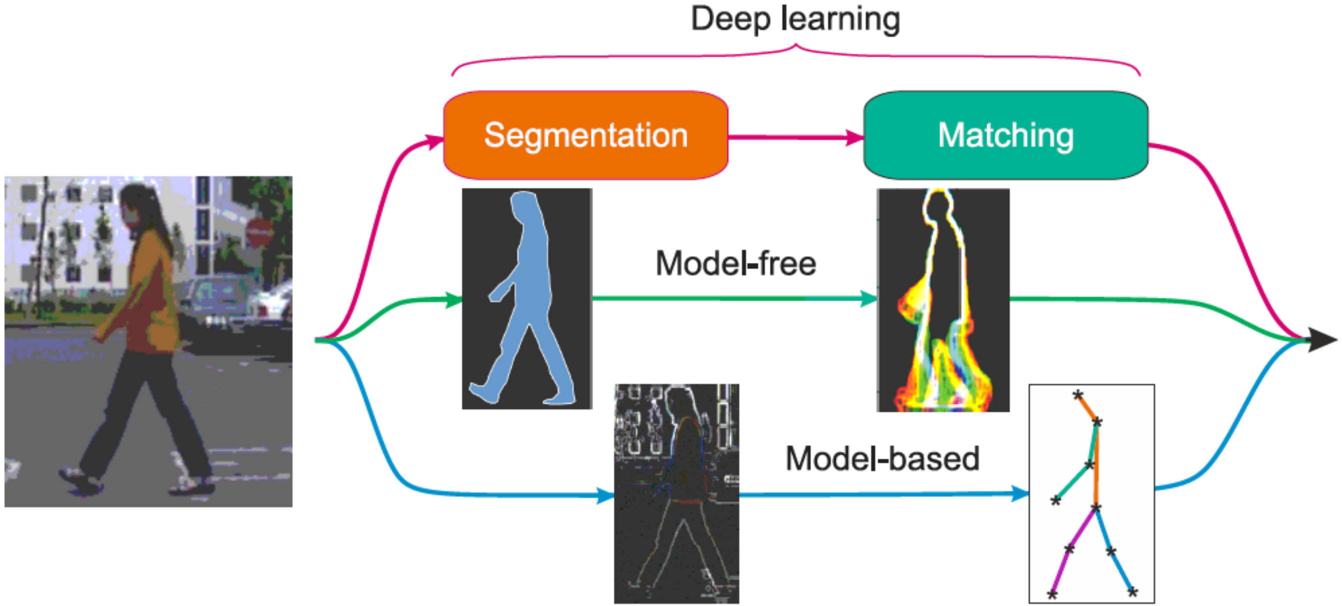
IEEE Biometrics Council Distinguished Lecturer

University of Southampton UK




2024 WINTER SCHOOL ON BIOMETRICS
21-25 January 2024 Shenzhen, China

Gait = body shape + movement



Deep learning

Segmentation

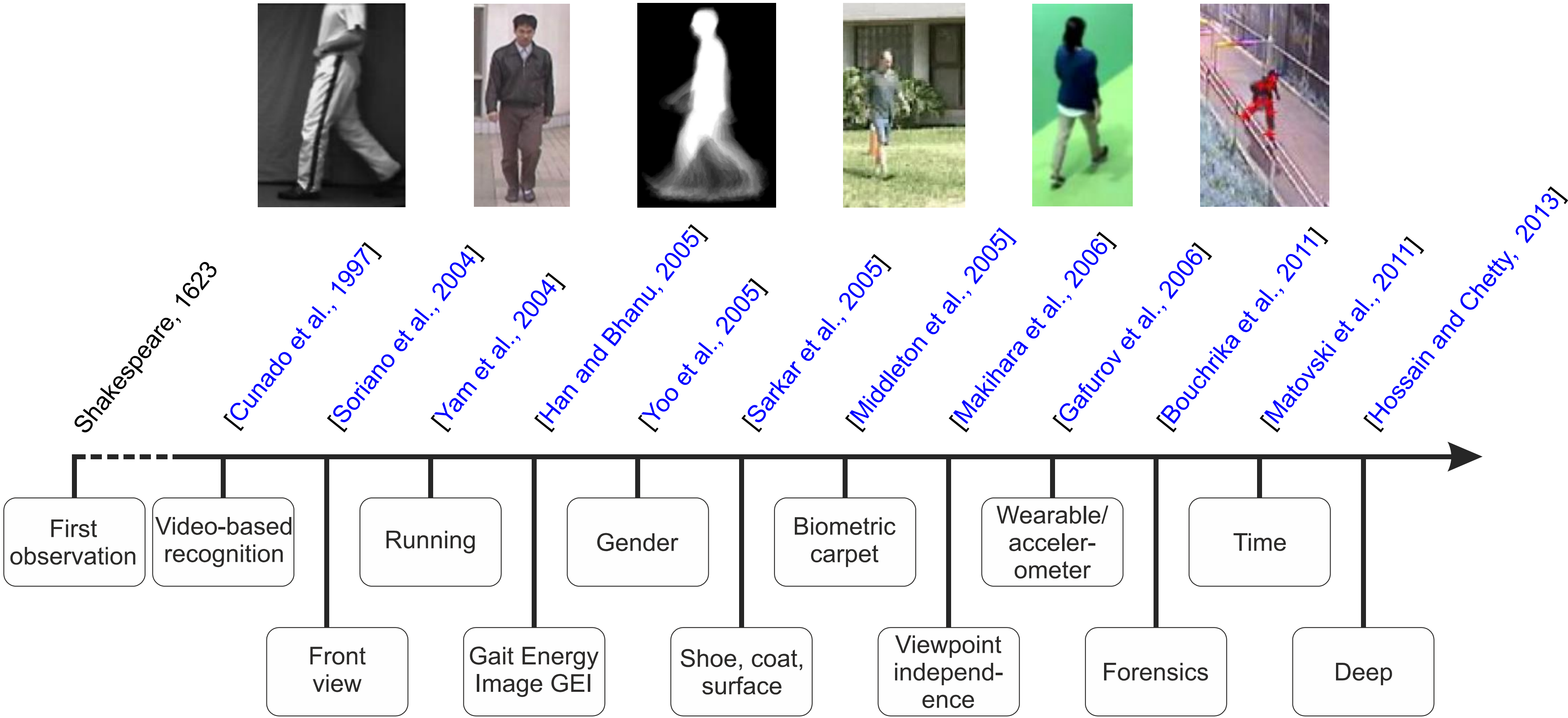
Matching

Model-free

Model-based

Covariates: viewpoint luggage clothing shoes health gender speed

History



Shakespeare, 1623 — First observation

[Cunado et al., 1997] — Video-based recognition

[Soriano et al., 2004] — Front view

[Yam et al., 2004] — Running

[Han and Bhanu, 2005] — Gait Energy Image GEI

[Yoo et al., 2005] — Gender

[Sarkar et al., 2005] — Shoe, coat, surface

[Middleton et al., 2005] — Biometric carpet

[Makihara et al., 2006] — Viewpoint independence

[Gafurov et al., 2006] — Wearable/ accelerometer

[Bouchrika et al., 2011] — Forensics

[Matovski et al., 2011] — Time

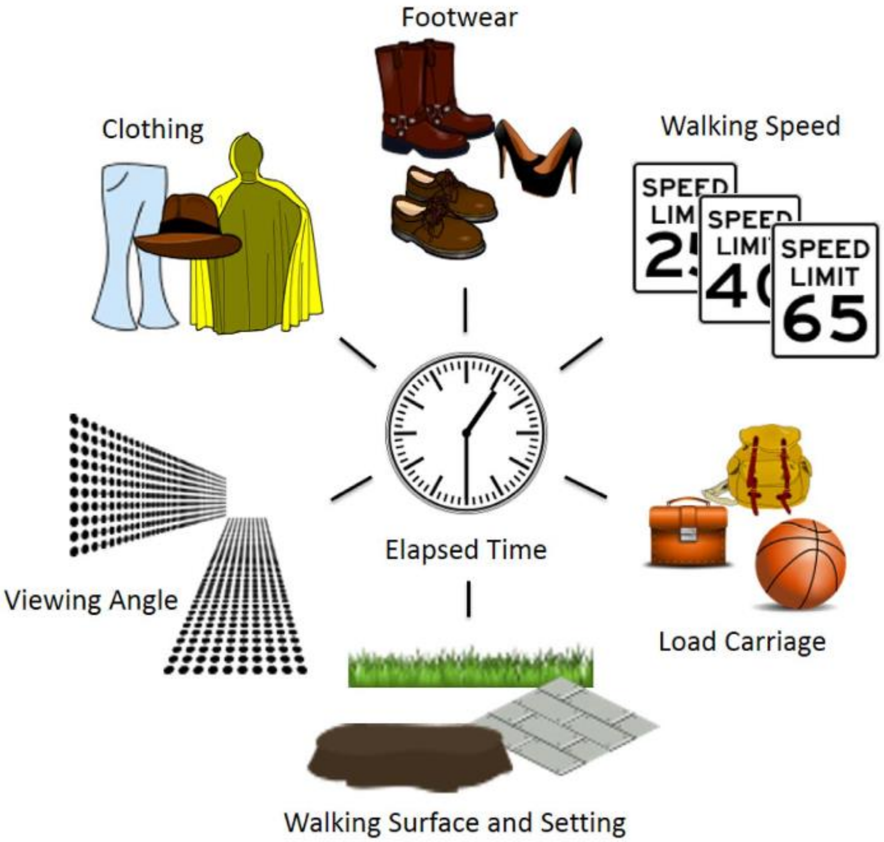
[Hossain and Chetty, 2013] — Deep

What changes?

Many covariates can affect walking style

…. + health, drugs, mood,

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



Gait biometrics databases

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

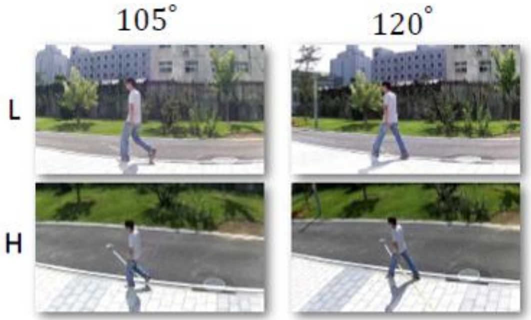
1. Where are we now?
2. How did we get here?
3. Where are we going?

Gait Recognition –state of the art

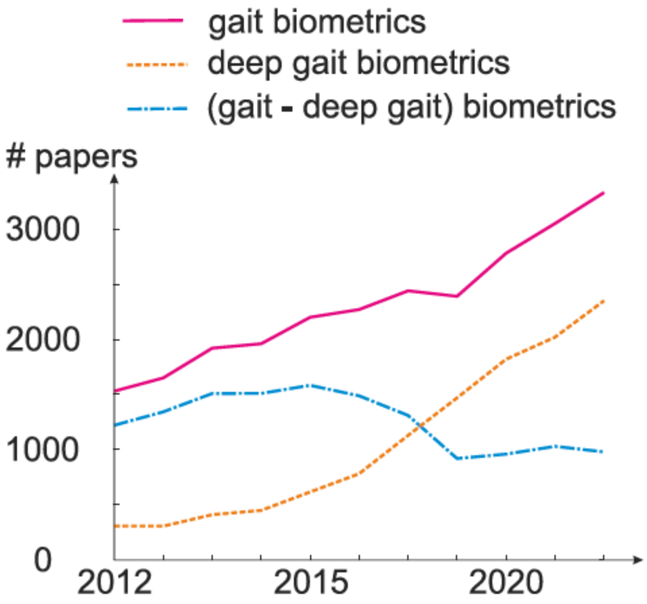
Technique: mainly deep

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

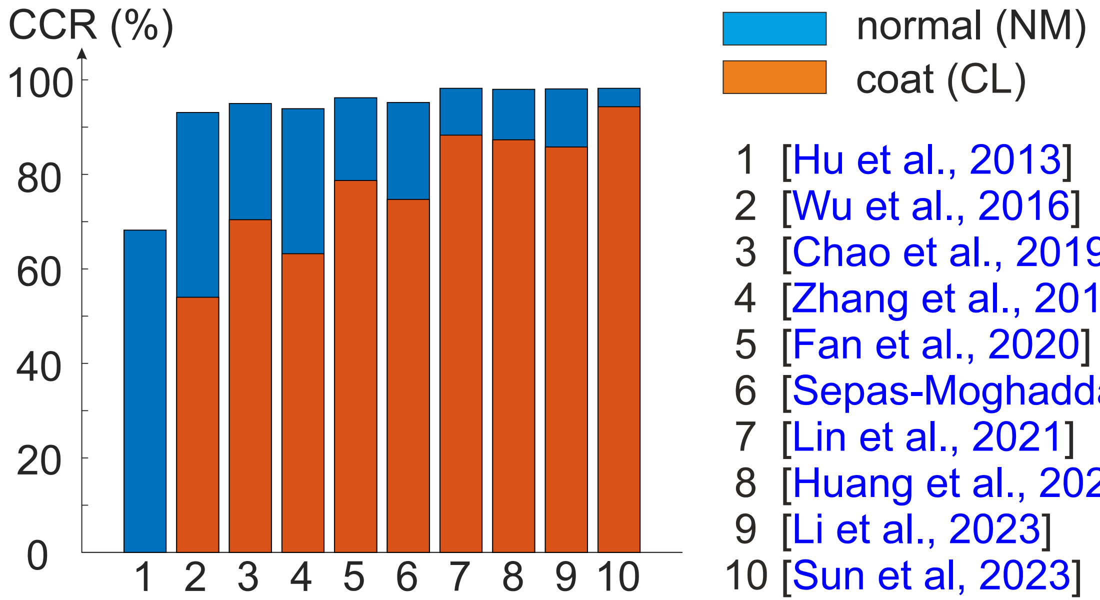
Applications: increasing use in crime scene analysis



Gait Recognition –state of the art



Papers on GS



1 [Hu et al., 2013]
2 [Wu et al., 2016]
3 [Chao et al., 2019]
4 [Zhang et al., 2019]
5 [Fan et al., 2020]
6 [Sepas-Moghaddam
7 [Lin et al., 2021]
8 [Huang et al., 2022]
9 [Li et al., 2023]
10 [Sun et al, 2023]

Performance on CASIA B

Gait Recognition – the deep revolution

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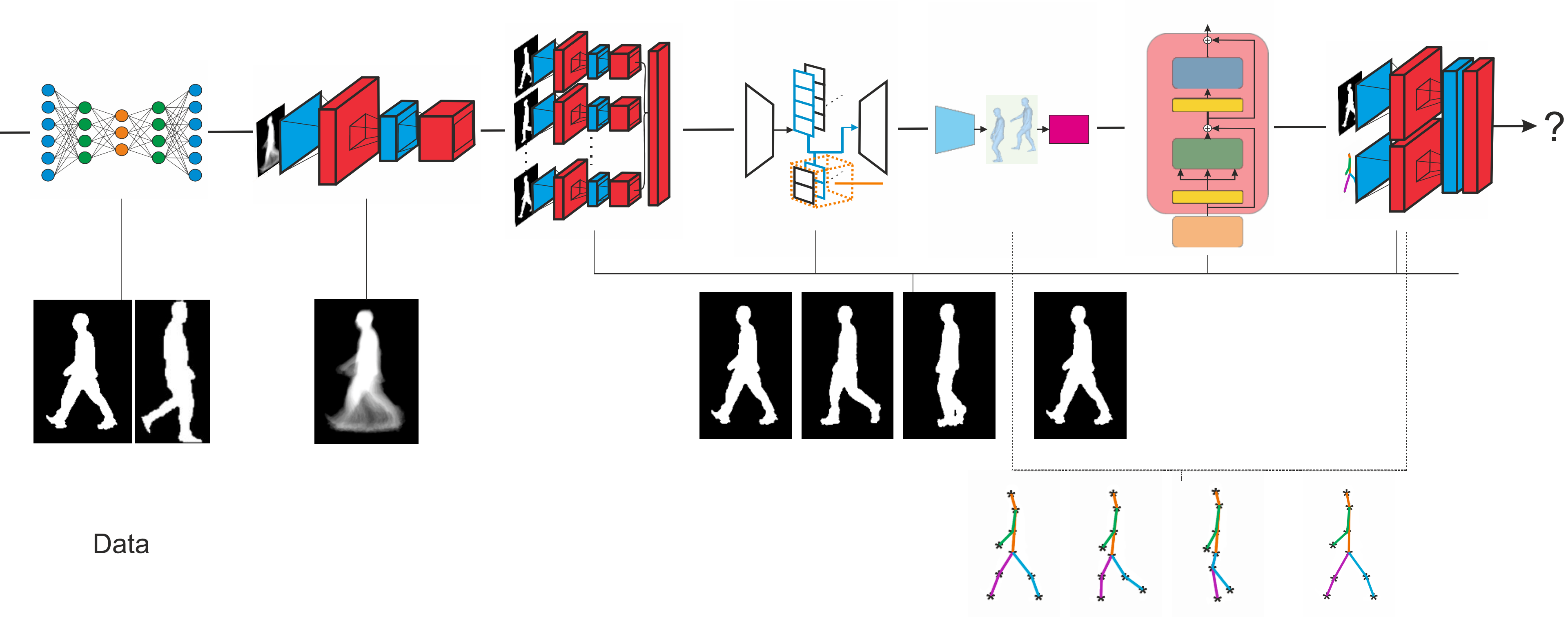
Autoencoder	Convolutional	Sequence	GANs/LSTM	Model	Transformer	Fusion
[Hossain +.., 2013]	[Wu +.., 2016]	[Chao +.., 2019]	[Zhang +.., 2019]	[Li +.., 2020]	[Li +.., 2023]	[Sun +.., 2023]



Data

By way of comparison

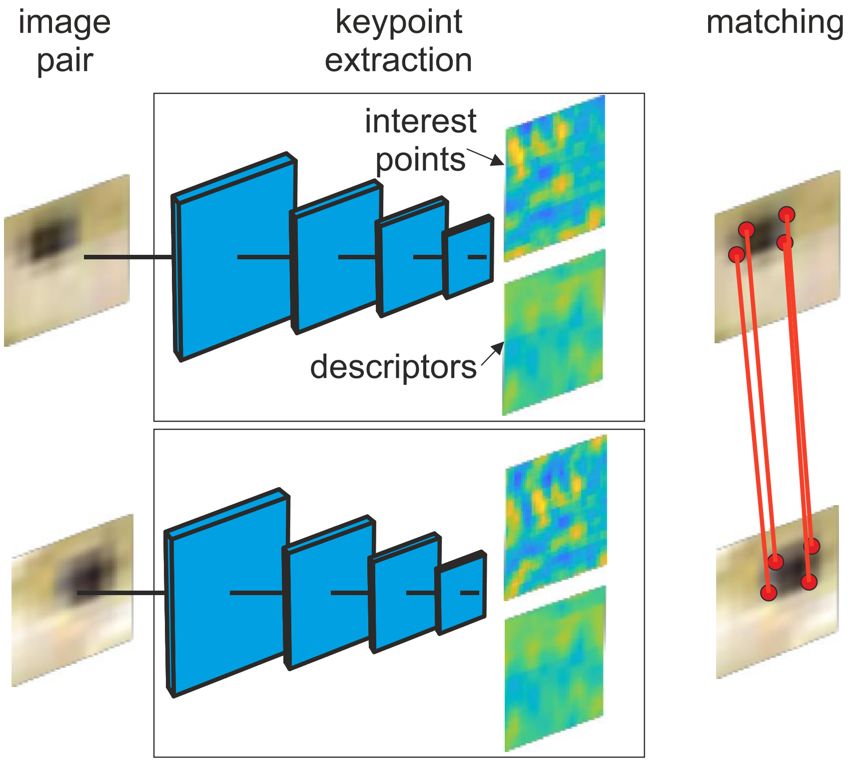


image pair

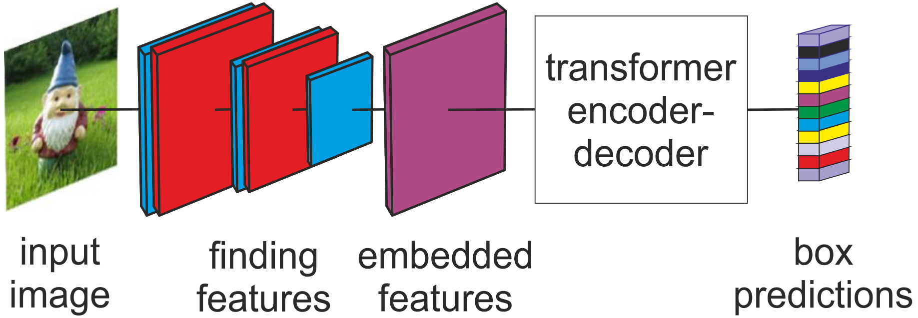
keypoint extraction

matching

interest points

descriptors

Patch matching



input image

finding features

embedded features

transformer encoder-decoder

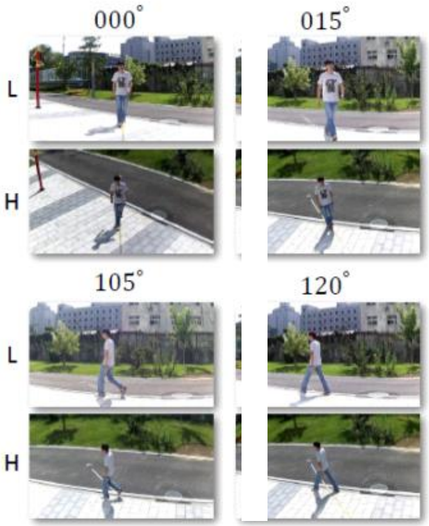
box predictions

Object detection

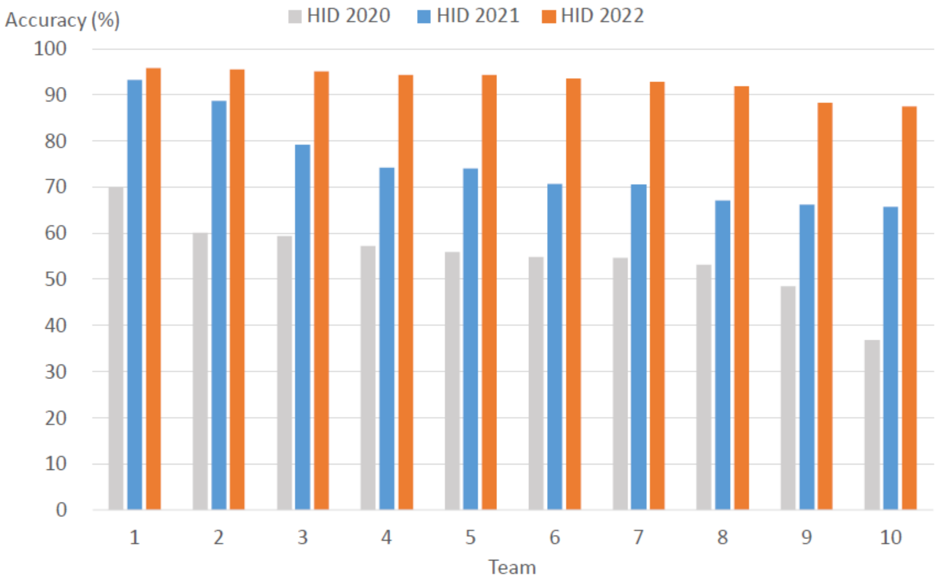
The 4th International Competition on Human Identification at a Distance 2023 (HID2023)

Organized by JingzheMa - Current server time: May 9, 2023, 1:32 p.m. UTC

First phase	End
Feb. 15, 2023, midnight UTC	April 15, 2023, 11:59 p.m. UTC

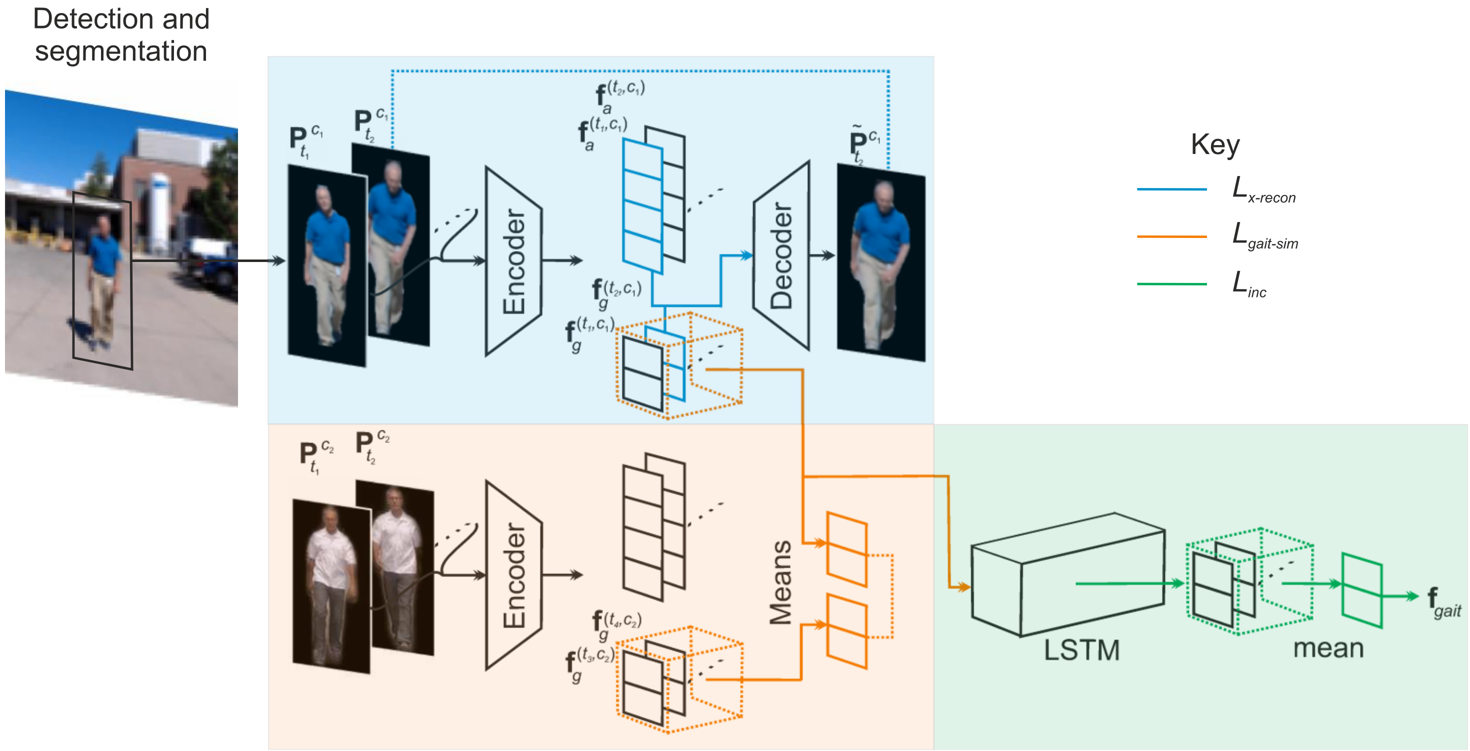


CASIA E



ACCV 2020/ IJCB 2021/ IJCB 2022/ IJCB 2023

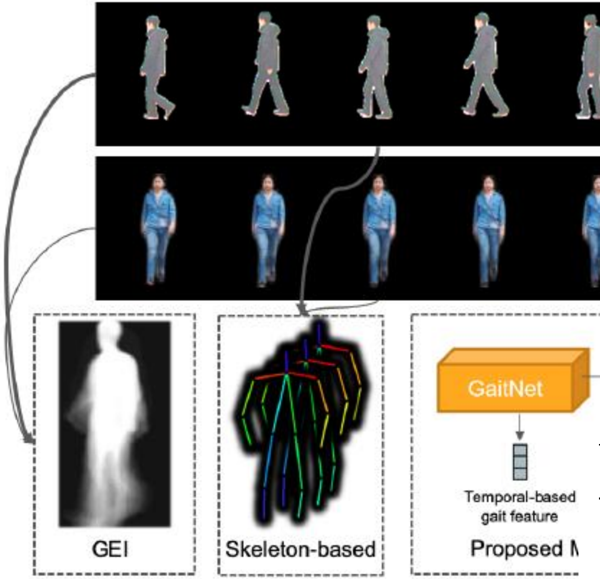
Gait recognition via disentangled representation learning

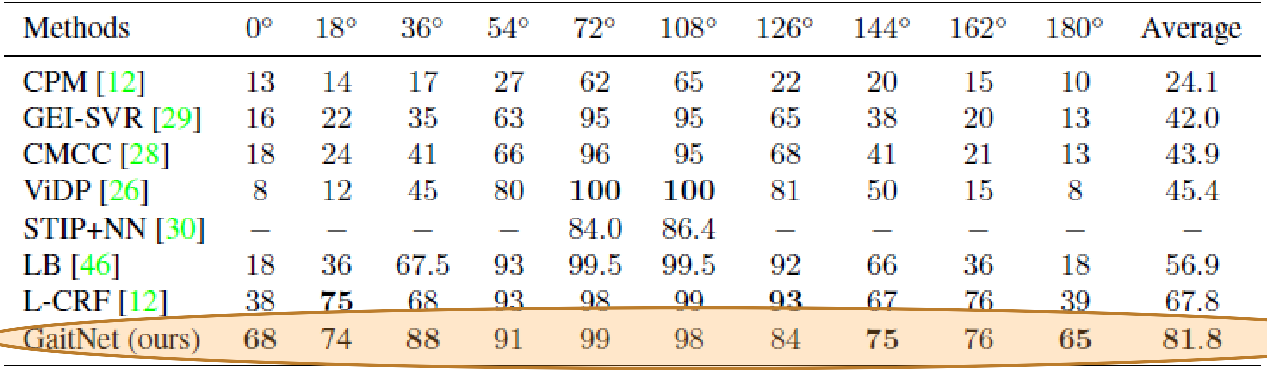


See also: Li, Makihara, Xu, Yagi: Gait recognition via semi-supervised disentangled representation learning to identity and covariate features, CVPR 2020

Zhang et al, *CVPR* 2019

Gait recognition via disentangled representation learning





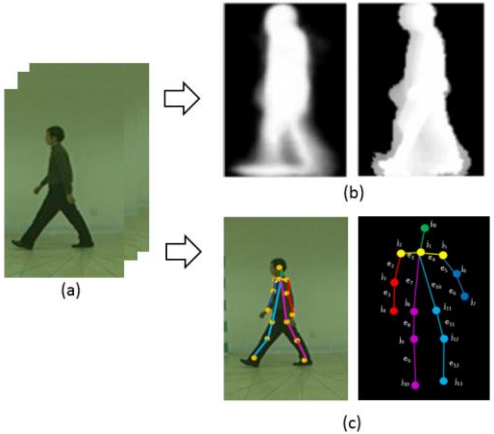
Methods	0°	18°	36°	54°	72°	108°	126°	144°	162°	180°	Average
CPM [12]	13	14	17	27	62	65	22	20	15	10	24.1
GEI-SVR [29]	16	22	35	63	95	95	65	38	20	13	42.0
CMCC [28]	18	24	41	66	96	95	68	41	21	13	43.9
ViDP [26]	8	12	45	80	**100**	**100**	81	50	15	8	45.4
STIP+NN [30]	–	–	–	–	84.0	86.4	–	–	–	–	–
LB [46]	18	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!!

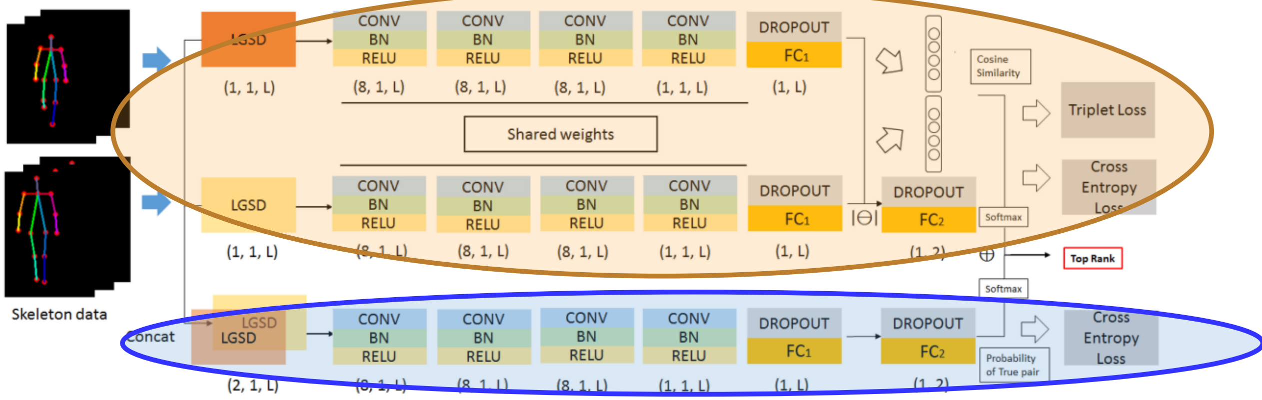
Zhang et al, *CVPR* 2019

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

University of Southampton
Electronics and Computer Science



Similarity of gait pair



Probability of gait pair

LGSD Local Graphical Skeleton Descriptor

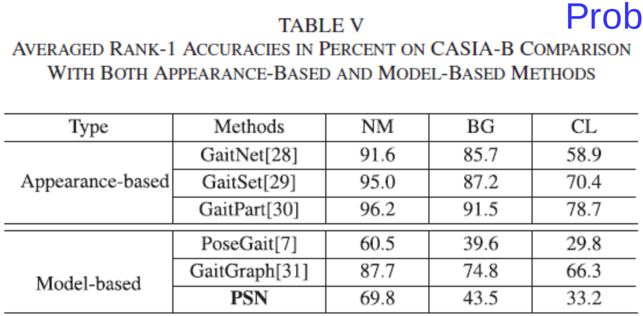
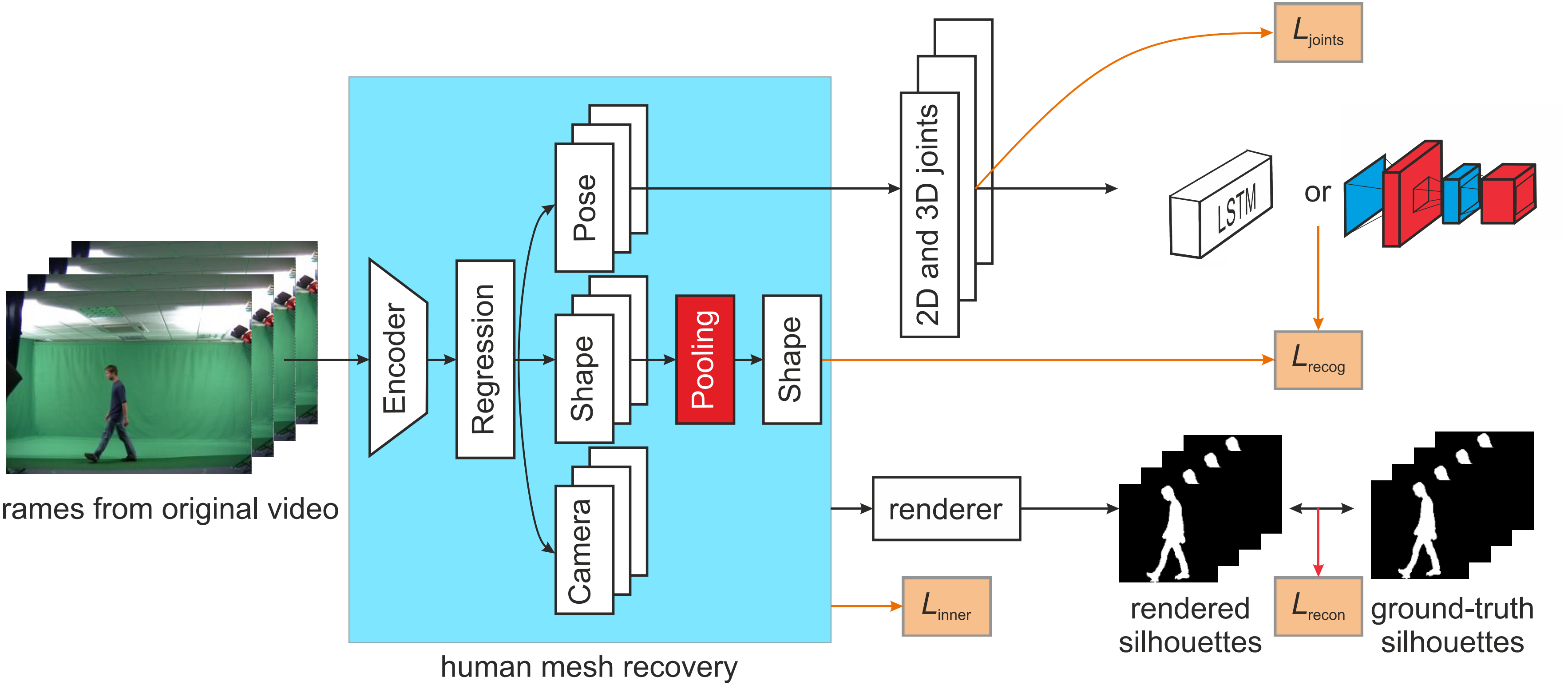


TABLE V
AVERAGED RANK-1 ACCURACIES IN PERCENT ON CASIA-B COMPARISON WITH BOTH APPEARANCE-BASED AND MODEL-BASED METHODS

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



Li et al, *ACCV* 2020

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

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

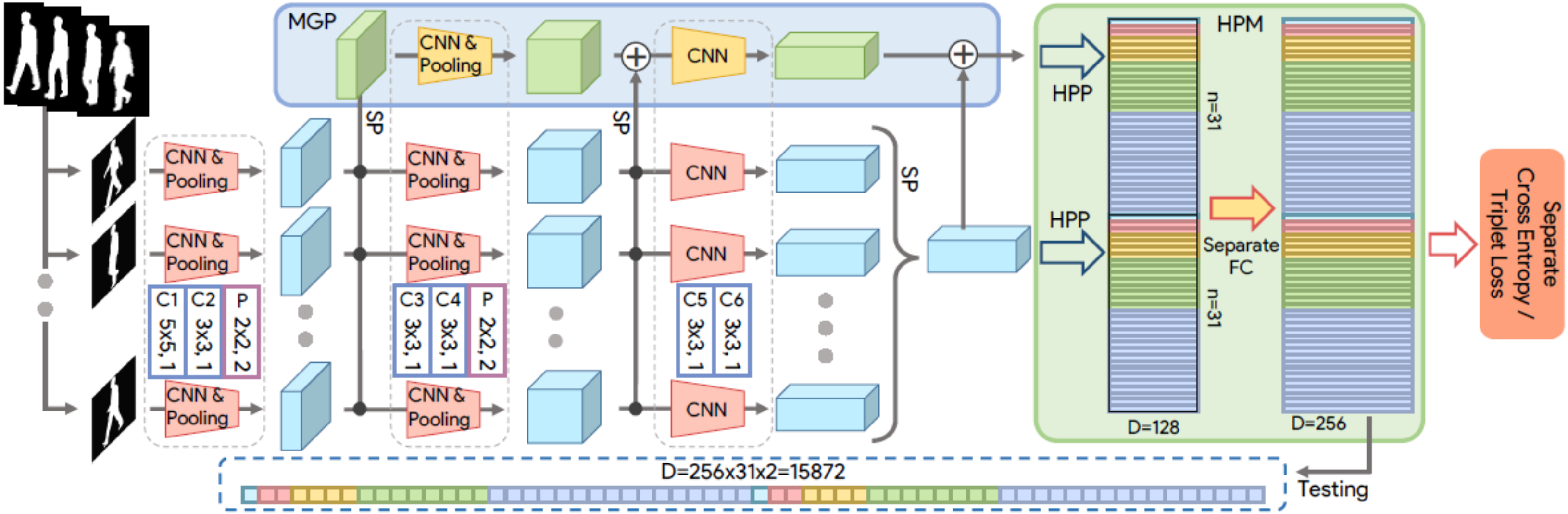


Fig. 2. The framework of GaitSet [26] . 'SP' represents set pooling. Trapezoids represent convolution and pooling blocks and those in the same column have the same configurations, as shown by the rectangles with capital letters. Note that although the blocks in MGP have the same configurations as those 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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Electronics and Computer Science

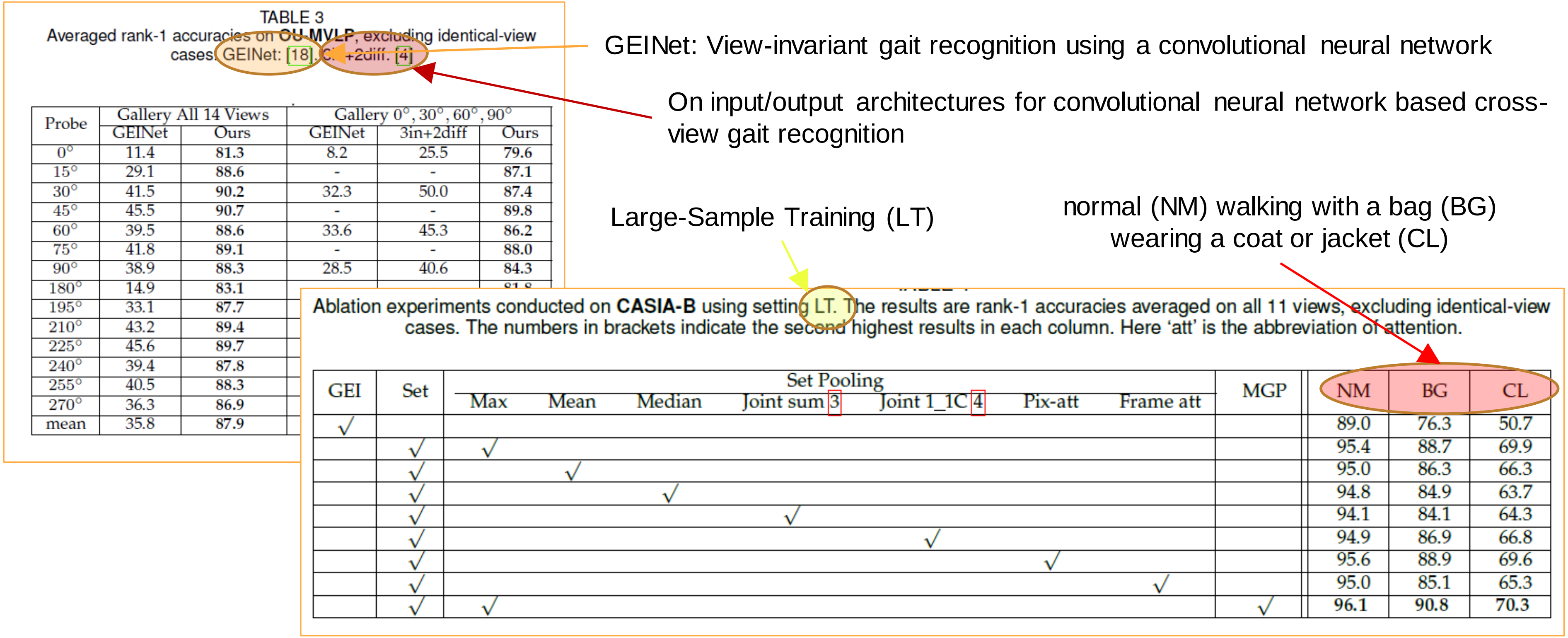


TABLE 3
Averaged rank-1 accuracies on OU-MVLP, excluding identical-view cases. GEINet: [18]. 3in+2diff: [4]

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)

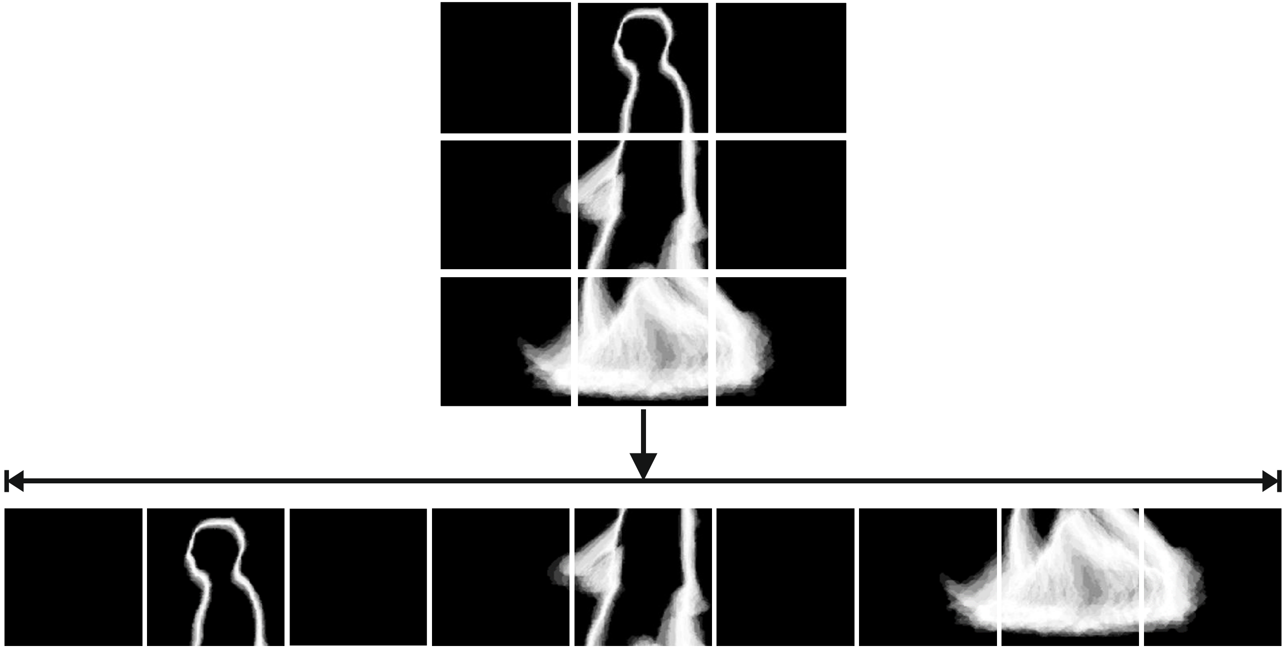
normal (NM) walking with a bag (BG)
wearing a coat or jacket (CL)

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.

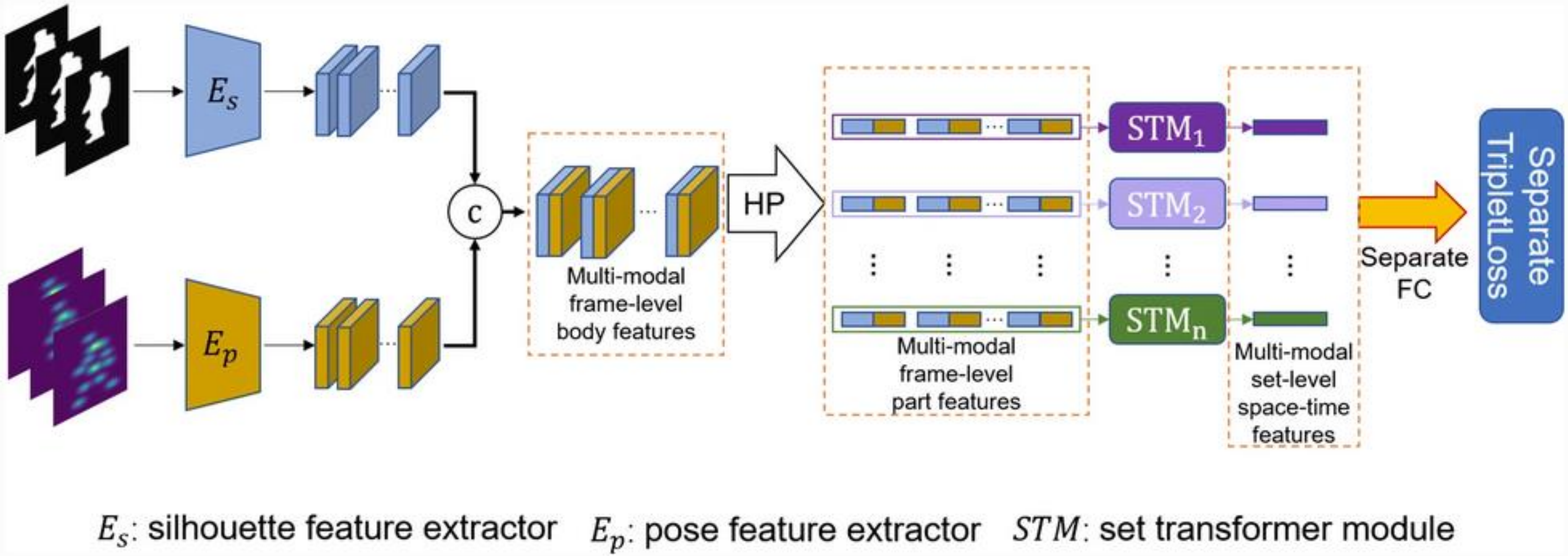
GEI	Set	Set Pooling							MGP	NM	BG	CL
		Max	Mean	Median	Joint sum 3	Joint 1_1C 4	Pix-att	Frame att				
√										89.0	76.3	50.7
	√	√								95.4	88.7	69.9
	√		√							95.0	86.3	66.3
	√			√						94.8	84.9	63.7
	√				√					94.1	84.1	64.3
	√					√				94.9	86.9	66.8
	√						√			95.6	88.9	69.6
	√						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

Chao et al, *IEEE TPAMI* 2022

Transforming gait



TransGait: Multimodal-based gait recognition with set transformer



Li et al, *Applied Intelligence*, 2023

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

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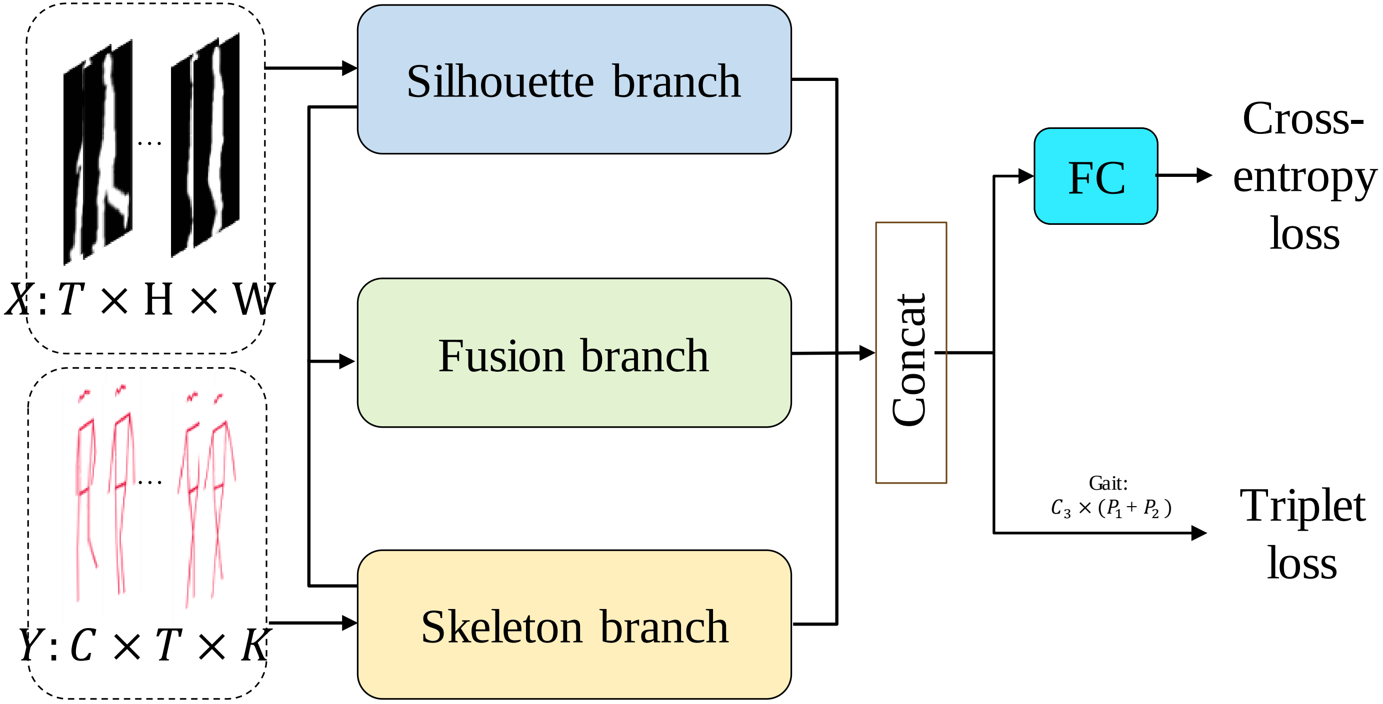
TriGait Network Architecture



$X: T \times \mathrm{H} \times \mathrm{W}$

$Y: C \times T \times K$

Silhouette branch

Fusion branch

Skeleton branch

Concat

FC

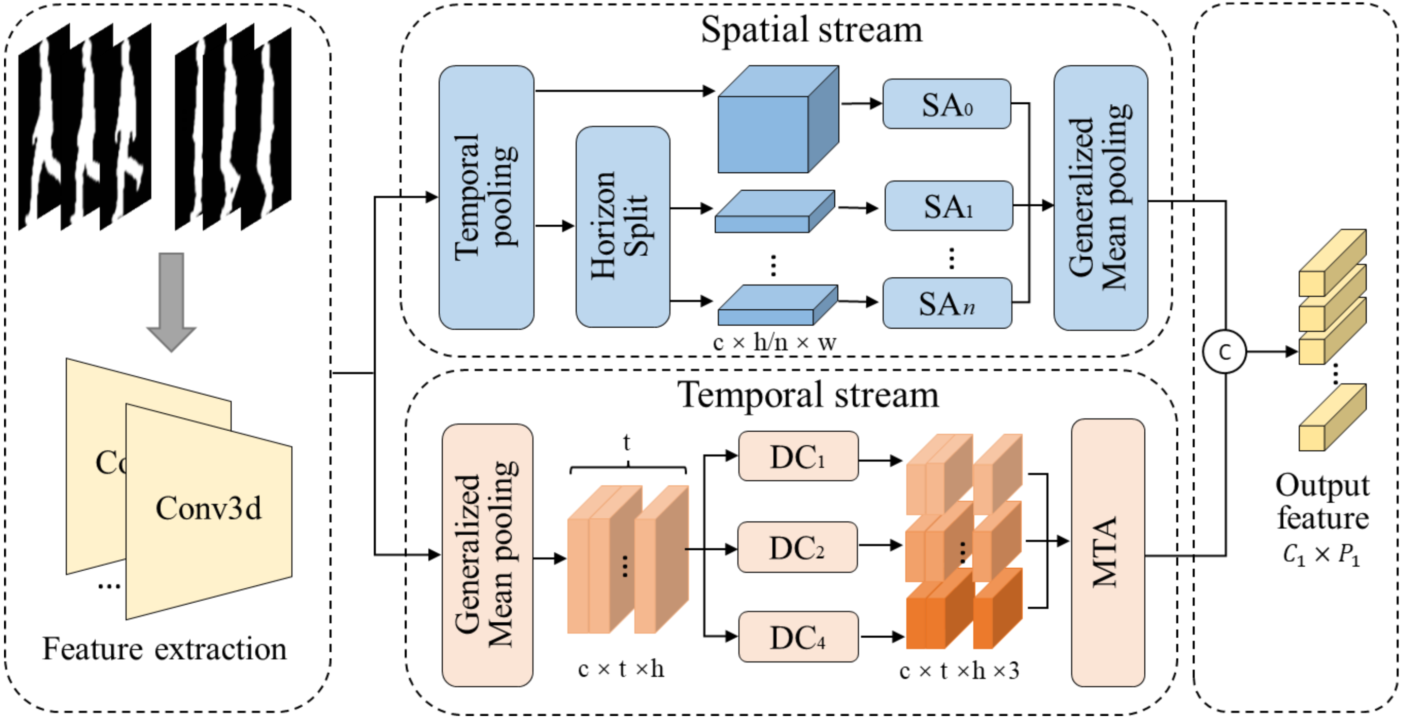
Cross-entropy loss

Gait: $C_3 \times (P_1 + P_2)$

Triplet loss

Sun et al, *IEEE IJCB*, 2023

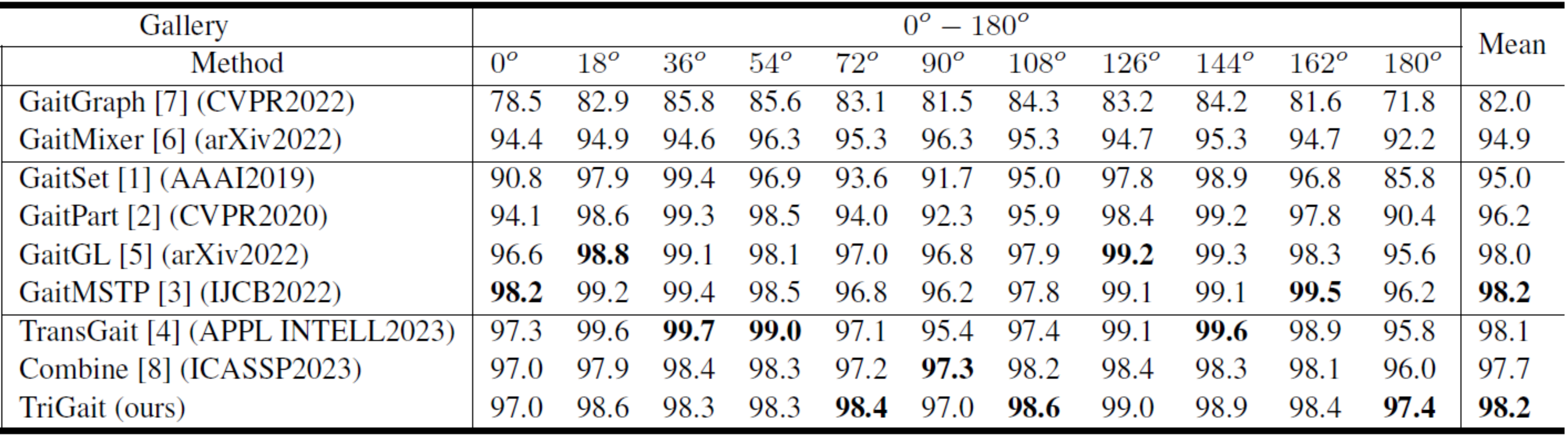
Trigait: silhouette branch



Sun et al, *IEEE IJCB*, 2023

Trigait: NM 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.

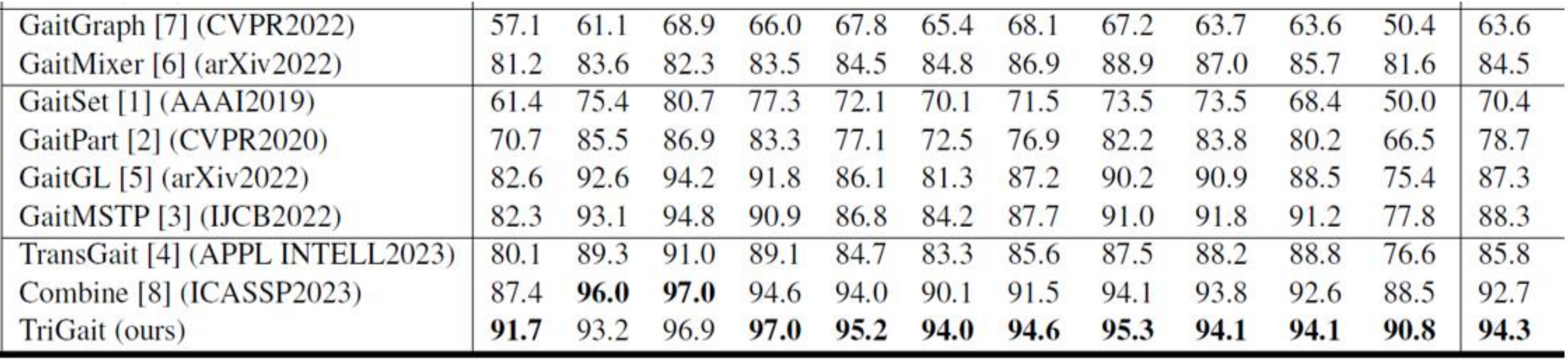


Gallery	$0^o - 180^o$											Mean
Method	0^o	18^o	36^o	54^o	72^o	90^o	108^o	126^o	144^o	162^o	180^o	
GaitGraph [7] (CVPR2022)	78.5	82.9	85.8	85.6	83.1	81.5	84.3	83.2	84.2	81.6	71.8	82.0
GaitMixer [6] (arXiv2022)	94.4	94.9	94.6	96.3	95.3	96.3	95.3	94.7	95.3	94.7	92.2	94.9
GaitSet [1] (AAAI2019)	90.8	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 = (ours)

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.



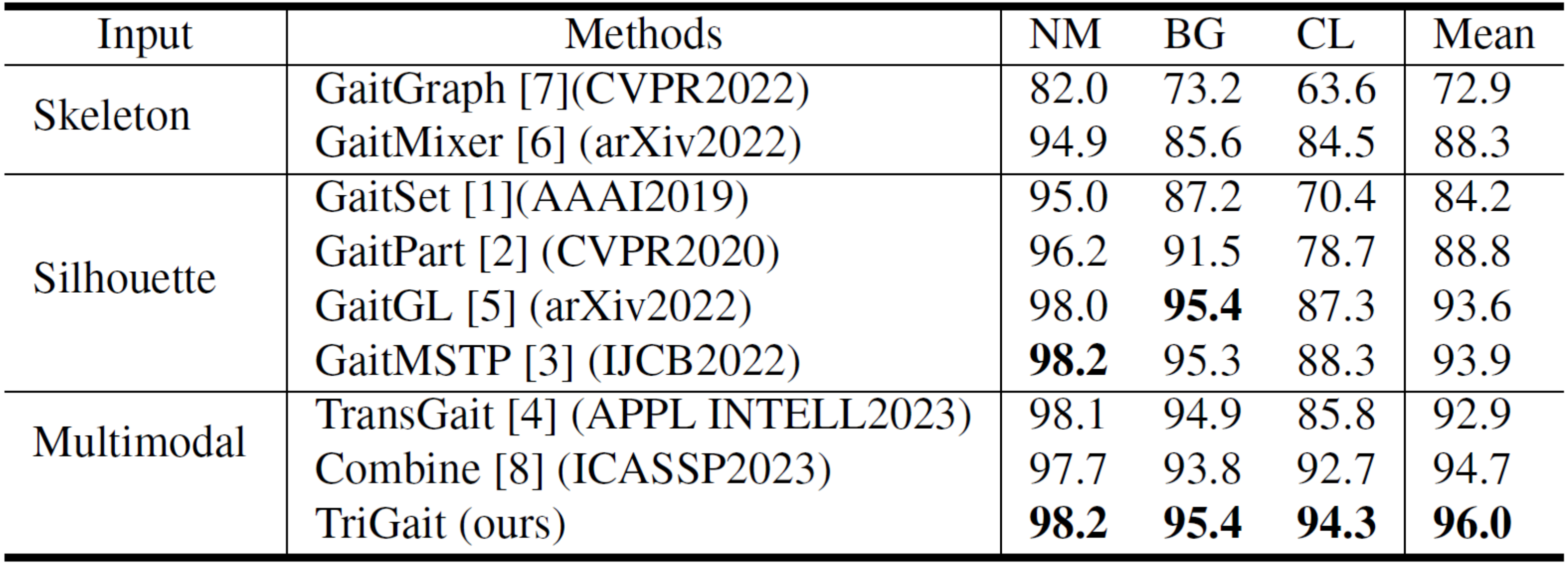
GaitGraph [7] (CVPR2022)	57.1	61.1	68.9	66.0	67.8	65.4	68.1	67.2	63.7	63.6	50.4	63.6
GaitMixer [6] (arXiv2022)	81.2	83.6	82.3	83.5	84.5	84.8	86.9	88.9	87.0	85.7	81.6	84.5
GaitSet [1] (AAAI2019)	61.4	75.4	80.7	77.3	72.1	70.1	71.5	73.5	73.5	68.4	50.0	70.4
GaitPart [2] (CVPR2020)	70.7	85.5	86.9	83.3	77.1	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

= (ours)

Trigait: comparison with SOTA

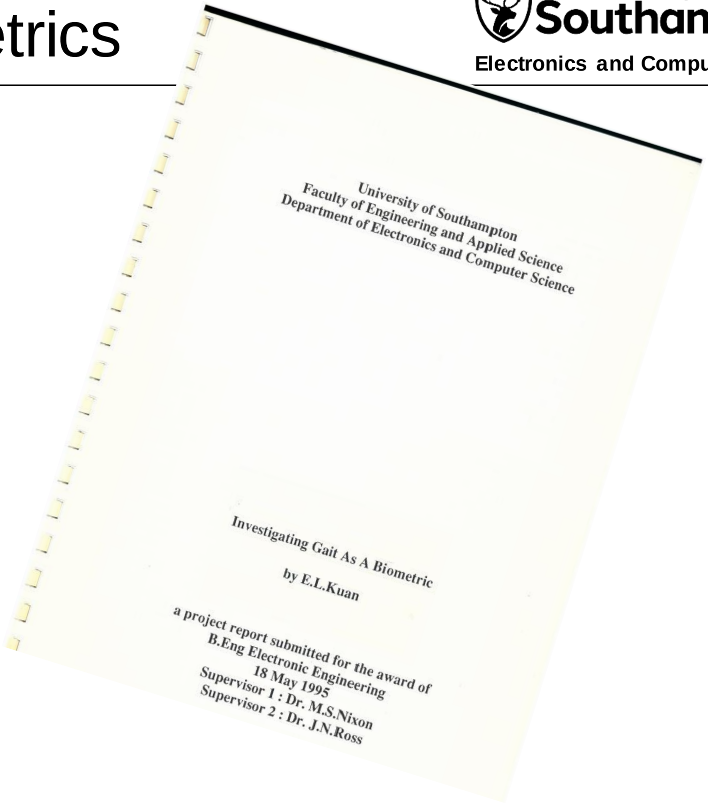
Rank 1 mean accuracy (%) on CASIA-B across different conditions and viewpoints.



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)

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

Doom 1 (1993)

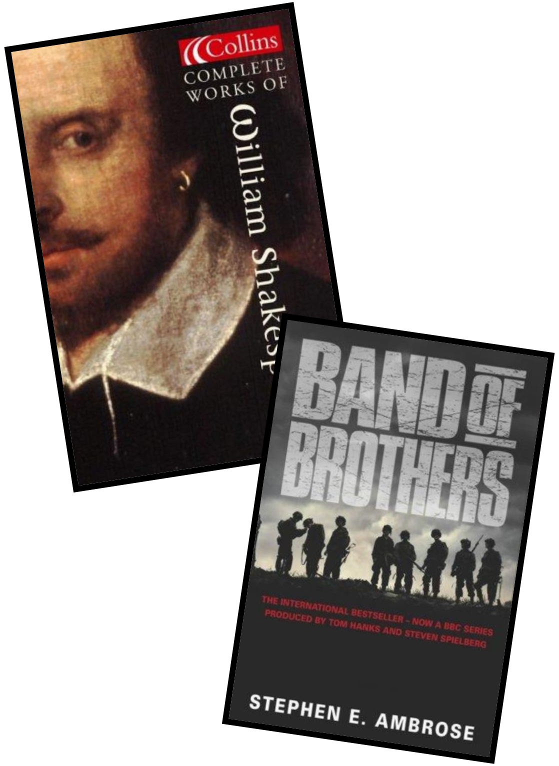
Gait and literature

Dictionary: “manner of walking”

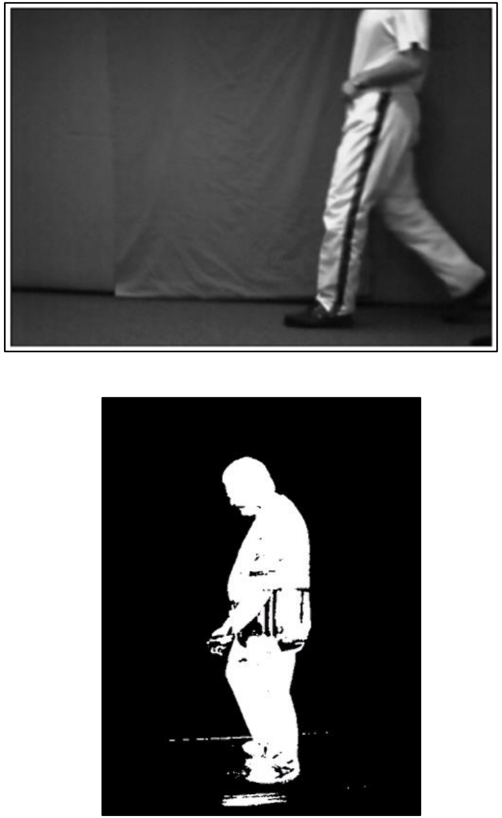
Shakespeare observed recognition:

> “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”

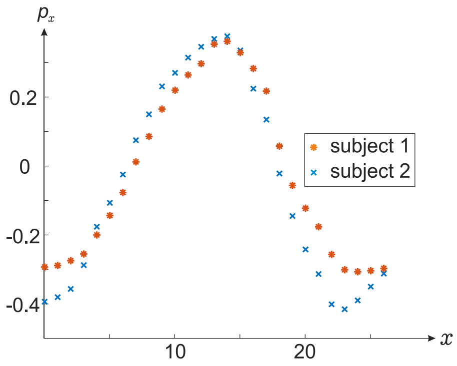


Early data

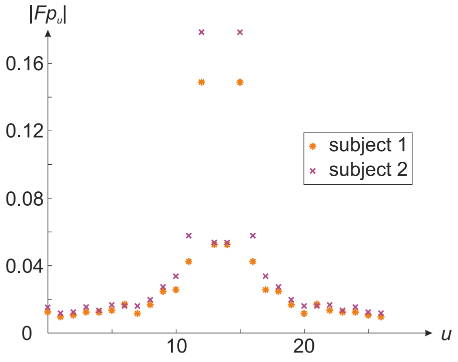


- 6 subjects; 7 sequences
- Sony Hi8 video camera
- Circular track ….exhausted subjects?
- We used a police digital video recorder

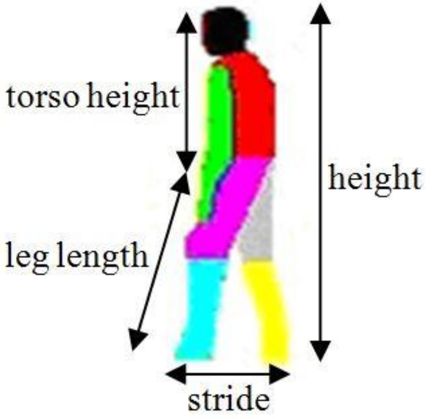
Model-based recognition

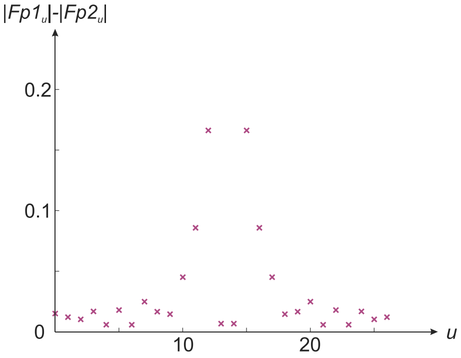


Inclination of thigh

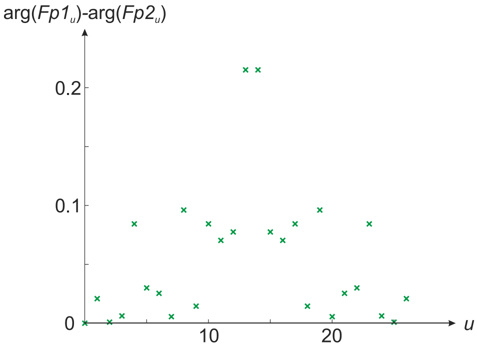


Magnitude of DFT





Difference between magnitude



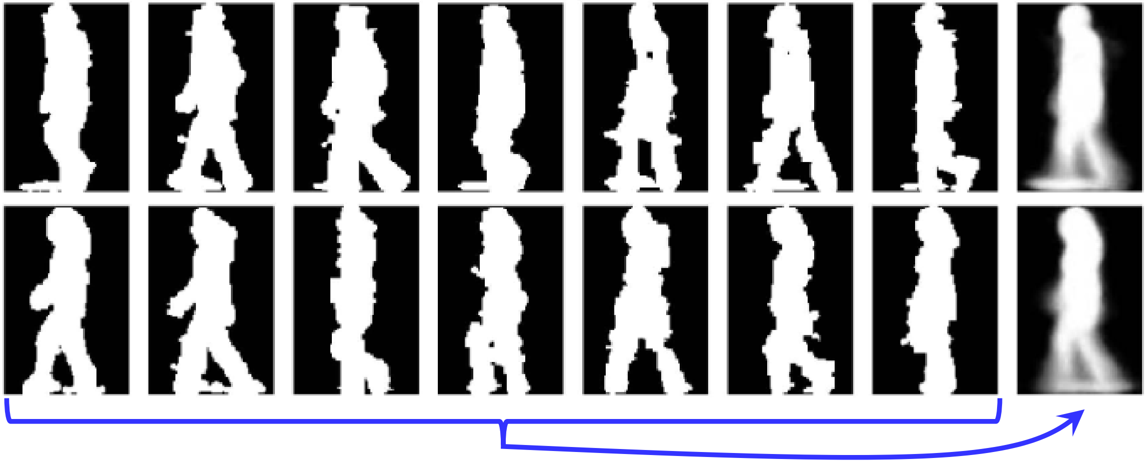
Difference between phase

Other models are possible

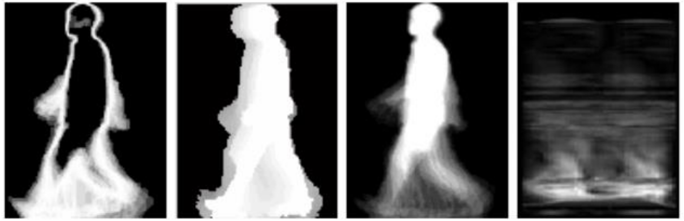
D Cunado, MS Nixon, JN Carter, Proc. AVBPA, 1997

Using silhouettes

Some names: average silhouette, GEI



Gait Energy Image



(a) GEnI (b) MSI (c) GEI (d) SVB

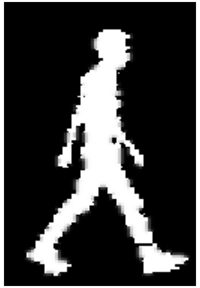
(e) Bag GEnI (f) Bag GEI (g) Coat GEnI (h) Coat GEI

Gait Entropy Image

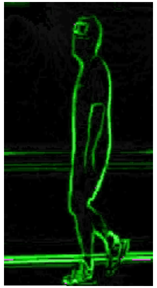
J Han, B Bhanu, *IEEE TPAMI*, 2005

Many gait representations possible

Recognising people from the motion of the whole body



silhouette

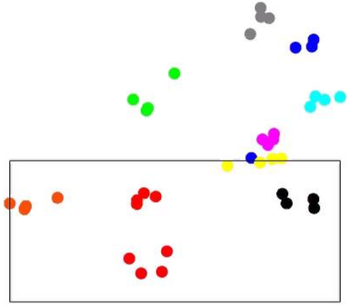


edges

flow

symmetry

acceleration



feature space

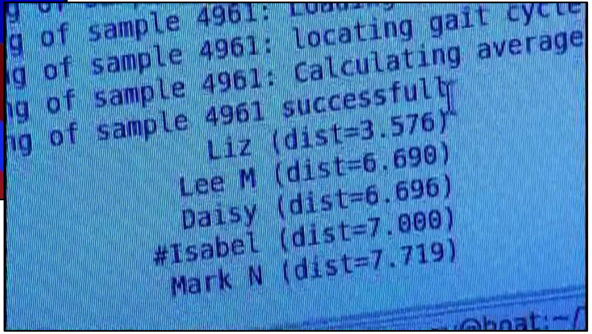
MS Nixon, T Tan, R Chellappa, Springer, 2005

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?

University of Southampton
Electronics and Computer Science



```
g of sample 4961: locating gait cycle
ng of sample 4961: Calculating average
ng of sample 4961: successful
ng of sample 4961     Liz (dist=3.576)
                    Lee M (dist=6.690)
                    Daisy (dist=6.696)
                  #Isabel (dist=7.000)
                   Mark N (dist=7.719)
```

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

BBC1 Bang Goes the Theory Episode 1, 2009

Time for a quiz….

Given

1. A laboratory environment; and
2. A silhouette

What is unusual about this person's appearance

From the silhouette:

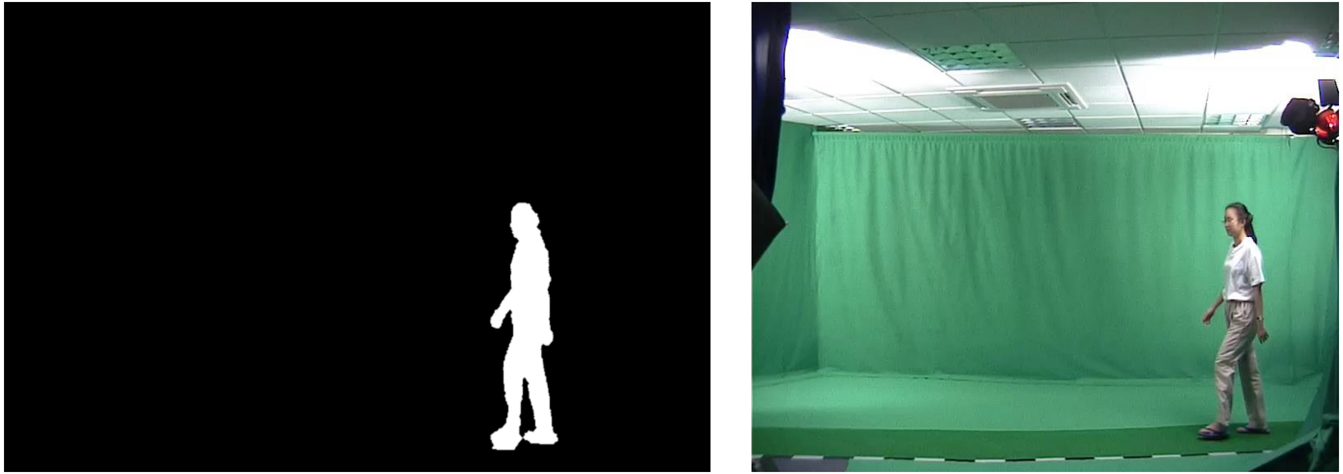
1. She was wearing Wellington boots
2. She was carrying a bag
3. She was filming for the hunchback of Notre Dame

And ladies wear…

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

What is unusual this person’s gait

1. Her shirt
2. Her trousers
3. Her footwear



Major difficulty 1 - viewpoint

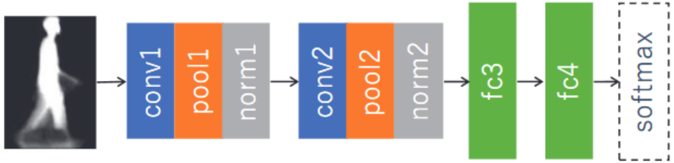


Figure 1: The structure of GEINet.

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

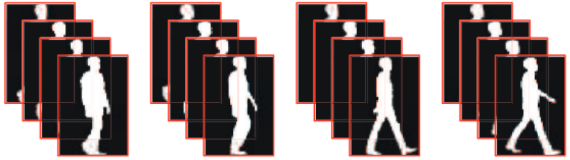
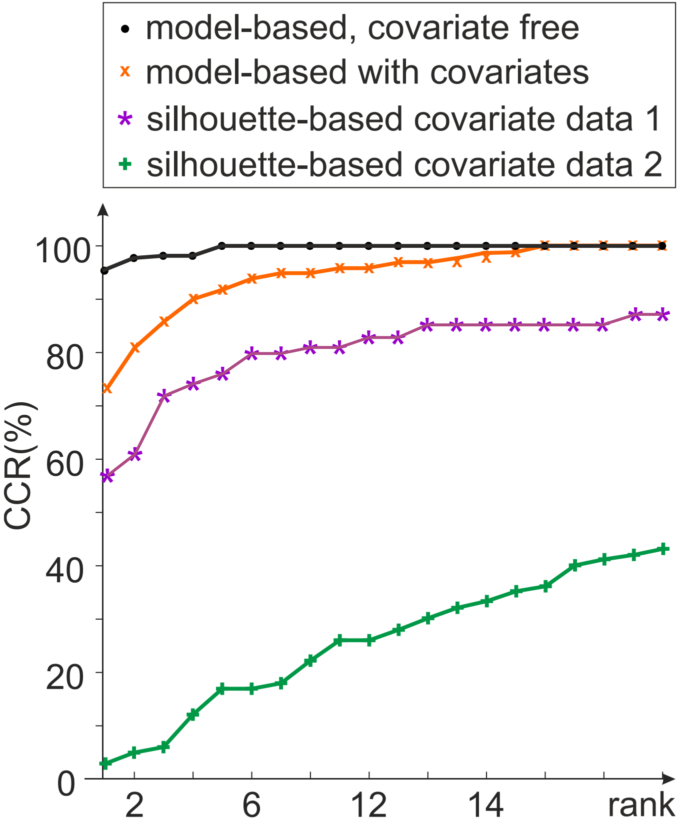


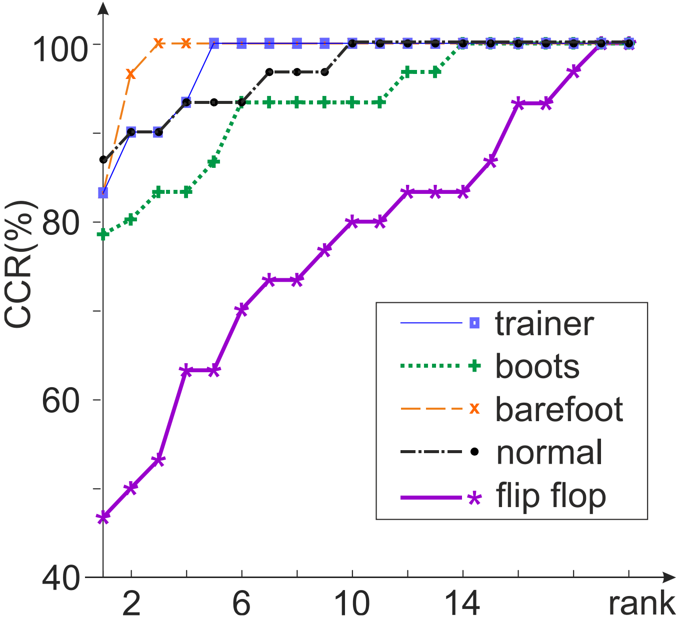
Figure 2: Examples of gait image sequences with four observation views in the OU-ISIR dataset

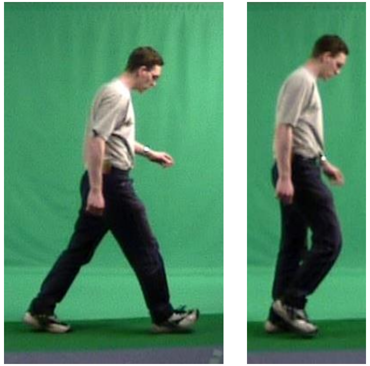
Gallery view	Method	Probe view			
		55	65	75	85
55	GEINet	(94.7)	**93.2**	**89.1**	***79.9***
	w/ FDF	(92.7)	***91.4***	***87.2***	**80.0**
	TCM+		79.9	70.8	54.5
	wQVTM		78.3	64.0	48.6

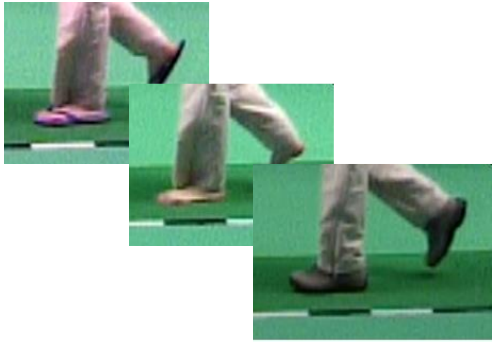
Shiraga, Makihara and Muramatsu ICB 2016

Major difficulty 2 - covariates

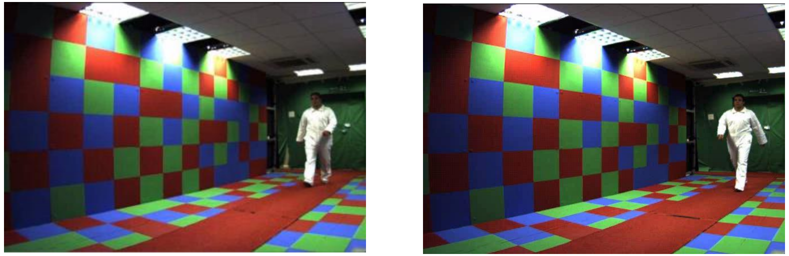




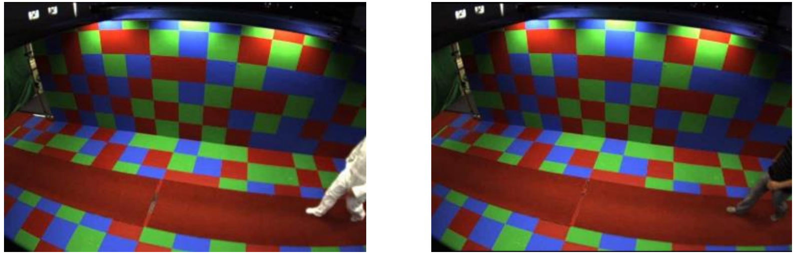




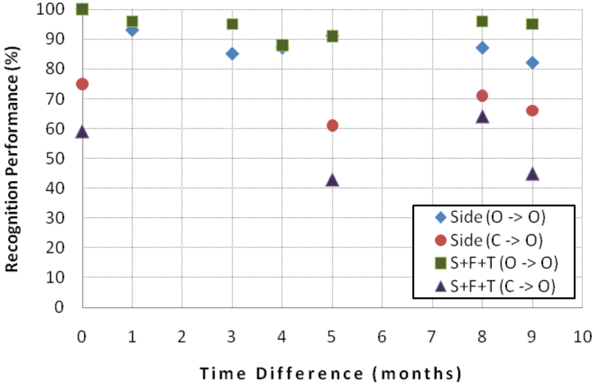
Major difficulty 3 - time



Nine months difference



Few minutes apart, different clothes



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

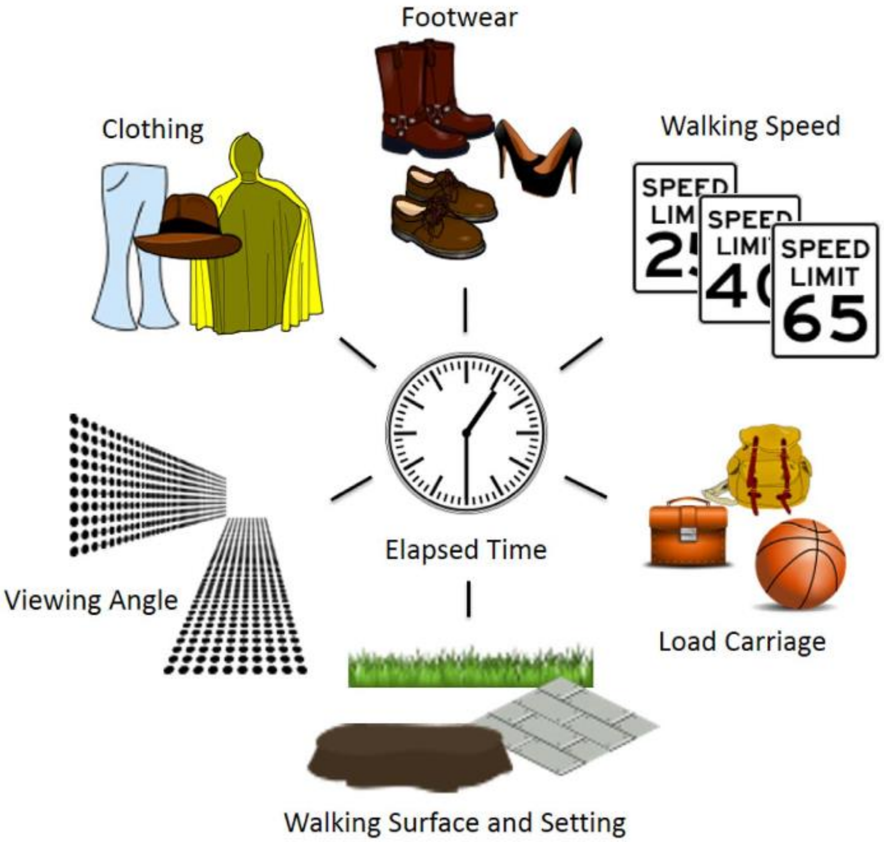
Identity science

Science/ technology

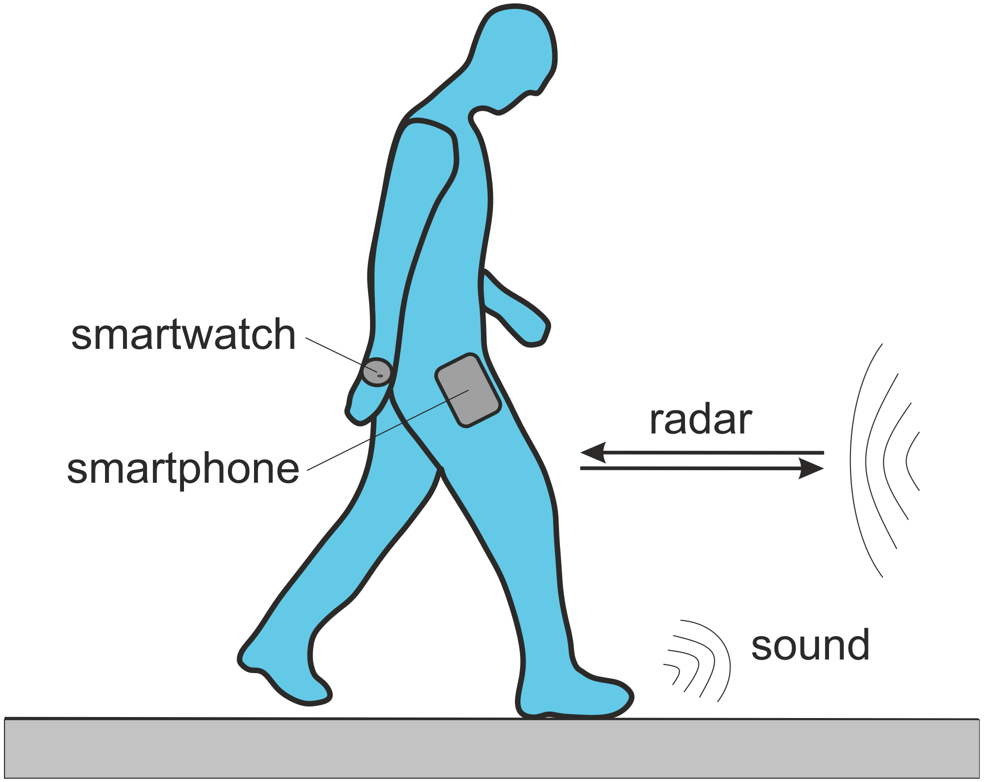
- Covariates and exploratory variables
- Soft biometrics
- Spoofing
- Deep architectures

Applications

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



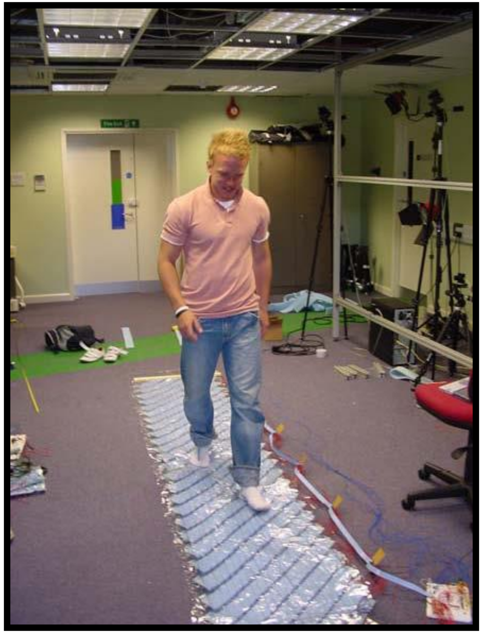
Non video gait



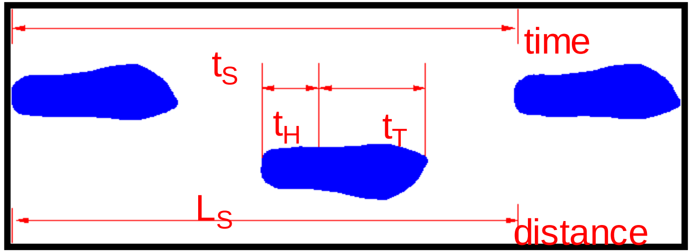
floor-based systems

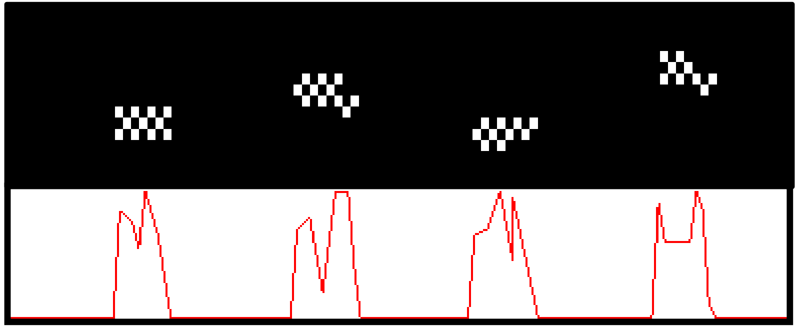
MD Marsico, A Mecca - ACM Computing Surveys (CSUR), 2019

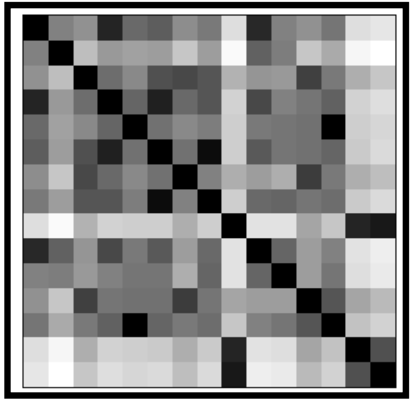
The first intelligent carpet



192×32 binary sensor array

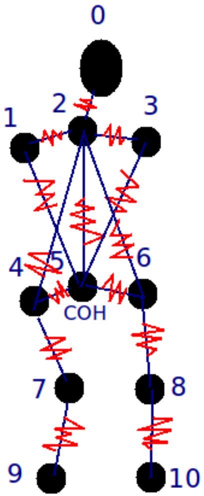


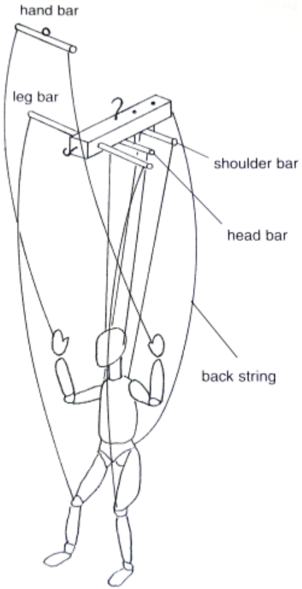


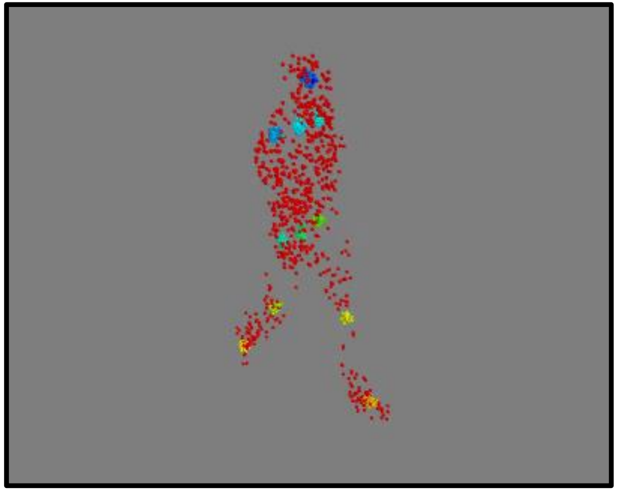


Middleton, Buss and Nixon, *AutoID* 2005

3D recognition – marionette based







3D is completely viewpoint invariant

Ariyanto and Nixon, Proc. ICB 2013

Forensics

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

The question ….

You are a biometrics expert

… and are contacted by the police

… who have a suspect.

What do you do?

What are forensics?

> *“scientific tests or techniques used in connection*
>
> *with the detection of crime”*

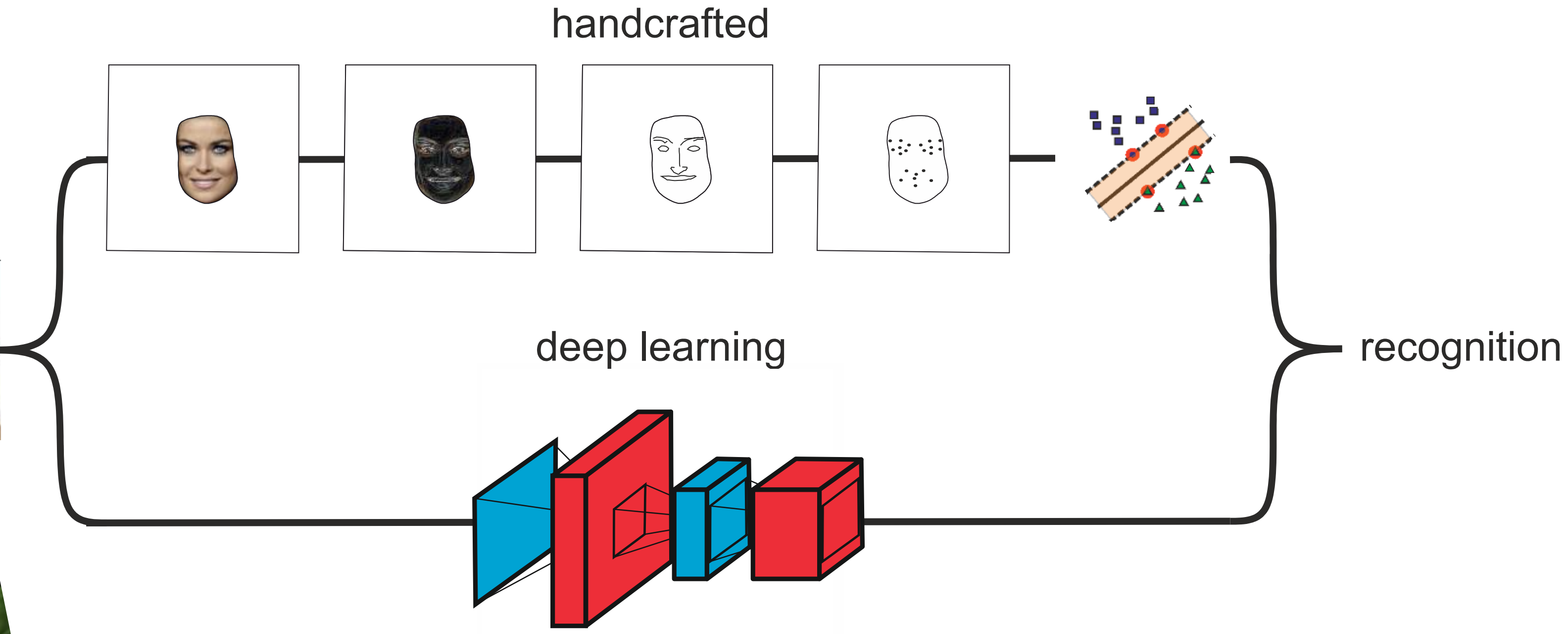
So what is a crime?

> *“an action or omission which constitutes an offence and is punishable by law”*

So forensics are

> *scientific tests used in connection with punishment by law*

Approaches to recognition



FEATURE EXTRACTION AND IMAGE PROCESSING FOR COMPUTER VISION
FOURTH EDITION
MARK S. NIXON
ALBERTO S. AGUADO

Who is this?

Otroshi et al, *IEEE TPAMI*, 2023

Evidence and admissibility

- Many things are evidence, but not all are admissible
- Rules and procedures differ
- Daubert is for expert witnesses

(not much biometrics in forensics, so for a new technique)

1. *Whether the theory and methodology have been tested, peer-reviewed, or published:*

   write a paper, apply it to something else

2. *The potential and known error rates for a particular technique:*

   include error bars

3. *Any standards and controls applicable to the science.*
4. *The degree of acceptance in the scientific community:*

   organise special session/ special edition/ competition,
   edit book, get on television, podcast, tutorial

Mr. Bean’s evidence

No, it’s not admissible
It fails Daubert, but it’s great!

Judicial systems – presenting the evidence

Differing types of system

1. Adversarial – convince a jury
    A. Civic duty
    B. 'Random' composition
2. Inquisitorial – convince magistrates/ committees
1. Autocratic – hmm, better less said!!

You have to convince people who are not experts in biometrics

Gait as evidence – first use

Bag snatcher, London 2008

Note controlled trajectory

Using gait as evidence -database

Use multiview gait data

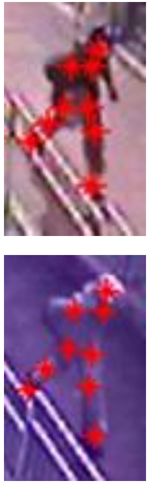
CASIA B at the time

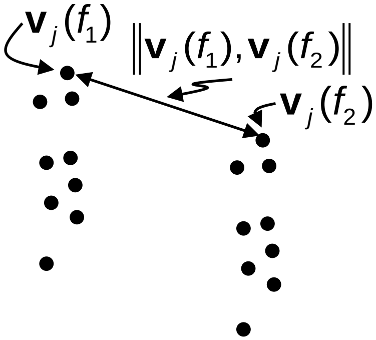
*

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

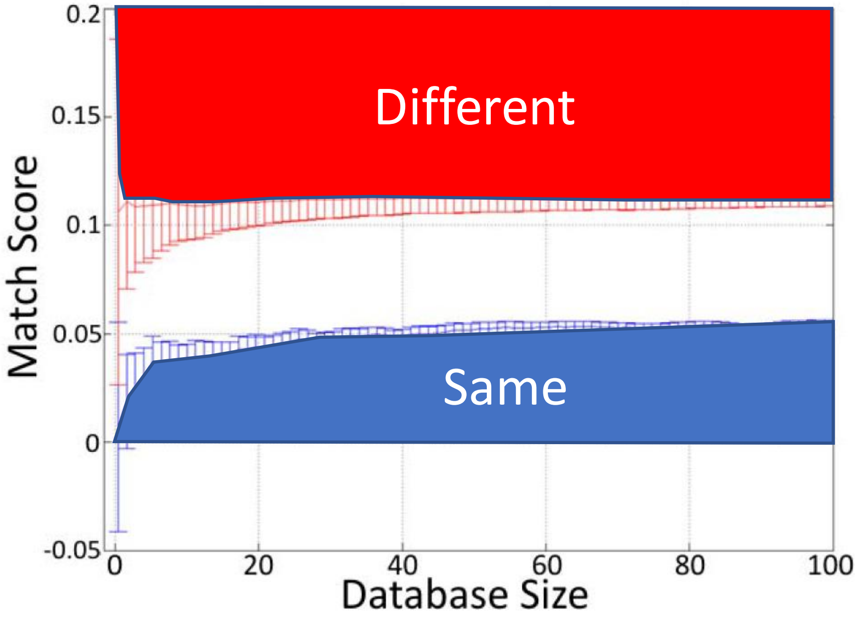
Between class $$d_b = \left(\sum_{s1,s2\in database|s1\neq s2}\ \sum_{f_1,f_2\in W|f_1\neq f_2}\ \sum_{j,k\in N}\left\|\mathbf{v}_j(f_1,s_1),\mathbf{v}_j(f_2,s_2)\right\| \Big/ (N\times W)\right)\Big/ S\ \text{-1}$$

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

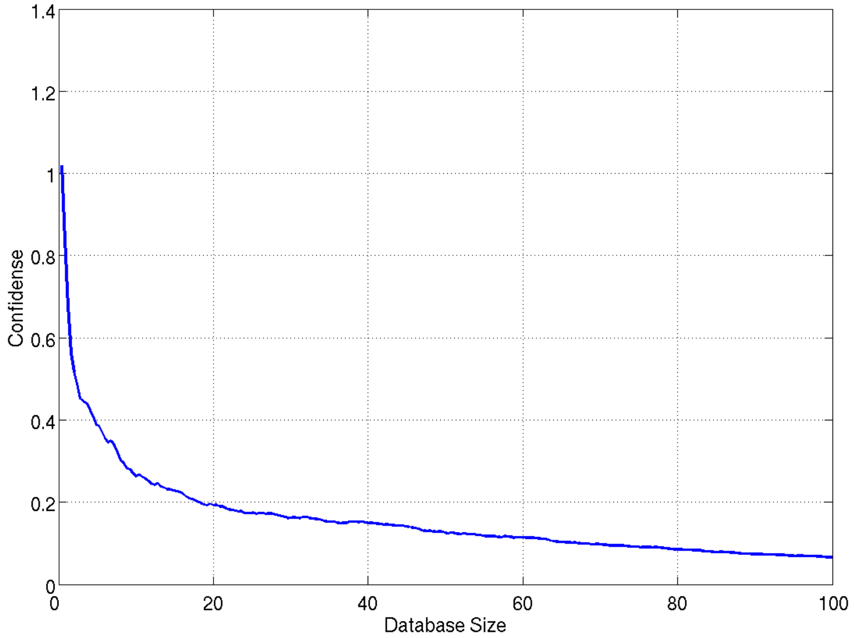
Match success = $$d \subset range(d_i)$$

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

Gait as evidence –analvsis on database

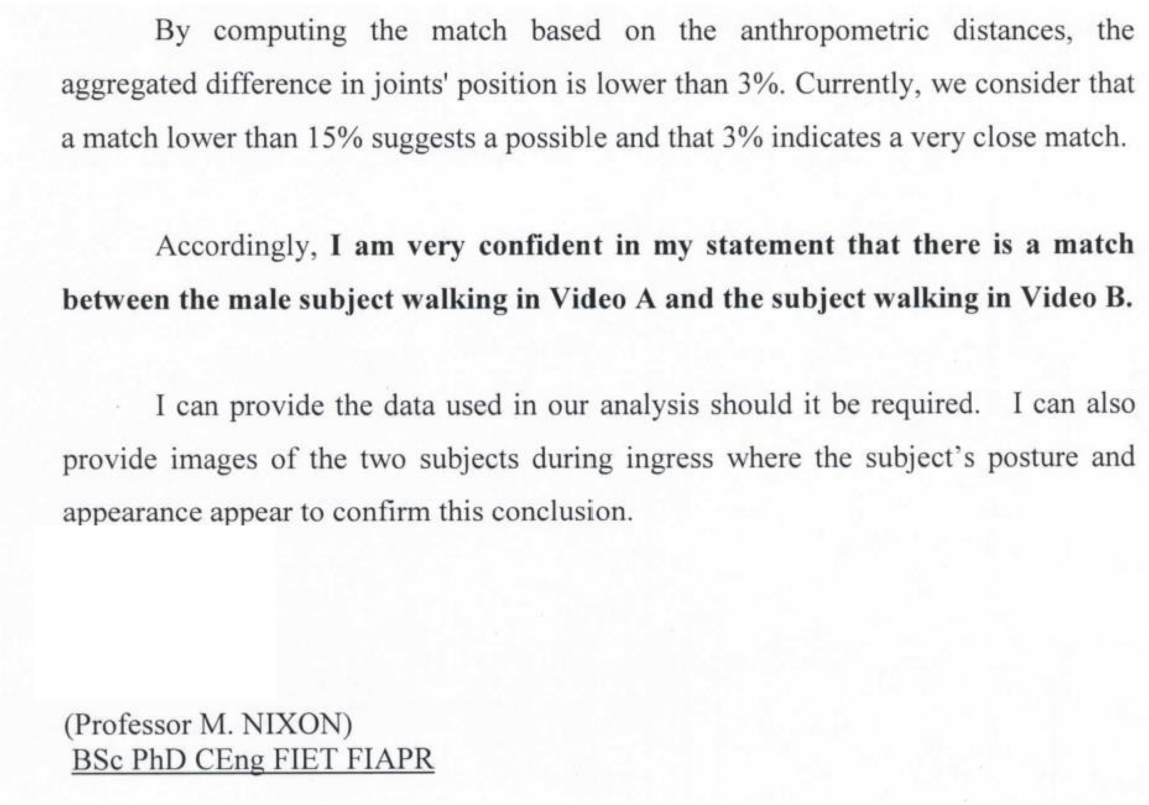


Distances



Confidence

Evidence



By computing the match based on the anthropometric distances, the aggregated difference in joints' position is lower than 3%. Currently, we consider that a match lower than 15% suggests a possible and that 3% indicates a very close match.

Accordingly, **I am very confident in my statement that there is a match between the male subject walking in Video A and the subject walking in Video B.**

I can provide the data used in our analysis should it be required. I can also provide images of the two subjects during ingress where the subject's posture and appearance appear to confirm this conclusion.

(Professor M. NIXON)
BSc PhD CEng FIET FIAPR

Plus:
Statement on self
Statement on gait
Description of data
Witness to signature

Gait as evidence: murder case in Australia 2014

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

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

60 Minutes Australia: Eye Catching

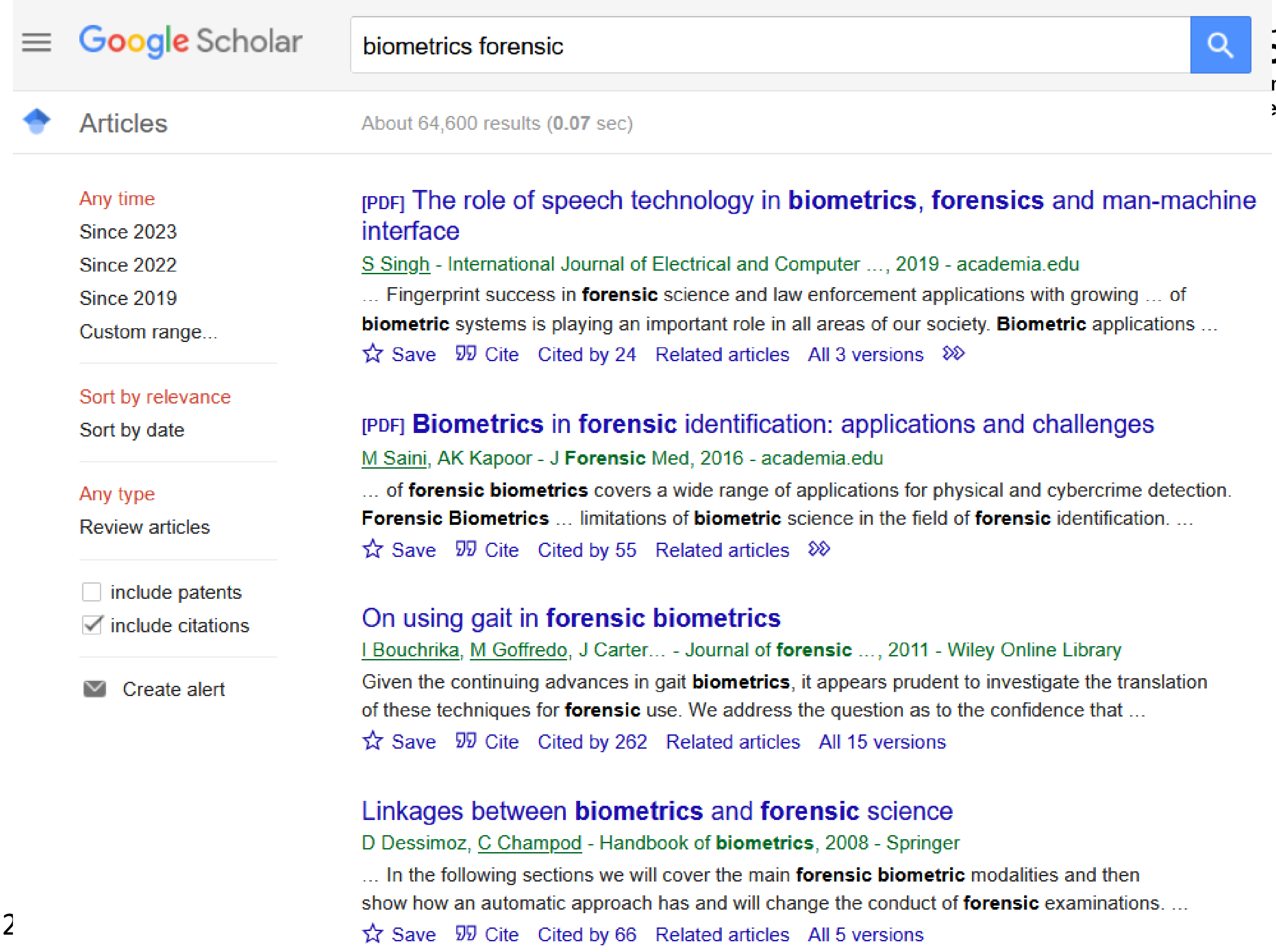
Bouchrika, Nixon, Carter, *J. Forensic Science* 2011, and *Eusipco* 2010

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

Likelihood ratio

- Introduces probabilistic reasoning to evidence
- Describes the degree of support of one proposition vs its alternative
- Prosecution proposition H_p: accused is same as perpetrator (intra-class)
- Defence proposition H_d: accused differs from perpetrator (inter-class)
- Likelihood ratio $$LR = \frac{p(E|H_p)}{p(E|H_d)}$$ $LR > 1$ supports prosecution
  $LR < 1$ supports defence
- H_p is intra-class probability density; H_d is inter-class
- Needs score to LR calculation, (logistic regression, kernel density, GMM)
- Needs calibration
- Needs standards
- Difficult for H_p Posterior odds = likelihood * prior odds

Ramos, Krish, Fierrez, Meuwly, *Handbook of Biometrics for Forensic Science*, 2017



About 64,600 results (**0.07** sec)

[PDF] The role of speech technology in **biometrics**, **forensics** and man-machine interface
S Singh - International Journal of Electrical and Computer …, 2019 - academia.edu
… Fingerprint success in **forensic** science and law enforcement applications with growing … of **biometric** systems is playing an important role in all areas of our society. **Biometric** applications …
☆ Save 99 Cite Cited by 24 Related articles All 3 versions

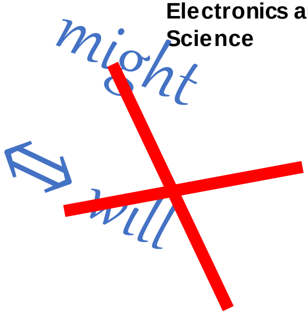
[PDF] **Biometrics** in **forensic** identification: applications and challenges
M Saini, AK Kapoor - J **Forensic** Med, 2016 - academia.edu
… of **forensic biometrics** covers a wide range of applications for physical and cybercrime detection. **Forensic Biometrics** … limitations of **biometric** science in the field of **forensic** identification. …
☆ Save 99 Cite Cited by 55 Related articles

On using gait in **forensic biometrics**
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 …
☆ Save 99 Cite Cited by 262 Related articles All 15 versions

Linkages between **biometrics** and **forensic** science
D Dessimoz, C Champod - Handbook of **biometrics**, 2008 - Springer
… In the following sections we will cover the main **forensic biometric** modalities and then show how an automatic approach has and will change the conduct of **forensic** examinations. …
☆ Save 99 Cite Cited by 66 Related articles All 5 versions

Search 7 Dec 2

Prosecutor's fallacy



- Prosecutor's fallacy is a one of statistical reasoning
- It’s misapplied statistics
- E.g. a defence argument

Gait achieves 99% correct recognition, so in a population of 30 million 300000 people are not identified correctly, so the perpetrator could be one of those 300000 (…and is therefore innocent)

- Riposte:

did everyone in Australia walk through that shop the same day?

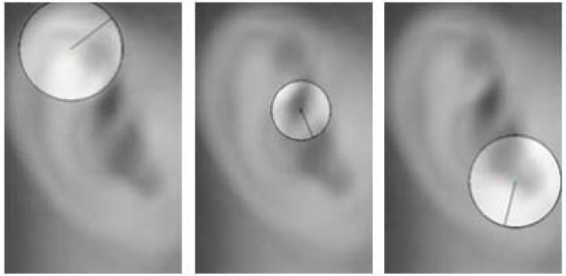
OJ Simpson: the prosecution assertion that, because the story before the court is highly improbable, the defendant's innocence is equally improbable.

Ears by same procedure

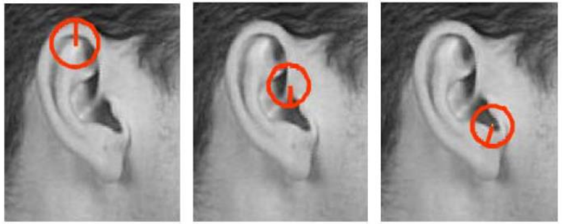
Ears are unique and permanent, and rarely hidden (for ID)

Nixon, Bouchrika, Arbab-Zavar, Carter, *Eusipco* 2010

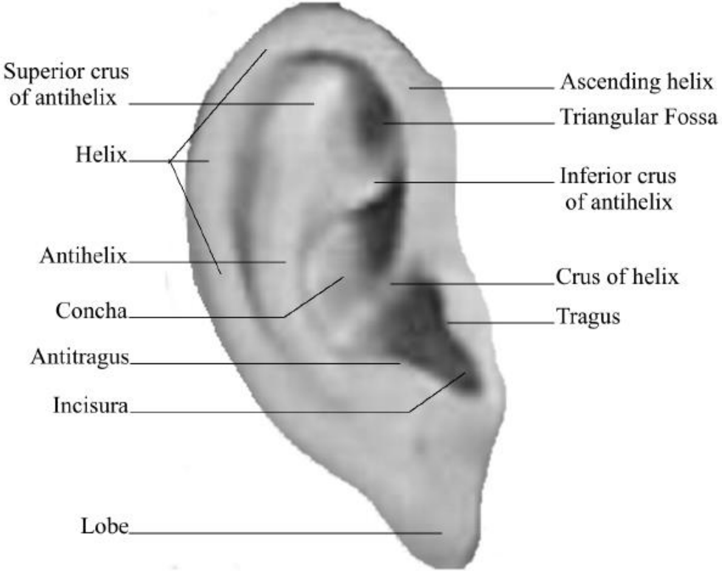
Ears have many interesting features



(a) Model parts

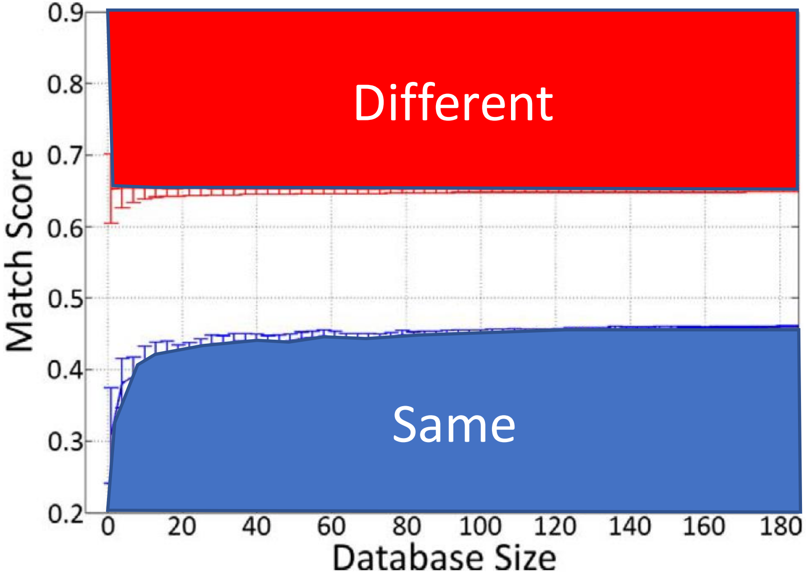


(b) Detected parts



Nixon, Bouchrika, Arbab-Zavar, Carter, *Eusipco* 2010

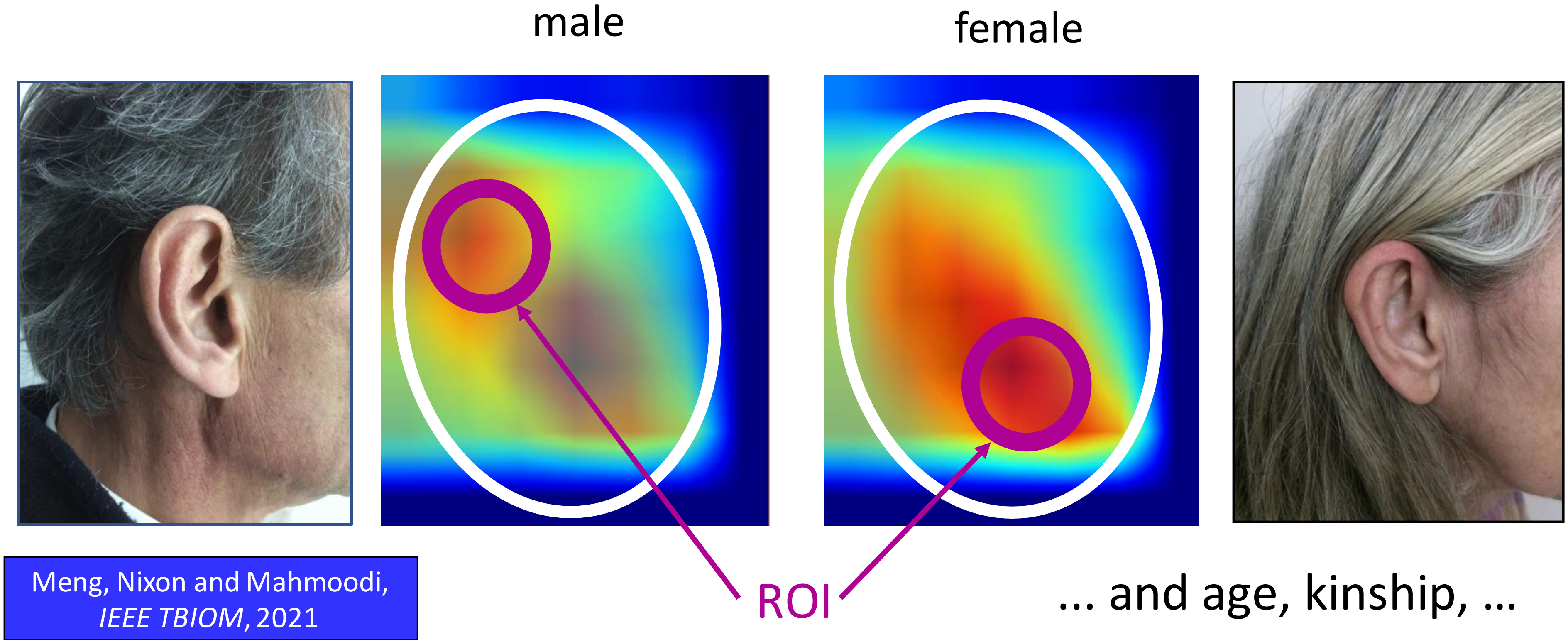
On an ear database



Variance is much smaller

Nixon, Bouchrika, Arbab-Zavar, Carter, *Eusipco* 2010

Identity science: where is gender in ears?



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

… and age, kinship, …

What (and how old) is whom?

Woman

70 [✓ 40] 10

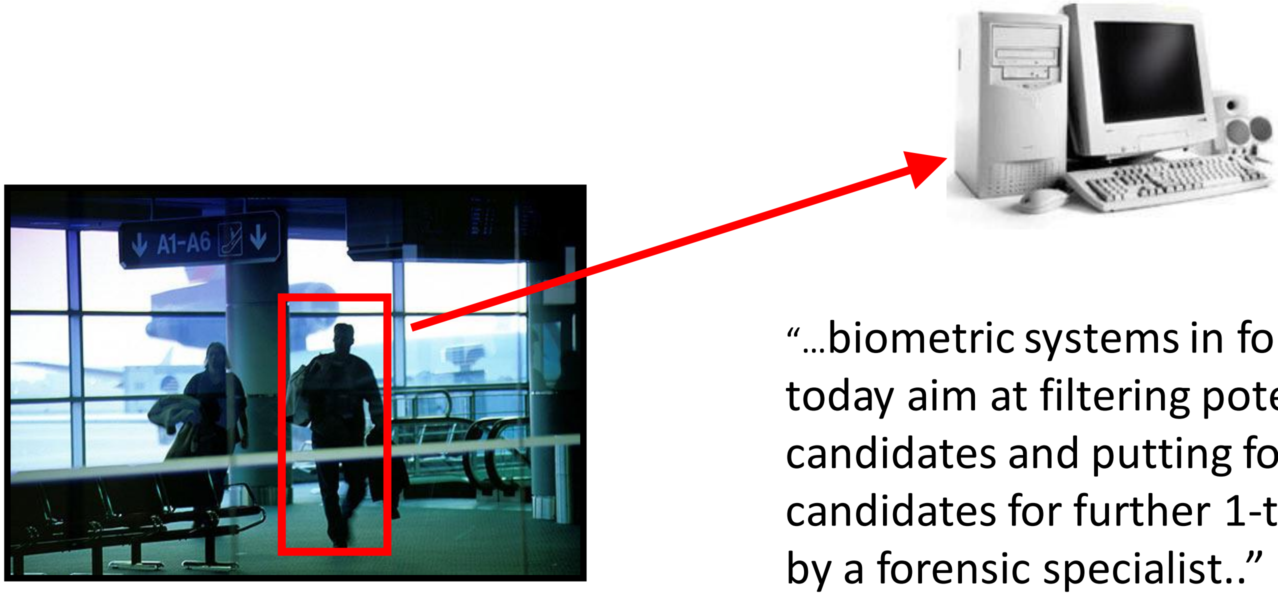
Man

[✓ 70] 40 10

Man

70 [✓ 40] 10

Biometrics in the forensics literature 1



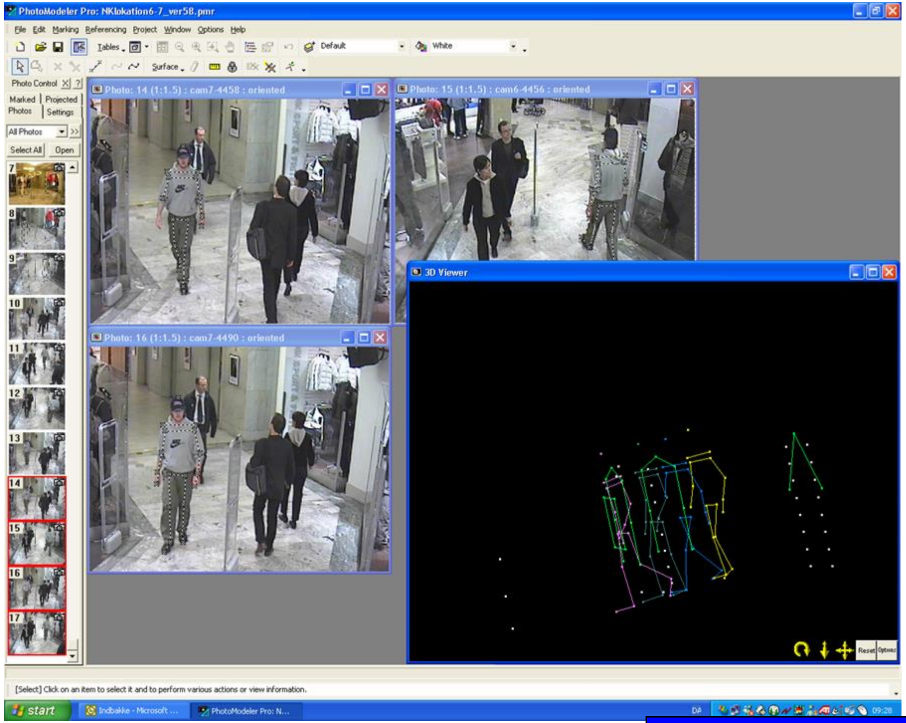
"...biometric systems in forensic science today aim at filtering potential candidates and putting forward candidates for further 1-to-1 verification by a forensic specialist.."

Dessimoz and Champod, *Biometrics Handbook,* Springer, 2007, Chap 21

Biometrics in the forensics literature 2

Forensic anthropology

Murder of Swedish foreign secretary, Anna Lindh



[Select] Click on an item to select it and to perform various actions or view information.

N. Lynnerup and J. Vedel
J. Forensic Sci., 2005

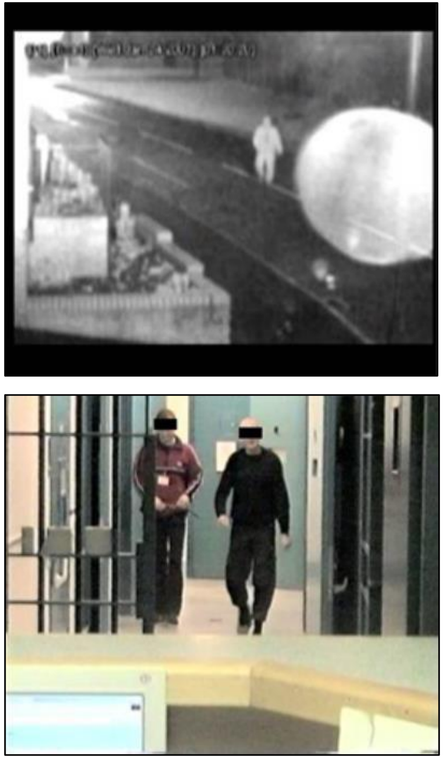
Biometrics in the forensics literature 3 Forensic podiatry

“Forensic gait analysis, the direct visual comparison of two or more video recordings to establish whether they are of the same individual … based on the gait pattern alone”

- “There is no published standardised approach for forensic gait analysis comparison”
- “There appears to be little consistency in the formal recording … for forensic gait analysis”
- “the strength of the conclusion … is often only a subjective estimate”
- “no credible database”, “no published and verified error rates”, “no published black-box studies”

And (!!)

- automated methods … differ from forensic gait analysis …make use of a much richer dataset



S Black, M Wall, R Abboud, R Baker, J Stebbins *Royal Society: Forensic gait analysis: A primer for courts*, 2017

End of forensic podiatry?

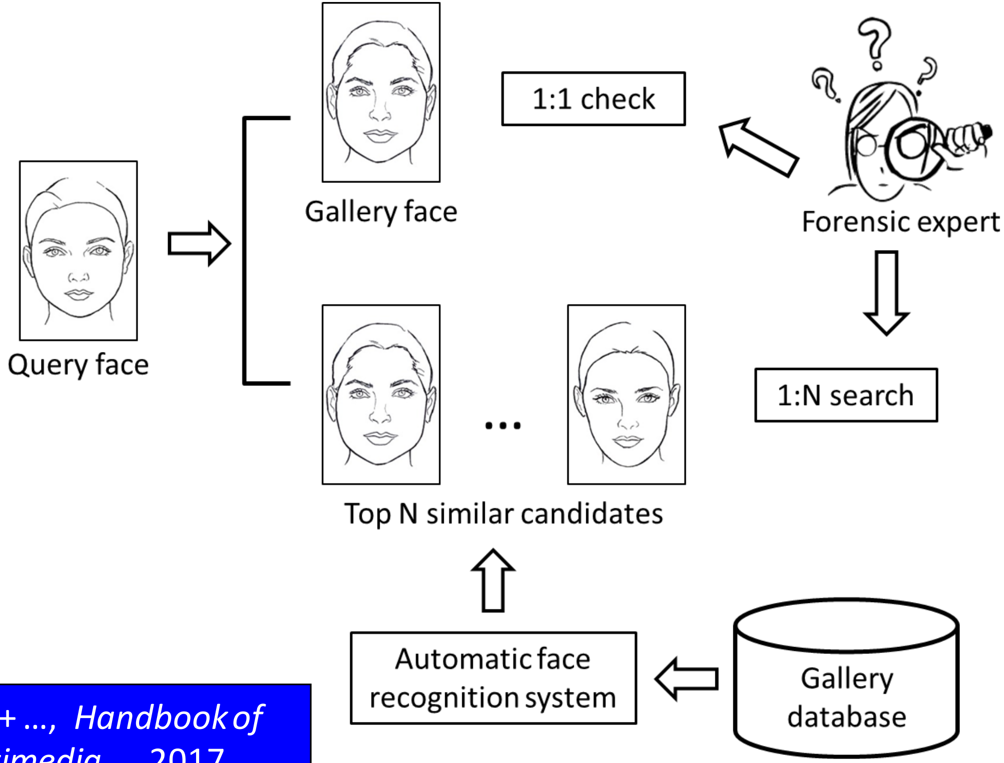
“The methods remain insufficiently robust, considering the recent paradigm shift witnessed in the forensic science community regarding quality of evidence.”

“However, there is persistence in attempting to prove that as it stands, forensic gait analysis should not fall into disrepute in the forensic science community”

“Automated gait recognition has greatly surpassed forensic gait analysis”

Macoveciuc, Rando +, Forensic gait analysis and recognition: standards of evidence admissibility, *J. Forensic Science*, 2019

Biometrics in the forensics literature 4 - face



Query face

Gallery face

1:1 check

Forensic expert

1:N search

…

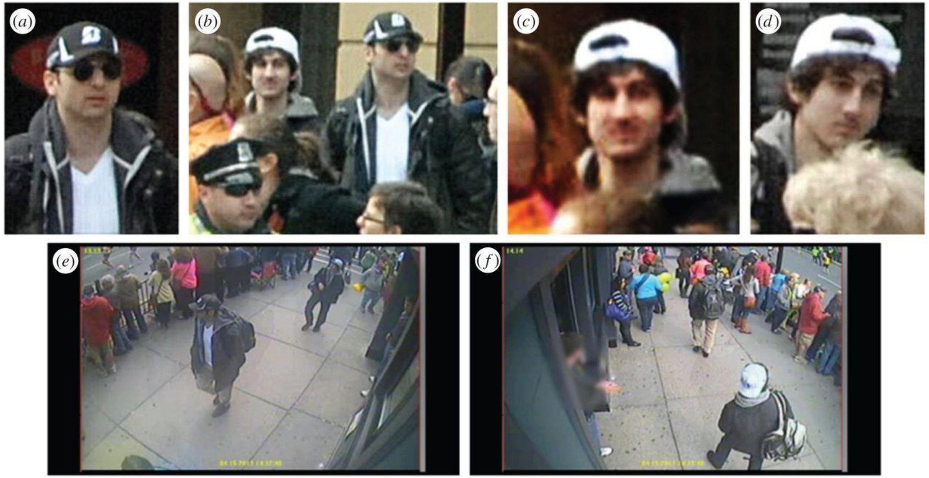
Top N similar candidates

Automatic face recognition system

Gallery database

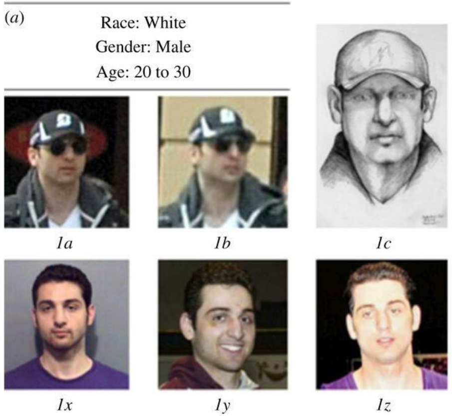
Arbab-Zavar, Wei, Bustard + …, *Handbook of Digital Forensics of Multimedia …*, 2017

Biometrics in the forensics literature 3 Face recognition



Boston police video:
The public was asked to help identify these two individuals

Jain, Ross, *Transactions of the Royal Society B*, 2015



(*b*) with demographic filtering (white male, 20–30)

	1a	*1b*	*1c*	mean
1x	5432	27 617	112	353
1y	518	25 780	1409	686
1z	3958	14 670	1142	1416
mean	424	5790	71	82

Biometrics:
composite-to-photo matching

Composite of Tamerlan Tsarnaev (*1c*) resulted in a better match with the gallery image (*1x*) than any of the probe images (*1a* and *1b*) released by the police

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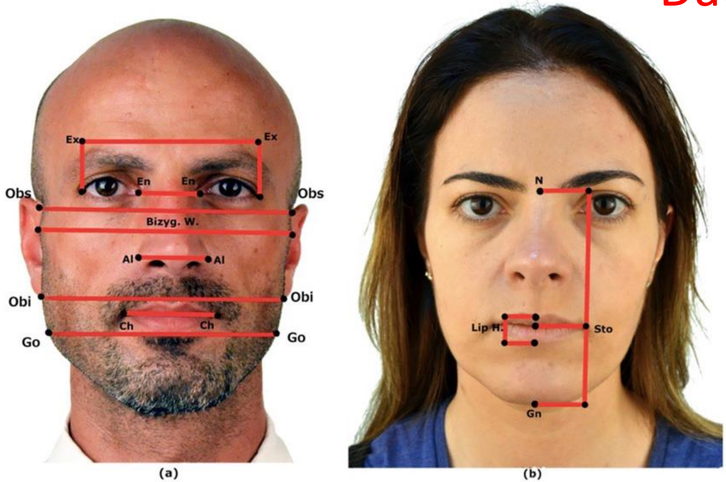
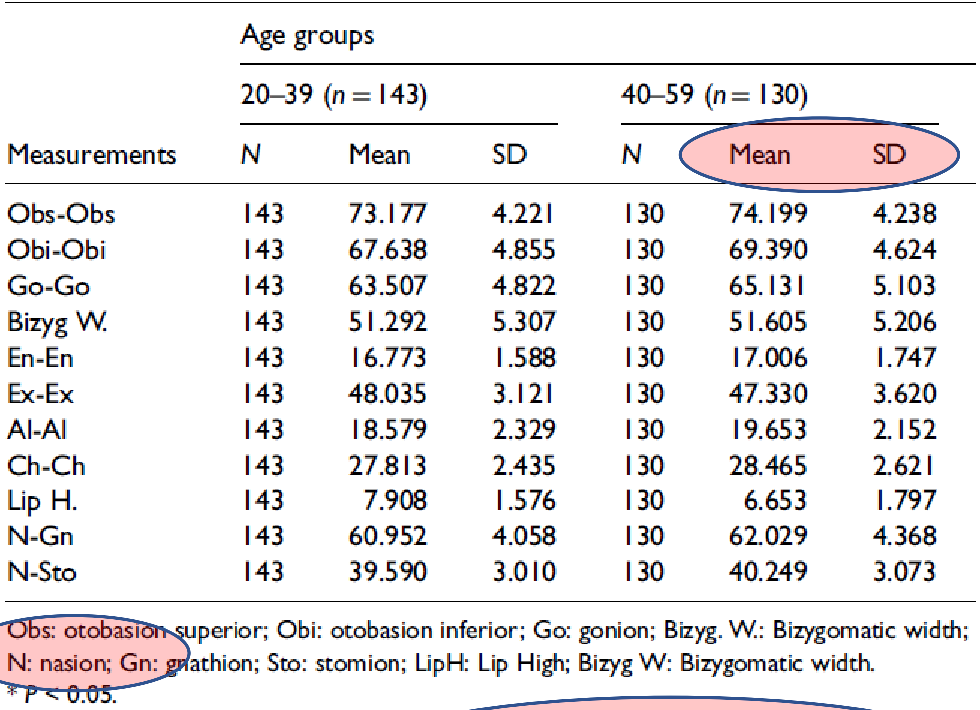
Sex estimation from biometric face photos for forensic purposes

Daubert

sex estimation could be made with an accuracy of 80.5%



(left), (right) Distances taken between landmarks (Obs: otobasion superior, Obi: otobasion inferior, Go: gonion, bizyg. W.: Bizygomatic width, En: endocanthion, Ex: exocanthion, Al: alare, Ch: chellion, N: nasion, Gn: gnathion, Sto: stomion).



	Age groups					
	20–39 ($n = 143$)			40–59 ($n = 130$)		
Measurements	N	Mean	SD	N	Mean	SD
Obs-Obs	143	73.177	4.221	130	74.199	4.238
Obi-Obi	143	67.638	4.855	130	69.390	4.624
Go-Go	143	63.507	4.822	130	65.131	5.103
Bizyg W.	143	51.292	5.307	130	51.605	5.206
En-En	143	16.773	1.588	130	17.006	1.747
Ex-Ex	143	48.035	3.121	130	47.330	3.620
Al-Al	143	18.579	2.329	130	19.653	2.152
Ch-Ch	143	27.813	2.435	130	28.465	2.621
Lip H.	143	7.908	1.576	130	6.653	1.797
N-Gn	143	60.952	4.058	130	62.029	4.368
N-Sto	143	39.590	3.010	130	40.249	3.073

Obs: otobasion superior; Obi: otobasion inferior; Go: gonion; Bizyg. W.: Bizygomatic width; N: nasion; Gn: gnathion; Sto: stomion; LipH: Lip High; Bizyg W: Bizygomatic width.
$* P < 0.05$.

N Sezgin, B Karadayi, *Medicine, Science and the Law*, 2019

Advantages of biometrics in forensics

1. Large databases – representative of large modern populations

   (vs databases of criminals; lineups/ identity parades)

2. Large databases – reduce cognitive bias

   (vs. subjective reality of criminal data)

3. Automated processing

   fast and reproducible results

   chain of reasoning

   error bars

Problems

There are many advantages to using biometrics in forensics…

But the coverage/ usage is lower

We need:

1. To engage the constituents
2. Prepare appropriate modes of evidence
3. Justify our technology in means other than usual in our science

Suggestions for generating biometric evidence

1. Write a paper, apply it to something else
2. Include error bars
3. Generate likelihood ratio
4. Use biometric standards
5. Organise workshop/ special session/ tutorial/ special edition/ competition
6. Edit book, write news article/ get on television
7. Get advice on writing statement

Soft Biometrics

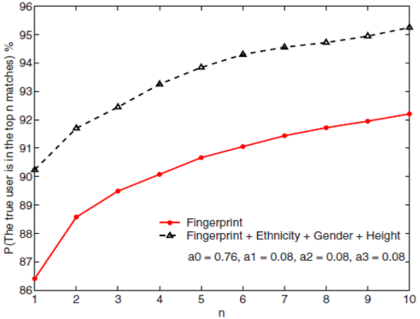
1. What are they?
2. How do they work?
3. Where are we going?

Soft Biometrics

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

Nandakumar and Jain 2004
(augmenting traditional biometrics

FIGURE 11. 2D.
LEFT MIDDLE FINGER.
Enlargement of the position of the fingers in the third movement.



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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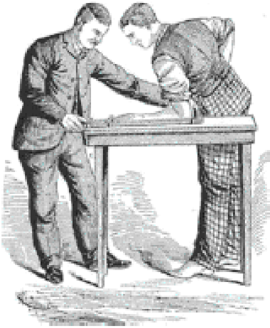
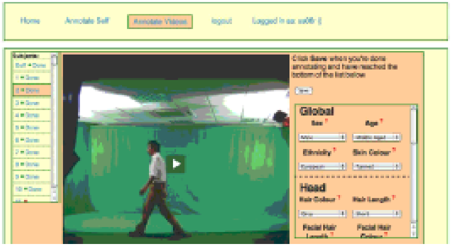
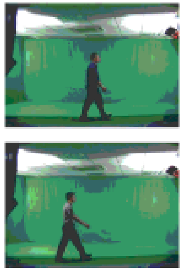
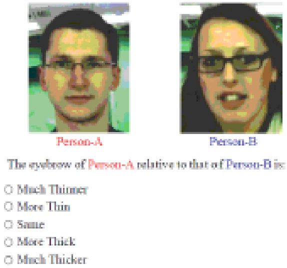




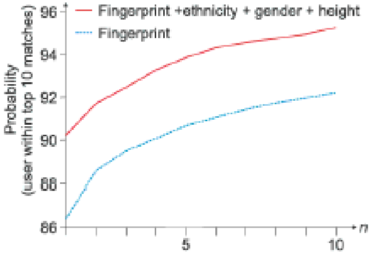
Click Save when you're done annotating and have reached the bottom of the list below

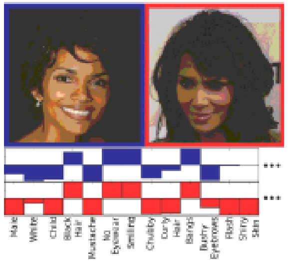


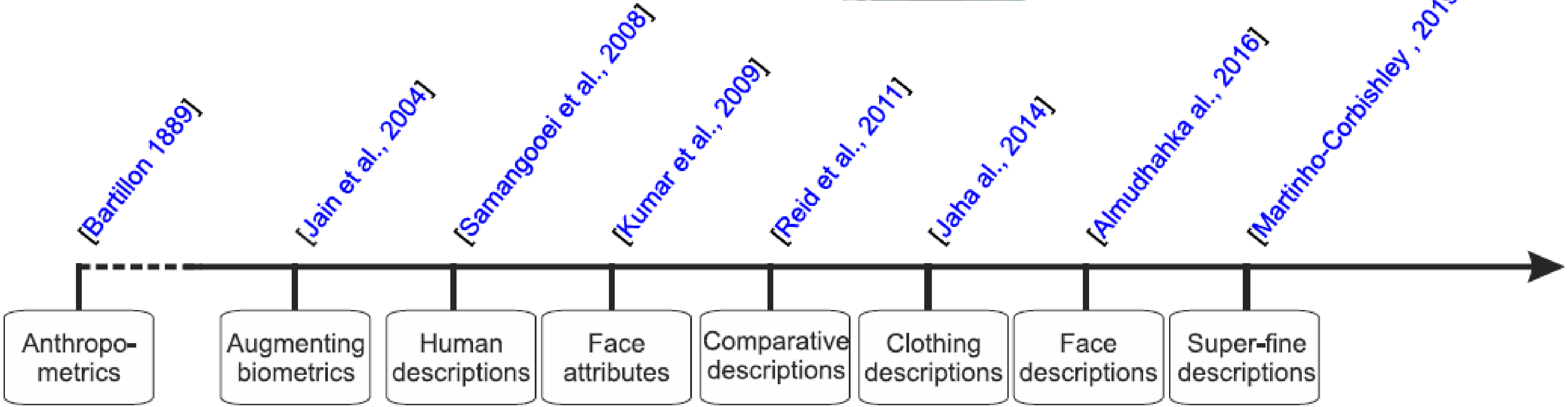


The eyebrow of Person-A relative to that of Person-B is:

- ○ Much Thinner
- ○ More Thin
- ○ Same
- ○ More Thick
- ○ Much Thicker







on

ence

Advantages of Soft Biometrics

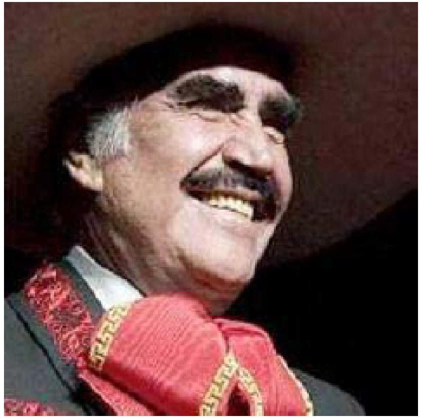
1. Human understandable description
   - rich in semantics, e.g., a face image described as a "young Asian male"
   - bridges gap between human and machine descriptions
1. Robustness to image quality
   - soft biometric attributes and low quality data
   - subject at a distance from the camera
1. Privacy
   - lack of distinctiveness implies privacy friendly
   - … but we can recognise you anywhere
1. Performance improvement
   - use in conjunction with biometric cues such as face, fingerprint and iris
   - fusion to improve accuracy. ID invariance to viewpoint, illumination.

Soft biometrics – the state of art

Technique: predominantly deep

Data: Maad-face, Annotated pedestrians

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



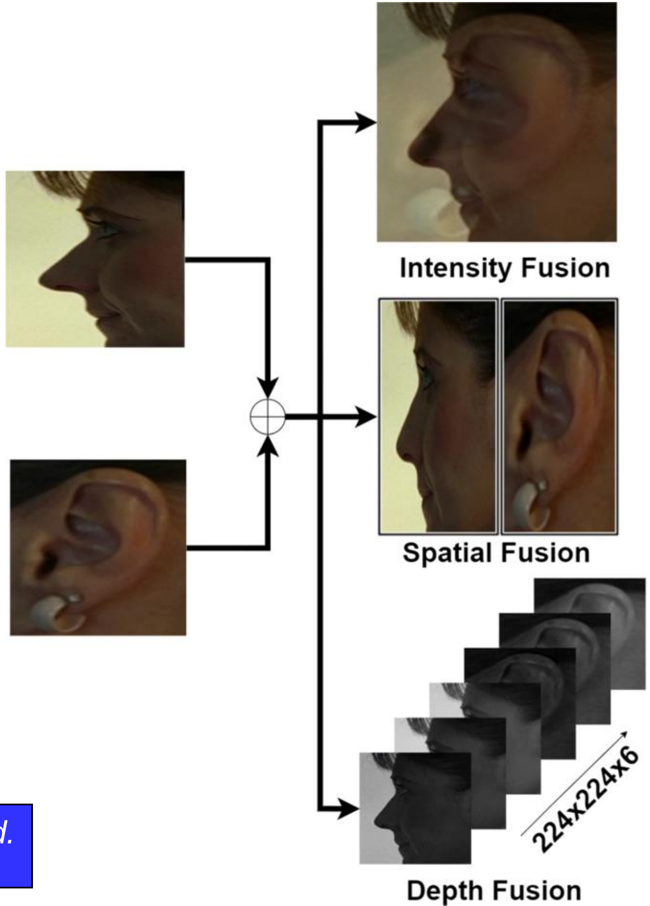
Male	1	Bangs	-1	Round Face	0	Big Lips	0
Young	-1	Sideburns	1	Double Chin	1	Big Nose	1
Middle Aged	-1	Black Hair	0	High Cheekbones	0	Pointy Nose	-1
Senior	1	Blond Hair	-1	Chubby	1	Heavy Makeup	-1
Asian	-1	Brown Hair	-1	Obstructed Forehead	1	Wearing Hat	1
White	0	Gray Hair	1	Fully Visible Forehead	-1	Wearing 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		

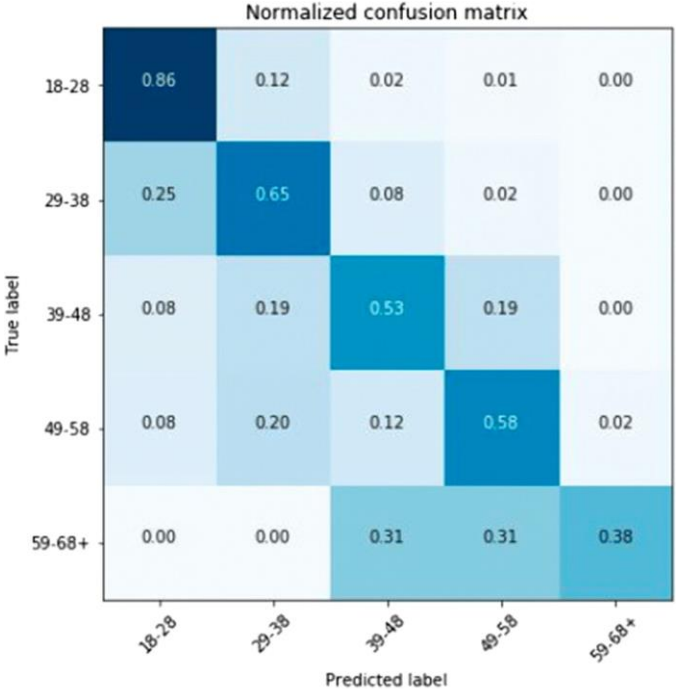
Terhörst et al, *IEEE TIFS* 2021

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%





	18-28	29-38	39-48	49-58	59-68+
18-28	0.86	0.12	0.02	0.01	0.00
29-38	0.25	0.65	0.08	0.02	0.00
39-48	0.08	0.19	0.53	0.19	0.00
49-58	0.08	0.20	0.12	0.58	0.02
59-68+	0.00	0.00	0.31	0.31	0.38

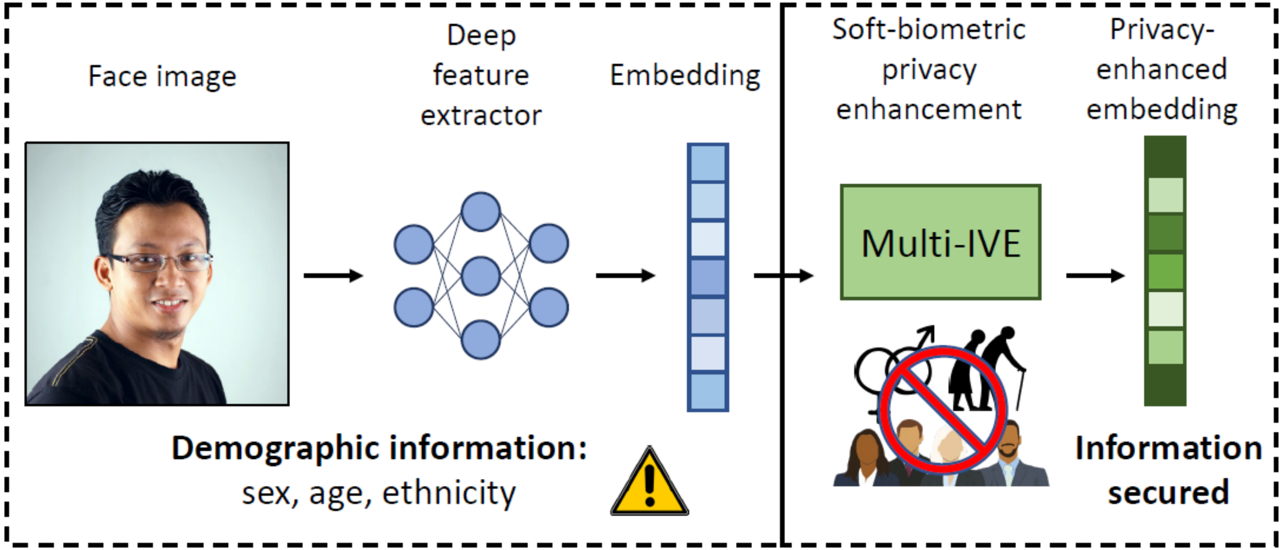
Age confusion

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

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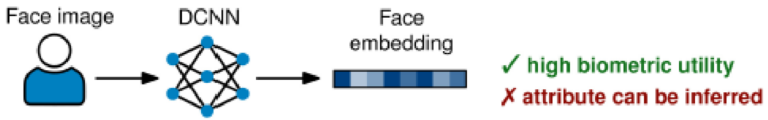
PrivacyProber: Assessment and Detection of Soft–Biometric Privacy–Enhancing Techniques



Face image

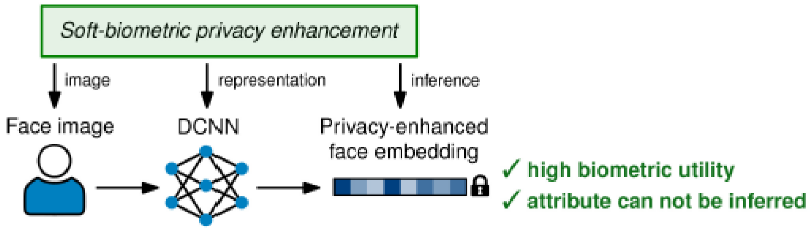
DCNN

Face embedding

✓ high biometric utility

✗ attribute can be inferred

(a) Original (unprotected)



Soft-biometric privacy enhancement

image

representation

inference

Face image

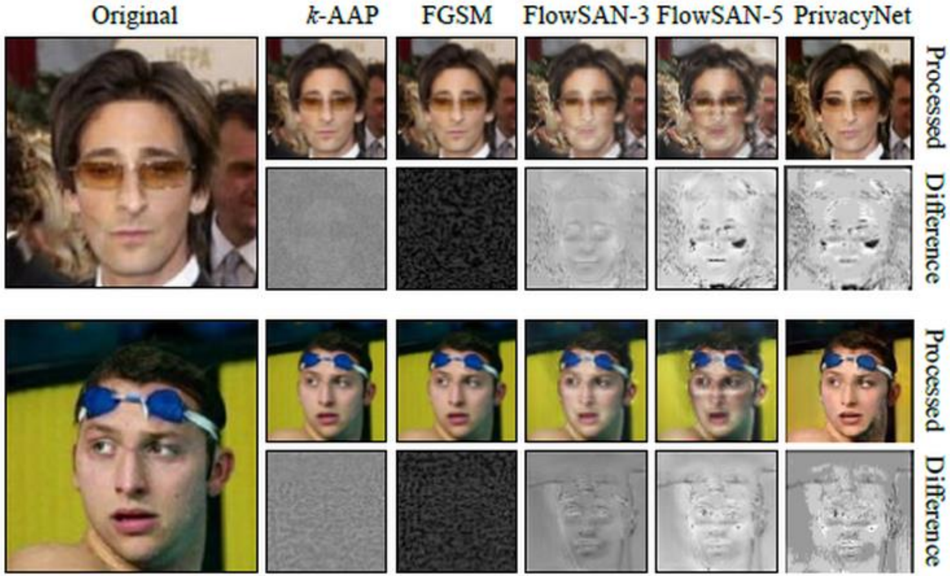
DCNN

Privacy-enhanced face embedding

✓ high biometric utility

✓ attribute can not be inferred

(b) Privacy-enhanced (protected)



Adding privacy enhancement

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

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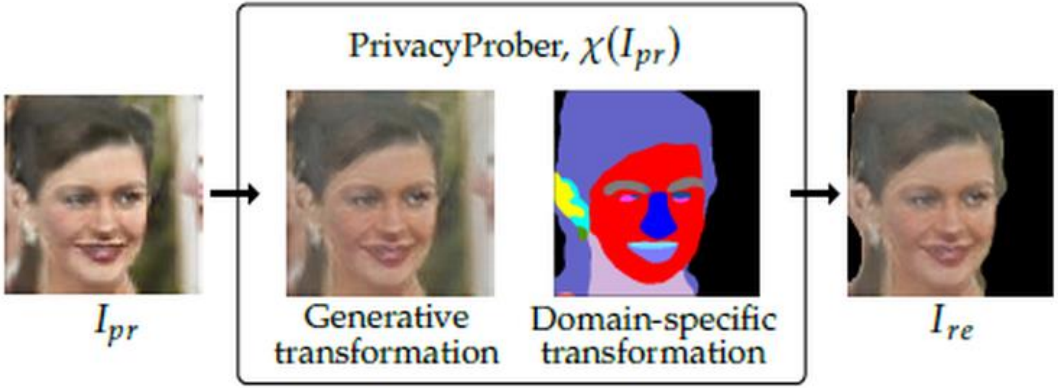
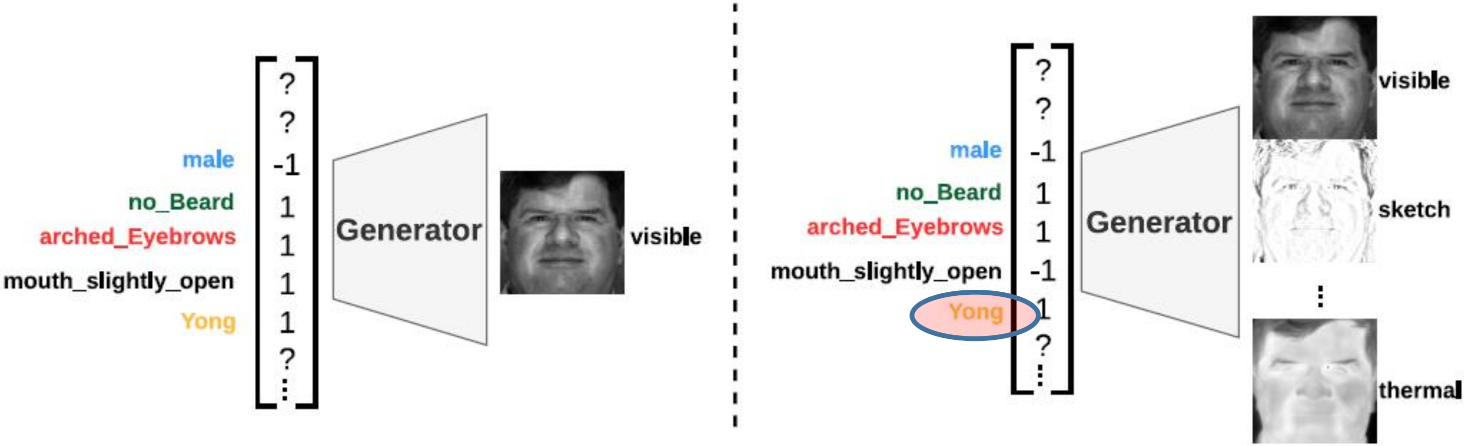
PrivacyProber: Assessment and Detection of Soft–Biometric Privacy–Enhancing Techniques



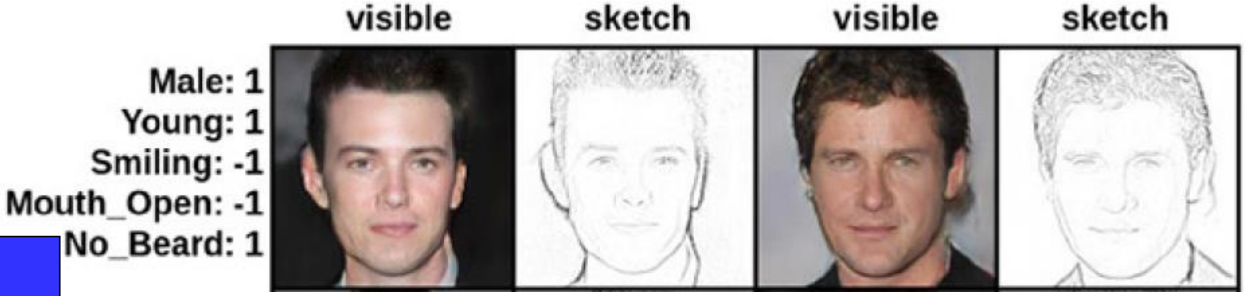
Detecting privacy enhancement

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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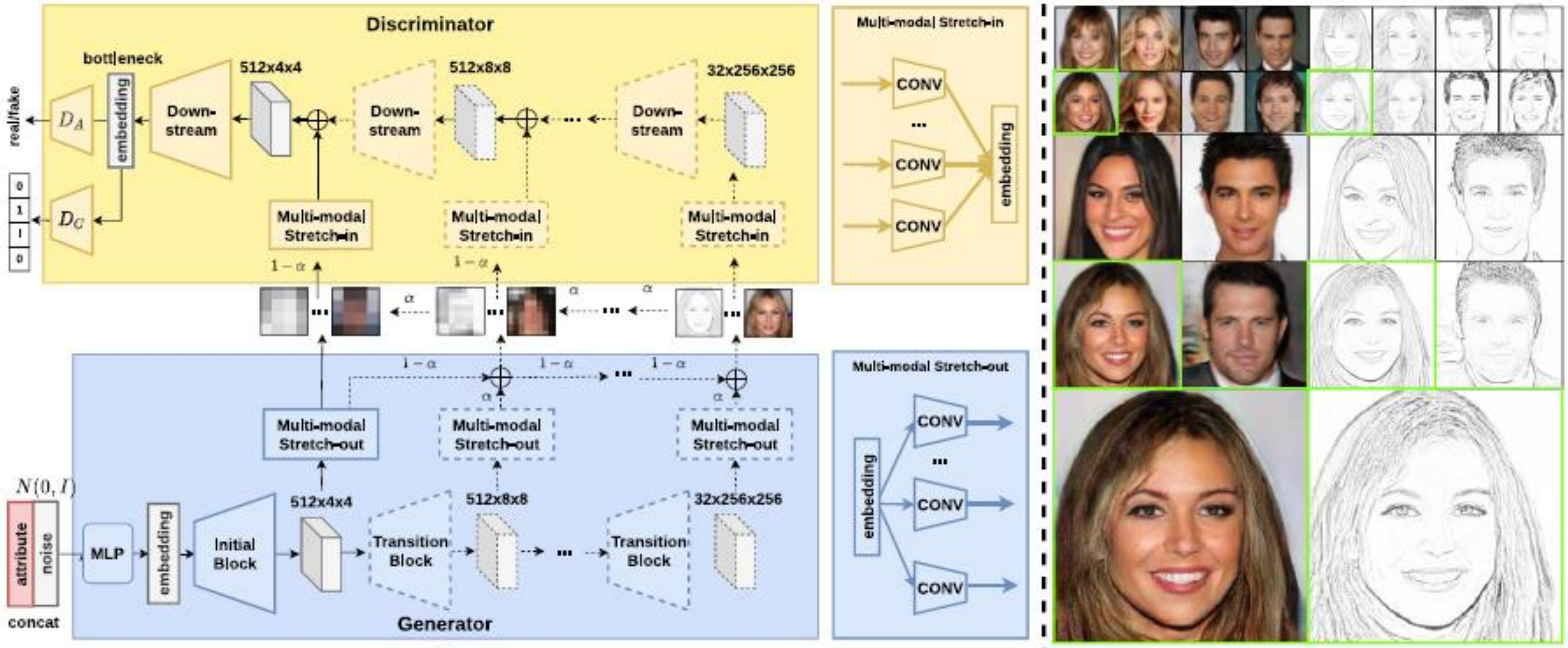
Electronics and Computer Science

Multimodal Face Synthesis From Visual Attributes

Xing Di and Vishal M. Patel (JHU)



(a)

(b)

Di and Patel, *IEEE TBIOM*, 2021

What can you recognise?

64×97

128×194

256×386

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!!

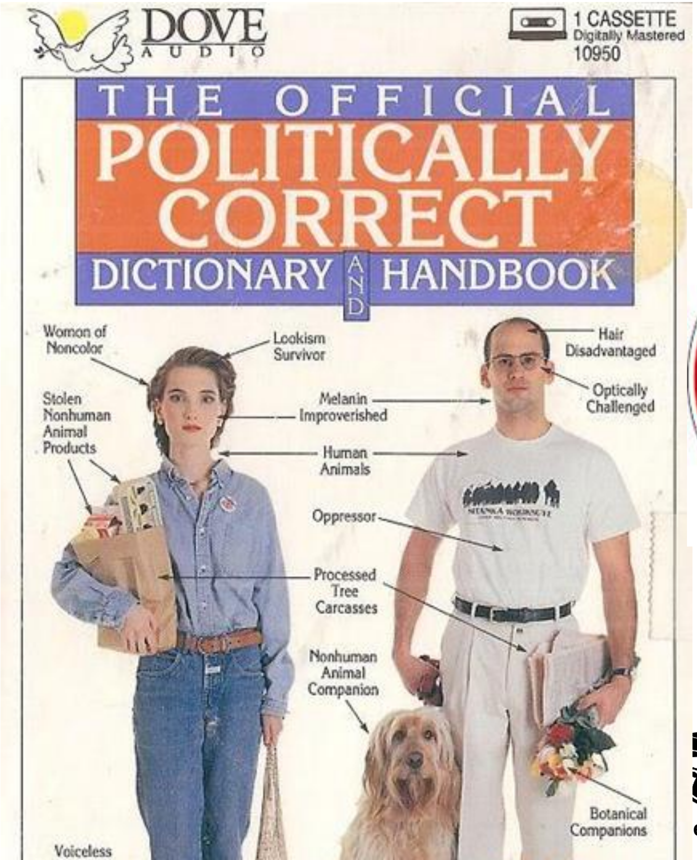
- Global
  - Sex
  - Ethnicity
  - Skin Colour
  - Age
- Body Shape
  - Figure
  - Weight
  - Muscle Build
  - Height
  - Proportions
  - Shoulder Shape
  - Chest Size
  - Hip size
  - Leg/Arm Length
  - Leg/Arm Thickness
- Head
  - Hair Colour
  - Hair Length
  - Facial Hair Colour/Length
  - Neck Length/Thickness

Phrasing questions

- No ‘political correctness’
- Note, or avoid, homonyms and polysemes
- Eschew completely argot and colloquialism

    E.g. nose: hooter, snitch, conk (UK), schnozzle (US?)

….. and avoid words like eschew



Recognition by fine-grained attributes

Database of images

Set of labels

Crowd sourced comparative labels

1. Label the data

Ranking labels

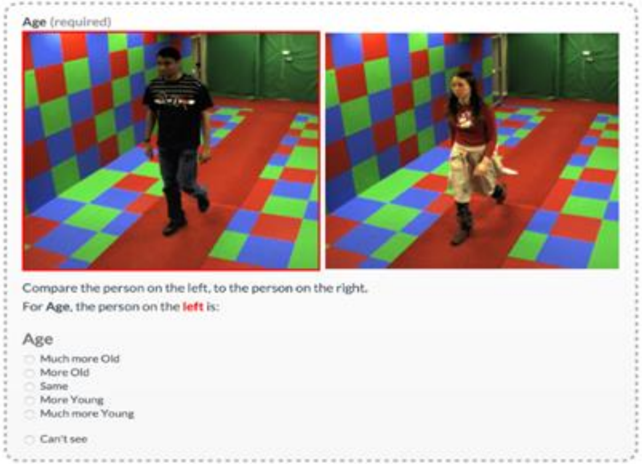
2. Turn the data into features

Learning label structure

3. Learn how recognition can be achieved

Recognise

4. Generate new labels



Age (required)

Compare the person on the left, to the person on the right.
For **Age**, the person on the **left** is:

Age

○ Much more Old
○ More Old
○ Same
○ More Young
○ Much more Young

○ Can't see

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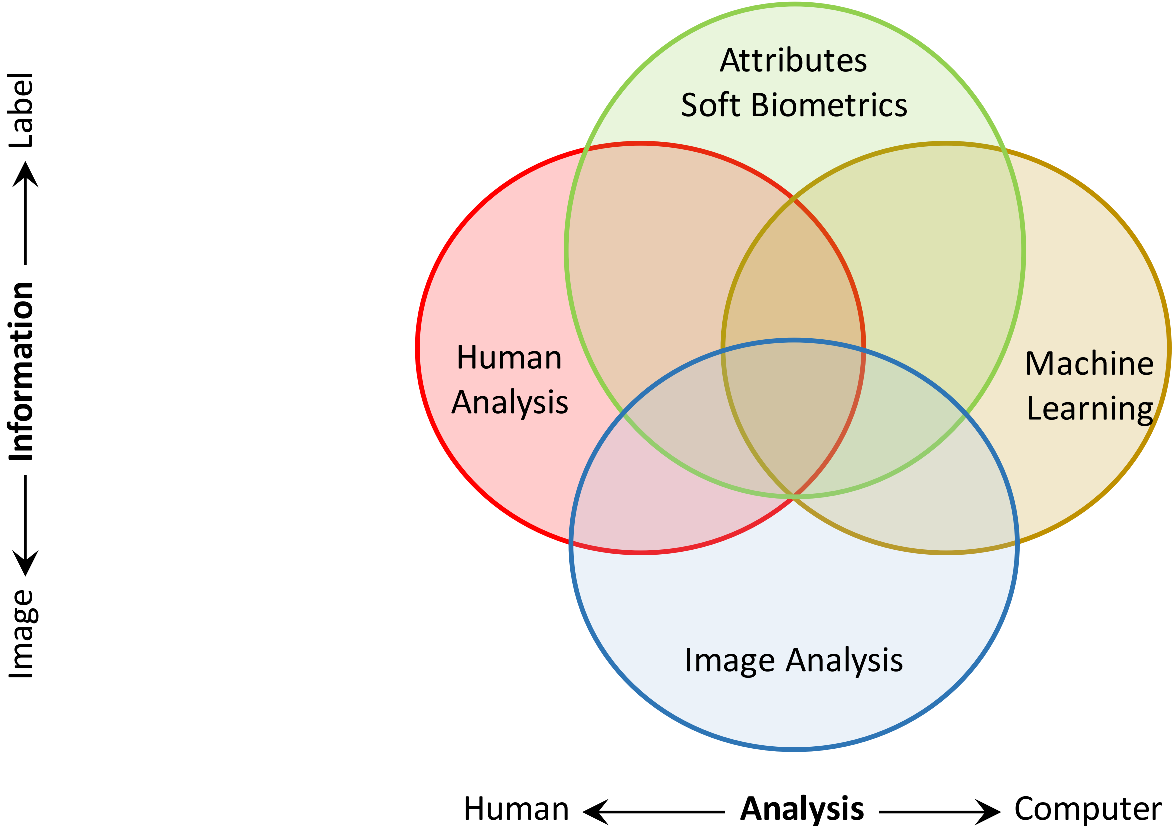
How does this fit with computer vision?



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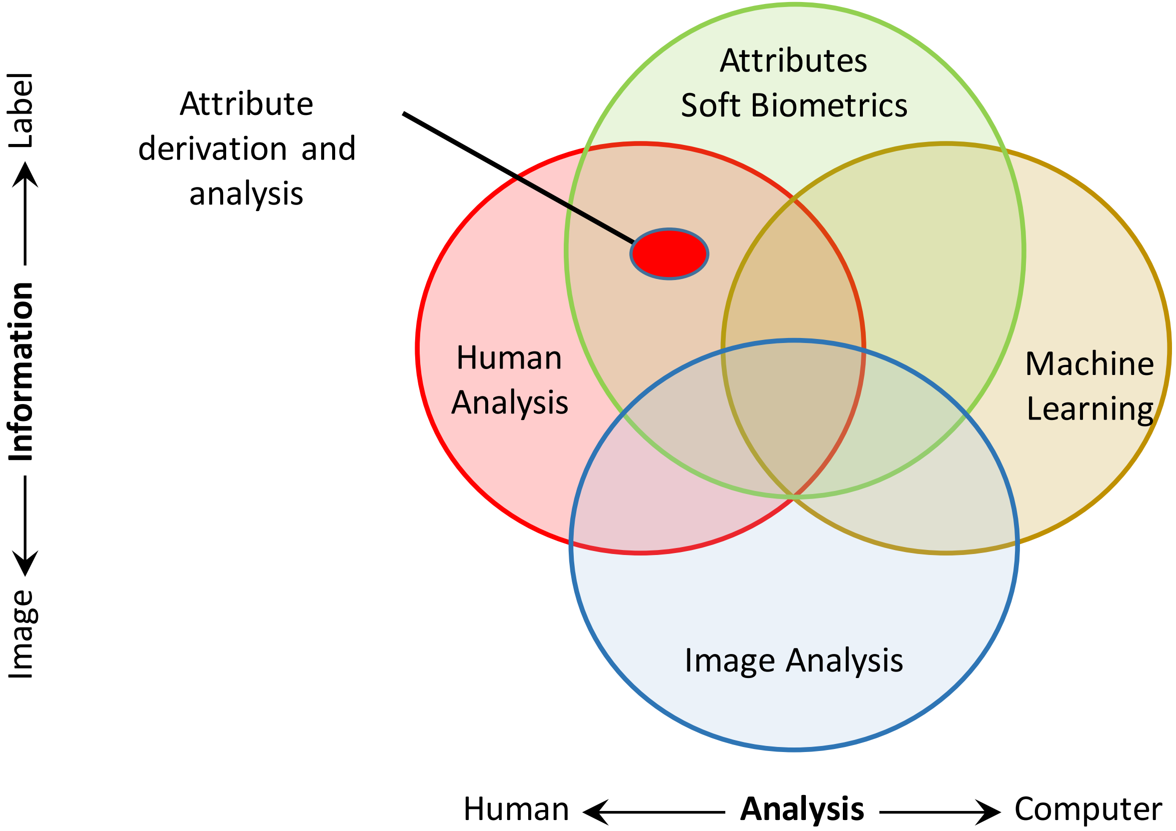


Attribute derivation and analysis

Attributes
Soft Biometrics

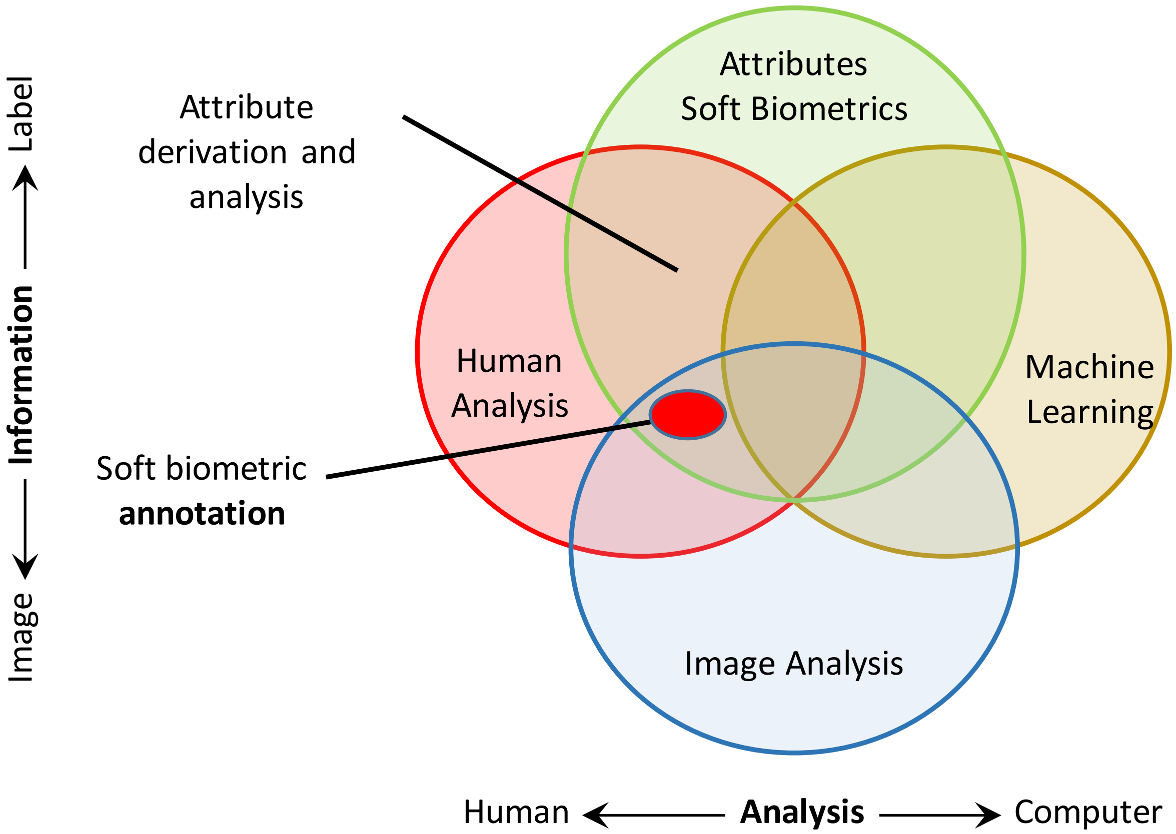
Human Analysis

Machine Learning

Image Analysis

Image ← **Information** → Label

Human ← **Analysis** → Computer



Attributes
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Human
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Soft biometric
annotation

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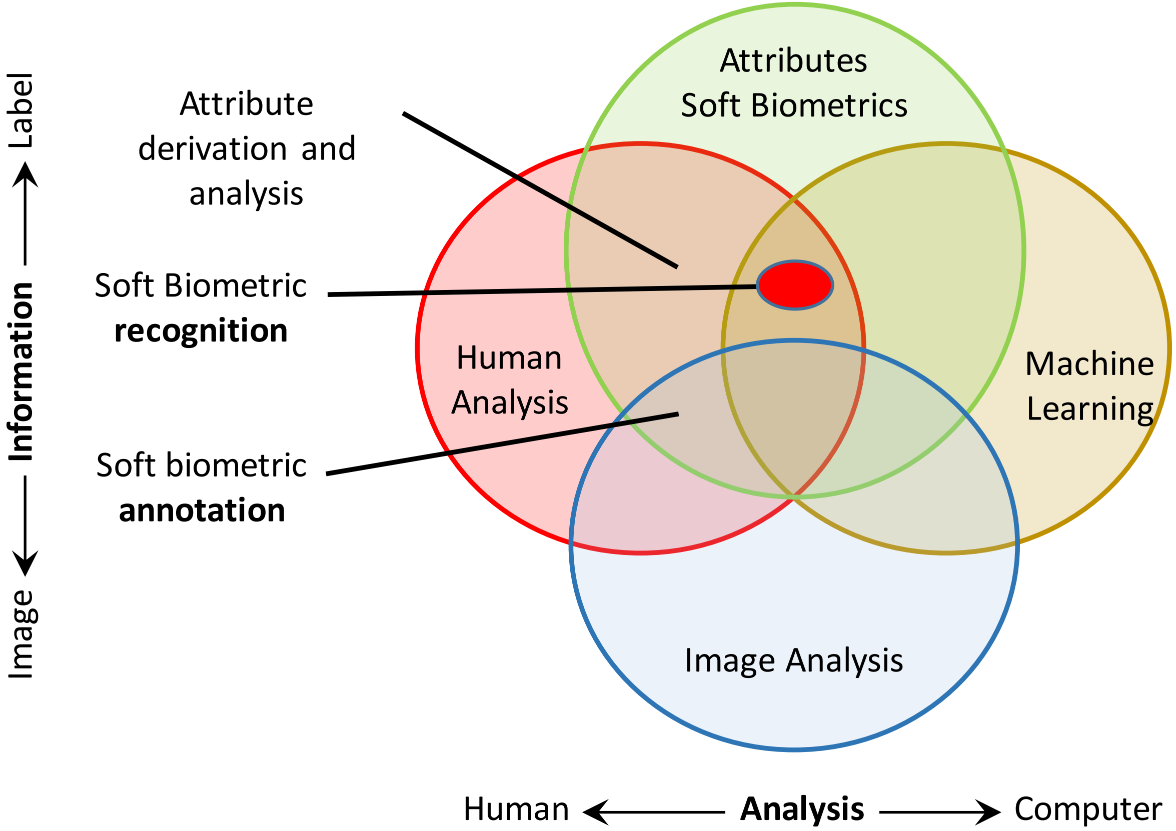

Image ← **Information** → Label

Attribute derivation and analysis

Soft Biometric **recognition**

Soft biometric **annotation**

Attributes
Soft Biometrics

Human Analysis

Machine Learning

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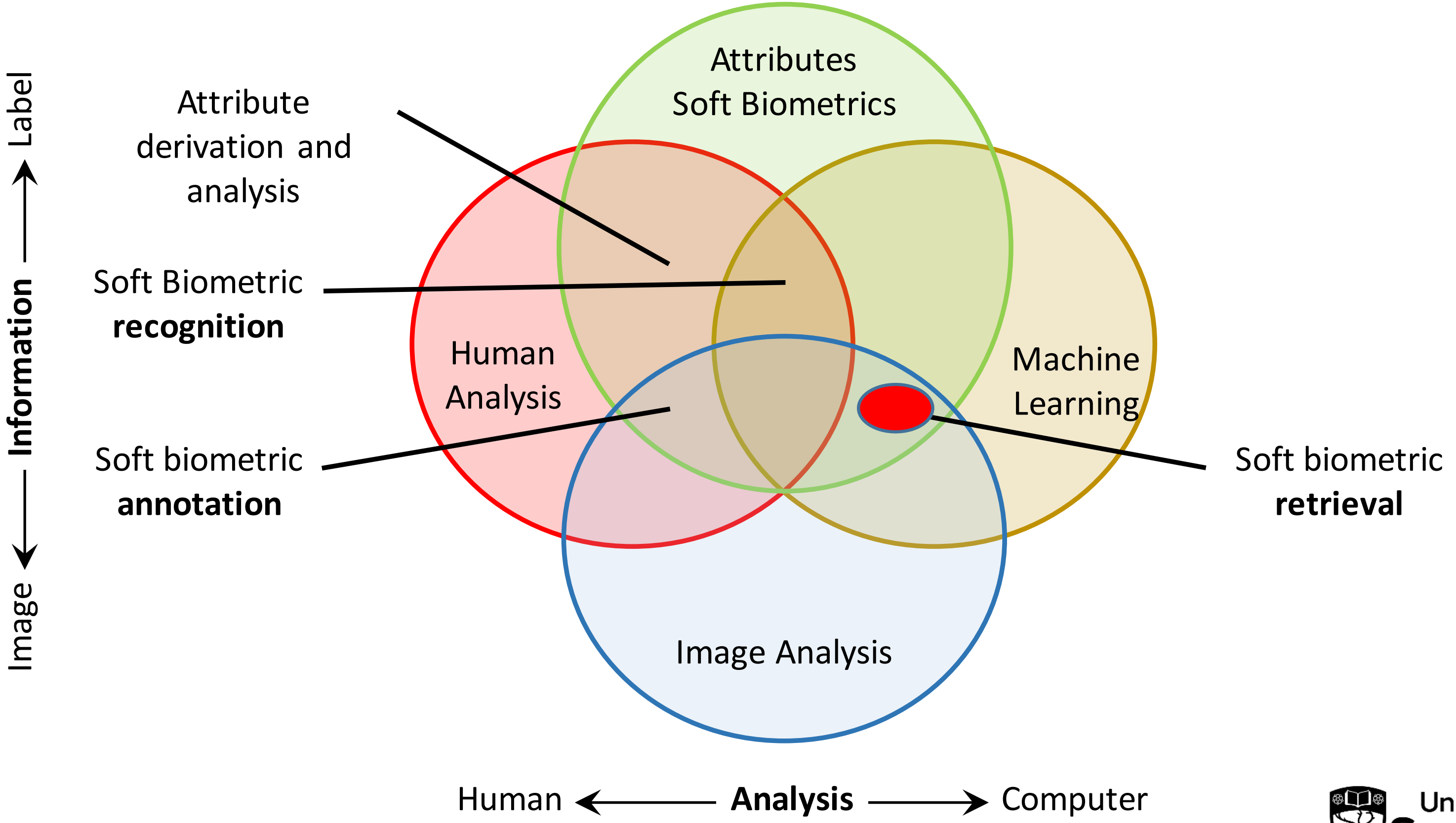
Human ← **Analysis** → Computer



Attributes
Soft Biometrics

Attribute
derivation and
analysis

Soft Biometric
recognition

Human
Analysis

Machine
Learning

Soft biometric
annotation

Soft biometric
retrieval

Image Analysis

Label ← **Information** → Image

Human ← **Analysis** → Computer

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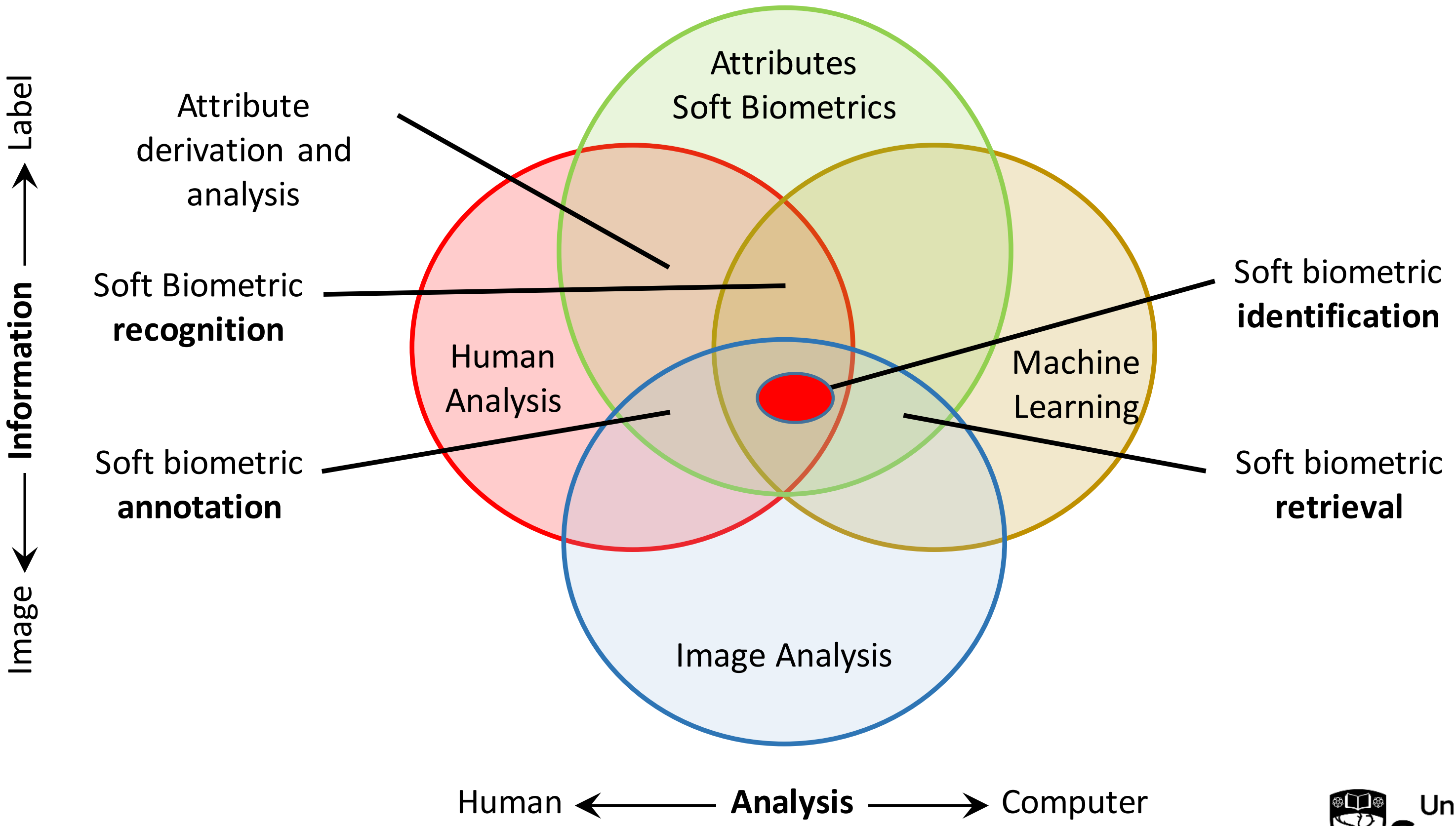

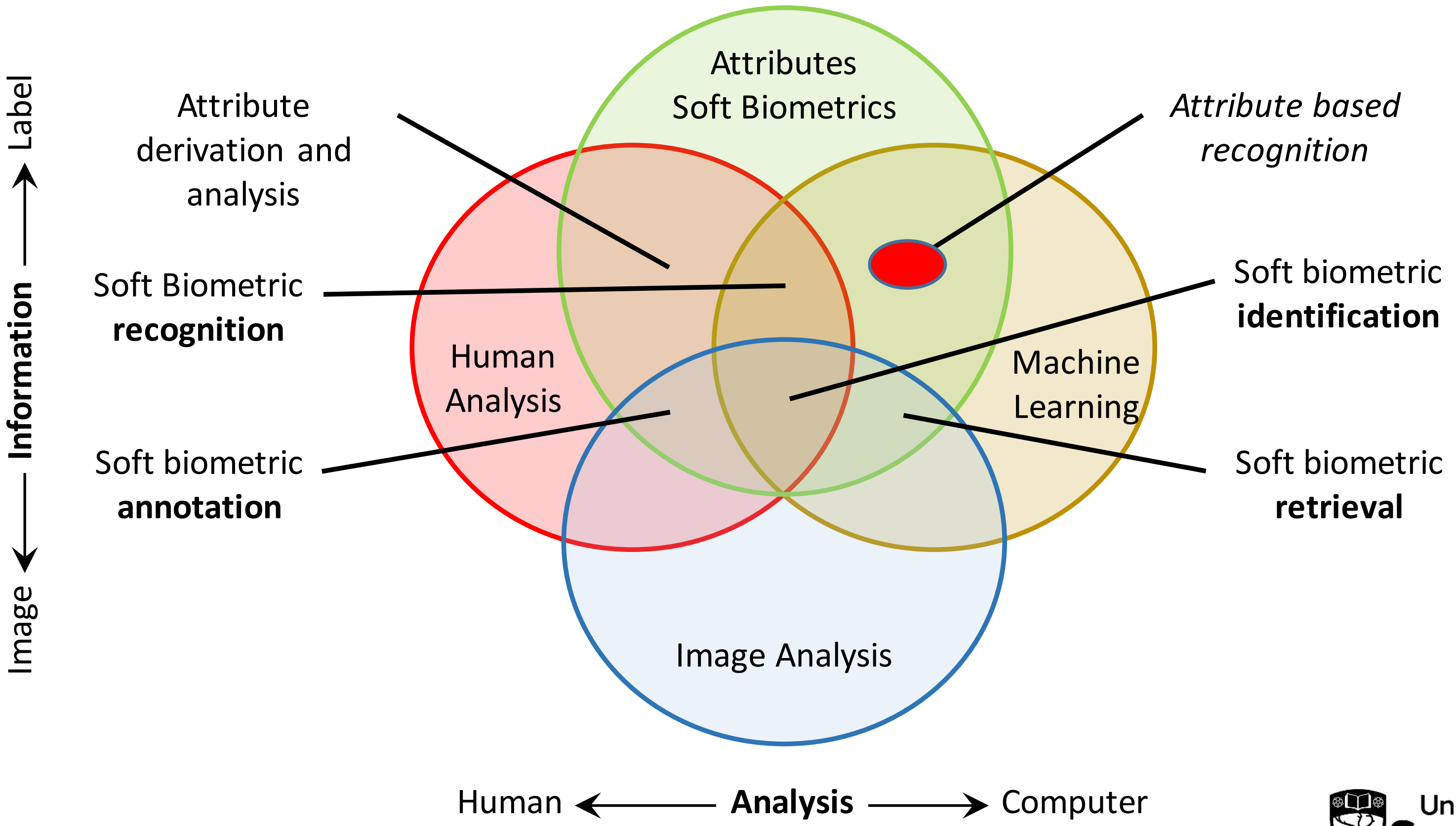

Attributes
Soft Biometrics

Attribute
derivation and
analysis

Attribute based
recognition

Soft Biometric
recognition

Soft biometric
identification

Human
Analysis

Machine
Learning

Soft biometric
annotation

Soft biometric
retrieval

Image Analysis

Image ← **Information** → Label

Human ← **Analysis** → Computer

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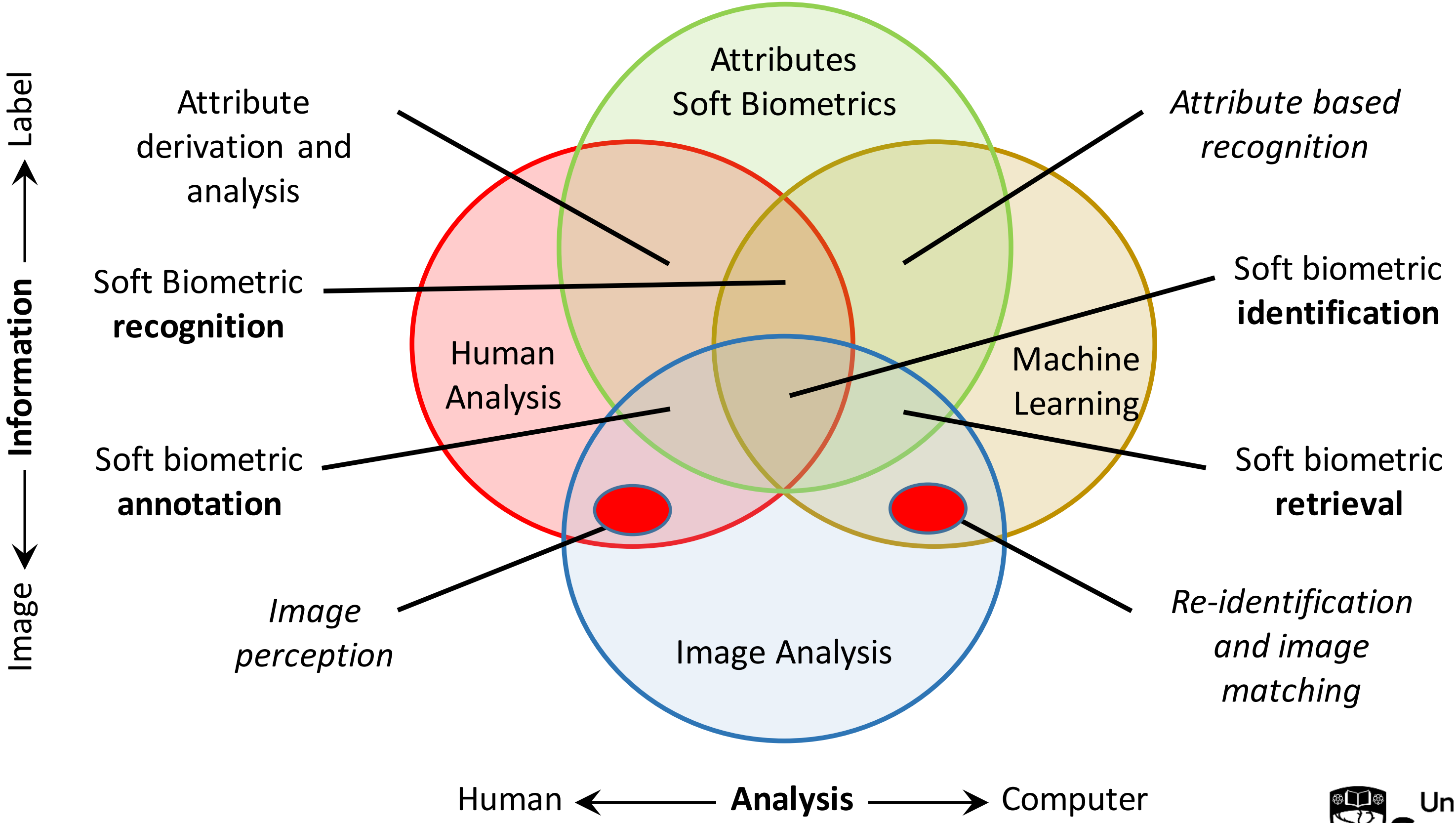

Image ← **Information** → Label

Attributes
Soft Biometrics

Human
Analysis

Machine
Learning

Image Analysis

Attribute
derivation and
analysis

Attribute based
recognition

Soft Biometric
recognition

Soft biometric
identification

Soft biometric
annotation

Soft biometric
retrieval

Image
perception

Re-identification
and image
matching

Human ← **Analysis** → Computer

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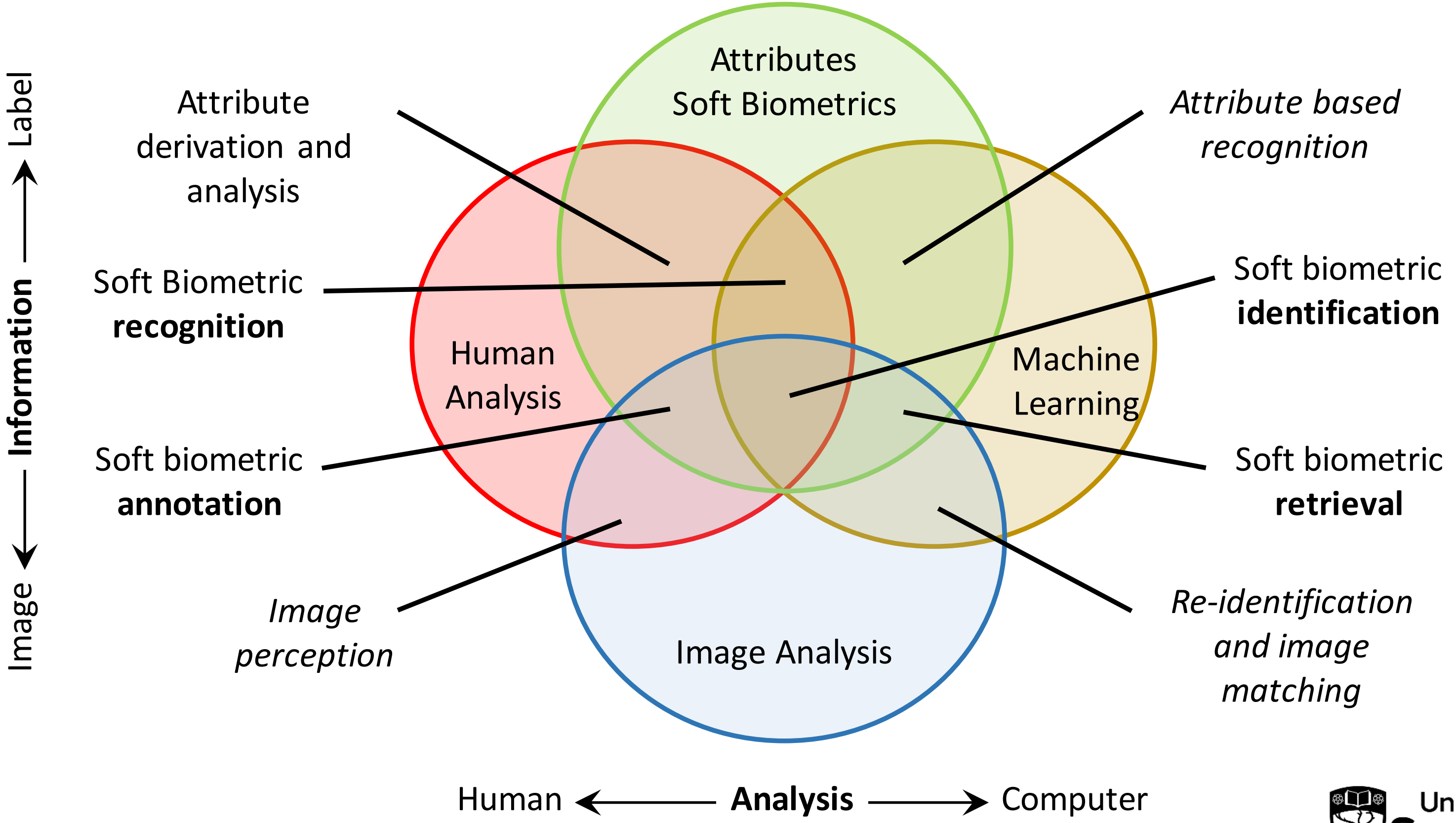

Attributes
Soft Biometrics

Human Analysis

Machine Learning

Image Analysis

Attribute derivation and analysis

Attribute based recognition

Soft Biometric **recognition**

Soft biometric **identification**

Soft biometric **annotation**

Soft biometric **retrieval**

Image perception

Re-identification and image matching

Image ← **Information** → Label

Human ← **Analysis** → Computer

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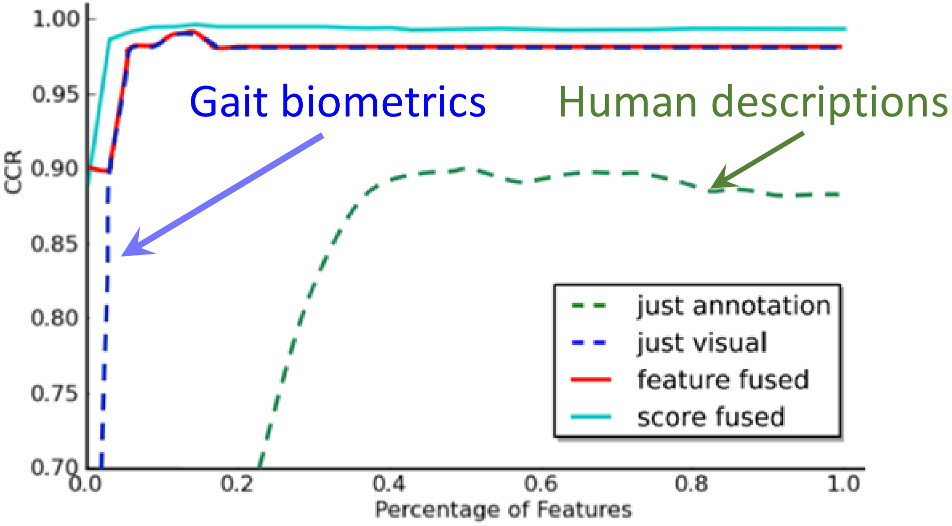
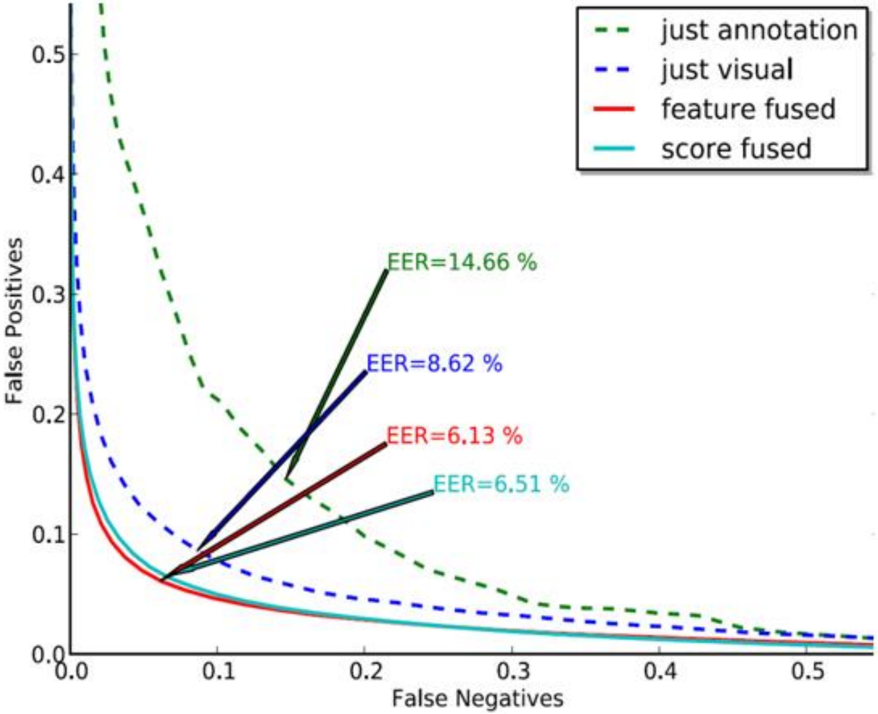
Human descriptions: recognition capability



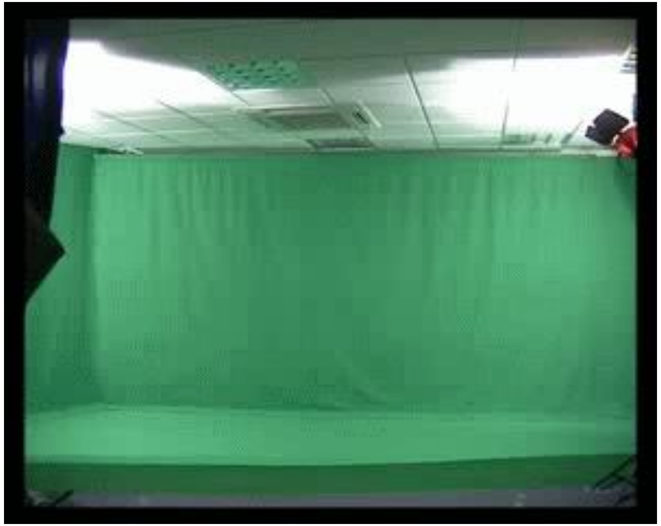


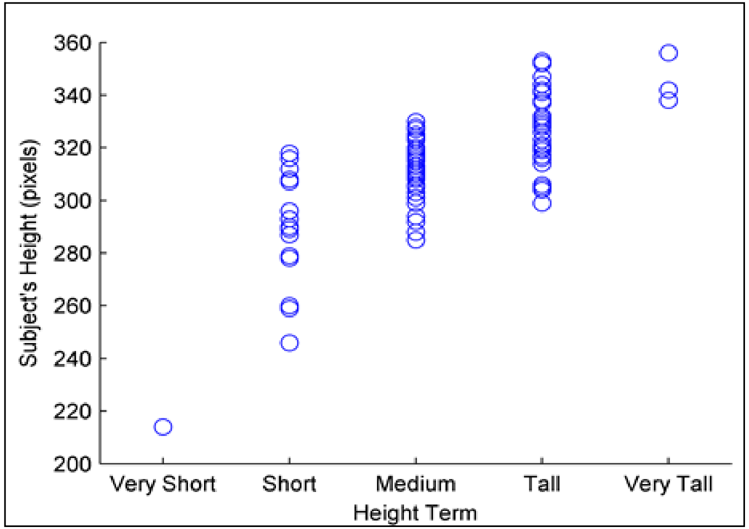
First result

Samangooei and Nixon,
IEEE BTAS 2008

Problems with absolute descriptors

Subjective = unreliable; Categorical = lacks detail

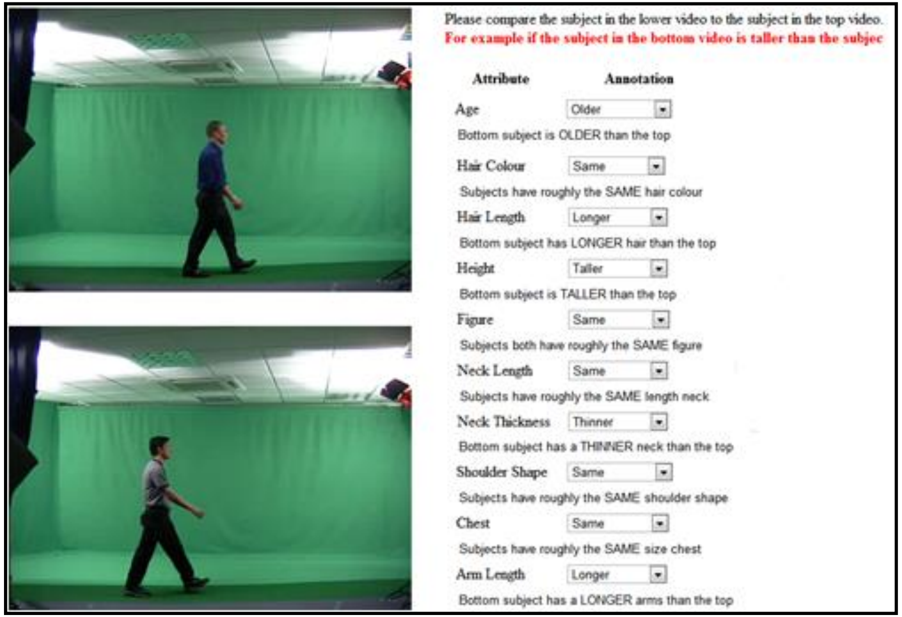




Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

Comparative human descriptions

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



Please compare the subject in the lower video to the subject in the top video.

For example if the subject in the bottom video is taller than the subjec

Attribute	Annotation
Age	Older
Bottom subject is OLDER than the top	
Hair Colour	Same
Subjects have roughly the SAME hair colour	
Hair Length	Longer
Bottom subject has LONGER hair than the top	
Height	Taller
Bottom subject is TALLER than the top	
Figure	Same
Subjects both have roughly the SAME figure	
Neck Length	Same
Subjects have roughly the SAME length neck	
Neck Thickness	Thinner
Bottom subject has a THINNER neck than the top	
Shoulder Shape	Same
Subjects have roughly the SAME shoulder shape	
Chest	Same
Subjects have roughly the SAME size chest	
Arm Length	Longer
Bottom subject has a LONGER arms than the top	

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

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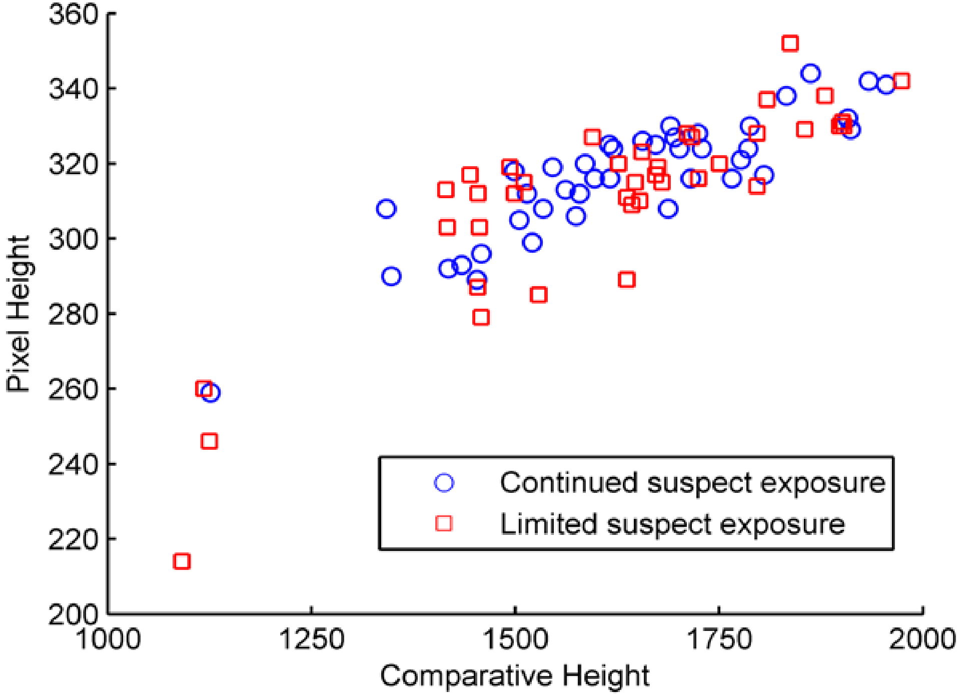
Height correlation (with time)



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

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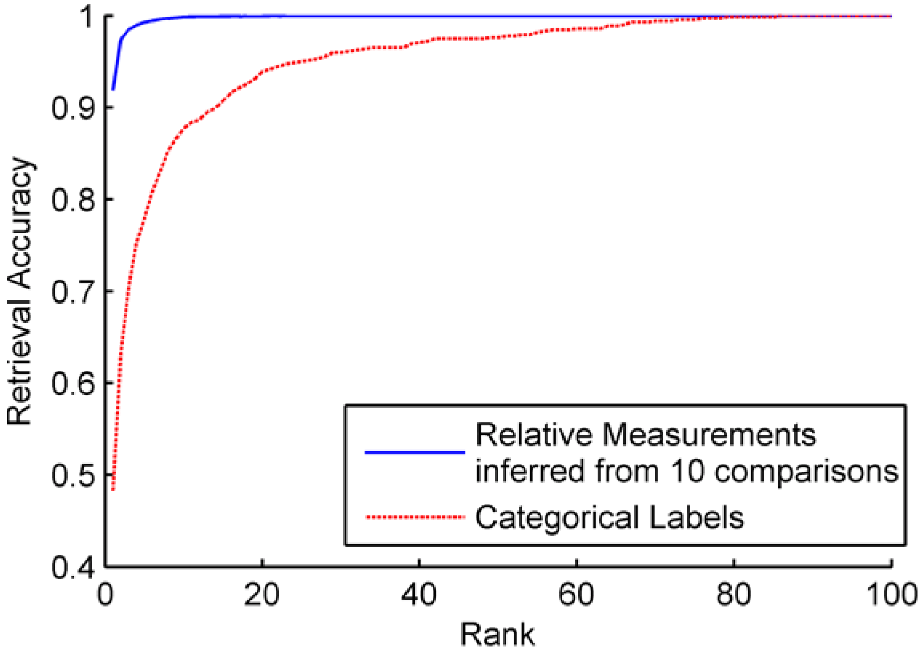
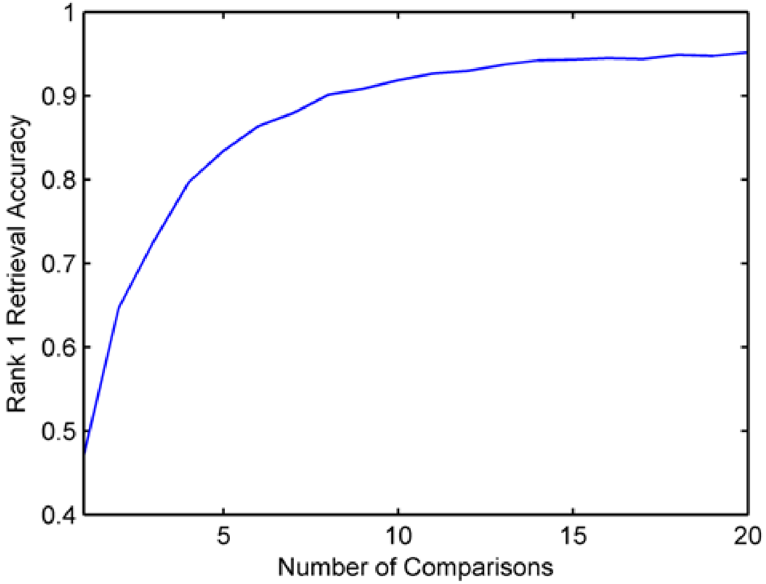
Recognition



Reid and Nixon,
IEEE ICDP 2011

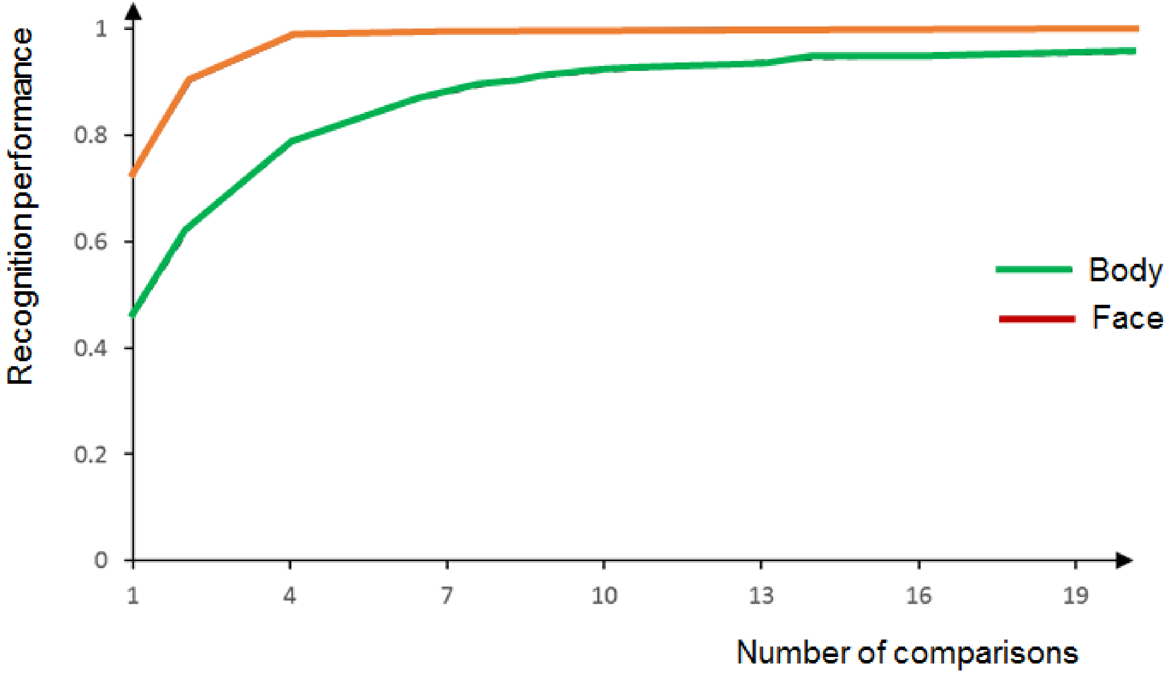
Ranking comparative descriptions

- Use ELO rating system from chess to infer relative descriptions
- Turn comparative labels into a ranked list
- Comparative › categorical
- Alternatives?
- Parameters?

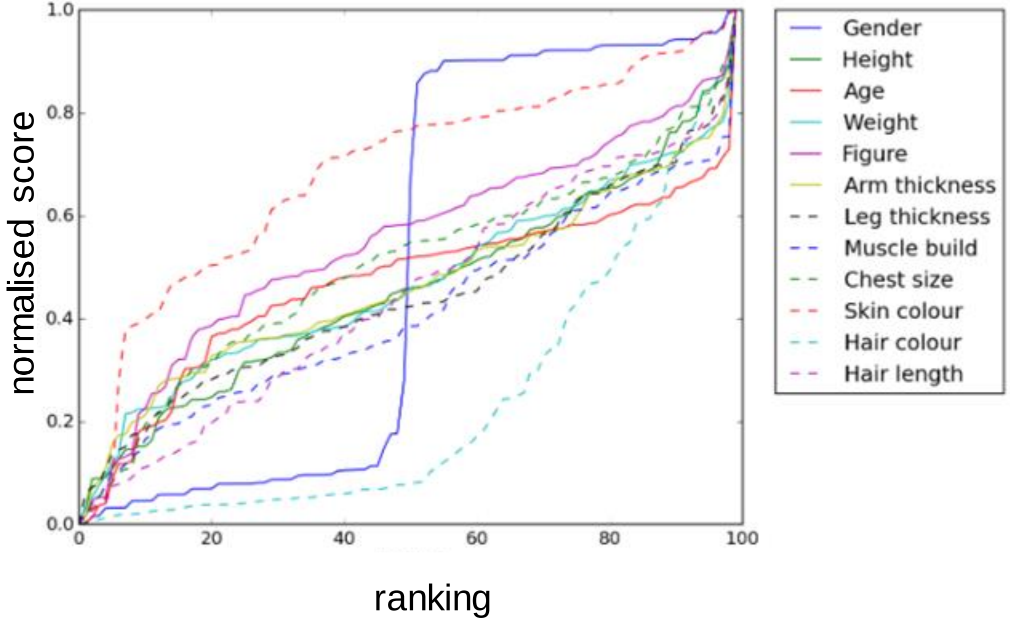


Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

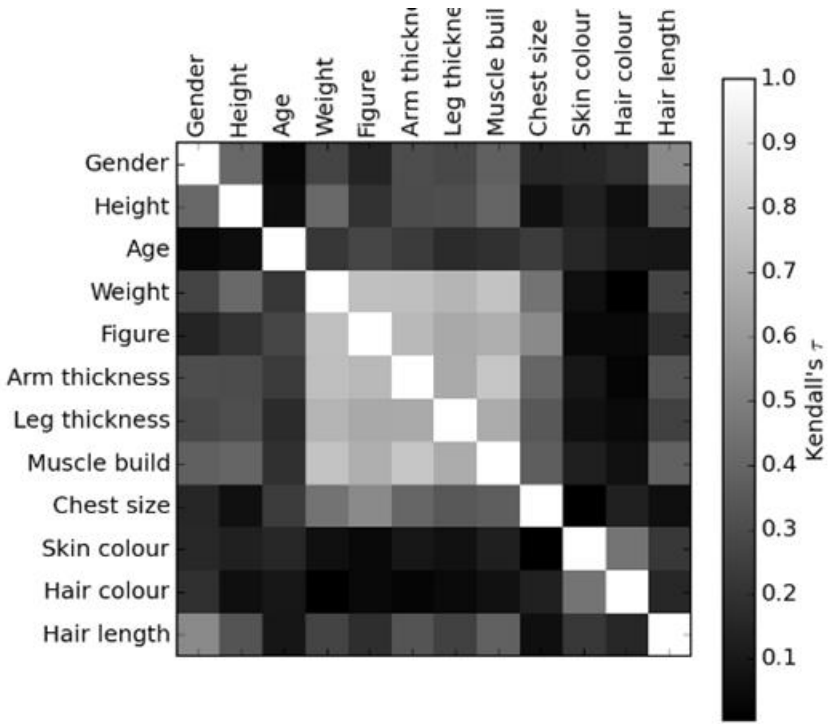
Evaluation: effect of number of comparisons on recognition



Body trait performance



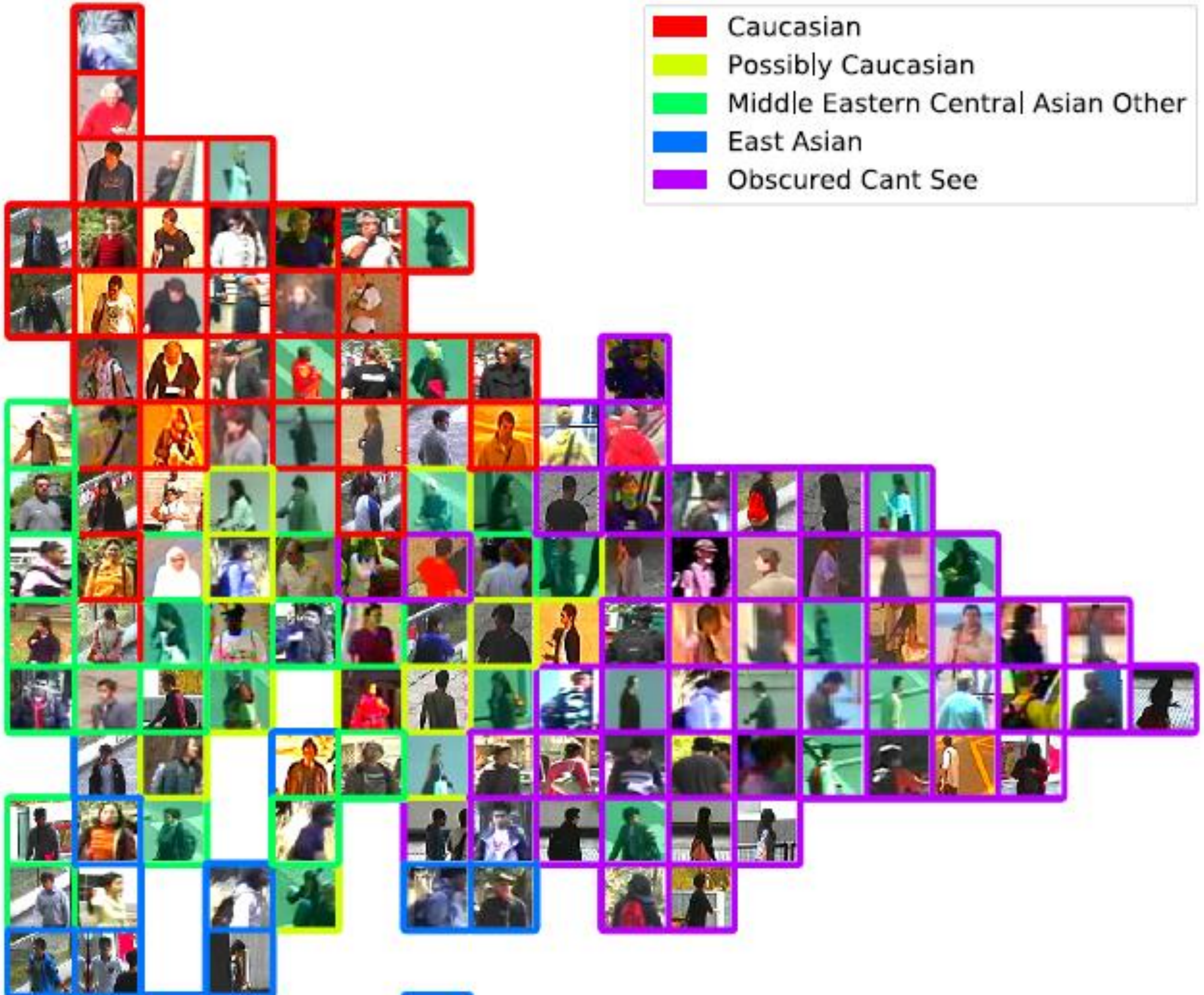
Normalised relative scores vs ranks



University of

Kentall’s τ correlation

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

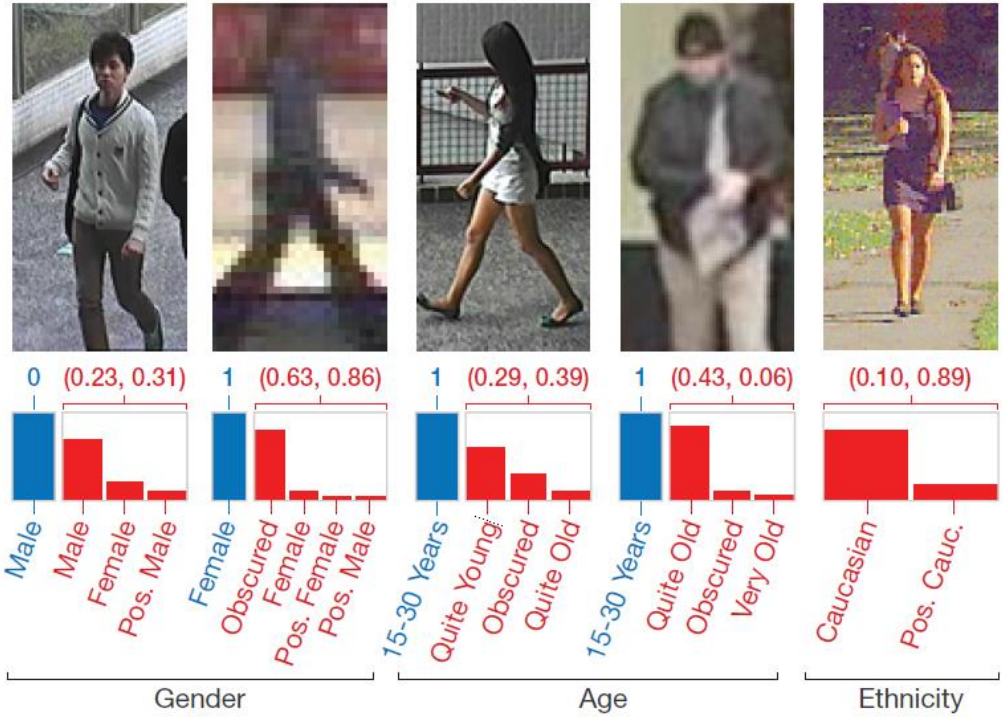
Martinho-Corbishley, Nixon and Carter, *Proc. BTAS 2016*

Superfine labels

Most ‘fine’ are actually coarse

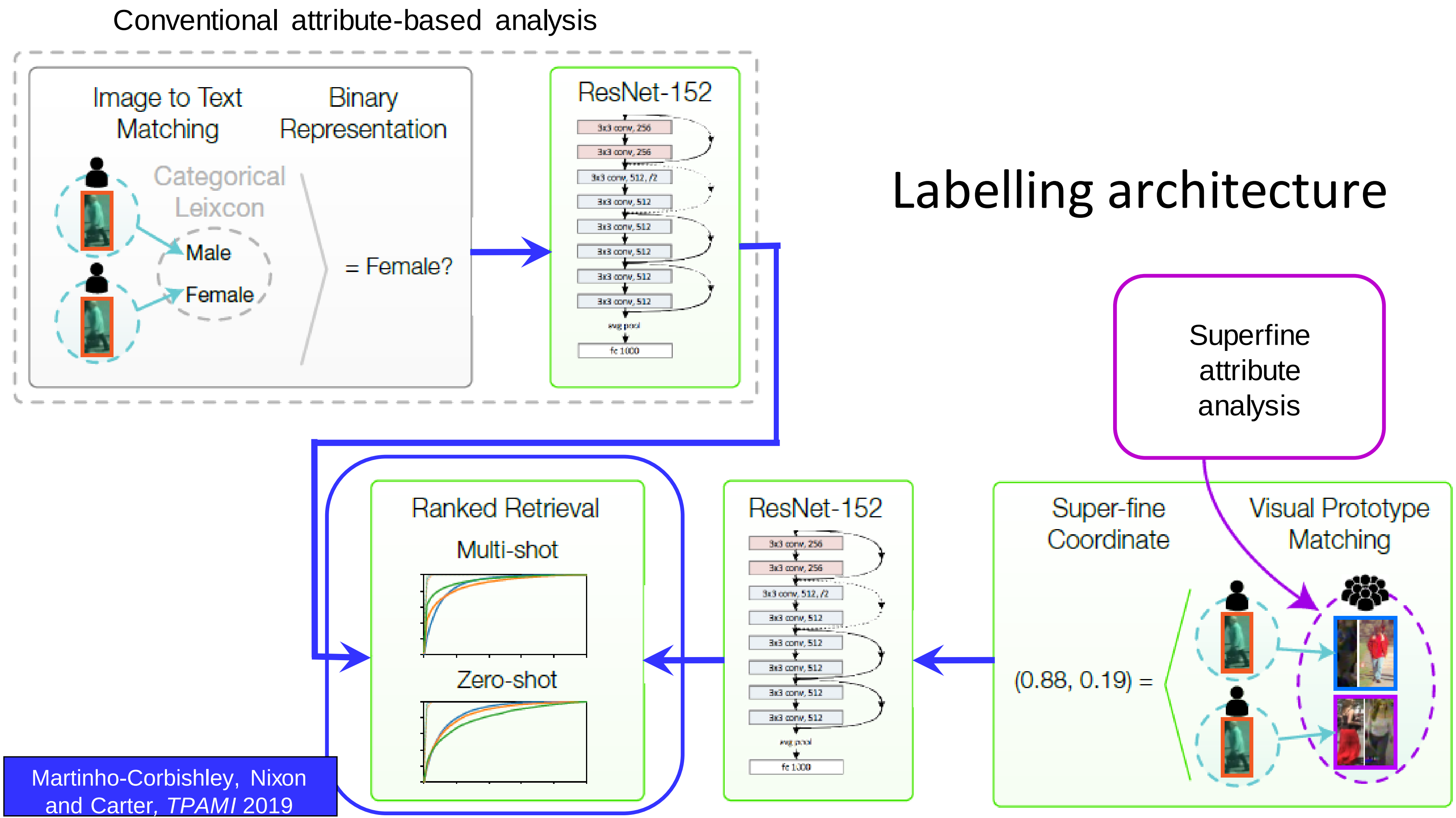
Our comparative attributes are superfine

Comparison/ ranking gives many advantages



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

Labelling architecture



Conventional attribute-based analysis

Image to Text Matching

Binary Representation

Categorical Leixcon

Male

Female

= Female?

ResNet-152

Superfine attribute analysis

Ranked Retrieval

Multi-shot

Zero-shot

ResNet-152

Super-fine Coordinate

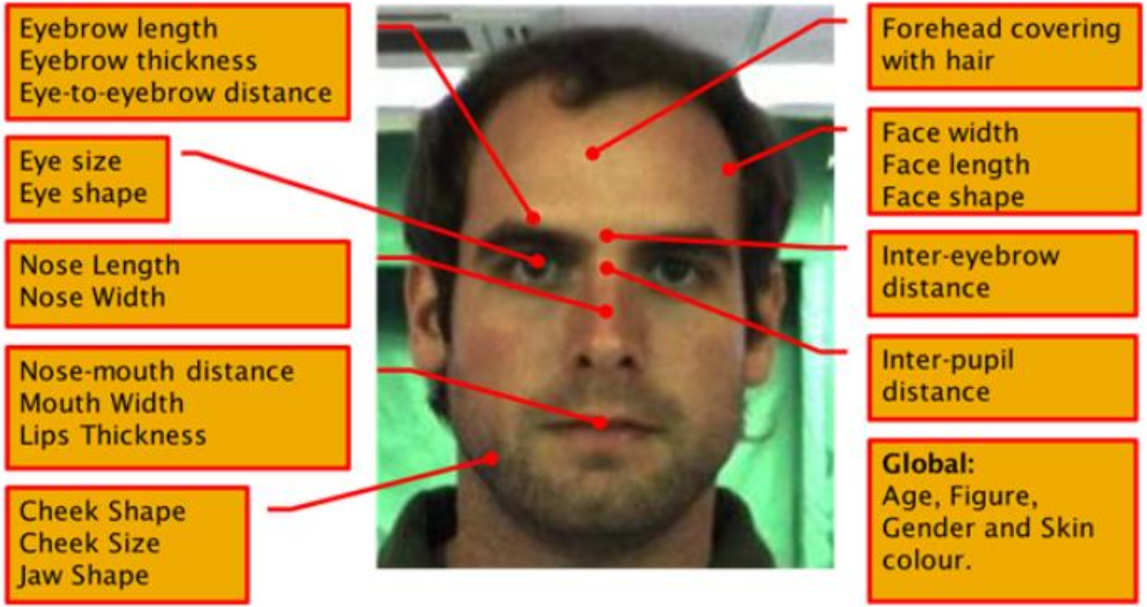
Visual Prototype Matching

(0.88, 0.19) =

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

Recognition by face attributes

Categorical labels
(gender, age +...)
Comparative labels



Eyebrow length
Eyebrow thickness
Eye-to-eyebrow distance

Eye size
Eye shape

Nose Length
Nose Width

Nose-mouth distance
Mouth Width
Lips Thickness

Cheek Shape
Cheek Size
Jaw Shape

Forehead covering with hair

Face width
Face length
Face shape

Inter-eyebrow distance

Inter-pupil distance

Global:
Age, Figure, Gender and Skin colour.

Reid and Nixon, *IEEE ICB 2013*

Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

Recognition by face via comparative attributes on LFW

	Collected	Inferred	Total
Traits comparisons	241560	132879504	133121064
Subjects' comparisons	10065	5536646	5546711
Average number of comparisons per subject	4.98	1371.1	N/A
Number of annotators	9901		

Person-A **Person-B**

The eyebrow horizontal length of **person-A** relative to that of **person-B** is:

- ○ More Short
- ○ Same
- ○ More Long
- ○ Don't know

Almudhahka, Nixon and Hare, *IEEE BTAS 2016*

Compression of 5 point scale: for comparative face labels

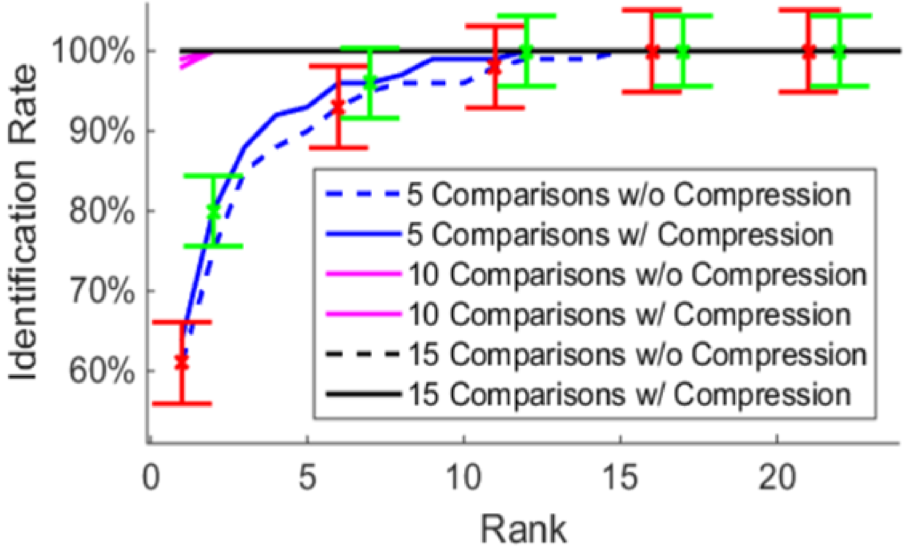
Label compression improves recognition

Data is Southampton tunnel

New system just 3:

bigger, **same**, **smaller**

Had we previously added categorical to comparative?



Almudhahka, Nixon and Hare, *IEEE ISBA* 2016

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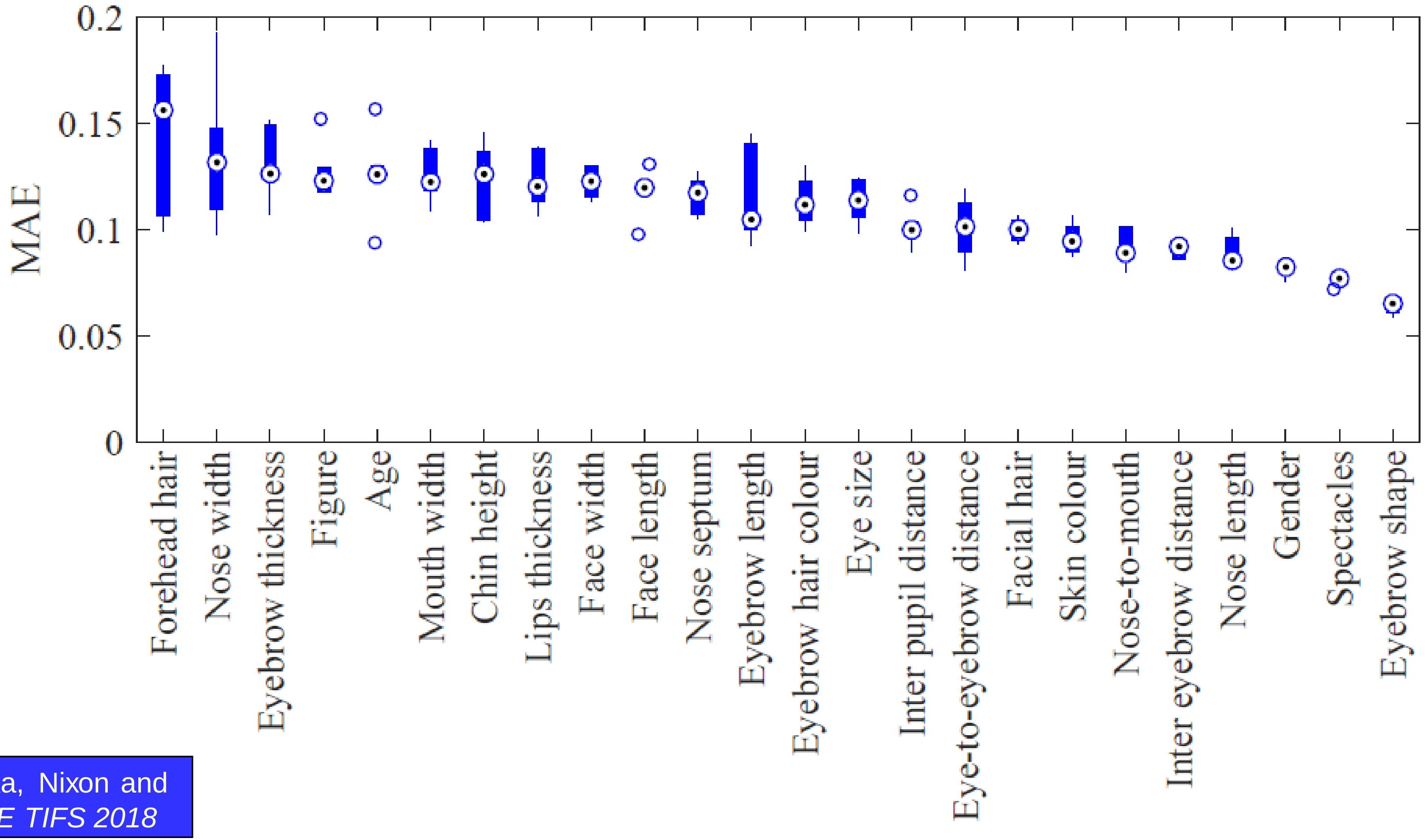
Estimating face attributes



Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Ranking subjects (images) by estimated face attributes

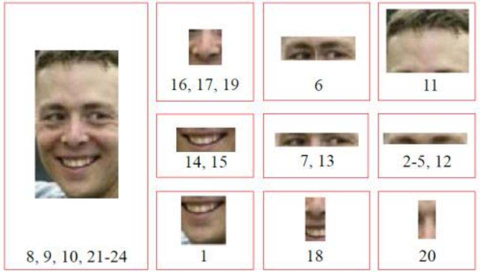
(a) Age (b) Gender

Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Crossing the semantic gap: estimating relative face attributes

Face alignment

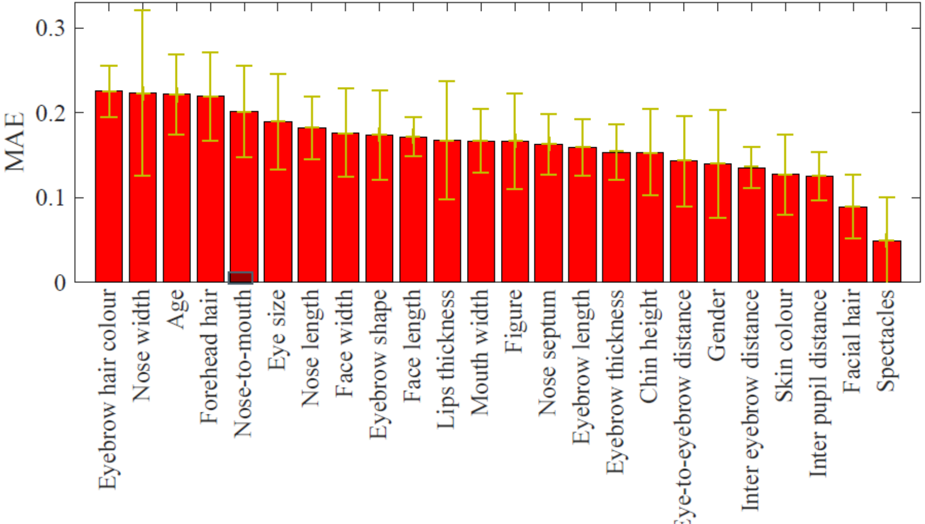
Constrained Local Models/ AAMs



Segmented face parts

Features HOG/GIST/ULBP

Estimation of comparative labels



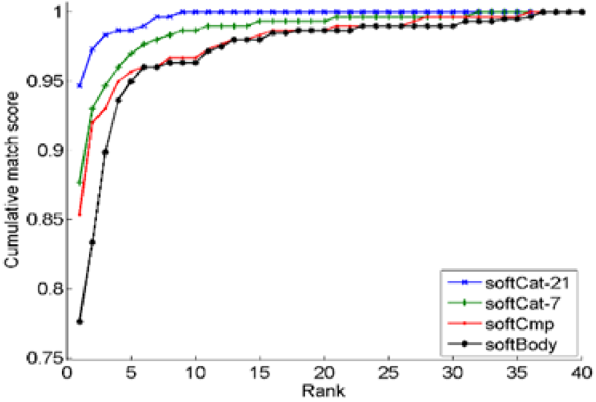
Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Subject recognition, by clothing

- Clothing generally unique
- Shakespeare

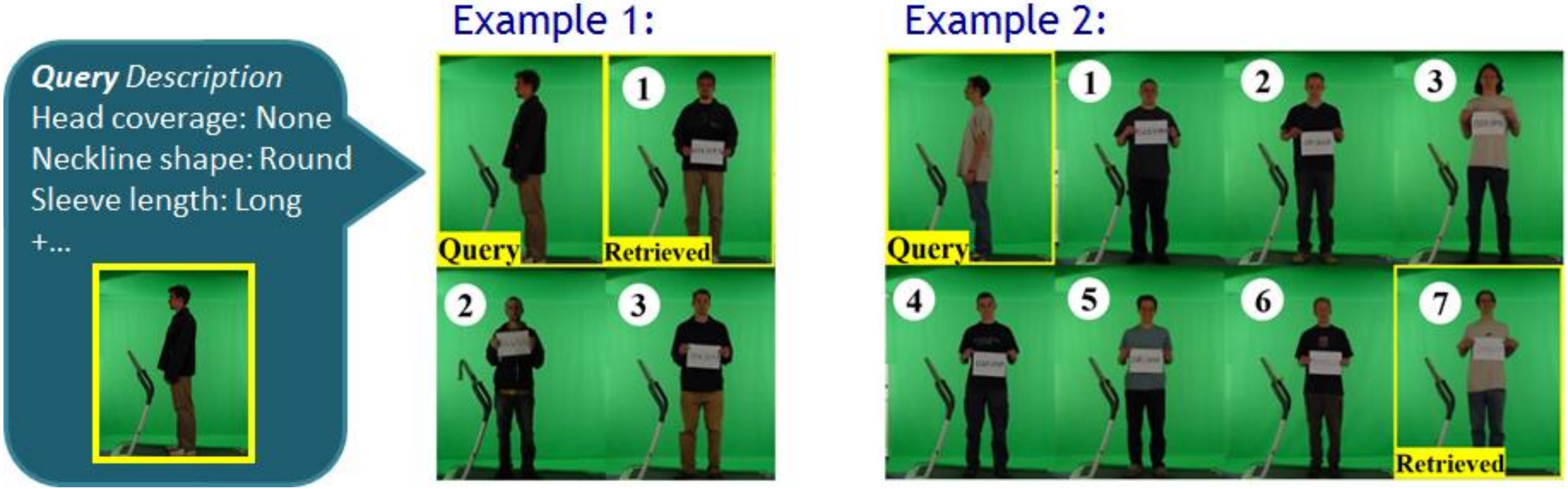
  "Know'st me not by my clothes?"

  (Cymbeline Act 4 Scene 2)
- Short term biometric
- Has strong invariance
- Links with computer vision and automatic clothing analysis/ re-identification



Jaha and Nixon, *IEEE IJCB 2014*

Viewpoint invariant recognition, by clothing



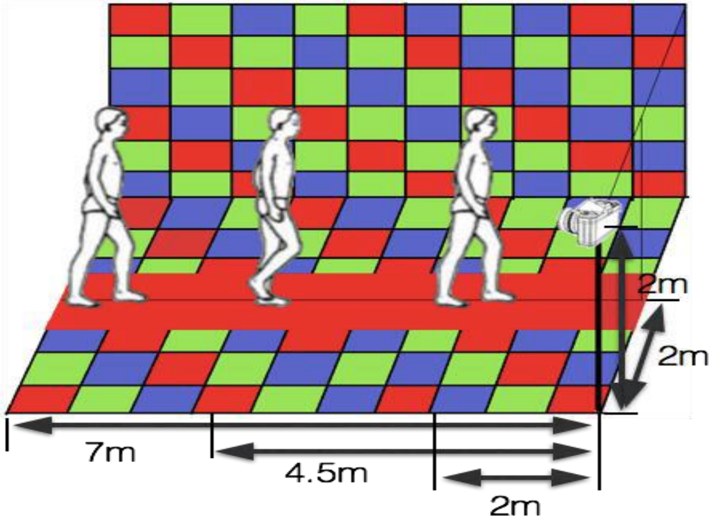
***Query** Description*
Head coverage: None
Neckline shape: Round
Sleeve length: Long
+...

Clothing has ability to handle 90 degree change

Jaha and Nixon, *IEEE ICB 2015*

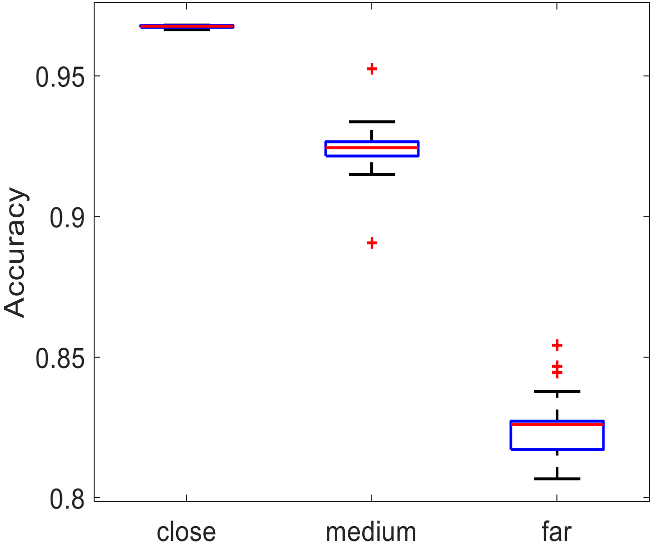
Soft biometric fusion – synthesised data

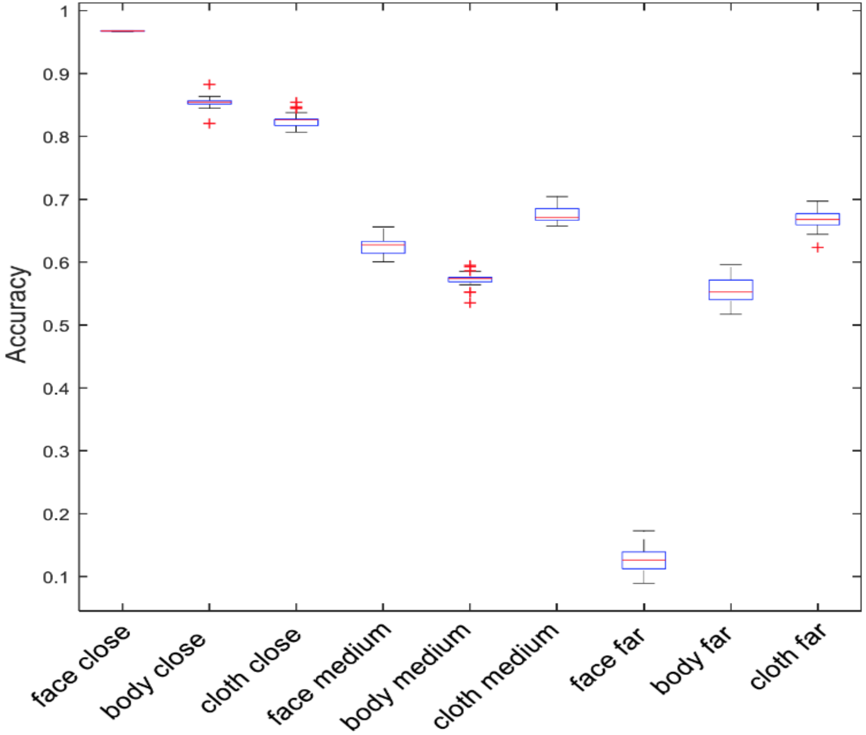
Gait tunnel



Guo, Nixon and Carter, *IEEE TBIOM* 2019

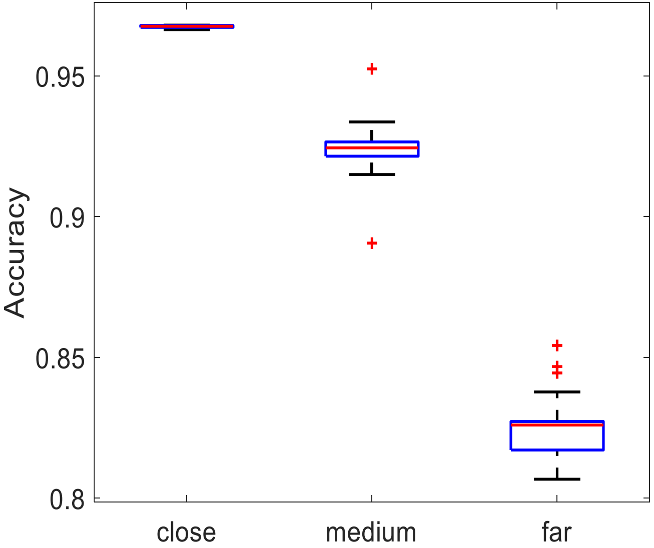
Fusion performance

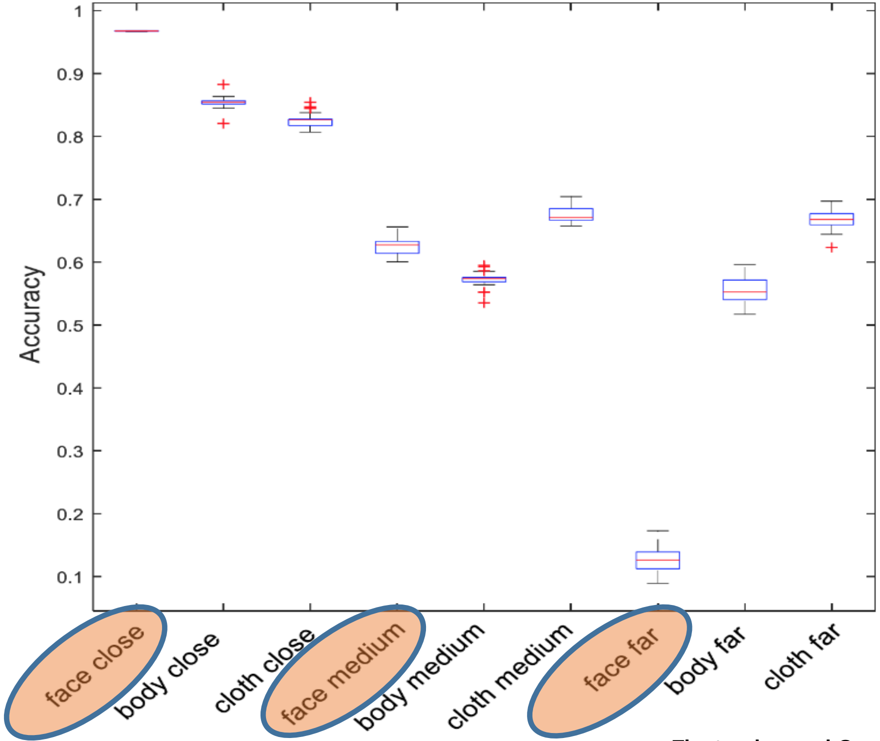




Guo, Nixon and Carter, *IEEE TBIOM* 2019

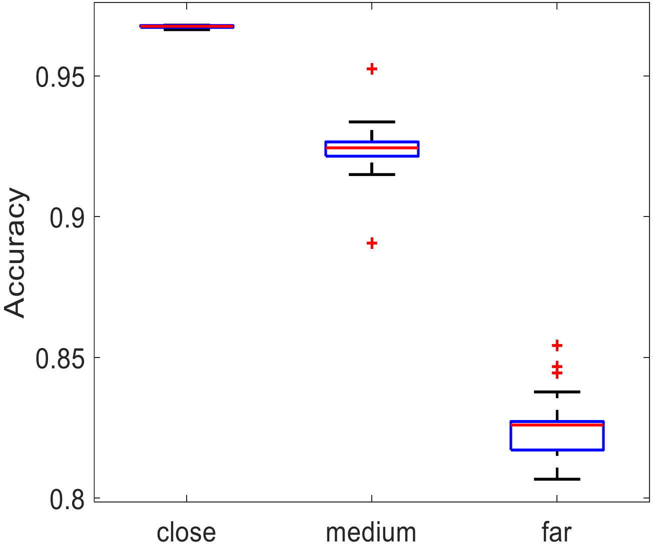
Fusion performance

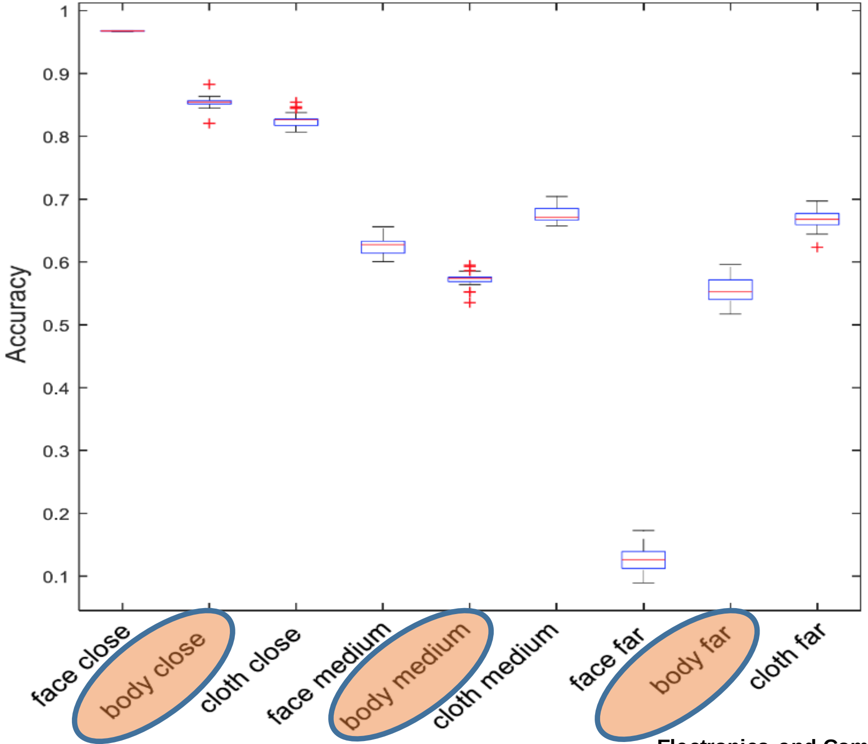




Guo, Nixon and Carter, *IEEE TBIOM* 2019

Fusion performance





Guo, Nixon and Carter, *IEEE TBIOM* 2019

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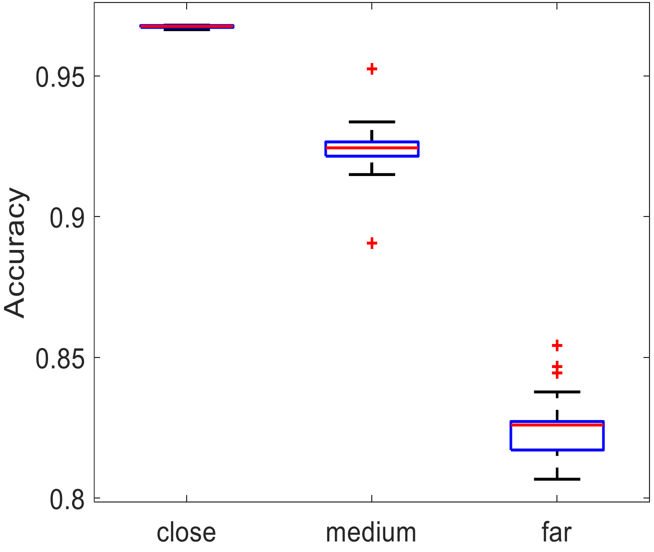

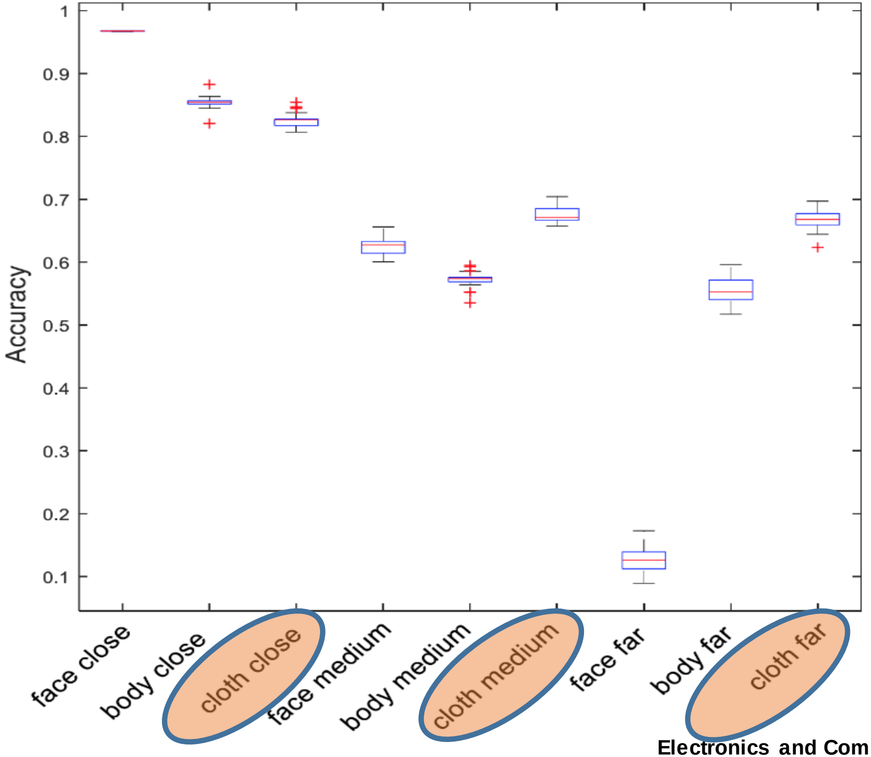

Guo, Nixon and Carter, *IEEE TBIOM* 2019

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 ….

Dr John Carter, Dr Sasan Mahmoodi, Prof Jon Hare

Dr Hani Muammar, Prof Adrian Evans, Prof Xiaoguang Jia, Prof Yan Chen, Prof Steve Gunn, Dr Colin Davies, Dr Mark Jones, Dr Alberto Aguado, *Dr David Cunado*, Dr Jason Nash, *Prof Ping Huang*, Dr David Hurley, Dr David Benn, Dr Liang Ng, Dr Mark Toller, Dr John Manslow, *Dr Mike Grant*, *Prof Jamie Shutler*, *Dr Karl Sharman*, Prof Andrew Tatem, *Layla Gordon*, *Dr Richard French*, *Dr Vijay Laxmi*, *Prof James Hayfron-Acquah*, *Dr Chew-Yean Yam*, Prof Yalin Zheng, *Dr Jeff Foster*, *Dr Jang Hee Yoo*, *Dr Nick Spencer*, *Dr Stuart Prismall*, Wan Mohd.-Isa, Dr Peter Myerscough, Dr Richard Evans, *Dr Stuart Mowbray*, *Dr Rob Boston*, *Dr Ahmad Al-Mazeed*, Prof Peter Gething, *Dr Dave Wagg*, *Dr Alex Bazin*, Dr Mike Jewell, *Dr Lee Middleton*, *Dr Galina Veres*, *Dr Imed Bouchrika*, Dr Xin Liu, Dr Cem Direkoglu, Hidayah Rahmalan, Dr Banafshe Arbab-Zavar, **Dr Baofeng Guo**, **Dr Sina Samangooei**, *Dr Michaela Goffredo*, Dr Daniel Thorpe, *Dr Richard Seely*, Dr John Bustard, Dr Alastair Cummings, *Dr Muayed Al-Huseiny*, Dr Mina Ibrahim, *Dr Darko Matovski*, *Dr Gunawan Ariyanto*, *Dr Sung-Uk Jung*, Dr Richard Lowe, **Dr Dan Reid**, Dr George Cushen, Dr Ben Waller, Dr Nick Udell, Dr Anas Abuzaina, Dr Thamer Alathari, Dr Musab Sahrim, Dr Ah Reum Oh, **Dr Tim Matthews**, **Dr Emad Jaha**, Dr Peter Forrest, Dr Jaime Lomeli, **Dr Dan Martinho-Corbishley**, **Dr Bingchen Guo**, Dr Jung Sun, **Dr Nawaf Almudhahka**, **Tom Ladyman,** Dr Wenshu Zheng, Dr Di Meng, **Moneera Alnamnakani**

Sponsors: EPSRC, Home Office, MoD (GD), DARPA, ARL, EU

Selection of further reading on gait

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. LidarGait: Benchmarking 3D Gait Recognition With Point Clouds, C Shen, C Fan, W Wu, R Wang, GQ Huang, S Yu, *CVPR 2023*
10. 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*

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