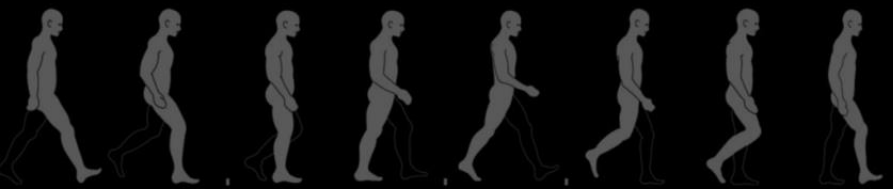
Biometric Authentication Systems

Chapter 11:

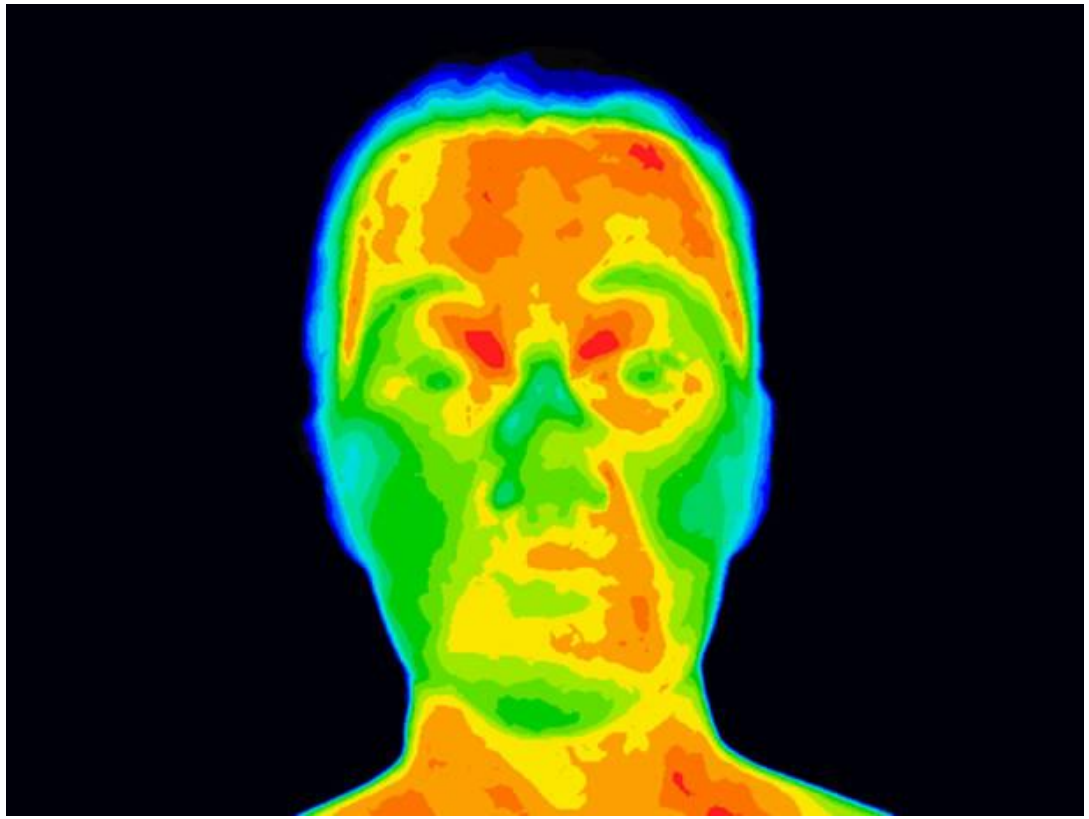
Gait

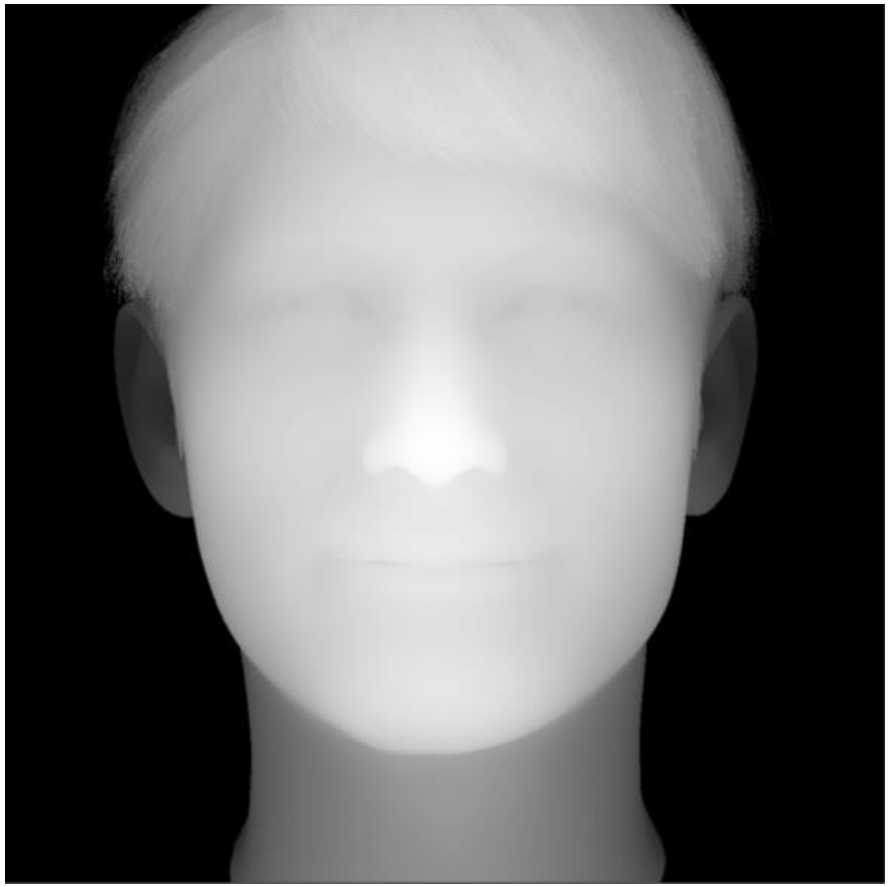
Ngo Thanh Trung



Reviewing questions

- 1- Why our brain do not recognize face easily with image modality like infrared image or depth images





Reviewing questions

- 2- List some face features at level 1?

Reviewing questions

- 3- List some face feature at level 3?

Reviewing questions

- 4- What can you tell the most significant diference between the different level features?

Reviewing questions

- 5- Why do we need multispectral camera for face recognition?

Reviewing questions

- 6- Why do we need Pan-Tilt-Zoom camera for practical face recognition?

Reviewing questions

- 7- Why do we use integral image in Viola-Johns face detector?

Reviewing questions

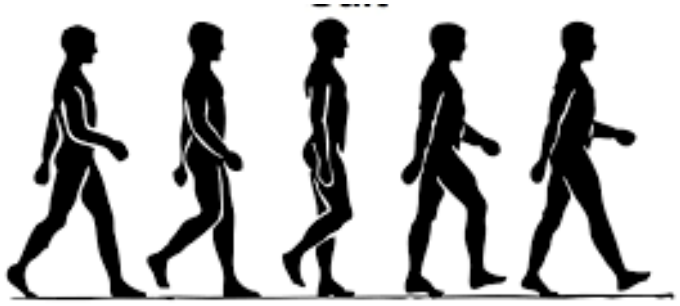
- 8- Why do we use PCA in face recognition?

Outline

1. Introduction
2. History of gait recognition
3. Gait feature extraction
4. Gait recognition

Introduction

- Gait: the way we walk
- Gait recognition: recognize people from the way we walk
- Gait is a behavioral biometrics
- More information from gait
  - Physical (health) condition
  - Gender, Age
  - Mood,



Is gait recognition necessary?

Short distance

Cooperative

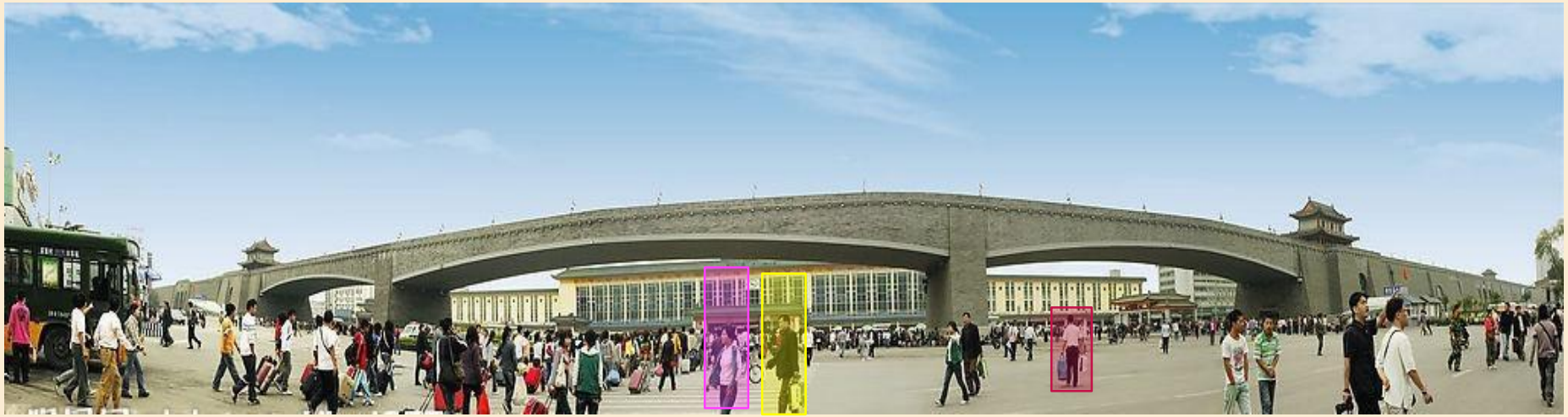
Fingerprint

Iris

Face

Long distance

Uncooperative



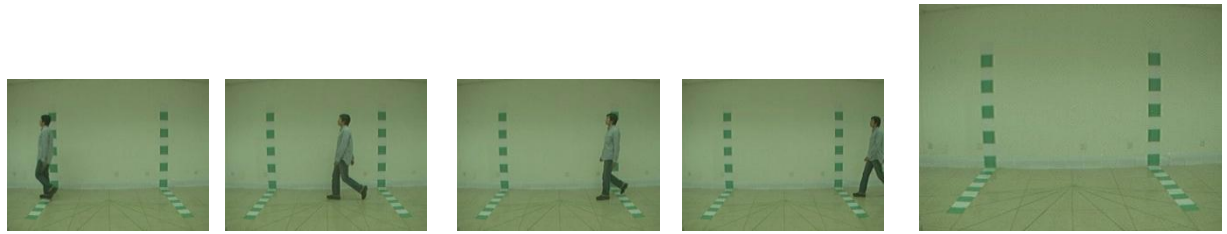
Gait

Is gait recognition necessary?

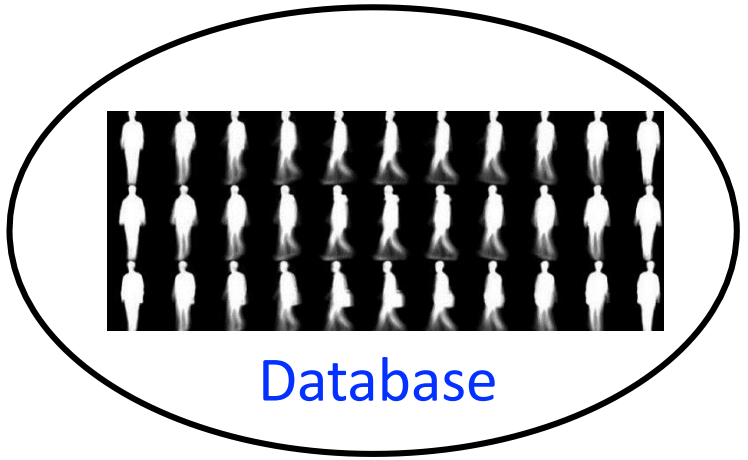
As a biometric, gait is still available at a distance when other biometrics are obscured or at too low resolution. Therefore, we need gait recognition.

Advantages: insensitive to distance, resolution, view, illumination

How does a gait recognition system work?



Intermediate representation
e.g Gait Energy image



Database

Learning Algorithm

Human ID

Applications of gait recognition

Suspect searching


Access control

Airport security

Robotics & Smart home

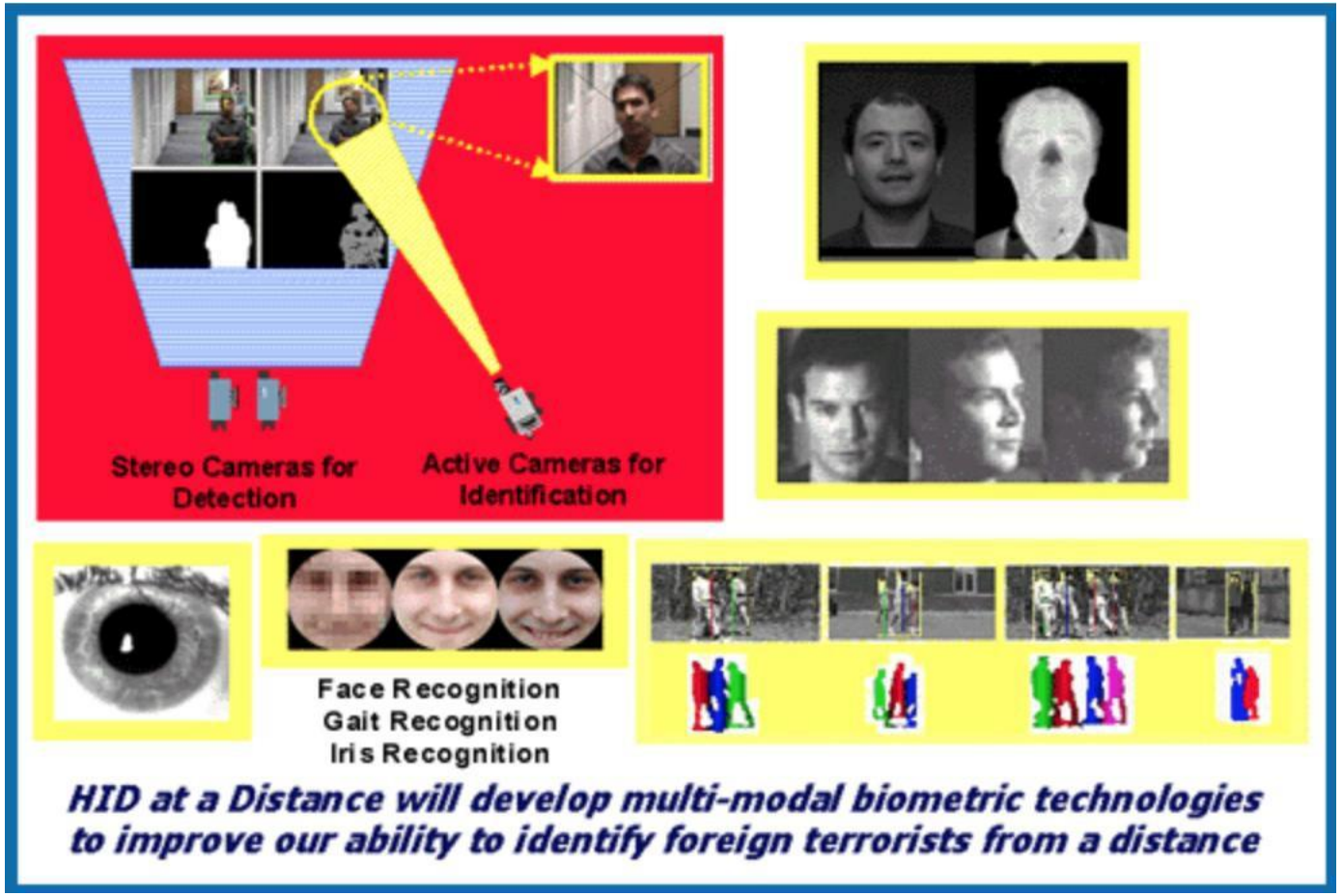
2- History of gait recognition:

[Slide Credit: Mark Nixon]

~350 BC 1500s 1600s

- Aristotle (~350 BC): The first to analyze gait. “On the gait of animals”
- Leonardo da Vinci (~1500): movement sketches
- Borelli (1600s): Father of biomechanics, study the mechanical principles of locomotion. *‘De Motu Animalium’*

DARPA program: Human ID at a distance

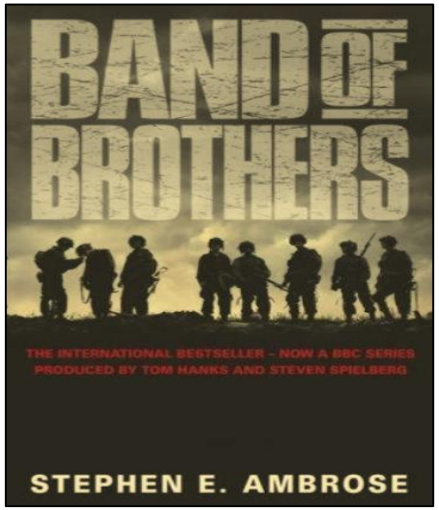


The DARPA program motivated the research on gait recognition

https://vrphobia.com/research/darpa-human-identification-at-a-distance-hid/

2- History of gait recognition:

[Slide Credit: Mark Nixon]



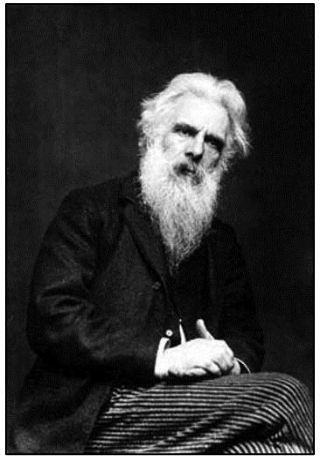
1600s

Shakespeare observed recognition:

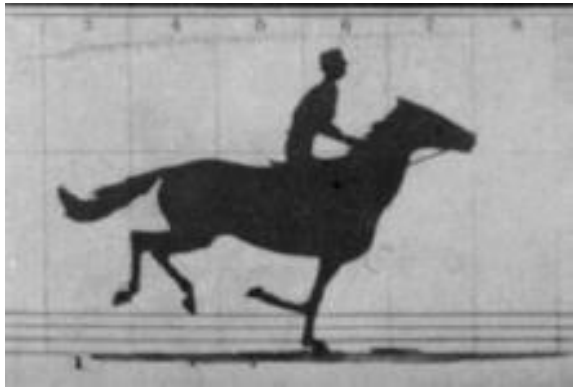
- "High'st Queen of state; Great Juno comes; I know her by her gait" [The Tempest]
- "For that John Mortimer....in face, in gait in speech he doth resemble" [Henry IV/2]

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

2-History of gait recognition:



Galloping horse, animated in 2006, using photos by Eadweard Muybridge



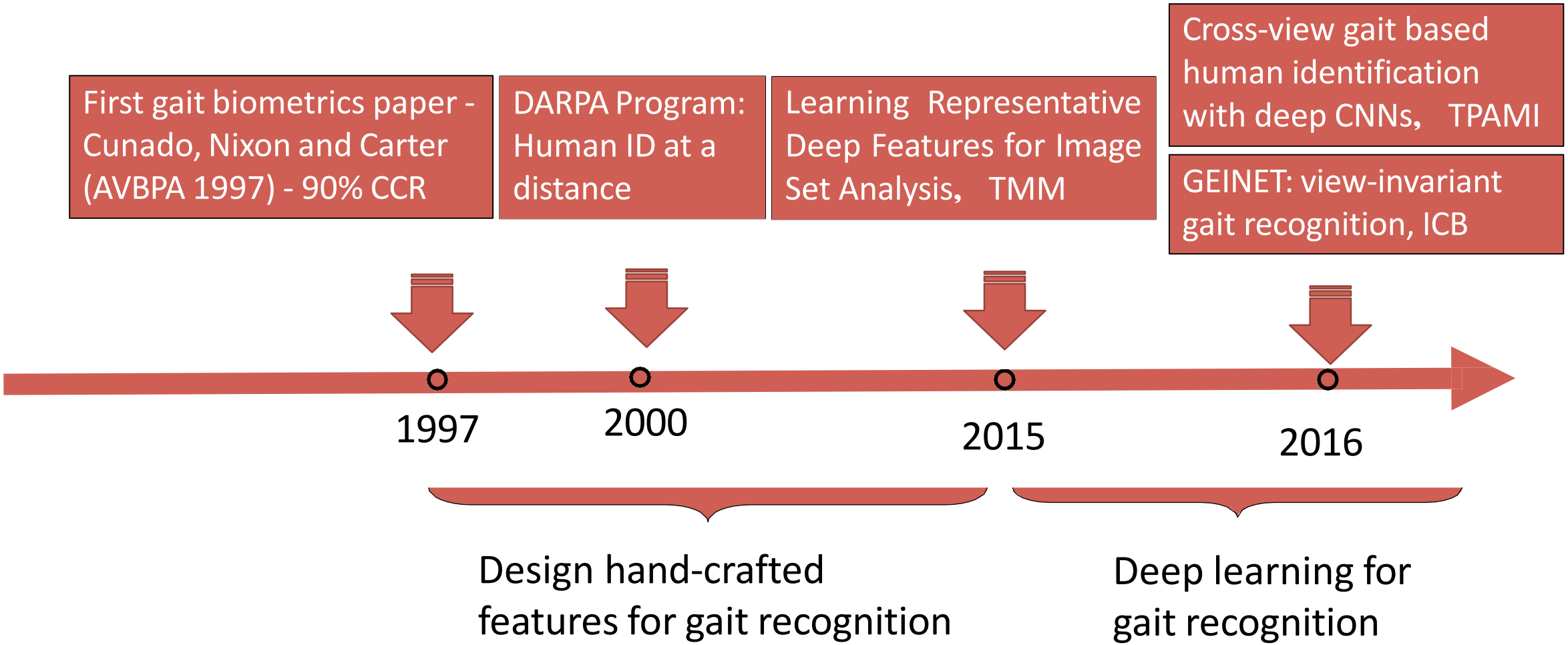
The Horse in Motion by Eadweard Muybridge. running at a 1:40 pace. Frames 1-11 used for animation

1800s

Eadweard Muybridge (1830-1904):

- Pioneering work in photographic studies of motion and motion-picture projection.
- Studied horses (1872):whether all four feet of a horse were off the ground at the same time while trotting
- Studied movement (1884)

2- History of gait recognition:

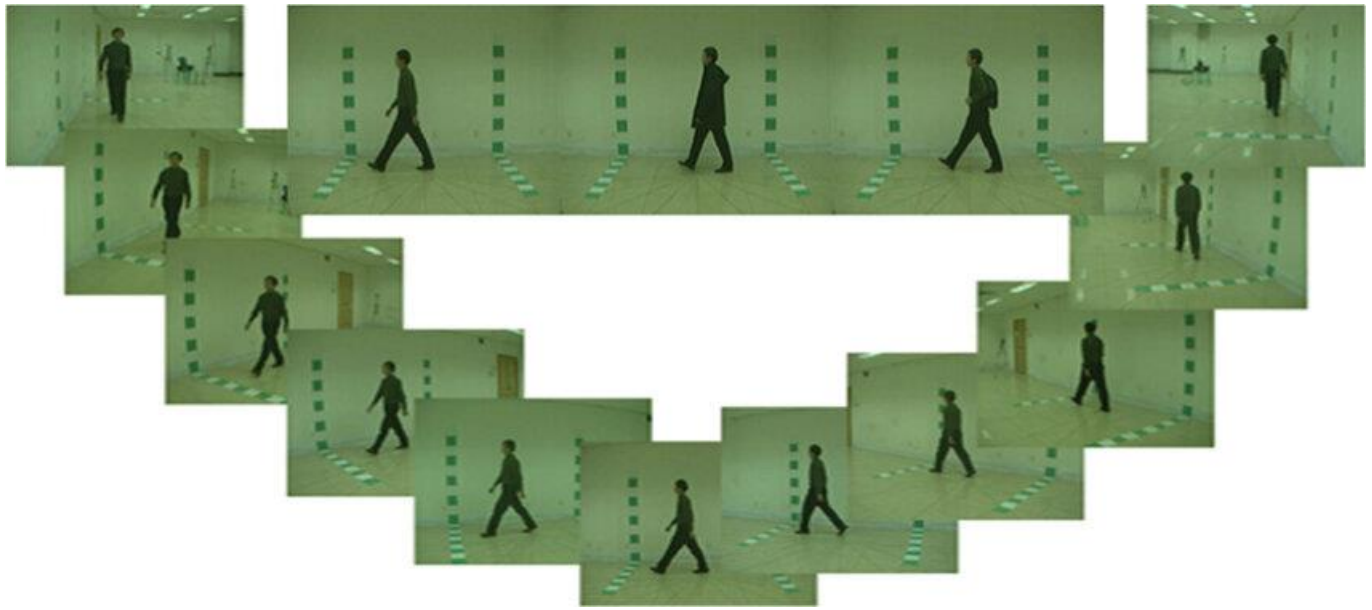


Gait variation

- Cloth, carrying variation

Gait variation

- View variation

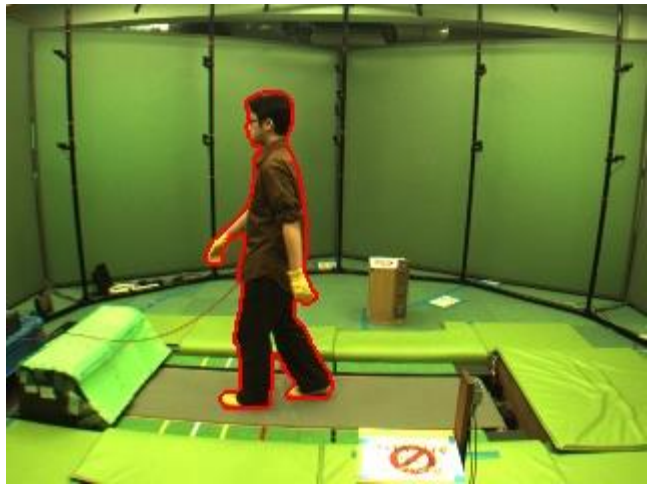


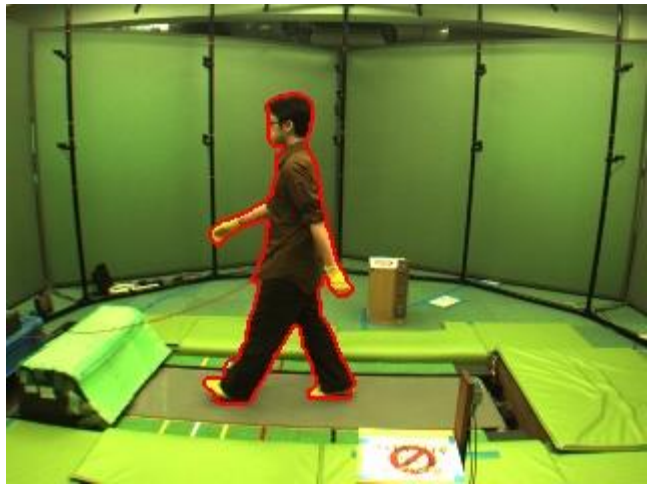
Gait variation

- Occlusion

Gait variation

- Speed variation





Gait variation

- Age variation

Gait variation

- Mood
- Physical condition
- Shoes
- Light
- …

Comparison with other biometric features

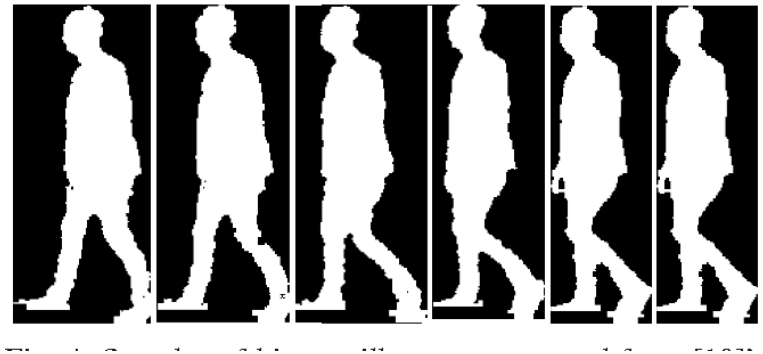
Biometric Features	Univ	Dist	Perm	Coll	Perf	Acce	Circ
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	H
Face	H	L	M	H	L	H	H
Facial Thermogram	H	H	L	H	M	H	L
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand Geometry	M	M	M	H	M	M	M
Hand Vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Palmprint	M	H	H	M	H	M	M
Retina	H	H	M	L	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

1. **Universality**
2. **Uniqueness**
3. **Permanence**
4. **Measurability**
5. **Performance**
6. **Acceptability**
7. **Circumvention**

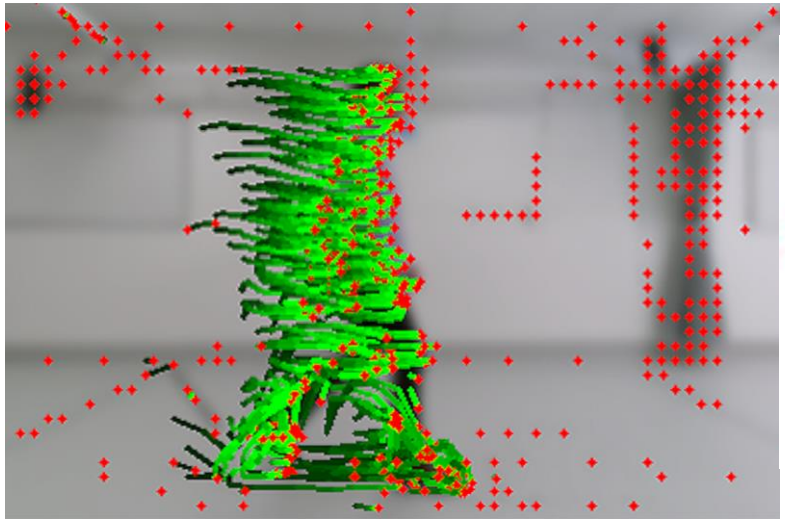
3- Gait feature extraction

Appearance-based features

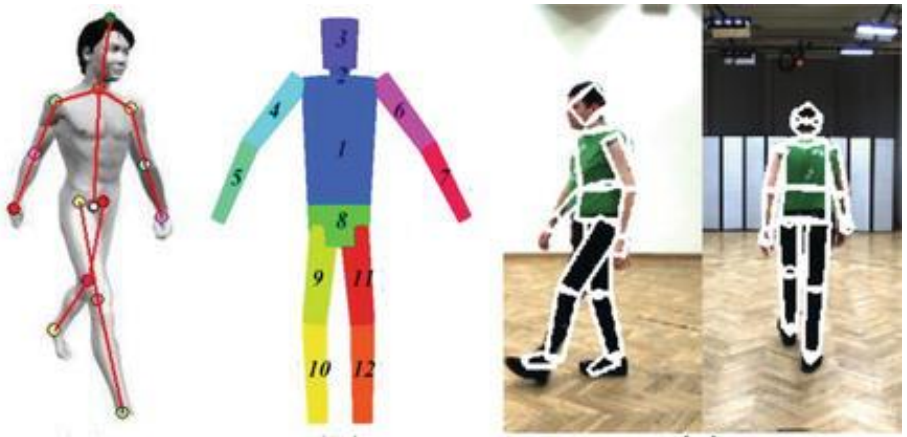
- Silhouette features
- Optical flows features
- Model-based features



Silhouette-based feature

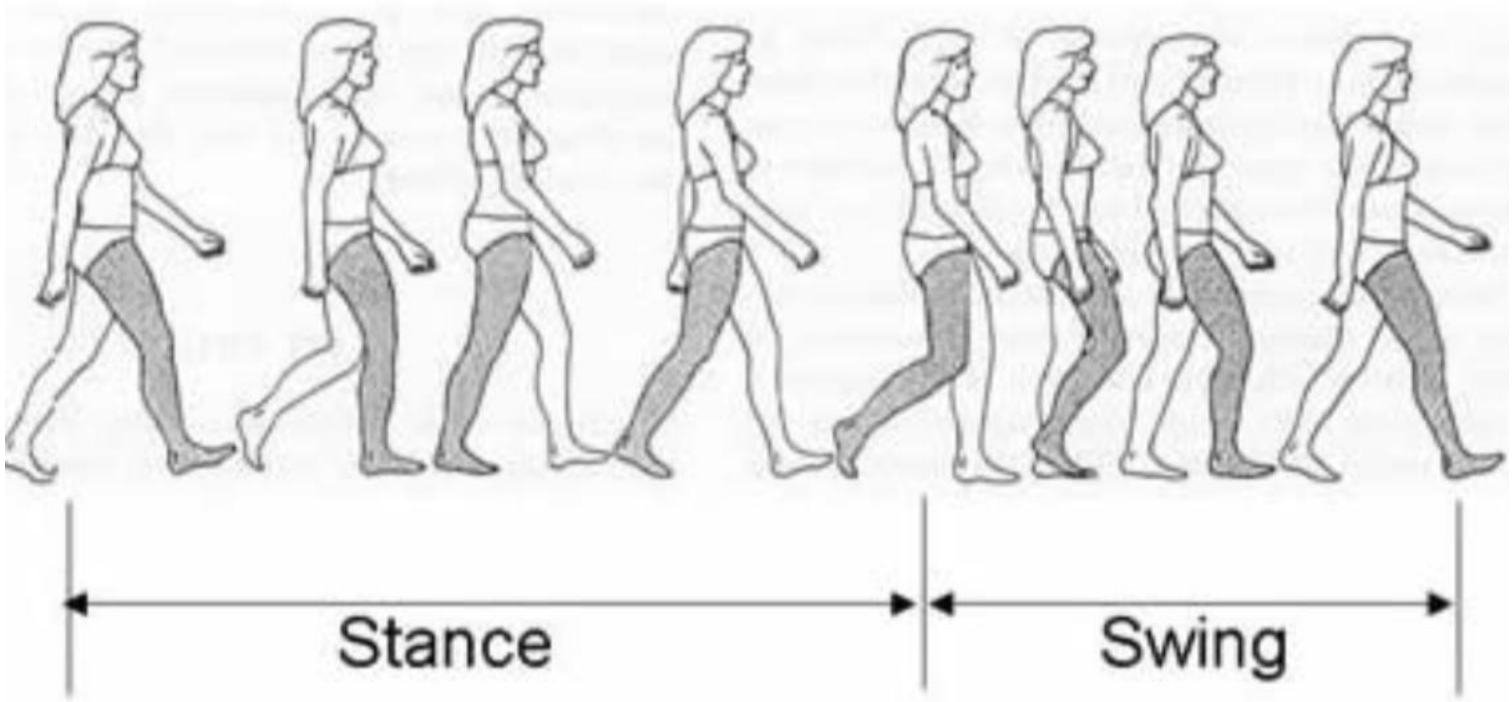


Optical flow-based feature



model-based feature

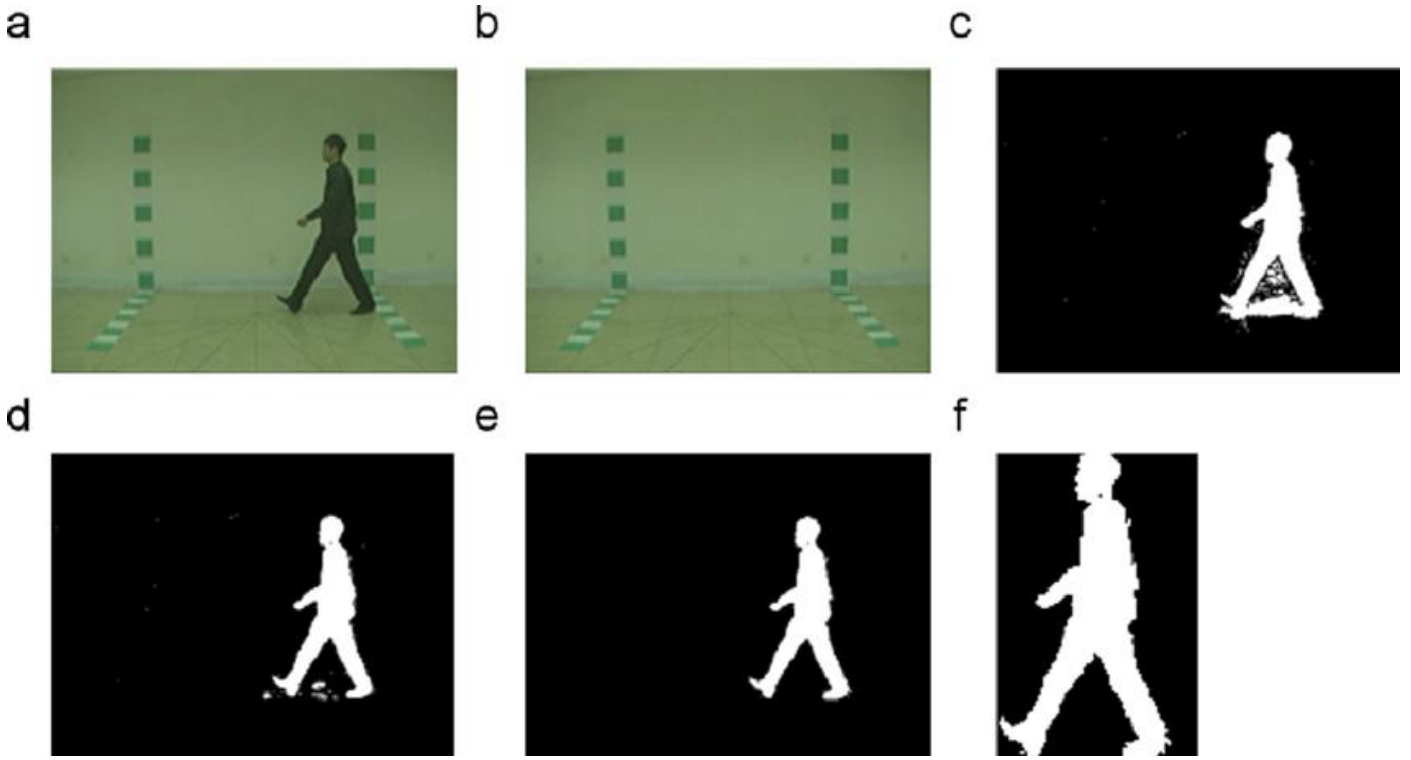
One key concept: gait cycle



- Between where the same foot touches the ground for the first and second time.
- Human gait cycle is about 1 second
- For the purpose of normalization of silhouettes and computing gait templates such as GEI

Gait silhouette extraction

- Background subtraction to get silhouette sequence
  - $I_c = I_a - I_b$
- Noise cleaning
  - I_e
- Normalize
  - I_f



Extract gait cycle

Normalized autocorrelation of silhouette sequence

Extract gait cycle

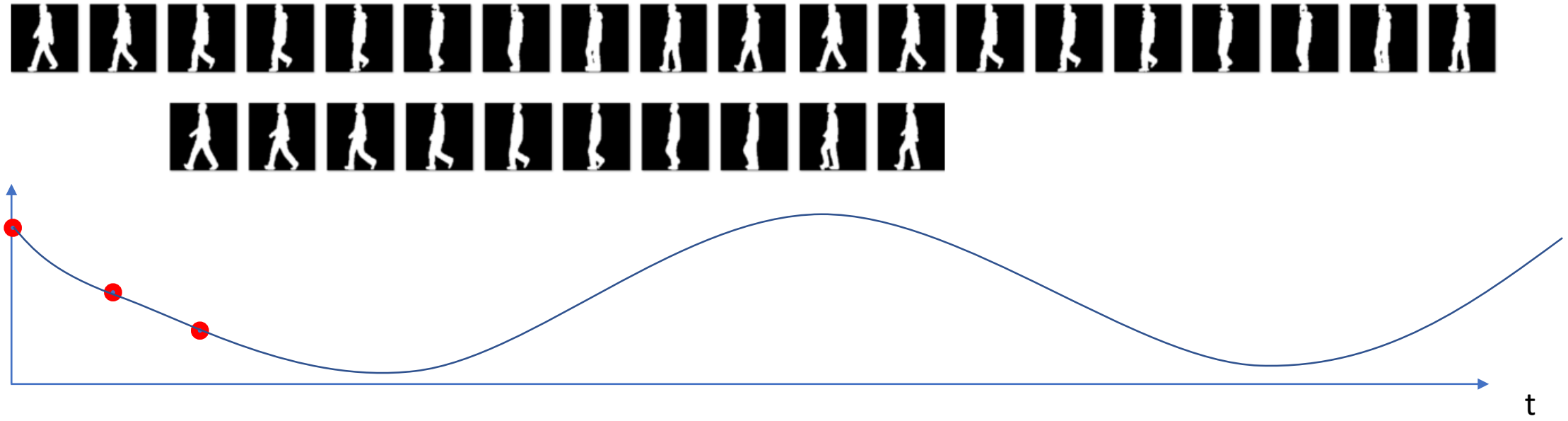
Normalized autocorrelation of silhouette sequence

Extract gait cycle

Normalized autocorrelation of silhouette sequence

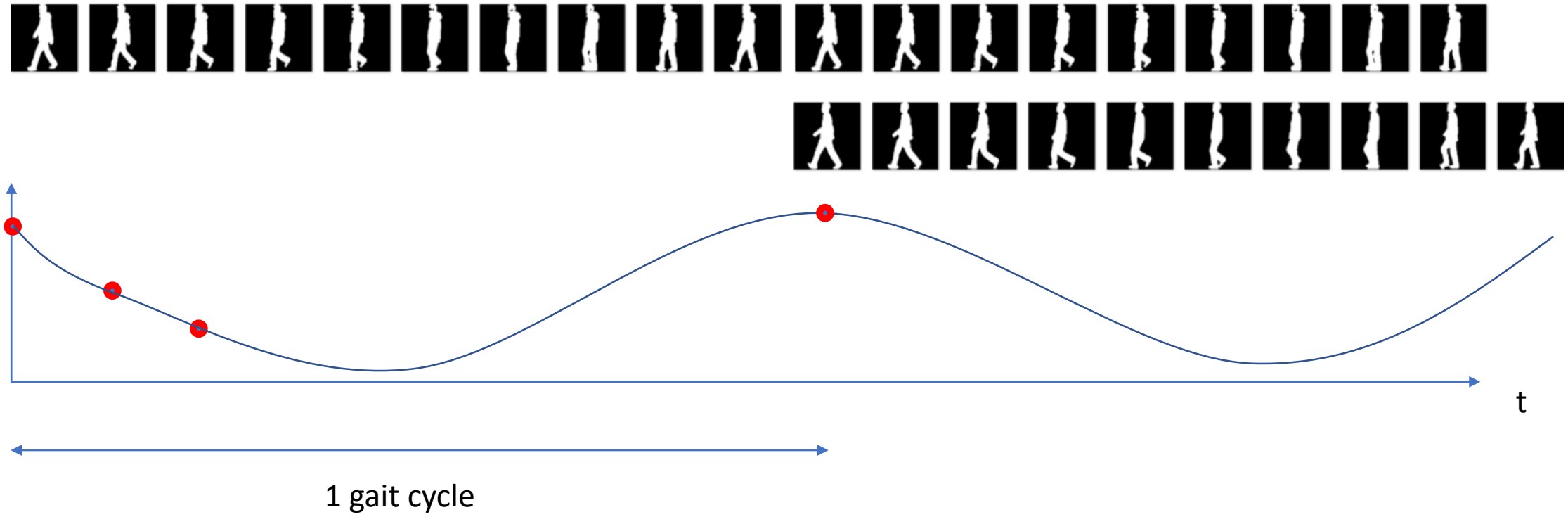
Extract gait cycle

Normalized autocorrelation of silhouette sequence

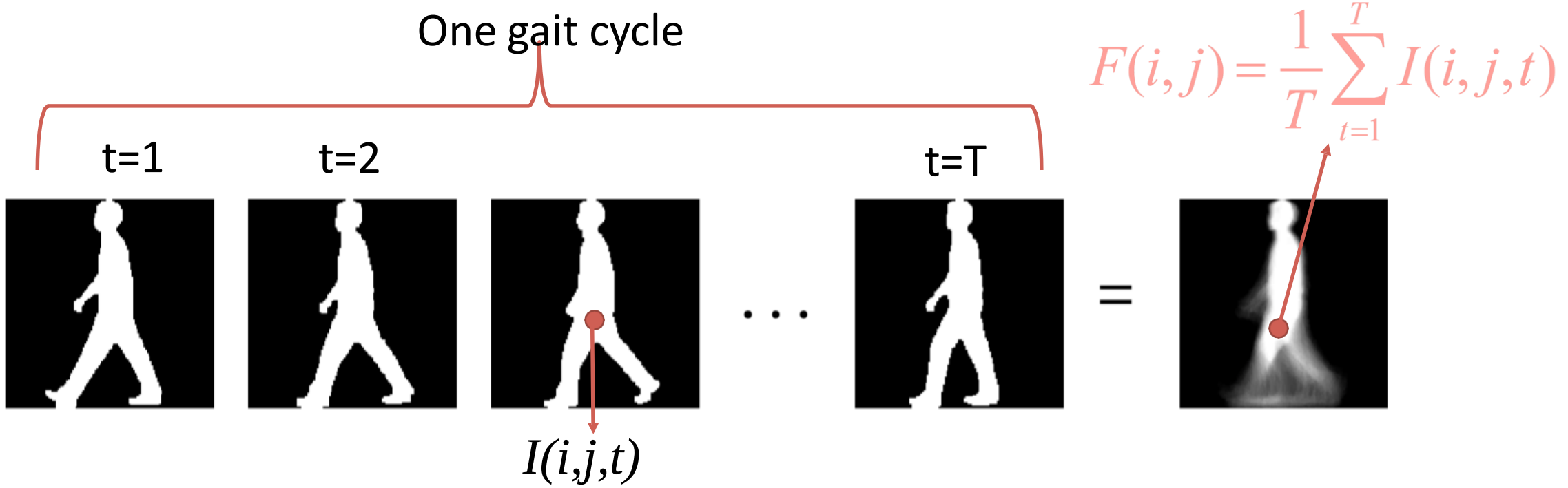


Extract gait cycle

Normalized autocorrelation of silhouette sequence



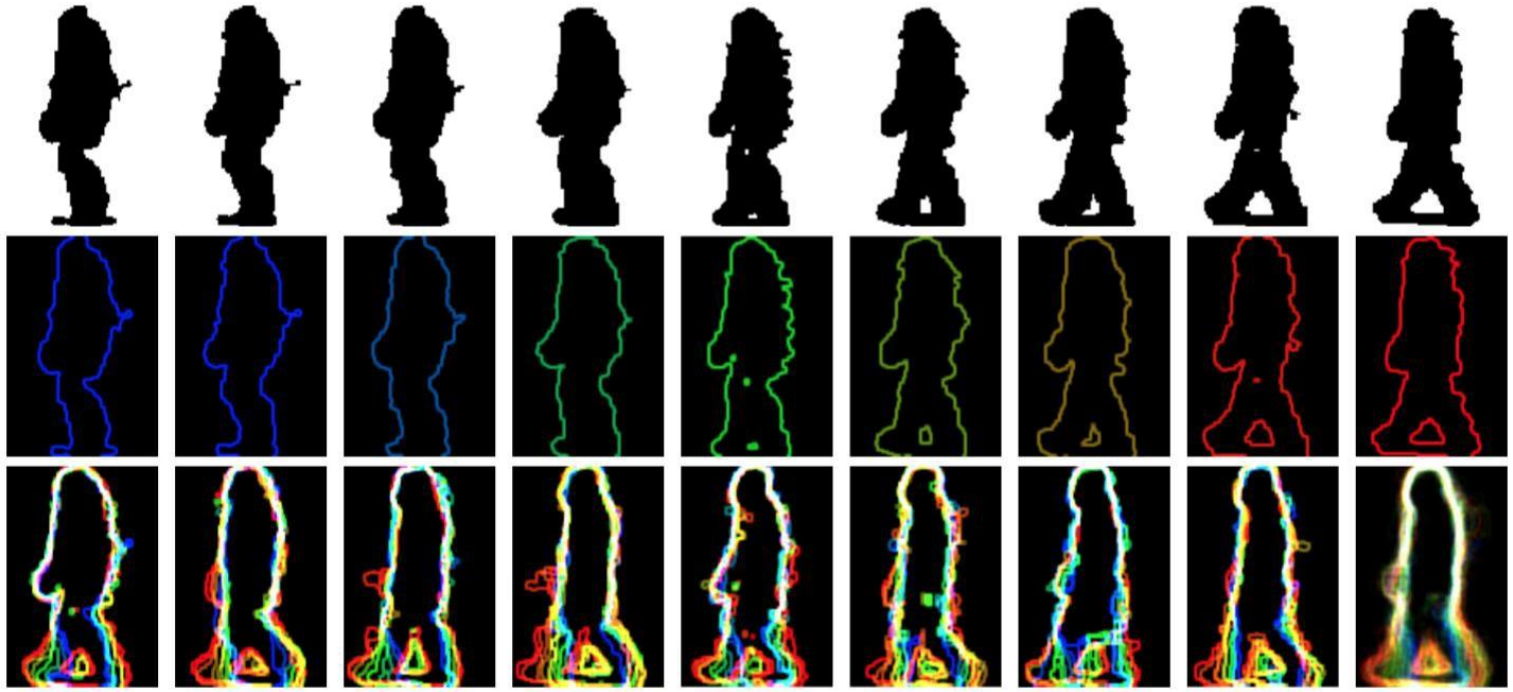
Gait Energy Image (GEI)



- Spatially well-aligned, temporally averaged gait frames within one gait cycle
- Empirically 30 frames/whole sequence of frames enough to cover a complete gait cycle.
- $F(i,j)$ indicates how likely there appears part of a human body in the position (i,j)
- GEI is robust to the silhouette noise, but may have a high dimensionality

J. Han & B. Bhanu, "Individual recognition using gait energy image," *TPAMI*, 2006.

Chrono Gait Image (CGI)



- We encode temporal information in the silhouette images with additional colors to generate a chrono-gait image.
- The goal of CGIs is to compress the silhouette images into a single image without losing too much temporal relationship between the images

C. Wang et al, “Chrono-gait image: A novel temporal template for gait recognition,” in *ECCV*, 2010.
C. Wang et al, Human Identification Using Temporal Information Preserving Gait Template, TPAMI, 2012.

Gait Entropy Image (GEnI)

$$H(x,y) = -\sum_{k=1}^{K} p_k(x,y)\log_2 p_k(x,y)$$

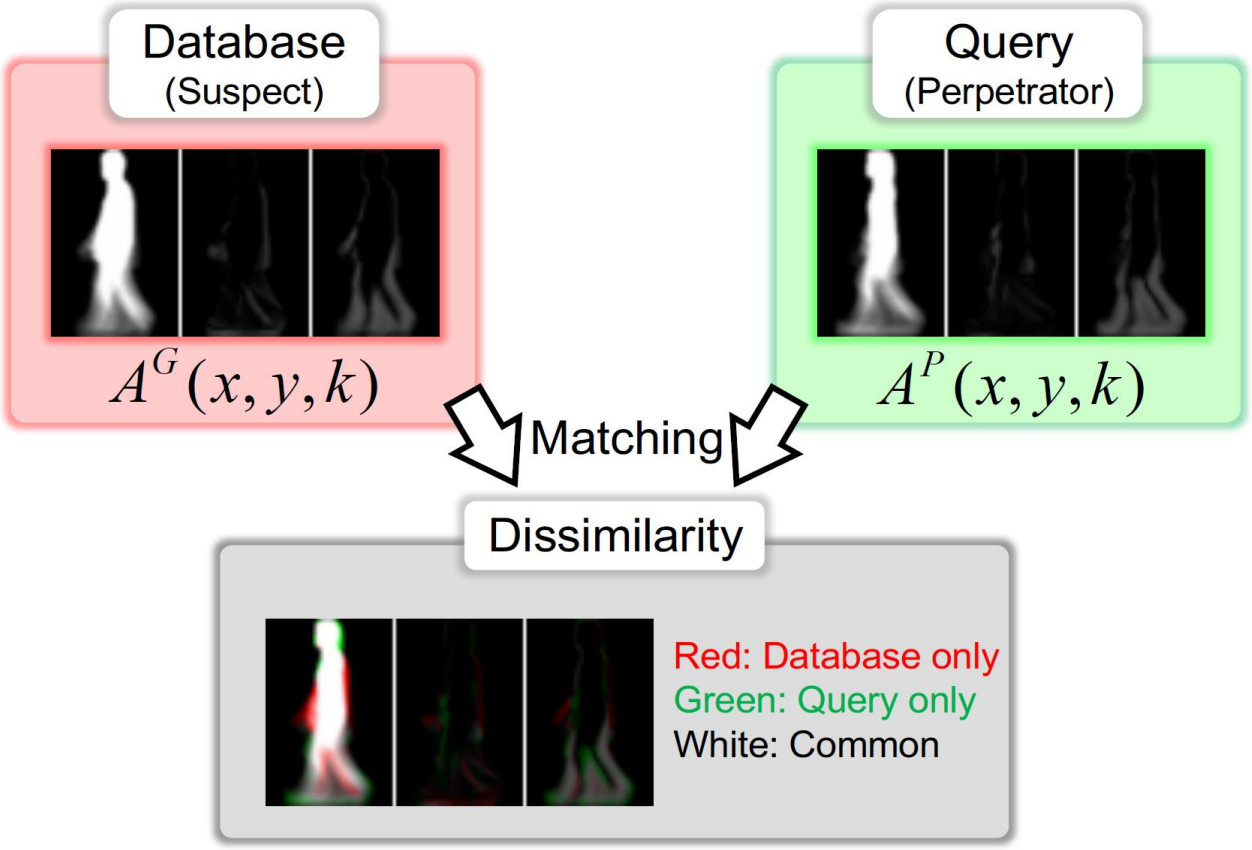
$$G(x,y) = \frac{(H(x,y) - H_{min}) * 255}{(H_{max} - H_{min})}$$

- Calculate Shannon entropy for each pixel in the silhouette images.
- The dynamic area of human body (legs and arms) are represented by higher intensity values in the GEnIs. In contrast, the static areas such as torso give rise to low intensity values.
- Silhouette pixel values in the dynamic areas are more uncertain and thus more informative leading to higher entropy values.

K.Bashir,T.Xiang,andS.Gong. Gait recognition using gait entropy image. In *Proc. of the 3rd Int. Conf. on Imaging for Crime Detection and Prevention*, pages 1–6, Dec. 2009.

4- Gait recognition

Simple Authentication



$$t = \sqrt{\sum_{x,y,k} \left(A^G(x,y,k) - A^P(x,y,k) \right)^2}$$

The pipeline of a typical GEI-based gait recognition method.

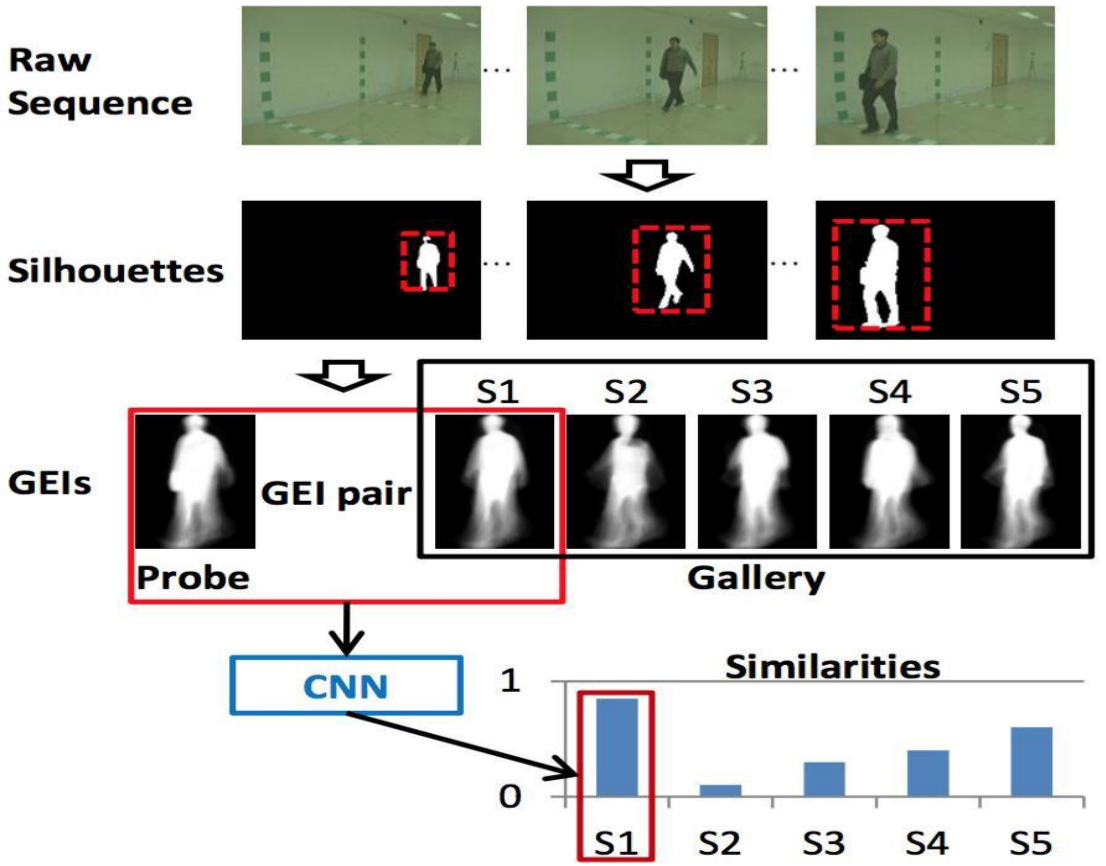
1. Extract human silhouettes from video sequences

2. Align and average the silhouettes along the temporal dimension to get a GEI.

3. Given a probe GEIs and those in the gallery, evaluate the similarities between each pair of probe and gallery GEIs.

4. Assign the identity of the probe GEI, usually with the nearest neighbor classifier.

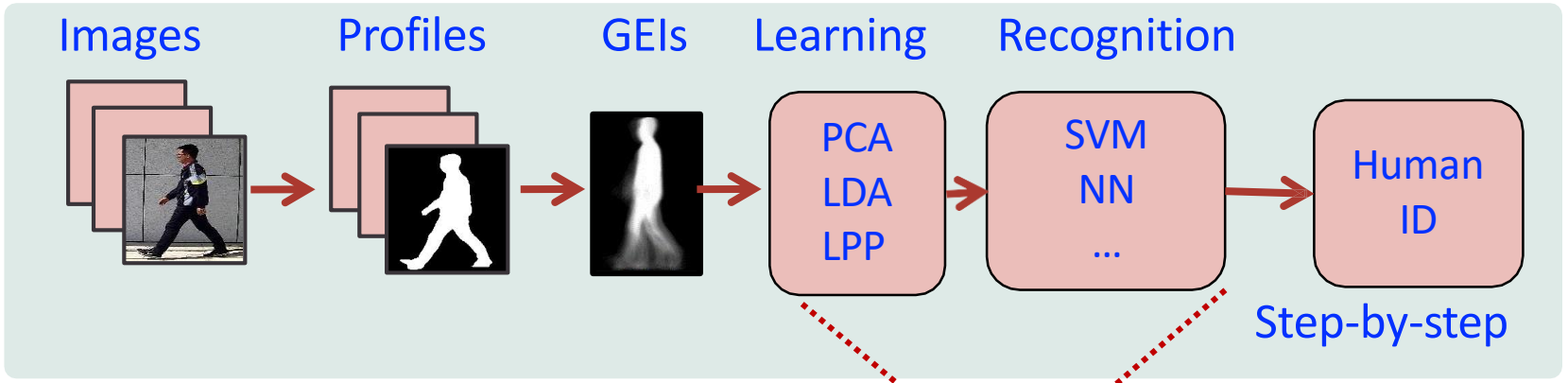
Different from previous methods, here the third step above is realized with deep convolutional neural networks (CNN).



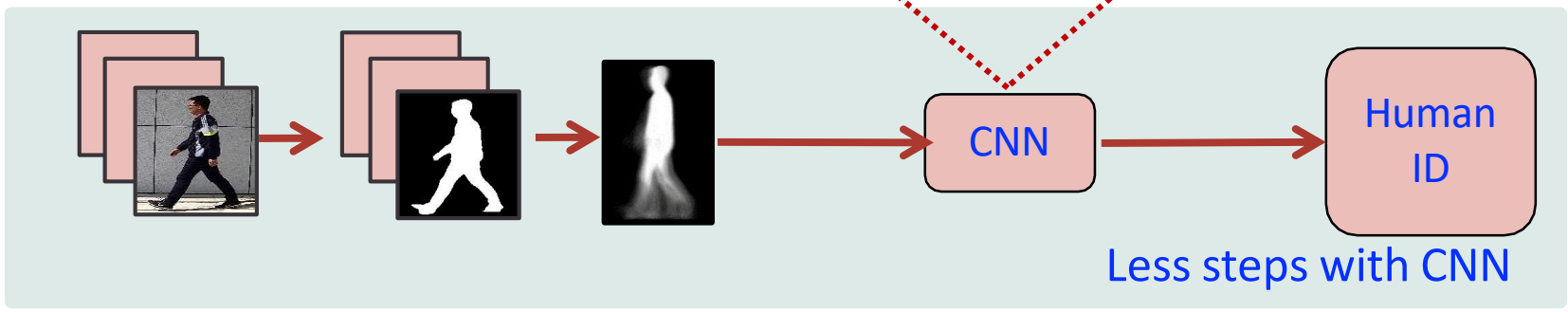
Z. Wu, Y. Huang, L. Wang, X. Wang, T. Tan, A comprehensive study on cross-view gait based human identification with deep CNNs, IEEE TPAMI, 2016

Feature learning for gait recognition

Traditional learning pipeline

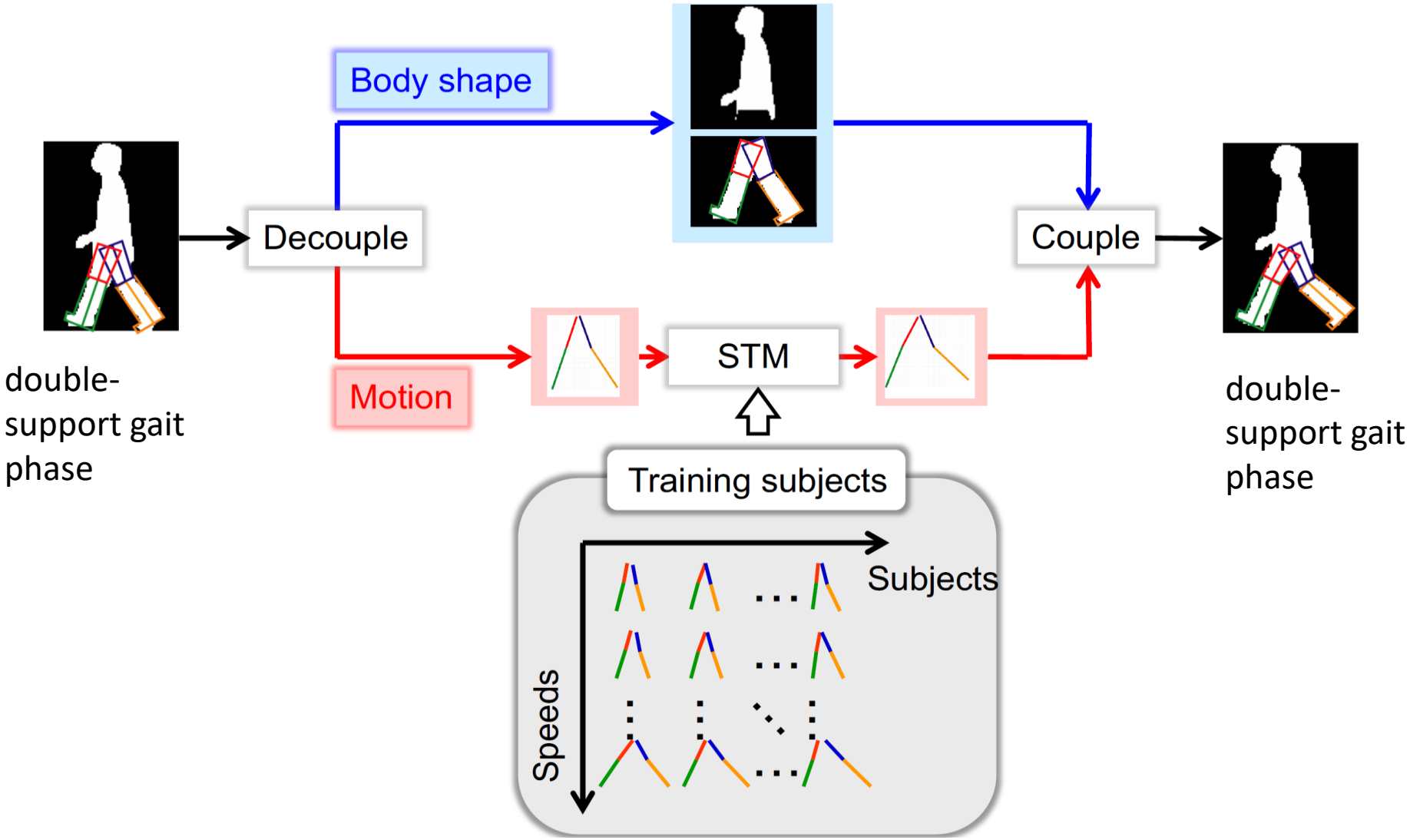


Deep learning pipeline



It is difficult to manually design view-invariant feature representations for gait recognition

Model-based approach: speed invariant gait recognition



Released gait databases

Name	Subjects	Sequences	Covariates	Viewpoints	Indoor(I)/ Outdoor(O)
CMU MoBo (30)	25	600	Y	6	I (Treadmill)
Georgia Tech (31)	15	268	Y	-	O
	18	20	Y	-	-
HID-UMD (32)	25	100	N	1	O
	55	222	Y	2	O
SOTON Small Database (33)	12	-	Y	3	I
SOTON Large Database (34)	115	2,128	Y	2	I/O
SOTON Multimodal (35)	>300	>5,000	Y	12	I
SOTON Temporal (36)	25	2,280	Y	12	I
USF HumanID (23)	122	1,870	Y	2	O
CASIA A (37)	20	240	Y	3	I
CASIA B (38)	124	1,240	Y	11	I
CASIA C (39)	153	1,530	Y	1	O
OU-ISIR, Treadmill A (40)	34	612	Y	1	I (Treadmill)
OU-ISIR, Treadmill B (41)	68	2,764	Y	1	I (Treadmill)
OU-ISIR, Treadmill C (42)	200	200	Y	25	I (Treadmill)
OU-ISIR, Treadmill D (43)	185	370	N	1	I (Treadmill)
OU-ISIR, LP (44)	4,007	7,842	N	2	I
TUM-IITKGP (45)	35	850	Y	1	O
TUM-GAID (46)	305	3,370	Y	1	O
WOSG (47)	155	684	Y	8	O

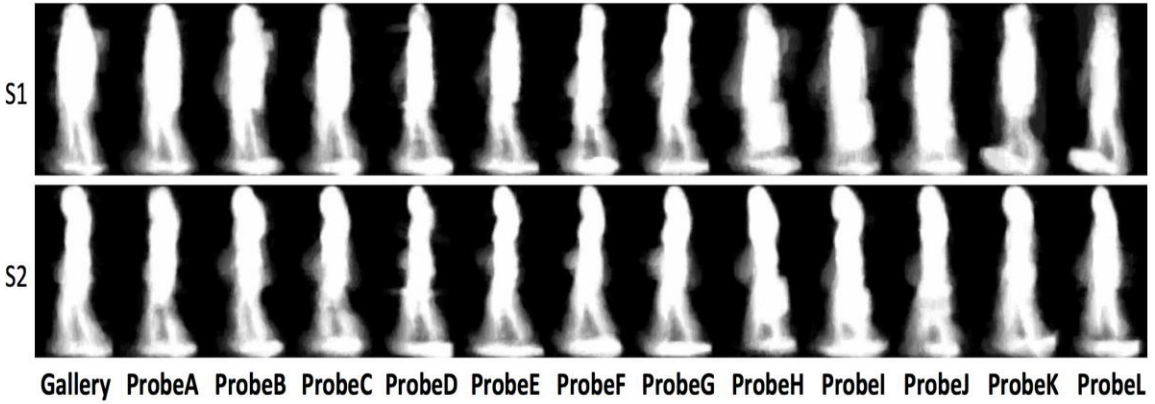
Widely used benchmarks in the community

a) CASIA-B
b) USF HumanID
c) OU-ISIR, Large Population

[Makihara *et al*. 2015]

USF Human ID database

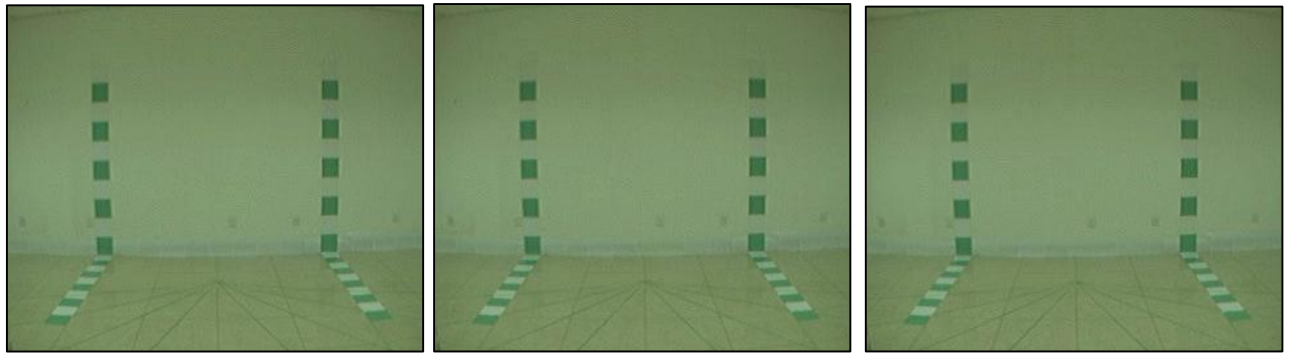
Details	
Indoor/Outdoor	outdoor
# of subjects	122
# of carrying conditions	2 (w/wo briefcase)
# of walking conditions	2 (shoe types)
# of viewpoints	2 (left/right)
# of backgrounds	2 (grass/concrete)
# of time instants	2



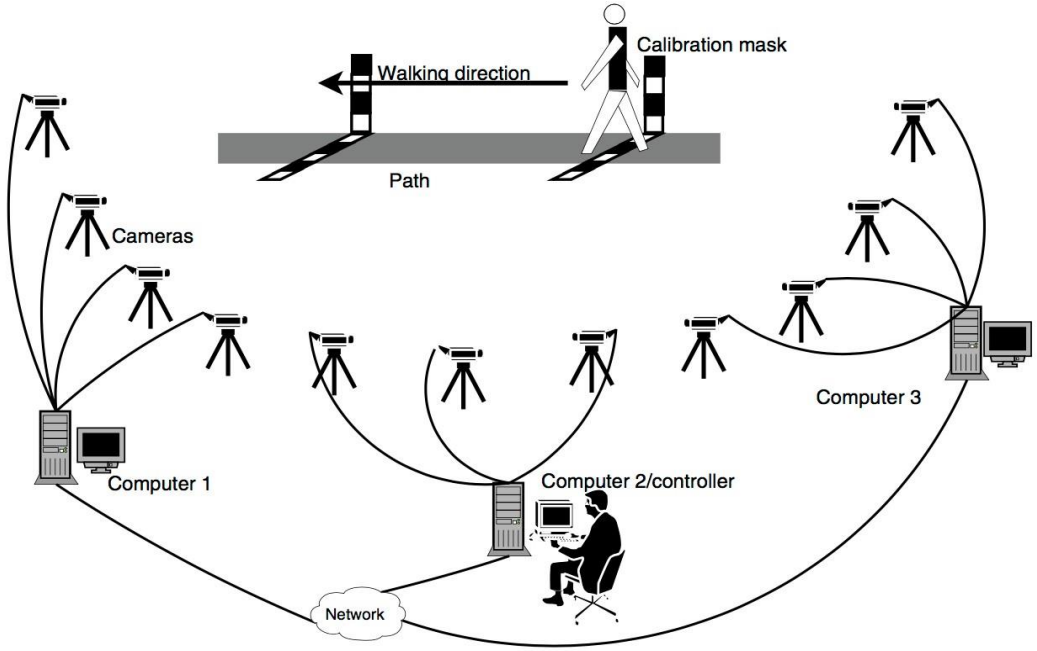
GEIs of two subjects under different conditions. The obtained GEIs are more noisy and of lower quality due to the complex backgrounds

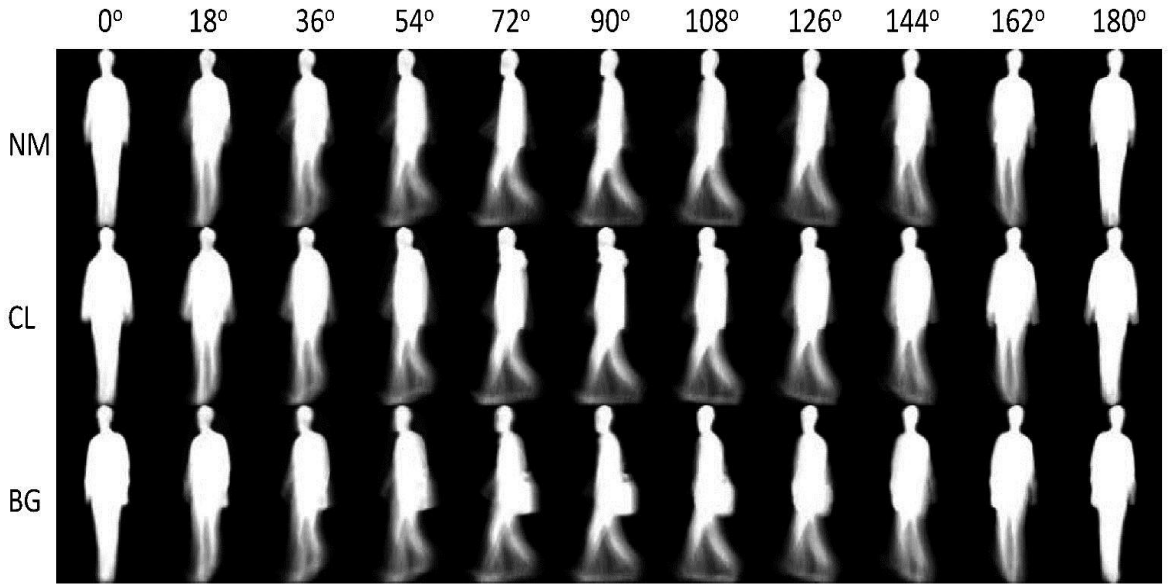
CASIA-B database

Details	
Indoor/Outdoor	indoor
# of subjects	124
# of carrying/walking conditions	3
# of viewpoints	11



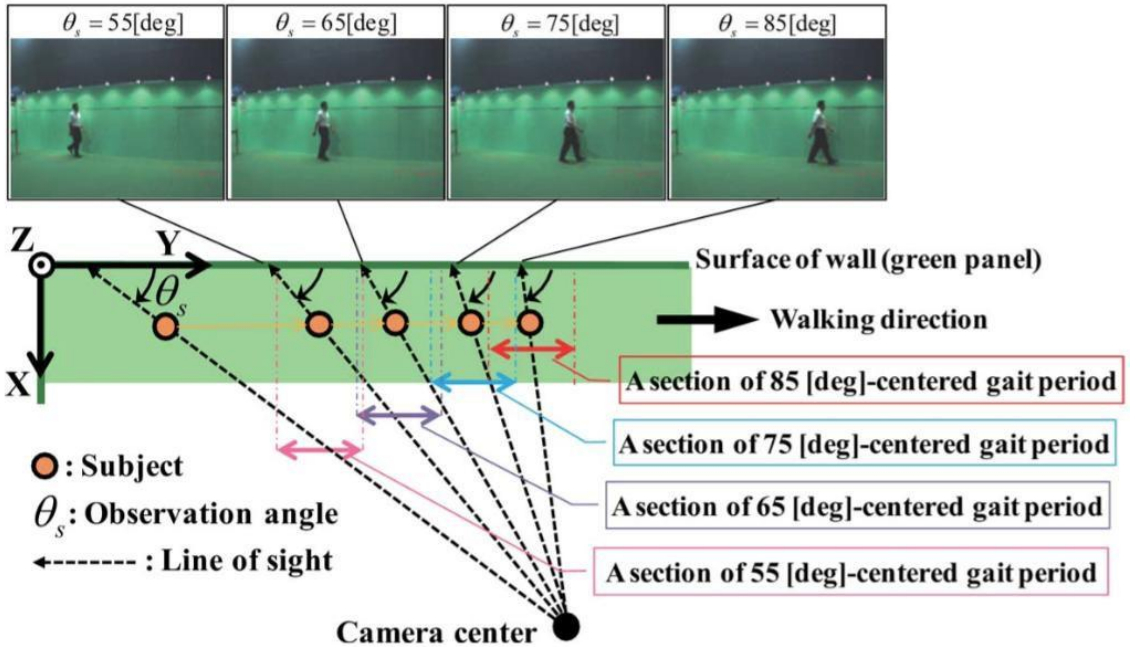
Normal Walk Wearing Coats Carrying bags

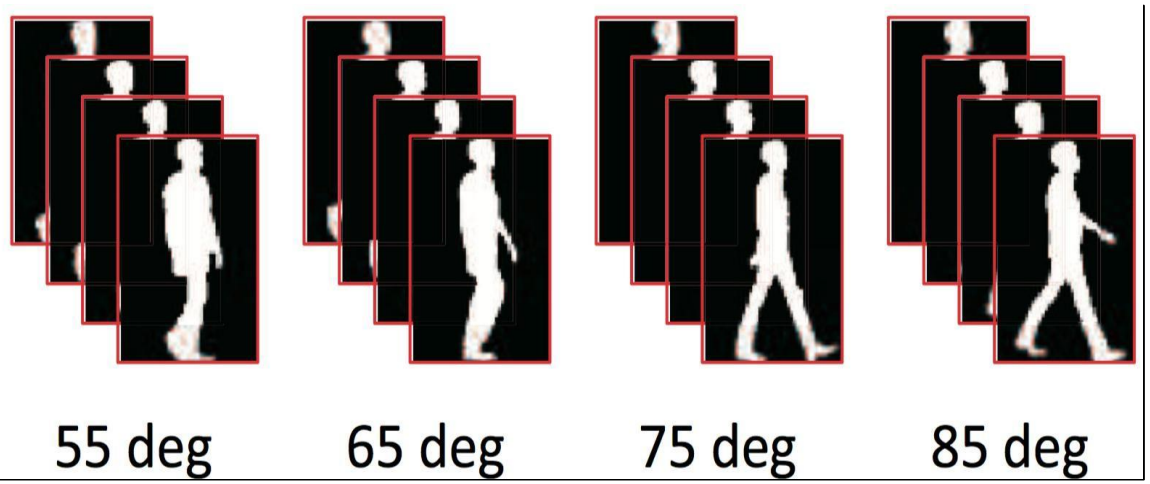




OU-ISIR database, Large population dataset

Details	
Indoor/Outdoor	indoor
# of subjects	4,007(v1), 4,016(v2)
Age range	1-94 years old
# of walking conditions	1
# of viewpoints	4 (55,65,75,85)
# of backgrounds	1



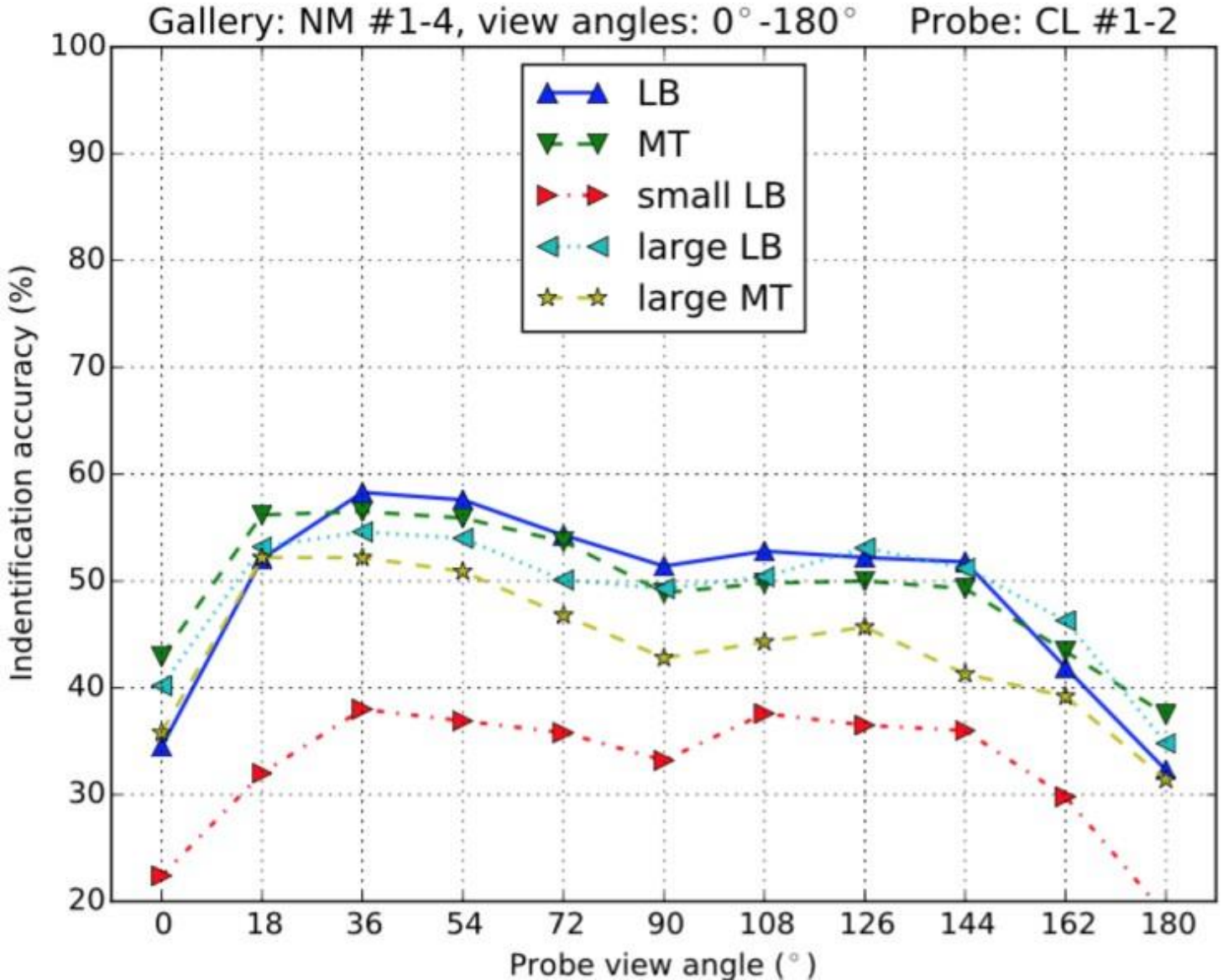


CASIA-HT database (expected to be released early next year)

Details	
Indoor/Outdoor	outdoor
# of subjects	1000
# of carrying conditions	3
# of walking conditions	2
# of viewpoints	13 horizontal, 2 vertical
# of backgrounds/scenarios	2
# of sequences	>760,000

Another super large database for gait recognition [C. Song, Y. Huang, et al.]

Gait recognition performance vs. viewing direction



Thank you for listening !

Reference

- Liang Wang: https://www.comp.hkbu.edu.hk/wsb17/slides/Liang_Wang.pdf