Biometrics Winter School 2021

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School of Electronics and Computer Science

Soft Biometrics (for Human Identification):
recognising people from human descriptions

Mark Nixon

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Topical?

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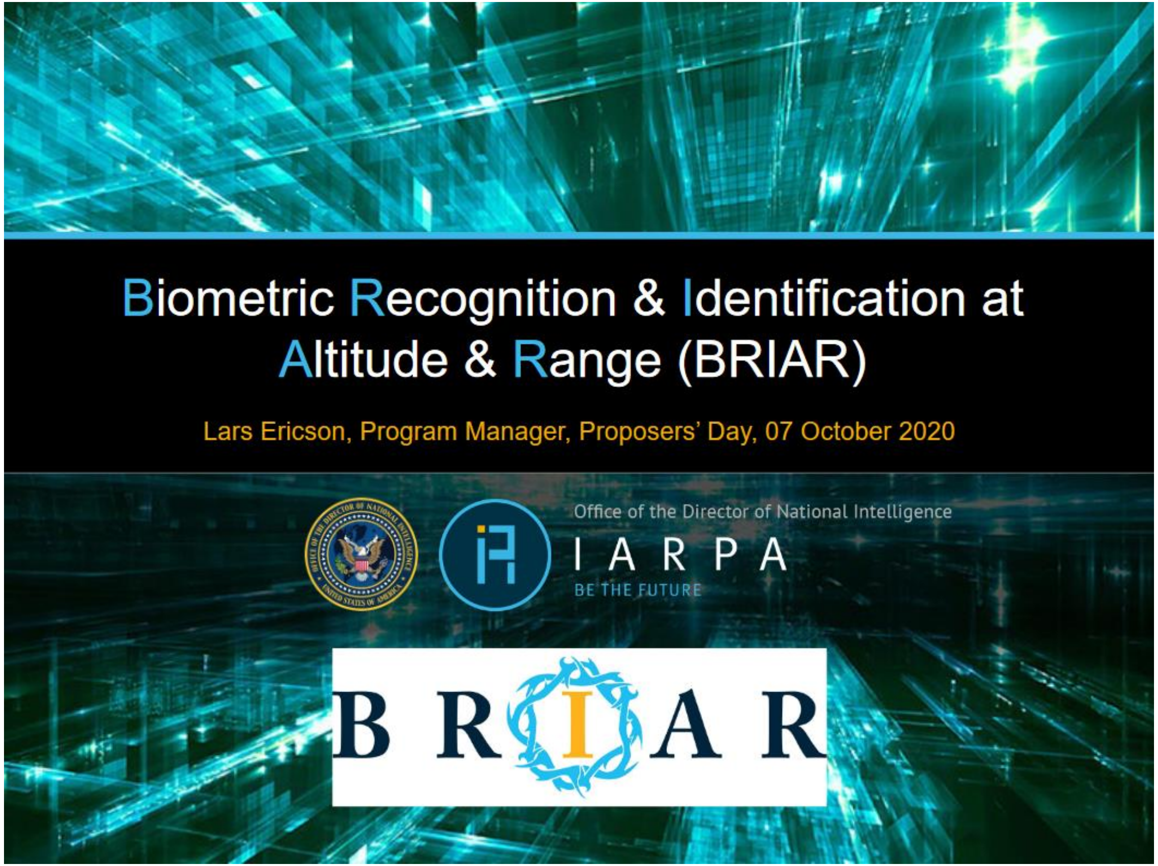


Challenge

Office of the Director of National Intelligence
IARPA
BE THE FUTURE

Challenge #2: Revisited

Permission granted by subjects for use of imagery in public presentations

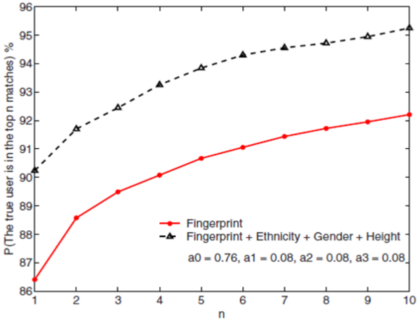
Let’s find a single person in Southampton

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	

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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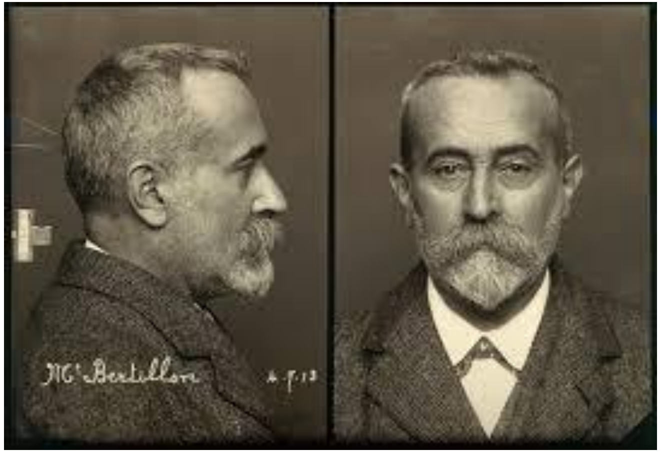
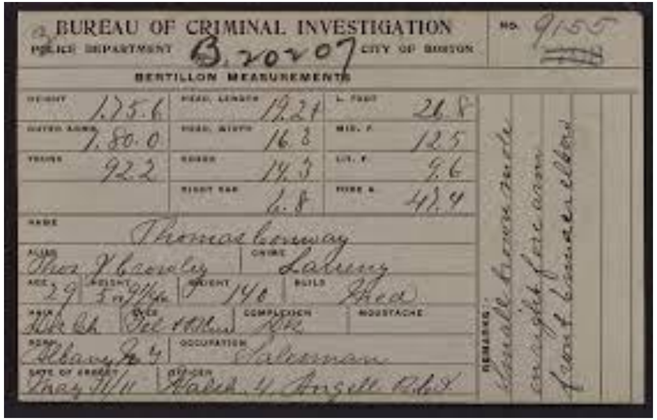
Advantages of Soft Biometrics

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.

History of Soft Biometrics: Bertillonage

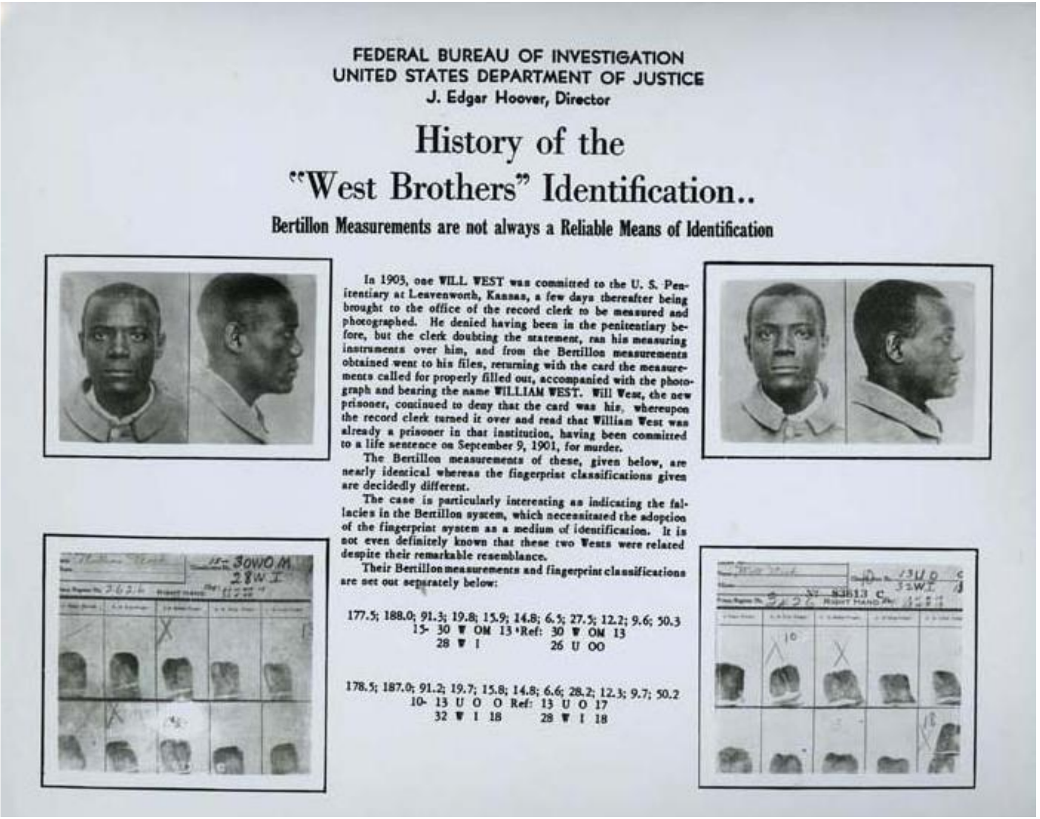




A. Bertillon, *Identification of Criminals* 1889

West vs West

- 1903, Will West committed to penitentiary at Leavenworth, Kansas
- Bertillon measurements matched William West, who was committed for murder in 1901
- Led to fingerprints
- Story is true?


FEDERAL BUREAU OF INVESTIGATION
UNITED STATES DEPARTMENT OF JUSTICE
J. Edgar Hoover, Director

History of the "West Brothers" Identification..

Bertillon Measurements are not always a Reliable Means of Identification

In 1903, one WILL WEST was committed to the U. S. Penitentiary at Leavenworth, Kansas, a few days thereafter being brought to the office of the record clerk to be measured and photographed. He denied having been in the penitentiary before, but the clerk doubting the statement, ran his measuring instruments over him, and from the Bertillon measurements obtained went to his files, returning with the card the measurements called for properly filled out, accompanied with the photograph and bearing the name WILLIAM WEST. Will West, the new prisoner, continued to deny that the card was his, whereupon the record clerk turned it over and read that William West was already a prisoner in that institution, having been committed to a life sentence on September 9, 1901, for murder.

The Bertillon measurements of these, given below, are nearly identical whereas the fingerprint classifications given are decidedly different.

The case is particularly interesting as indicating the fallacies in the Bertillon system, which necessitated the adoption of the fingerprint system as a medium of identification. It is not even definitely known that these two Wests were related despite their remarkable resemblance.

Their Bertillon measurements and fingerprint classifications are set out separately below:

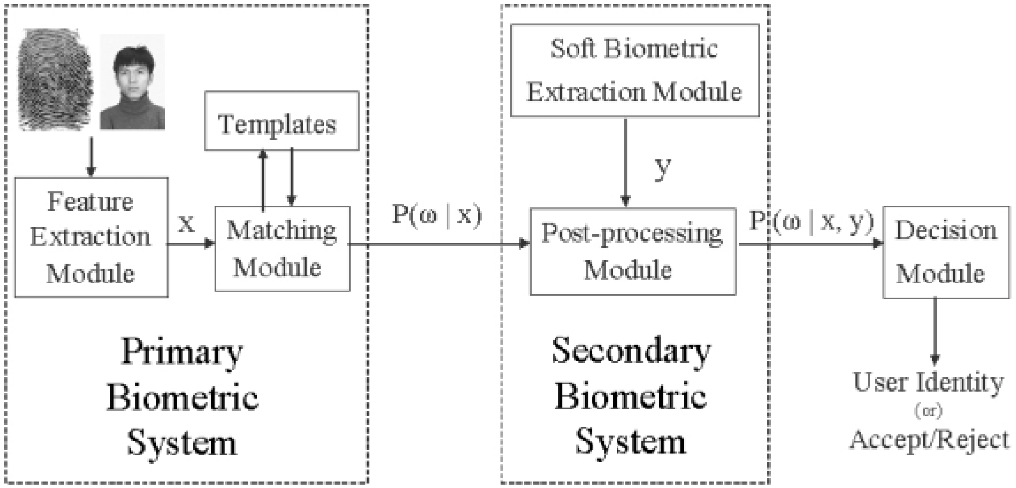
177.5; 188.0; 91.3; 19.8; 15.9; 14.8; 6.5; 27.5; 12.2; 9.6; 50.3
15- 30 W OM 13 Ref: 30 W OM 13
28 W I 26 U OO

178.5; 187.0; 91.2; 19.7; 15.8; 14.8; 6.6; 28.2; 12.3; 9.7; 50.2
10- 13 U O O Ref: 13 U O 17
32 W I 18 28 W I 18

"This image was probably used in a ca. 1960s FBI training session"
www.LawEnforcementMuseum.org

First mention of Soft Biometrics

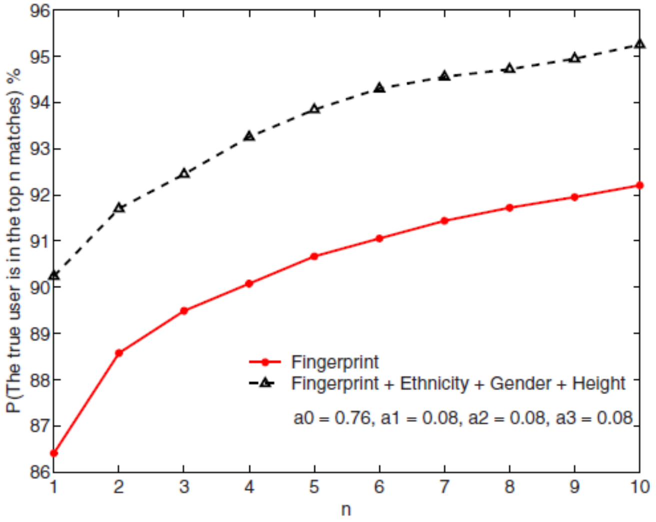
- Integration of Soft Biometric Traits with a Fingerprint Biometric System
- x is the fingerprint, y is the soft biometric

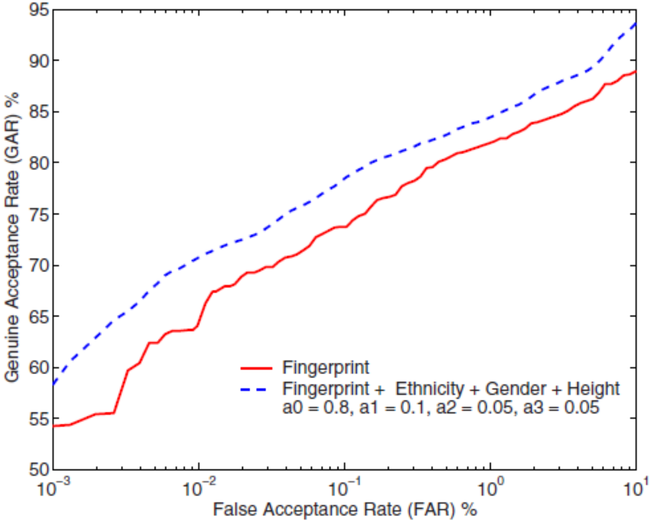


Jain, Dass, and Nandakumar, *ICBA* 2004

Performance

- Recognition performance of a fingerprint system after including soft biometrics
- Identification and verification
- Fingerprint + ethnicity + gender + height





Jain, Dass, and Nandakumar, *ICBA* 2004

Soft Biometrics from Face

MICHIGAN STATE

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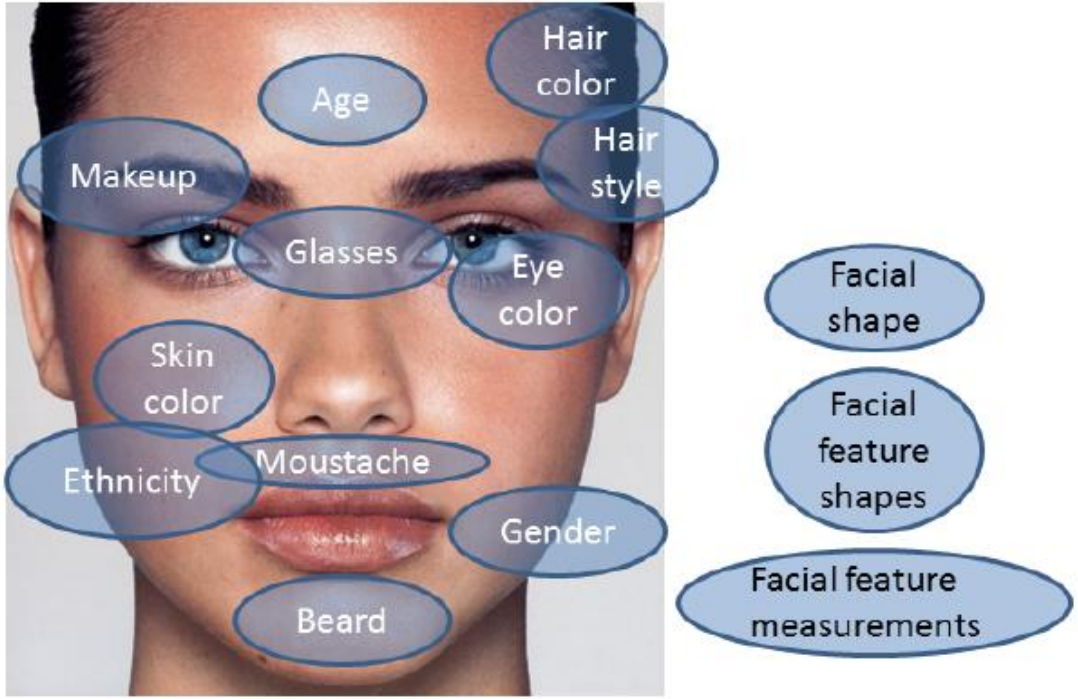
What’s in a Face?



MICHIGAN STATE

Face and Age

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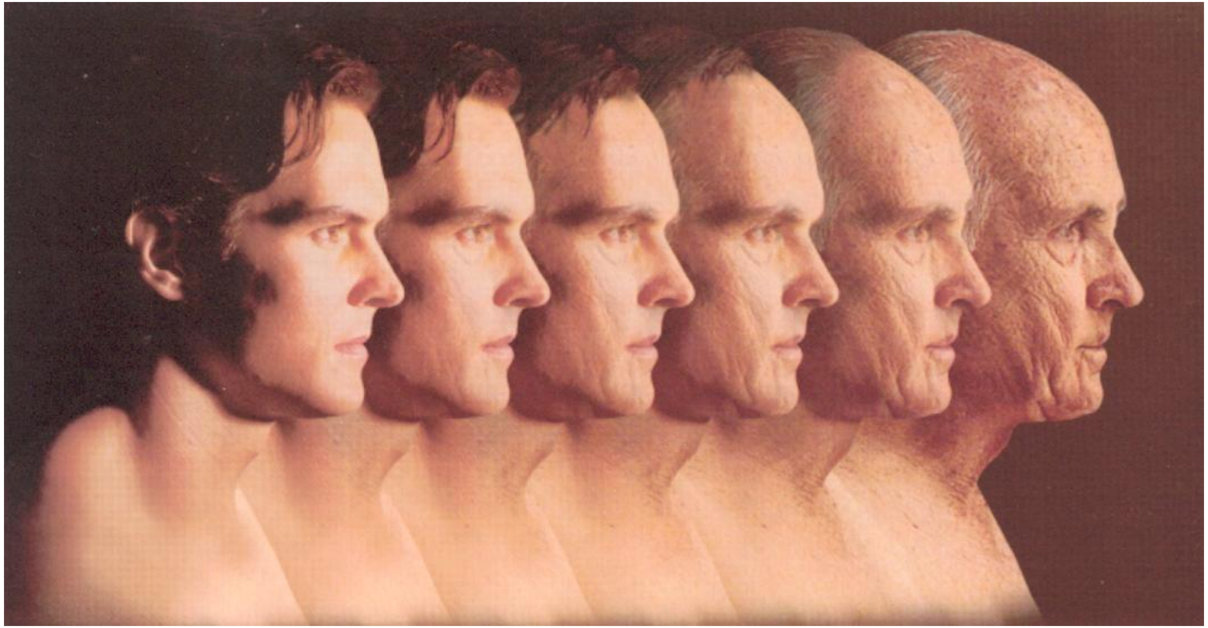


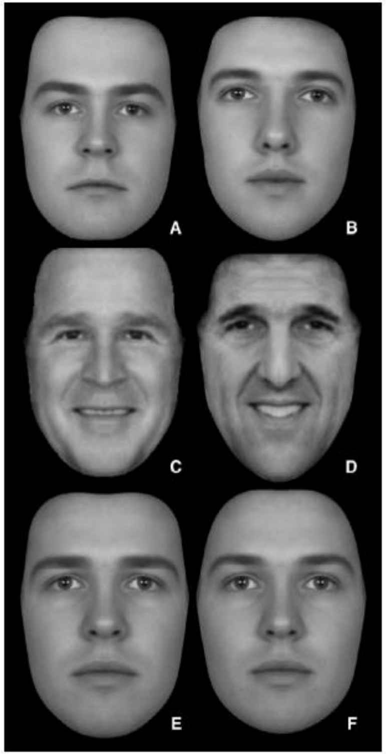
Beautyanalysis.com

Face and Kinship

2018 onwards, many inc.
[Hu 2018], [Aliradi 2018], Yan 2018]
[Tan 2017]
[Lu 2013]
[Guo 2012]
[Fang 2010]
[Shao 2011]

Also, *Kinship Face in the Wild data set*
But
“most of the image kinship pairs are cropped from the same photographs” [Lopez 2016]

Face and Decisions



- The role of facial shape in voting behavior
- Face and sentencing
- Face and trustworthiness
- Face and sexual inclination??????

[Todorov 2015]
[Little 2007]
[Todorov 2005]

Performance

gender recognition

age estimation

Antipov, Baccouche, Berrani, Dugelay, *Patt Recog.* 2017

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

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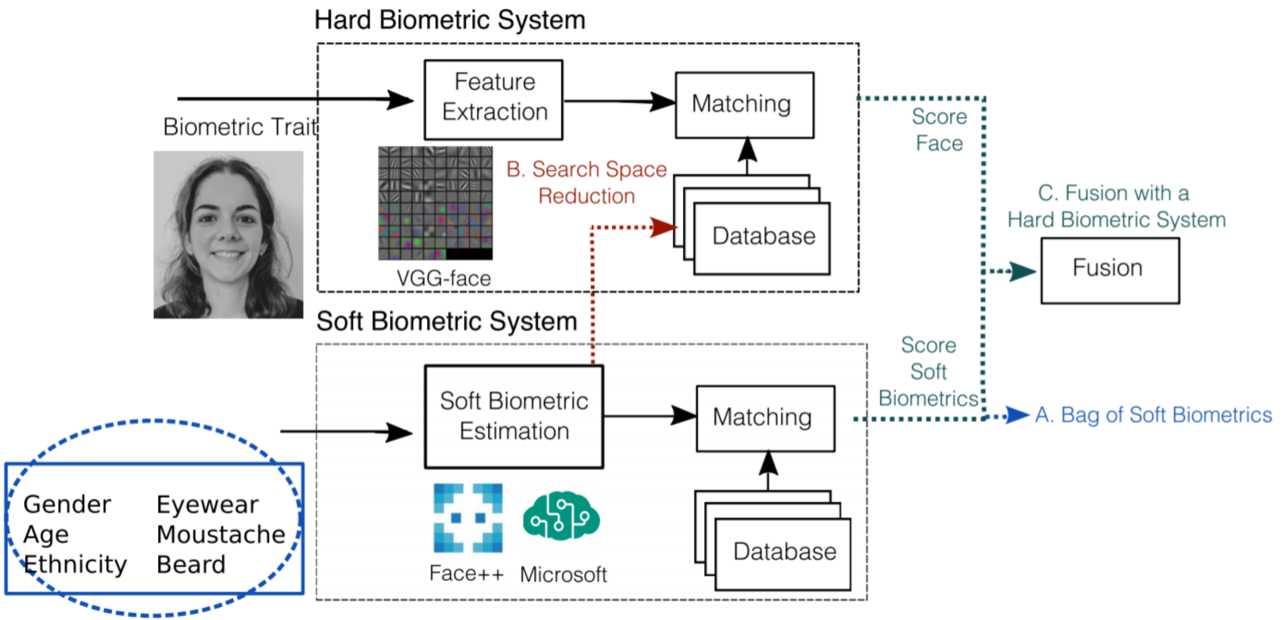
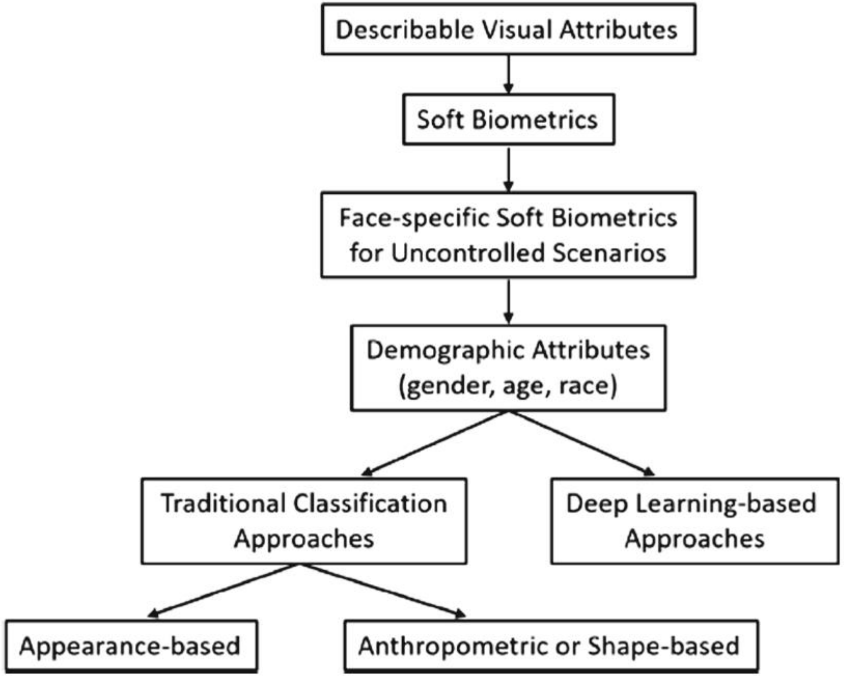


Soft Biometrics for Recognition: A) Bag of Soft Biometrics; B) Search Space Reduction; and C) Fusion with a Hard Biometric System

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

A survey on facial soft biometrics for video surveillance and forensic applications



Becerra-Riera, Morales-González, Méndez-Vázquez, *AI Review* 2019

Demographic Analysis from Biometric Data: Achievements, Challenges, and New Frontiers

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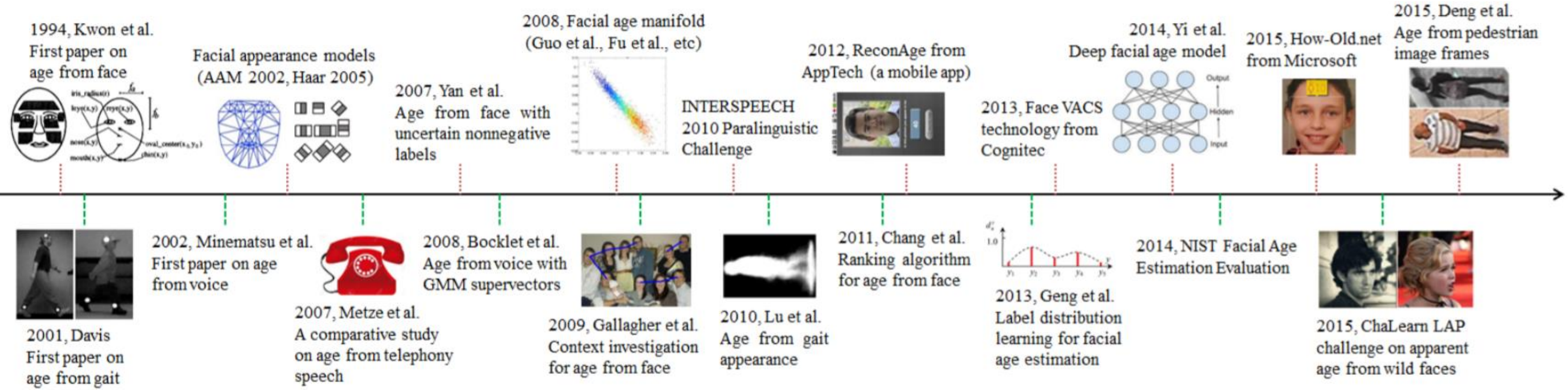

Major milestones in the history of automatic age estimation from biometric data

Sun, Zhang, Sun, Tan
IEEE TPAMI 2018

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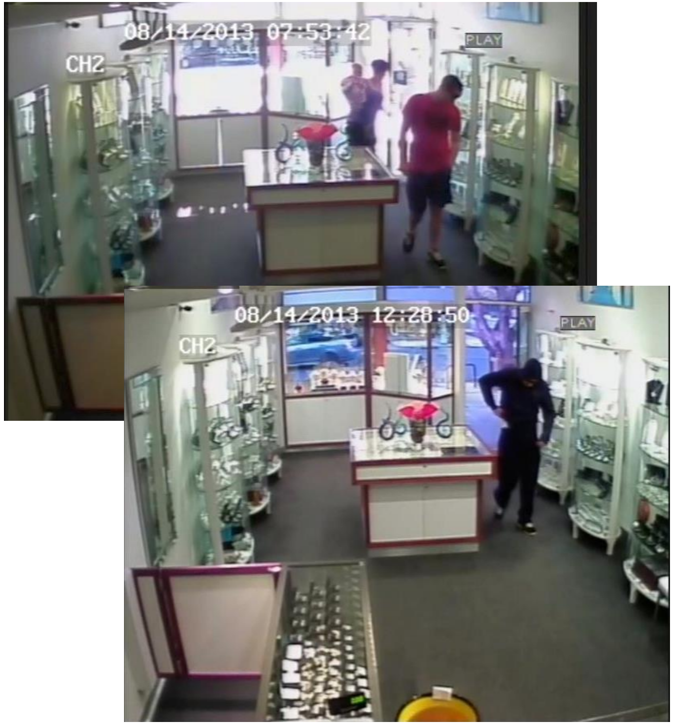
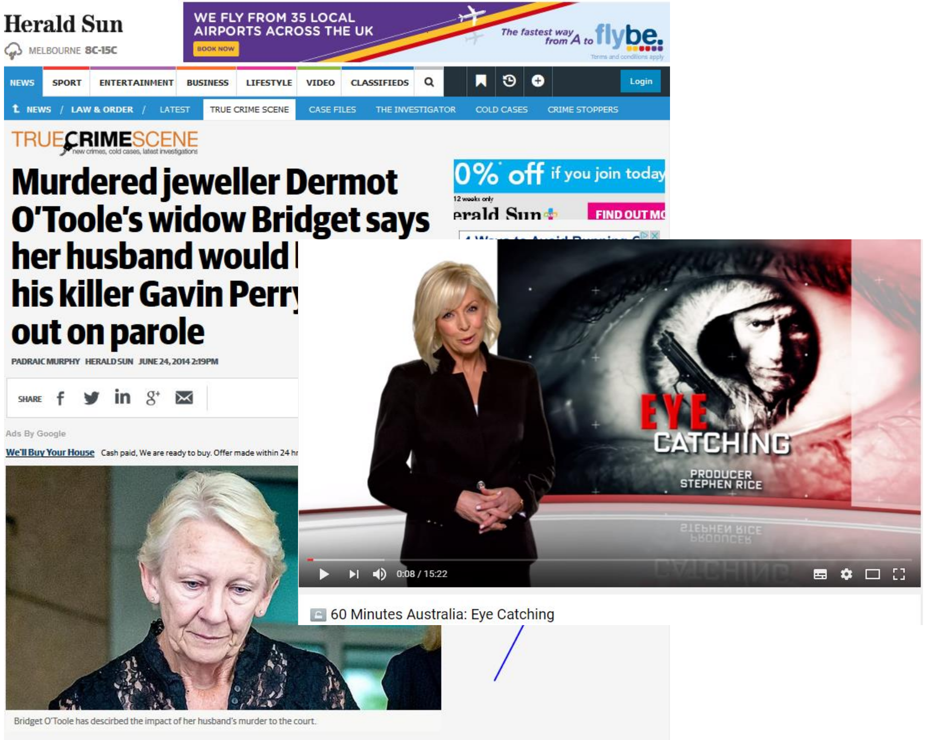
Motivation: Murder case in Australia 2014




Herald Sun
MELBOURNE 8C-15C
WE FLY FROM 35 LOCAL AIRPORTS ACROSS THE UK
BOOK NOW
The fastest way from A to flybe.
NEWS SPORT ENTERTAINMENT BUSINESS LIFESTYLE VIDEO CLASSIFIEDS Login
NEWS / LAW & ORDER / LATEST TRUE CRIME SCENE CASE FILES THE INVESTIGATOR COLD CASES CRIME STOPPERS
TRUECRIMESCENE

Murdered jeweller Dermot O'Toole's widow Bridget says her husband would l... his killer Gavin Perr... out on parole

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

SHARE

Ads By Google
We'll Buy Your House Cash paid, We are ready to buy. Offer made within 24 hr

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

Descriptions and attributes for identification

Eyewitness statement

"24 year old male average height wearing shirt"

Image of crime

Generate description

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

What can you recognise?

64×97

128×194

256×386

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Gender Estimation on PETA

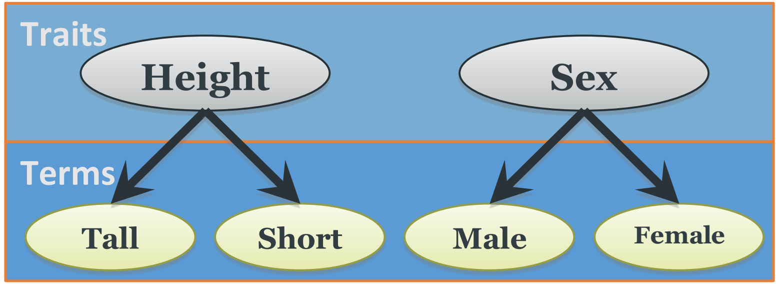
- Gender?

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

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

Exploring Human Descriptions

- We explore semantic descriptions of:
  - physical traits
  - semantic terms
  - visible at a distance



Samangooei and Nixon, *SAMT* 2008

Samangooei, Guo and Nixon, *IEEE BTAS* 2008

On Semantic Descriptions

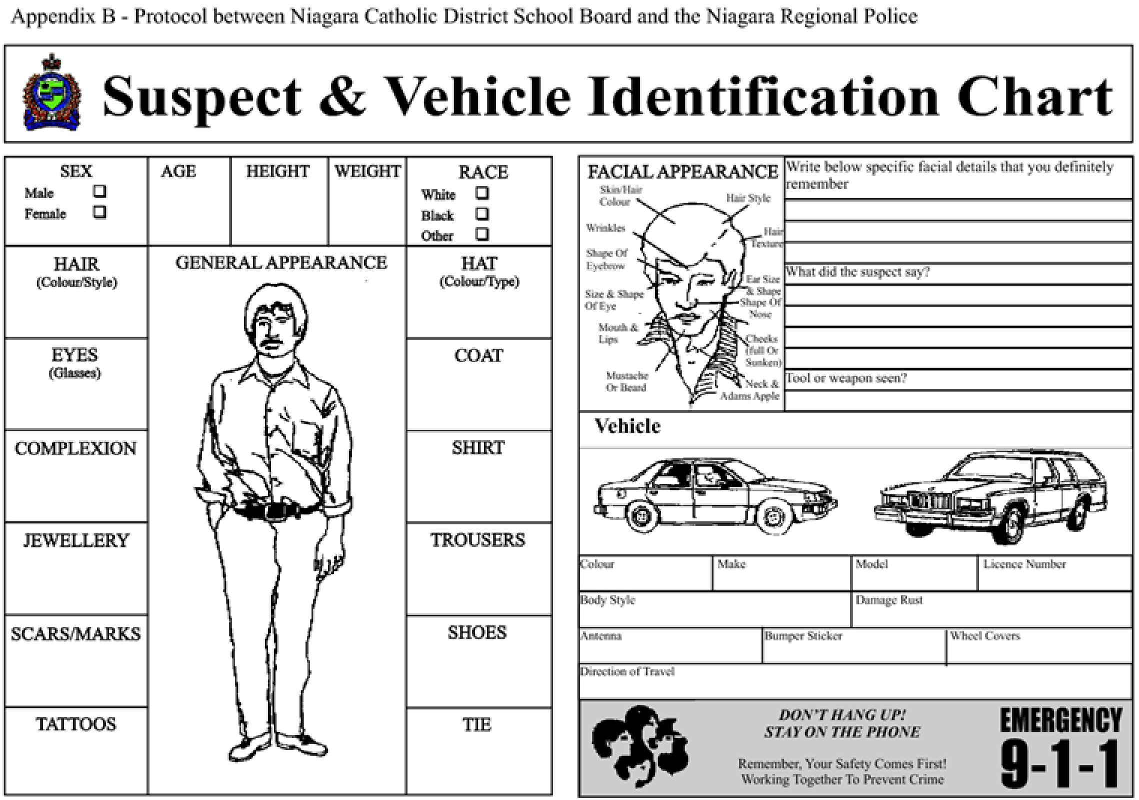
Advantages

1. No (feature/ sensor) ageing
2. Available at a distance/ low resolution/ poor quality
3. Fit with human (eyewitness) description/ forensics
4. Complement automatically-perceived measures
5. Need for search mechanisms

Disadvantages

1. Psychology/ perception
2. Need for labelling

Google: “suspect description form”


Appendix B - Protocol between Niagara Catholic District School Board and the Niagara Regional Police

Suspect & Vehicle Identification Chart

SEX	AGE	HEIGHT	WEIGHT	RACE
Male ☐ Female ☐				White ☐ Black ☐ Other ☐

	GENERAL APPEARANCE	
HAIR (Colour/Style)		HAT (Colour/Type)
EYES (Glasses)		COAT
COMPLEXION		SHIRT
JEWELLERY		TROUSERS
SCARS/MARKS		SHOES
TATTOOS		TIE

FACIAL APPEARANCE

Skin/Hair Colour; Hair Style; Wrinkles; Hair Texture; Shape Of Eyebrow; Ear Size & Shape; Size & Shape Of Eye; Shape Of Nose; Mouth & Lips; Cheeks (full Or Sunken); Mustache Or Beard; Neck & Adams Apple

Write below specific facial details that you definitely remember

What did the suspect say?

Tool or weapon seen?

Vehicle

Colour	Make	Model	Licence Number
Body Style		Damage Rust	
Antenna	Bumper Sticker	Wheel Covers	
Direction of Travel			

DON'T HANG UP!
STAY ON THE PHONE

Remember, Your Safety Comes First!
Working Together To Prevent Crime

EMERGENCY
9-1-1

Traits and terms

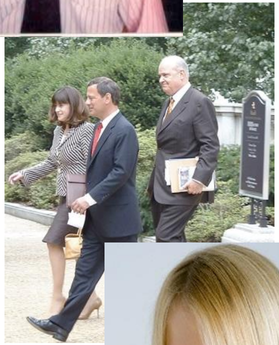
Global Features

- 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

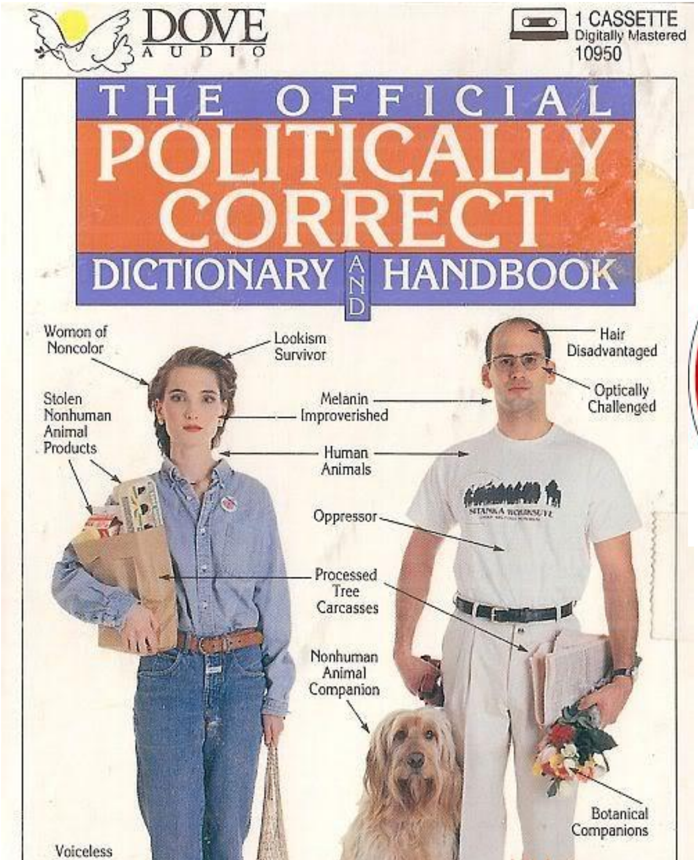


Phrasing questions

- 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



Traits and terms

Body Features

- Based on whole body description stability analysis by MacLeod et al.
  - Features showing consistency by different viewers looking at the same subjects
- Mostly comprised of 5 point qualitative measures

e.g. very fat, fat, average, thin, very thin

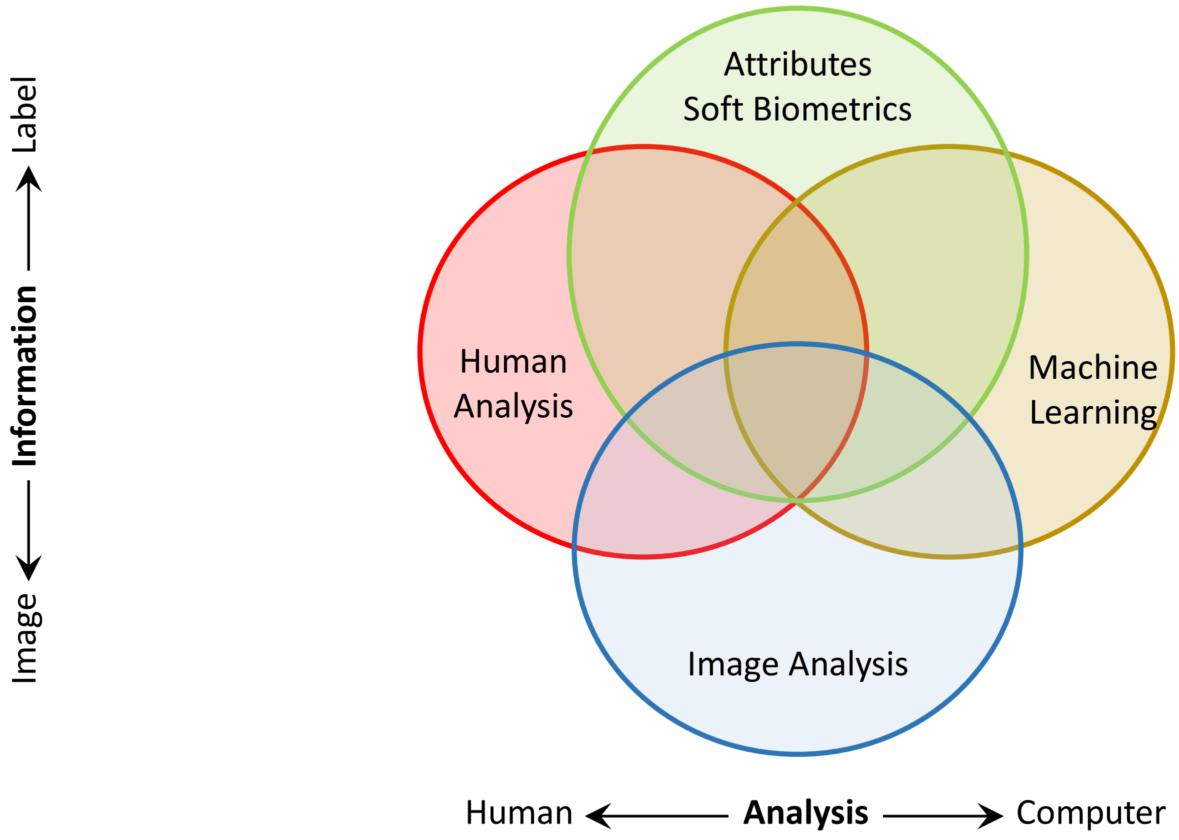
- Most likely candidate for fusion with gait

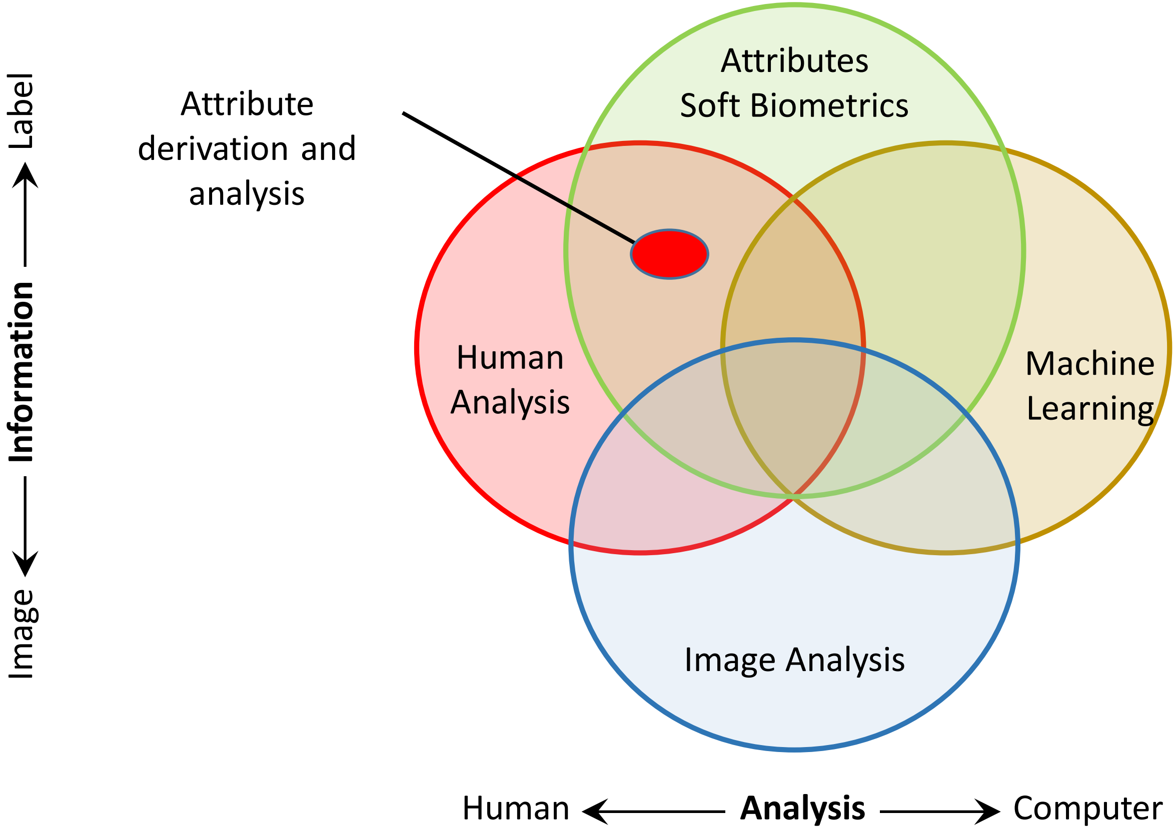
This changed

Samangooei, Guo and Nixon, *IEEE BTAS* 2008

- 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

How does this fit with computer vision?





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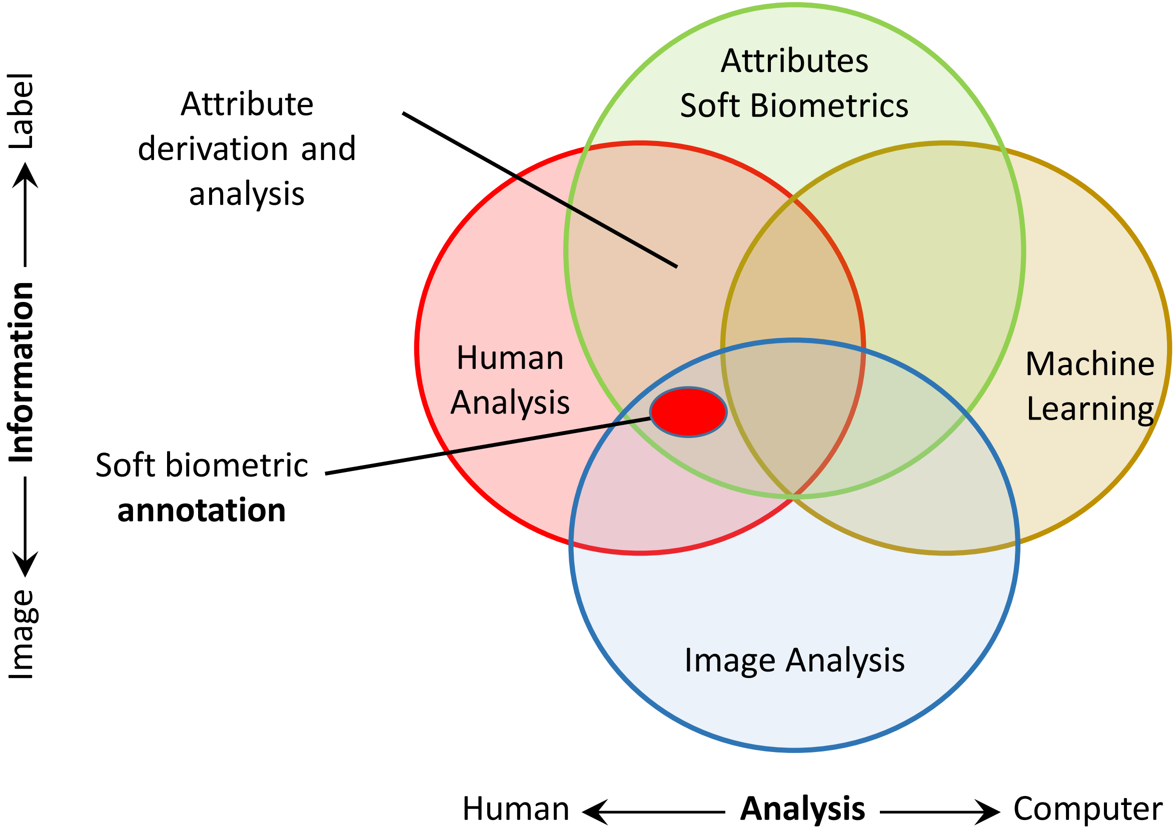

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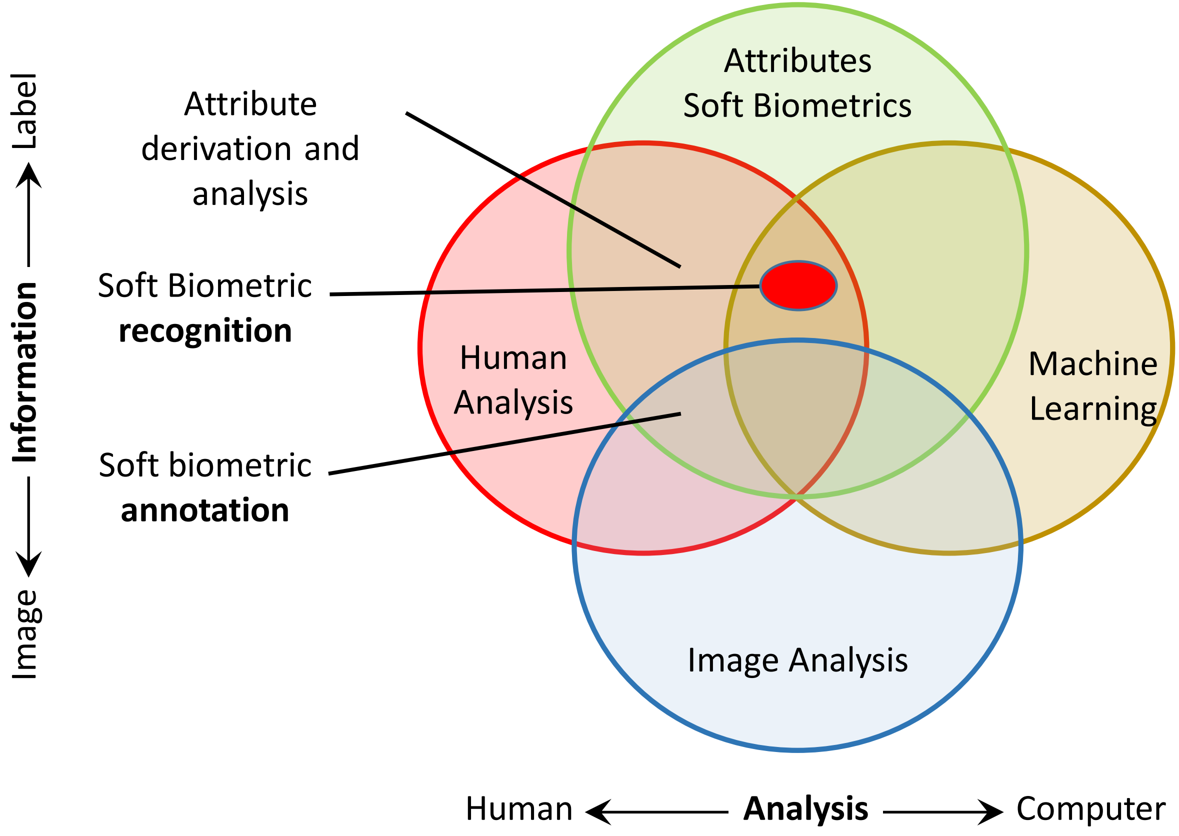
Attributes
Soft Biometrics
Attribute derivation and analysis
Soft Biometric **recognition**
Soft biometric **annotation**
Human Analysis
Machine Learning
Image Analysis
Label
Information
Image
Human
Analysis
Computer

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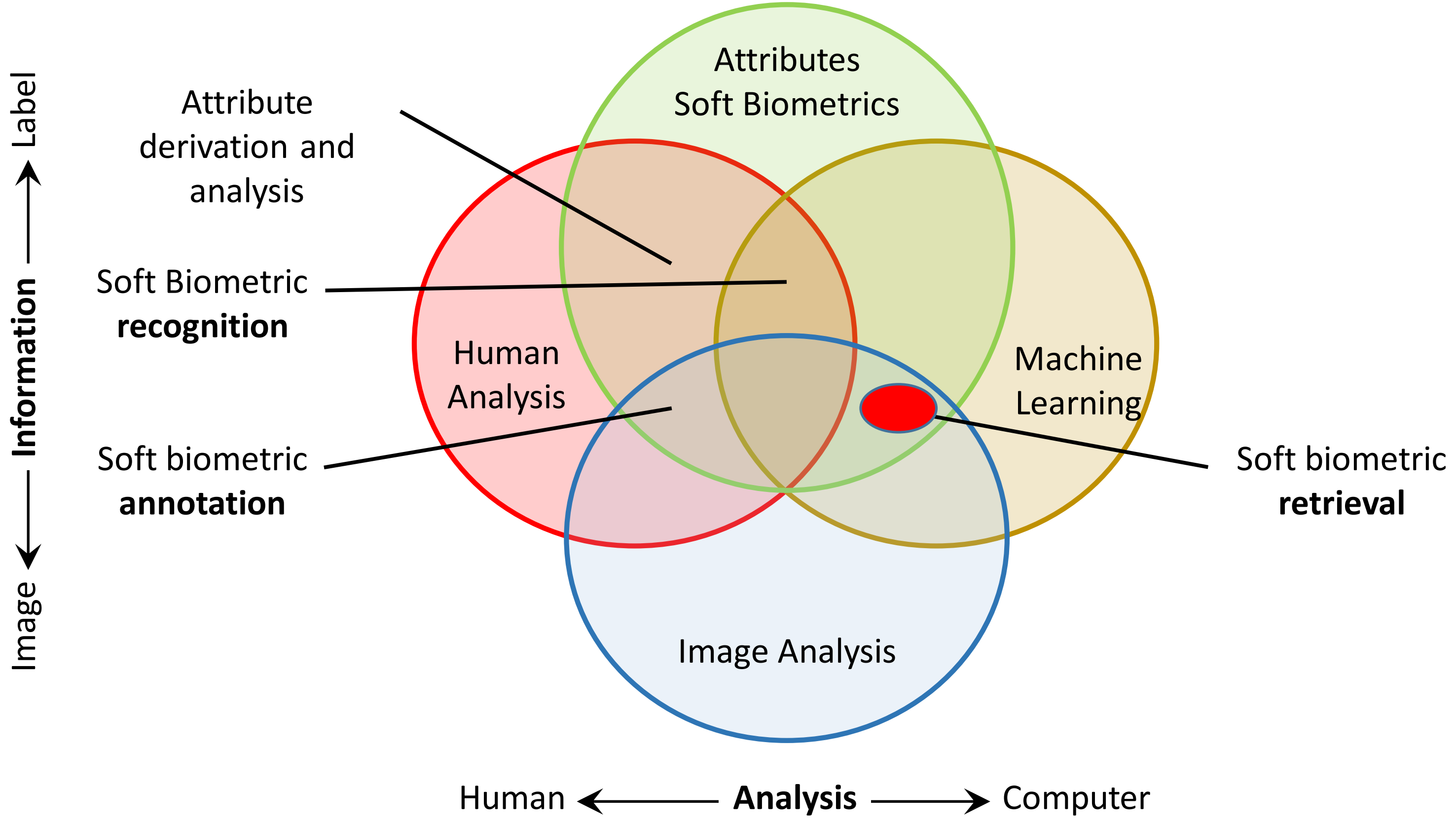

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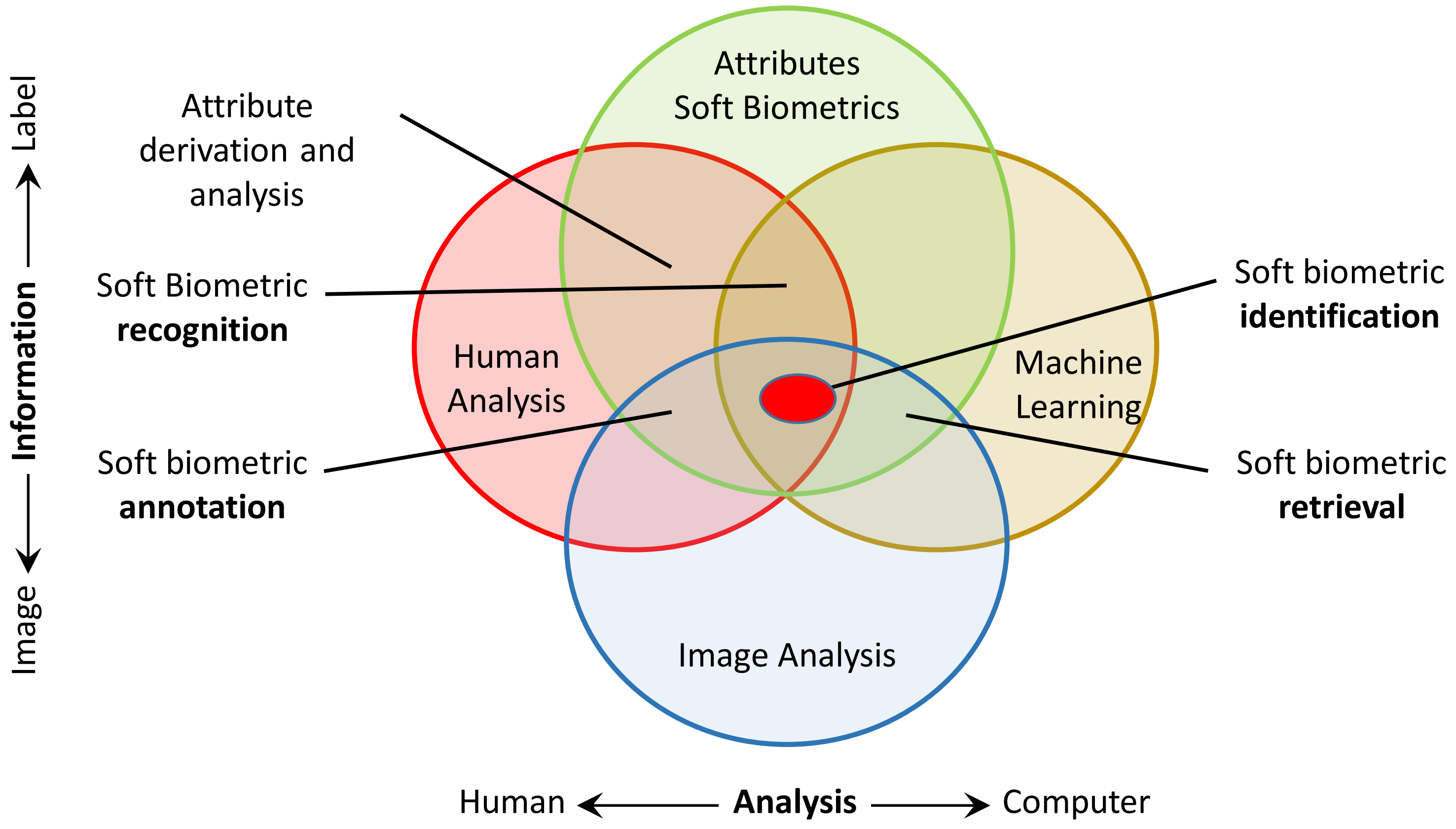

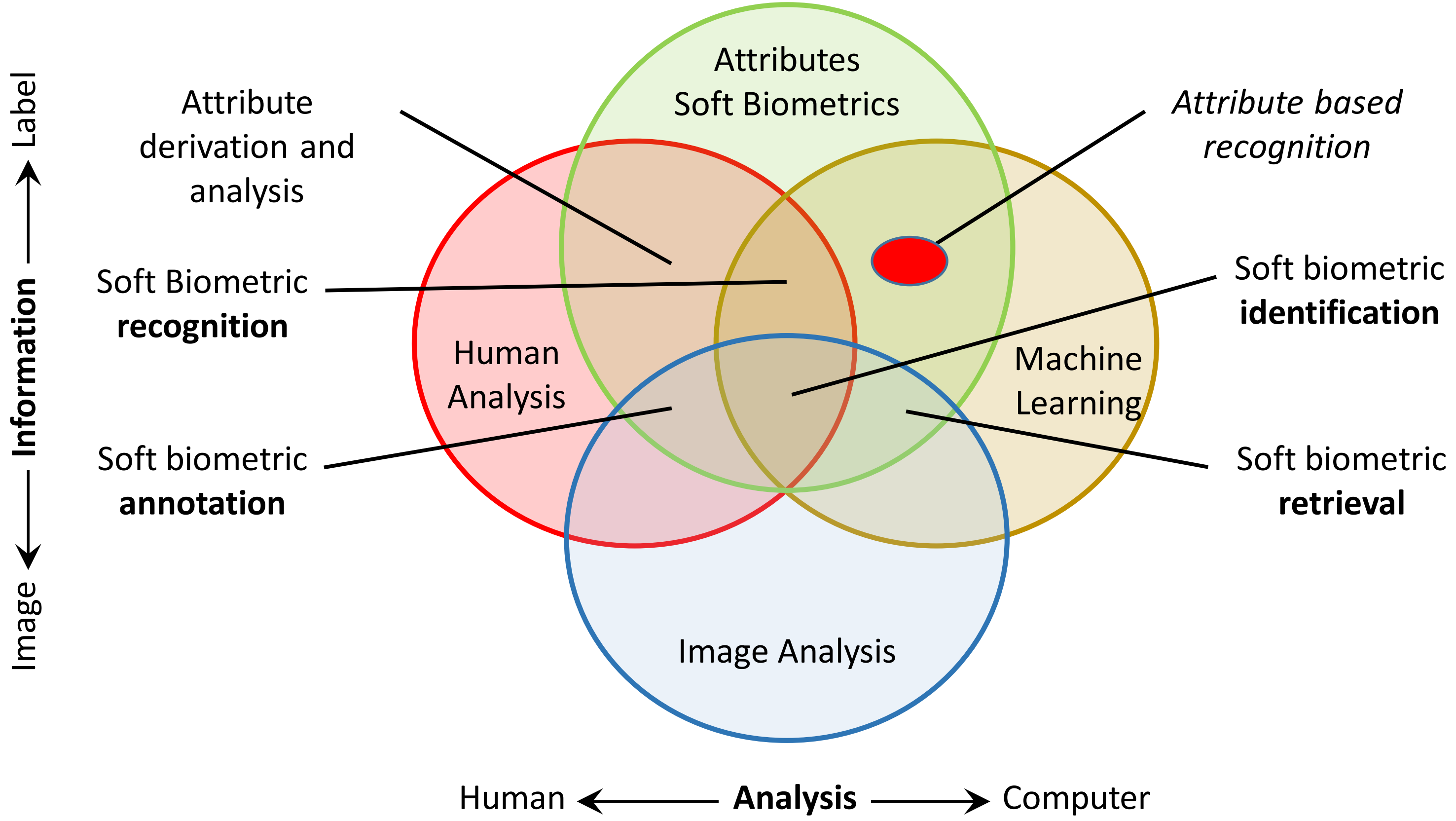
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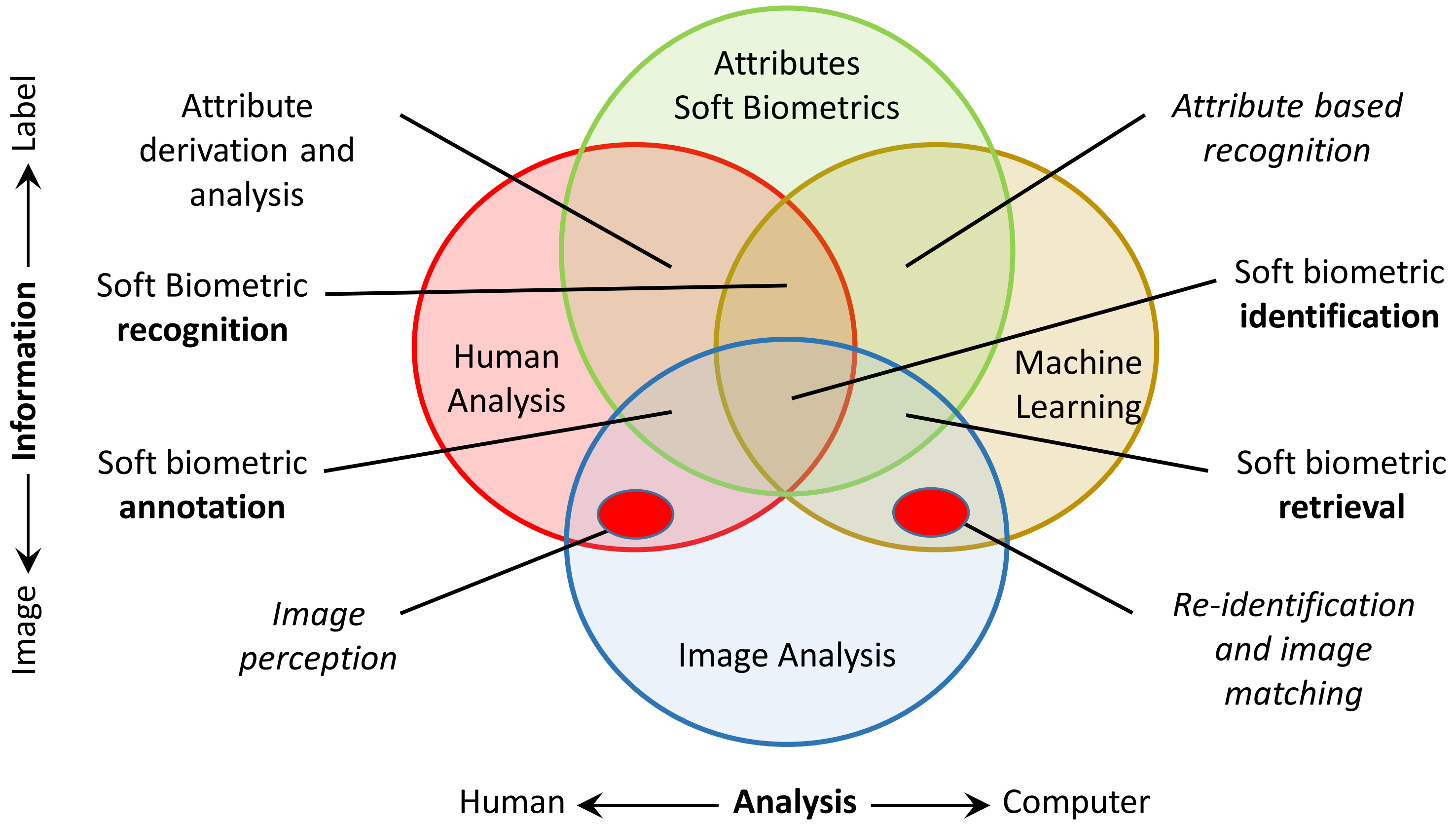
Label
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Attributes Soft Biometrics
Attribute based recognition
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Soft biometric annotation
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Image perception
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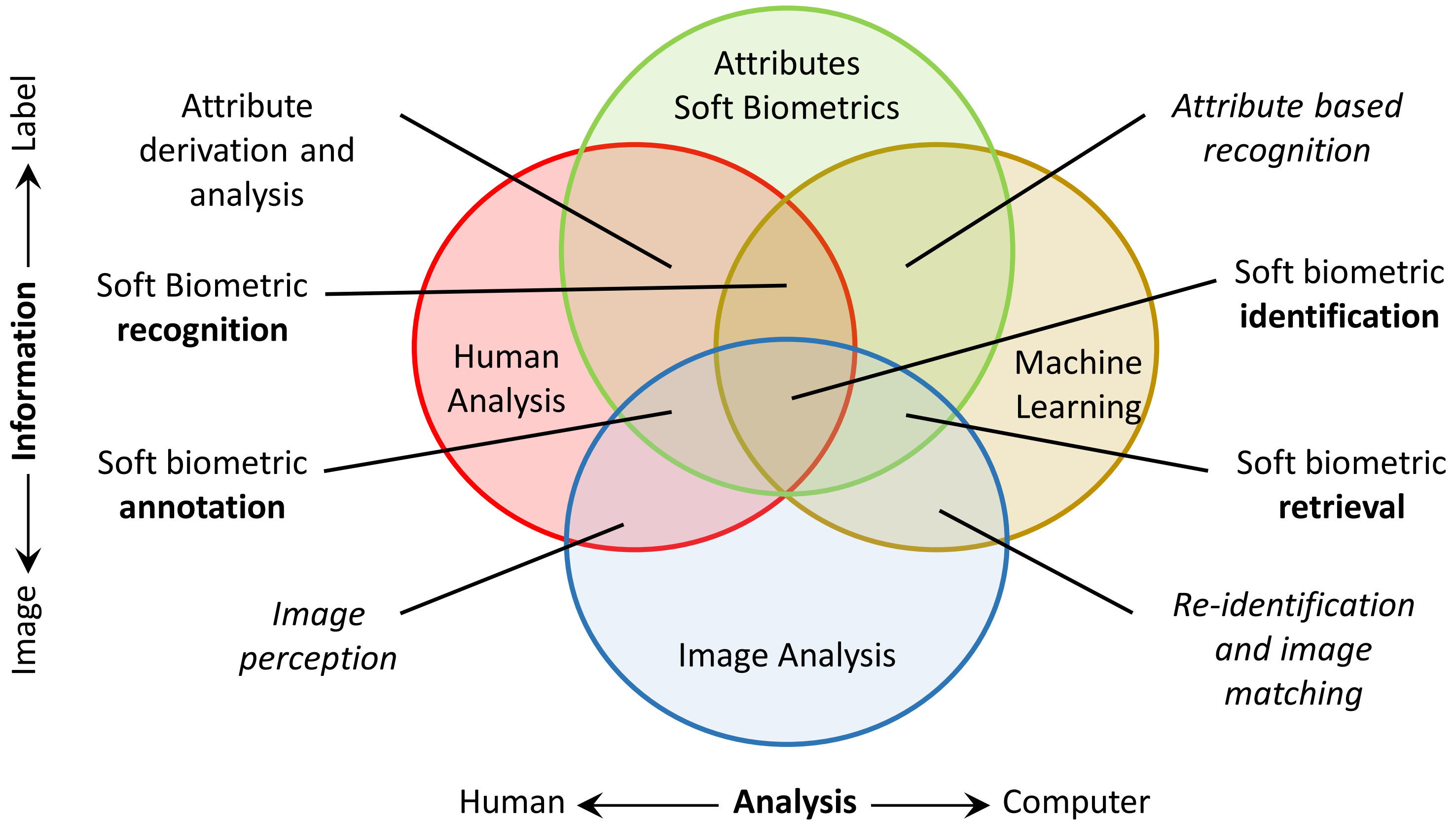
Re-identification and image matching
Human
Analysis
Computer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recognition
Soft biometric
identification
Soft biometric
annotation
Soft biometric
retrieval
Image
perception
Re-identification
and image
matching
Image
Information
Label
Human
Analysis
Computer

A bit of psychology

Need to gather labels from humans

- *Memory issues:* view a subject as many times as needed
- *Defaulting:* explicitly asked to fill out every feature
- *Value Judgments:* categorical qualitative values.
- *Observer variables:* collect description of annotators
- *Other race effect* is very difficult to handle

Labelling via CrowdFlower

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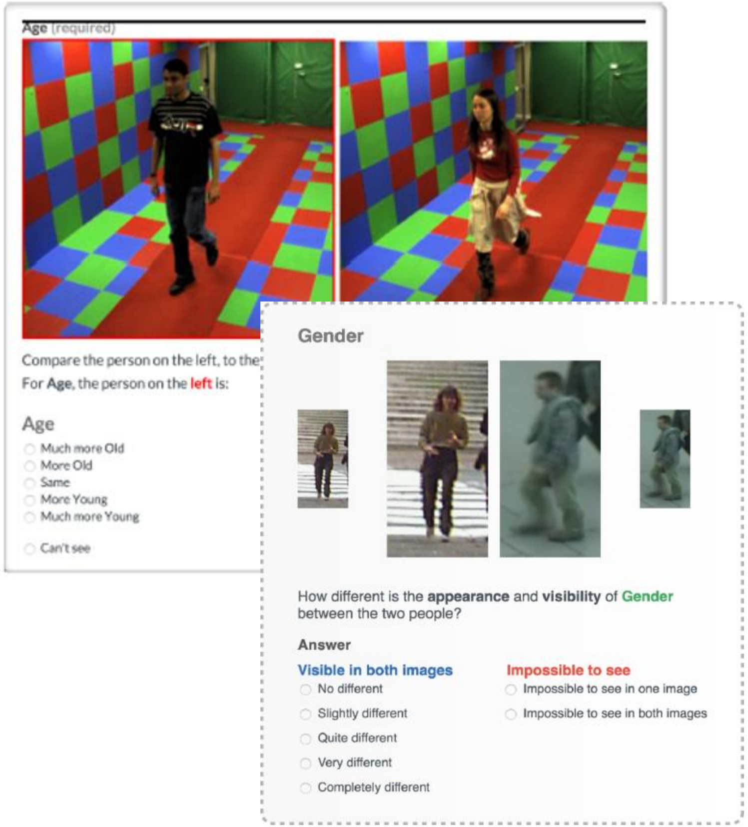

- Professional labelling environment
- Can evaluate labellers (continuously)
- Ensure wide population of labellers
- Not expensive
- Others available (Amazon Mechanical Turk not available in UK)

https://www.crowdflower.co

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

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Databases

Laboratory

- Southampton Gait Database
- Southampton 3D Gait and Face

'Real' World

- PEdesTrian Attribute (PETA)
- LFW
- Clothing Attribute Dataset

Human descriptions: recognition capability

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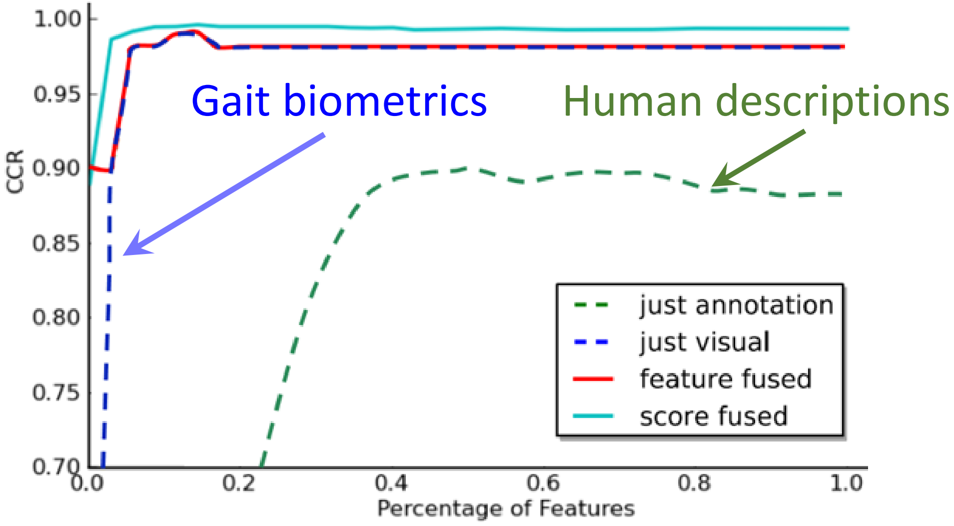
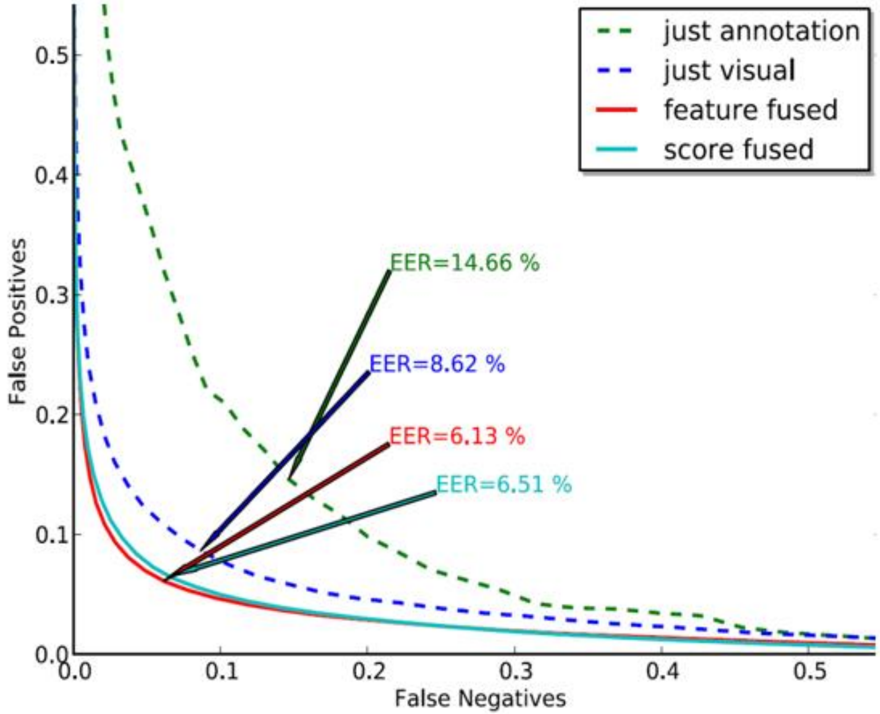
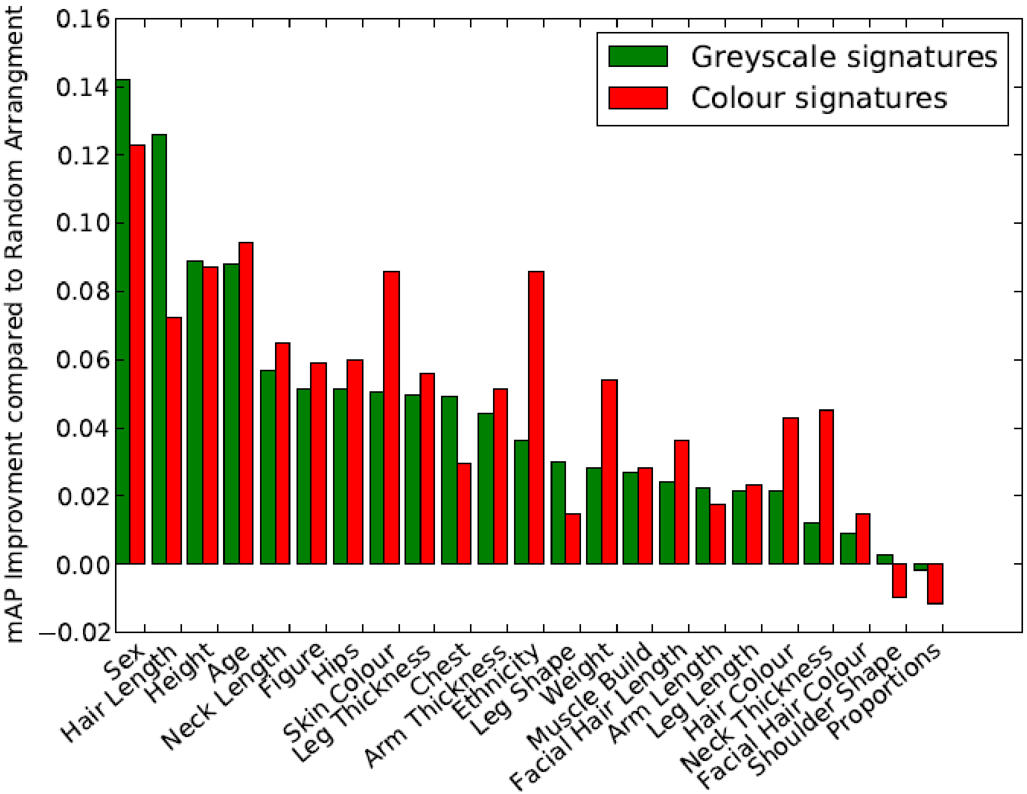




First result

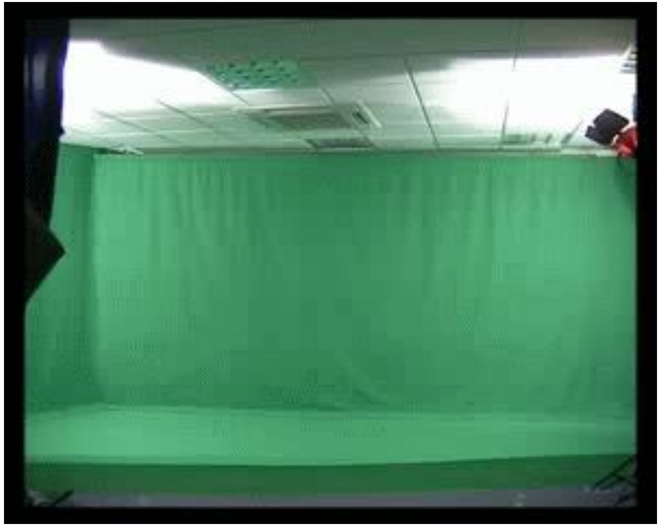
Samangooei and Nixon, *IEEE BTAS* 2008

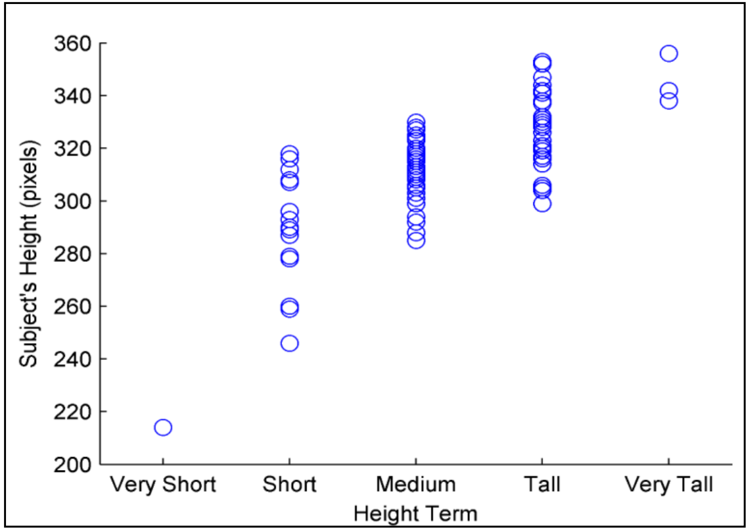
Perspicacity of categorical labels



Problems with absolute descriptors

Subjective = unreliable; Categorical = lacks detail





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

Comparative human descriptions

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

Reid and Nixon, *IEEE IJCB 2011*

Context: relative attributes

(a) Smiling (b) ? (c) Not smiling

(d) Natural (e) ? (f) Manmade

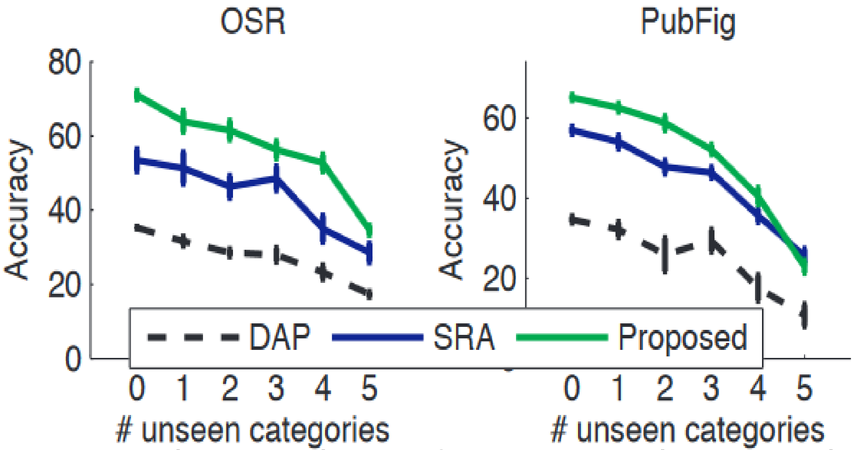
Used ranking SVM

PubFig	ACHJ MS V Z	
Masculine-looking	1 1 1 1 0 0 1 1	S≺M≺Z≺V≺J≺A≺H≺C
White	0 1 1 1 1 1 1 1	A≺C≺H≺Z≺J≺S≺M≺V
Young	0 0 0 0 1 1 0 1	V≺H≺C≺J≺A≺S≺Z≺M
Smiling	1 1 1 0 1 1 0 1	J≺V≺H≺A∼C≺S∼Z≺M
Chubby	1 0 0 0 0 0 0 0	V≺J≺H≺C≺Z≺M≺S≺A
Visible-forehead	1 1 1 0 1 1 1 0	J≺Z≺M≺S≺A∼C∼H∼V
Bushy-eyebrows	0 1 0 1 0 0 0 0	M≺S≺Z≺V≺H≺A≺C≺J
Narrow-eyes	0 1 1 0 0 0 1 1	M≺J≺S≺A≺H≺C≺V≺Z
Pointy-nose	0 0 1 0 0 0 0 1	A≺C≺J∼M∼V≺S≺Z≺H
Big-lips	1 0 0 0 1 1 0 0	H≺J≺V≺Z≺C≺M≺A≺S
Round-face	1 0 0 0 1 1 0 0	H≺V≺J≺C≺Z≺A≺S≺M

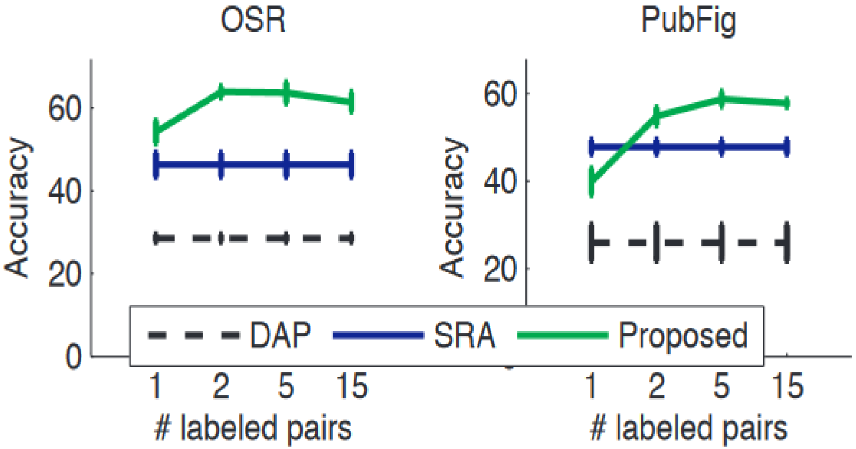
Subset of attributes and Alex Rodriguez (A), Clive Owen (C), Hugh Laurie (H), Jared Leto (J), Miley Cyrus (M), Scarlett Johansson (S), Viggo Mortensen (V) and Zac Efron (Z)

Parikh and Grauman, *IEEE ICCV* 2011

Context: relative attributes



Zero-shot learning performance as the proportion of unseen categories increases. Total number of classes N remains constant at 8



Zero-shot learning performance as more pairs of seen categories are related (i.e. labeled) during training

DAP Direct Attribute Prediction

SRA score-based relative attributes

Parikh and Grauman, *IEEE ICCV* 2011

Height correlation (with time)

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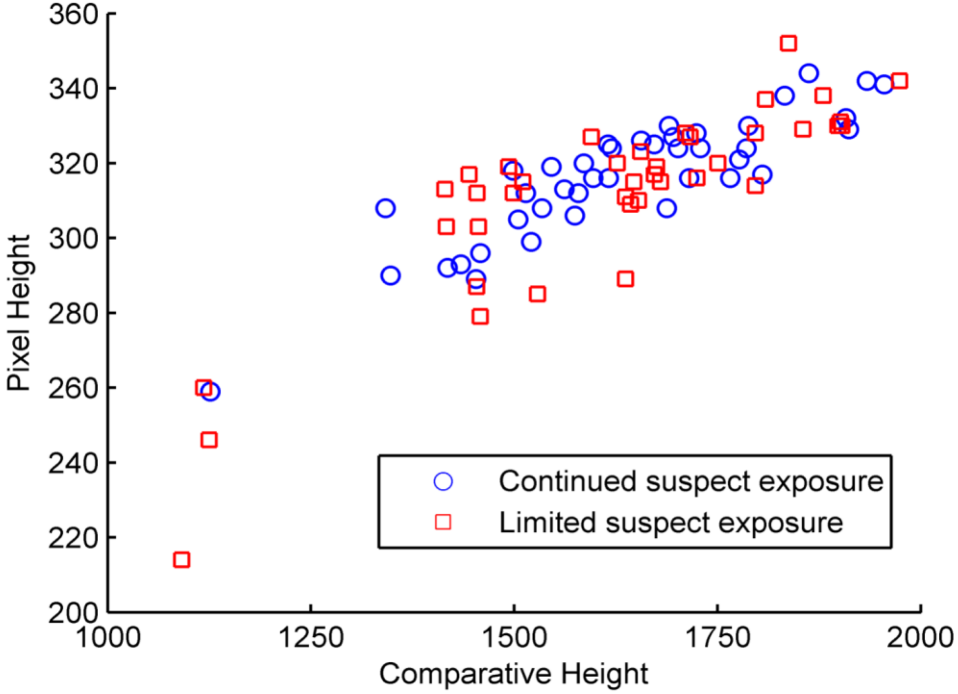
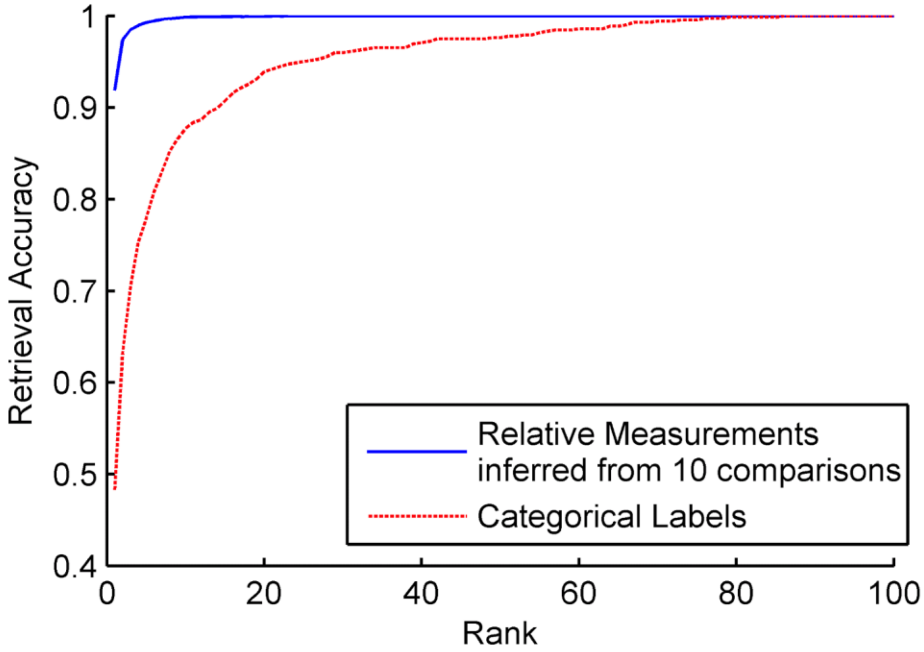


Reid and Nixon, *IEEE ICDP* 2011

Recognition



Reid and Nixon, *IEEE ICDP* 2011

Recognition/ retrieval

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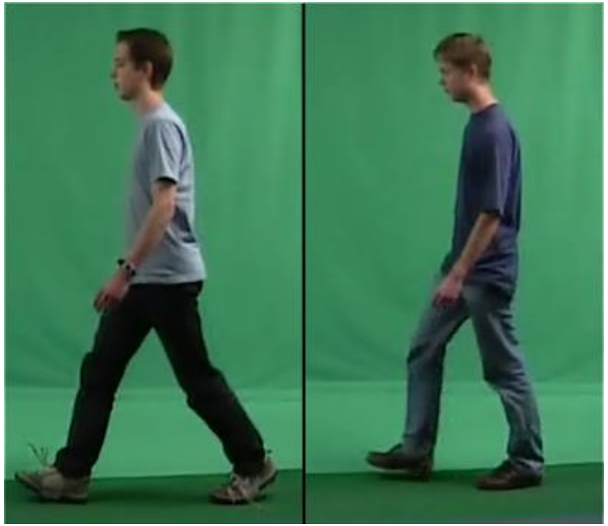


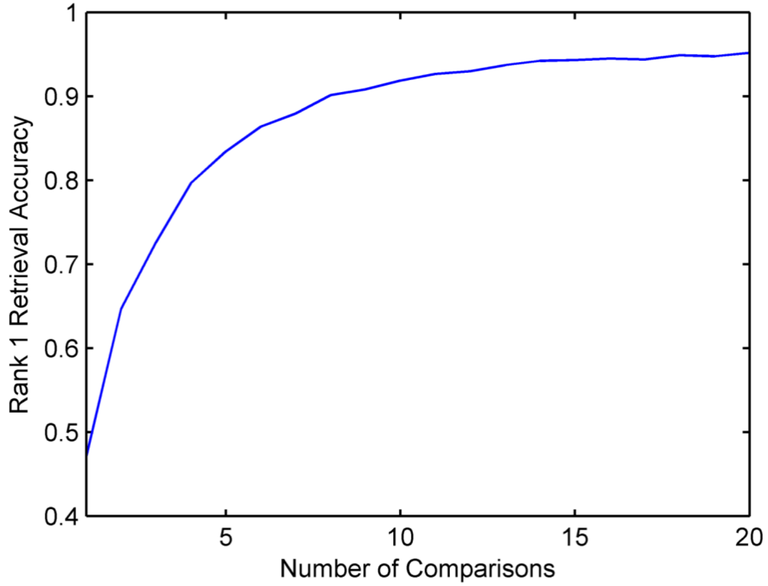
Incorrect with 10 comparisons

Correct with 1 comparison

Reid and Nixon, *IEEE TPAMI* 2015

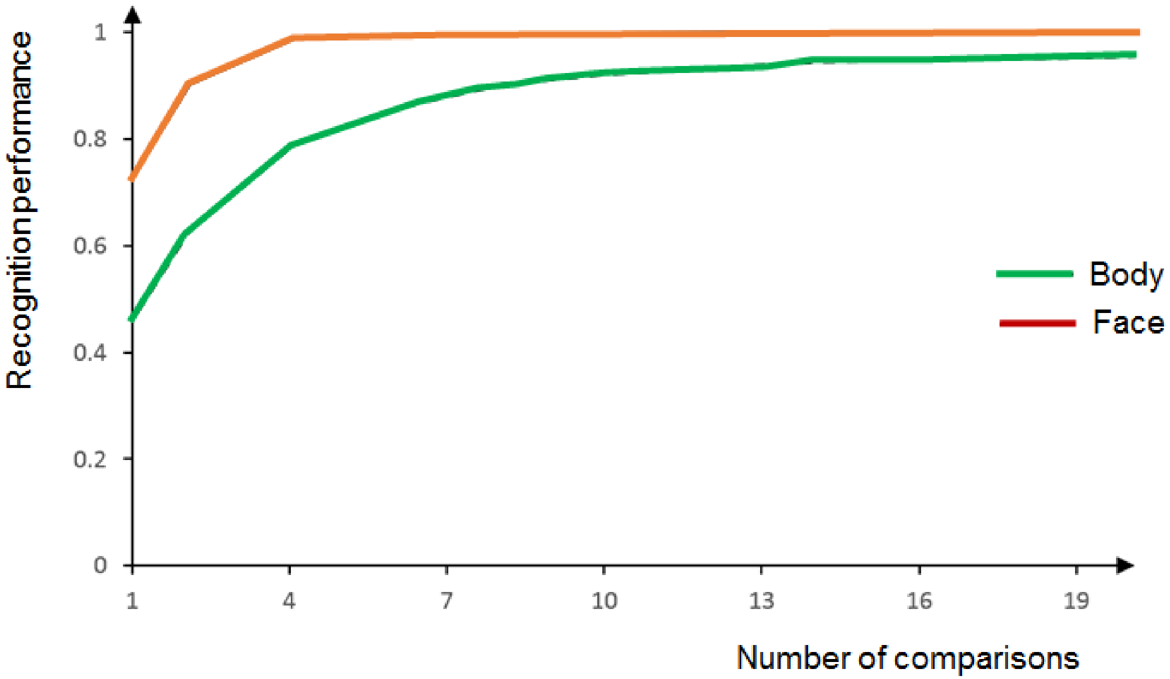
Ranking comparative descriptions

- 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 the number of comparisons on recognition



‘Give us the tools to finish the job’

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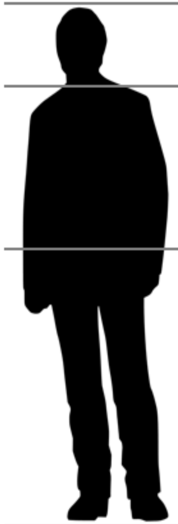
Components

- Data
- Labels (categorical or comparative)
- Ranking algorithm (for comparative labels)
- Feature selection (e.g. SFSS, entropy)
- Computer vision (feature extraction, colour mapping,)
- Classifier (e.g. kNN, SVM, DBN)

http://ww2today.com

Labelling the body, face and clothing



All: gender, age, ethnicity, skin colour

General

Body: figure, weight

Face: length, width, fleshiness

Clothing: tattoos, attachment(s), overall style category

Head/ Face

Body: skin colour, hair colour/ length, neck length/ thickness

Face: parts of skin, hair, forehead, eyes, ears, nose, lips, chin

Clothing: hat, face/ head coverage

Upper Body

Body: arm length/ thickness, chest,

Clothing: neckline, clothing category, sleeve length

Lower Body

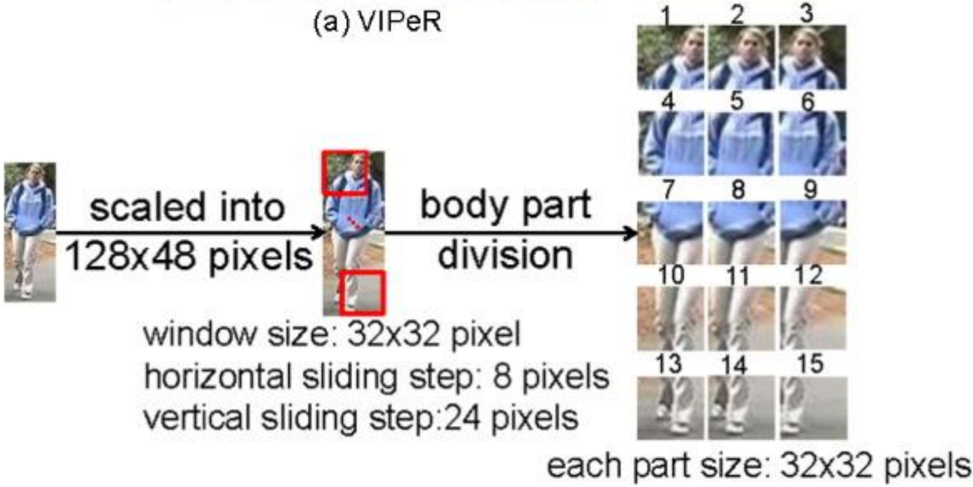
Body: leg length/ shape/ thickness, hips' width

Clothing: clothing category/ length, belt, shoes, heel

Context: attribute estimation

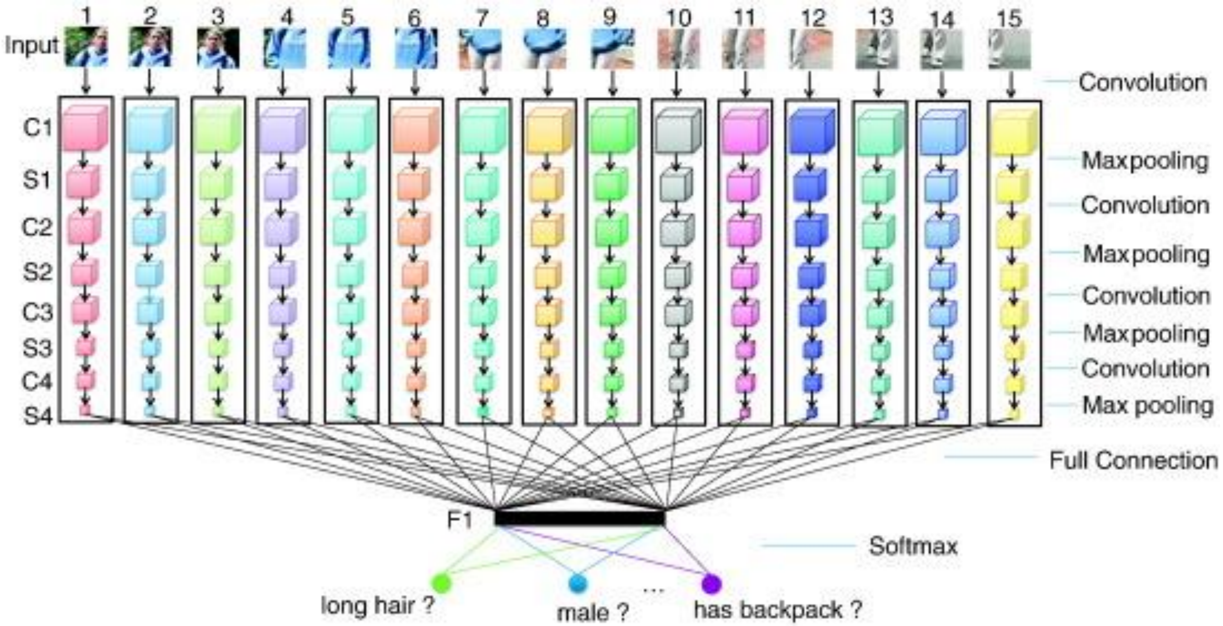
- Pedestrian attribute estimation (gender, clothing)
- Pre-segment pedestrian image
- Use multi label CNN
- Applied to VIPeR , GRID and PETA
- Increased average attribute estimation
- Can be used for re-identification

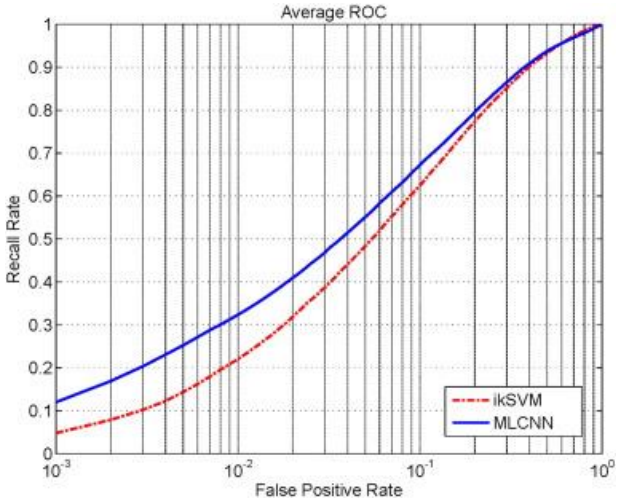
(a) VIPeR



Zhu, Liao, …, Li, *Proc ICB* 2015, *IVC* 2016

Context: attribute estimation





Analysis on PETA

Zhu, Liao, …, Li, *IVC* 2016

Context: attribute estimation

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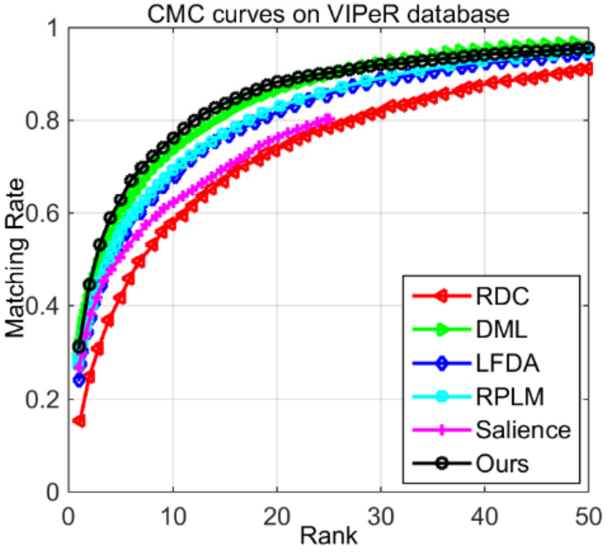
attribute	accuracy rate (%)		recall rate (%) @ FPR=10%		AUC(%)	
	ikSVM	MLCNN	ikSVM	MLCNN	ikSVM	MLCNN
accessoryHat	92.04	96.05	81.37	86.06	91.27	92.62
accessoryMuffler	94.84	97.17	90.68	88.42	95.09	94.47
accessoryNothing	78.87	86.11	35.37	52.57	81.79	86.09
carryingBackpack	76.39	84.30	46.19	58.40	84.52	85.19
carryingMessengerBag	74.51	79.58	50.22	58.30	78.44	82.01
carryingNothing	75.84	80.14	49.36	55.15	81.60	83.08
carryingOther	76.18	80.91	38.57	46.90	74.11	77.68
carryingPlasticBags	86.86	93.45	70.57	67.30	87.69	86.01
footwearBlack	74.29	75.97	50.37	57.24	81.42	84.07

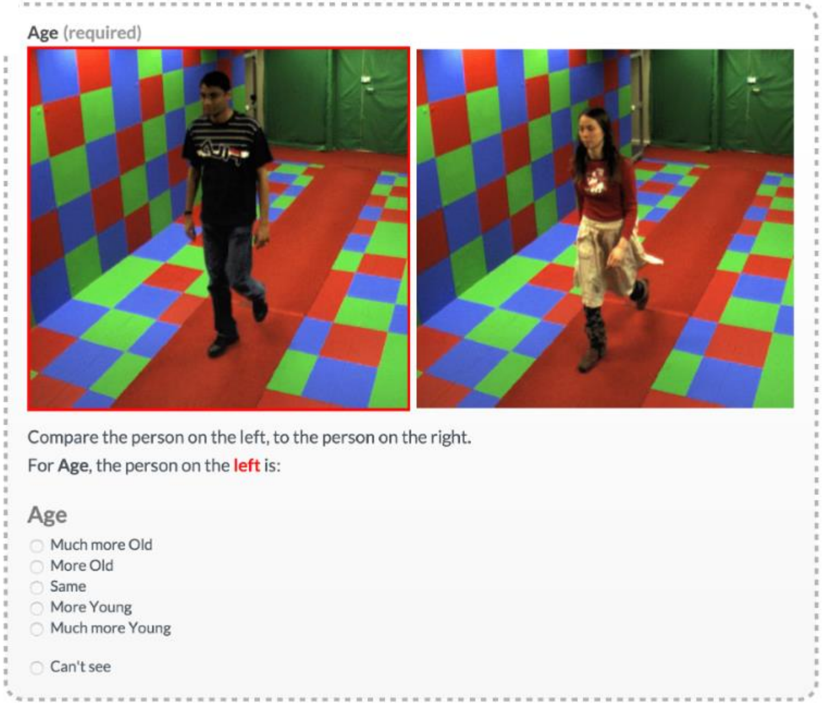


Analysis on ViPER

Zhu, Liao, …, Li, *Proc ICB* 2015, *IVC* 2016

Crowdsourcing body labels

Soft traits	Response labels (5-p 5
Gender	Much more Feminine
Age	Much more Old
Height	Much more Tall
Weight	Much more Heavy
Figure	Much more Fat
Chest size	Much more Big
Arm thickness	Much more Thick
Leg thickness	Much more Thick
Skin colour	Much more Dark
Hair colour	Much more Dark
Hair length	Much more Long
Muscle build	Much more Muscle



Martinho-Corbishley, Nixon and Carter, *IET Biometrics* 2015

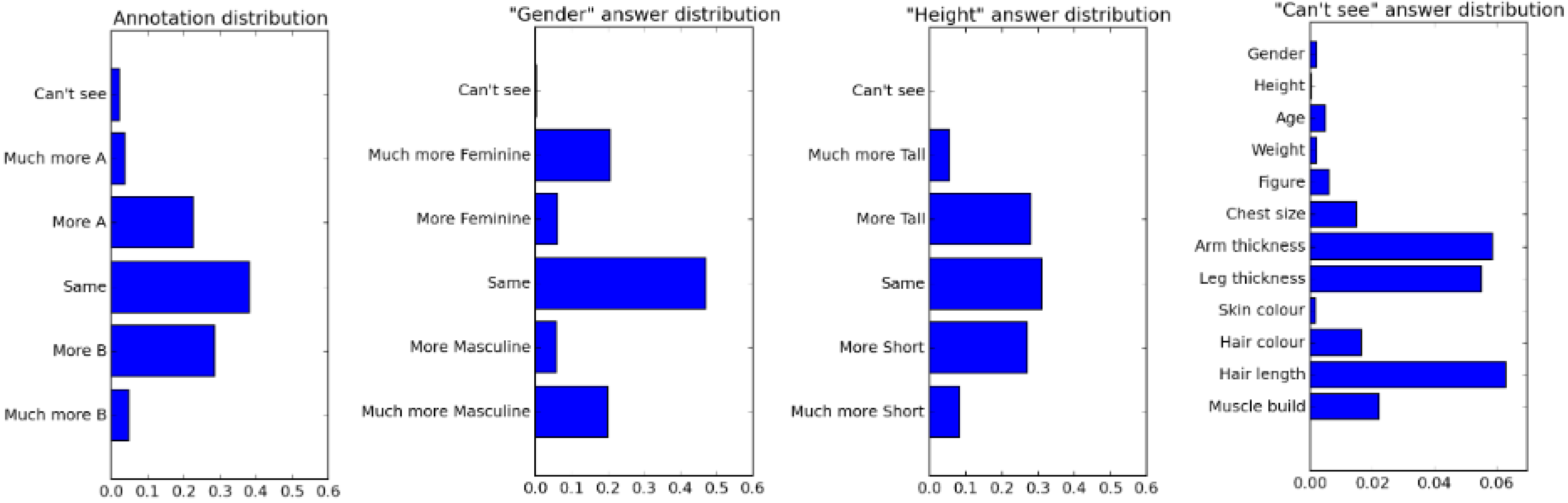
Considerations on crowdsourcing

- Initial trial questions used, successful respondents proceed
- "Can't see" acceptable for all annotations (respondents capped at a maximum rate)
- Respondents rejected if response distribution varied largely from average
- Questions included text and highlighting, reiterating task question
- Layout consistent with easy use
- Initial answers blank to avoid anchoring

Statistics	
# respondents	892
# annotations	59400
# resp. flagged	124
# annot. rejected	4383
cost	$303

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

Distributions of body labels



All Gender Height Uncertainty

Martinho-Corbishley, Nixon and Carter, *IET Biometrics* 2015

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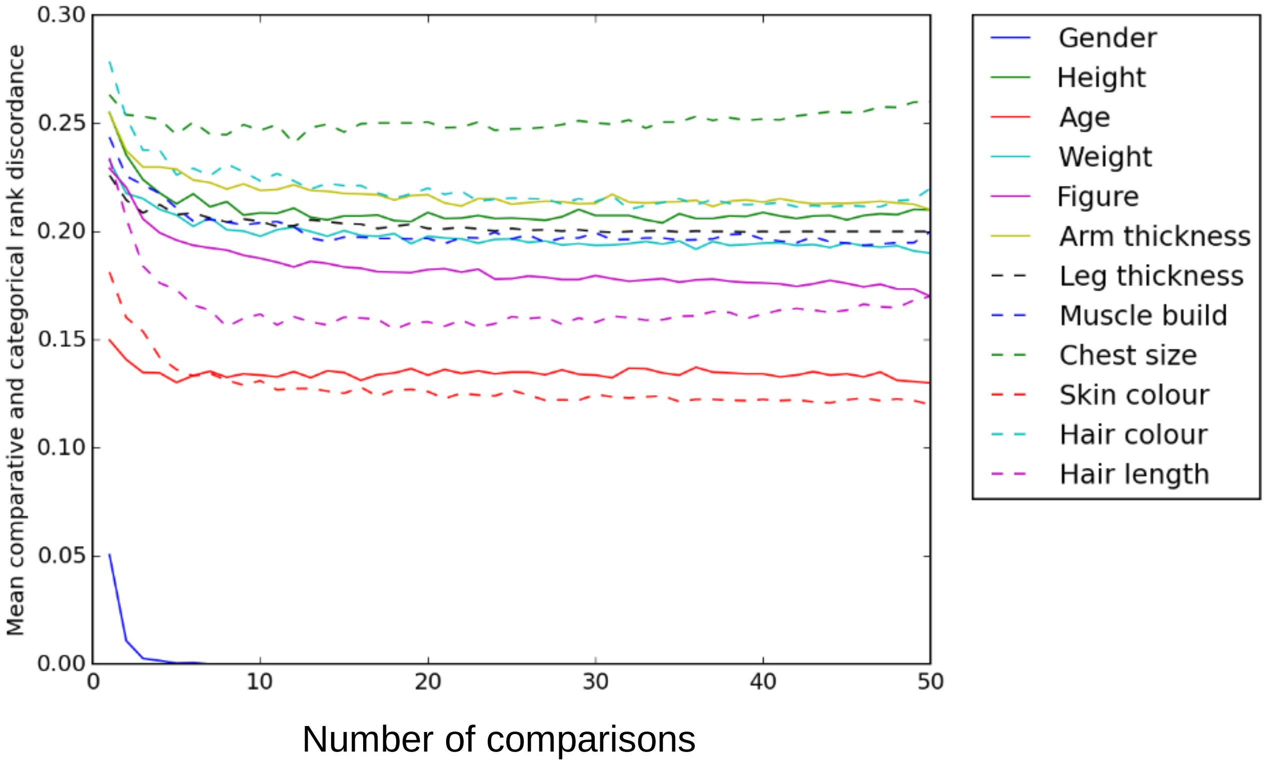
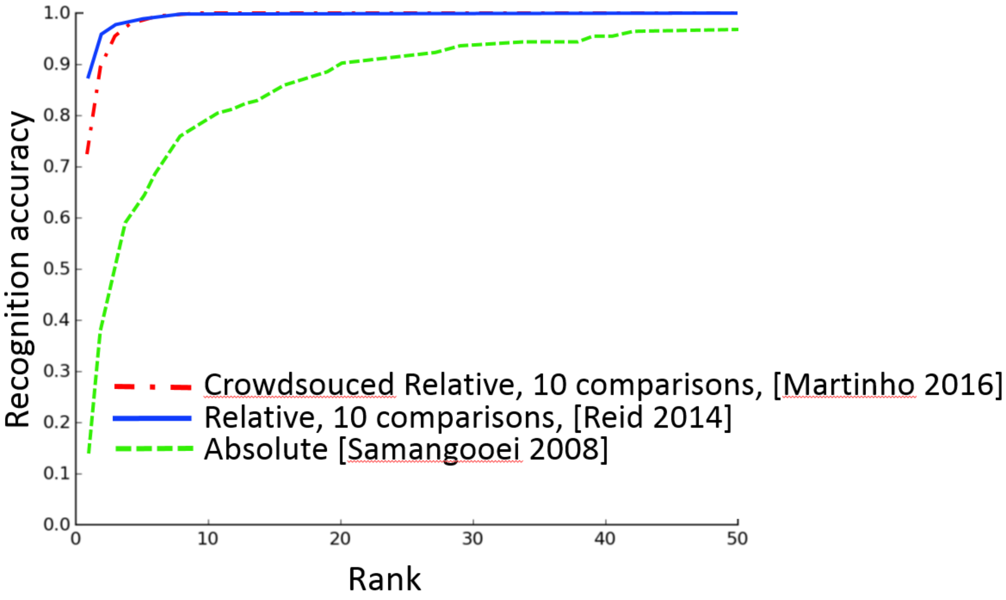
Influence of # comparisons

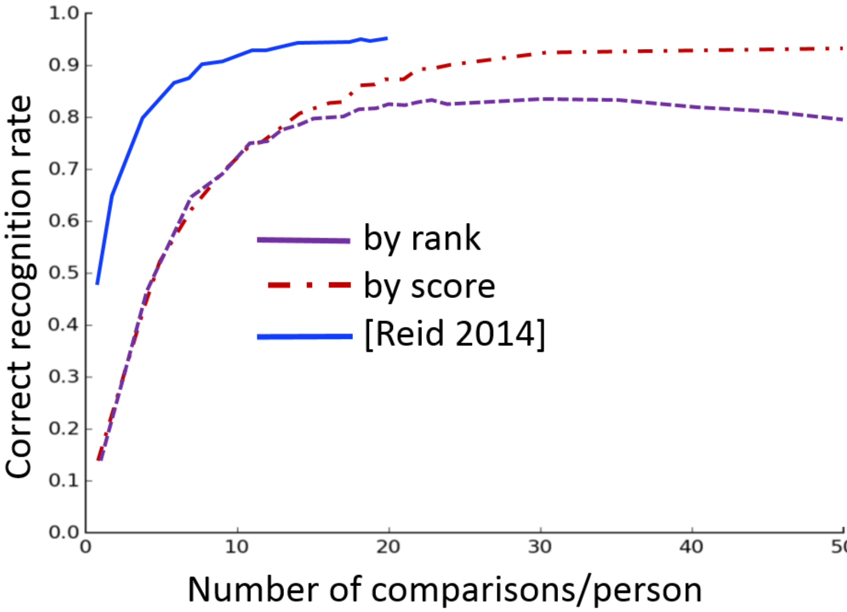


Mean rank discordance vs number of comparisons

Martinho-Corbishley, Nixon and Carter, *IET Biometrics* 2015

Recognition by crowdsourced body labels



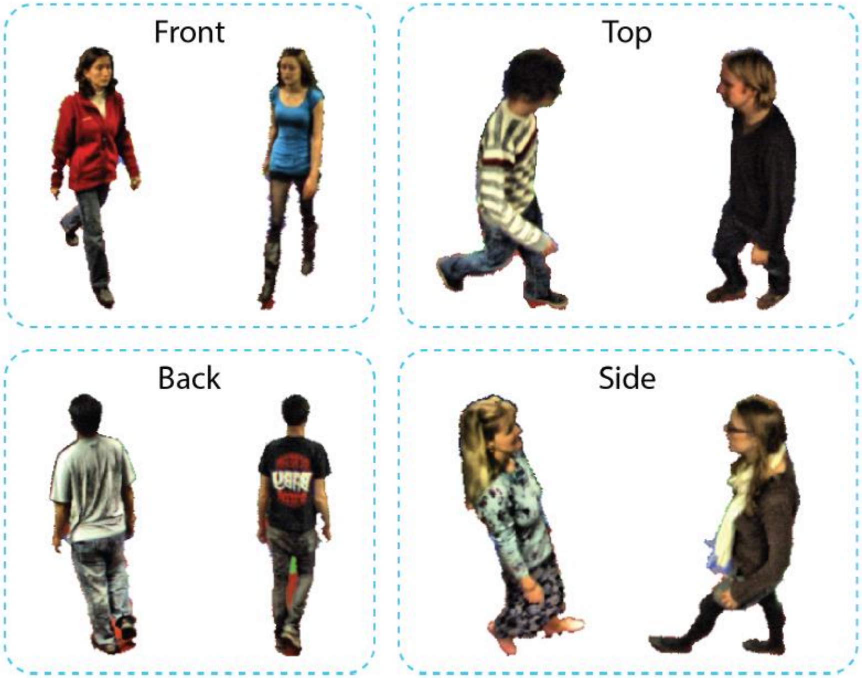


Lower recognition accuracy (expected)

More labels and comparisons increase accuracy (expected)

Identification by body labels

- label ranking via ranking SVM
- image split into horizontal strips characterised by colour
- Histogram of Oriented Gradients applied to whole image
- learning functions trained to predict soft biometric labels given image features and annotations
- used Extra-Trees (ET) supervised ensemble learning algorithm

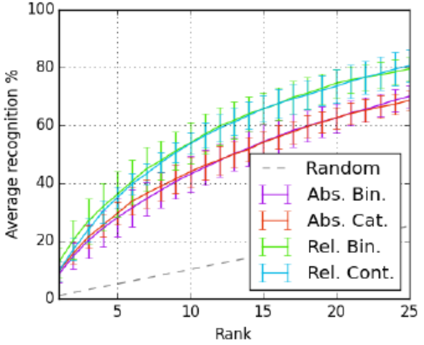


Views from SOBIR dataset

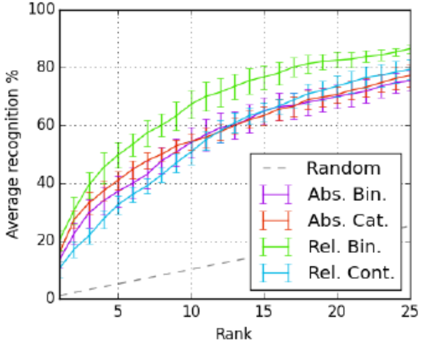
Martinho-Corbishley, Nixon and Carter, *IEEE ISBA 2016*

Identification by body labels

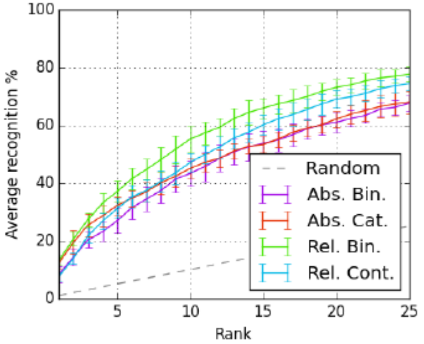
- One shot re-ID is matching
- Multi-shot re-ID randomly samples 1 image/ subject for test, remaining 7 training
- Disjoint re-ID randomly samples 1 image per subject, and only 6 to training set
- Zero-shot ID simulates eye witness description of a subject



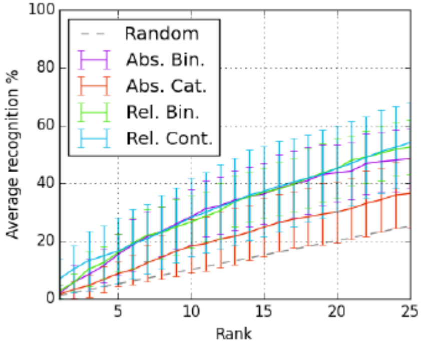
(a) One-shot re-identification (average across camera pairs)



(b) Multi-shot re-identification



(c) Disjoint re-identification



(d) Zero-shot identification

Martinho-Corbishley, Nixon and Carter, *IEEE ISBA 2016*

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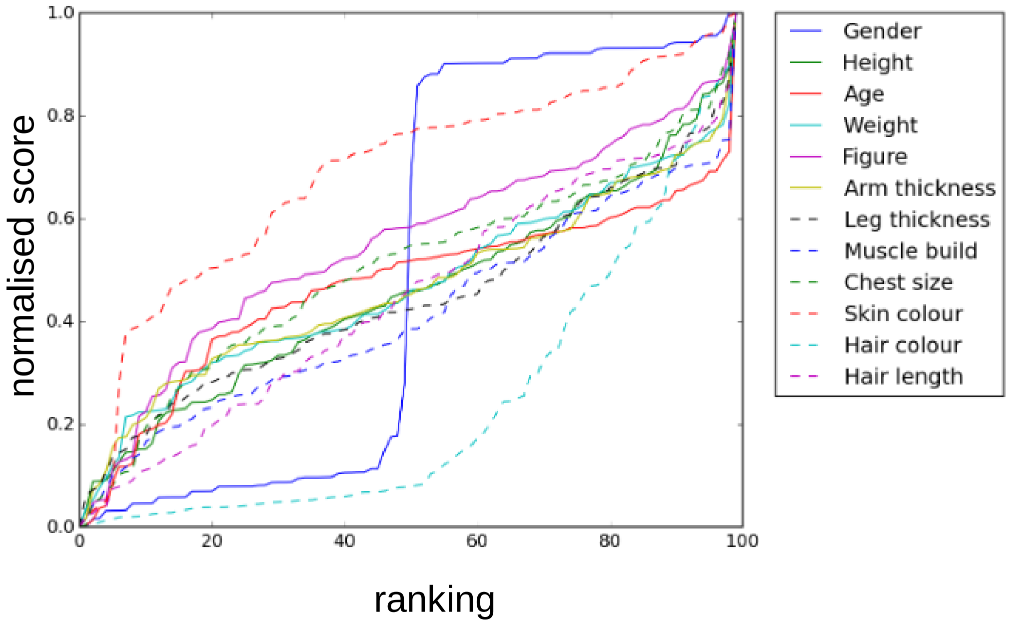
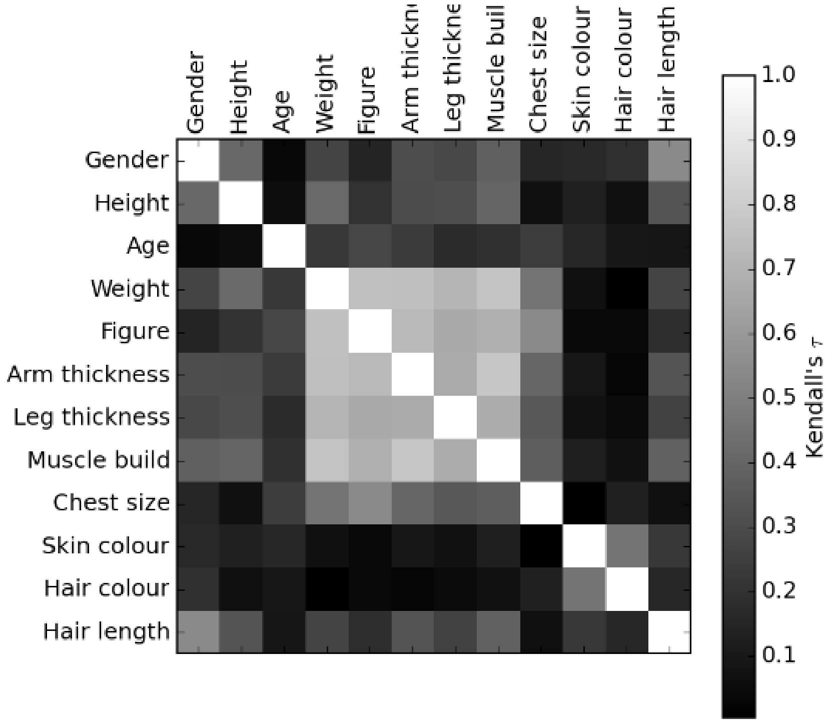
Trait performance



Normalised relative scores vs ranks



Kentall's τ correlation

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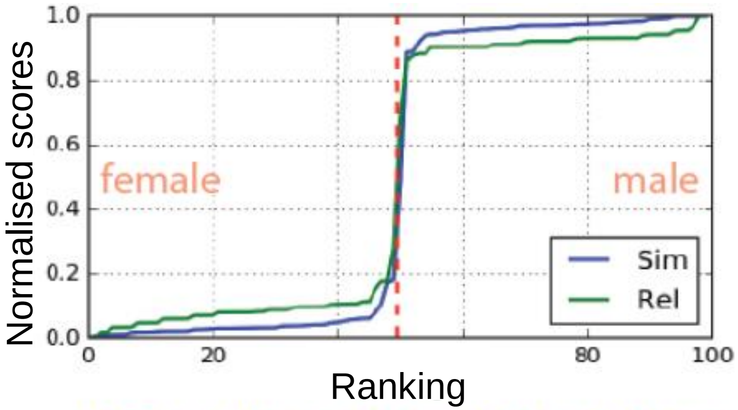
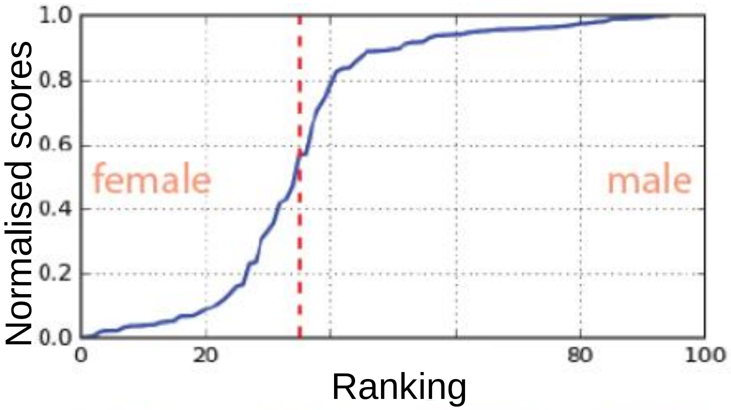
Pairwise similarity comparisons on PETA



Relative	0.18	0.28	0.68	0.86	0.88
Similarity	0.17	0.18	0.47	0.89	0.89



Binary	male	female	female	female
Similarity	0.47	0.57	0.83	0.95

Gender distribution not binary

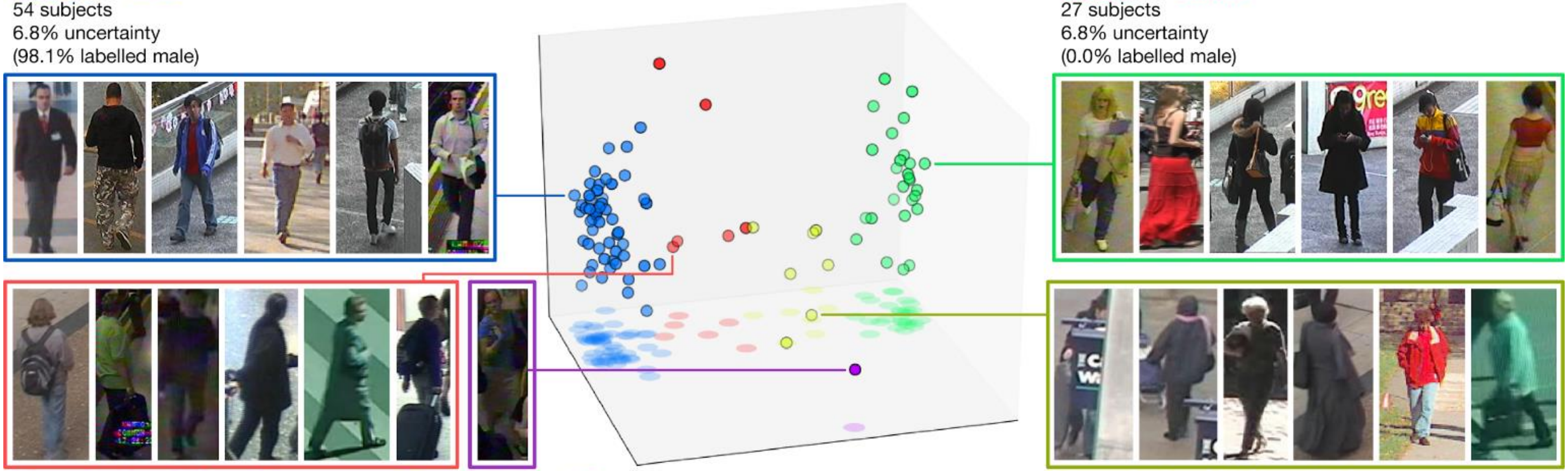
Can measure confidence

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

Analysing gender on PETA

Group 0 - "male"
54 subjects
6.8% uncertainty
(98.1% labelled male)

Group 1 - "female"
27 subjects
6.8% uncertainty
(0.0% labelled male)



Group 2 - "possibly male"
6 subjects
25.8% uncertainty
(66.7% labelled male)

Group 3 - "neutral"
1 subject
3.2% uncertainty
(0.0% labelled male)

Overall
95 subjects
9.7% uncertainty
(61.1% labelled male)

Group 4 - "possibly female"
7 subjects
31.5% uncertainty
(14.3% labelled male)

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

Superfine labels

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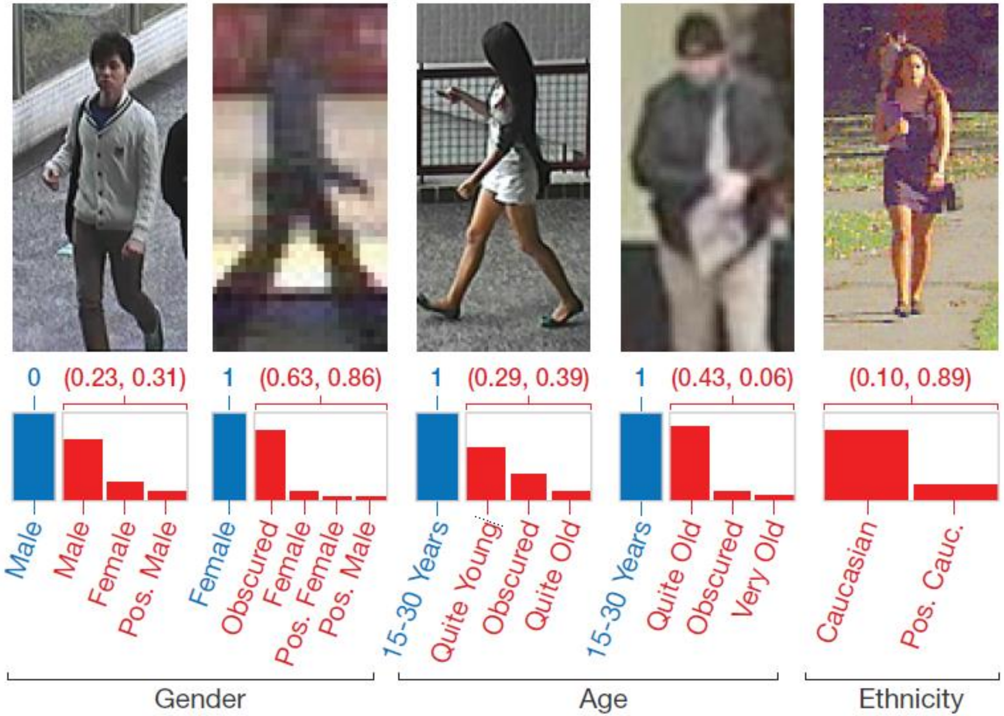
Most ‘fine’ are actually coarse

Our comparative attributes are superfine

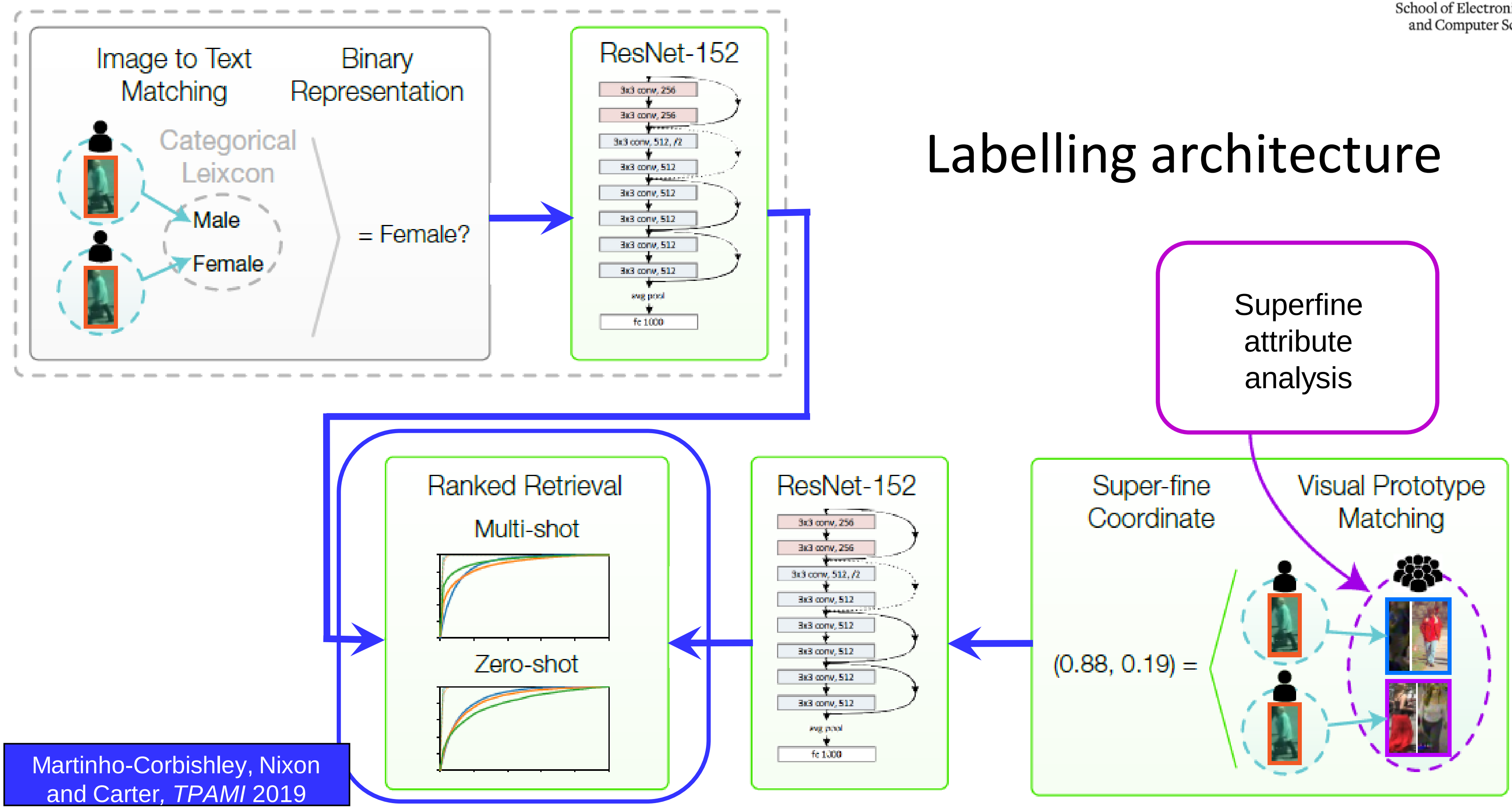
Comparison/ ranking gives many advantages



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

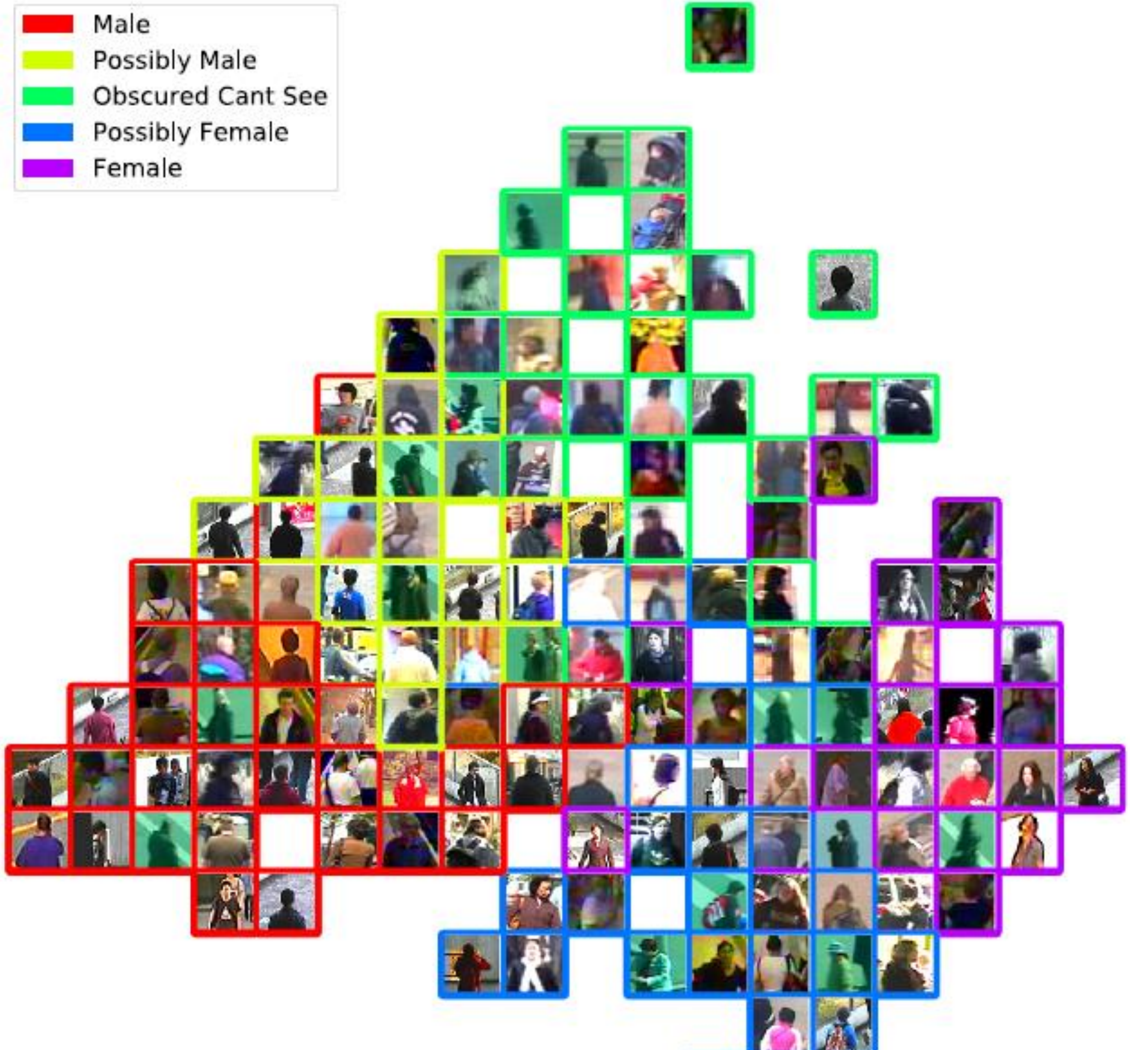
Labelling architecture

Conventional attribute-based analysis



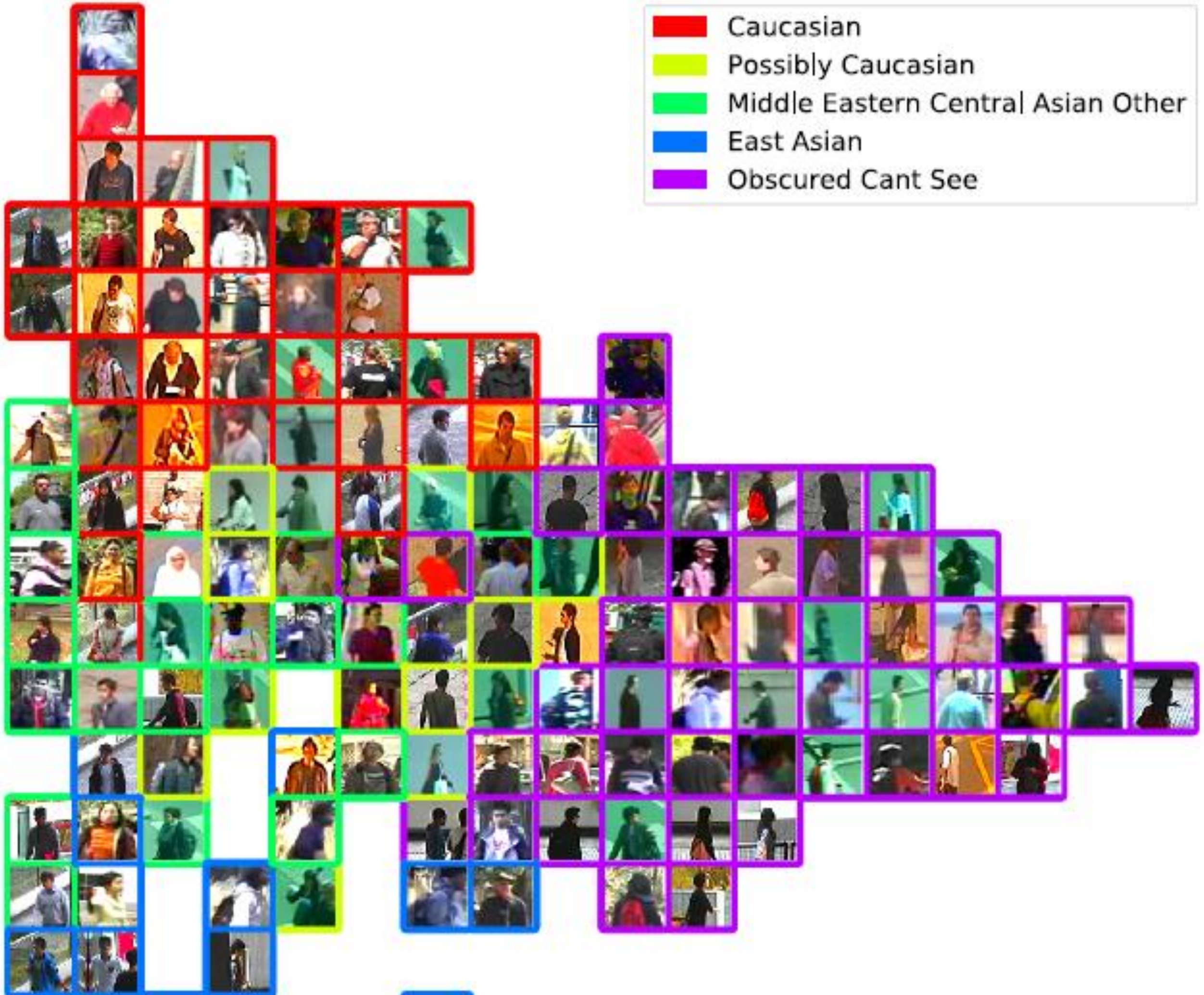
Martinho-Corbishley, Nixon and Carter, *TPAMI* 2019

Gender



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

Ethnicity



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

Analysing gender (??!!)

- Gender?

Subject	1	2	3
			
Gender			A. Male B. Female

Recognition by face attributes

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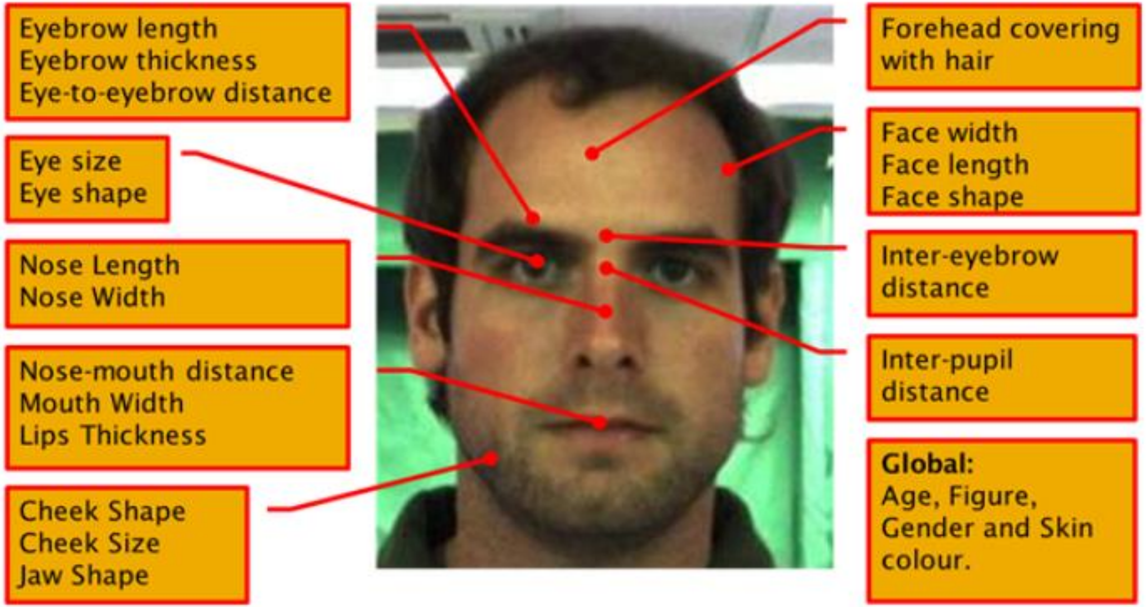
Categorical labels
(gender, age +...)
Comparative labels



Reid and Nixon, *IEEE ICB 2013*

Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

Context: attribute and simile classifiers for face verification

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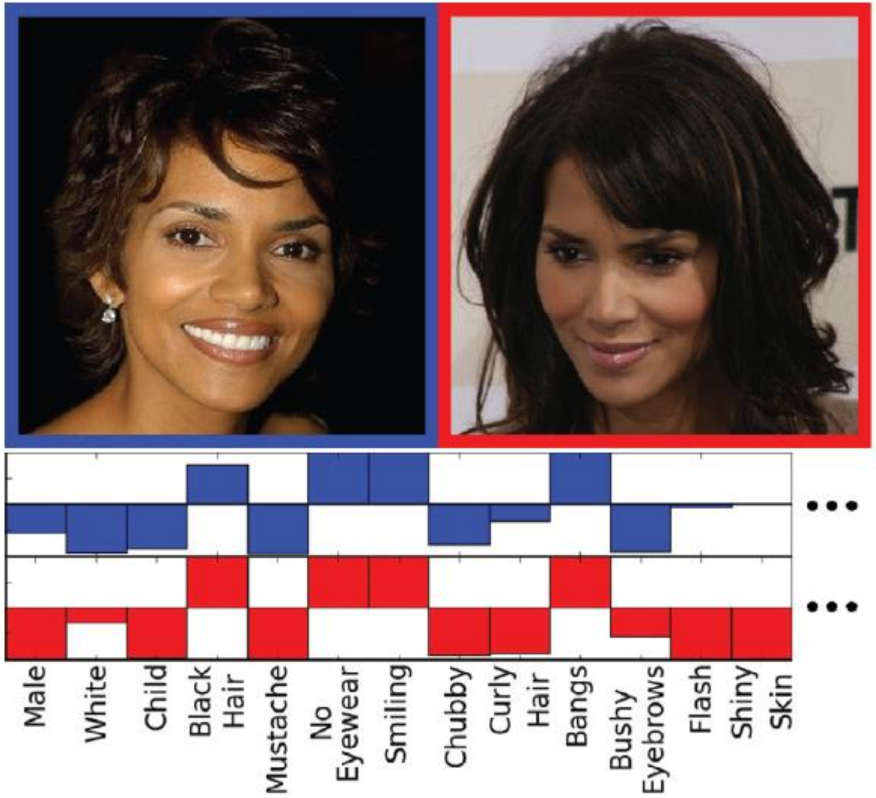

Attribute	Accuracy	Attribute	Accuracy
Asian	92.32%	Mouth Wide Open	89.63%
Attractive Woman	81.13%	Mustache	91.88%
Baby	90.45%	No Beard	89.53%
Bags Under Eyes	86.23%	No Eyewear	93.55%
Bald	83.22%	Nose Shape	86.87%
Bangs	88.70%	Nose Size	87.50%
Black	88.65%	Nose-Mouth Lines	93.10%
Black Hair	80.32%	Obstructed Forehead	79.11%
Blond Hair	78.05%	Oval Face	70.26%
Blurry	92.12%	Pale Skin	89.44%
Brown Hair	72.42%	Posed Photo	69.72%
Child	83.58%	Receding Hairline	84.15%
Chubby	77.24%	Rosy Cheeks	85.82%
Color Photo	95.50%	Round Face	74.33%
Curly Hair	68.88%	Round Jaw	66.99%

Accuracies of the 65 attribute classifiers (part) trained using positive and negative examples

Used Mechanical Turk

Kumar, Berg et al, *IEEE ICCV* 2009

Context: attribute and simile classifiers for face verification

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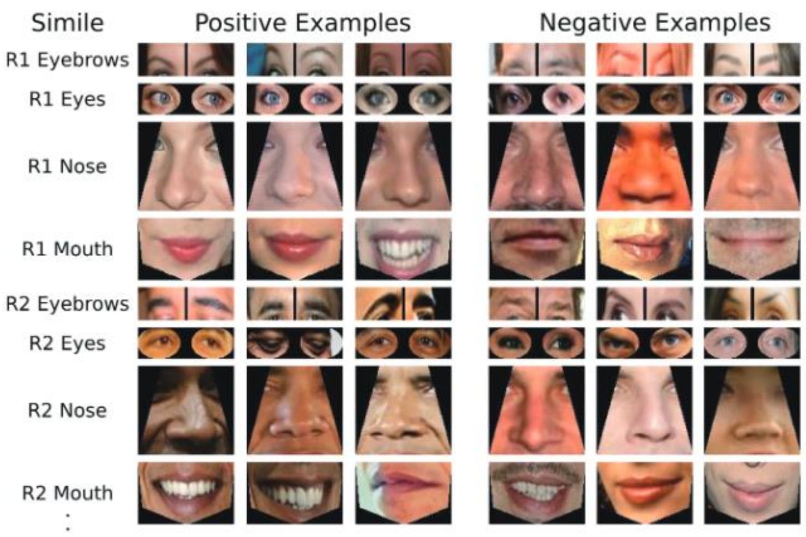
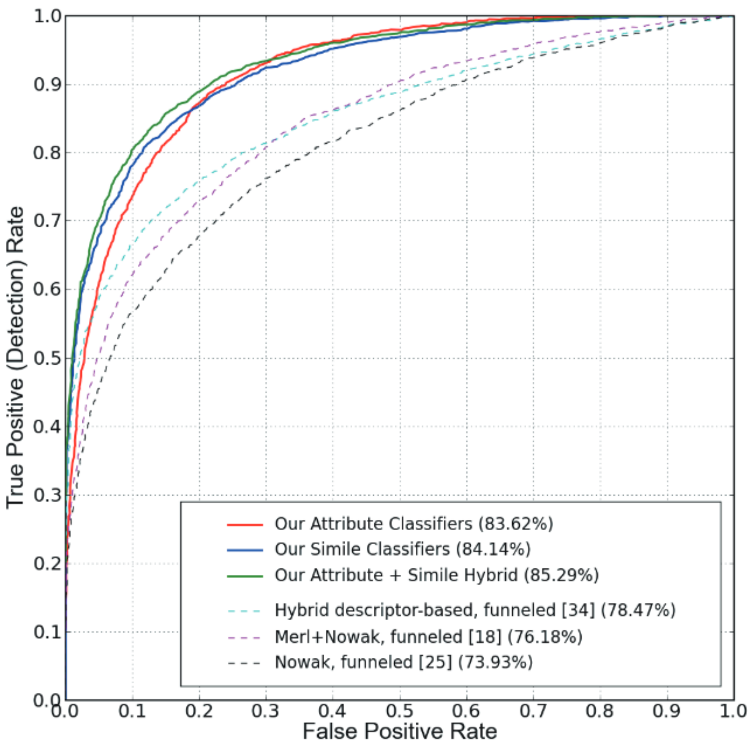


Similes for Training

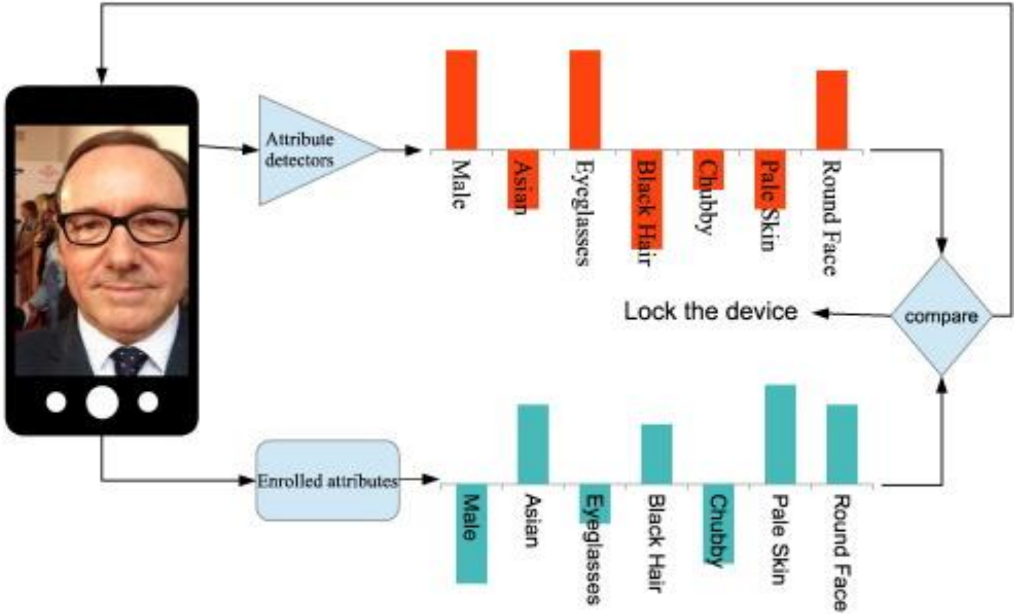


Face Verification Results on LFW

Kumar, Berg et al, *IEEE ICCV* 2009

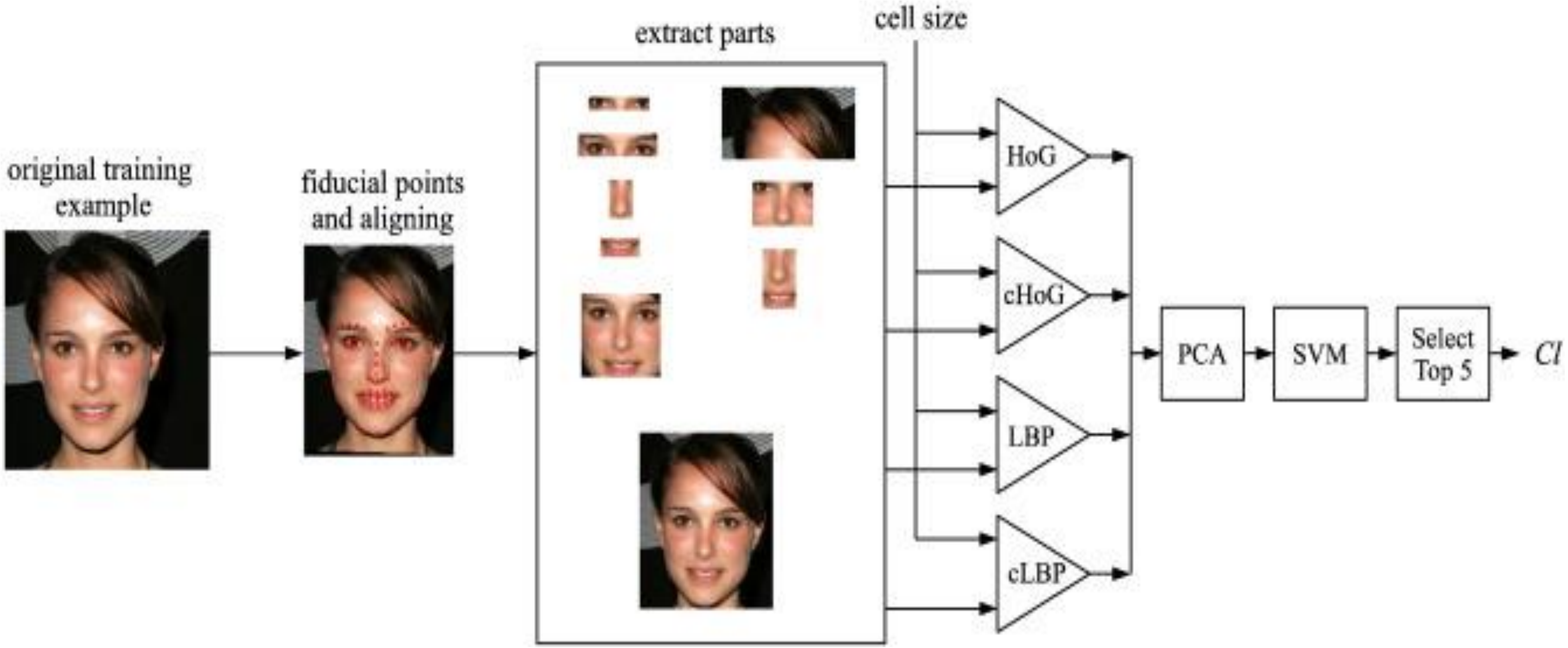
Context: Facial attributes for active authentication on mobile devices

- Effective for continuous authentication on mobile devices.
- Attribute-based features more robust than low-level ones for authentication
- Fusion of attribute-based and low-level features gives best result.
- Proposed approach allows fast and energy efficient enrollment and authentication



Samangouei, Patel and Chellappa, *IVC*, 2016

Context: Facial attributes for active authentication on mobile devices



Samangouei, Patel and Chellappa, *IVC*, 2016

Context: Facial attributes for active authentication on mobile devices

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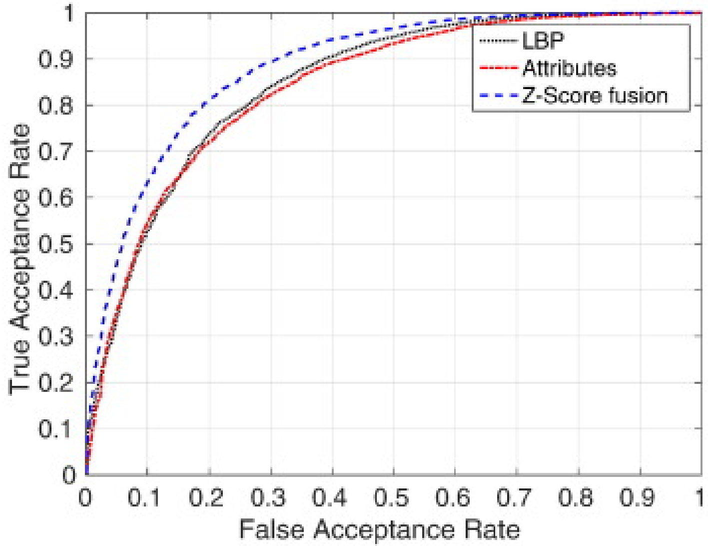
Attribute	Accuracy	Attribute	Accuracy
Asian	0.8786	Middle aged	0.7321
Eyeglasses	0.7214	Black	0.808
Sunglasses	0.89	Female	0.88
Smiling false	0.8	Senior	0.7933
No eyewear	0.7481	Hair color blond	0.7875
Child	0.8276	White	0.763
Mustache	0.815	Youth	0.692

Analysis on FaceTracer dataset



Analysis on MOBIO

Samangouei, Patel and Chellappa, *IVC*, 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: recognition by comparative face labels

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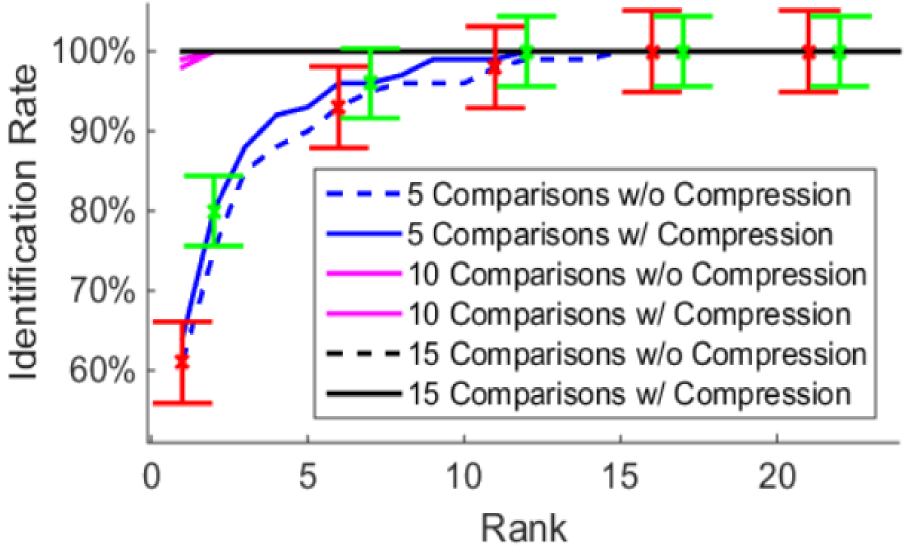
Label compression improves recognition

Data is Southampton tunnel

New system just 3:

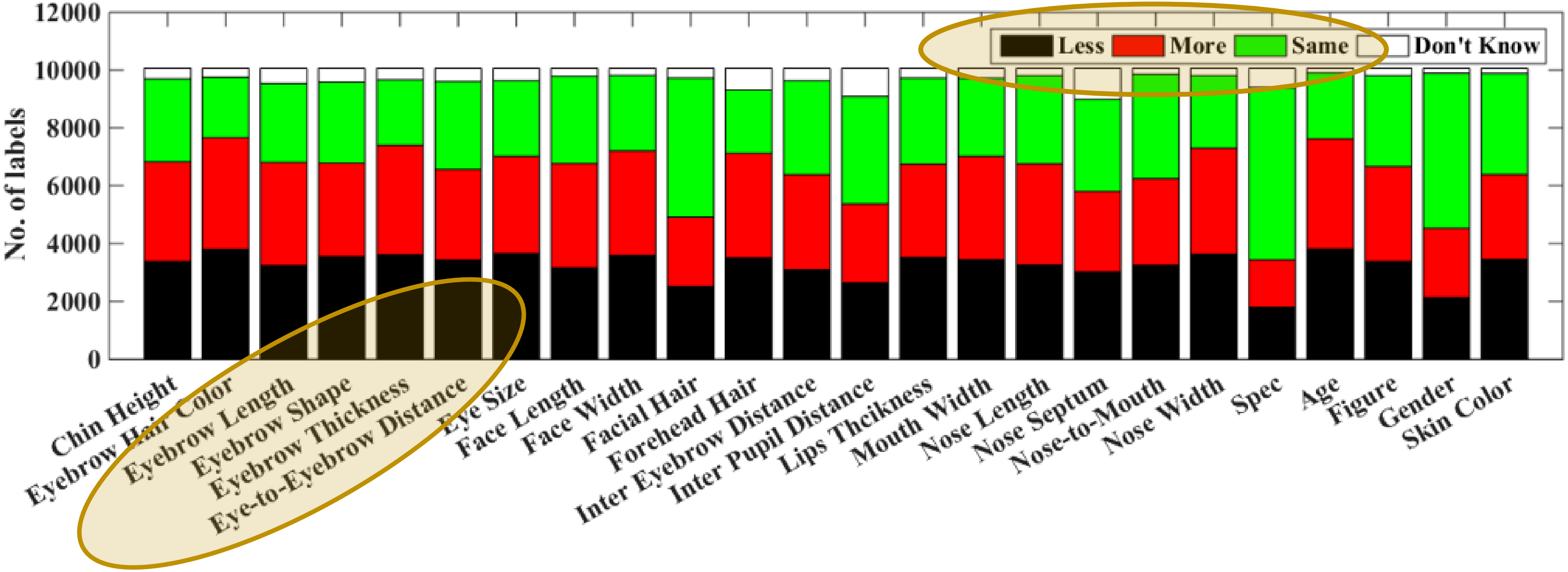
bigger, **same**, **smaller**

Had we previously added categorical to comparative?



Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

Face label distribution



Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

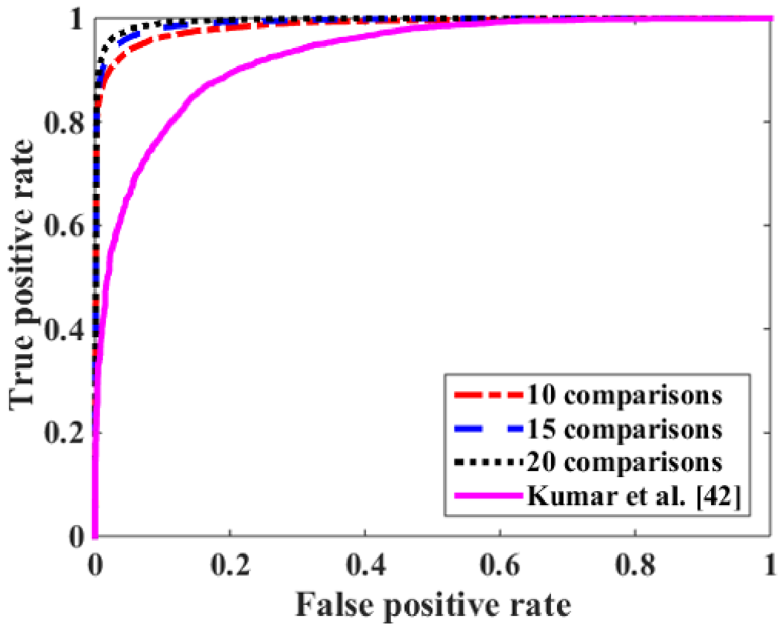
Face recognition and verification on LFW

6-fold cross validation: 4038 subjects, 6 folds each with 673 subjects

Rank-10 identification rate 96.14%, 99.18%, 99.8% using 10, 15, and 20 comparisons

EERs were: 23.43%, 20.64%, and 18.22%, using 10, 15, and 20 comparisons

Kumar et al [42] achieved a verification accuracy of 85.25% on View 2 of LFW using trained classifiers for 73 binary attributes.



Almudhahka, Nixon and Hare, *IEEE BTAS 2016*

Crossing the semantic gap: estimating relative face attributes

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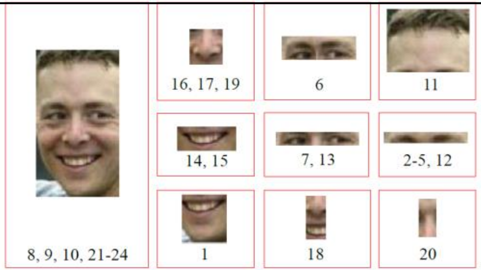
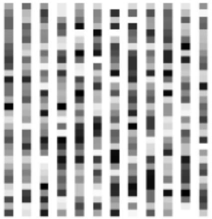




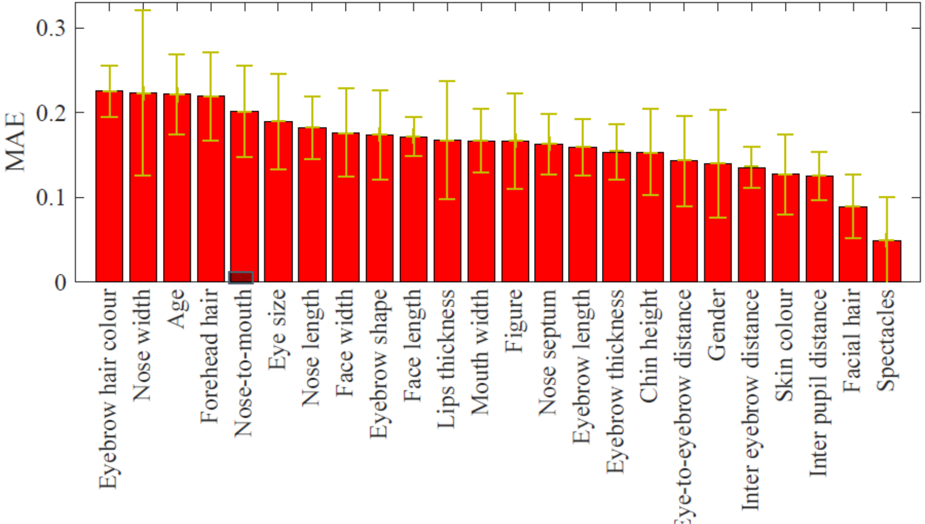
Face alignment

Segmented face parts

Features HOG/GIST/ULBP

Constrained Local Models/ AAMs

Estimation of comparative labels



Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Estimating face attributes

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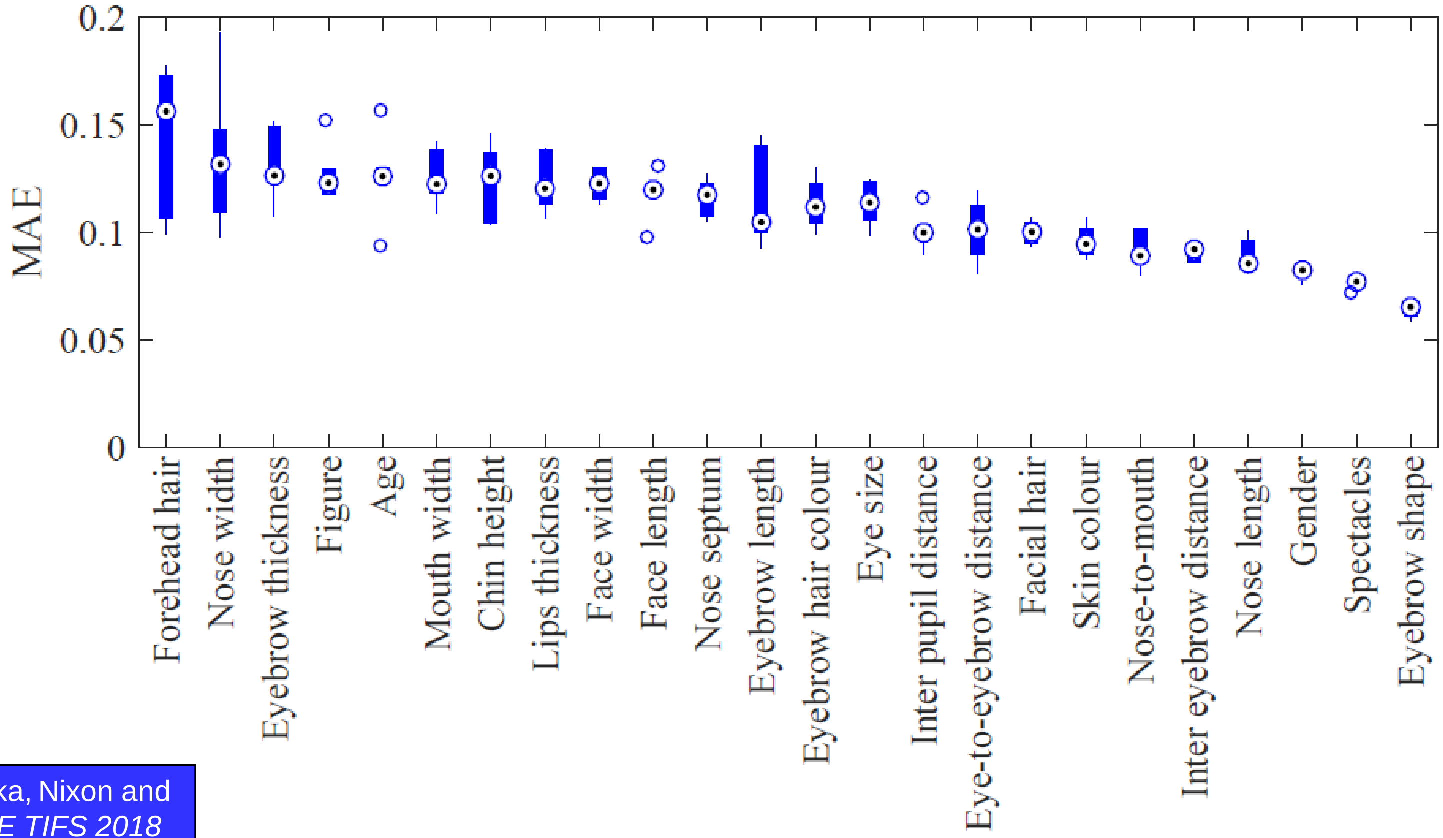

Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Ranking subjects (images) by estimated face attributes

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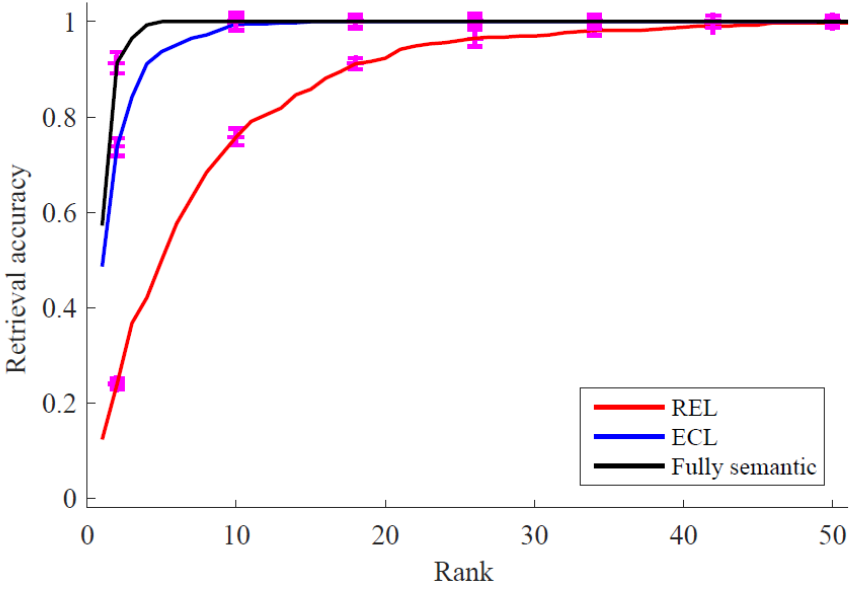
(a) Age

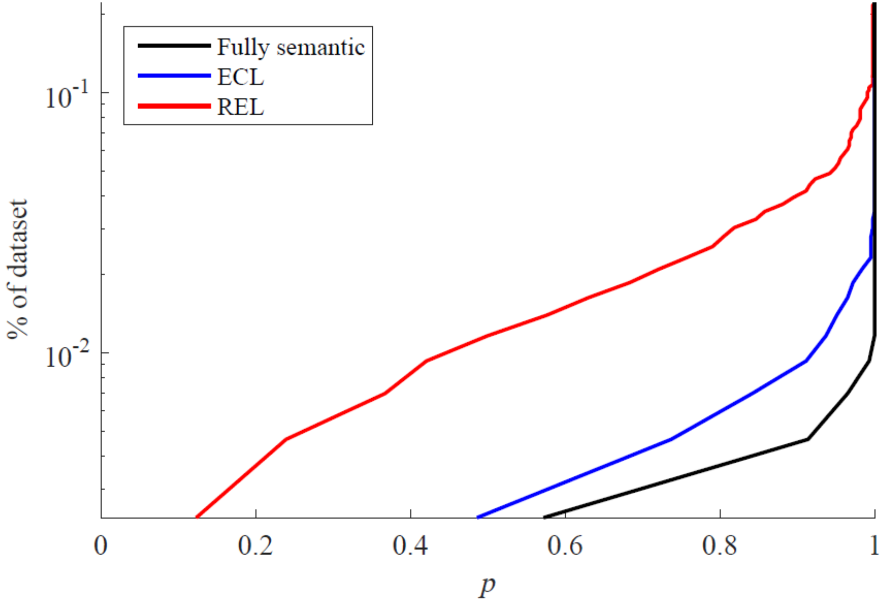
(b) Gender

Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

Recognition on LFW



Retrieval performance



Compression of 430 subject LFW-MS4 dataset

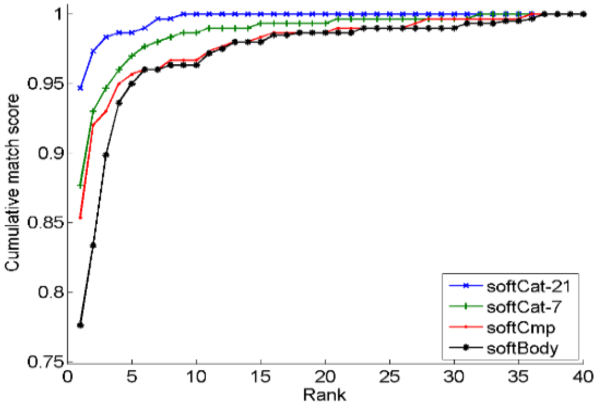
Almudhahka, Nixon and Hare, *IEEE TIFS 2018*

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*

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Clothing labels

Body zone	Semantic Attribute	Categorical Labels	Comparative Labels
Head	1. Head clothing category	[None, Hat, Scarf, Mask, Cap]	
	2. Head coverage	[None, Slight, Fair, Most, All]	[Much Less, Less, Same, More, Much more]
	3. Face covered	[Yes, No, Don't know]	[Much Less, Less, Same, More, Much more]
	4. Hat	[Yes, No, Don't know]	
Upper body	5. Upper body clothing category	[Jacket, Jumper, T-shirt, Shirt, Blouse, Sweater, Coat, Other]	
	6. Neckline shape	[Strapless, V-shape, Round, Shirt collar, Don't know]	
	7. Neckline size	[Very Small, Small, Medium, Large, Very Large]	[Much Smaller, Smaller, Same, Larger, Much Larger]
	8. Sleeve length	[Very Short, Short, Medium, Long, Very Long]	[Much Shorter, Shorter, Same, Longer, Much Longer]
Lower body	9. Lower body clothing category	[Trouser, Skirt, Dress]	
	10. Shape	[Straight, Skinny, Wide, Tight, Loose]	
	11. Leg length (of lower clothing)	[Very Short, Short, Medium, Long, Very Long]	[Much Shorter, Shorter, Same, Longer, Much Longer]
	12. Belt presence	[Yes, No, Don't know]	
Foot	13. Shoes category	[Heels, Flip flops, Boot, Trainer, Shoe]	
	14. Heel level	[Flat/low, Medium, High, Very high]	[Much Lower, Lower, Same, Higher, Much higher]
Attached to body	15. Attached object category	[None, Bag, Gun, Object in hand, gloves]	
	16. Bag (size)	[None, Side-bag, Cross-bag, Handbag, Backpack, Satchel]	[Much Smaller, Smaller, Same, Larger, Much Larger]
	17. Gun	[Yes, No, Don't know]	
	18. Object in hand	[Yes, No, Don't know]	
	19. Gloves	[Yes, No, Don't know]	
General style	20. Style category	[Well-dressed, Business, Sporty, Fashionable, Casual, Nerd, Bibes, Hippy, Religious, Gangsta, Tramp, Other]	
Permanent	21. Tattoos	[Yes, No, Don't know]	

Jaha and Nixon, *IEEE IJCB 2014*

Context: describing clothing by semantic attributes

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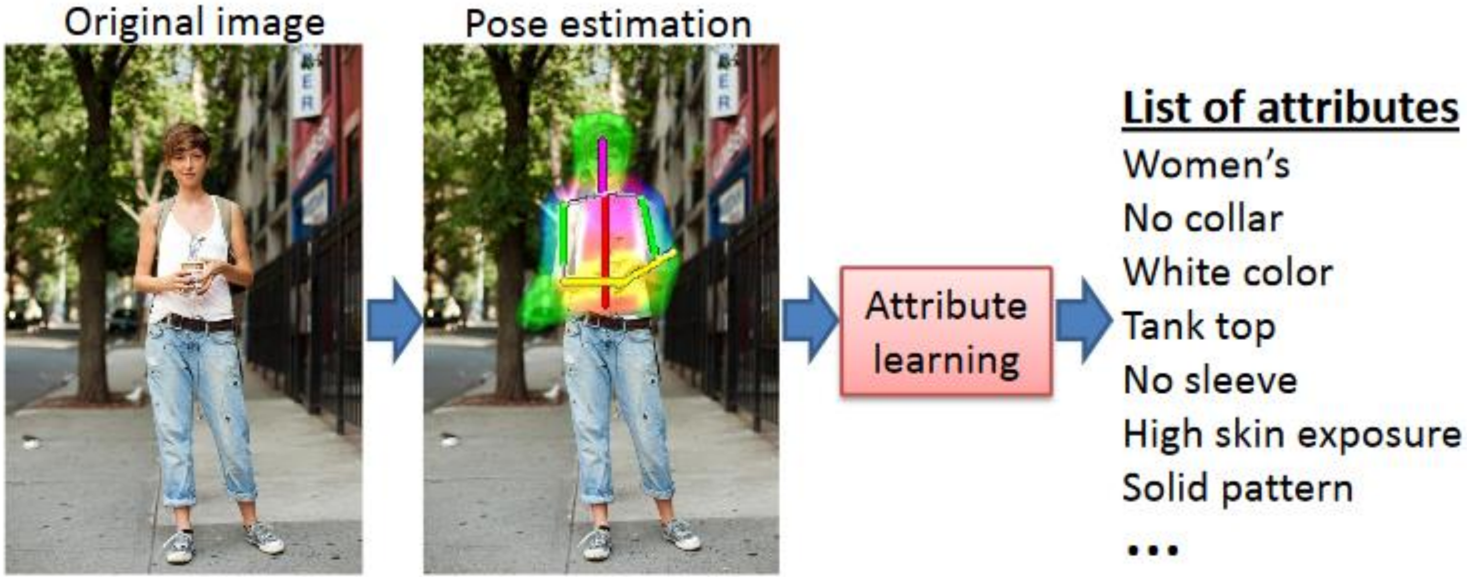

CAT: Clothing attribute dataset

Chen, Gallagher and Girod, *ECCV* ,*2012*

Context: describing clothing by semantic attributes

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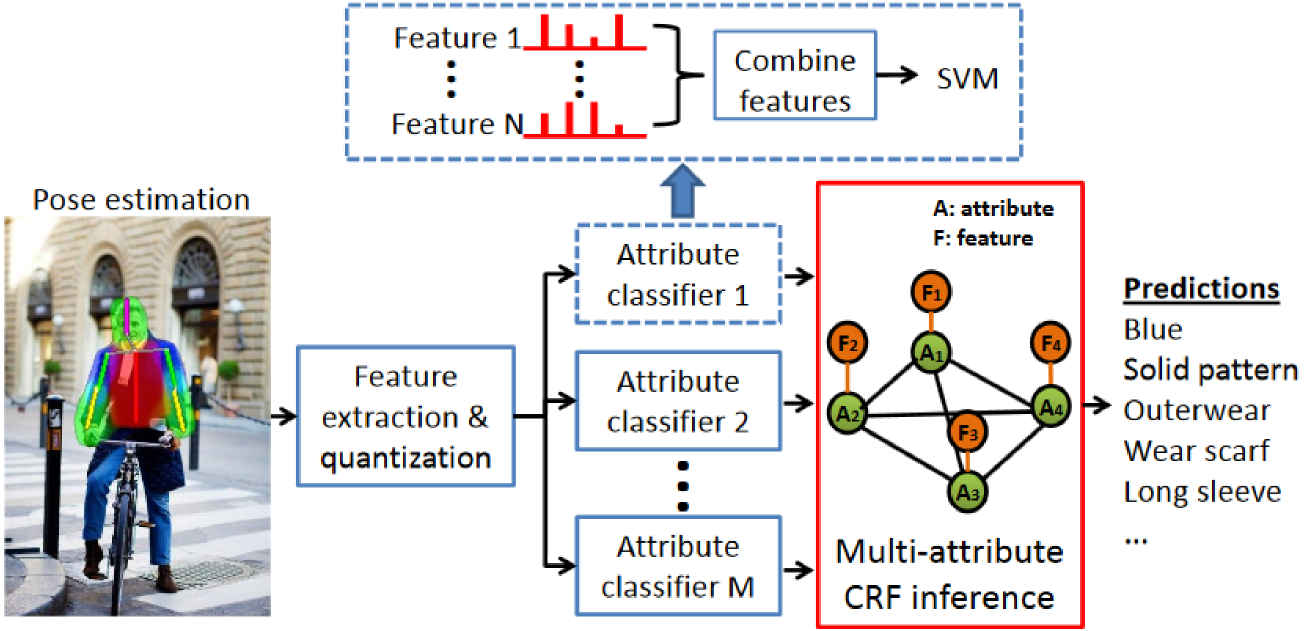

Just clothing ID, not person ID

Chen, Gallagher and Girod, *ECCV ,2012*

Context: Deep Domain Adaptation for Describing People Based on Fine-Grained Clothing

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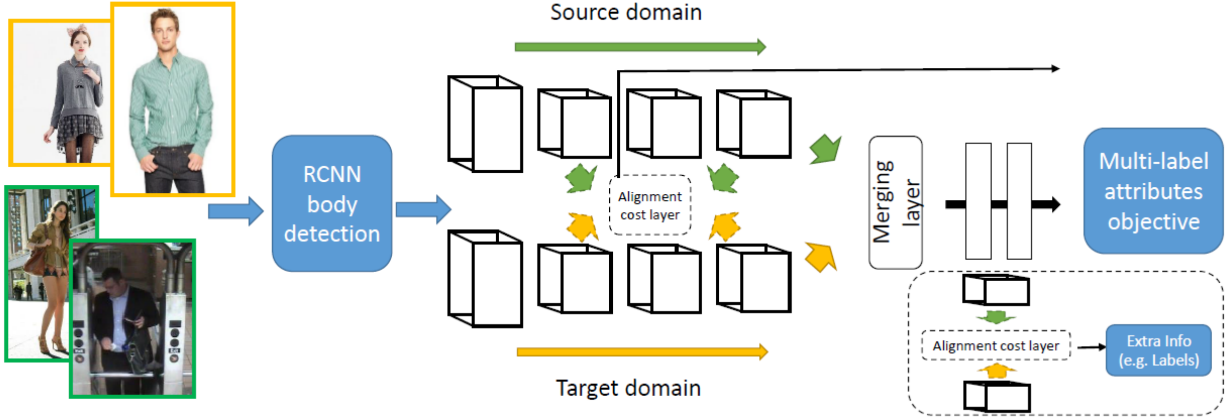
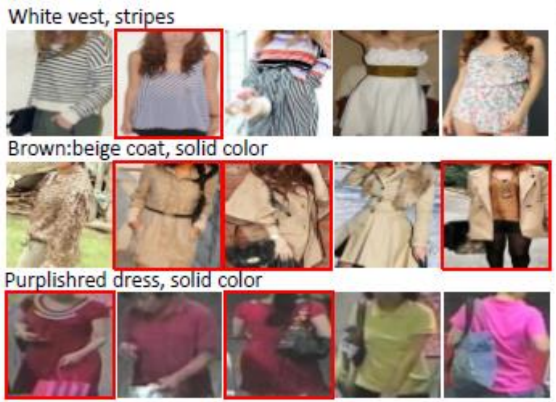
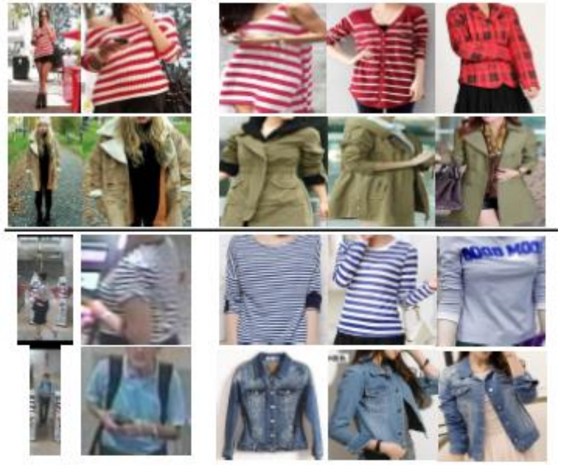






Chen, Huang ...,
CVPR, 2015

Clothing alone and in addition to body descriptions

By clothing alone 100% accuracy achieved at rank:

tradCat-21: 29 tradCat-7: 37 tradCmp: 63

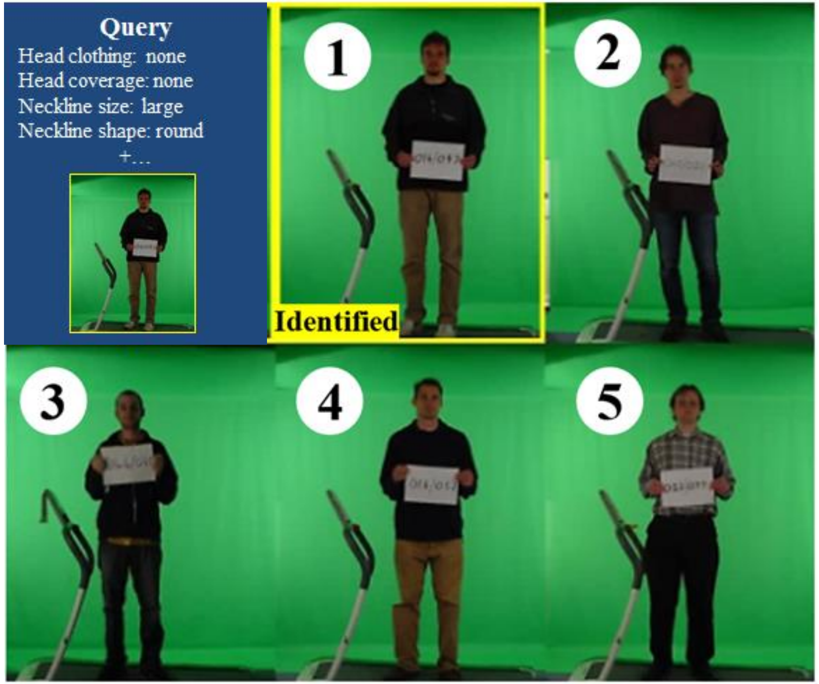
As expected, less power than body

Adding clothing to body allows much greater power

Approach	Top rank	AVG sum match scores up to rank		100% accuracy achieved at rank	EER	AUC	*d'*
	=1	*=10*	*=128*				
softBody	0.78	0.92	0.991	37	0.087	0.028	2.785
softCat-21	**0.95**	**0.99**	**0.999**	**9**	**0.050**	**0.014**	2.634
softCat-7	0.88	0.96	0.996	32	0.063	0.018	2.814
softCmp	0.85	0.94	0.994	36	0.080	0.026	**2.827**

Jaha and Nixon, *IEEE IJCB 2014*

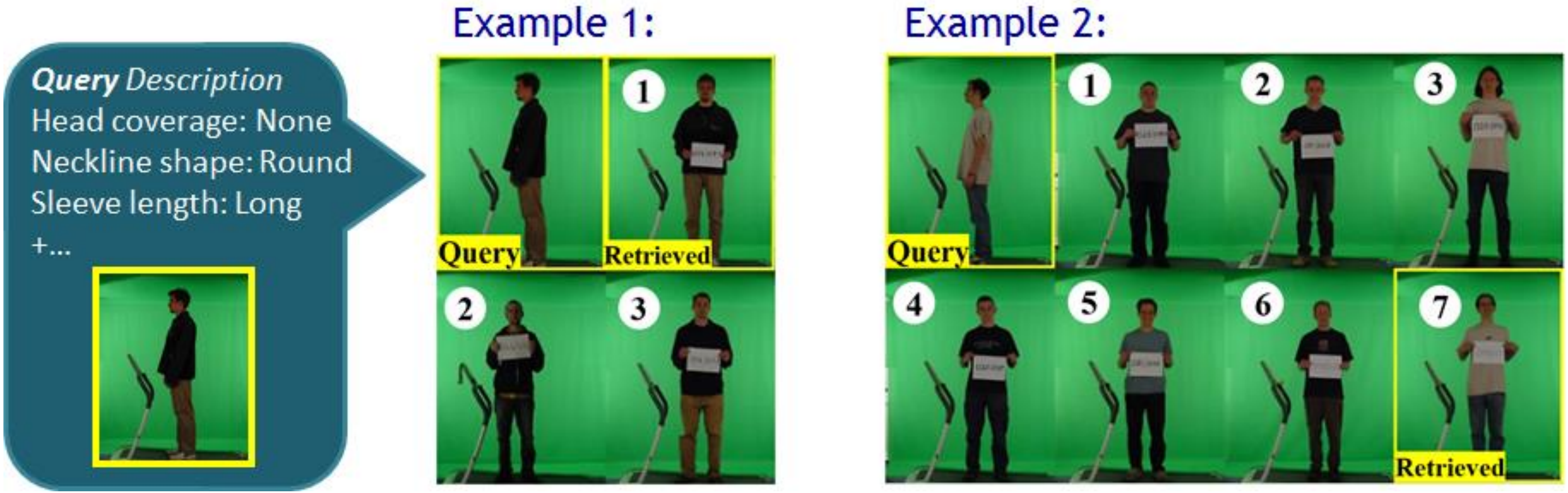
Recognition by clothing



Good match Poor matches

Jaha and Nixon, *IEEE IJCB 2014*

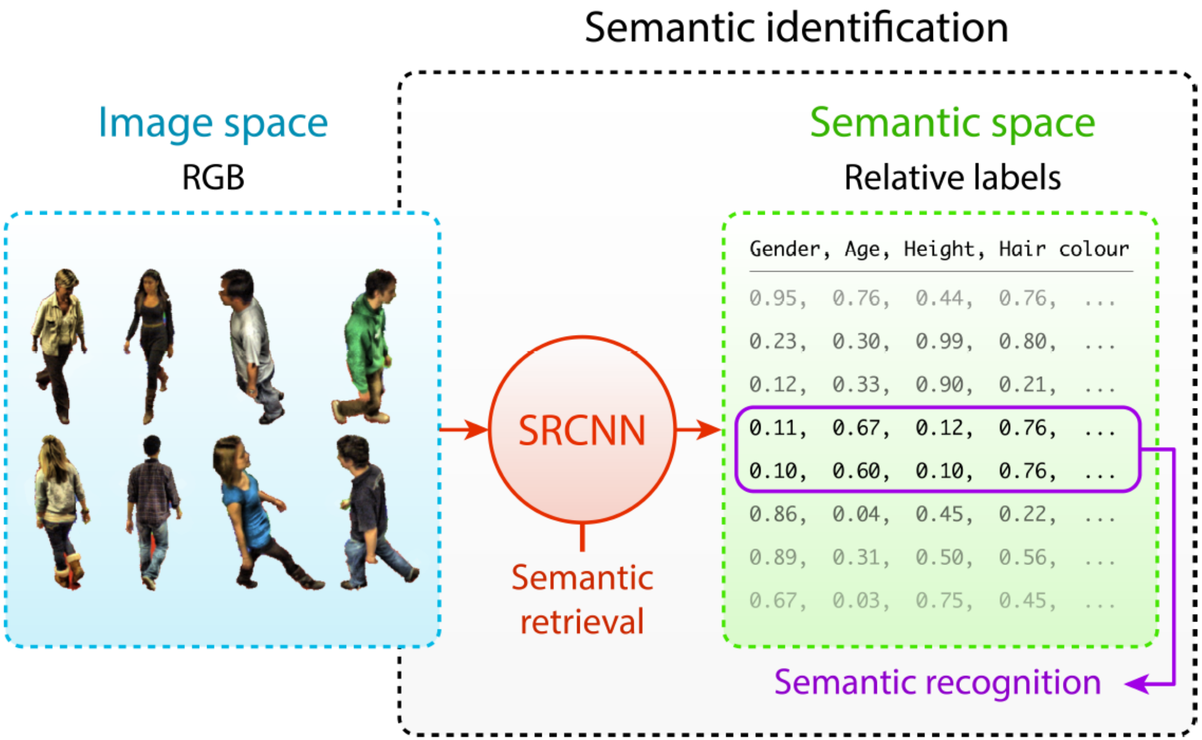
Viewpoint invariant recognition, by clothing



Clothing has ability to handle 90 degree change

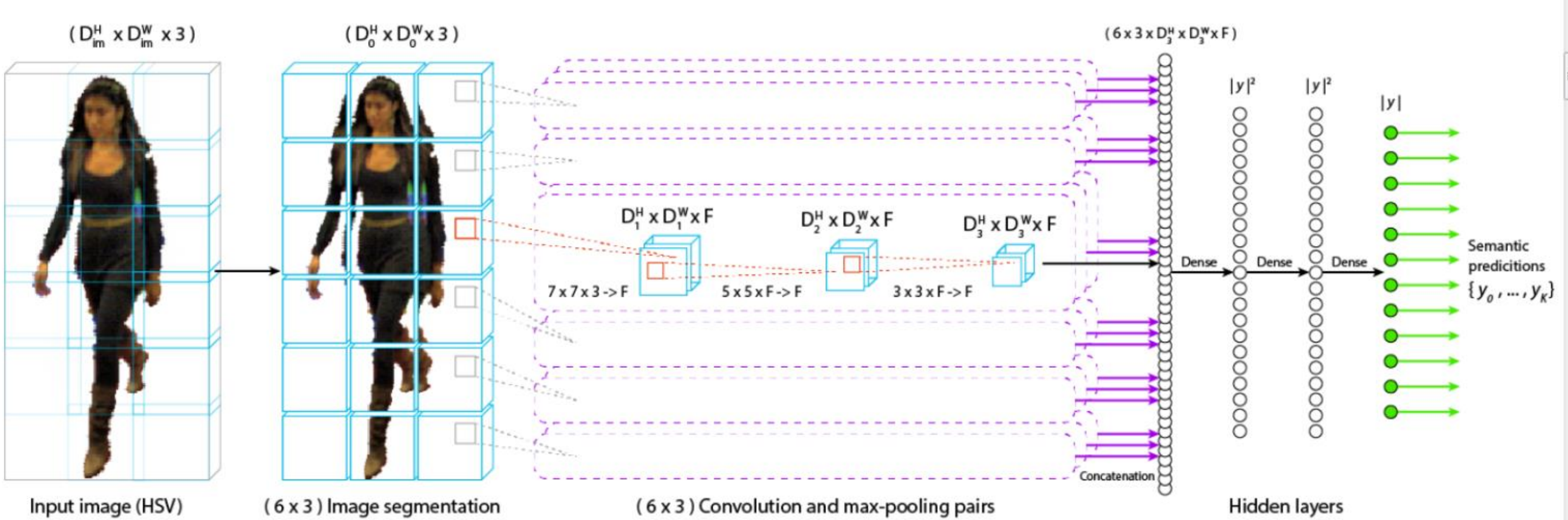
Jaha and Nixon, *IEEE ICB 2015*

Estimating labels



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

Architecture



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

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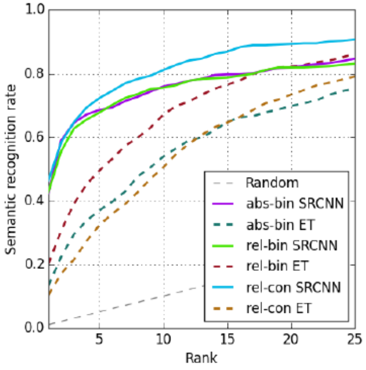
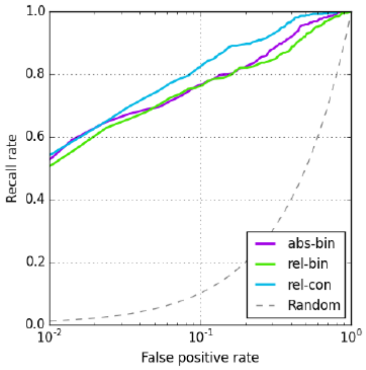
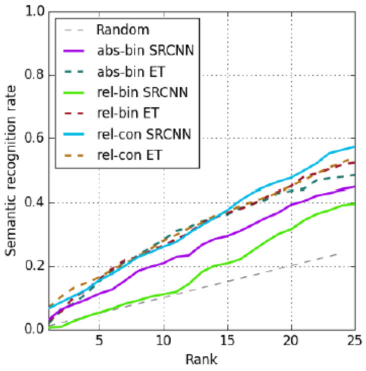
Recognition by estimated semantics



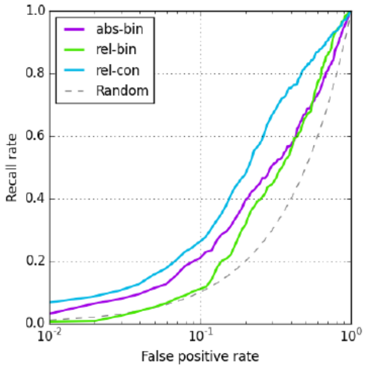
(a) Multi-shot CMC.



(b) Multi-shot ROC.



(c) Zero-shot CMC.



(d) Zero-shot ROC.

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

From Clothing to Identity: Manual and Automatic Soft Biometrics

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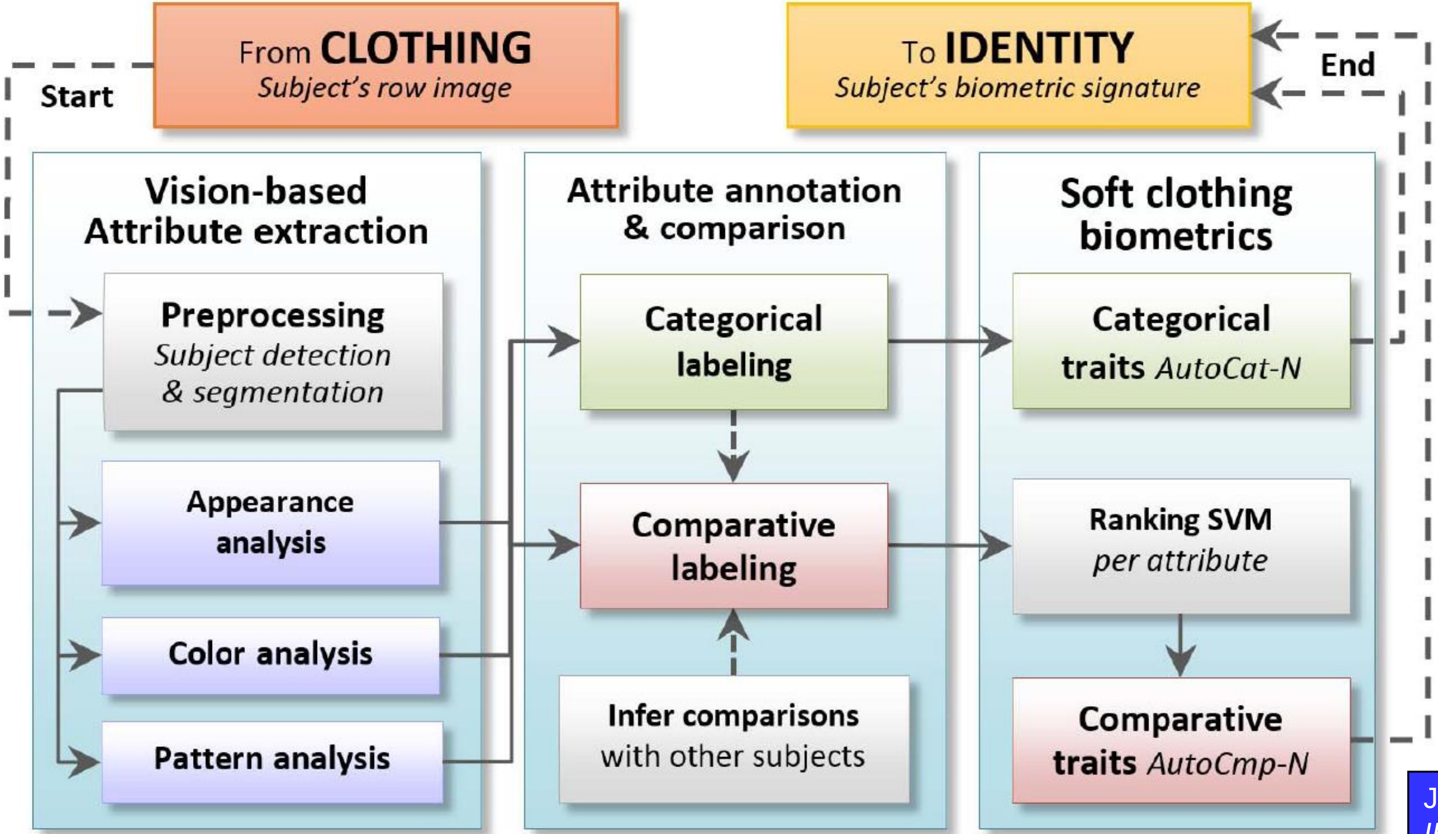

Jaha and Nixon, *IEEE TIFS 2016*

Automated clothing: grabcut person/ clothing initialisation

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- Color models used to initialize the Grabcut person extractor
- Color models arranged to highlight foreground/ background
- Result highlighted for (later) subject segmentation

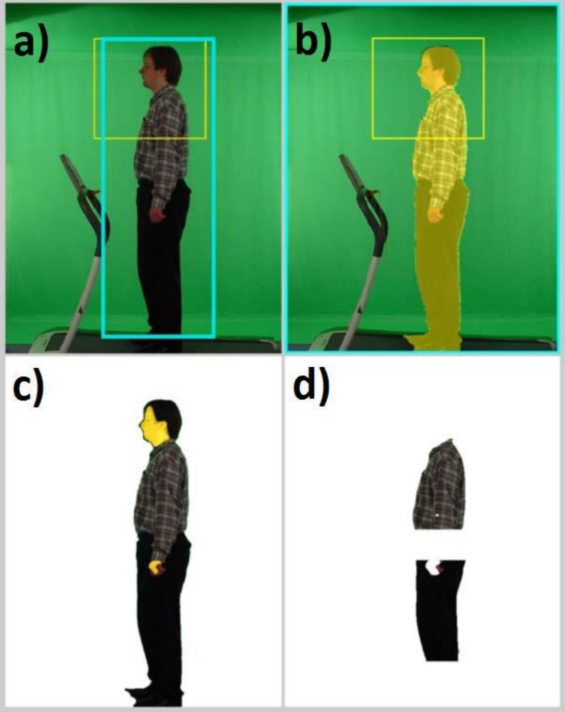
Jaha and Nixon, *IEEE TIFS 2016*

Automatic clothing analysis

Automatically extract 17 categorical soft clothing attributes

a. detection;
b. head and body;
c. minus background and with skin;
d. final clothing segmentation

(Subject 094) Automatic soft biometric labeling



Soft Clothing Traits:

A1. Overall Skin exposure: Very Low
A2. Overall Clothing season: Cold
A3. Upper vs Lower Contrast: Medium
A4. Overall Color-scheme: Neutral

A5. Upper Skin exposure: Very Low
A6. Upper Clothing season: Cold
A7. Upper Brightness: Medium
A8. Upper Color-scheme: Neutral
A9. Upper Dominant color: Dual
A10. Upper Pattern: Complex

A11. Lower Skin exposure: Very Low
A12. Lower Clothing season: Cold
A13. Lower Brightness: Very Dark
A14. Lower Color-scheme: Neutral
A15. Lower Dominant color: Single
A16. Lower Pattern: None
A17. Footwear Category: Closed Toed

Jaha and Nixon, *IEEE TIFS 2016*

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	Clothing-based soft biometrics	
MANUAL	***Cat-6***	6 *manual* categorical clothing traits; the best correlated and most discriminative via ANOVA
	Cmp	7 *manual* comparative soft clothing traits
AUTOMATIC	***AutoCat-14***	Top 14 *automatic* categorical clothing traits via ANOVA
	AutoCmp-5	Top 5 *automatic* comparative clothing traits via ANOVA
	Auto(Cat-14&Cmp-5)	Fusion of ***AutoCat-14*** and ***AutoCmp-5***

	Body-based soft biometrics	
	tradSoft	4 categorical soft body biometrics (*Age*, *Ethnicity*, *Sex*, and *Skin Color*)
	softBody	17 categorical soft body biometrics including ***tradSoft***

	Combined soft clothing & body biometrics	
Clothing & ***tradSoft***	***tradAutoCat-14***	***AutoCat*-14** combined with ***tradSoft***
	tradAutoCmp-5	***AutoCmp-5*** combined with ***tradSoft***
	tradAuto(Cat-14&Cmp-5)	***Auto(Cat-14&Cmp-5)*** combined with ***tradSoft***
	tradCat-6	***Cat-6*** combined with ***tradSoft***
	tradCmp	***Cmp*** combined with ***tradSoft***
Clothing & ***softBody***	***softAutoCat-14***	***AutoCat*-14** combined with ***softBody***
	softAutoCmp-5	***AutoCmp-5*** combined with ***softBody***
	softAuto(Cat-14&Cmp-5)	***Auto(Cat-14&Cmp-5)*** combined with ***softBody***
	softCat-6	***Cat-6*** combined with ***softBody***
	softCmp	***Cmp*** combined with ***softBody***

Recognition by automatic and human derived labels

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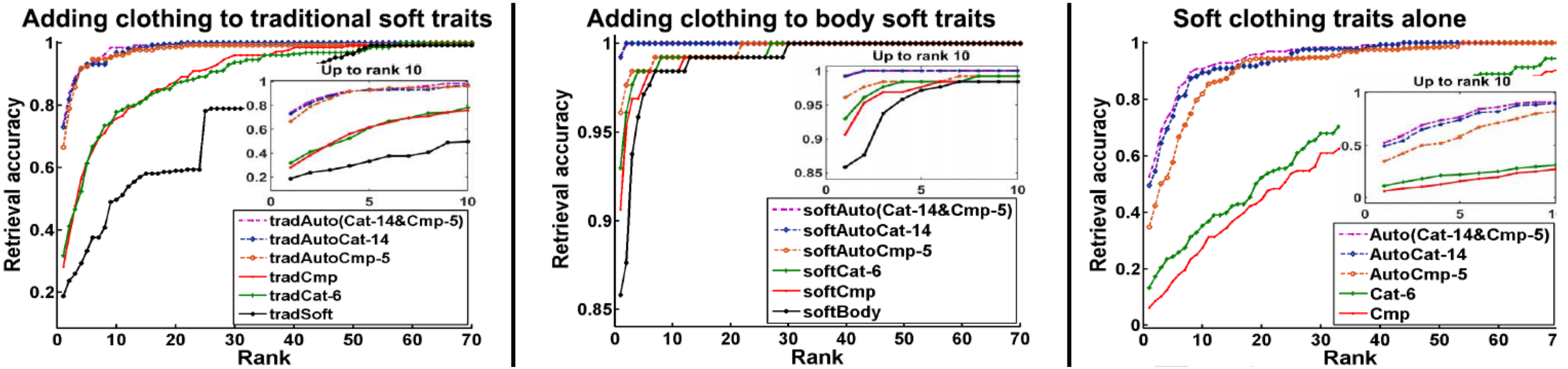

Recognition can be achieved by human derived labels and by automatically derived labels

We have crossed the semantic gap, both ways….

Jaha and Nixon, *IEEE TIFS 2016*

Automated clothing labelling on CAT

Jaha and Nixon, *IEEE TIFS 2016*

Soft biometric fusion – synthesised data

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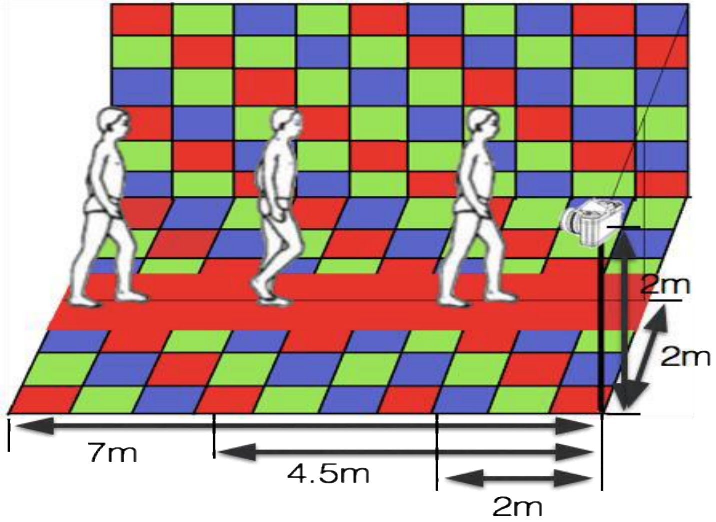
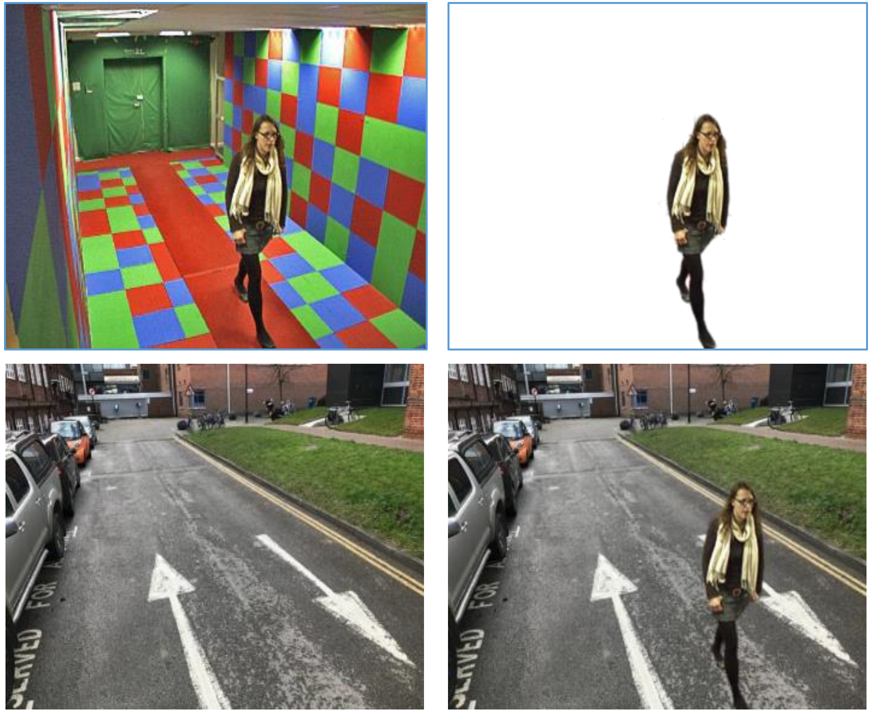
Gait tunnel





Guo, Nixon and Carter, *IEEE TBIOM* 2019

Soft biometric fusion – labels

Gathering body labels

Gathering clothing labels

Guo, Nixon and Carter, *IEEE TBIOM* 2019

Body performance

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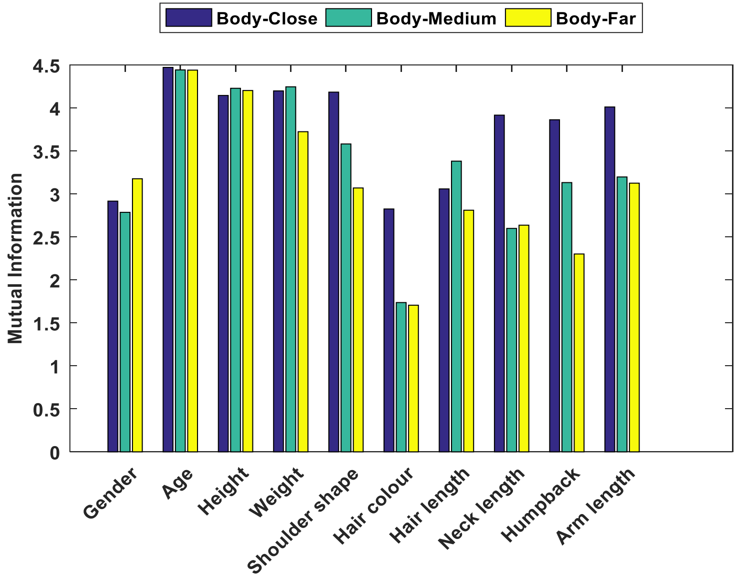

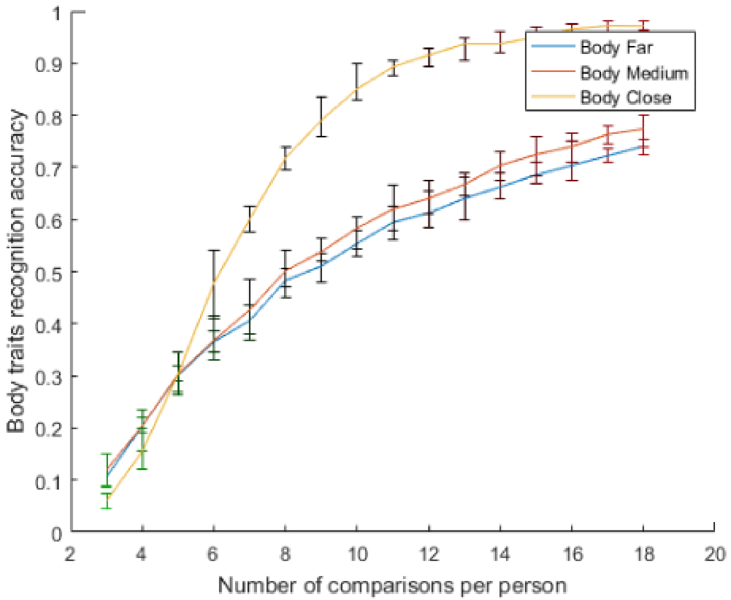

Guo, Nixon and Carter, *IEEE TBIOM* 2019

Face performance

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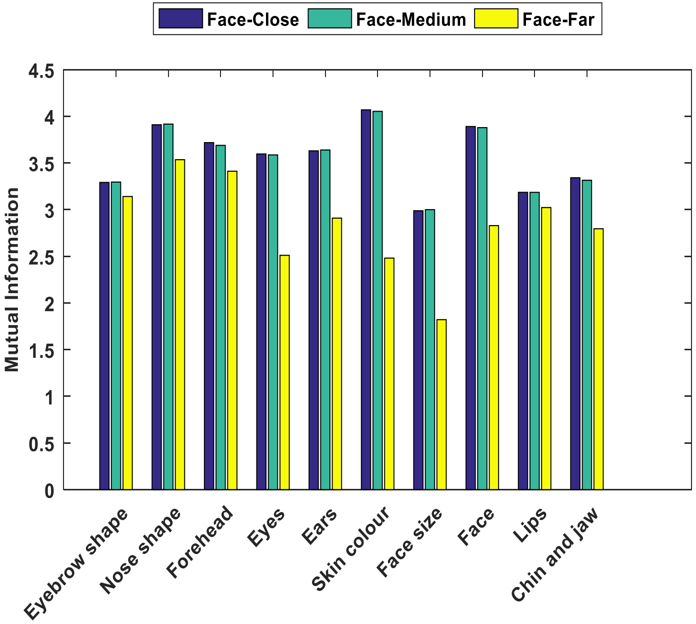

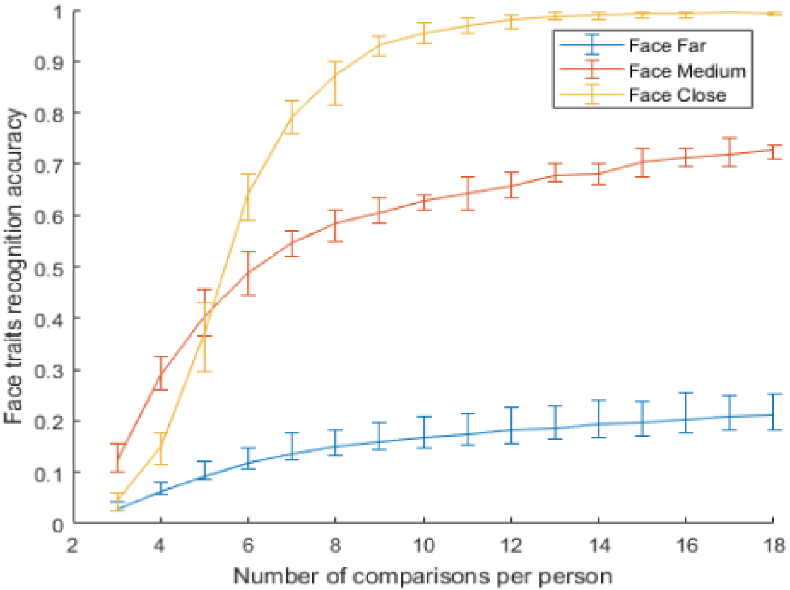

Guo, Nixon and Carter,
IEEE TBIOM 2019

Fusion performance

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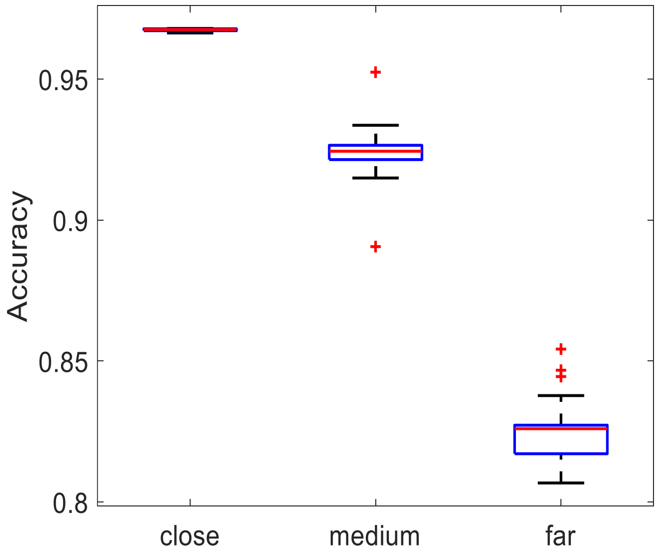

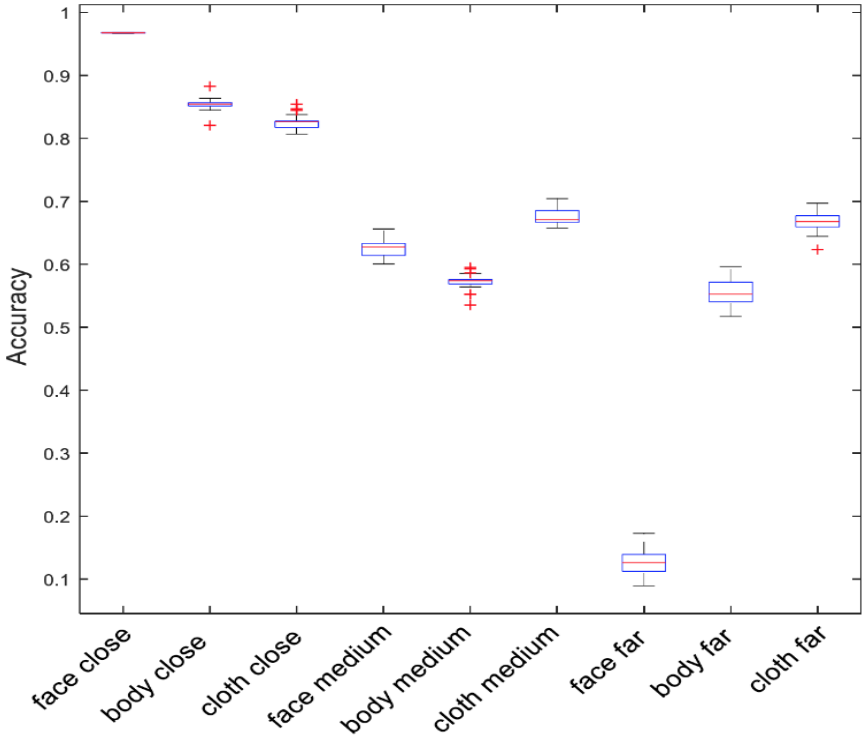

Guo, Nixon and Carter, *IEEE TBIOM* 2019

Conclusions

Soft biometrics

- ➔ are basis metrics for identification
- ➔ offer capability for new application scenarios
- ➔ are not restricted to performance enhancement
- ➔ have application advantages especially suited to surveillance (poor lighting and distance/ low resolution)
- ➔ need wider investigation (covariates, antispoofing) as to performance advantages
- ➔ motivate need for new insight as to automated identification vs. human identification

...and they are great fun. Questions and discussion please.

Further reading

1. On soft biometrics, MS Nixon, PL Correia, K Nasrollahi, TB Moeslund, A Hadid, M Tistarelli, *PRL* 2015
2. What else does your biometric data reveal? A survey on soft biometrics, A Dantcheva, P Elia, A Ross, *IEEE TIFS* 2016
3. Soft biometric traits for personal recognition systems, AK Jain, SC Dass, K Nandakumar, *ICBA* 2004
4. Facial soft biometrics for recognition in the wild: Recent works, annotation, and COTS evaluation E Gonzalez-Sosa, J Fierrez, R Vera-Rodriguez, F Alonso-Fernandez, *IEEE TIFS* 2018
5. Demographic analysis from biometric data: Achievements, challenges, and new frontiers Y Sun, M Zhang, Z Sun, T Tan, *IEEE TPAMI* 2018
6. The use of semantic human description as a soft biometric, S Samangooei, B Guo, MS Nixon, *IEEE BTAS* 2008
7. Soft biometrics; human identification using comparative descriptions, D Reid, MS Nixon, S Stevenage, *IEEE TPAMI* 2014
8. Soft biometrics and their application in person recognition at a distance, P Tome, J Fierrez, R Vera-Rodriguez, MS Nixon, *IEEE TIFS* 2014
9. From Clothing to Identity; Manual and Automatic Soft Biometrics, E Jaha, MS Nixon, *IEEE TIFS* 2016
10. Semantic face signatures: Recognizing and retrieving faces by verbal descriptions, N Almudhahka, MS Nixon, J Hare, *IEEE TIFS,* 2018
11. Super-fine attributes with crowd prototyping, D Martinho-Corbishley, MS Nixon, JN Carter, *IEEE TPAMI,* 2019
12. Soft biometric fusion for subject recognition at a distance, BH Guo, MS Nixon, JN Carter - *IEEE TBIOM* 2019

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Dr Hani Muammar, Dr 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 Benn, Dr Liang Ng, Dr Mark Toller, Dr John Manslow, Dr Mike Grant, Dr Jamie Shutler, Dr Karl Sharman, Prof Andrew Tatem, Layla Gordon, Dr Richard French, Dr Vijay Laxmi, Dr James Hayfron-Acquah, Dr Chew-Yean Yam, Dr 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, Di Meng, **Moneera Alnamnakani**

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