Biometrics Winter School, 2022

On Gait and Soft Biometrics

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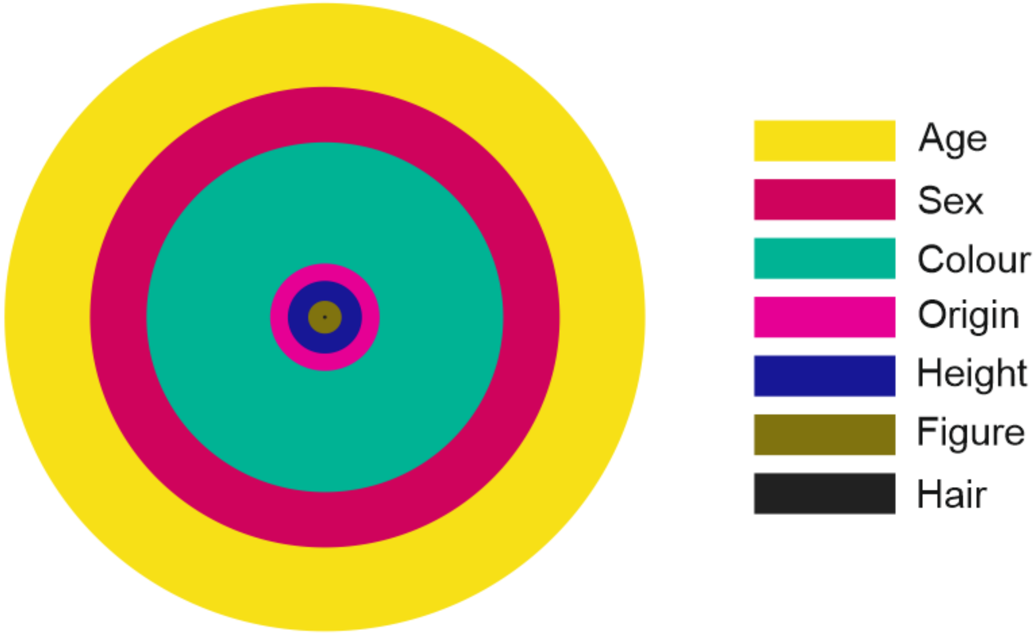
Intro: let's find a single person in Southampton

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	

Visualising the search

The whole page contains 750×400 pixels. I’m the dot in the middle!



Identifying people by their gait

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

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Gait biometrics

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

ABC News, July 13 2006

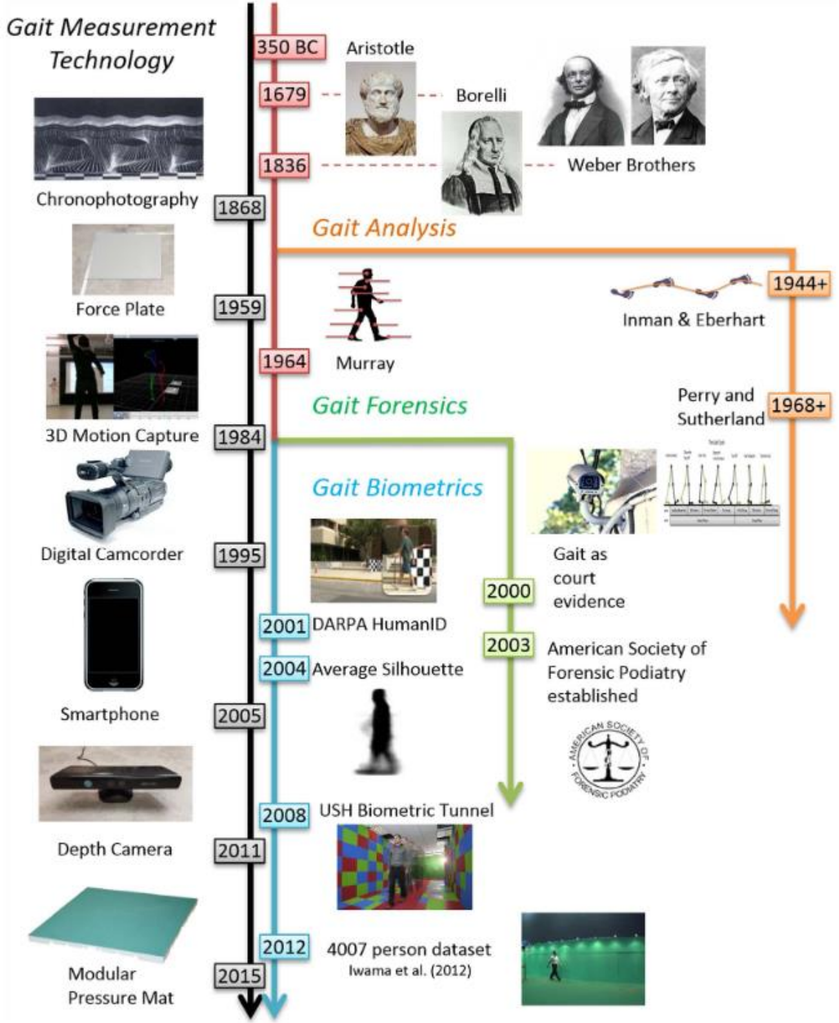
https://www.youtube.com/watch?v=6KuMe5n_jdQ

2000 years of progress

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

It is now widely accepted that people can be recognised by their gait

This is a consequence of desire, need and research, together with technological advance



Connor and Ross, Biometric recognition by gait, *CVIU* 2018

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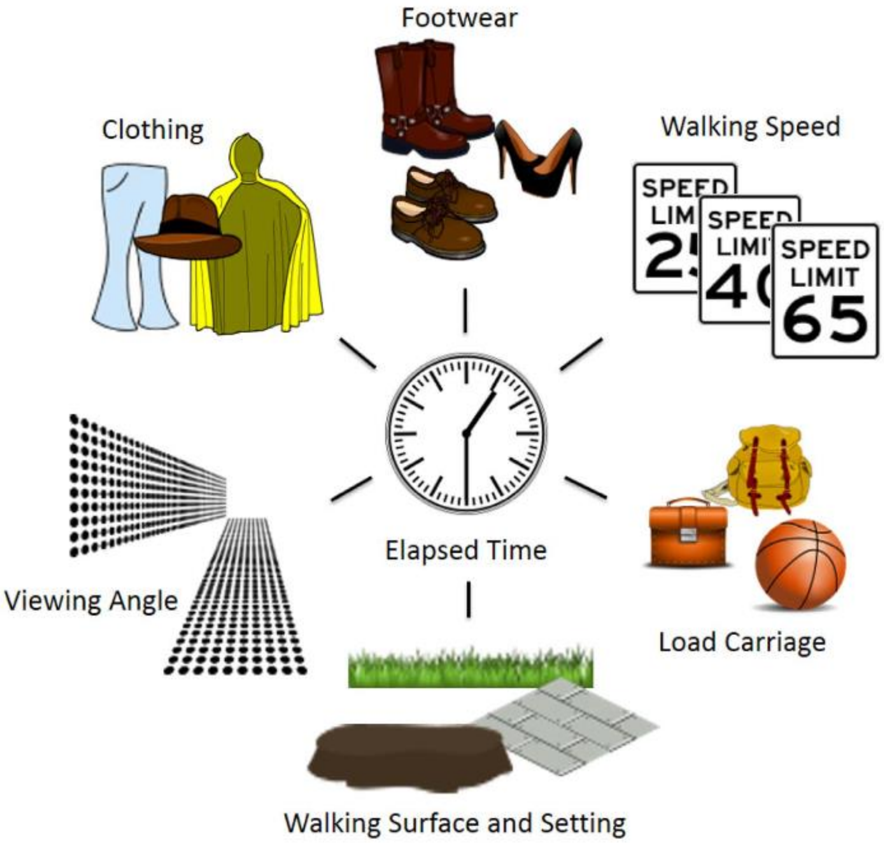
What changes?

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

+ accelerometer, footfall, medical

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

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Gait Recognition – the state of art

Technique: mainly deep

Data: Frontal-View Gait (FVG)
CASIA E

Applications: increasing use in crime scene analysis

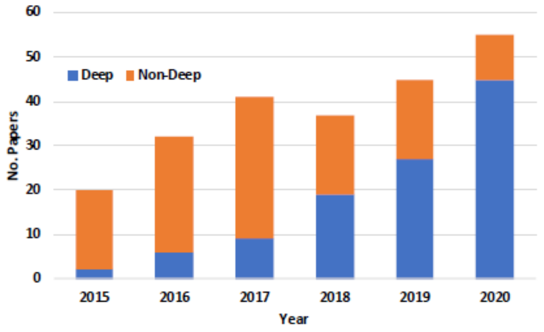
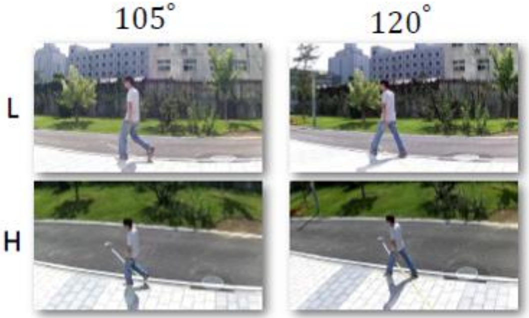


Fig. 1: The number of gait recognition papers published after 2015 using non-deep (orange) and deep (blue) gait recognition methods.

A Sepas-Moghaddam, *Deep Gait Recognition: A Survey*



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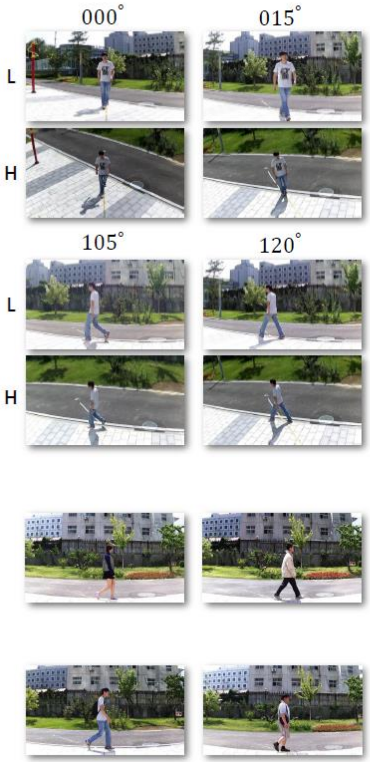
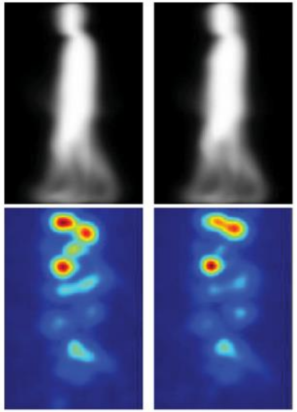
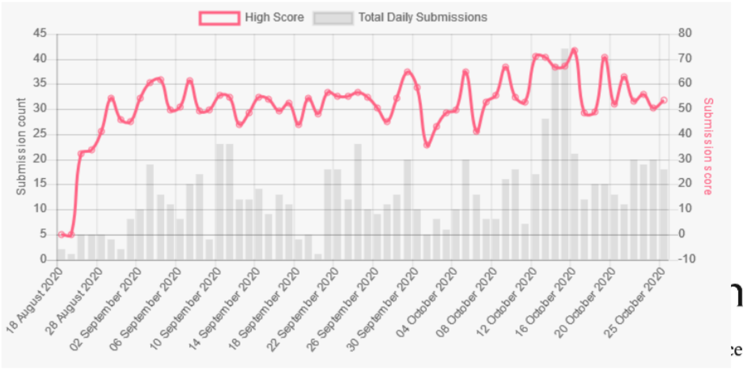
HiD competition, ACCV 2020/ IJCB 2021



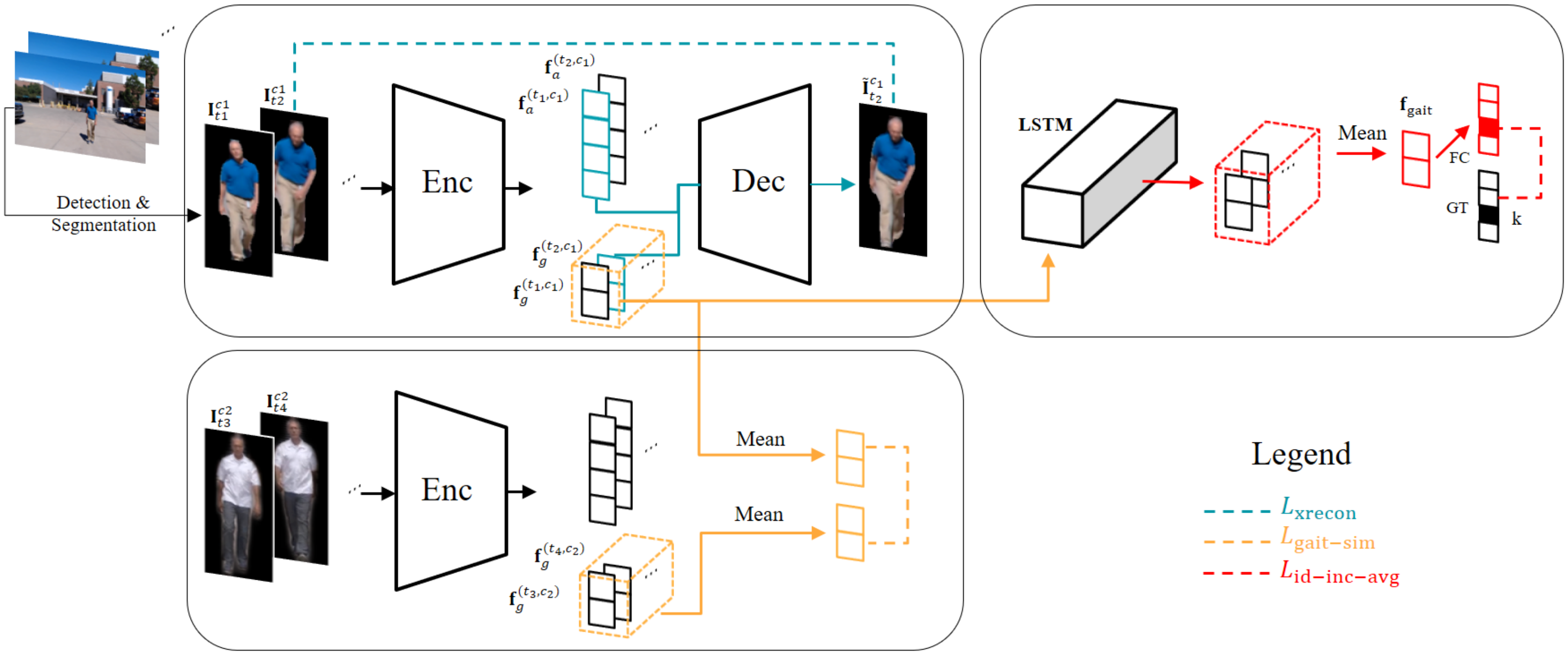


CASIA E GEIs



https://competitions.codalab.org/competitions/26085#learn_the_details

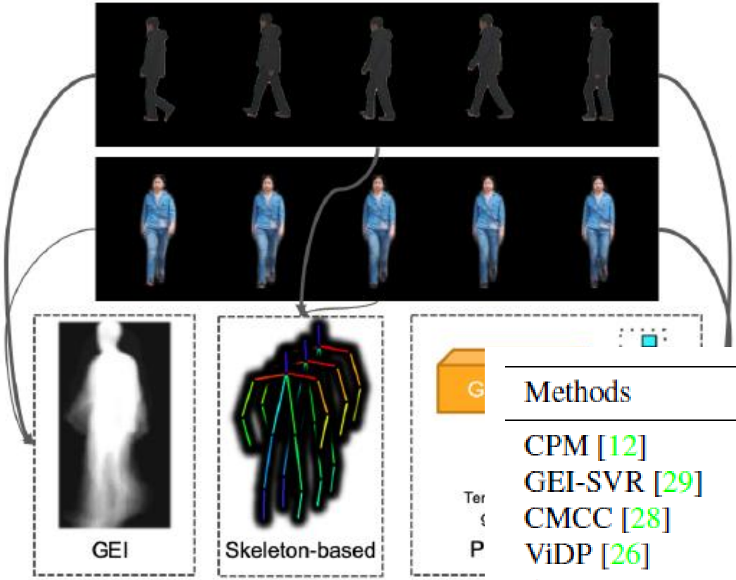
Gait recognition via disentangled representation learning



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



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

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

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

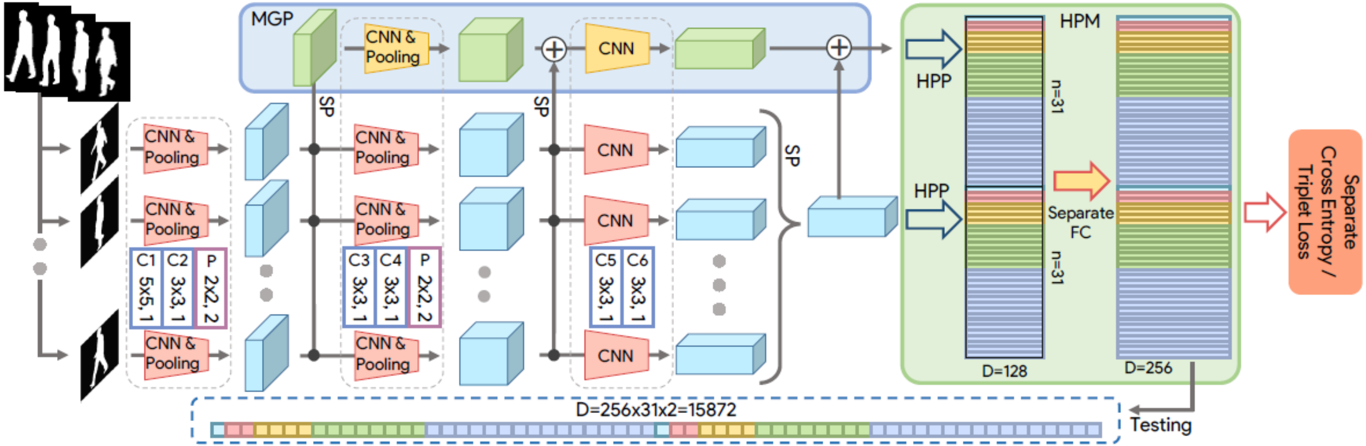

Fig. 2. The framework of GaitSet [26] . 'SP' represents set pooling. Trapezoids represent convolution and pooling blocks and those in the same column have the same configurations, as shown by the rectangles with capital letters. Note that although the blocks in MGP have the same configurations as those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

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			
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: Max	Mean	Median	Joint sum [3]	Joint 1_1C [4]	Pix-att	Frame att	MGP	NM	BG	CL
√										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

Identifying people by their gait

1. Where are we now?
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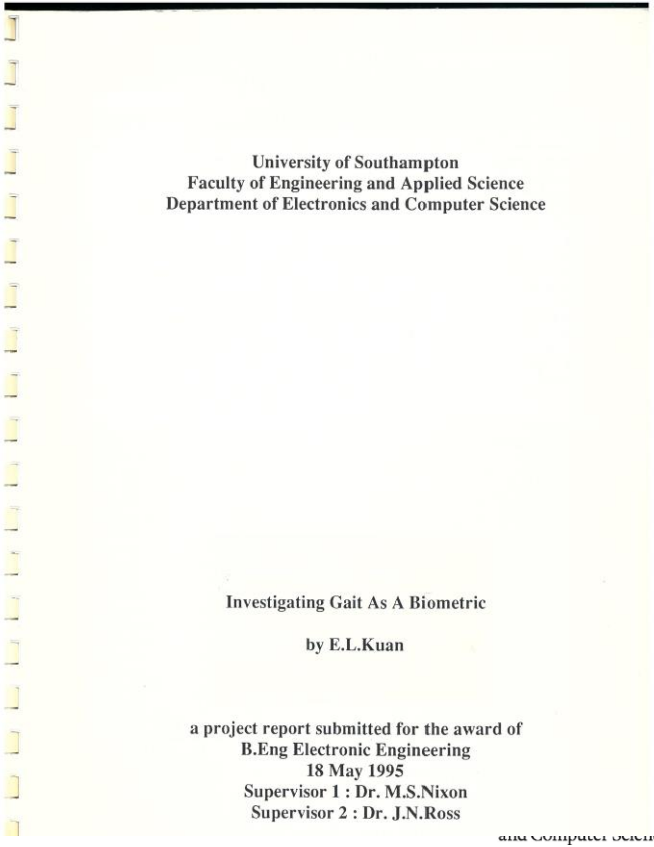
3. Where are we going?



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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

Technology in 1994

Gait and literature

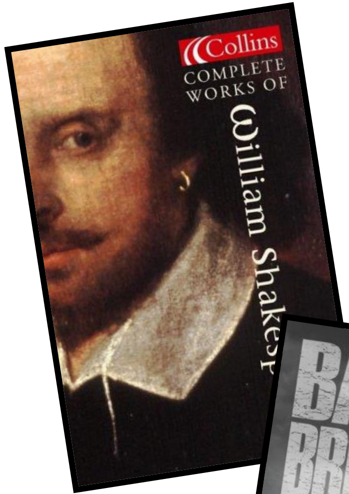
Dictionary: “manner of walking”

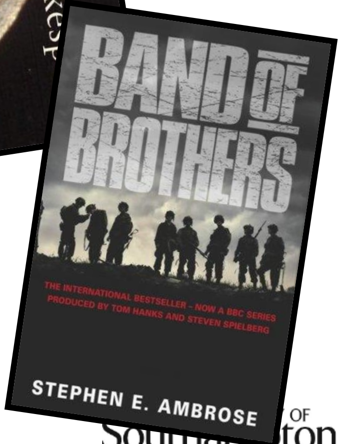
Shakespeare observed recognition:

“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

Little and Boyd, Videre, 1998

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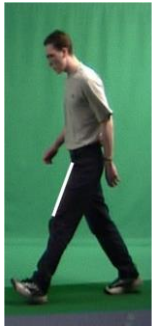
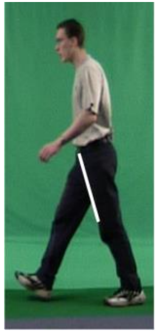
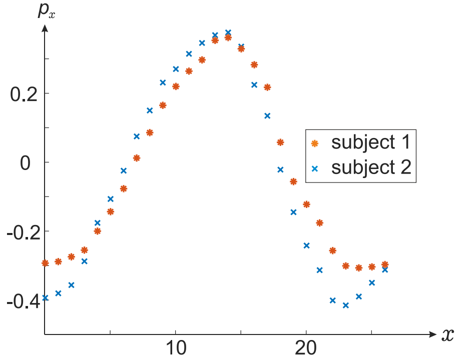
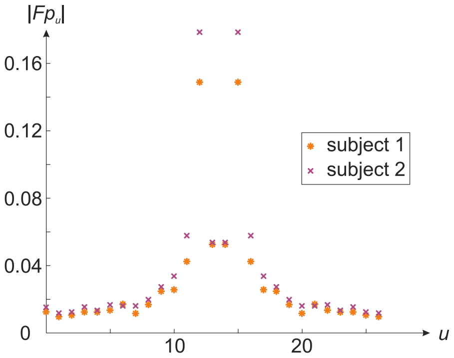
Model-based recognition

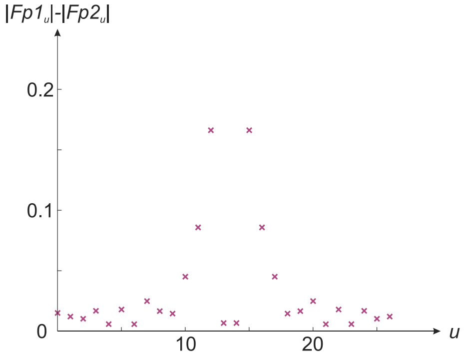



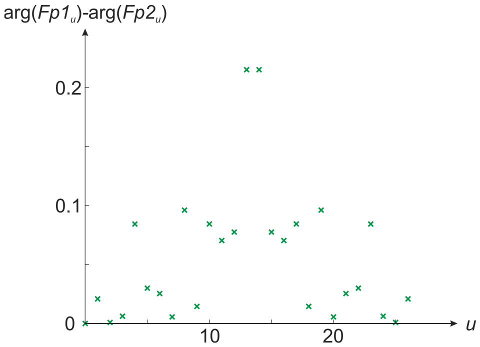
Inclination of thigh



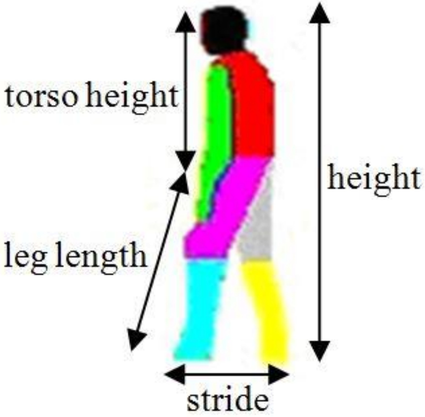
Magnitude of DFT



Difference between magnitude



Difference between phase

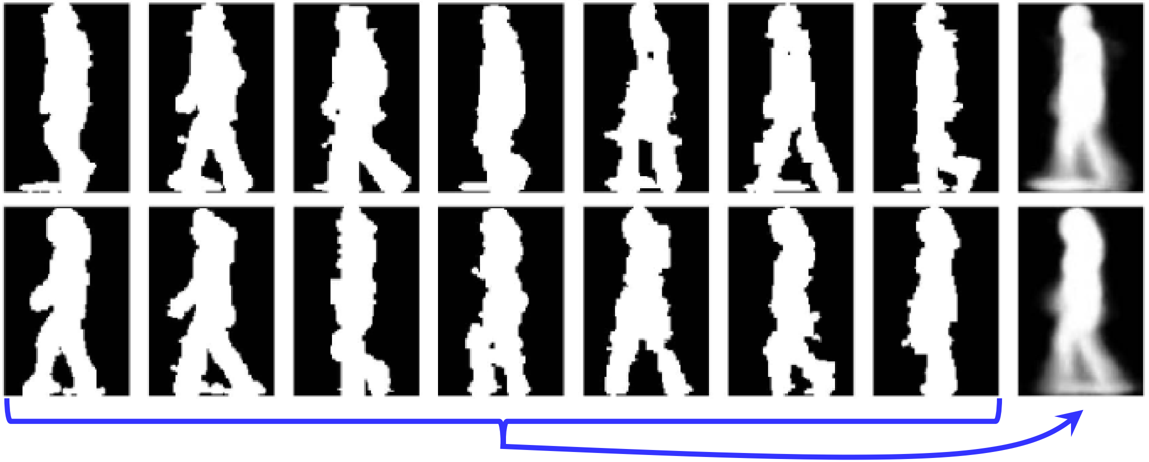


Other models are possible

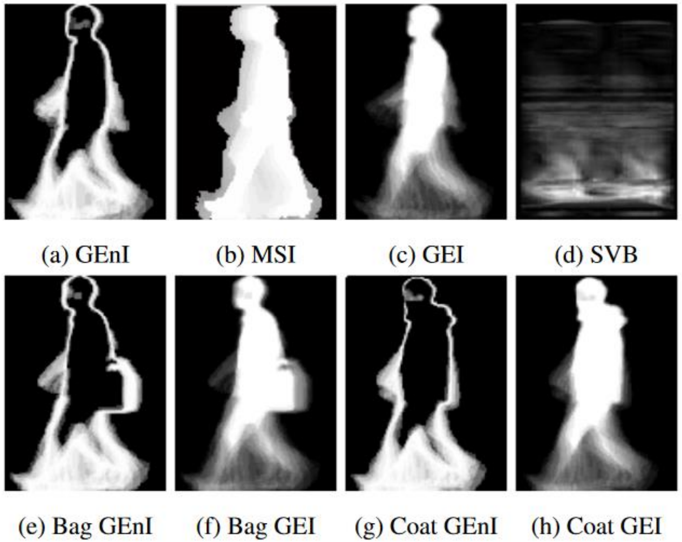
D Cunado, MS Nixon, JN Carter, Proc. AVBPA, 1997

Using silhouettes

Some names: average silhouette, GEI



Gait Energy Image

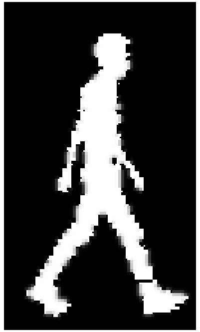
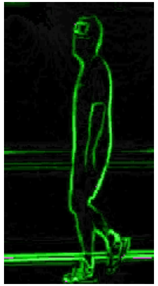


Gait Entropy Image

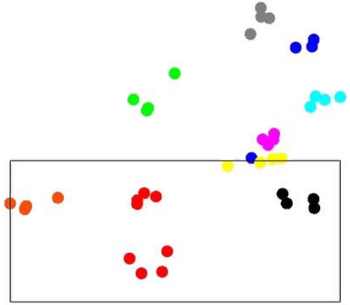
J Han, B Bhanu, *IEEE TPAMI*, 2005

Many gait representations possible

Recognising people from the motion of the whole body





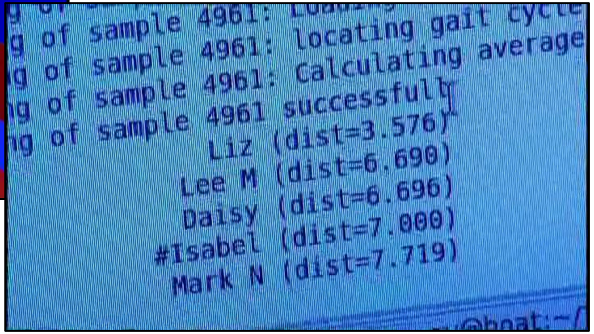
silhouette edges flow symmetry acceleration feature space

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

DARPA's Human ID at a Distance

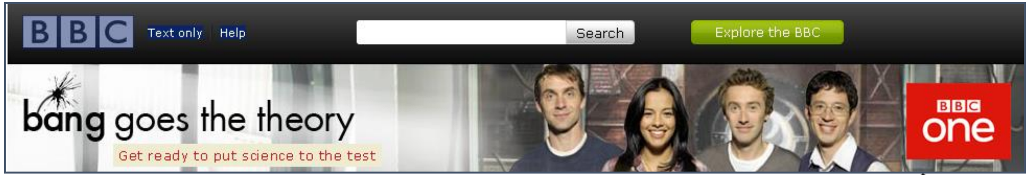
S Sarkar, PJ Phillips, Z Liu, IR Vega, P Grother, KW Bowyer, *IEEE TPAMI* 2005

Does gait biometrics really work?



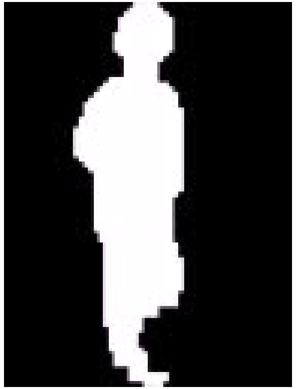
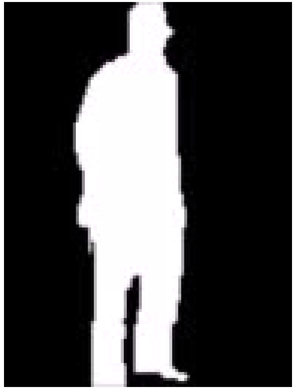
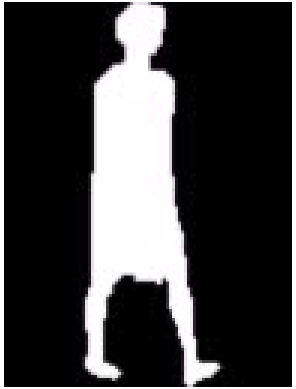
https://www.youtube.com/watch?v=PUwlNc0xAgQ

BBC1 Bang Goes the Theory Episode 1, 2009



Gait-based Age Estimation using a Whole-generation Gait Database

- How old is he/she?

Subject	1	2	3
Gait			
Age	A. 4 years old B. 14 years old C. 24 years old	A. 62 years old B. 72 years old C. 82 years old	A. 24 years old B. 34 years old C. 44 years old

Makihara, Okumura, Iwama, and Yagi, *Proc. IJCB 2011*

Major difficulty 1 - viewpoint

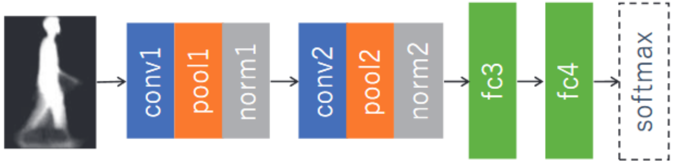


Figure 1: The structure of GEINet.

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

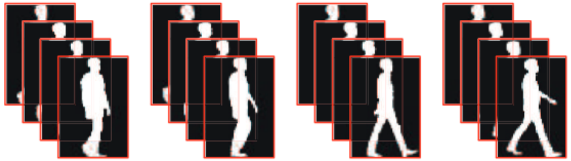
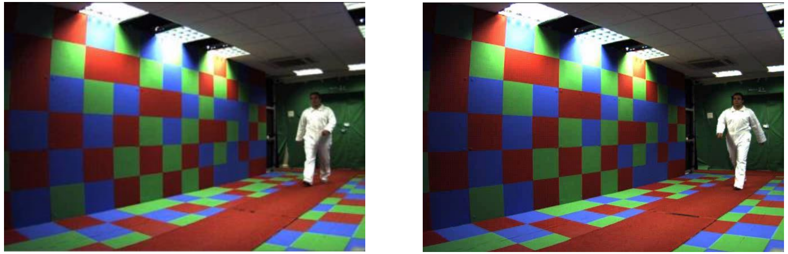


Figure 2: Examples of gait image sequences with four observation views in the OU-ISIR dataset

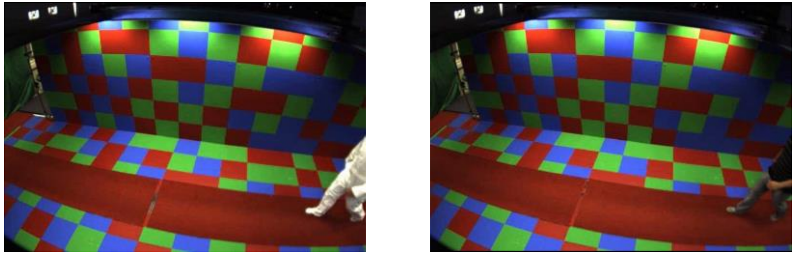
Gallery view	Method	Probe view 55	65	75	85
55	GEINet	(94.7)	**93.2**	**89.1**	***79.9***
	w/ FDF	(92.7)	***91.4***	***87.2***	**80.0**
	TCM+		79.9	70.8	54.5
	wQVTM		78.3	64.0	48.6

Shiraga, Makihara and Muramatsu ICB 2016

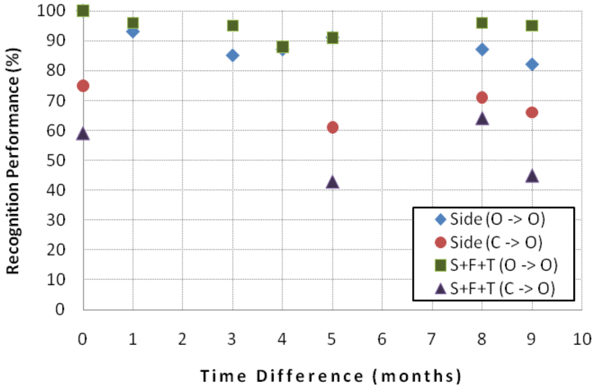
Major difficulty 2 - time



Nine months difference



Few minutes apart, different clothes



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

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US demonstration ……

Saturday Night Live 2002

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Identifying people by their gait

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

Other recent works

Fig. 1. Samples from the KinGaitWild dataset

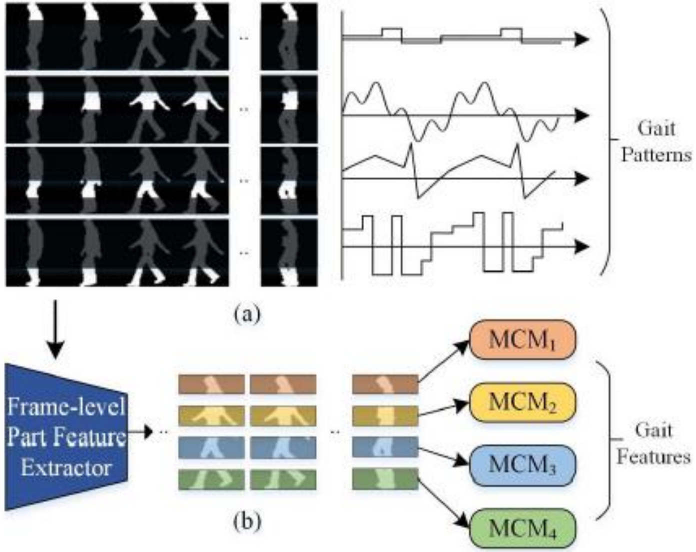

Figure 1. (a): Different parts of human gait possess evidently different shapes and moving patterns during walking. (b): Overview of the GaitPart, consisting of the Frame-level Part Feature Extractor(FPFE) and Micro-motion Capture Module(MCM).

SE Bekhouche, A Chergui, A Hadid…, ICIP 2020

Fan et al, CVPR 2020

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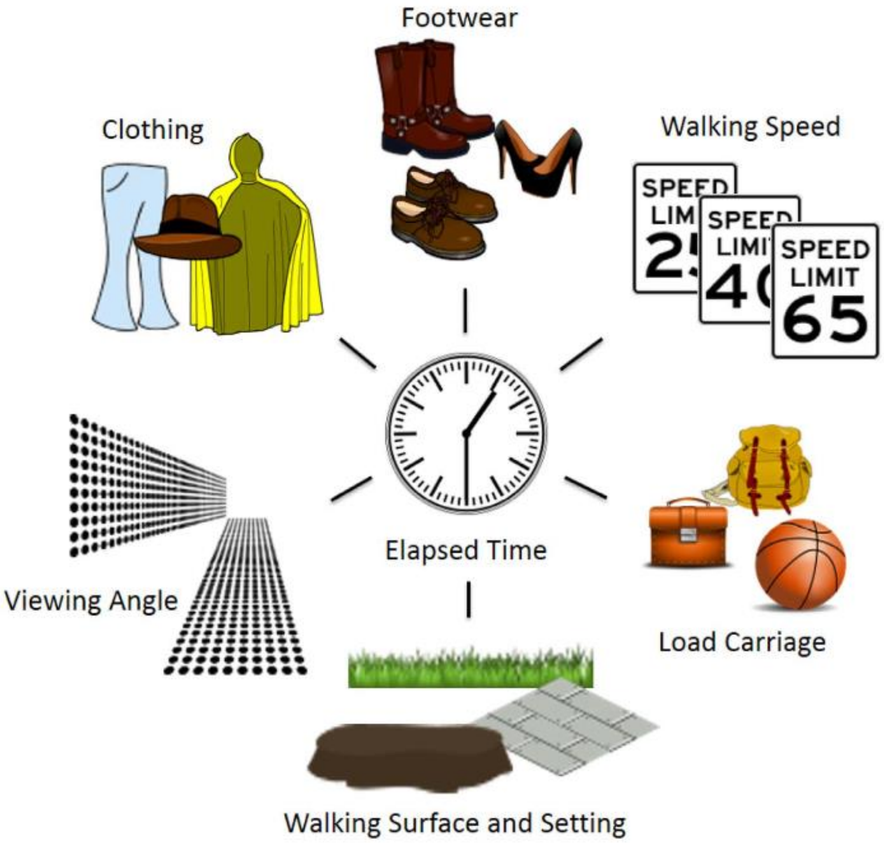
Identity science

Science/ technology

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

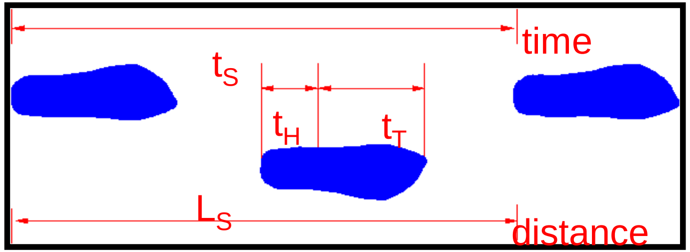
Applications

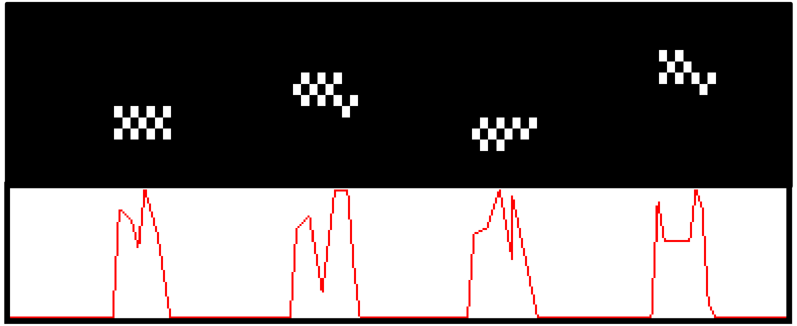
- Medicine (dementia, balance, falls)
- Sports
- Security
- Marketing

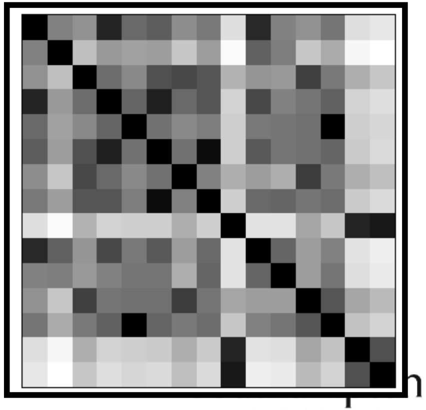


The first intelligent carpet

192×32 binary sensor array

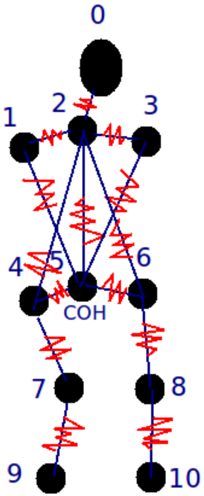


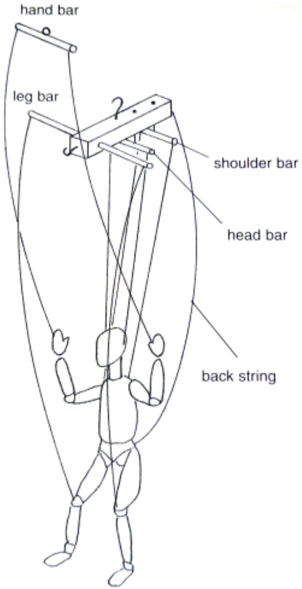


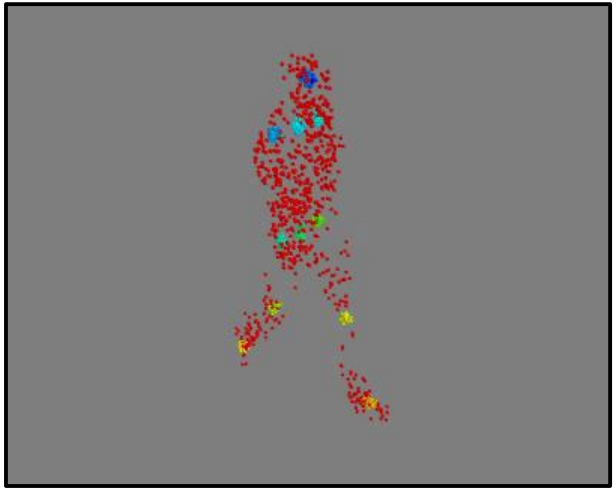


Middleton, Buss and Nixon, *AutoID* 2005

3D recognition – marionette based



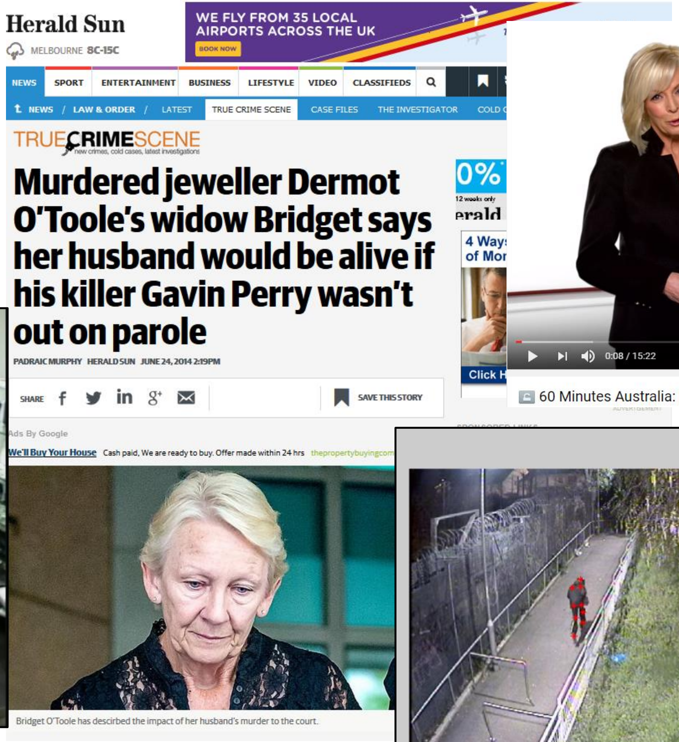




3D is completely viewpoint invariant

Ariyanto and Nixon, Proc. ICB 2013

Gait as evidence: murder case in Australia 2014


Herald Sun

MELBOURNE 8C-15C

NEWS SPORT ENTERTAINMENT BUSINESS LIFESTYLE VIDEO CLASSIFIEDS

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

TRUECRIMESCENE

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

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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

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Descriptions and attributes for identification

Image of crime

Generate description

Subject	Gender	Age	Height	Nose W	Top
?	M	24	171	2.4	Shirt

Eyewitness statement
"24 year old male average height wearing shirt"

Database of images

Generate descriptions

Subject	Gender	Age	Height	Nose W	Top
123456	M	25	172	2.3	Shirt
123457	F	36	156	2.2	Blouse
123458	M	58	182	1.2	T shirt

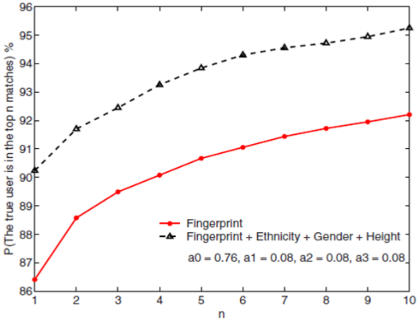
Database of descriptions

Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2019

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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Advantages of Soft Biometrics

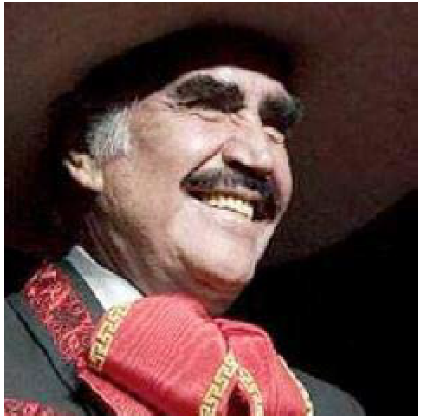
1. Human understandable description
   - rich in semantics, e.g., a face image described as a “young Asian male”
   - bridges gap between human and machine descriptions
1. Robustness to image quality
   - soft biometric attributes and low quality data
   - subject at a distance from the camera
1. Privacy
   - 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: mainly deep

Data: Maad-face

Applications: face



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

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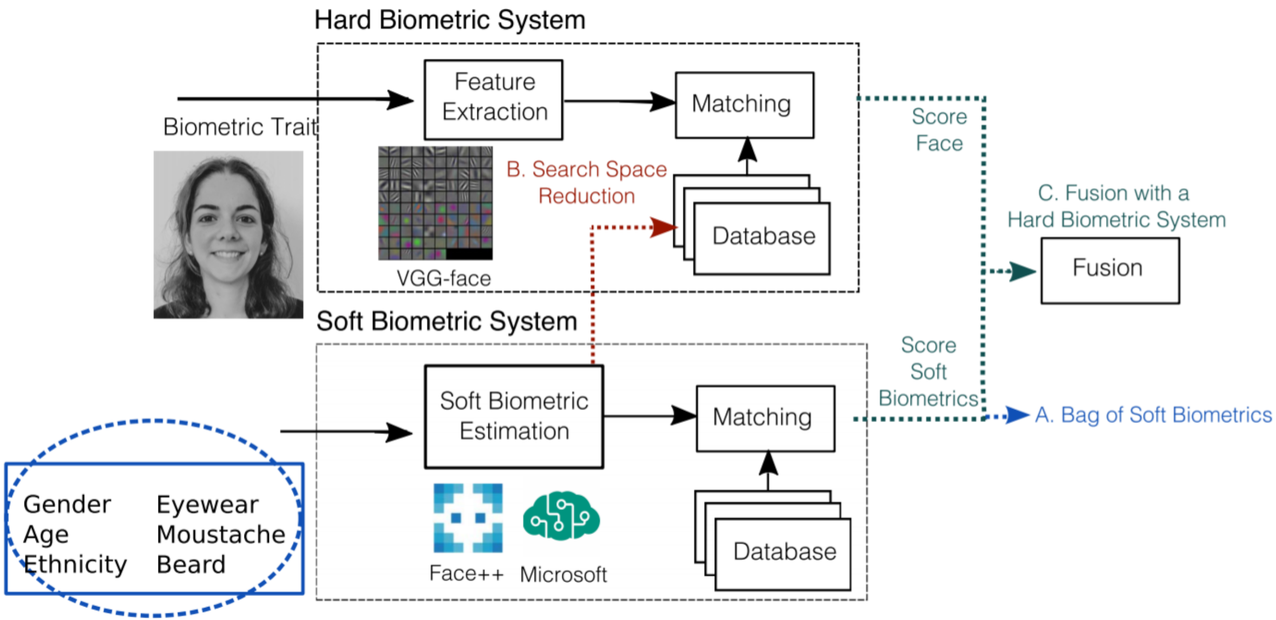
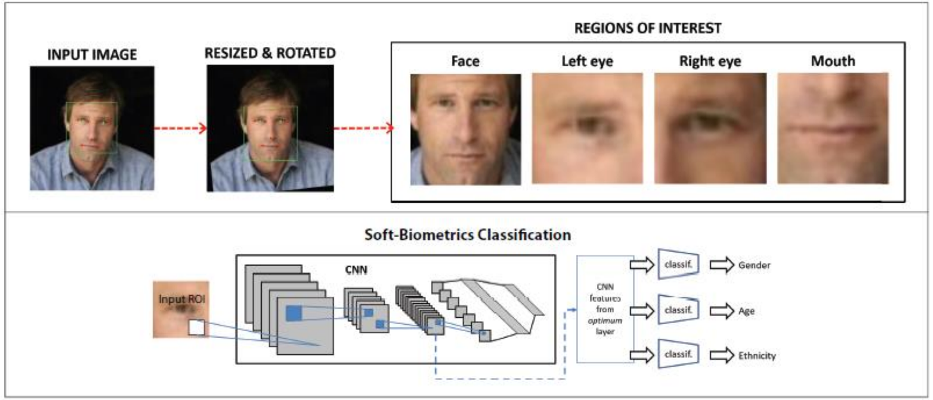
Facial Soft Biometrics for Recognition in the Wild: Recent Works, Annotation, and COTS Evaluation



Soft Biometrics for Recognition: A) Bag of Soft Biometrics; B) Search Space Reduction; and C) Fusion with a Hard Biometric System

Gonzalez-Sosa, Fierrez, Vera-Rodriguez, Alonso-Fernandez *IEEE TIFS* 2018

Soft-Biometrics Estimation In the Era of Facial Masks



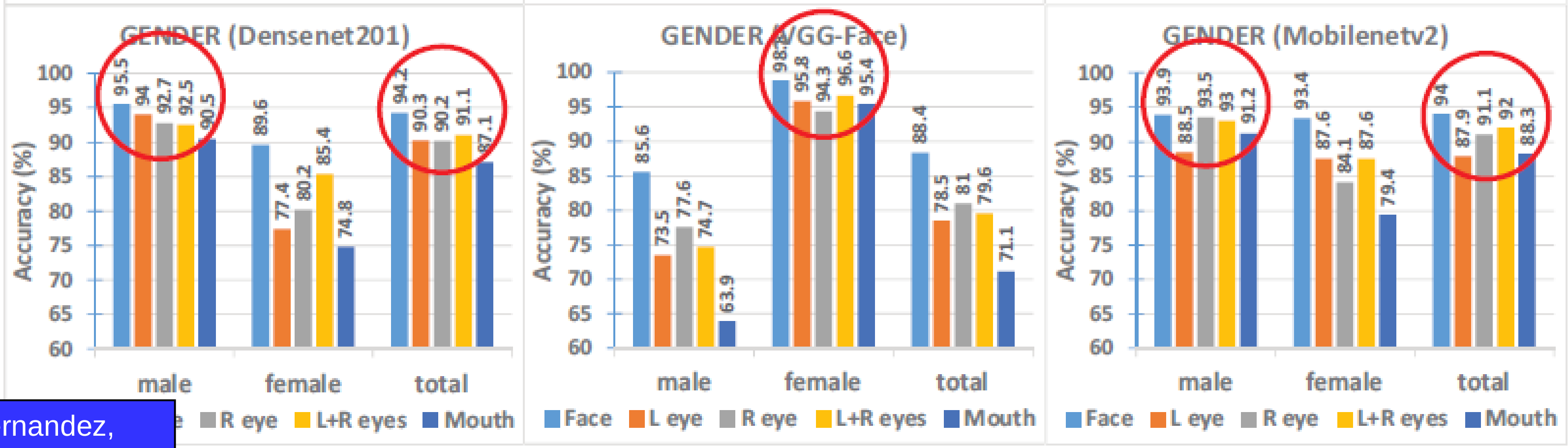
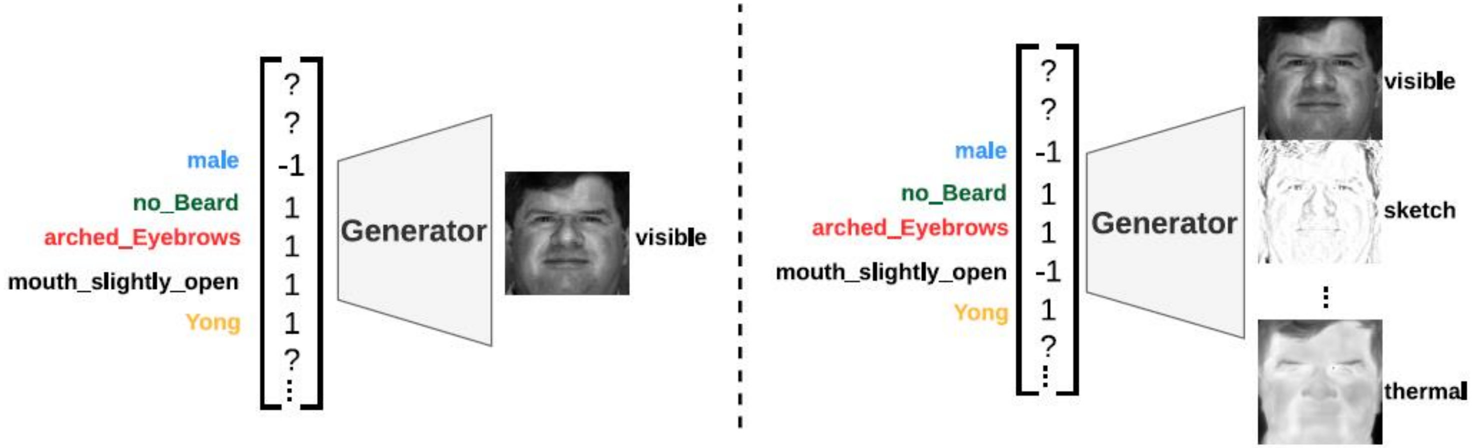


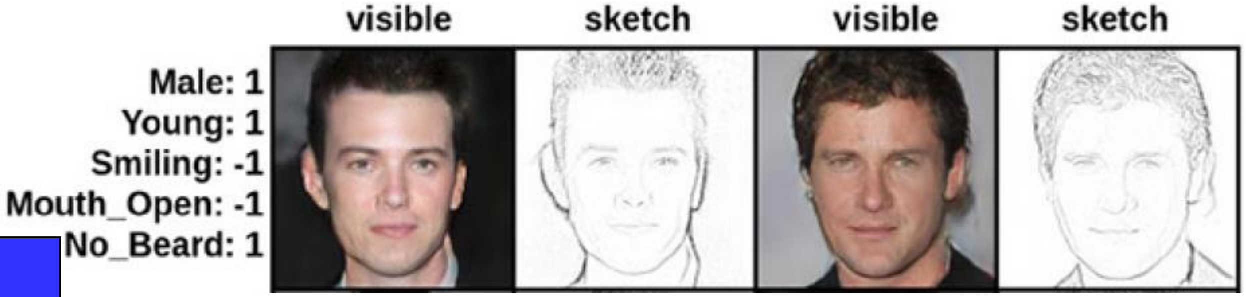
Fig. 2: Accuracy of gender estimation using different facial regions.

Alonso-Fernandez, BIOSIG 2020

Multimodal Face Synthesis From Visual Attributes

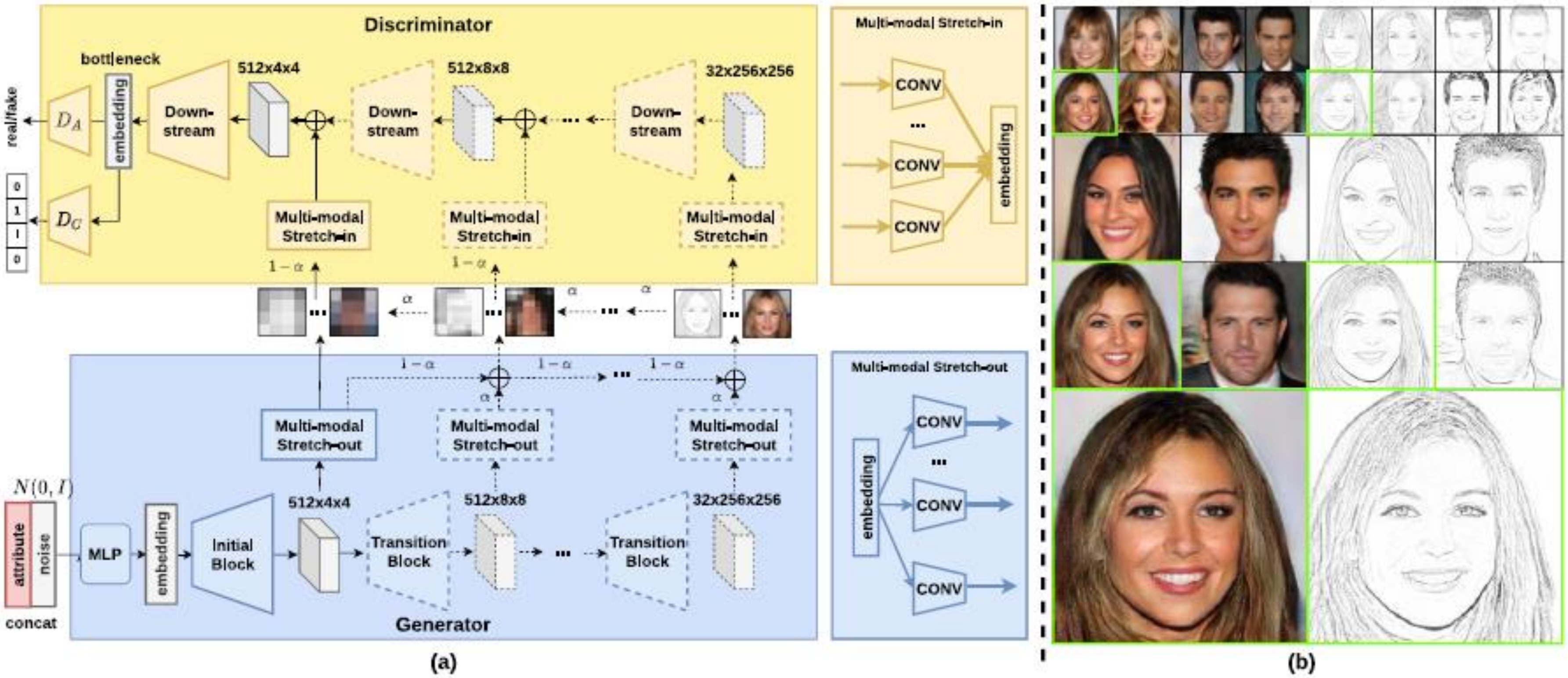


(a) Unimodal synthesis (b) Multimodal synthesis



Di and Patel, *IEEE TBIOM*, 2021

Multimodal Face Synthesis From Visual Attributes



Di and Patel, *IEEE TBIOM*, 2021

What can you recognise?

64×97

128×194

256×386

Traits and terms

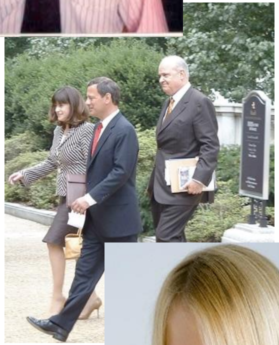
Global Features

- 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

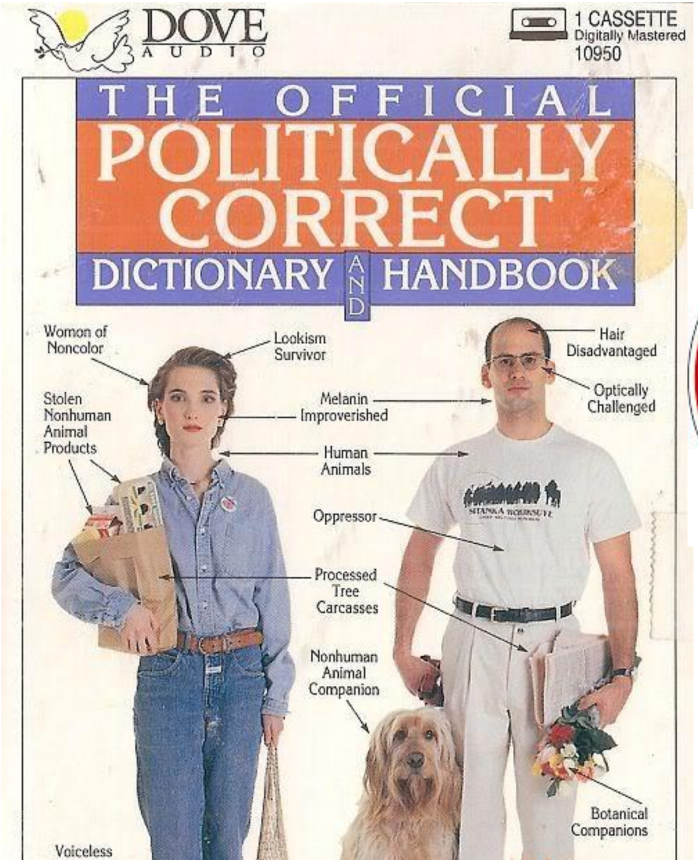


Phrasing questions

- 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

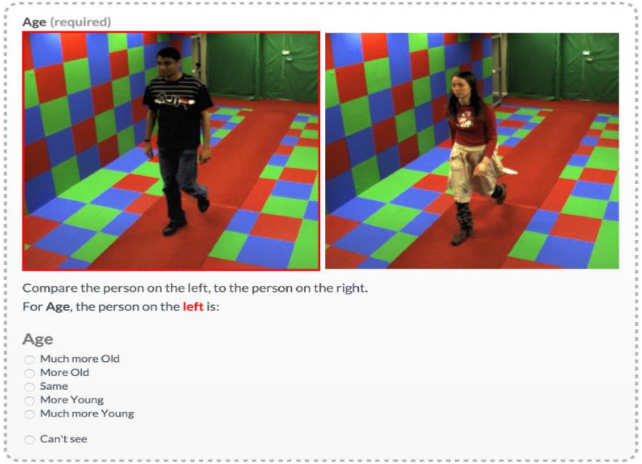
2. Turn the data into features

Learning label structure

3. Learn how recognition can be achieved

Recognise

4. Generate new labels



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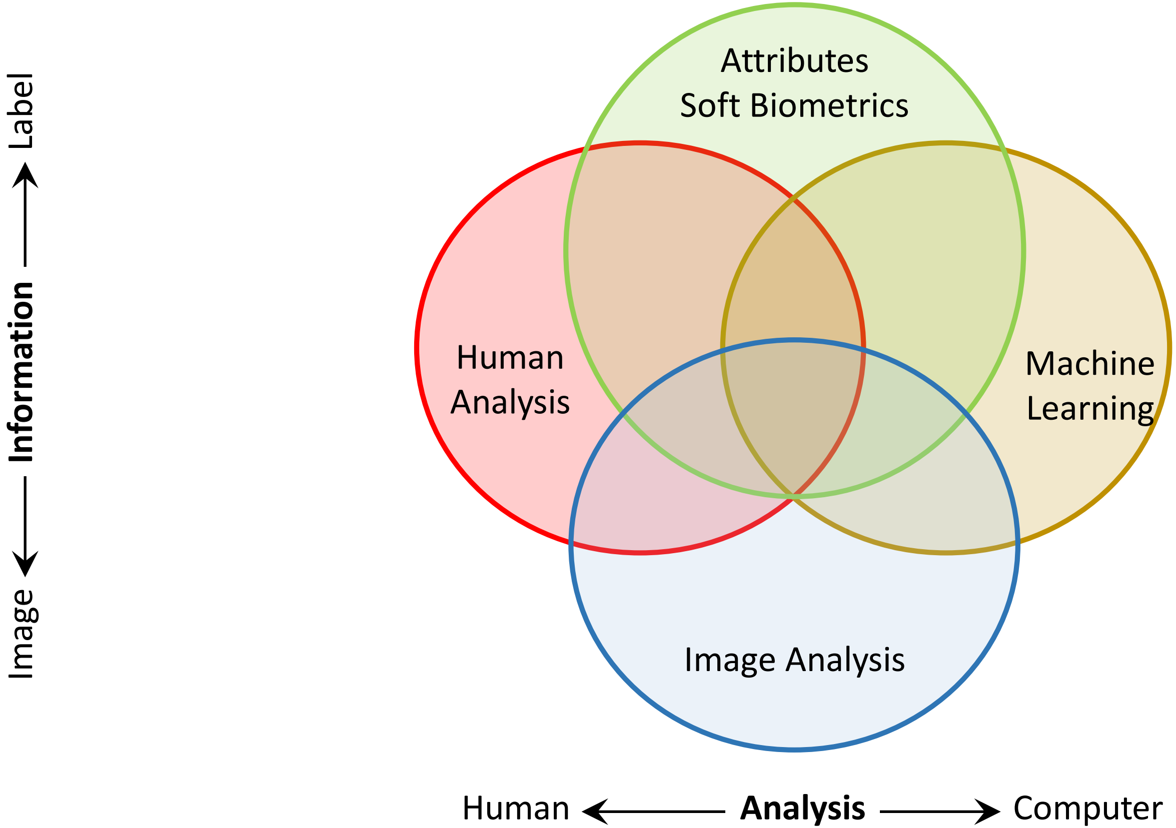
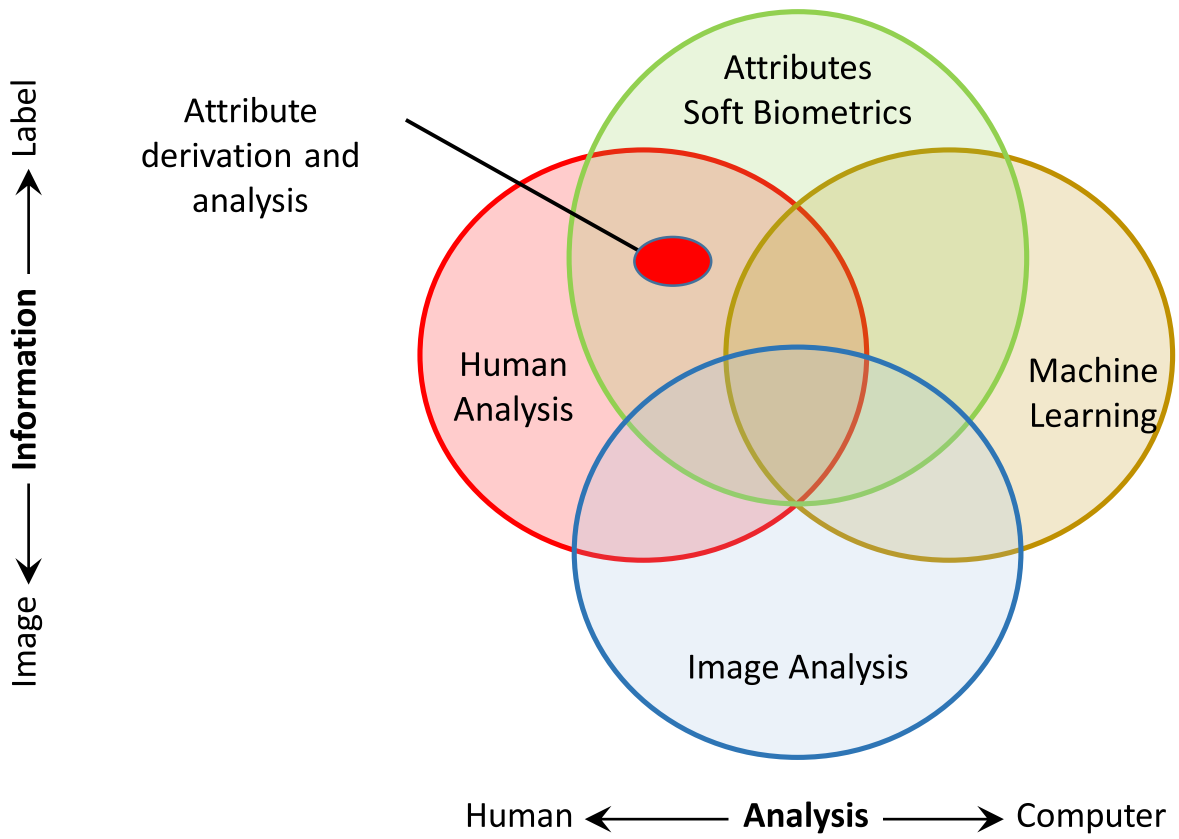
How does this fit with computer vision?





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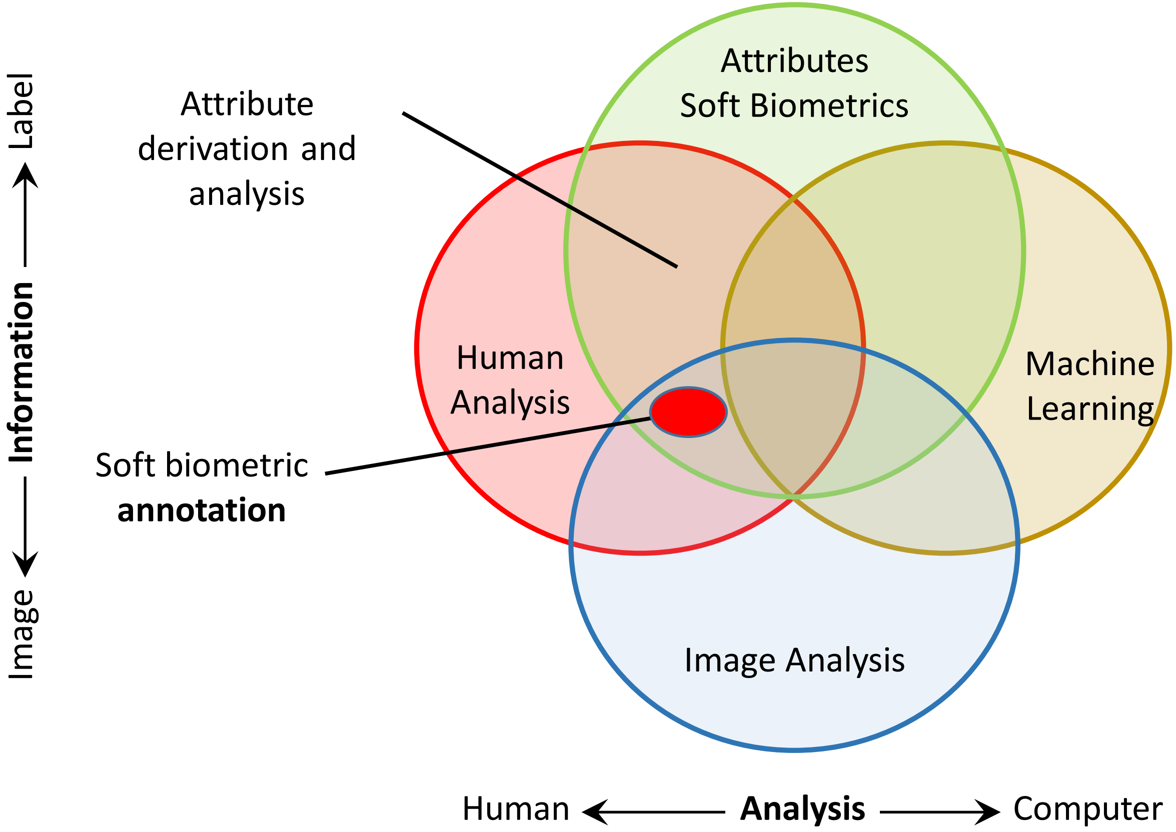
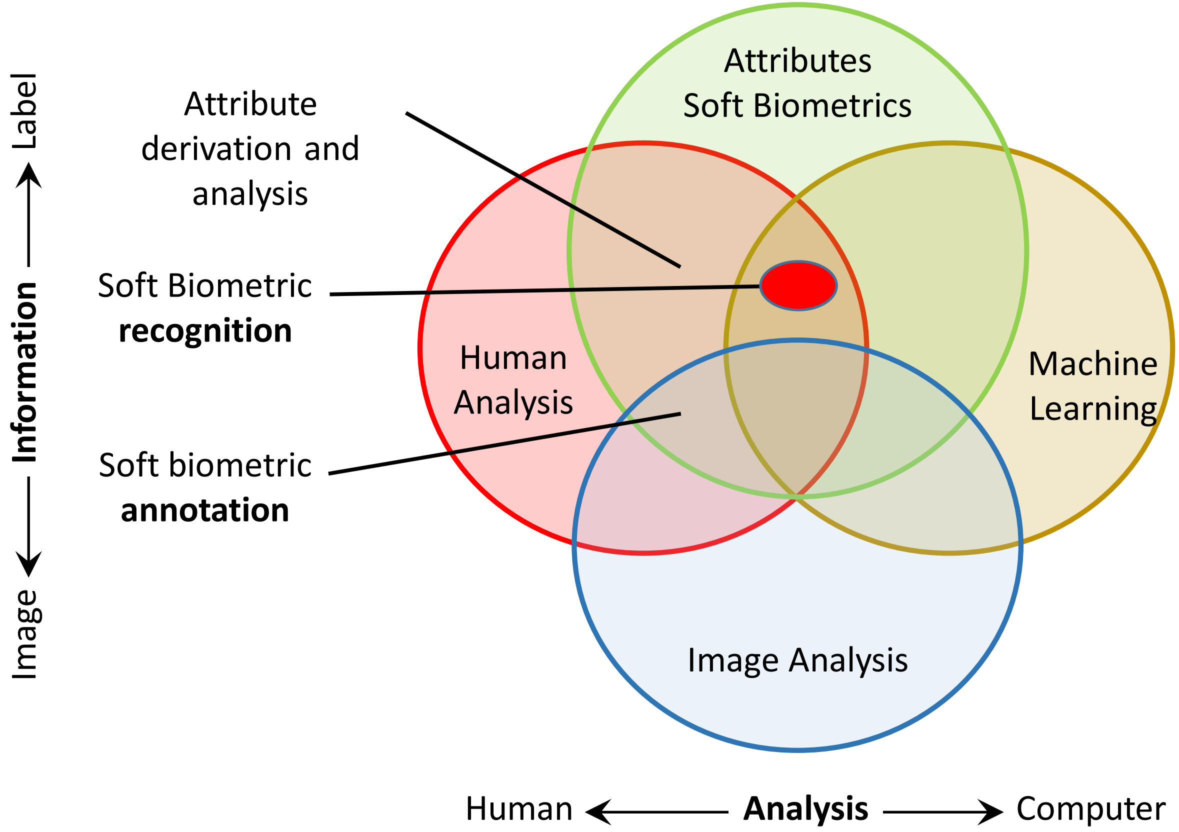

Attributes
Soft Biometrics
Attribute
derivation and
analysis
Human
Analysis
Machine
Learning
Soft biometric
annotation
Image Analysis
Label
Information
Image
Human
Analysis
Computer



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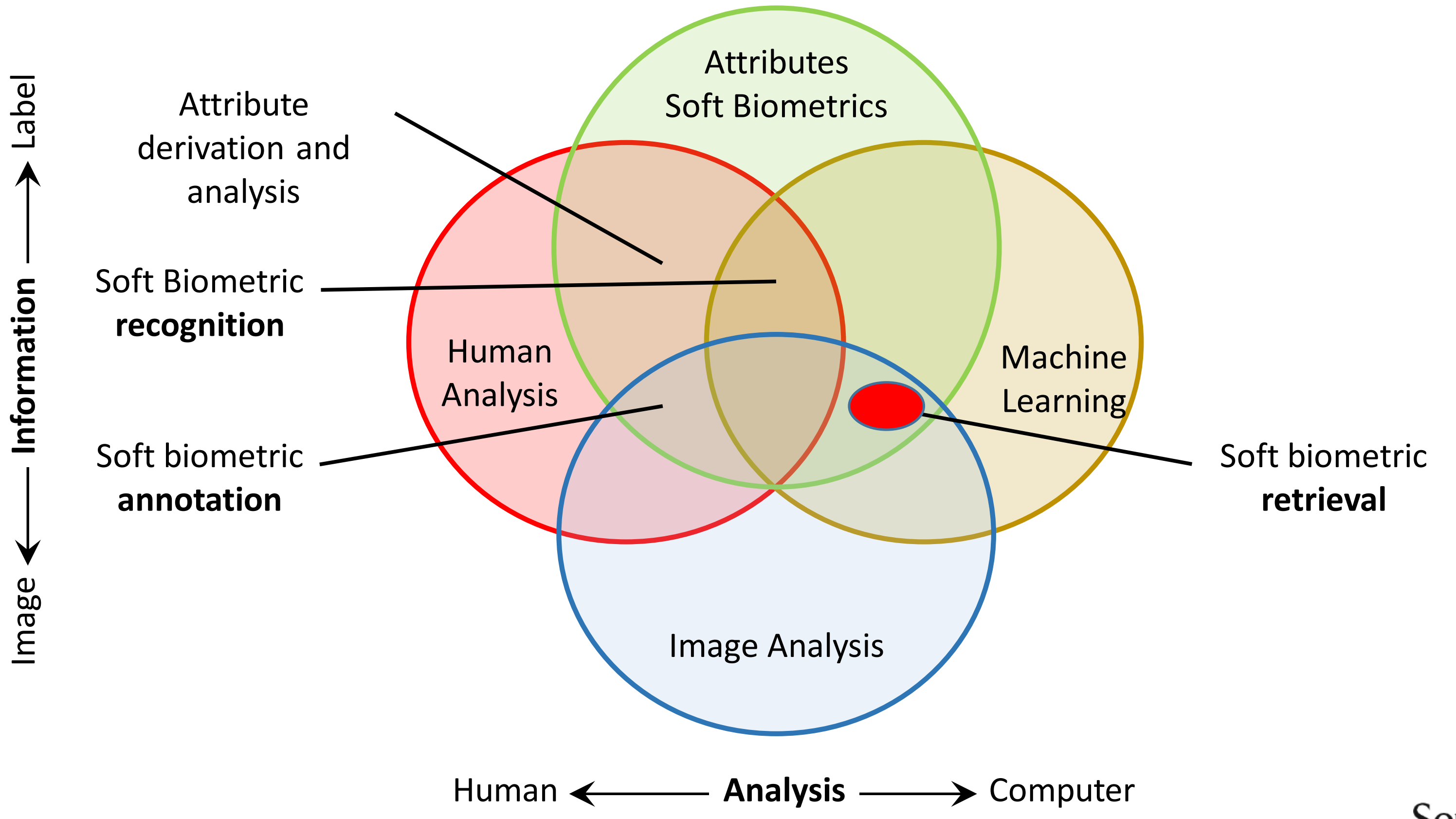

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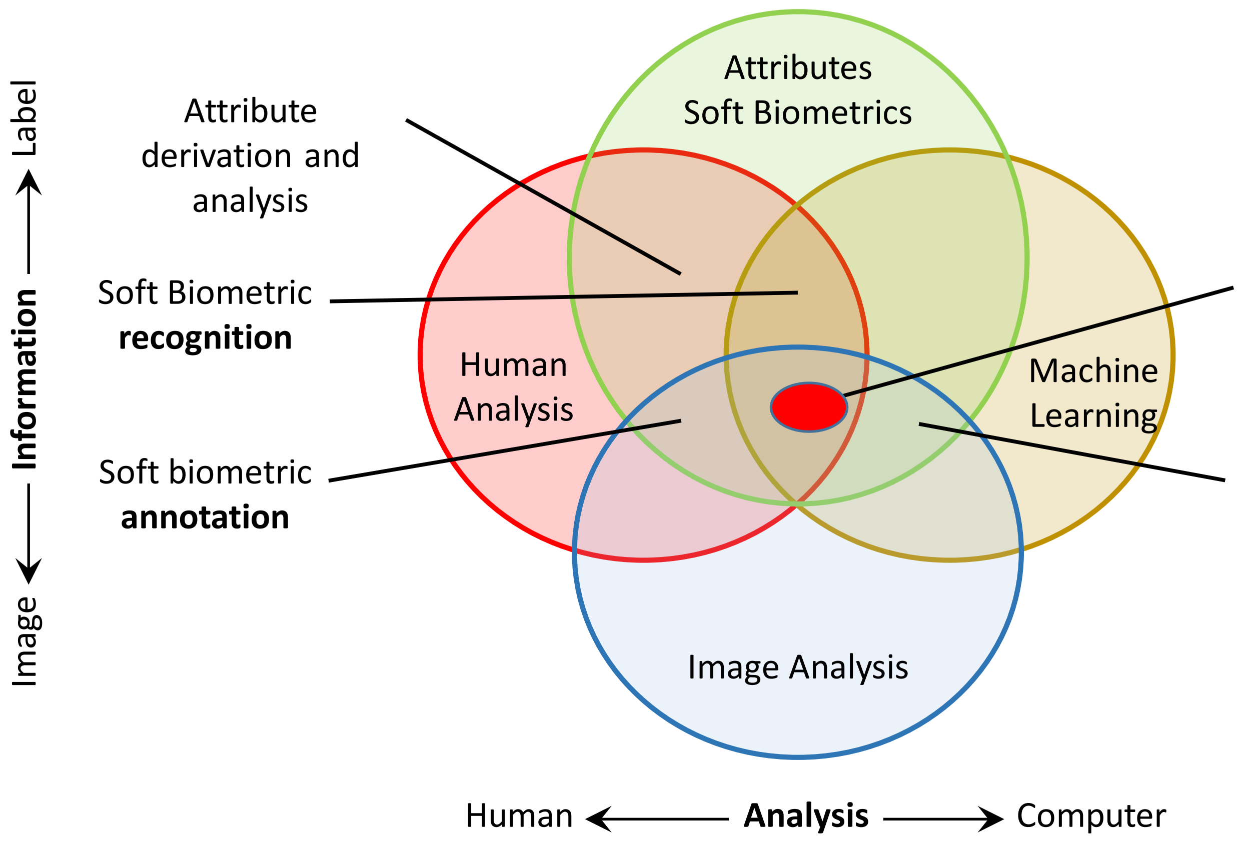

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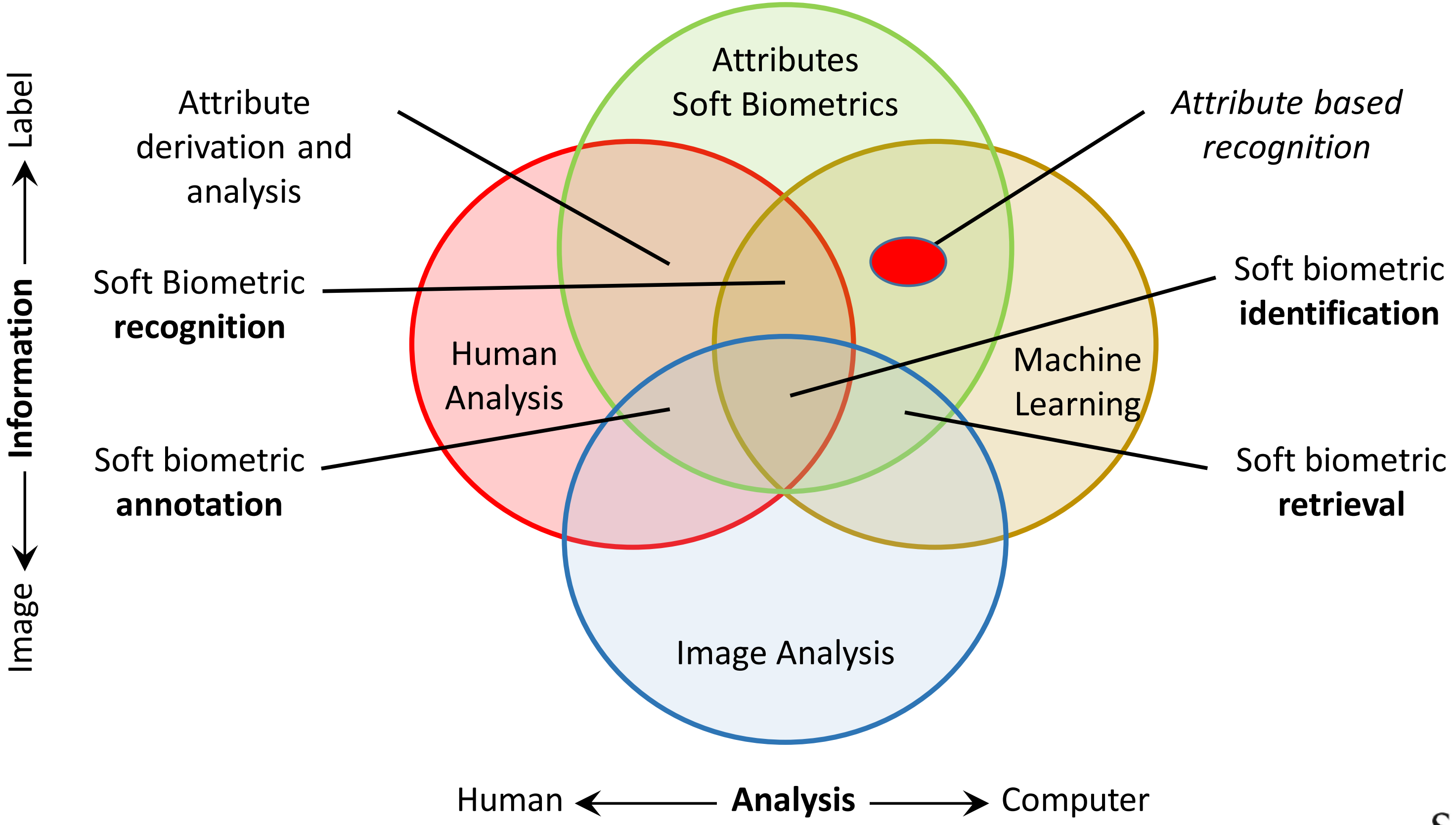

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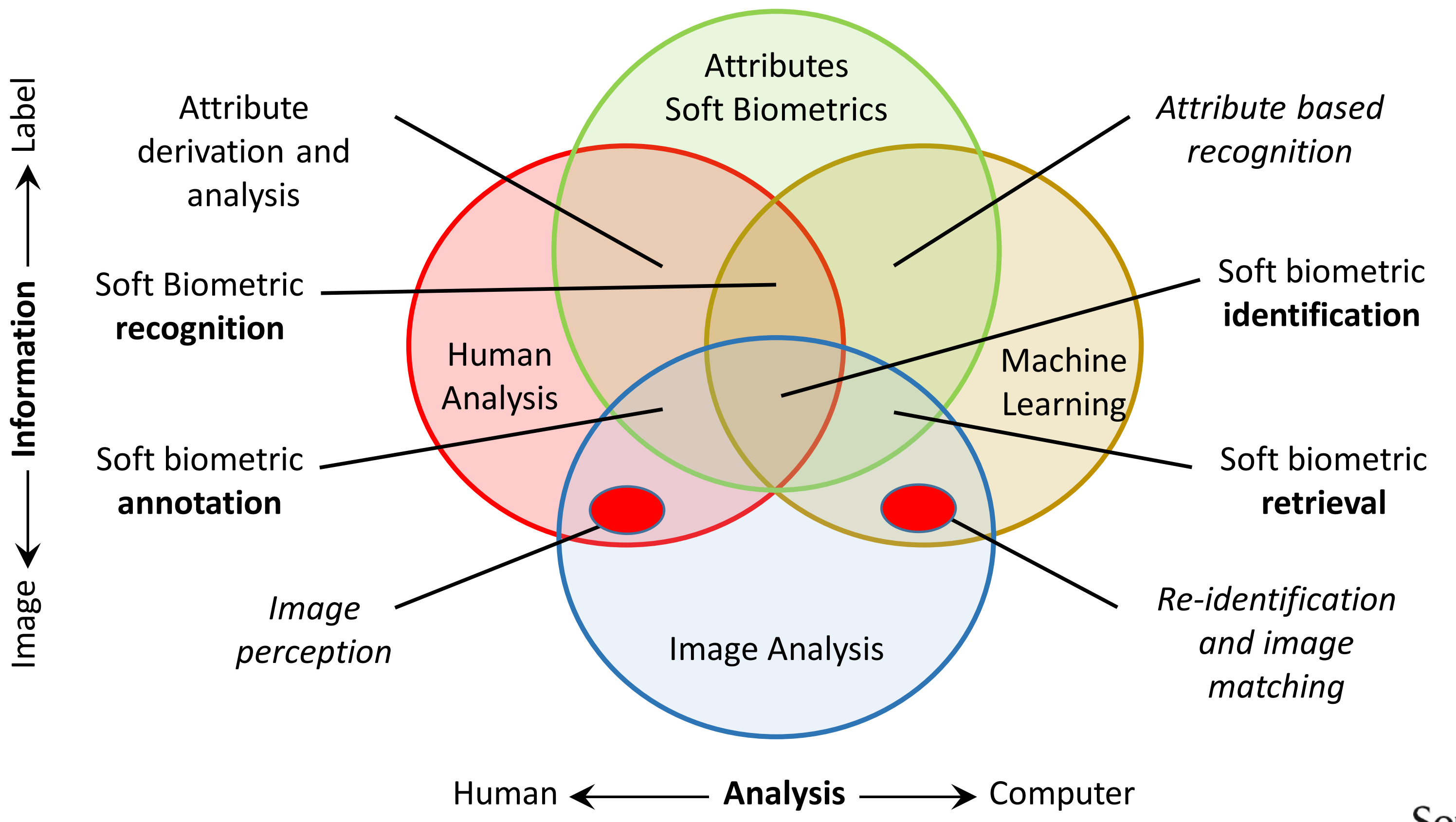

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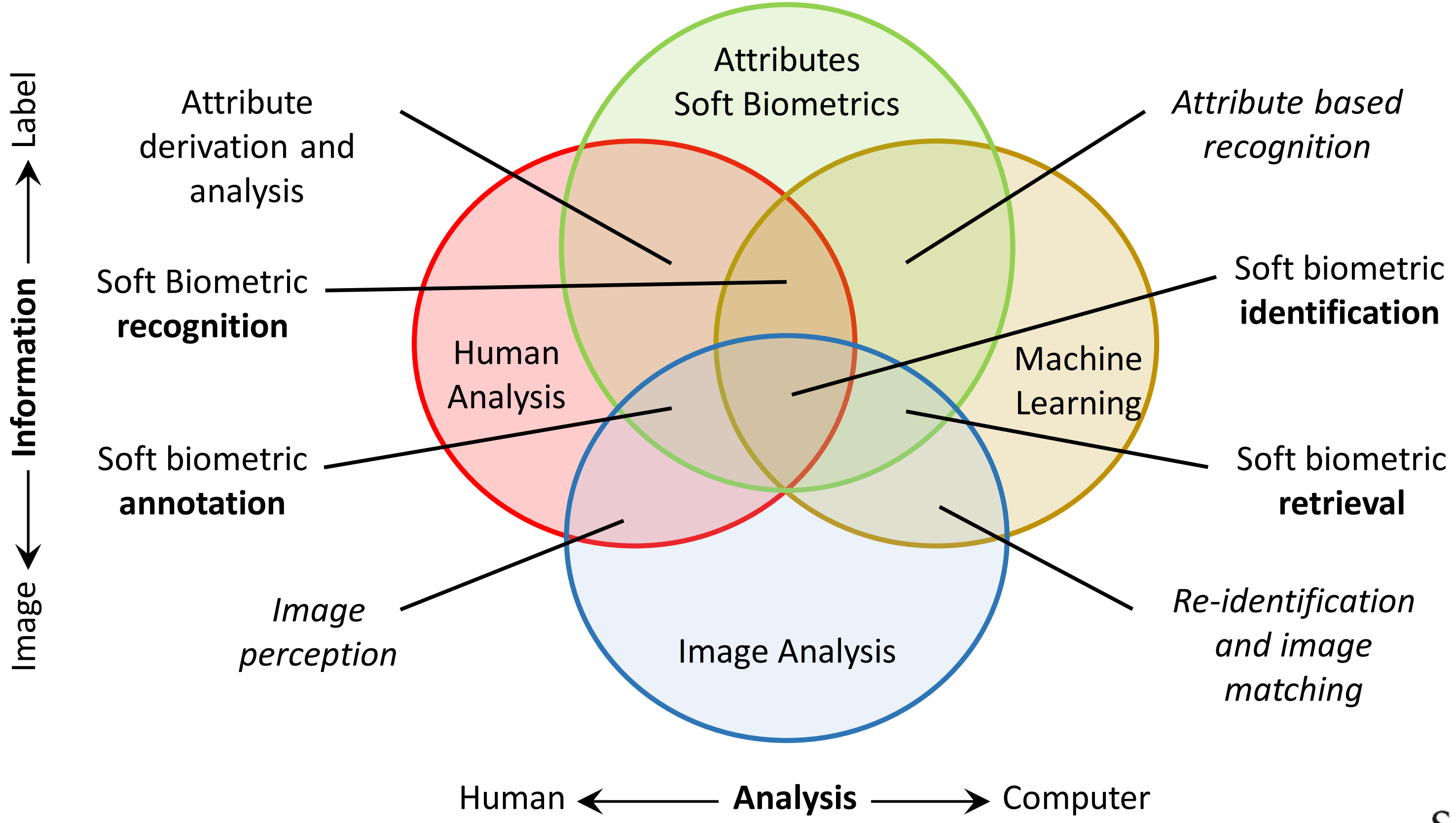
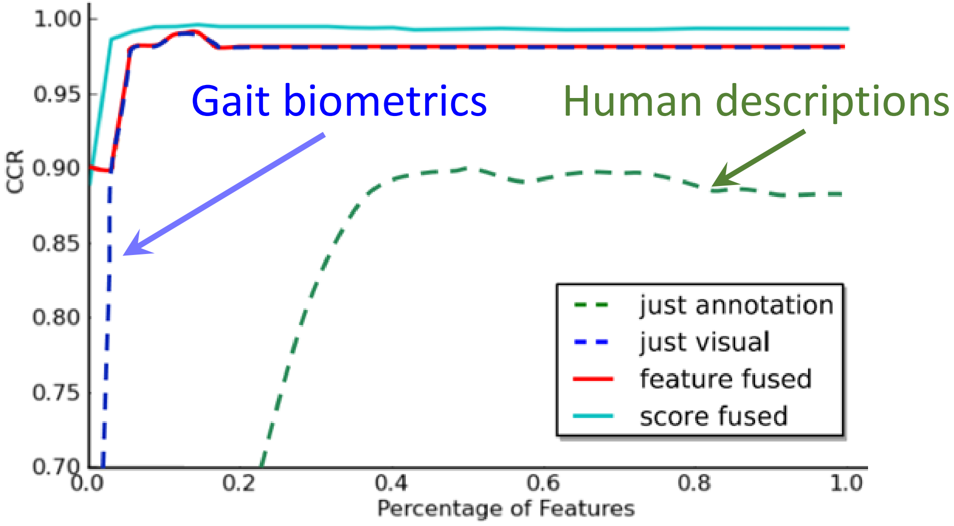
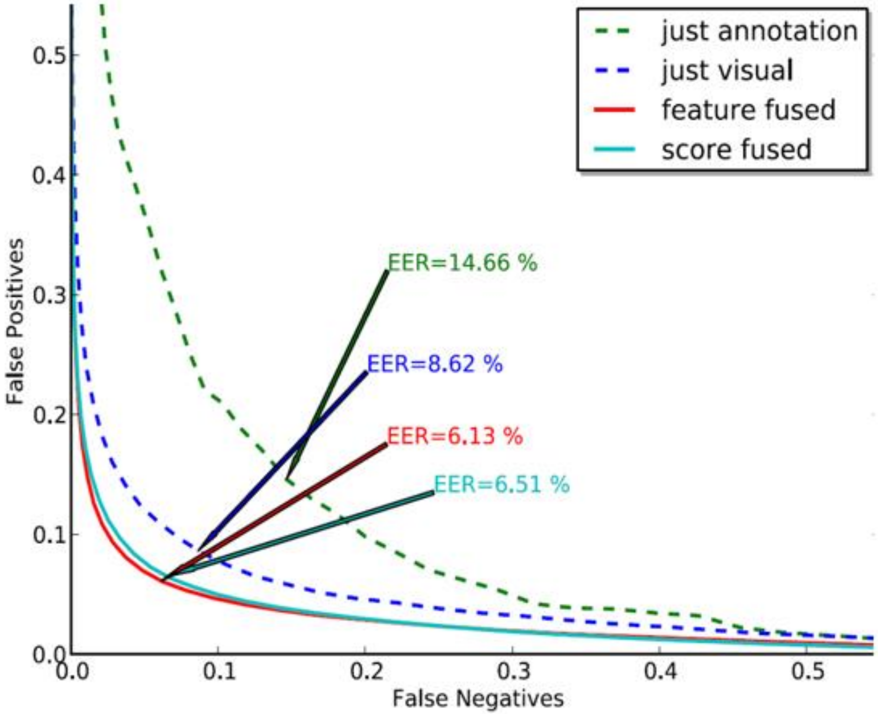

Attributes
Soft Biometrics
Human
Analysis
Machine
Learning
Image Analysis
Attribute
derivation and
analysis
Soft Biometric
recognition
Soft biometric
annotation
Image
perception
Attribute based
recognition
Soft biometric
identification
Soft biometric
retrieval
Re-identification
and image
matching
Label
Information
Image
Human
Analysis
Computer

Human descriptions: recognition capability



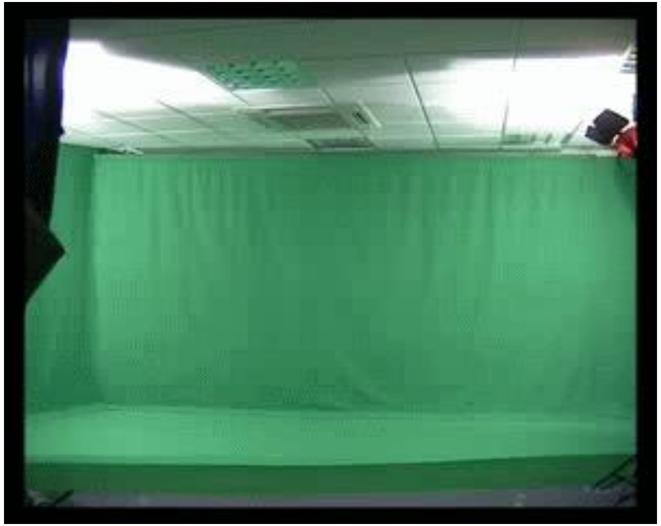


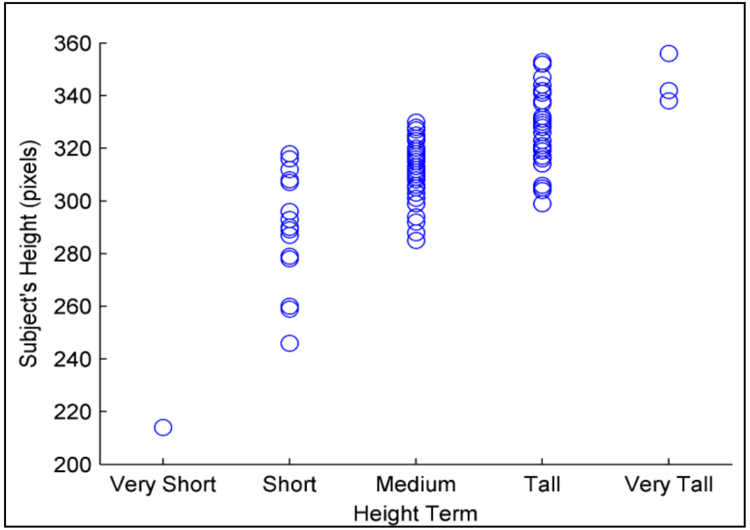
First result

Samangooei and Nixon, *IEEE BTAS* 2008

Problems with absolute descriptors

Subjective = unreliable; Categorical = lacks detail





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

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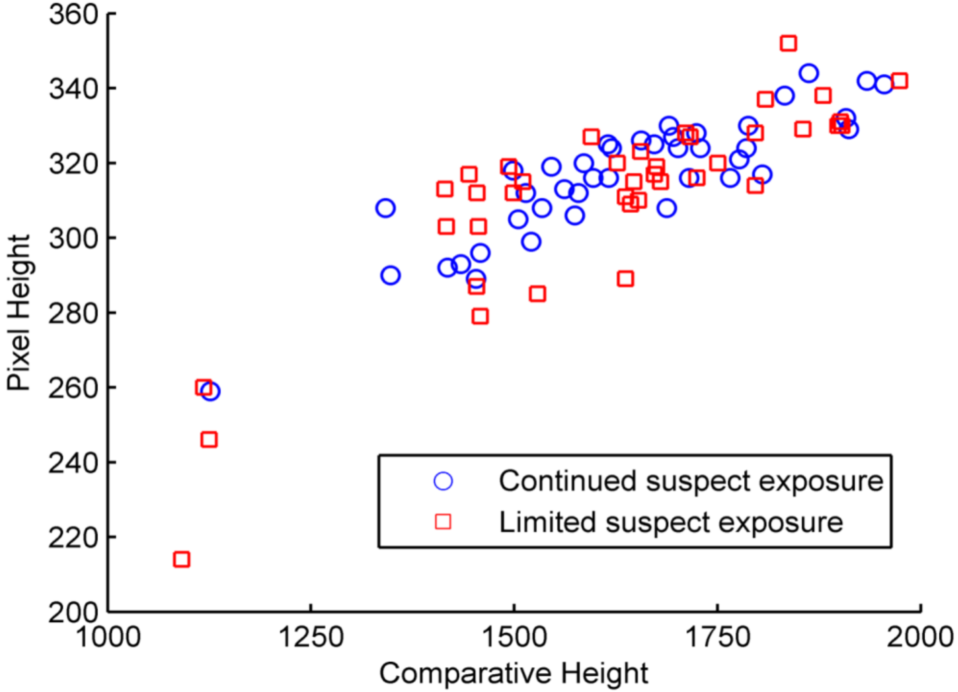
Comparative human descriptions

- 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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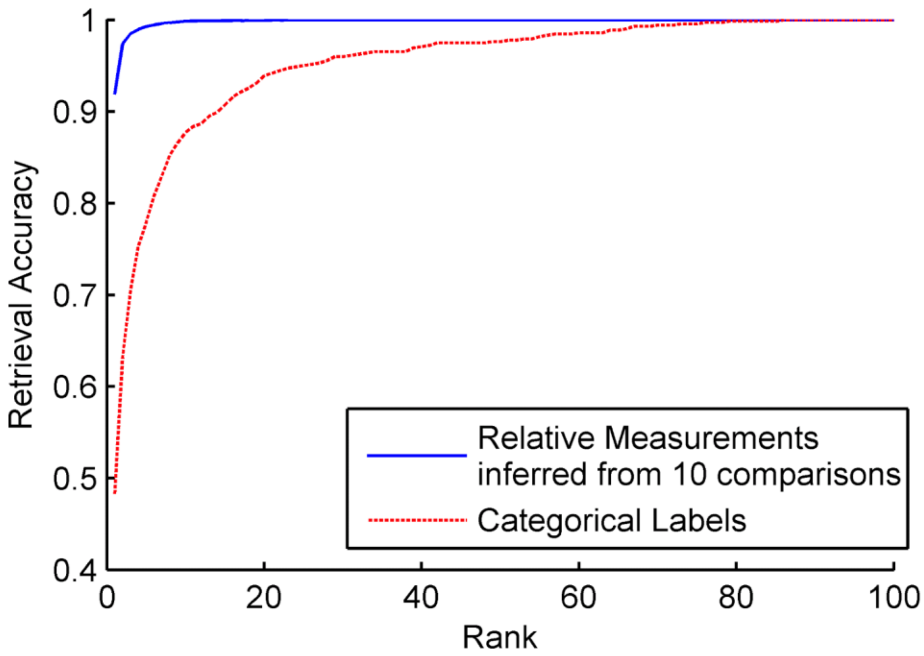
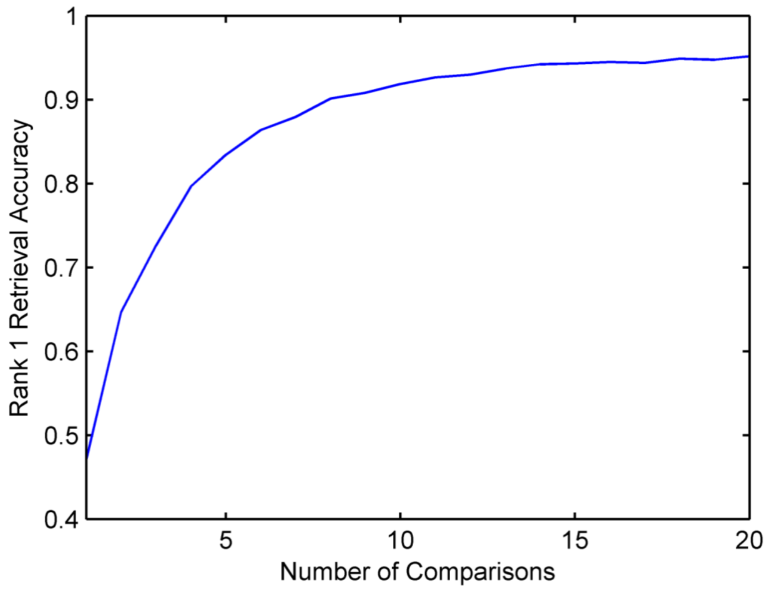
Recognition



Reid and Nixon, *IEEE ICDP* 2011

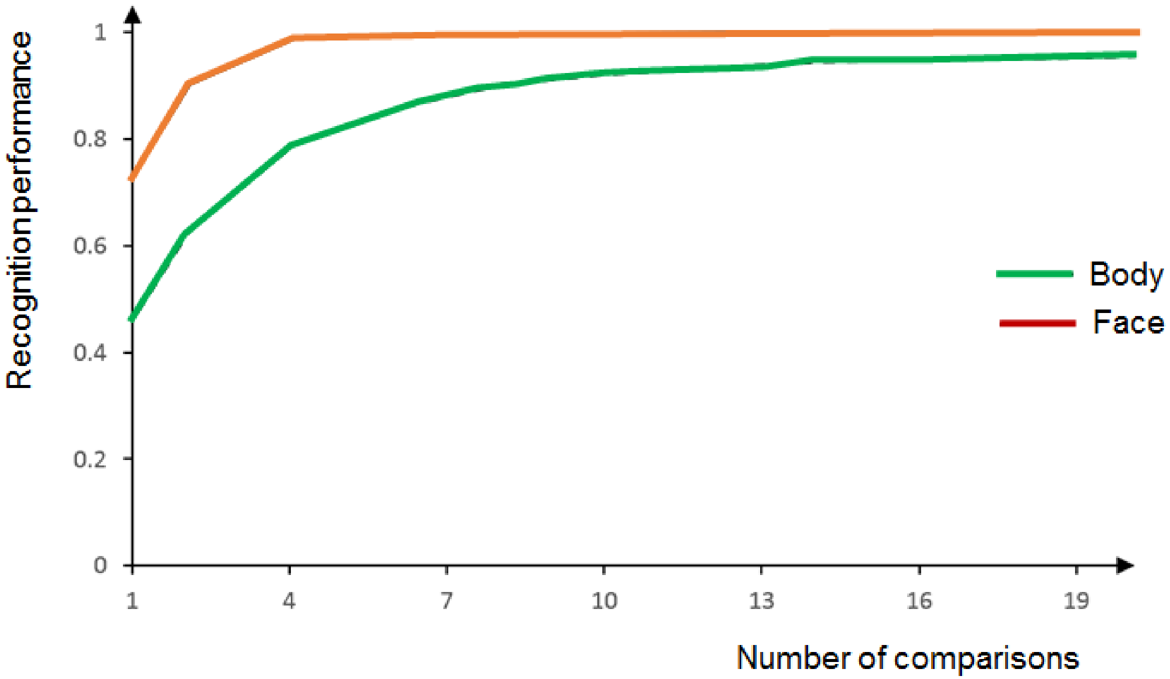
Ranking comparative descriptions

- 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

Evaluation: effect of number of comparisons on recognition



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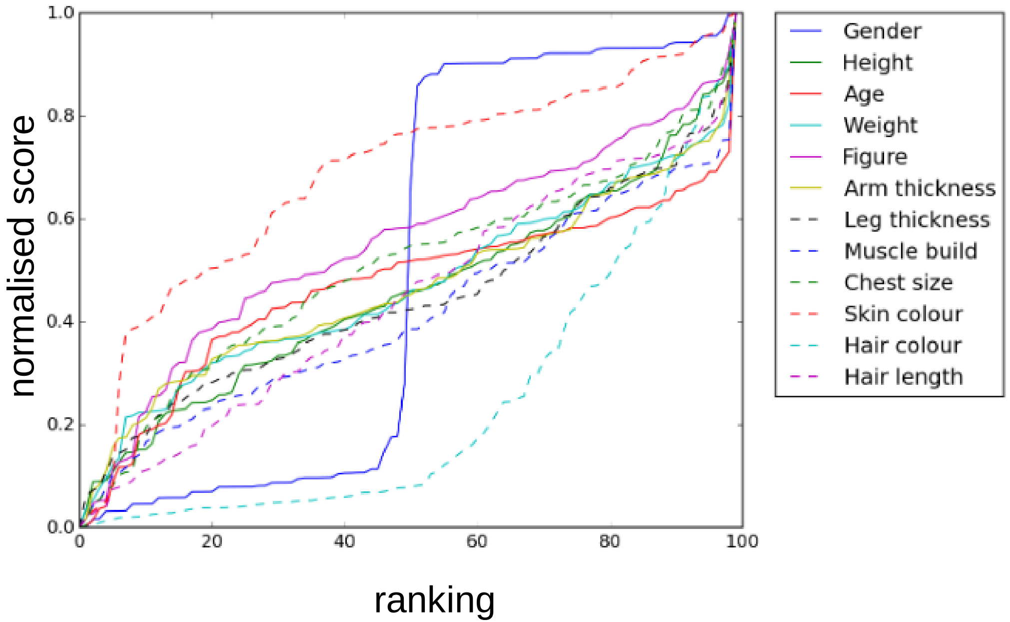
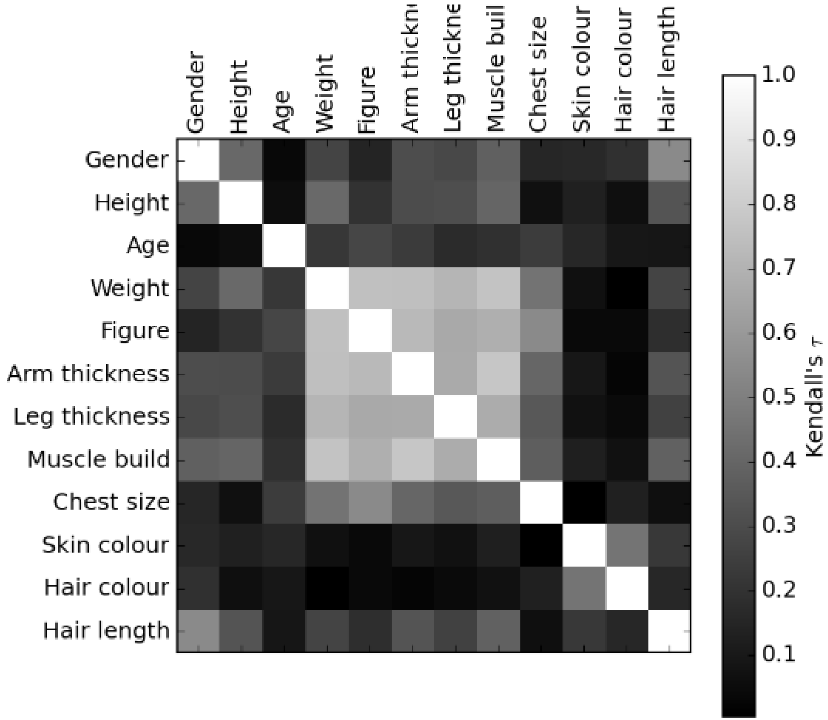
Body trait performance

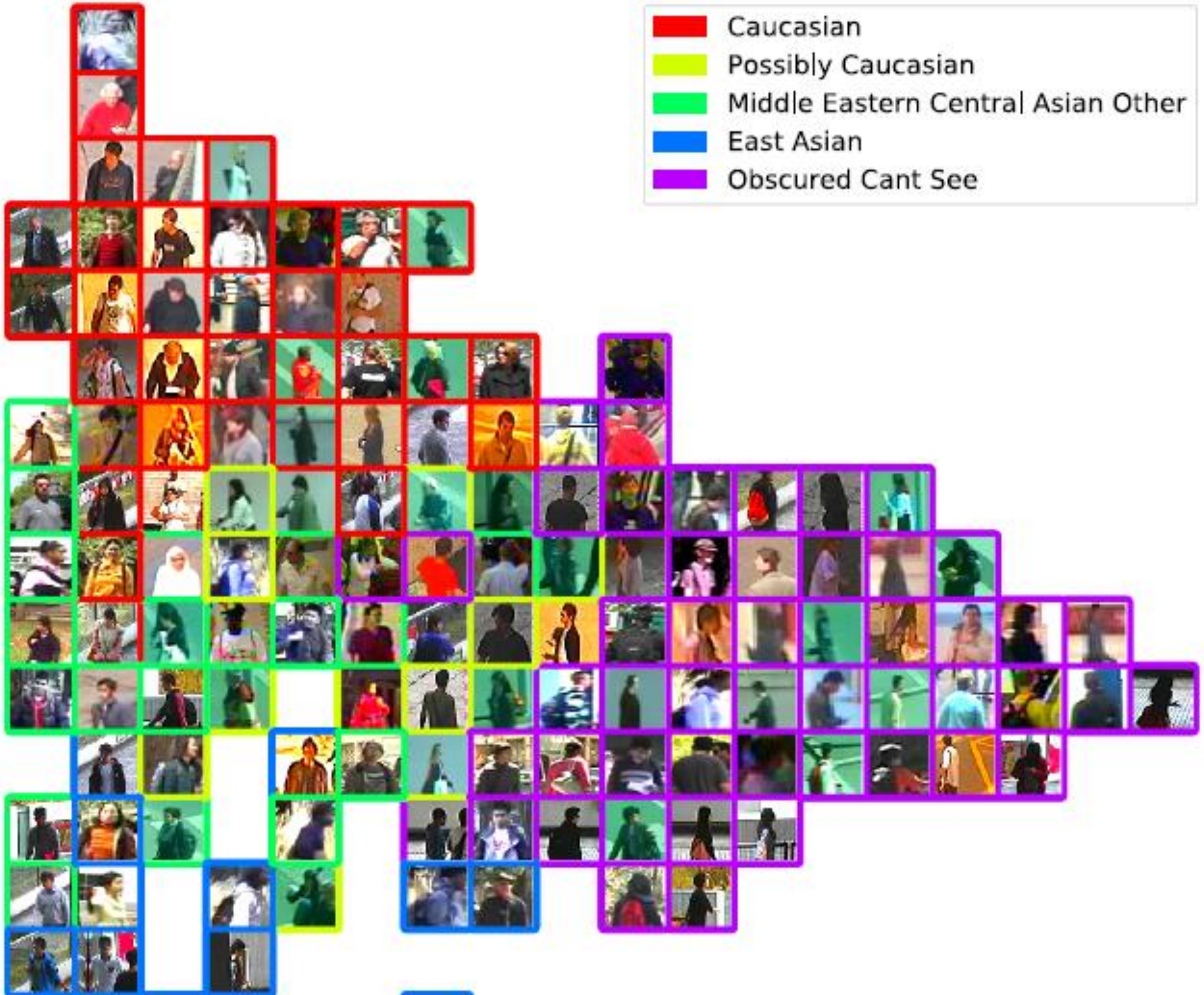


Normalised relative scores vs ranks



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*

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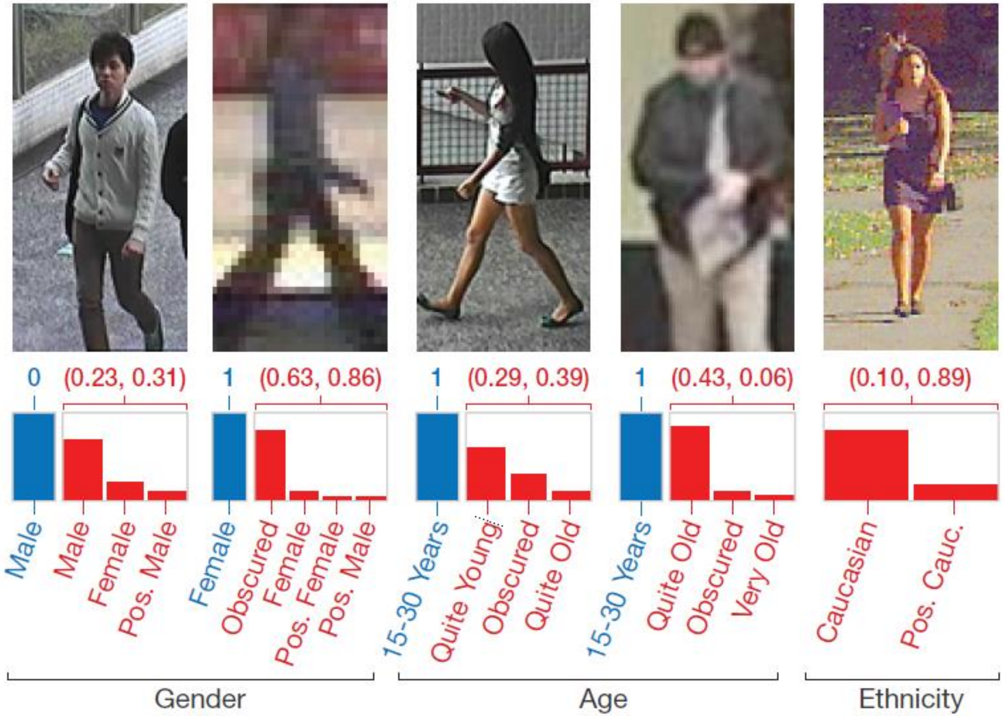
Superfine labels

Most ‘fine’ are actually coarse

Our comparative attributes are superfine

Comparison/ ranking gives many advantages



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

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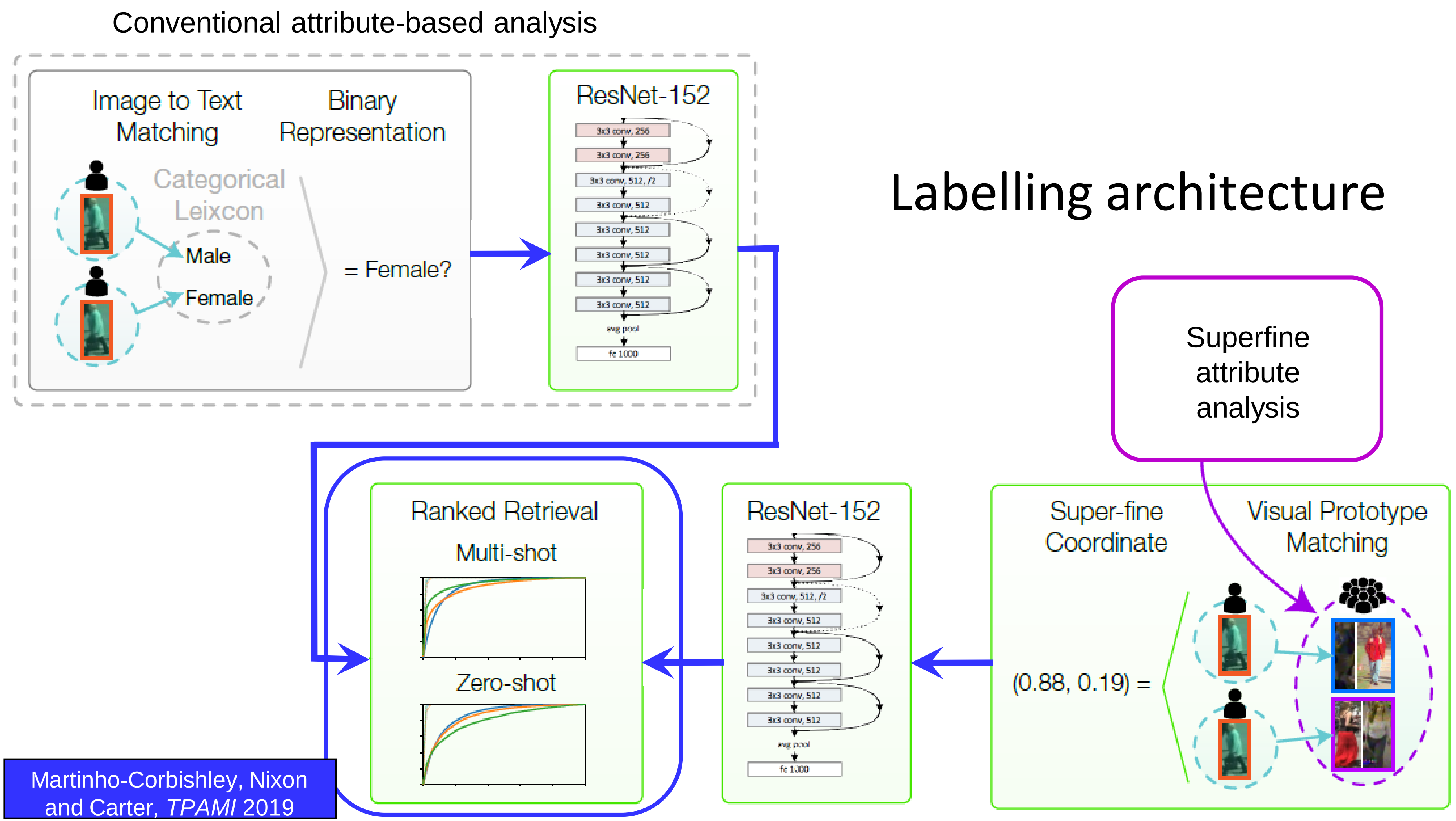
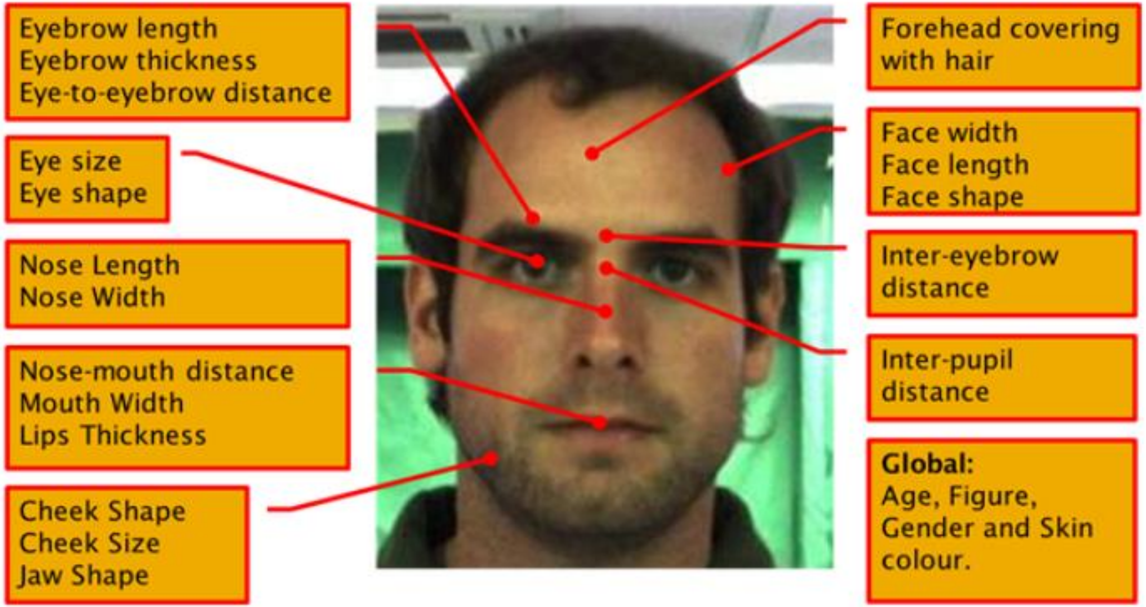
Labelling architecture



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

Recognition by face attributes

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



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		

Almudhahka, Nixon and Hare, *IEEE BTAS 2016*

Compression of 5 point scale: for comparative face labels

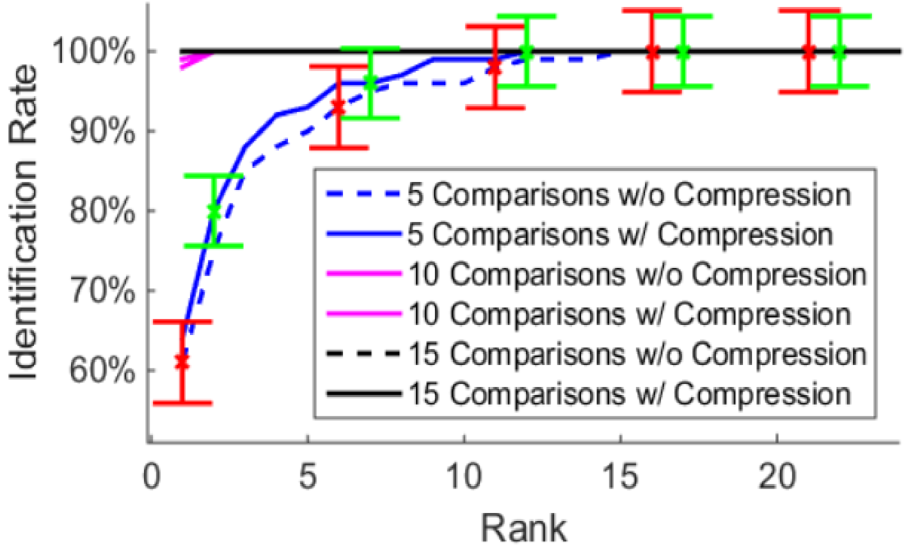
Label compression improves recognition

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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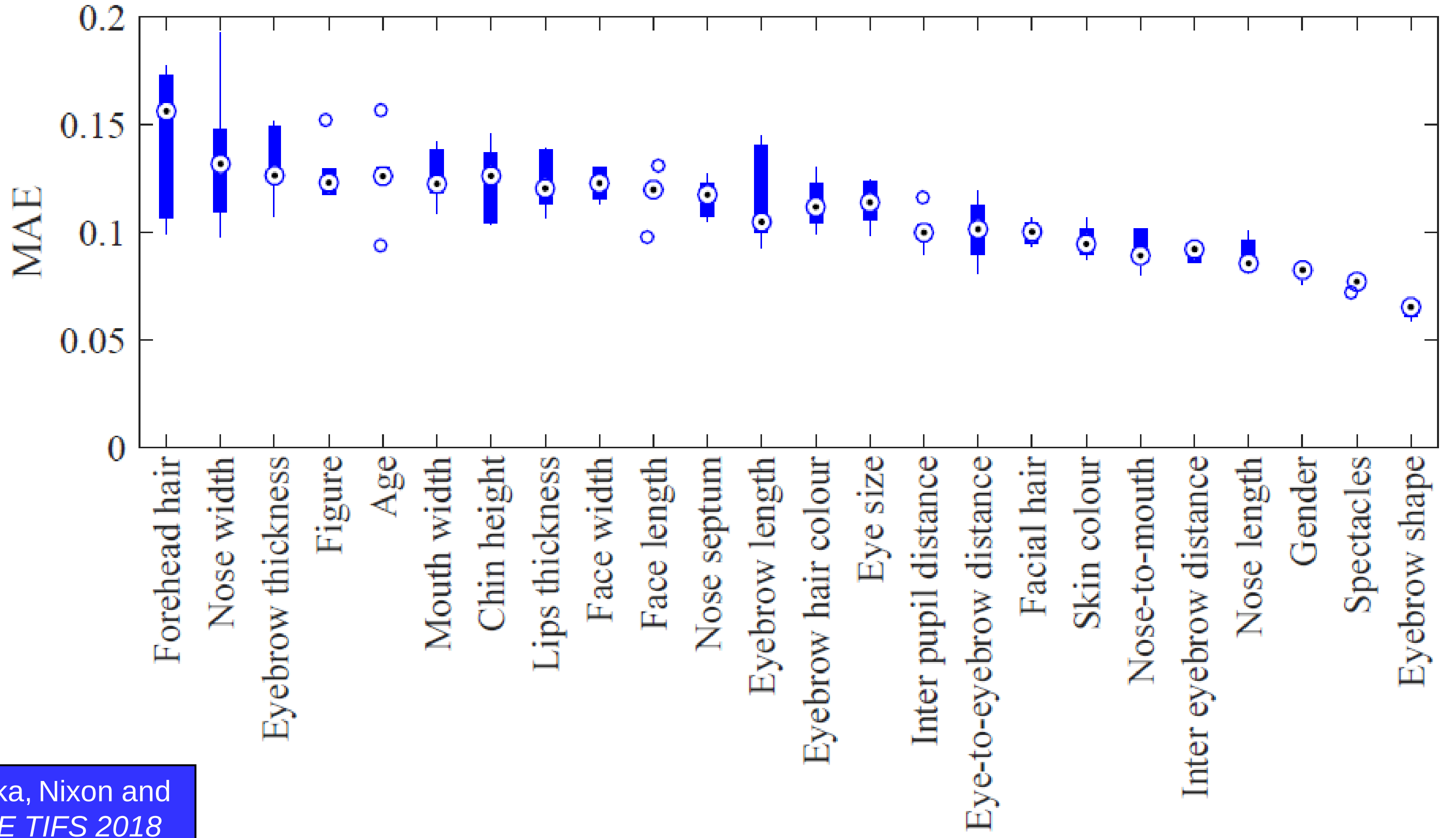
Estimating face attributes



Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

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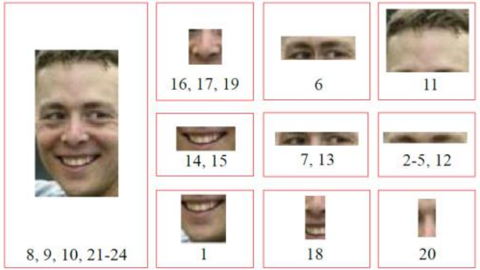
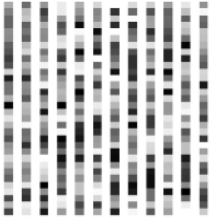
Ranking subjects (images) by estimated face attributes

(a) Age (b) Gender

Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Crossing the semantic gap: estimating relative face attributes





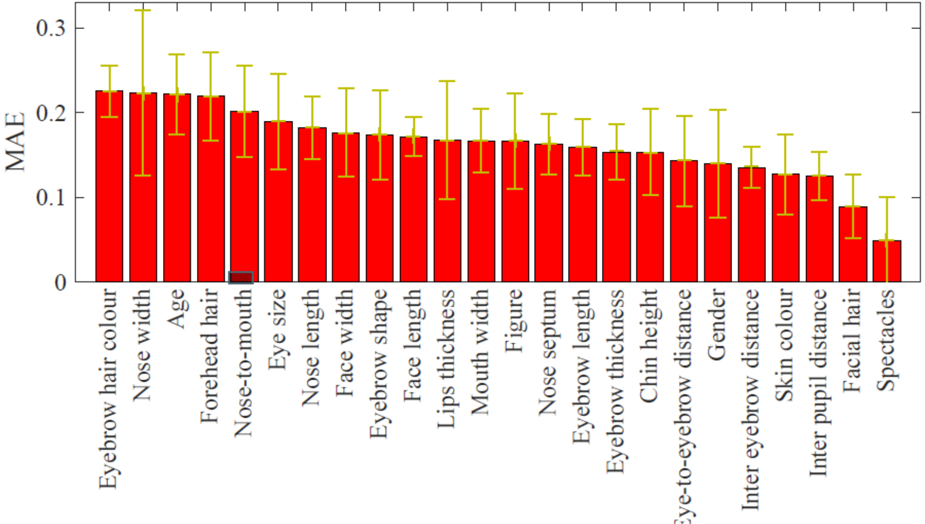
Face alignment

Segmented face parts

Features HOG/GIST/ULBP

Constrained Local Models/ AAMs

Estimation of comparative labels



Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

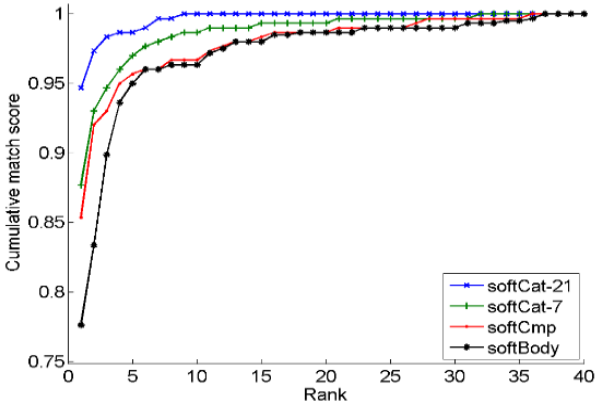
Subject recognition, by clothing

- Clothing generally unique
- Shakespeare

    “Know'st me not by my clothes?”

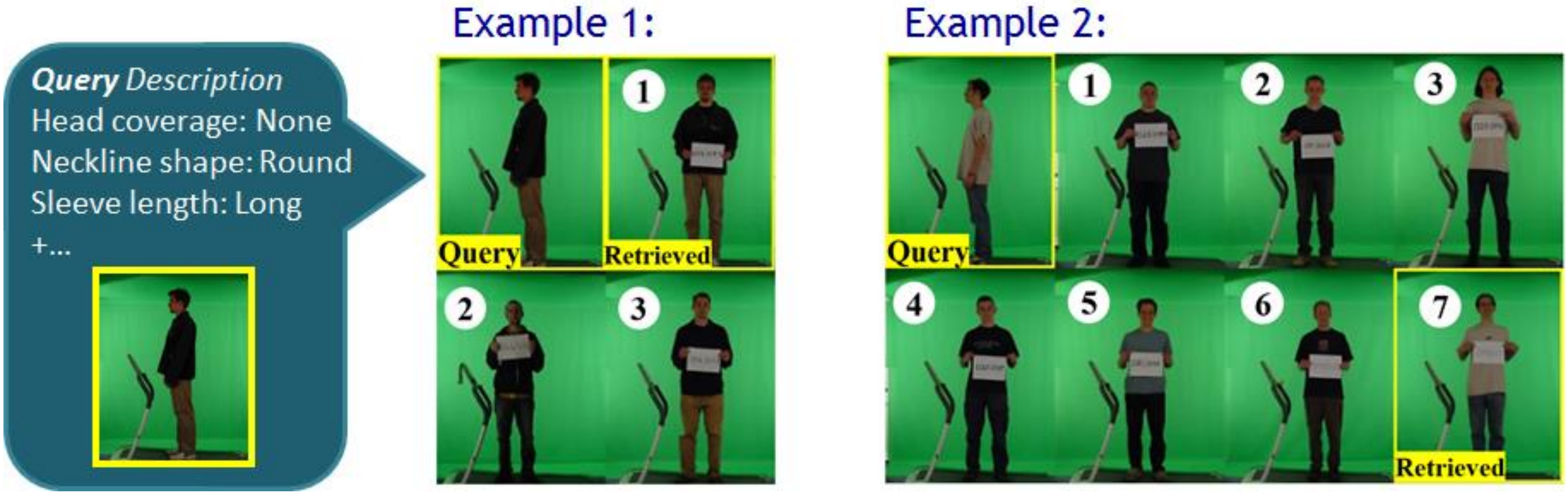
    (Cymbeline Act 4 Scene 2)

- 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



Clothing has ability to handle 90 degree change

Jaha and Nixon, *IEEE ICB 2015*

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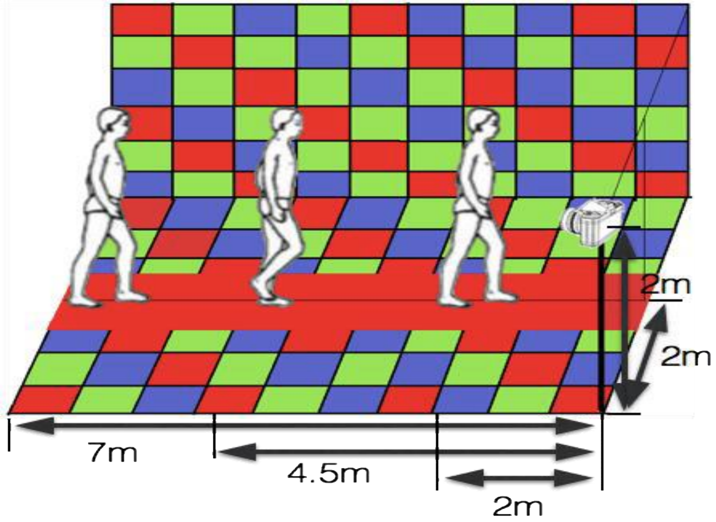
Soft biometric fusion – synthesised data

Gait tunnel



Guo, Nixon and Carter,
IEEE TBIOM 2019

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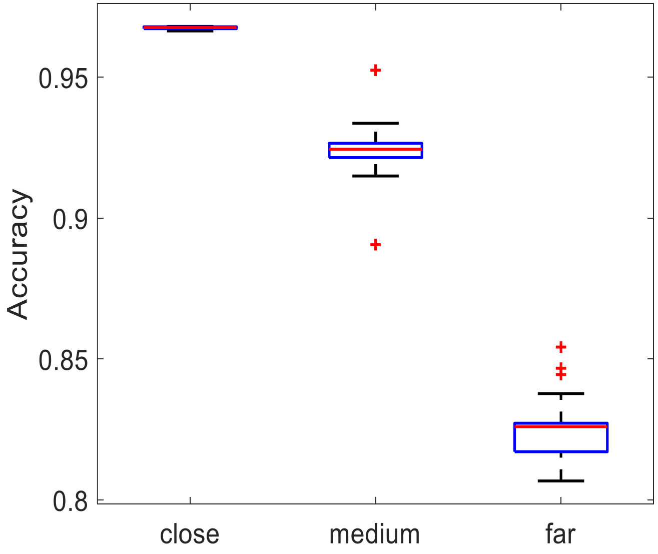
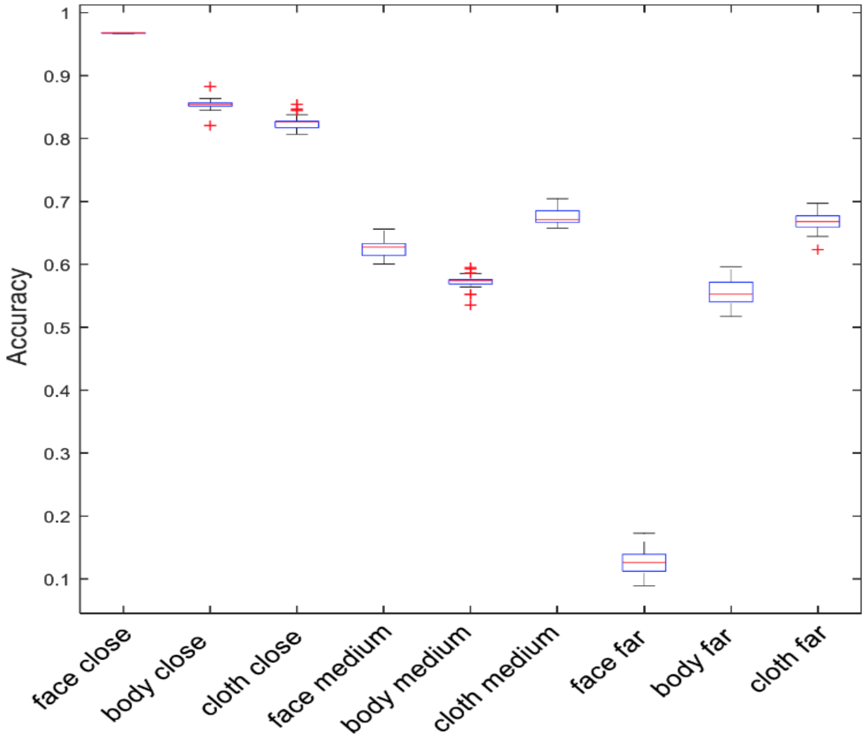
Fusion performance





Guo, Nixon and Carter, *IEEE TBIOM* 2019

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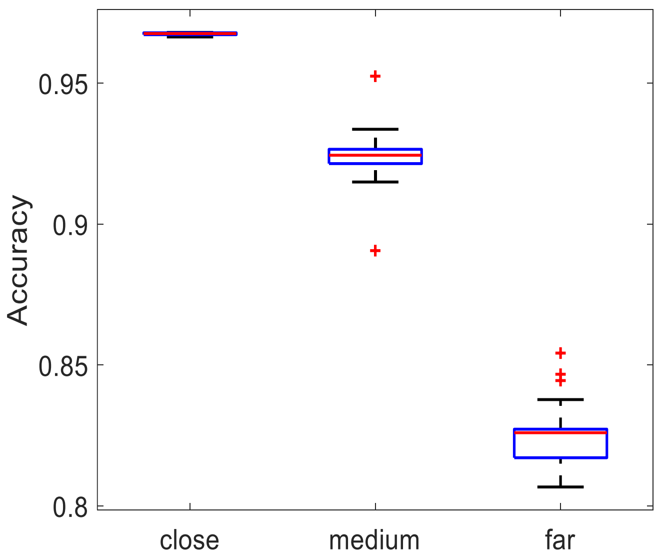
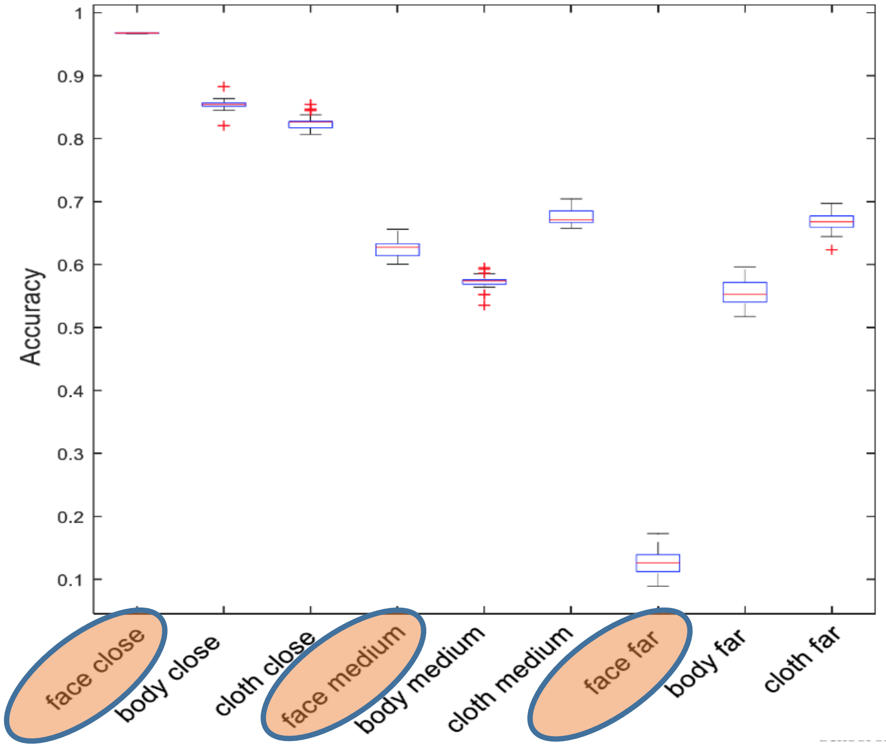
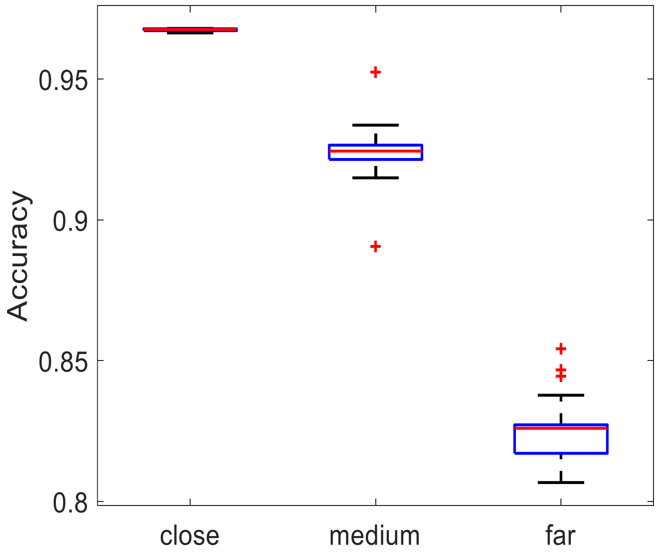
Fusion performance

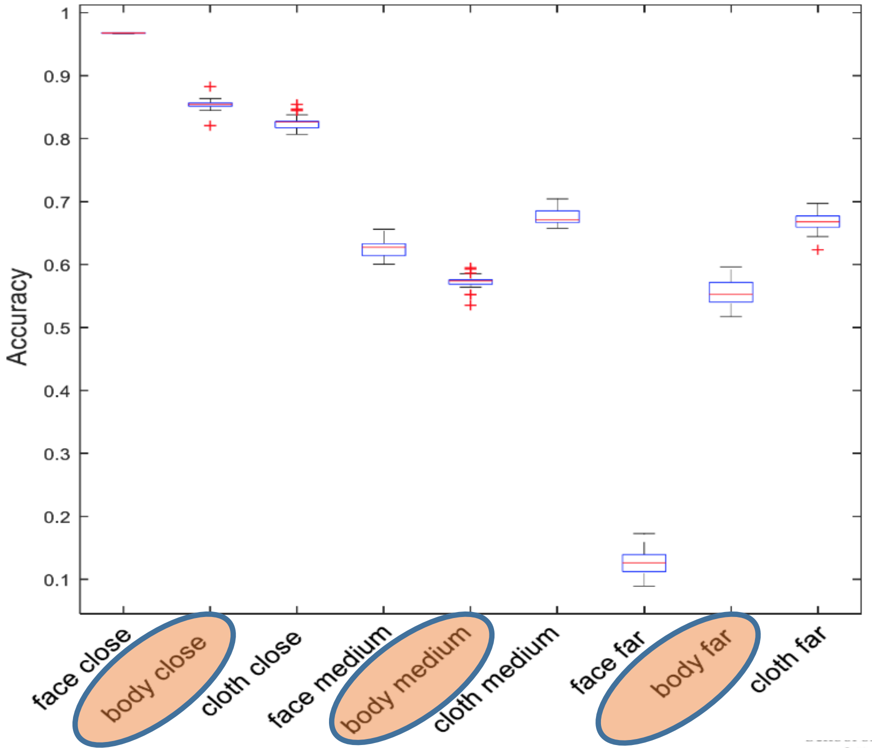




Guo, Nixon and Carter, *IEEE TBIOM* 2019

Fusion performance





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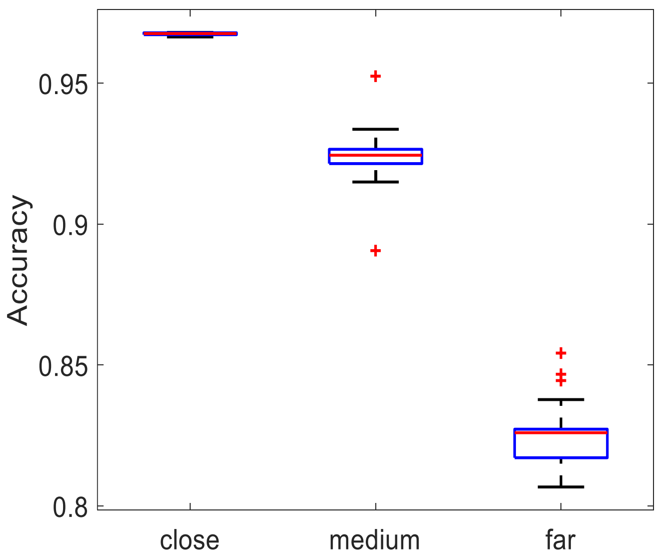
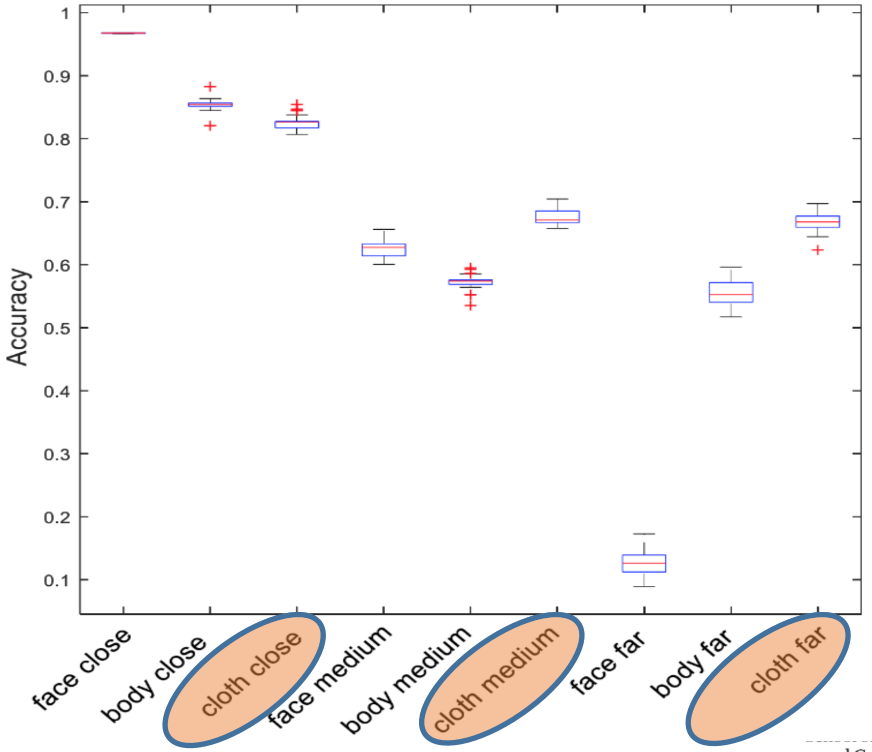
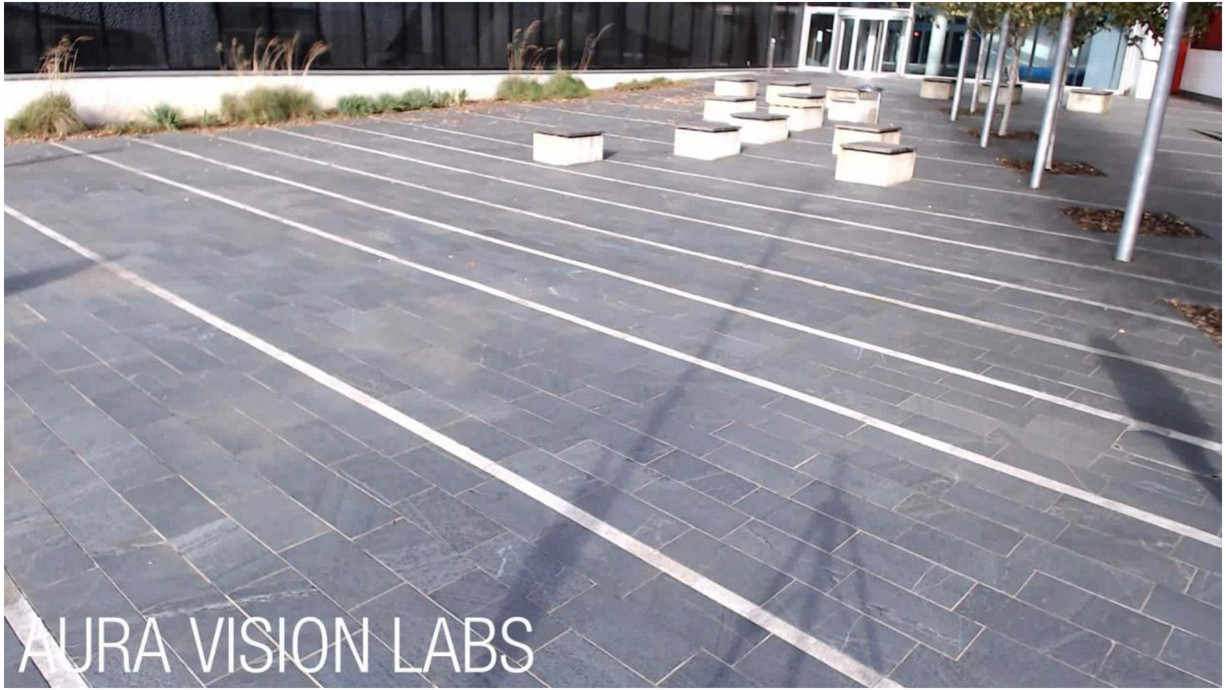
Fusion performance





Guo, Nixon and Carter,
IEEE TBIOM 2019

Biometrics and marketing …



https://vimeo.com/388480097

Conclusions

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BE THE FUTURE

Yes, gait works, so does/ do soft

Gait work continues, particularly in Asia

Soft need wider investigation (covariates, antispoofing) as to performance advantages

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

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

Society still needs identification

Privacy/ ethics/ accuracy/ new technology?

And thanks to ….

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