Human Gait Analysis

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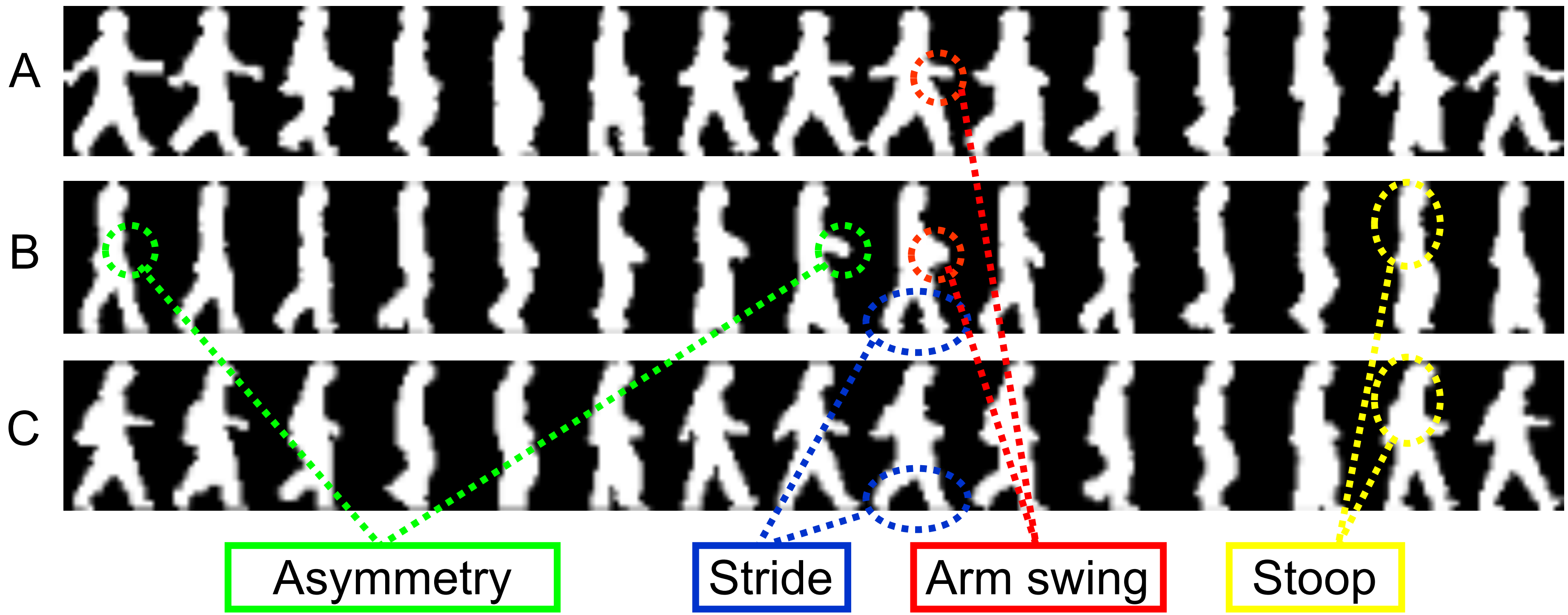
Human gait -Personality- Identity -

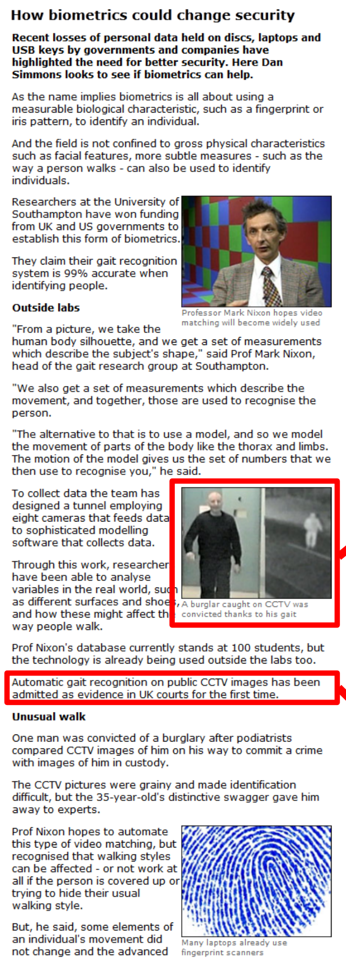
Human gait -Personality-



Gait recognition: Person authentication from gait personalities

Example of practical use (1)

- Gait recognition on burglar on CCTVs
  - Admitted as evidence in UK court[1]



How biometrics could change security

Recent losses of personal data held on discs, laptops and USB keys by governments and companies have highlighted the need for better security. Here Dan Simmons looks to see if biometrics can help.

As the name implies biometrics is all about using a measurable biological characteristic, such as a fingerprint or iris pattern, to identify an individual.

And the field is not confined to gross physical characteristics such as facial features, more subtle measures - such as the way a person walks - can also be used to identify individuals.

Researchers at the University of Southampton have won funding from UK and US governments to establish this form of biometrics.

They claim their gait recognition system is 99% accurate when identifying people.

Professor Mark Nixon hopes video matching will become widely used

Outside labs

"From a picture, we take the human body silhouette, and we get a set of measurements which describe the subject's shape," said Prof Mark Nixon, head of the gait research group at Southampton.

"We also get a set of measurements which describe the movement, and together, those are used to recognise the person.

"The alternative to that is to use a model, and so we model the movement of parts of the body like the thorax and limbs. The motion of the model gives us the set of numbers that we then use to recognise you," he said.

To collect data the team has designed a tunnel employing eight cameras that feeds data to sophisticated modelling software that collects data.

Through this work, researchers have been able to analyse variables in the real world, such as different surfaces and shoes, and how these might affect the way people walk.

A burglar caught on CCTV was convicted thanks to his gait

Prof Nixon's database currently stands at 100 students, but the technology is already being used outside the labs too.

Automatic gait recognition on public CCTV images has been admitted as evidence in UK courts for the first time.

Unusual walk

One man was convicted of a burglary after podiatrists compared CCTV images of him on his way to commit a crime with images of him in custody.

The CCTV pictures were grainy and made identification difficult, but the 35-year-old's distinctive swagger gave him away to experts.

Prof Nixon hopes to automate this type of video matching, but recognised that walking styles can be affected - or not work at all if the person is covered up or trying to hide their usual walking style.

But, he said, some elements of an individual's movement did not change and the advanced

Many laptops already use fingerprint scanners

A burglar caught on CCTV was convicted thanks to his gait

Automatic gait recognition on public CCTV images has been admitted as evidence in UK courts for the first time.

[1] http://news.bbc.co.uk/2/hi/programmes/click online/7702065.stm, "How biometrics could change security," BBC News, 31 Oct. 2008.

Example of practical use (2)

- Gait recognition on firer in Japan[2]

[2] 2009年2月20日 毎日放送 VOICE「指紋は不要？放火犯を追った驚きの科学捜査とは！-歩き方で捕まった放火男」
Mainichi Broadcast　VOICE (2009/2/20)

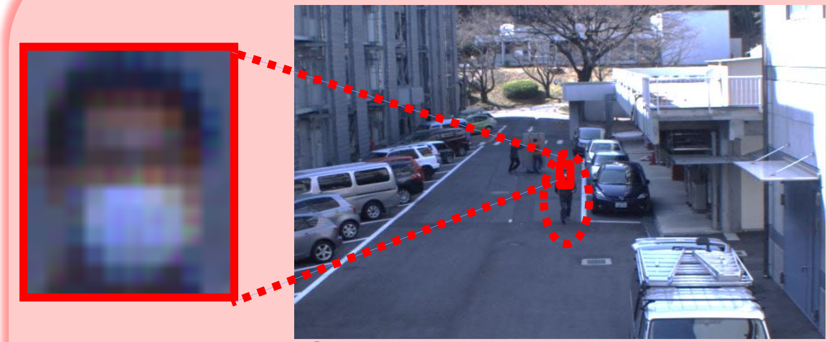
Advantage of gait recognition

Criminal investigation

CCTV of firer

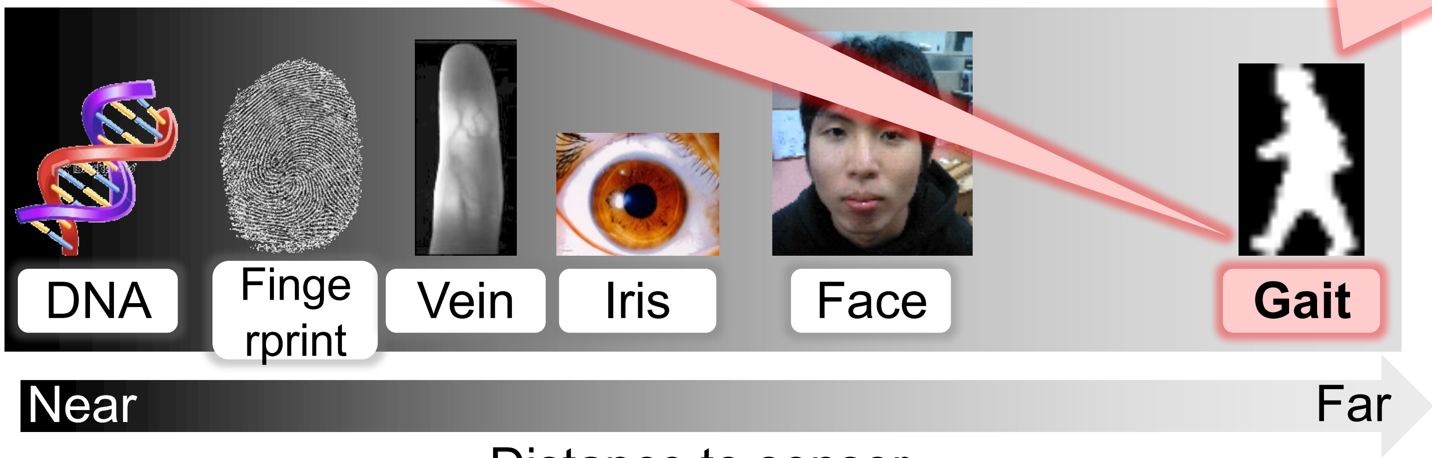
Judge whether a perpetrator and a suspect are the same or not from gaits

Authentication at a distance



Gait can be authenticated at a distance from a camera

Face recognition does not work due to heavy occlusions by mask



Distance to sensor

Gait Identification

Person authentication by biometrics

Fingerprint

Same?

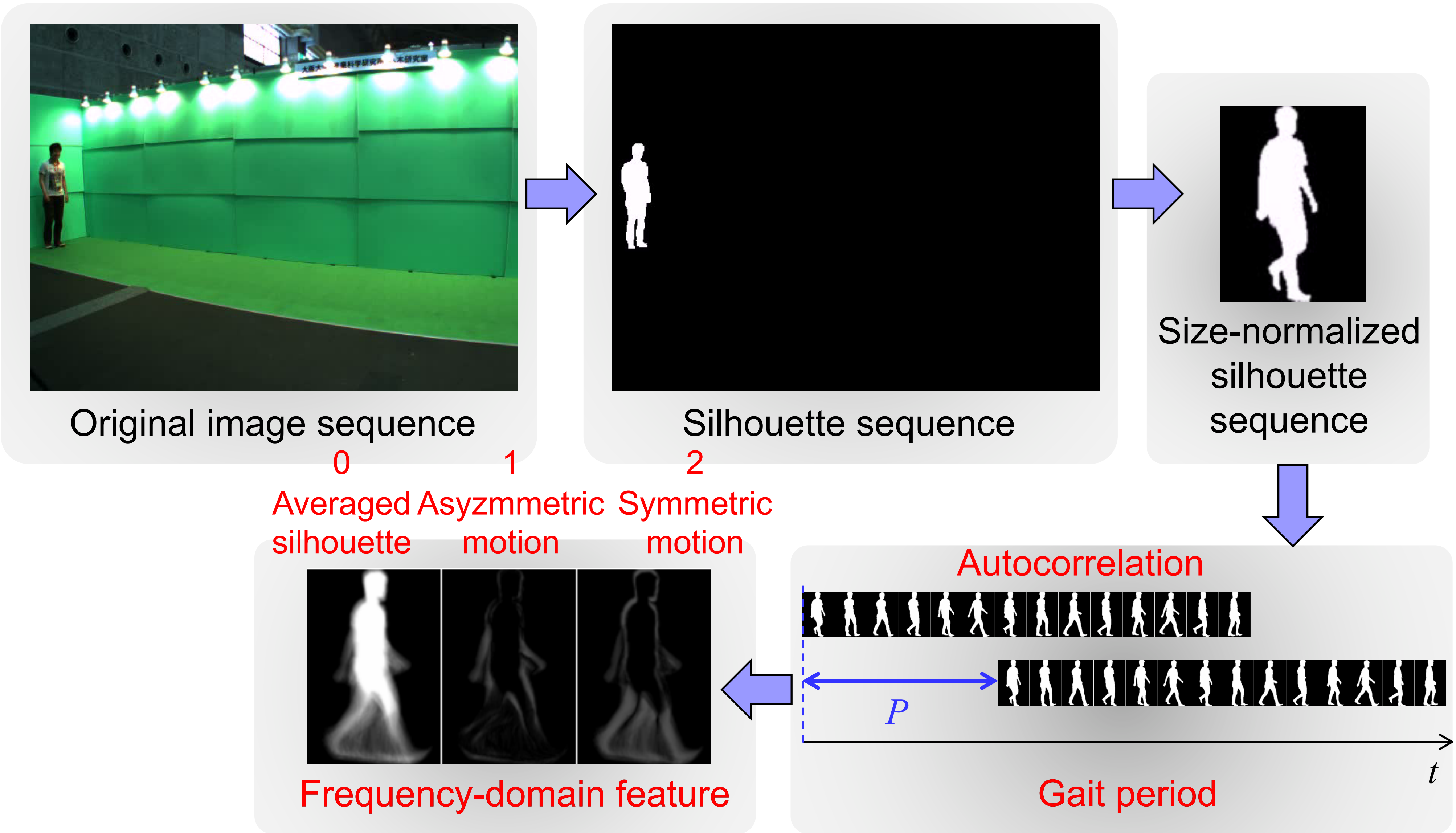
Face

Same?

Gait

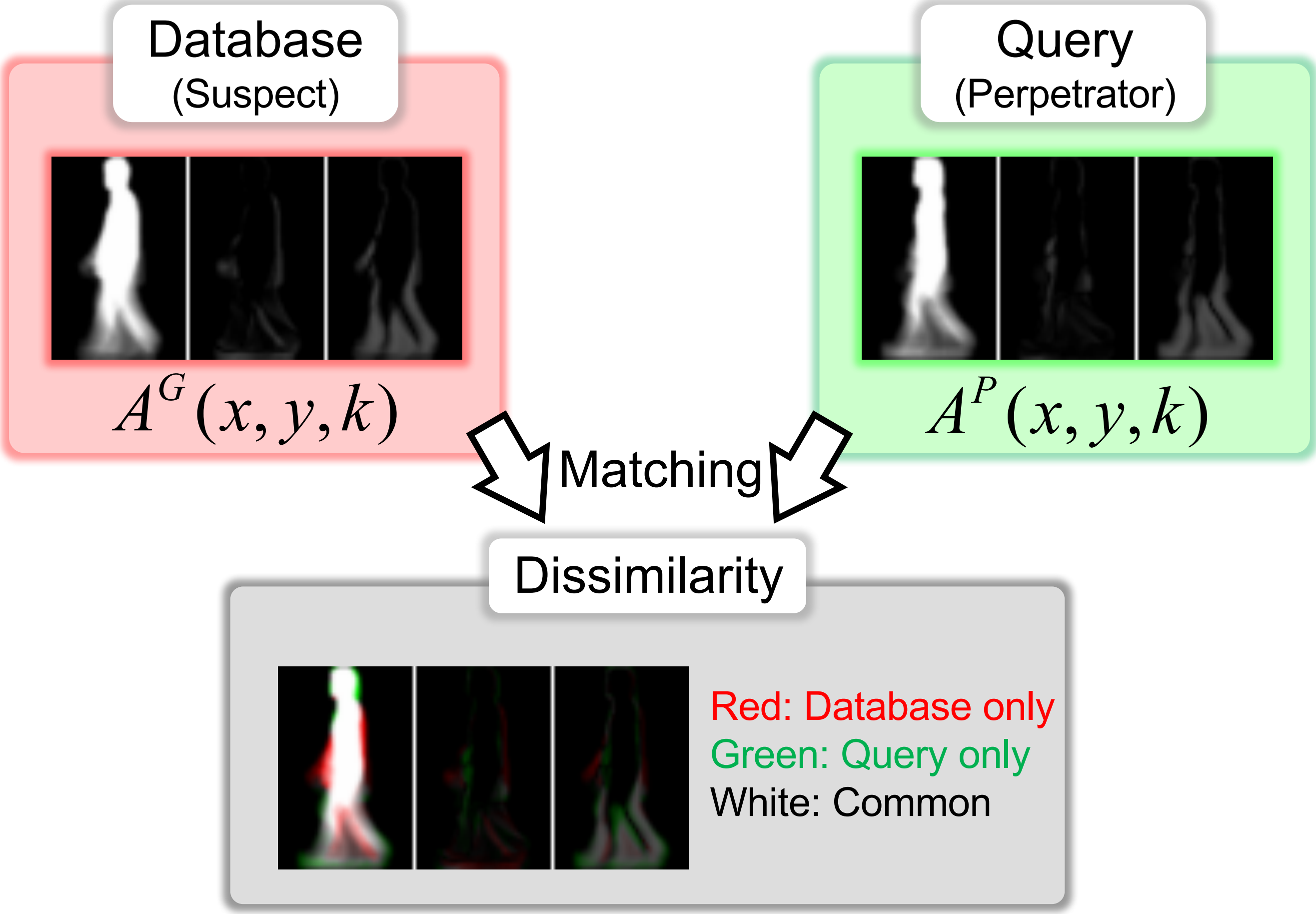
Same?

Gait feature extraction



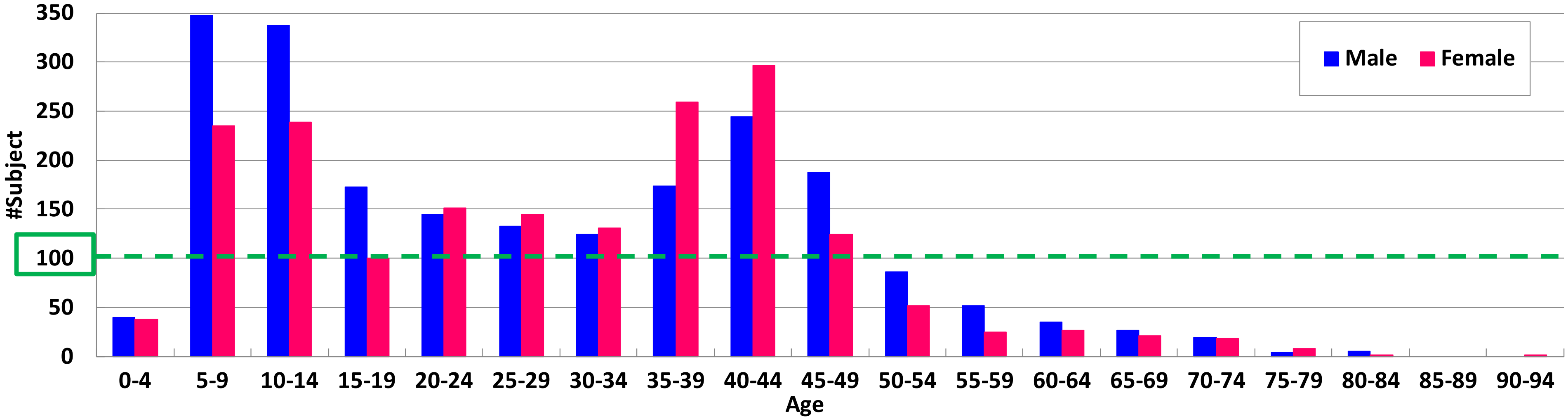
Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, and Y. Yagi, ``Gait Recognition Using a View Transformation Model in the Frequency Domain,'' 9th European Conf. on Computer Vision, Vol. 3, pp. 151-163, 2006.

Dissimilarity: Single feature



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

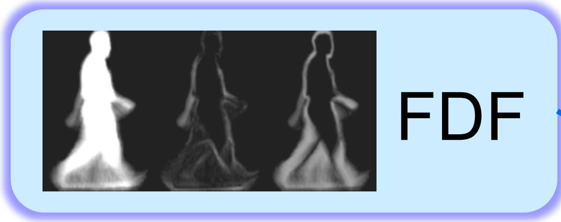
Database: OU-LP

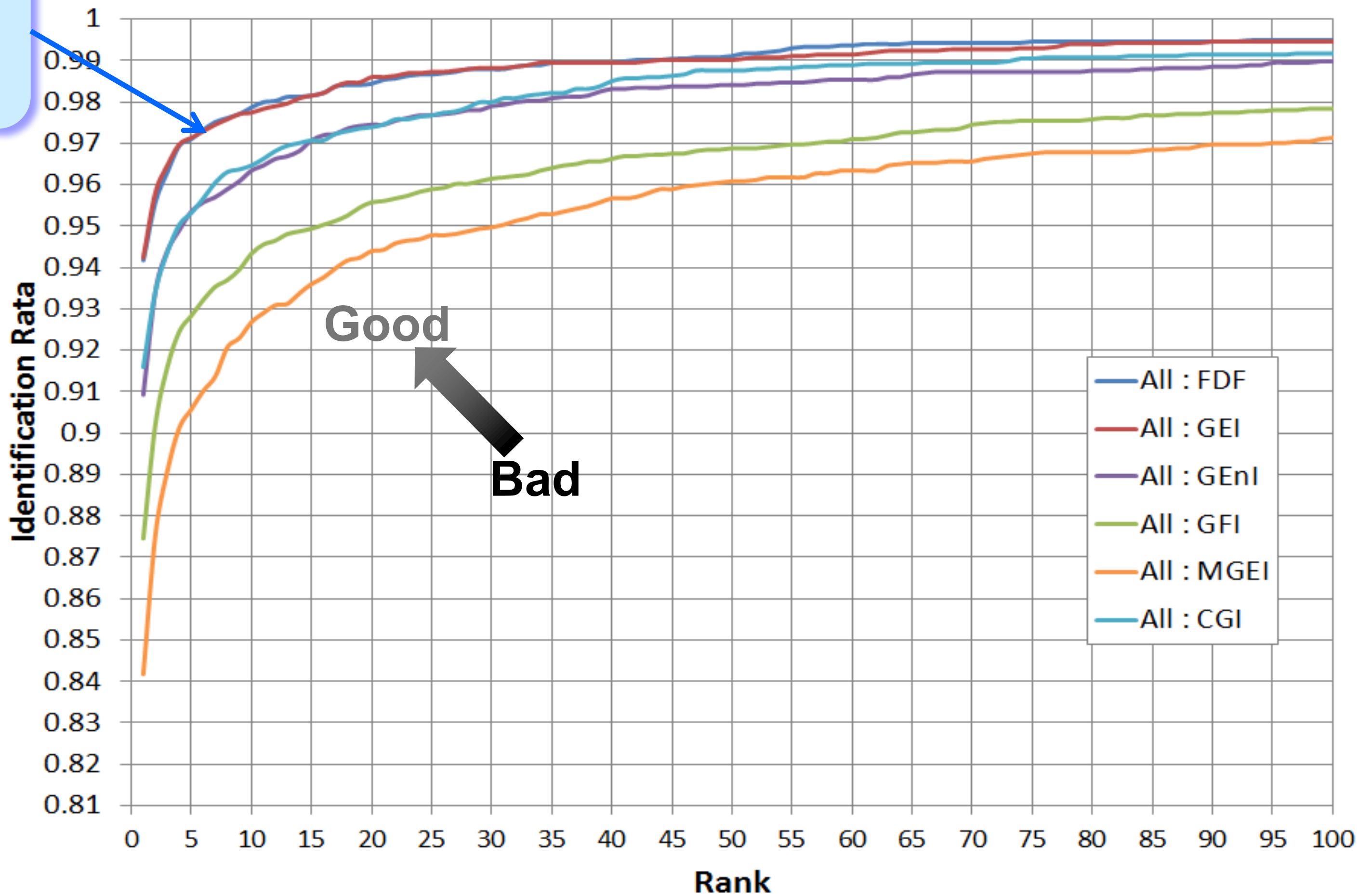


The world largest database with 4,007 subjects (Male: 2,135, Female: 1,872)

Performance evaluation: Identification

[Iwama et al. IFS 2012]



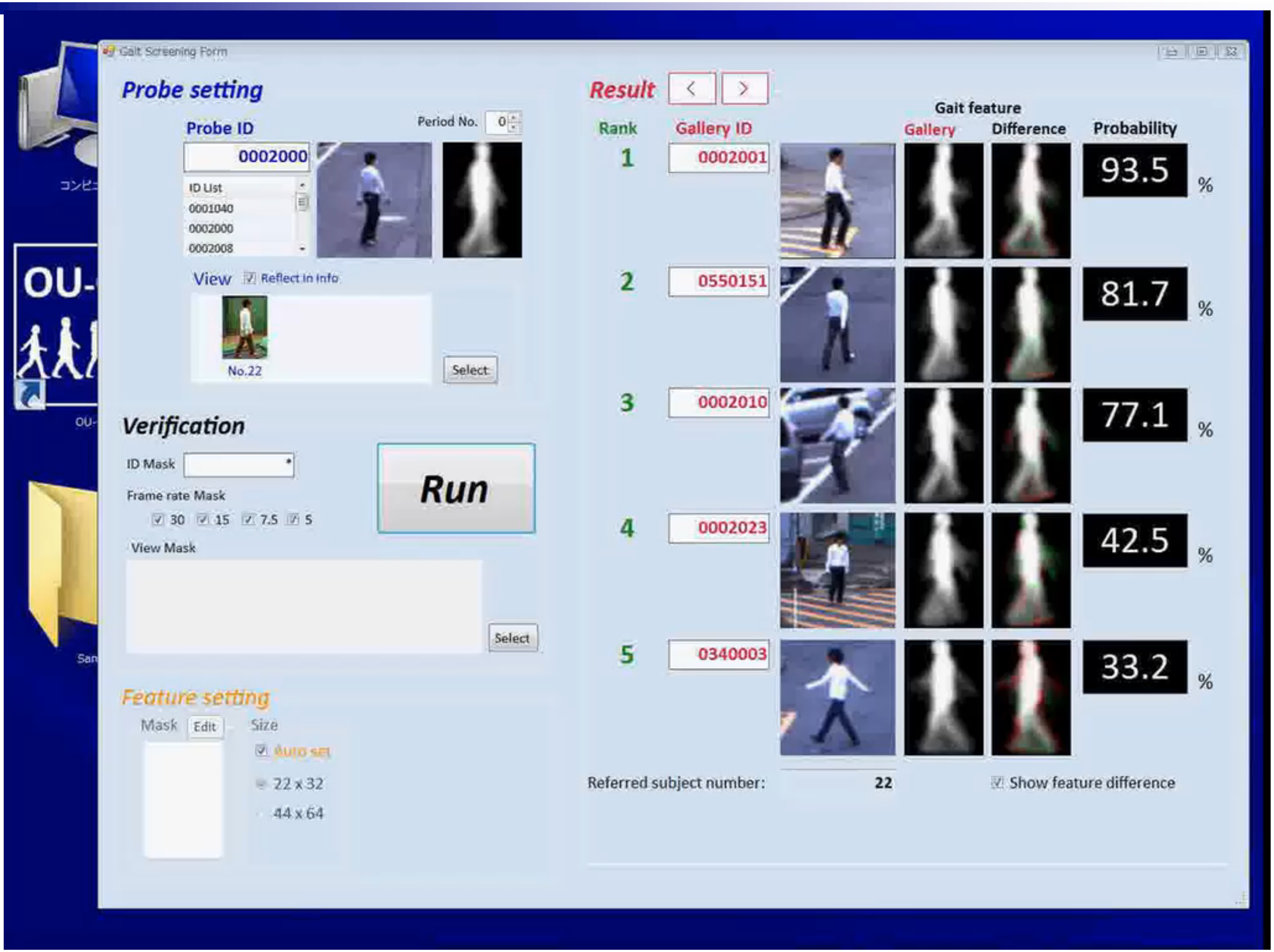


Cumulative matching characteristics (CMC) curve

94% rank-1 identification rate (N = 3,141)

World first packaged gait verification system for criminal investigation

Example of batch verification



What is the difficulty for applying gait recognition to wide-area surveillance ?

- The difference of the observation direction
  - ECCV2006
- Speed change CVPR2010
- The difference of clothes
  - Pattern Recognition 2010
- The difference of shoes
- Low sampling rate
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene

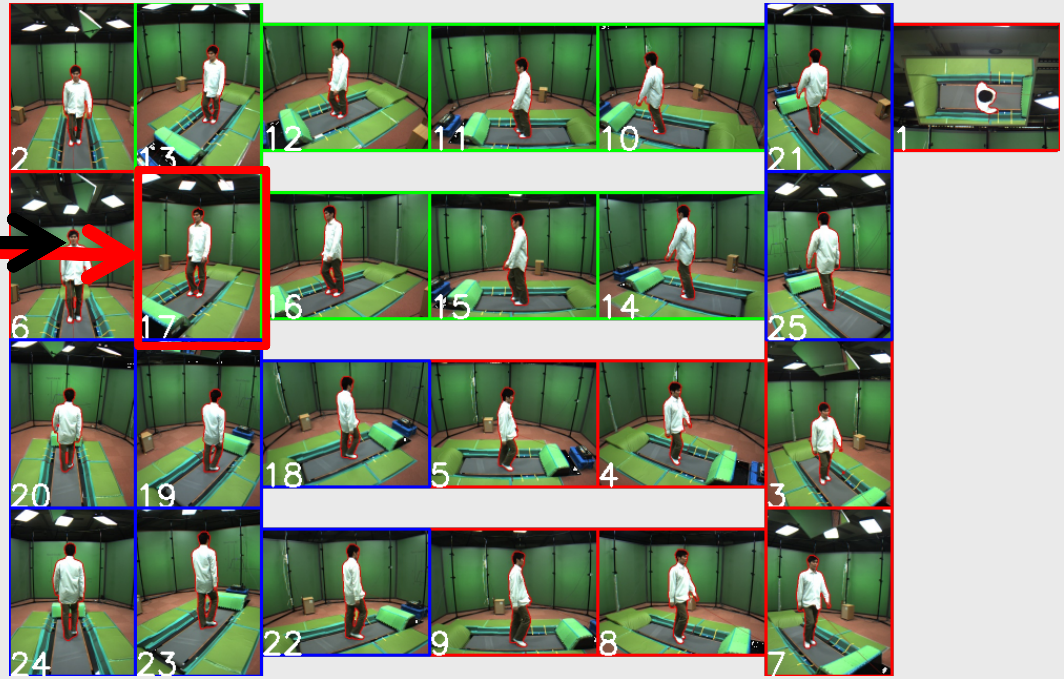
Challenge -View differences-

Probe
(E.g., perpetrator)

Direct matching does not work

Matching with the same view

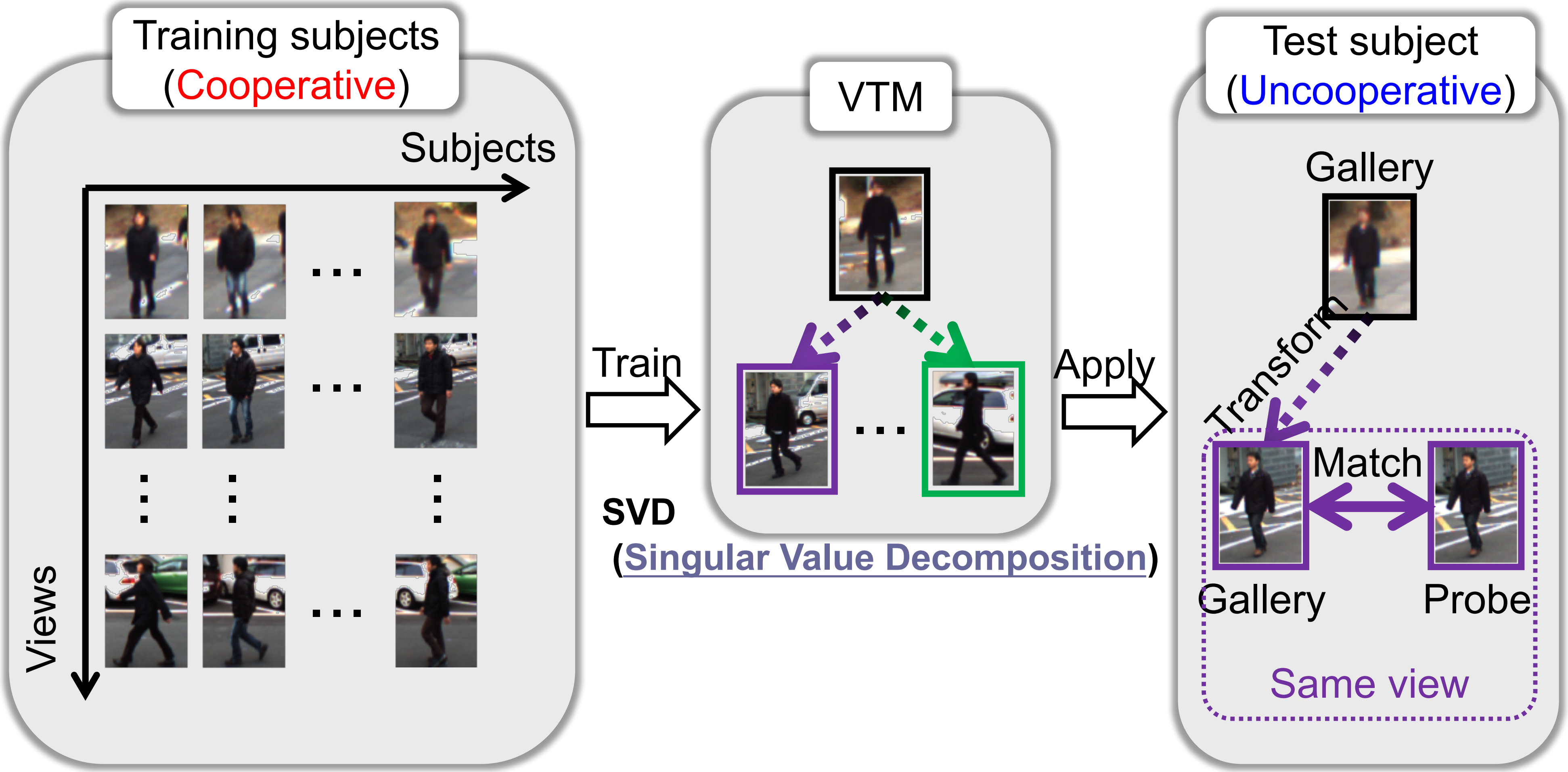
Gallery
(E.g., suspect)



Difficult to collect multi-view gait features for uncooperative subject

View transformation model (VTM)

[Makihara et al. ECCV 2006]



Formulation of VTM in frequency domain

- Decompose training data matrix of gait features into individuals and views by SVD

individual

view

$$\begin{bmatrix} \boldsymbol{a}_{\theta_1}^1 & \boldsymbol{a}_{\theta_1}^2 & \cdots & \boldsymbol{a}_{\theta_1}^M \\ \boldsymbol{a}_{\theta_2}^1 & \boldsymbol{a}_{\theta_2}^2 & \cdots & \boldsymbol{a}_{\theta_2}^M \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{a}_{\theta_K}^1 & \boldsymbol{a}_{\theta_K}^2 & \cdots & \boldsymbol{a}_{\theta_K}^M \end{bmatrix} = USV^T = \begin{bmatrix} P_{\theta_1} \\ P_{\theta_2} \\ \vdots \\ P_{\theta_K} \end{bmatrix} \begin{bmatrix} \boldsymbol{v}^1 & \boldsymbol{v}^2 & \cdots & \boldsymbol{v}^M \end{bmatrix}$$

Training data matrix

Transformation matrix to each view

View-independent individual vector

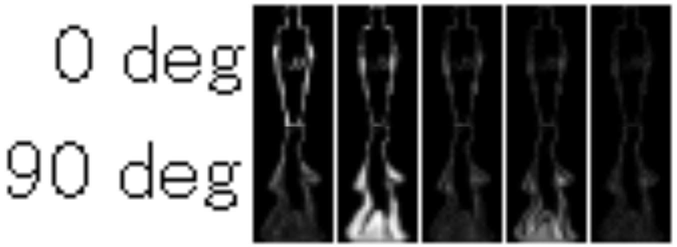
- Gait feature for mth subject from θ_i view

$$\boldsymbol{a}_{\theta_i}^m = P_{\theta_i} \boldsymbol{v}^m$$

View transformation

- From a single reference θ_j to θ_i

$$\left.\begin{aligned} \boldsymbol{a}_{\theta_i}^m &= P_{\theta_i}\boldsymbol{v}^m \\ \boldsymbol{a}_{\theta_j}^m &= P_{\theta_j}\boldsymbol{v}^m \end{aligned}\right\} \Rightarrow \boldsymbol{a}_{\theta_i}^m = P_{\theta_i} P_{\theta_j}^{+} \boldsymbol{a}_{\theta_j}^m$$

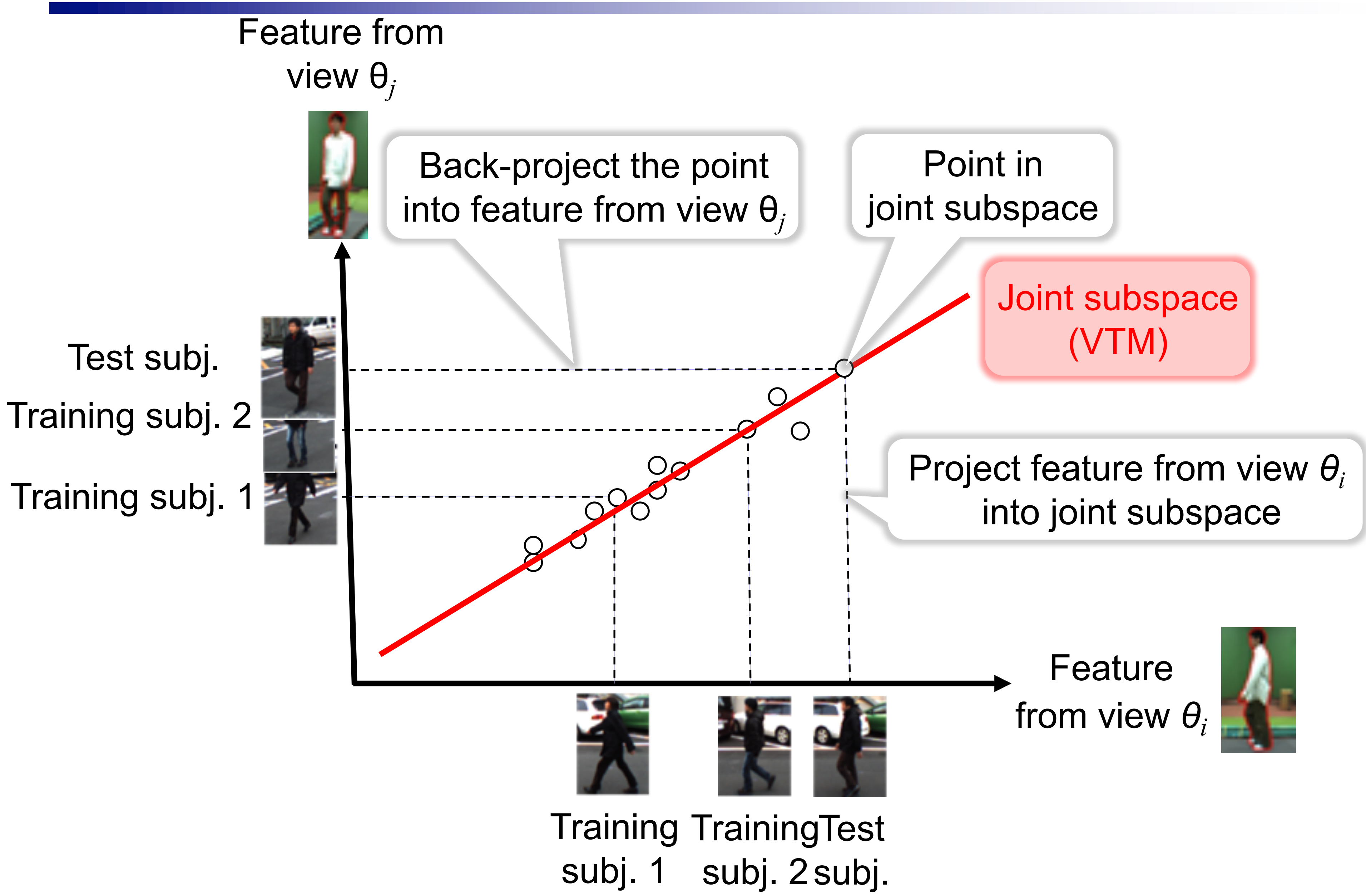


  - Orthogonal motion to reference θ_j is degenerated

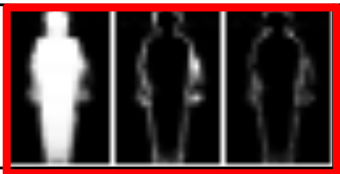
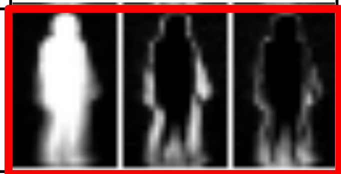
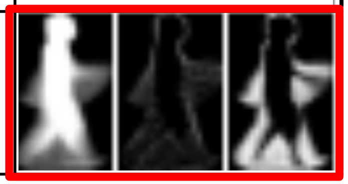
- From multiple references $\{\theta_j(1),\ldots,\theta_j(k)\}$ to θ_i

$$\left.\begin{aligned} \boldsymbol{a}_{\theta_i}^m &= P_{\theta_i}\boldsymbol{v}^m \\ \boldsymbol{a}_{\theta_j(1)}^m &= P_{\theta_j(1)}\boldsymbol{v}^m \\ &\vdots \\ \boldsymbol{a}_{\theta_j(k)}^m &= P_{\theta_j(k)}\boldsymbol{v}^m \end{aligned}\right\} \Rightarrow \boldsymbol{a}_{\theta_i}^m = P_{\theta_i} \begin{bmatrix} P_{\theta_j(1)} \\ \vdots \\ P_{\theta_j(k)} \end{bmatrix}^{+} \begin{bmatrix} \boldsymbol{a}_{\theta_j(1)}^m \\ \vdots \\ \boldsymbol{a}_{\theta_j(k)}^m \end{bmatrix}$$

How does it work?



Transformation results

	Gallery		
0 deg			
15 deg			
30 deg			
45 deg			
60 deg			
75 deg			
90 deg			

What is the difficulty for applying gait recognition to wide-area surveillance ?

- The difference of the observation direction
  - ECCV2006
- Speed change CVPR2010
- The difference of clothes
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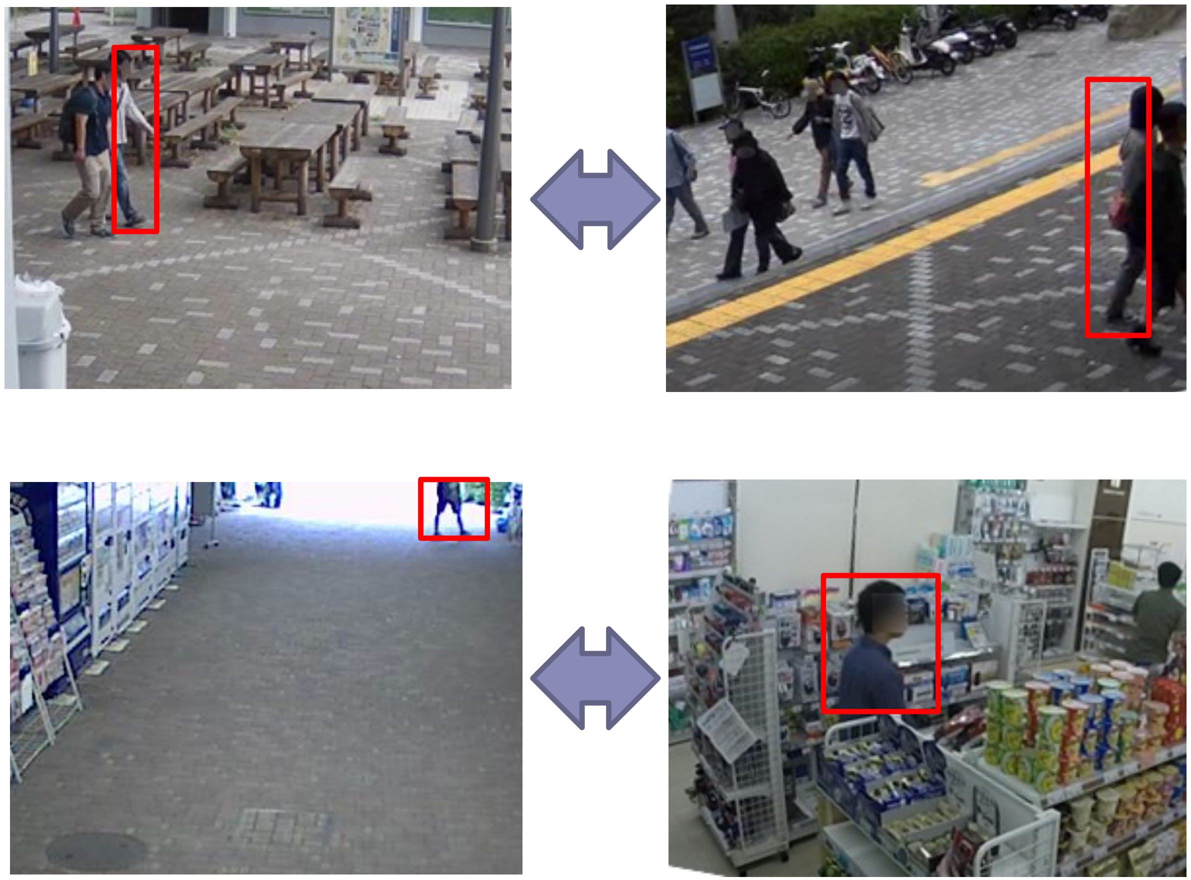
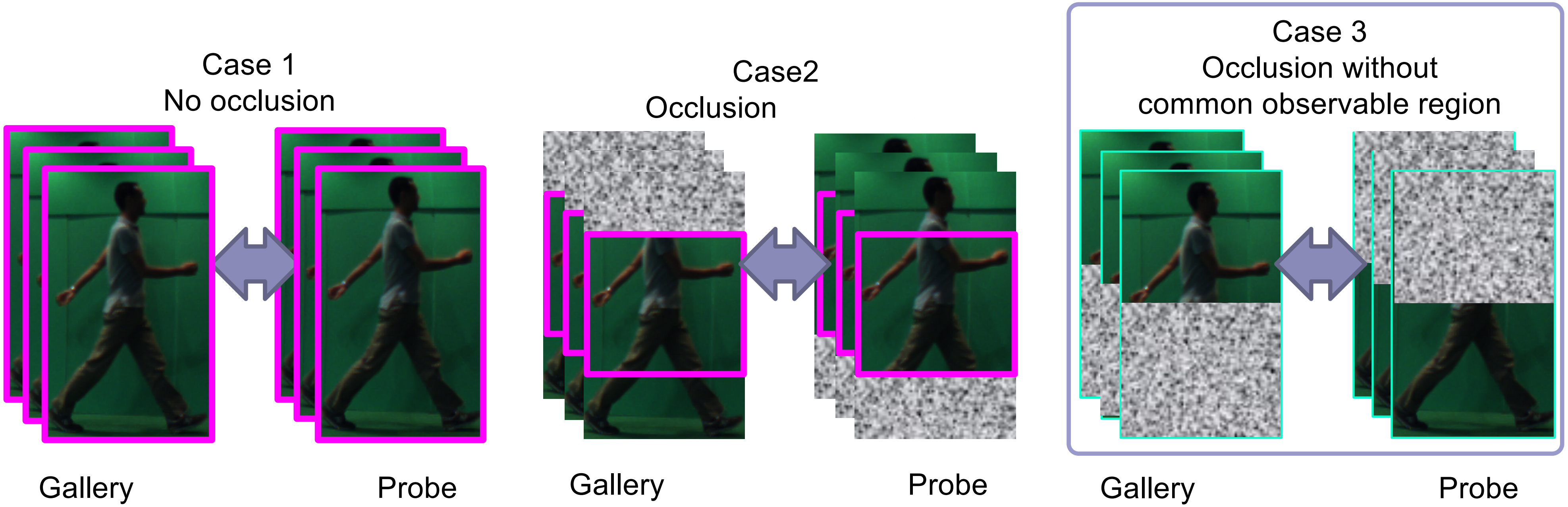
- The difference of shoes
- Low sampling rate
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene
  - ICB2015

Actual situation of observed gait in surveillance



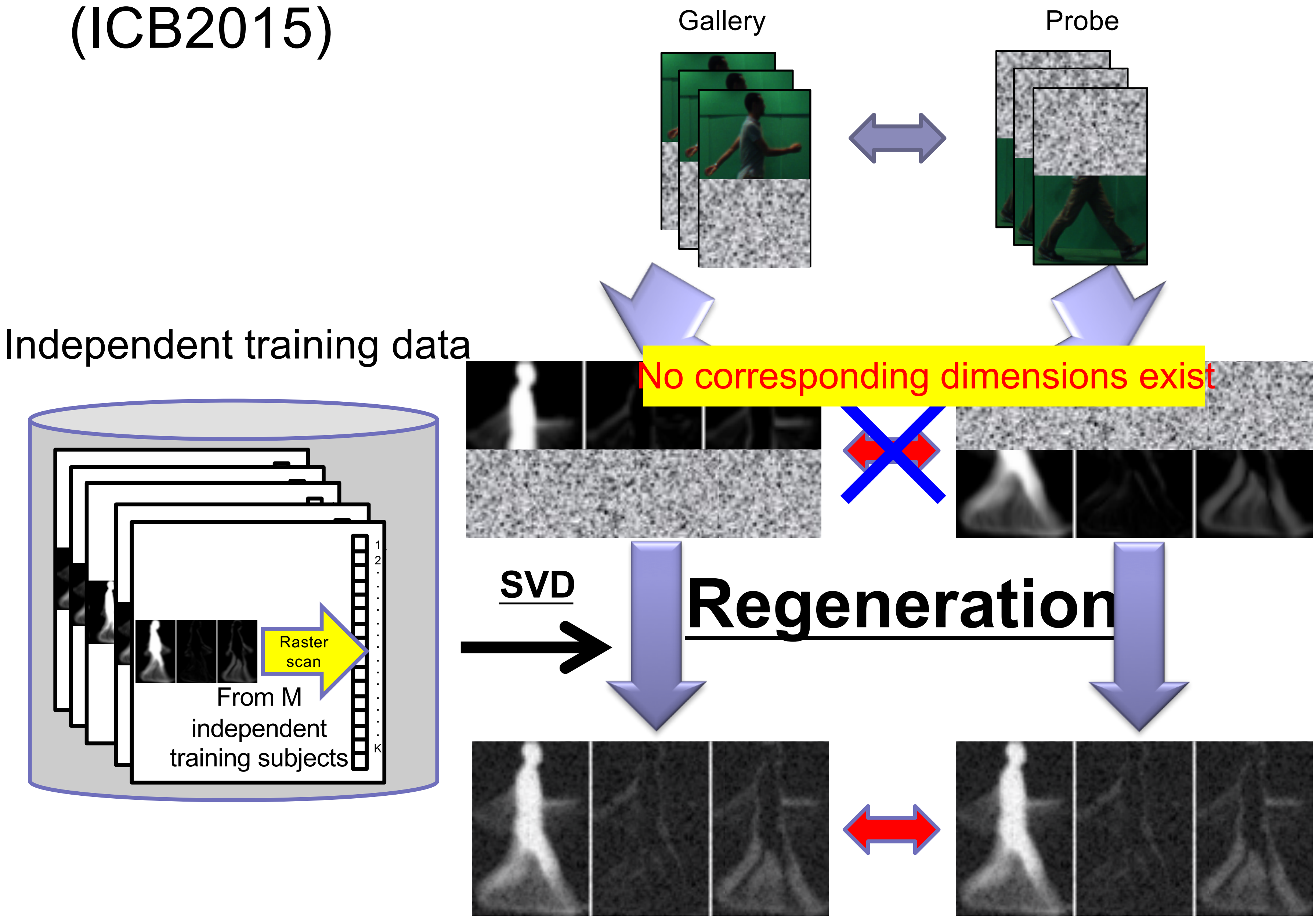
Challenge: Serious occlusion



- Common observable regions (COR) are used for recognition
- Direct comparisons are impossible in case 3
  because any common region cannot be observed

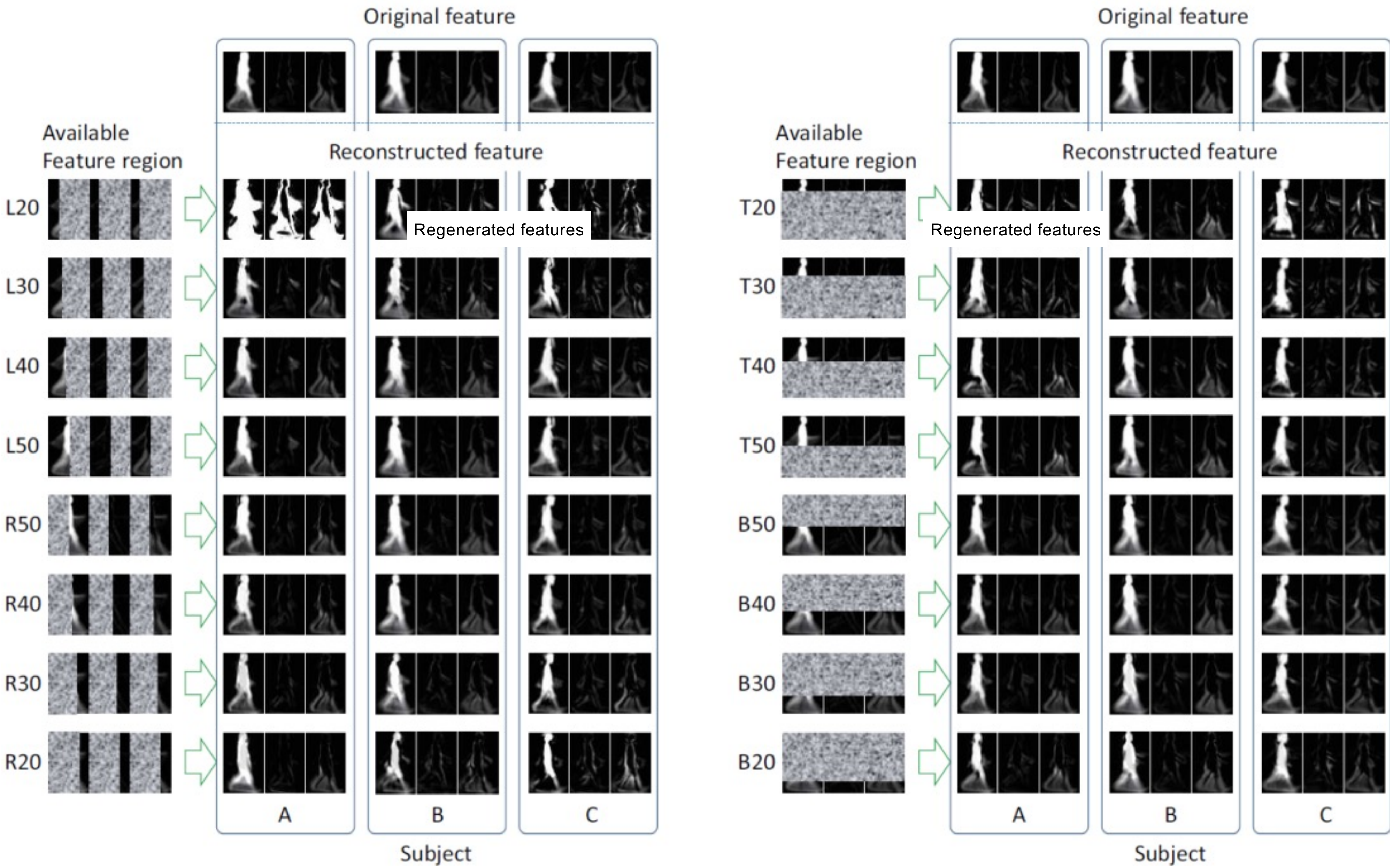
Gait Regeneration for Recognition

(ICB2015)



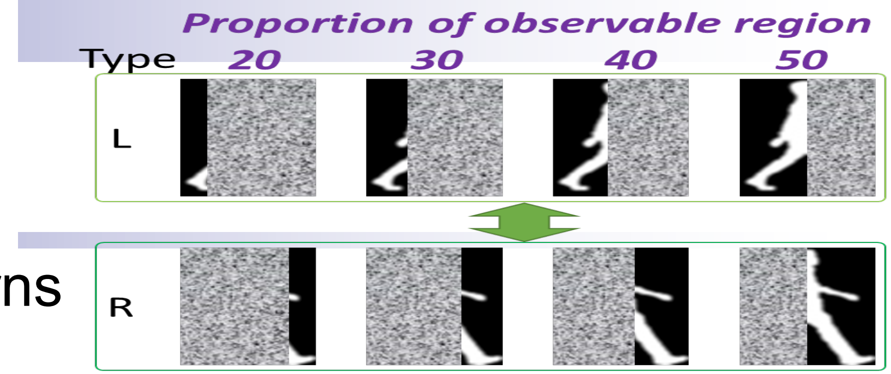
Experiment

Regenerated gait



Experiment

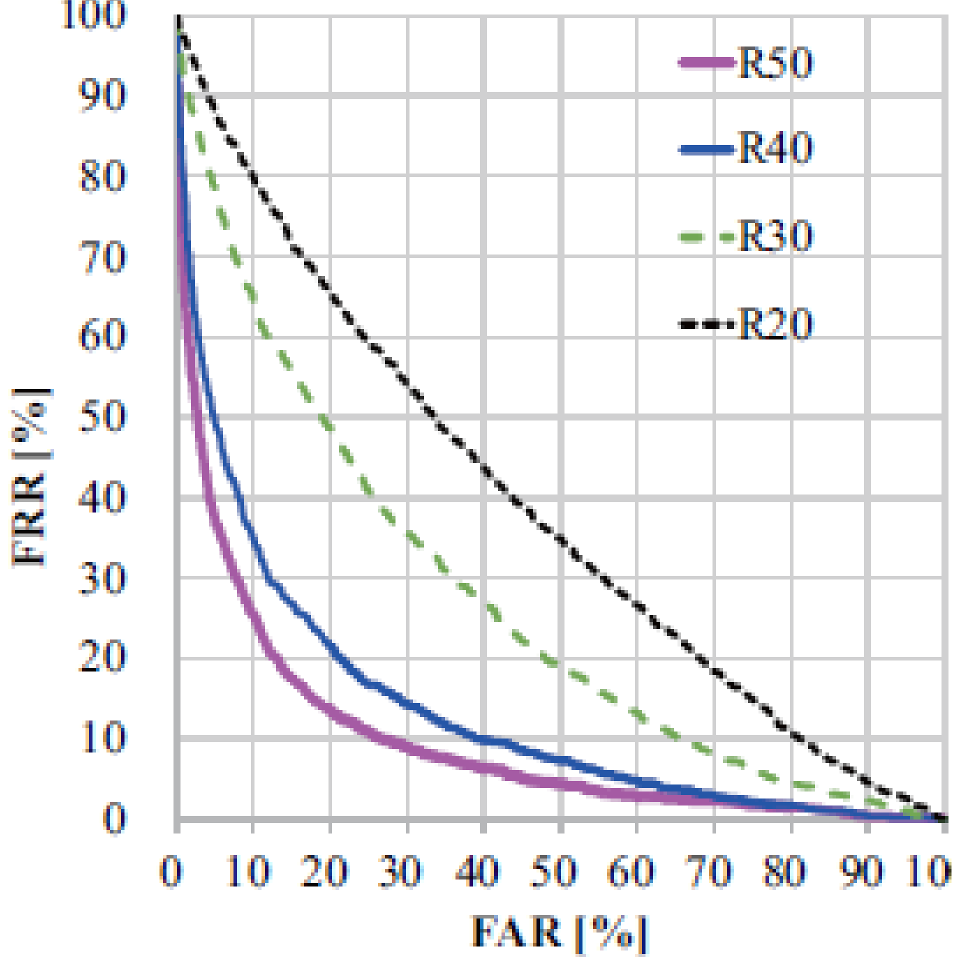
Results with horizontal observable patterns



Horizontal observable pattern

View Angle	Gallery / Probe	L50	L40	L30	L20
85	*R50*	16.4	23.6	39.3	47
	R40	20.6	25.6	38.9	48
	R30	32.9	34.6	42.2	48
	R20	41.8	41.4	44.4	48

Equal Error Rate



ROC curves of propose method against gait features with view 85 deg where L50 is used for the gallery

What is the difficulty for applying gait recognition to wide-area surveillance ?

- The difference of the observation direction
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- Speed change CVPR2010 ACCV2016
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- Low sampling rate
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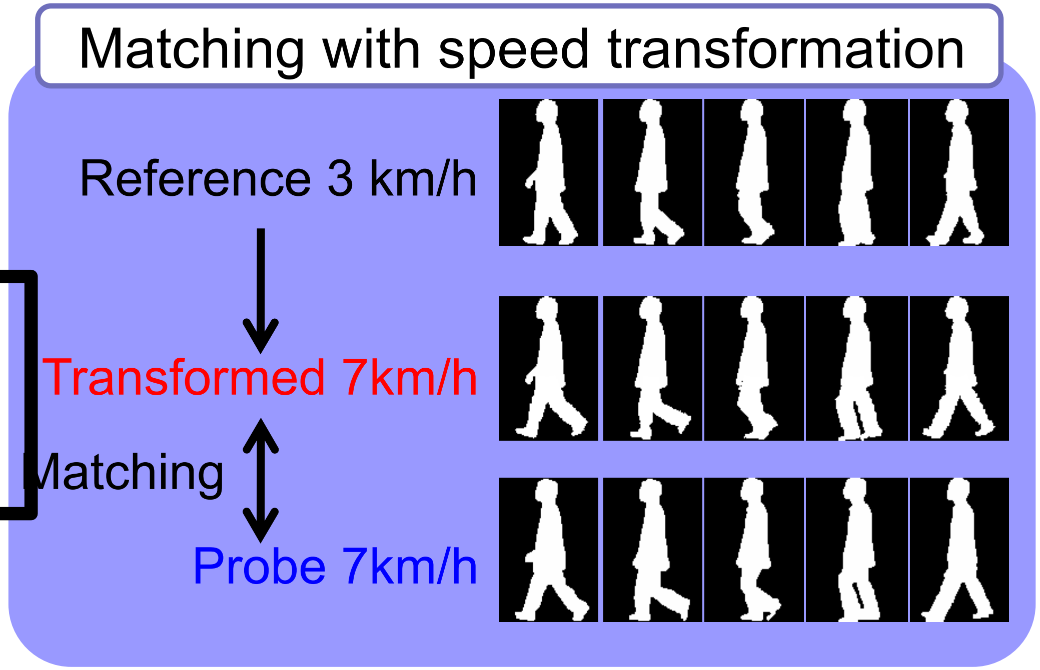
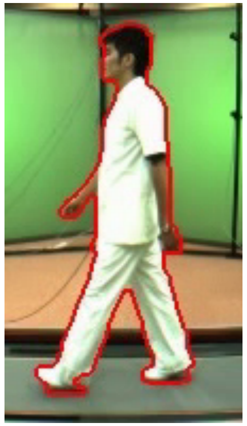


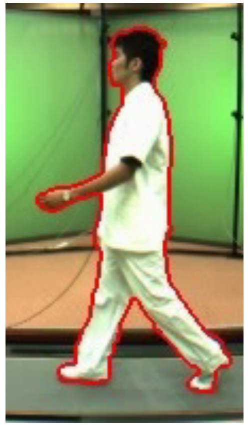
Speed transformation model

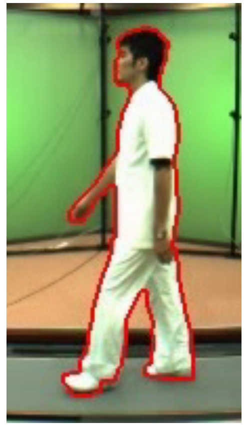
Challenge -Speed difference-


2 km/h

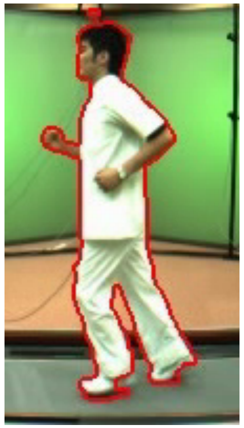

3 km/h


4 km/h


5 km/h


6 km/h

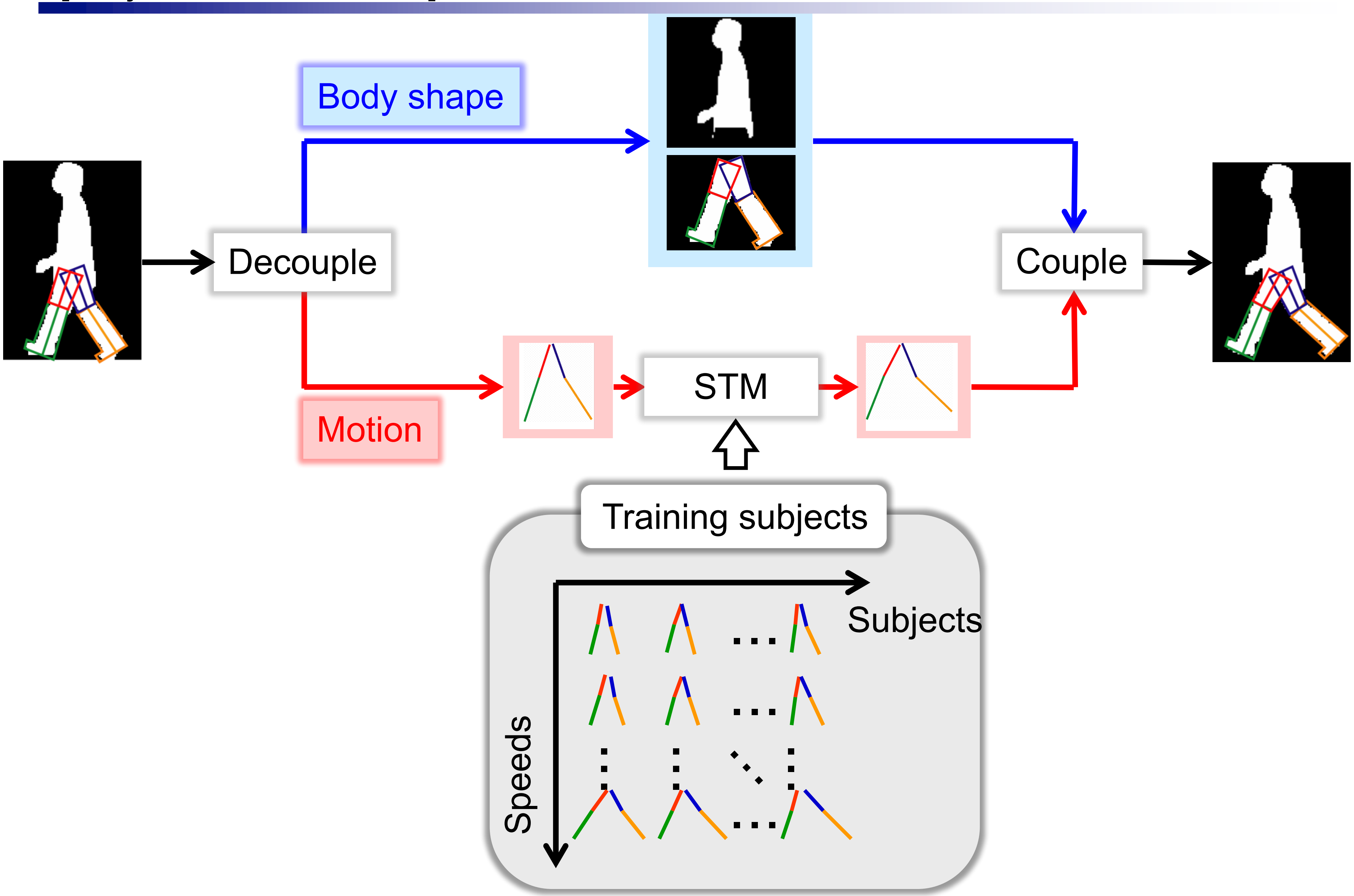

7 km/h


8 km/h

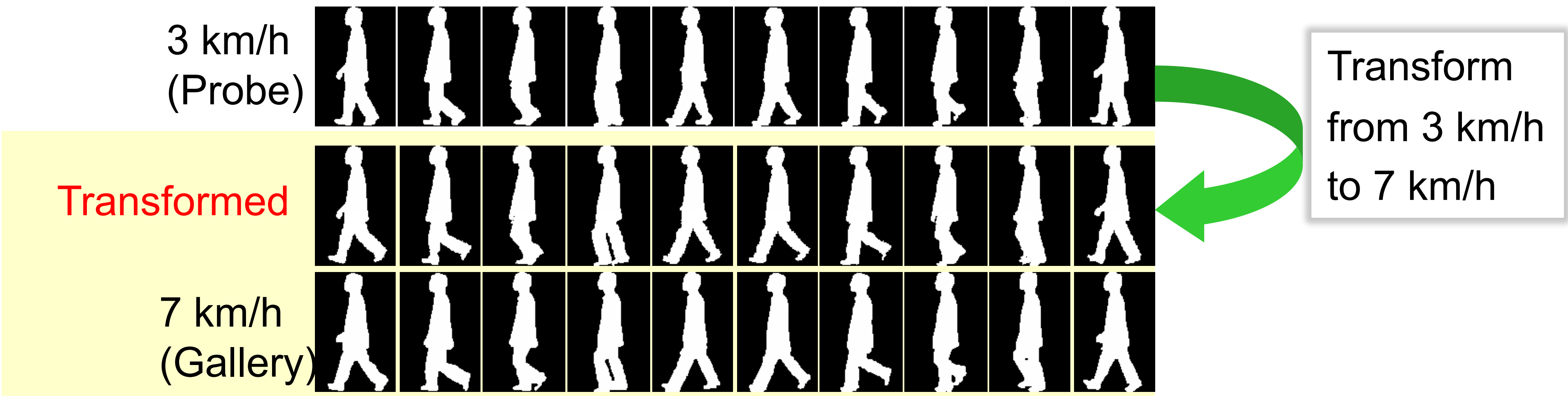

9 km/h


10 km/h

Speed transformation model (STM)
[Tsuji et al. CVPR 2010]

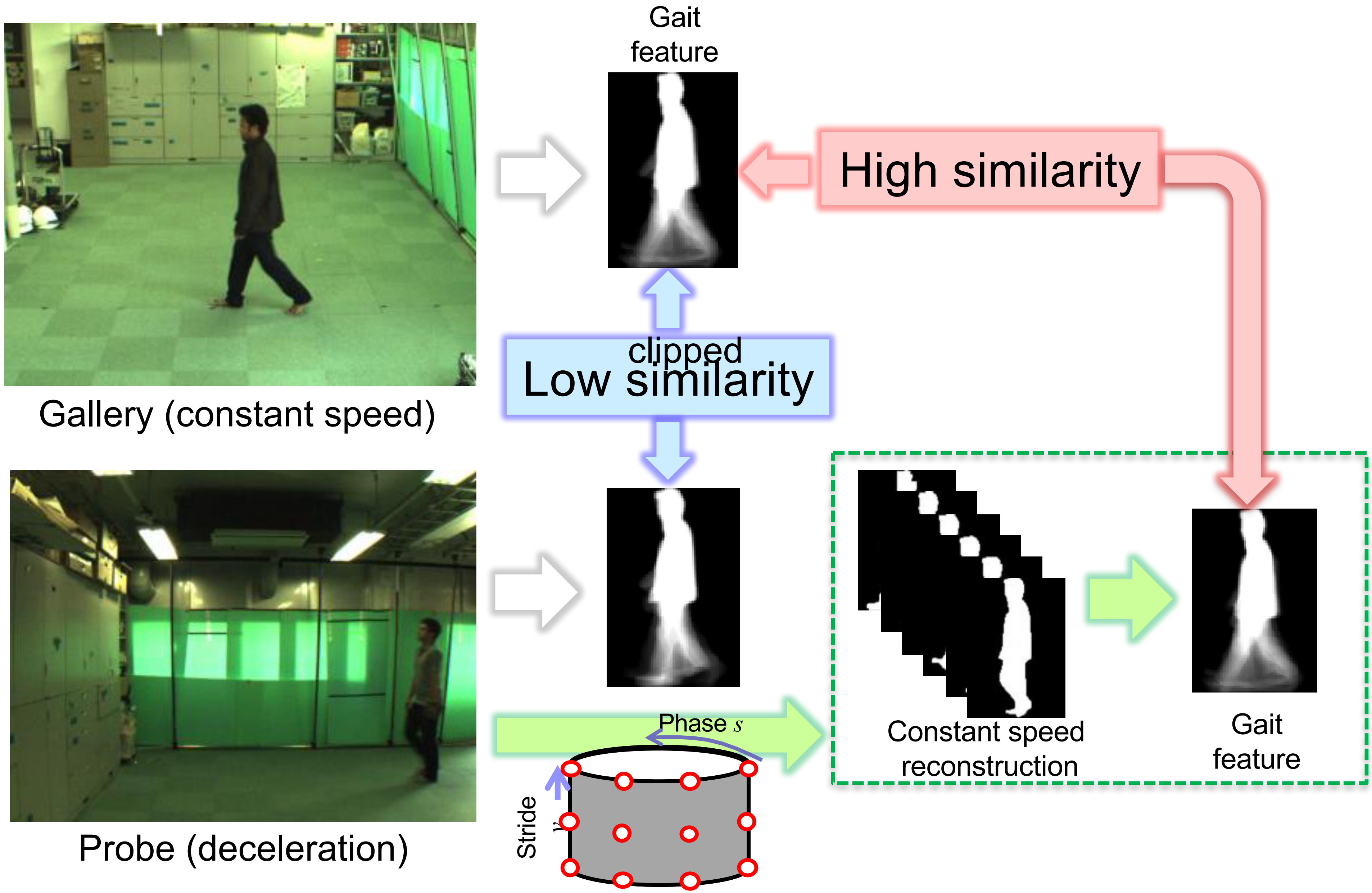


Transformation results



Extension to speed transition

[Mansur et al. CVPR 2014]

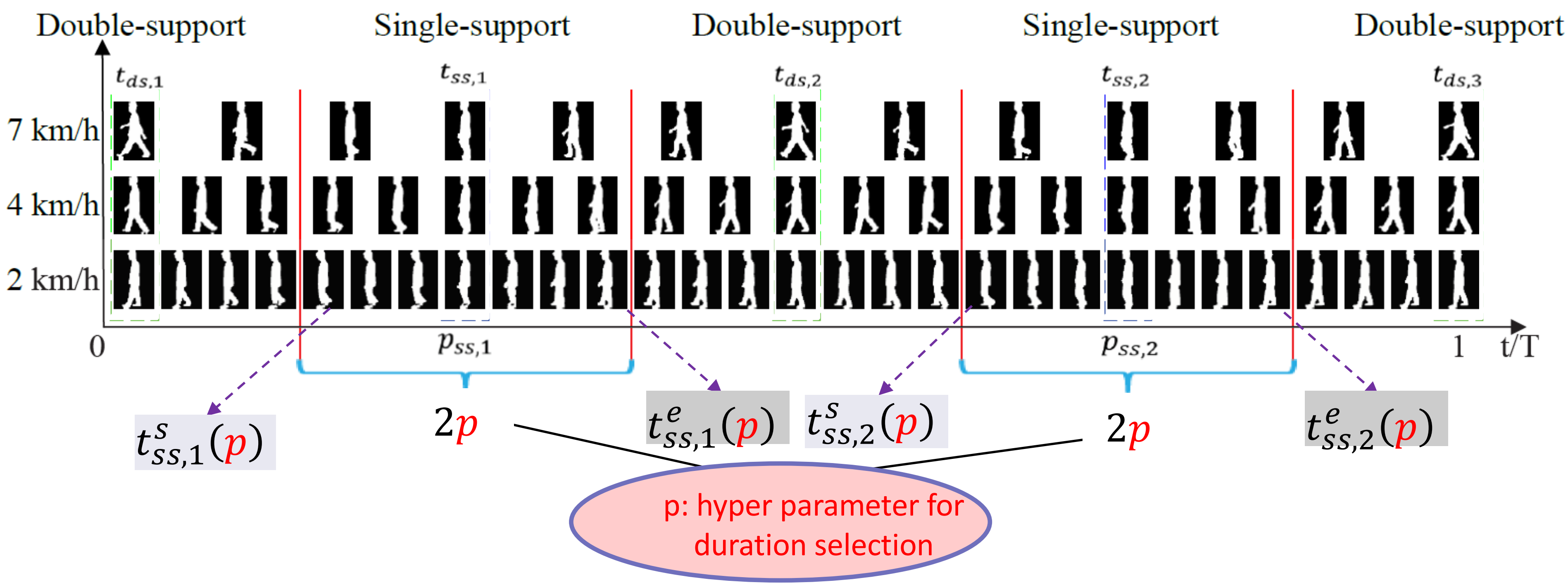


Speed Invariance vs. Stability: Cross-Speed Gait Recognition using Single-Support Gait Energy Image

C. Xu, Y. Makihara, X. Li, Y. Yagi, J. Lu, "Speed Invariance vs. Stability: Cross-Speed Gait Recognition Using Single-Support Gait Energy Image", In *Proc. of the 13th Asian Conf. on Computer Vision (ACCV 2016)*,

Single-Support GEI (SSGEI)

- Aggregate multiple frames of optimal duration around single support phase



- Representation:

$$S(x,y;p) = \frac{1}{2}\sum_{k=1}^{2}\frac{1}{t^e_{ss,k}(p) - t^s_{ss,k}(p) + 1}\sum_{t=t^s_{ss,k}(p)}^{t^e_{ss,k}(p)} I(x,y,t), \qquad (0 < p \leq {}^1/_4).$$

Optimal duration estimation

- Criterion: Fisher ratio on training set.

Mean of i-th class

Within-class distance: $$D_W(p) = \sum_{i=1}^{N_c} \sum_{j=1}^{n_i} \left\| S_{i,j}(p) - \bar{S}_i(p) \right\|_F^2 .$$

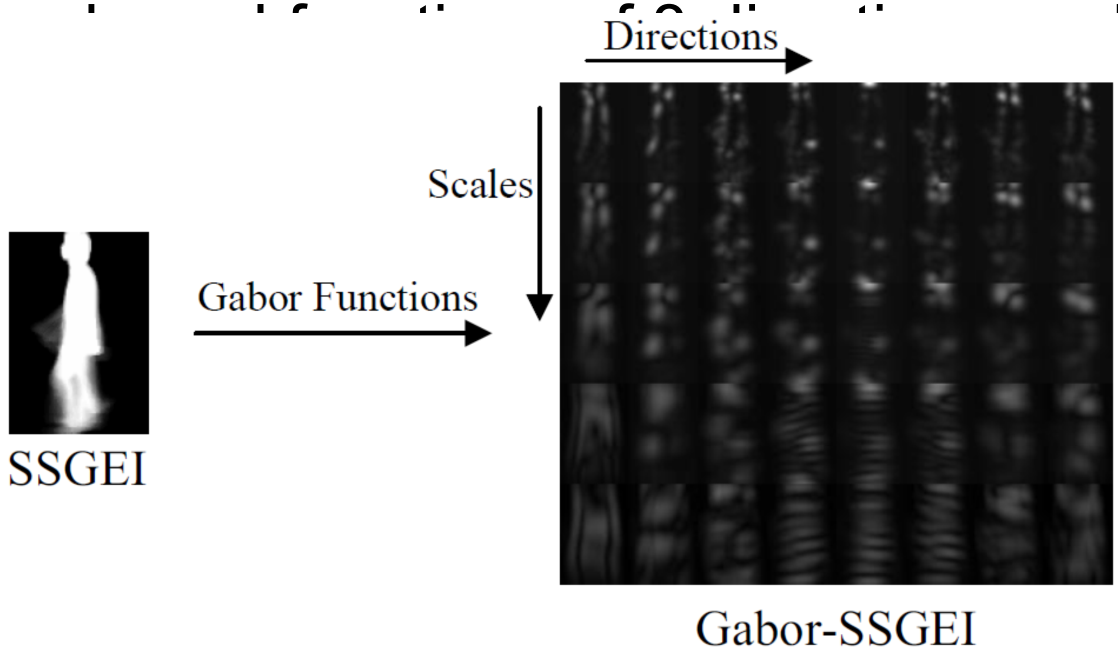
Between-class distance: $$D_B(p) = \sum_{i=1}^{N_c} n_i \left\| \bar{S}_i(p) - \bar{S}(p) \right\|_F^2 .$$

Mean of all samples

Optimal duration parameter: $$p^* = \arg\max_p \frac{D_B(p)}{D_W(p)} .$$

Post-process

- Gabor filtering [Tao et al. 2007]
  - Gab … 5 scales.



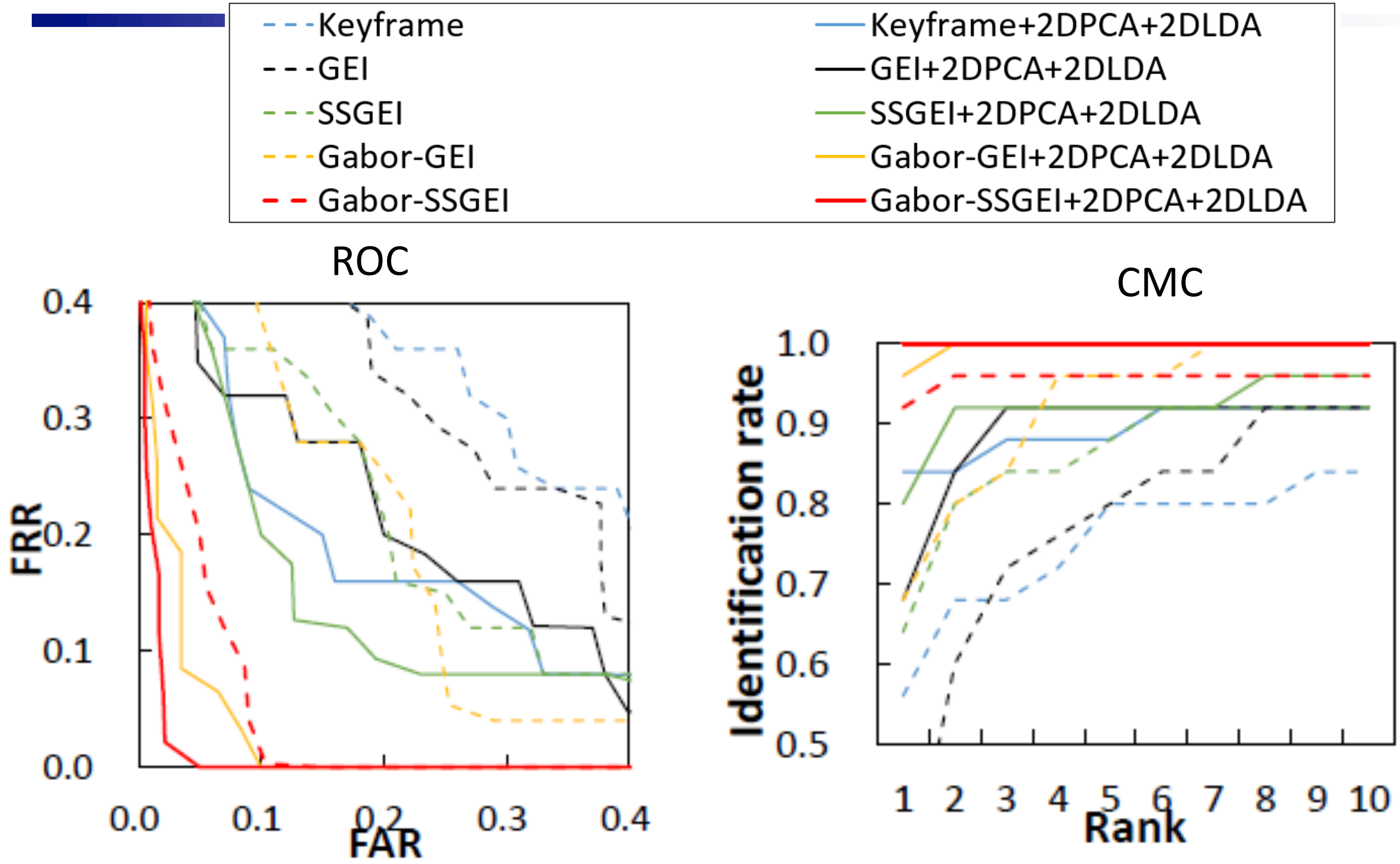
- Metric Learning

Experiments: Dataset 1

- **OU-ISIR Treadmill Dataset A** [Makihara et al. 2012]
  - Speed variation: 2 km/h ~ 7 km/h (walking)
  - Training set: 9 subjects, testing set: 25 subjects

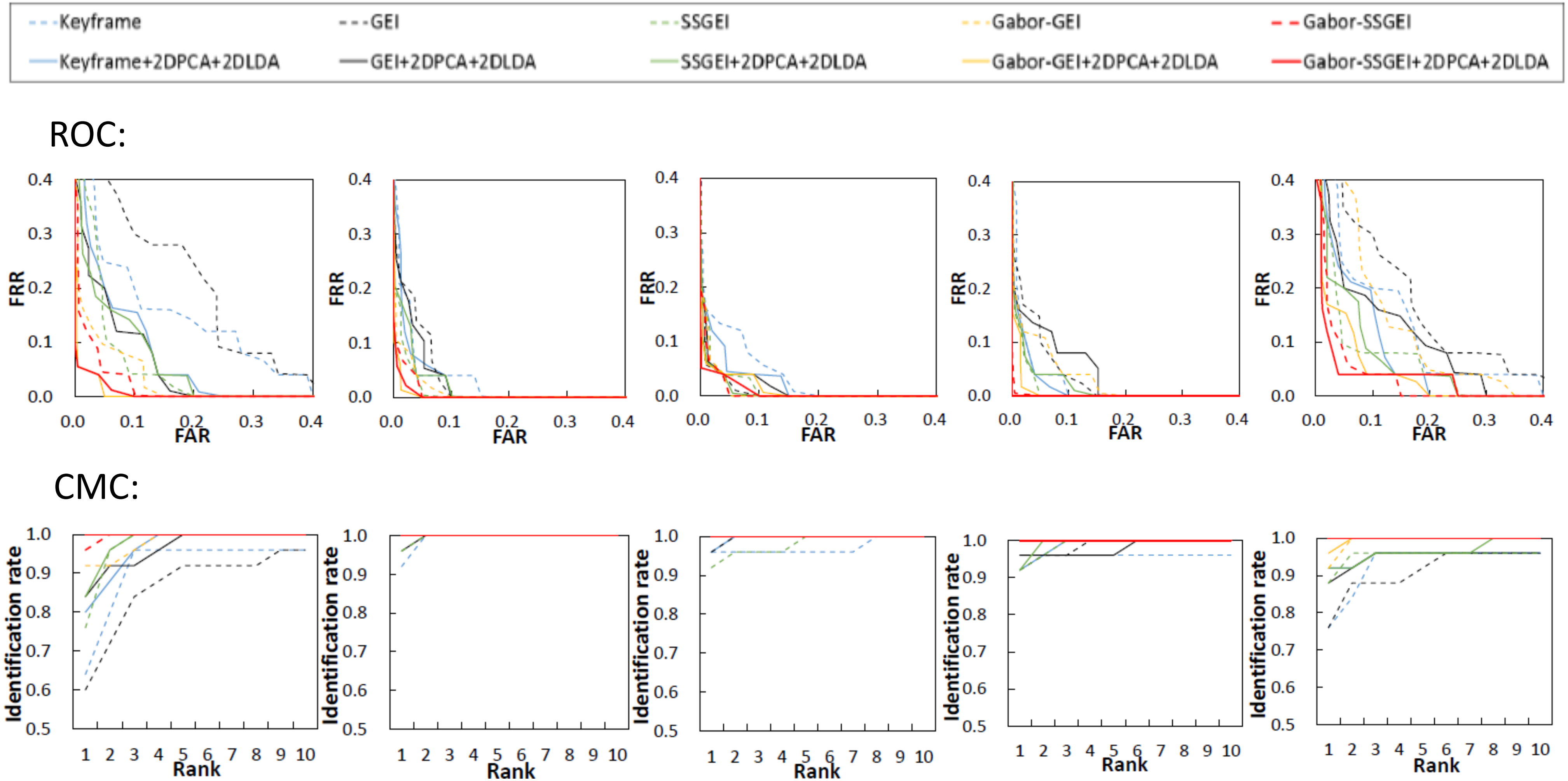
Contains the largest speed variations.

Experiments: Gallery 4 km/h vs. probe 7 km/h



The propose method achieves the best accuracy.

Experiments: Gallery 4 km/h vs. probe 2 km/h~ 6 km/h

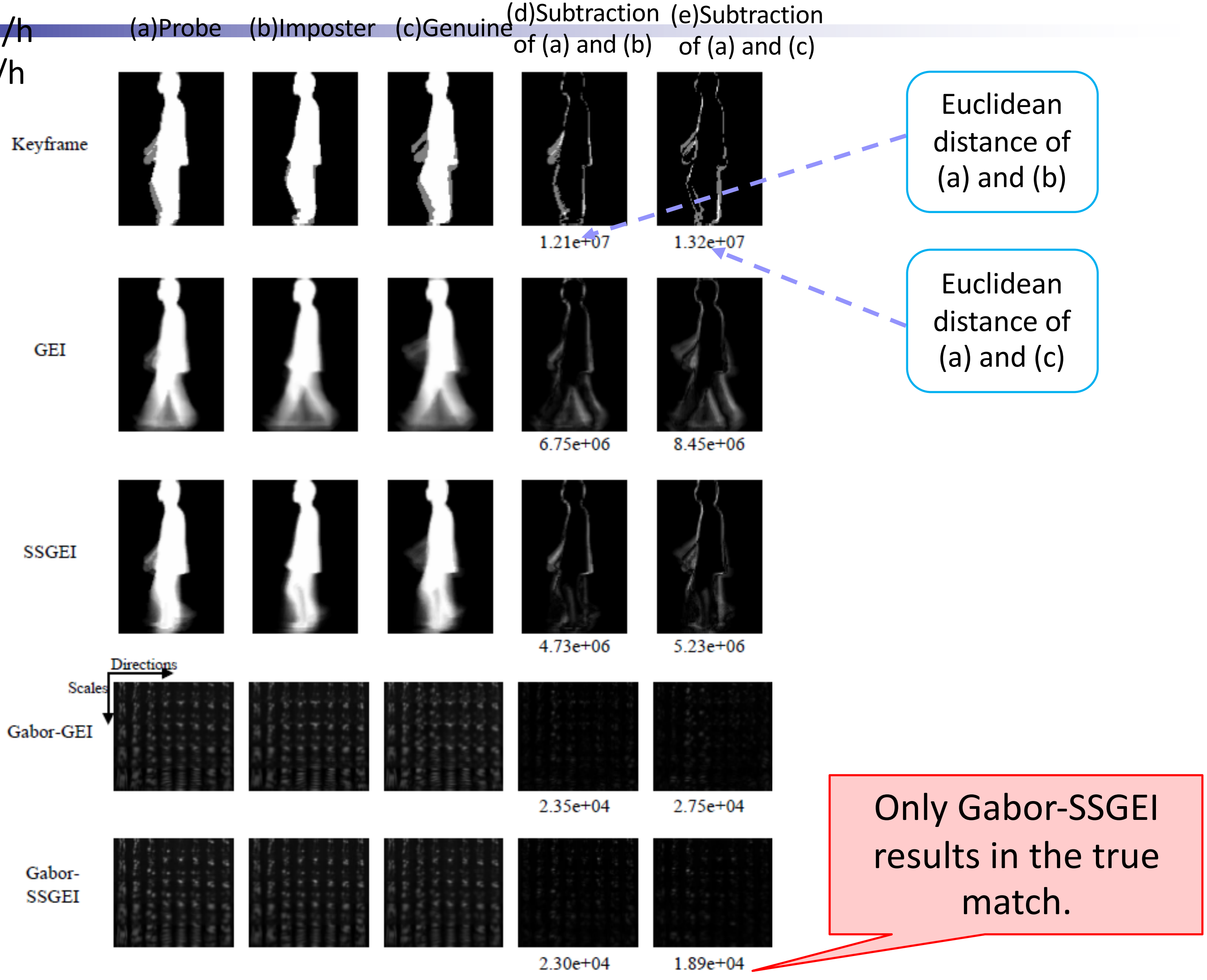


Probe: 2 km/h | Probe: 3 km/h | Probe: 4 km/h | Probe: 5 km/h | Probe: 6 km/h

The propose method achieves the best accuracy as a whole.

Experiments: Typical success examples

Gallery: 4 km/h
Probe: 2 km/h



Experiments: Rank-1 identification rates

- Rank-1 identification rates [%] averaged over all of the 36 (= 6 × 6) combinations of walking speeds in probe and gallery.

	Keyframe	GEI	SSGEI	Gabor-GEI	Gabor-SSGEI
w/o metric learning	74.9	62.6	80.3	***84.0***	**95.1**
w/ metric learning	84.4	85.9	87.7	***96.9***	**99.3**

- SSGEI outperforms other two features.
  - ➢ SSGEI realizes a good trade-off between the speed invariance and the stability.
- Individual components SSGEI, Gabor filtering and metric learning, all substantially contribute.

Experiments: Comparison with State-of-the-arts

- Rank-1 identification rates [%] of 36 individual combinations of walking speeds.

RSM [Guan et al. 2013]:

Gallery / Probe	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
2km/h	1000.00	1000.00	1000.00	97.62.07	97.62.80	942.83
3km/h	1000.00	1000.00	1000.00	1000.00	1000.00	98.42.07
4km/h	1000.00	1000.00	1000.00	1000.00	1000.00	90.42.80
5km/h	92.81.69	96.41.26	1000.00	1000.00	1000.00	960.00
6km/h	920.00	94.42.07	1000.00	1000.00	1000.00	1000.00
7km/h	920.00	942.11	94.81.93	1000.00	1000.00	1000.00

Proposed method:

Gallery / Probe	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
2km/h	100	100	100	100	96	96
3km/h	100	100	100	100	100	92
4km/h	100	100	100	100	100	92
5km/h	100	100	100	100	100	100
6km/h	100	100	100	100	100	100
7km/h	100	100	100	100	100	100

Blue number: worse result.

Red number: better result.

Black number: same result.

Experiments: Comparison with State-of-the-arts

- Rank-1 identification rate [%] in case of small and large speed changes.

Speed change	HMM [Liu et al. 2006]	SN [Tanawongsuwan and Bobick. 2004]	STM [Tsuji et al. 2010]	DCM [Kusakunniran et al. 2012]	RSM	Proposed method
Small (3 km/h and 4 km/h)	84	-	90	98	**100**	**100**
Large (2 km/h and 6 km/h)	-	35	58	82	***95***	**98**

- Averaged rank-1 identification rates [%] over 36 combinations of walking speeds of DCM, RSM and proposed method.

Algorithms	Rank-1 identification rate
DCM	92.44
RSM	***98.07***
Proposed method	**99.33**

The proposed method clearly outperforms the other algorithms, in particular in case of large speed changes.

Experiments: Evaluation of Running Time

- Run on PC with Intel Core i7 4.00 GHz processor and 32 GB RAM.

Running stage	Time cost [s]
Training time in optimizing duration parameter	0.009
Training time in 2DPCA and 2DLDA	0.115
Query time of each sequence	0.003

Computational cost of the proposed method is very low and suitable for real applications.

What is the difficulty for applying gait recognition to wide-area surveillance ?

- The difference of the observation direction
  - ECCV2006
- Speed change CVPR2010
- The difference of clothes
  - Pattern Recognition 2010, ACCV2016
- The difference of shoes
- Low sampling rate
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene
  - ICB2015

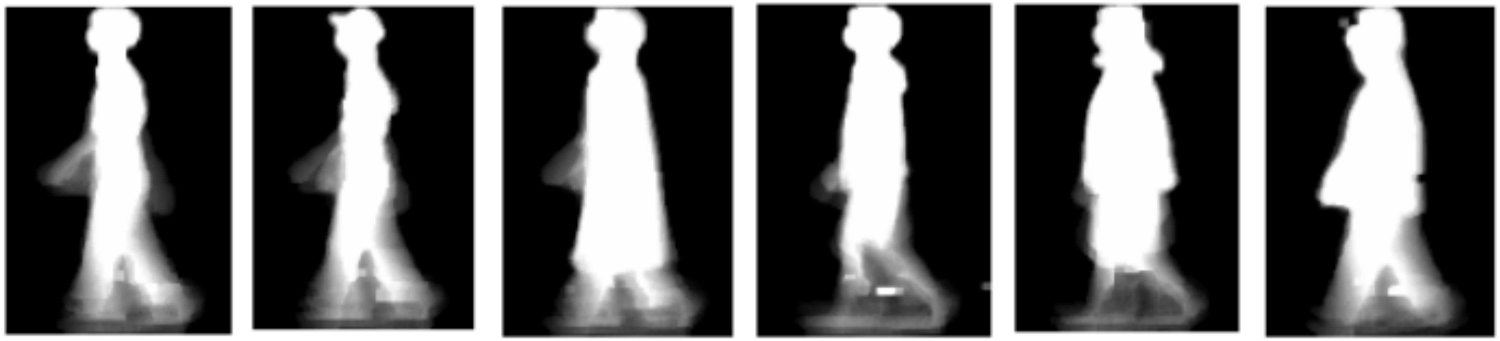
Gait Energy Response Function for Clothes-invariant Gait Recognition

X. Li, Y. Makihara, C. Xu, D. Muramatsu, Y. Yagi, M. Ren, "Gait Energy Response Function for Clothing-invariant Gait Recognition", In *Proc. of the 13th Asian Conf. on Computer Vision (ACCV 2016*

Background

- Gait recognition
  - Pros:
    - Availability at a distance for an uncooperative subject (c.f. face, iris)
  - Cons:

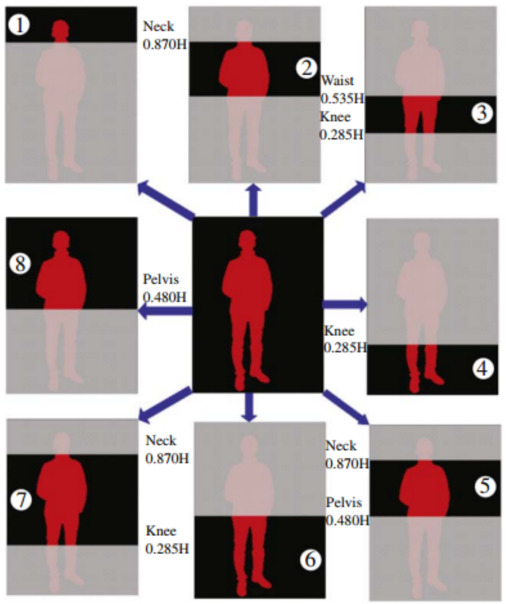
ew,

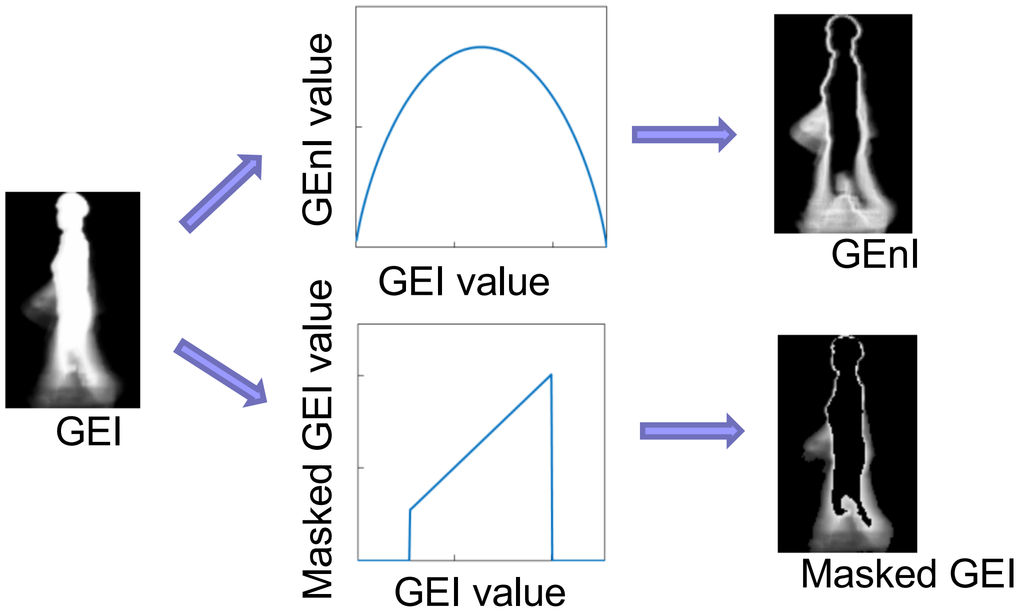


Gait energy images [Han and Bhanu 2006] under clothing variations

Related works

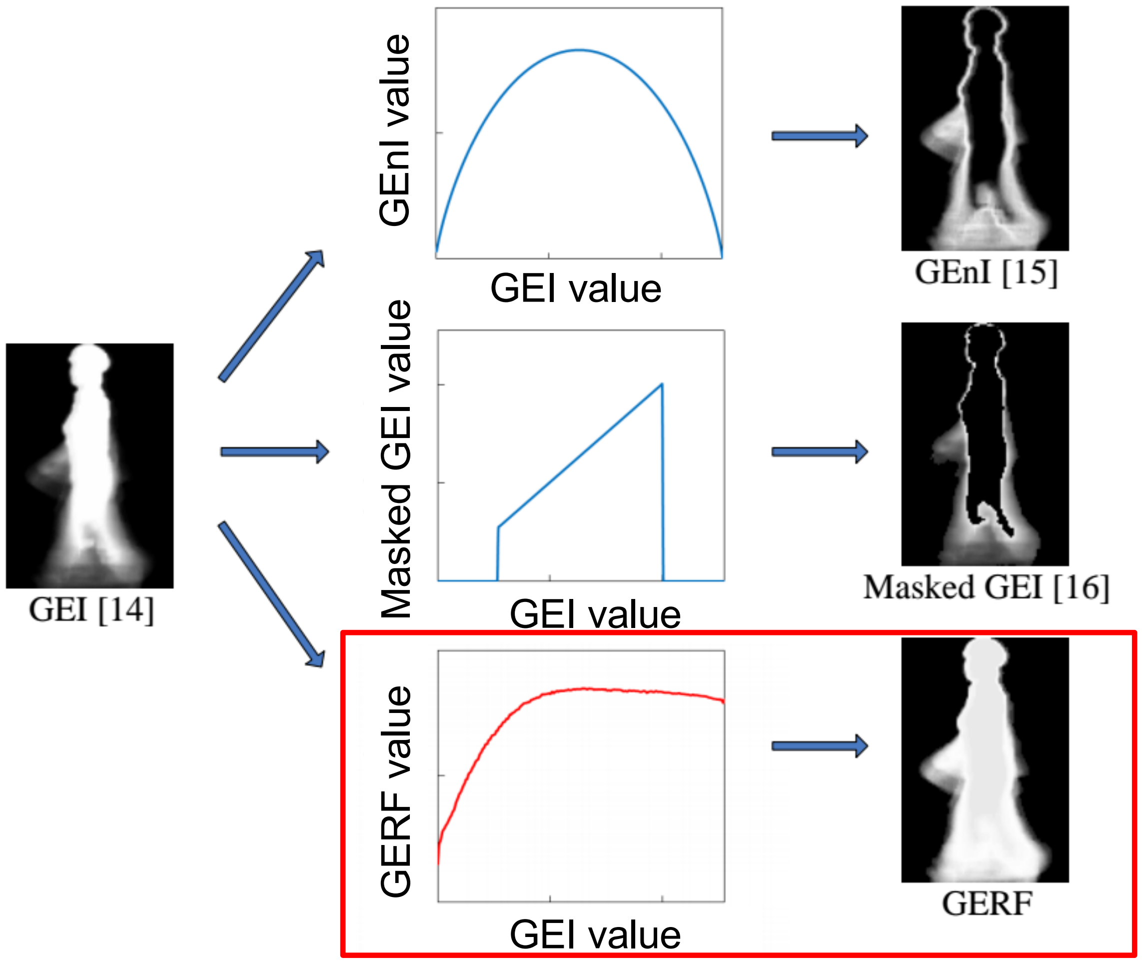
- Spatial metric learning-based
  - Whole-based
    - PCA+LDA [Han and Bhanu 2006]
    - RSM [Yu Guan et al. 2012]
  - Part-based [Hossain et al. 2010]
- Intensity transformation-based
  - GEnI: Gait entropy image [Bashir et al. 2009]
  - Masked GEI [Bashir et al. 2010]





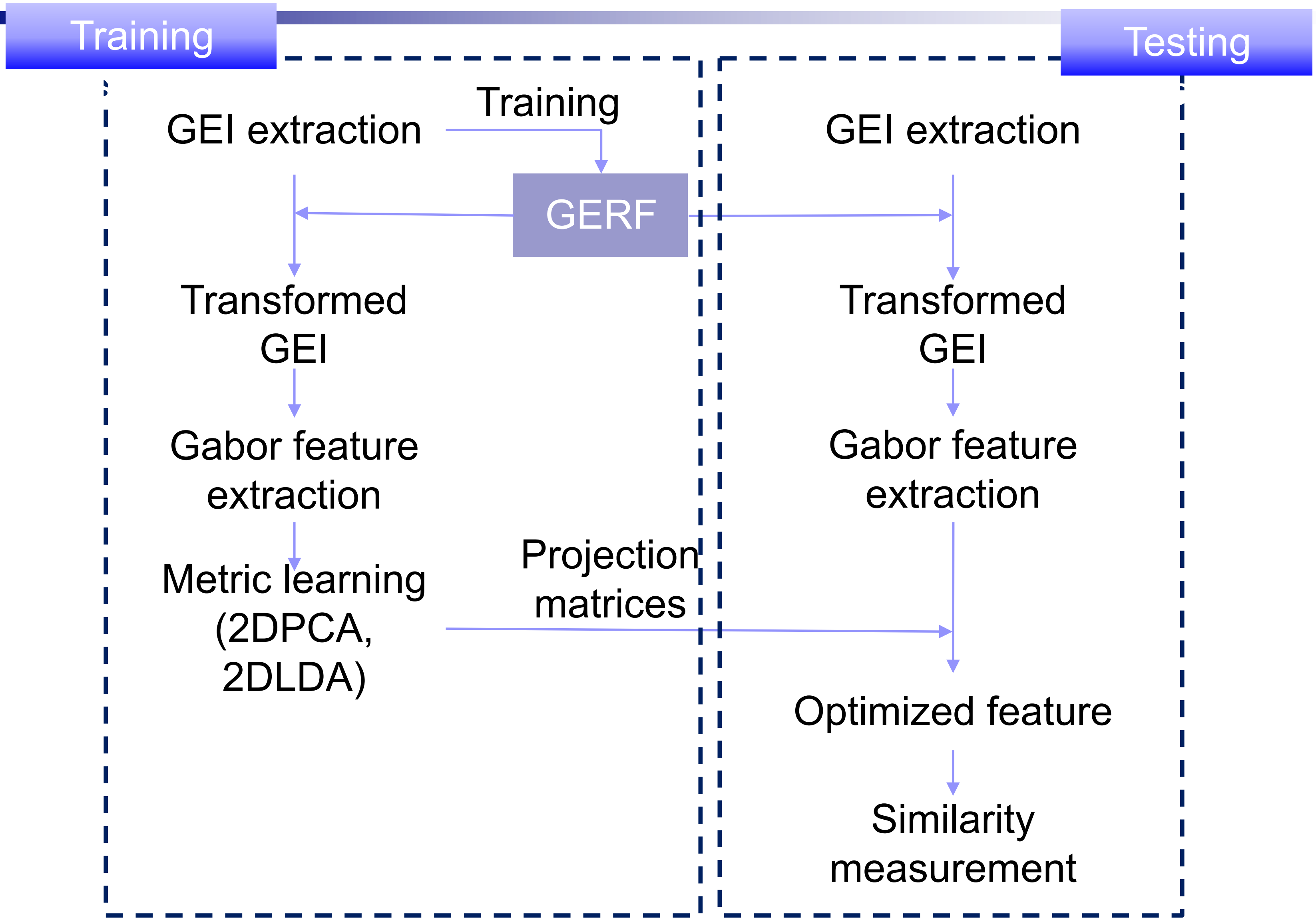
Objective

- Transform GEI into more discriminative feature under clothes variation



A sort of gait energy transformation process via a gait energy response function (GERF)

Outline of proposed method



GERF representation

- Definition

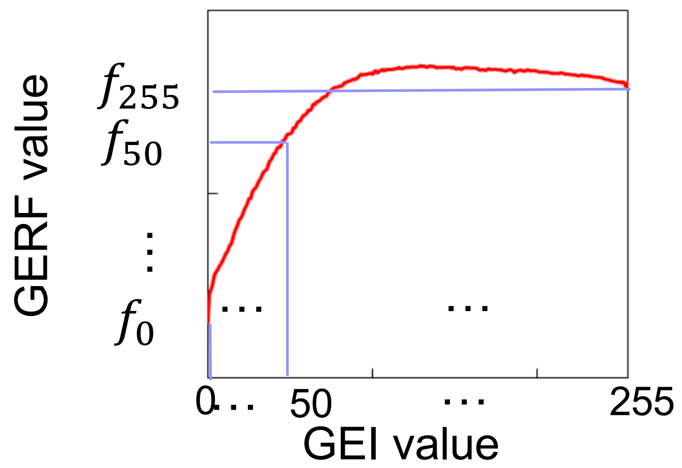
$$I'(x,y) = f\big(I(x,y)\big), \quad \forall(x,y).$$

$I \in \{0, \ldots, G_{max}\}$: Original gait energy
$I' \in \{0, \ldots, G_{max}\}$: Transformed gait energy
G_{max} : Maximum value of GEI
$f(.)$: Gait energy response function

- Look-up table representation

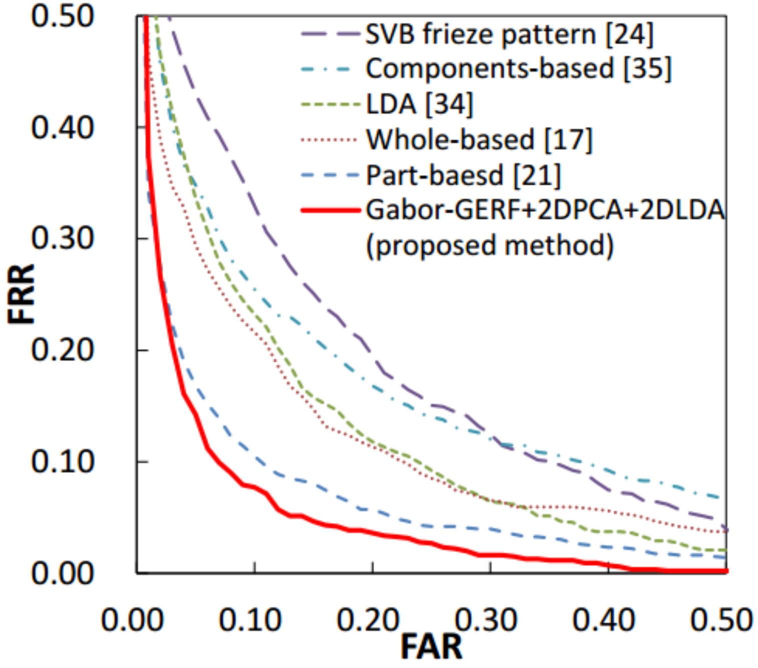
$$\boldsymbol{f} = \left[f_0, \ldots, f_{G_{max}}\right]^T \in R^{G_{max}+1}$$

$$I' = f_I$$

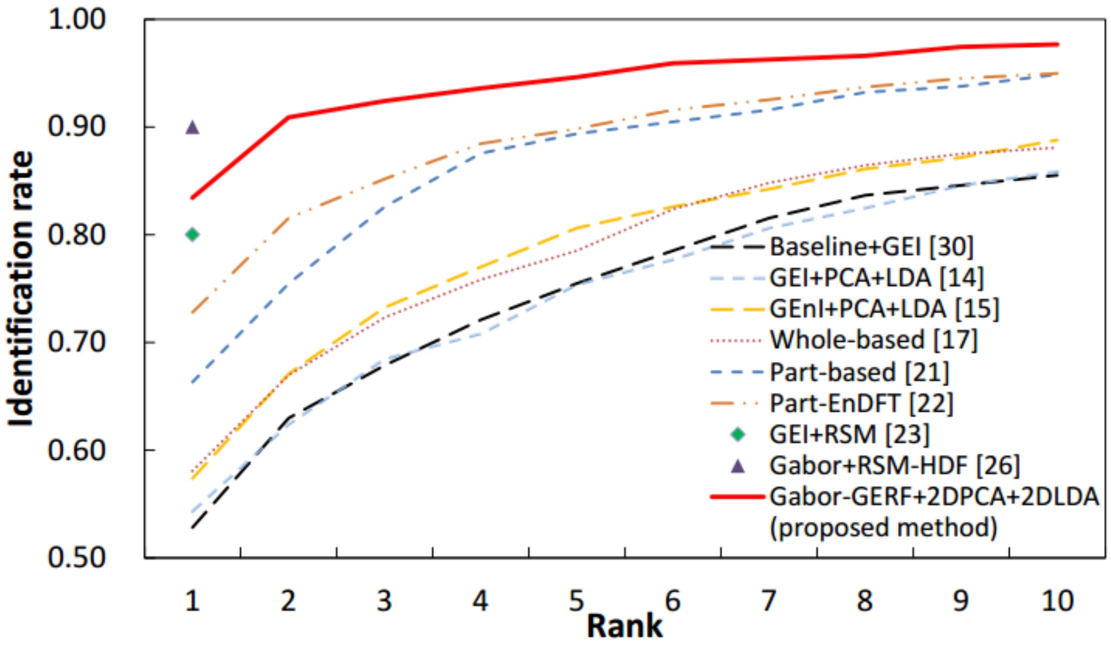


Comparison with state-of-the-arts methods

- Compare with the state-of-the-arts methods

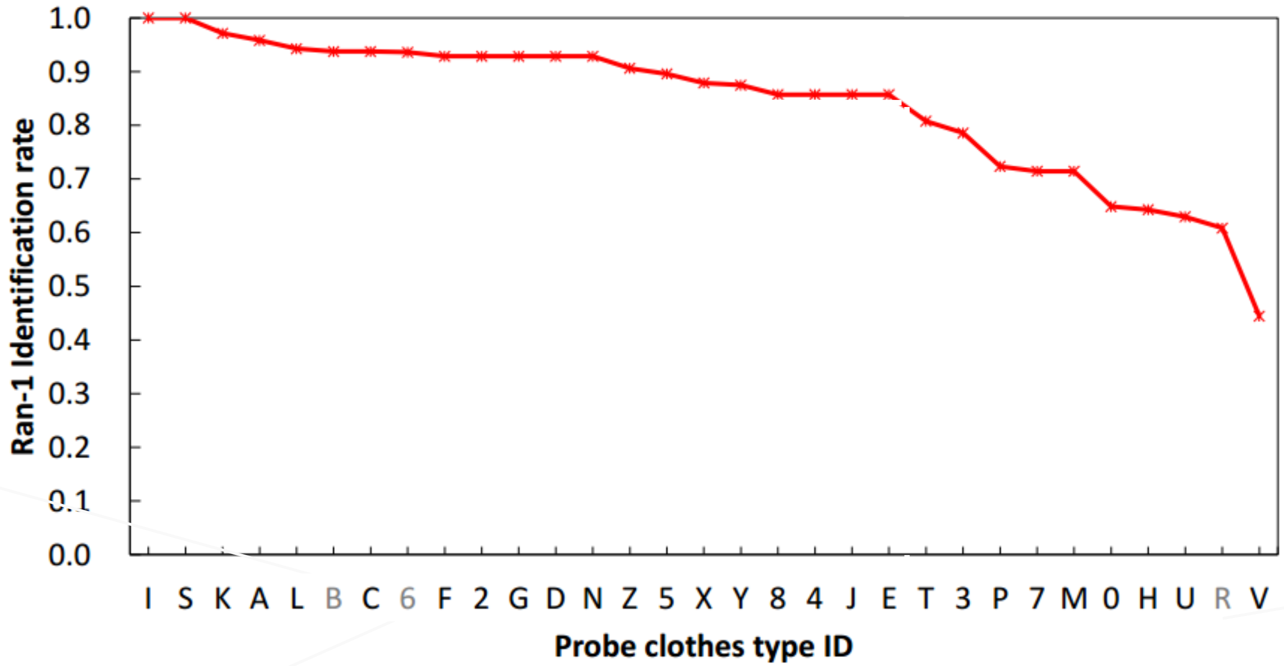


ROC curves



CMC curves

Analysis of difficulty levels by clothing type



0.85


type B

Regular pants + down jacket


type 6

Regular pants + long coat + muffler


type R

Raincoat

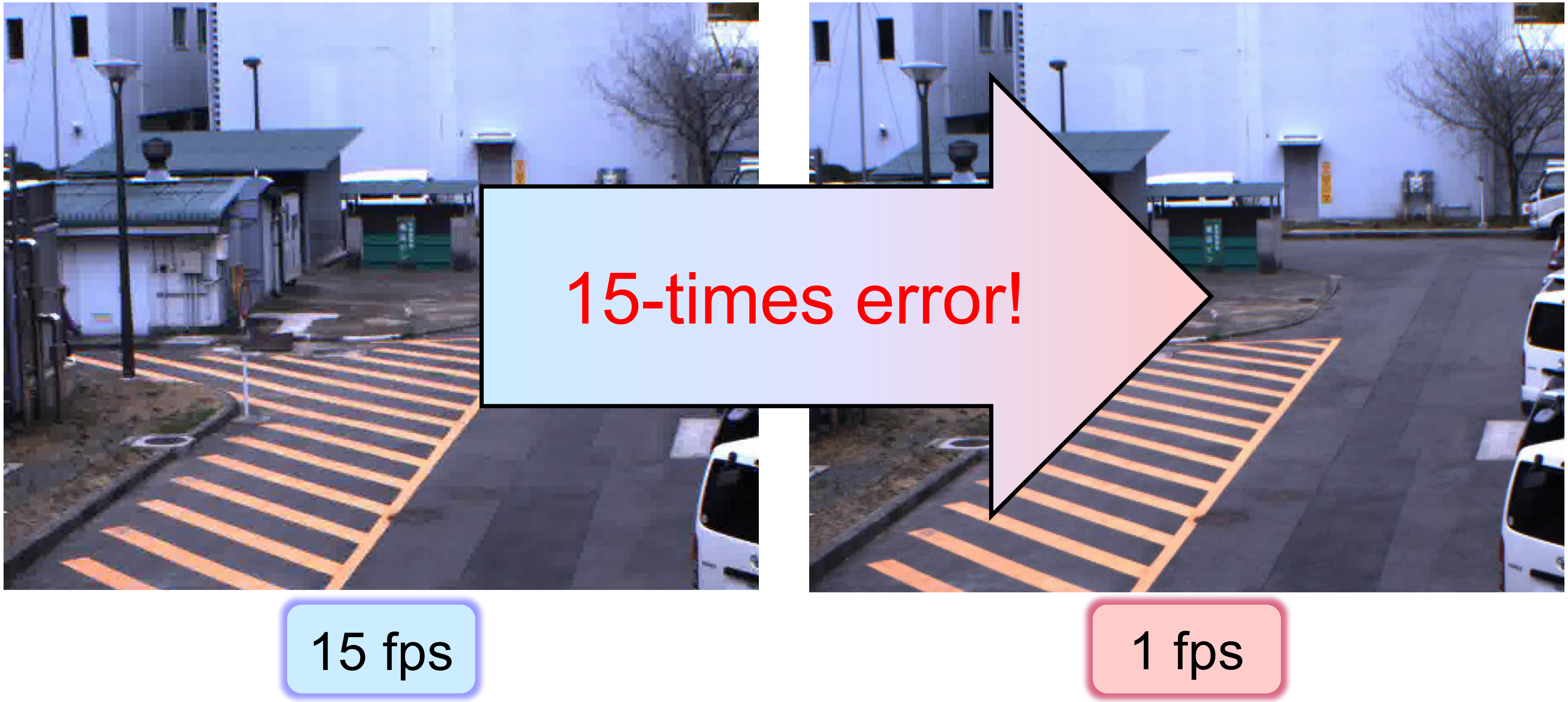
The proposed method effectively gains the discriminative features under a certain clothes types

But it still suffers from large intra-subject variations

What is the difficulty for applying gait recognition to wide-area surveillance ?

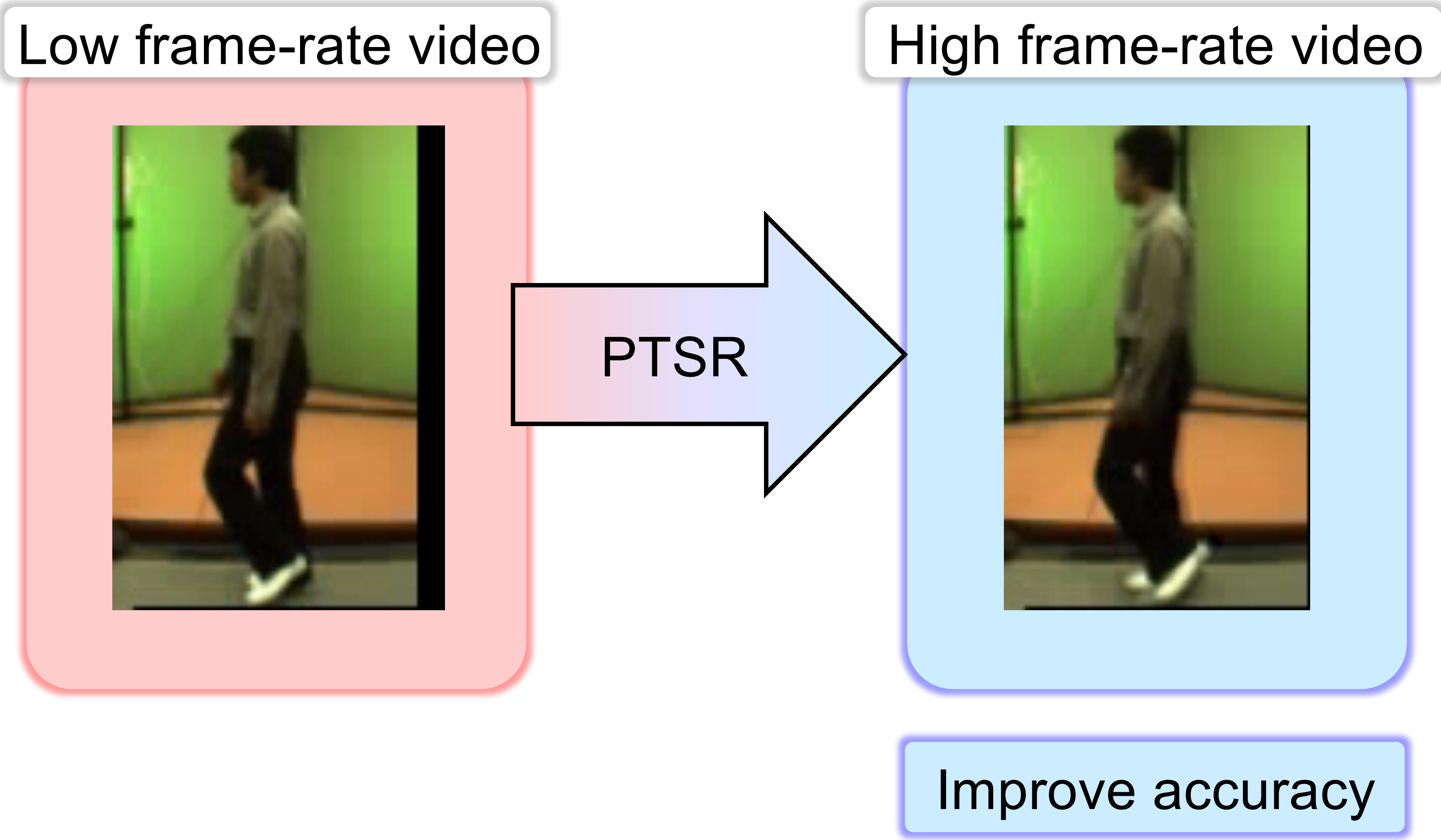
- The difference of
  the observation direction
  - ECCV2006
- Speed change CVPR2010
- The difference of clothes
  - Pattern Recognition 2010
- The difference of shoes
- Low sampling rate
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene
  - ICB2015

Challenge -Low frame-rate-



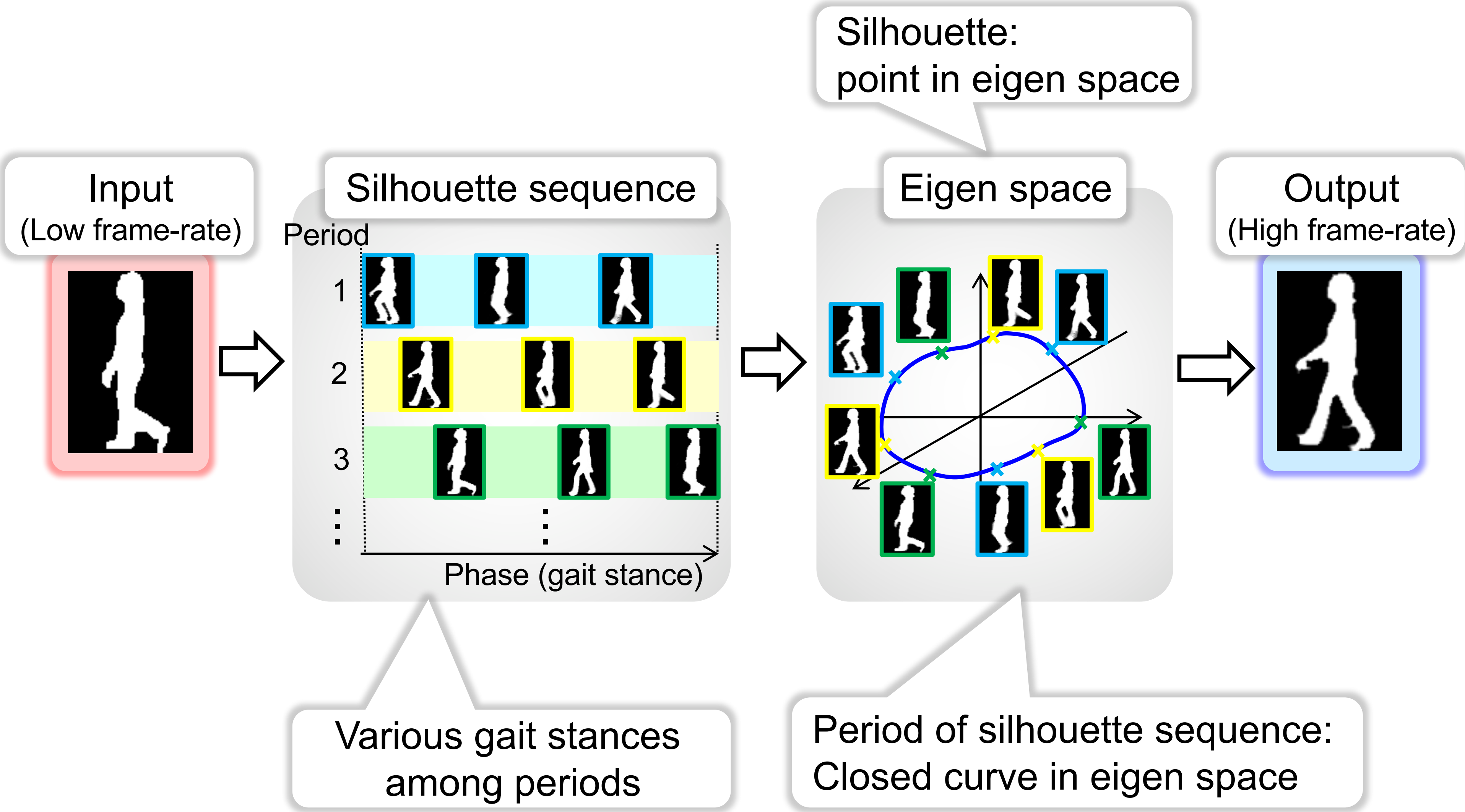
Solution

- Periodic Temporal Super Resolution (PTSR)

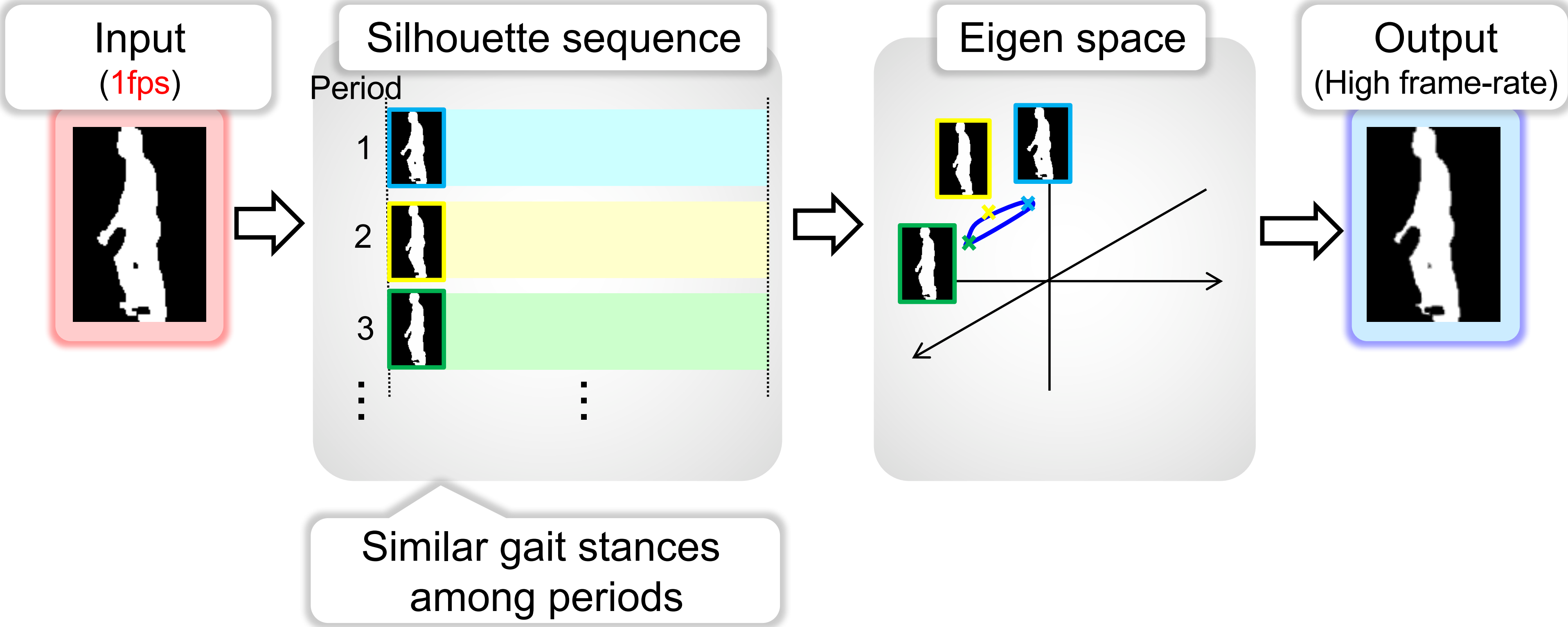


Reconstruction-based PTSR

-Overview- [Makihara et al. ACCV 2010]

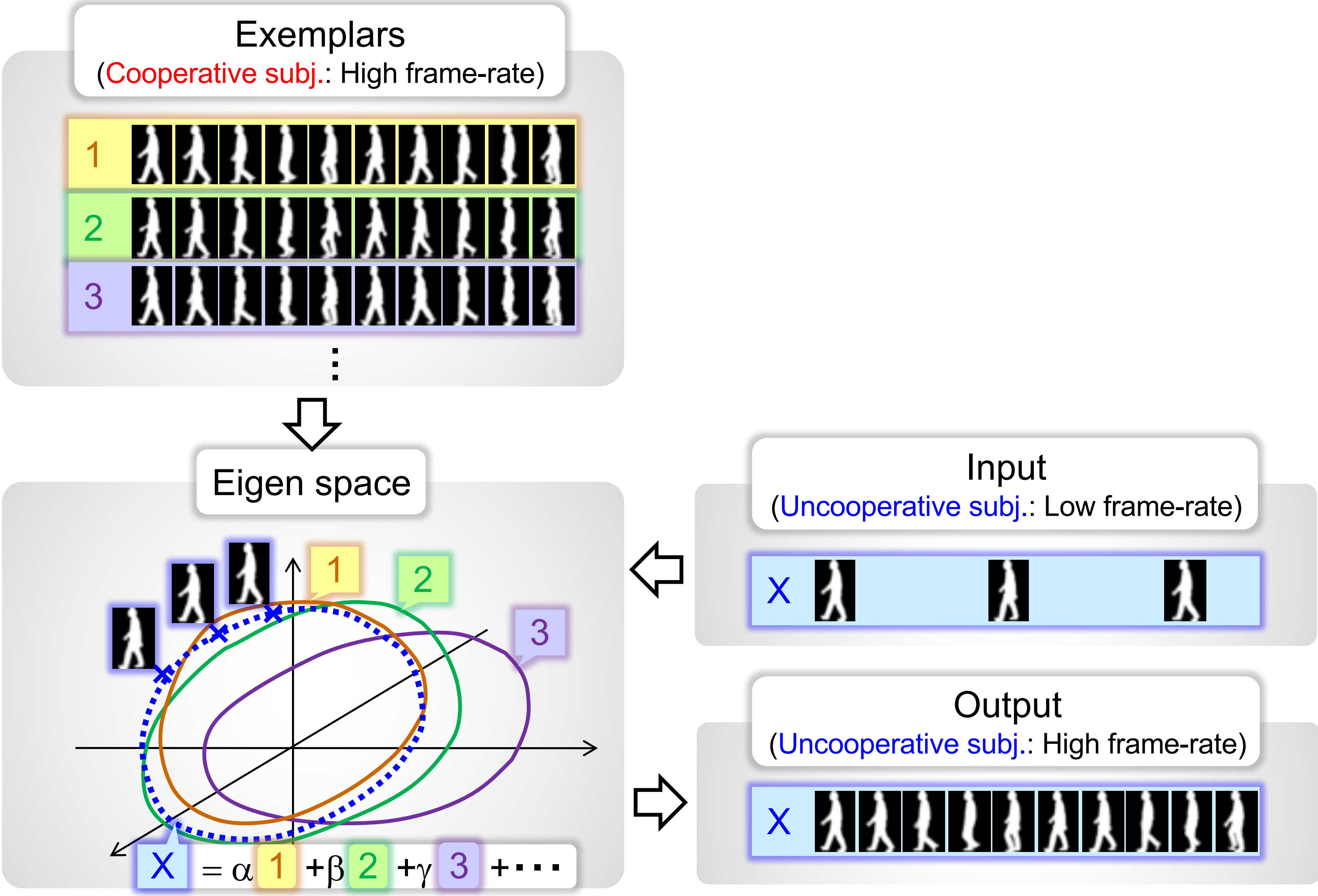


Reconstruction-based PTSR
-Failure mode-



Fail under stroboscopic effect

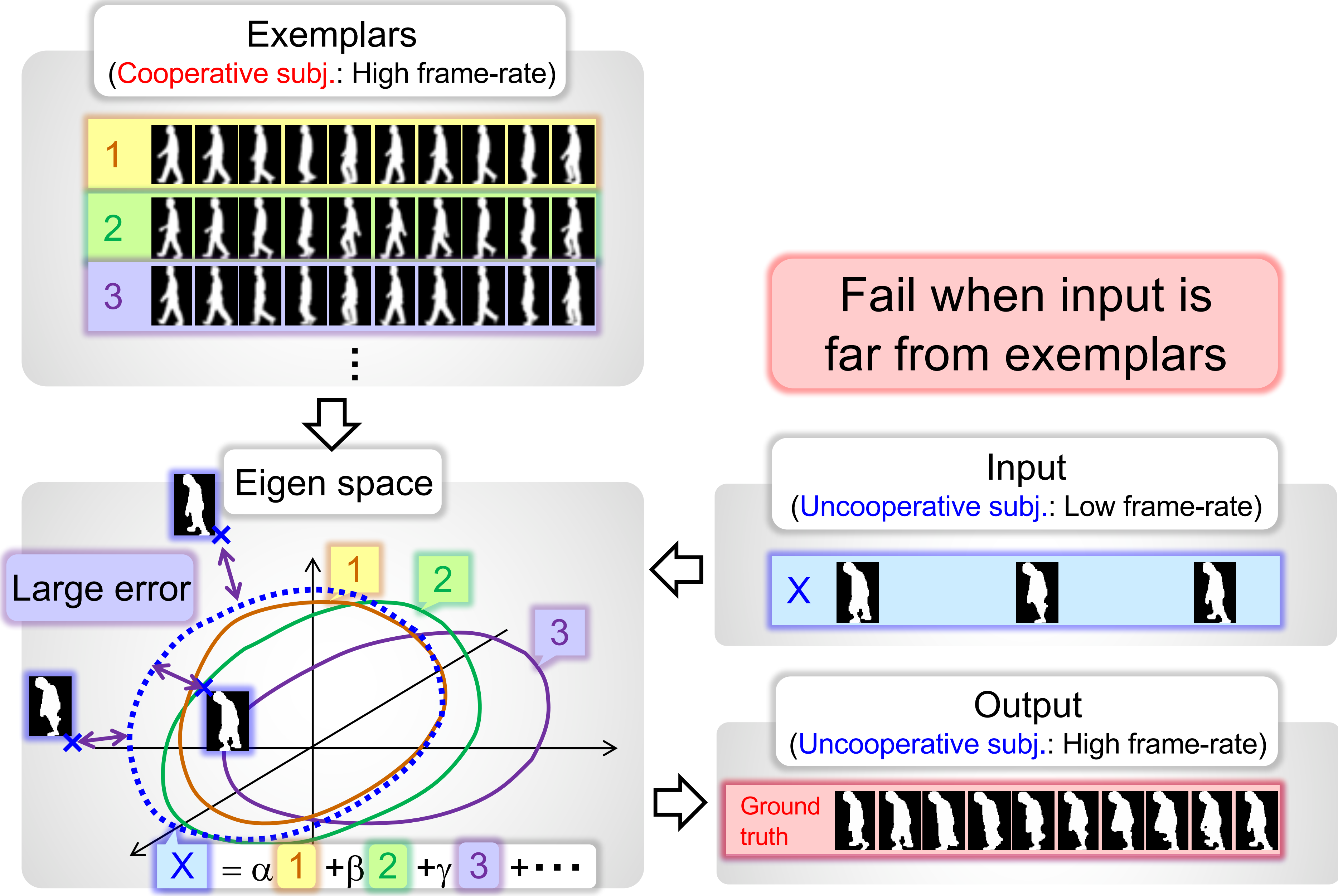
Example-based PTSR
-Overview-



Example-based PTSR

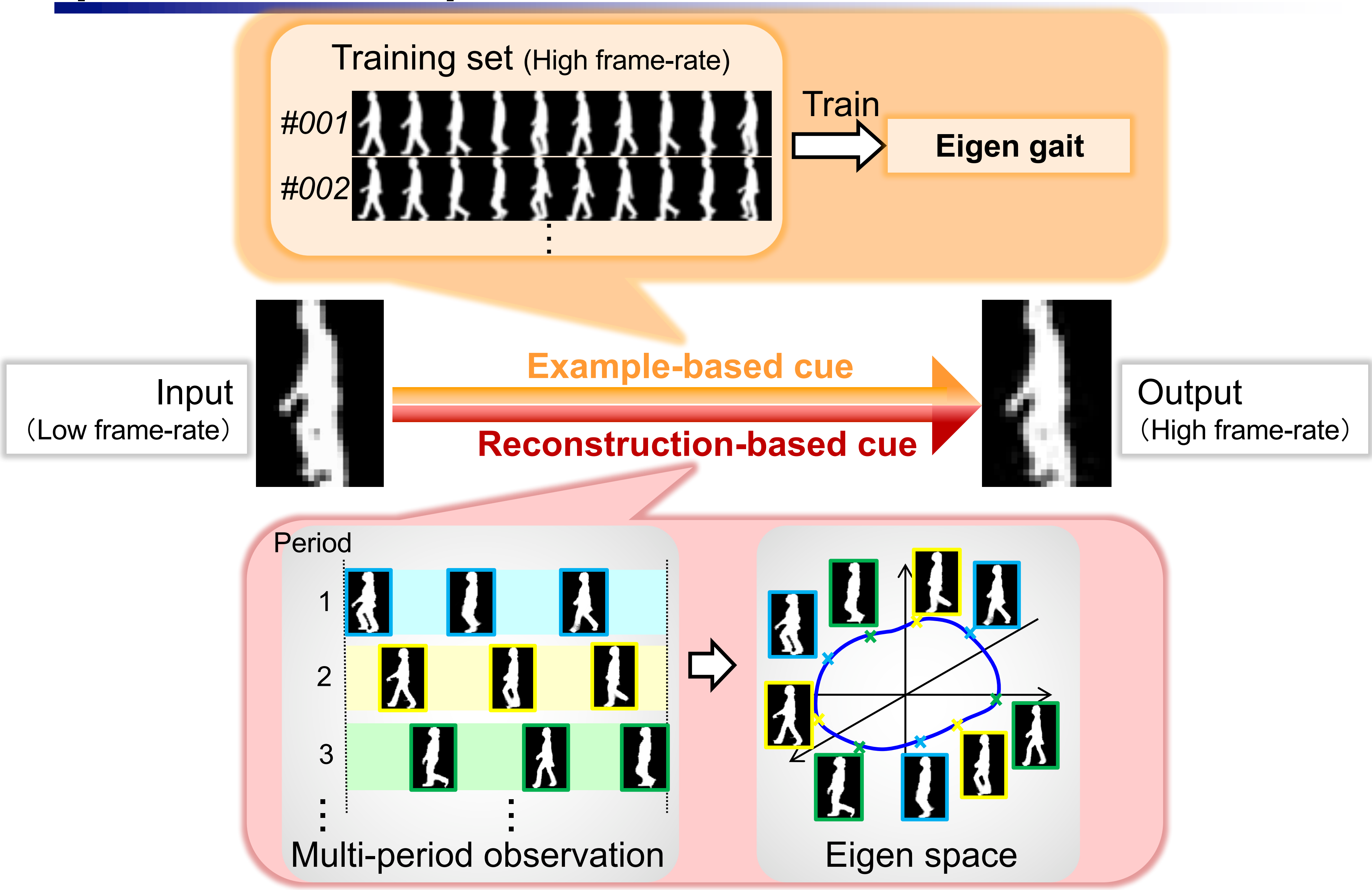
-Failure mode-

Fail when input is far from exemplars

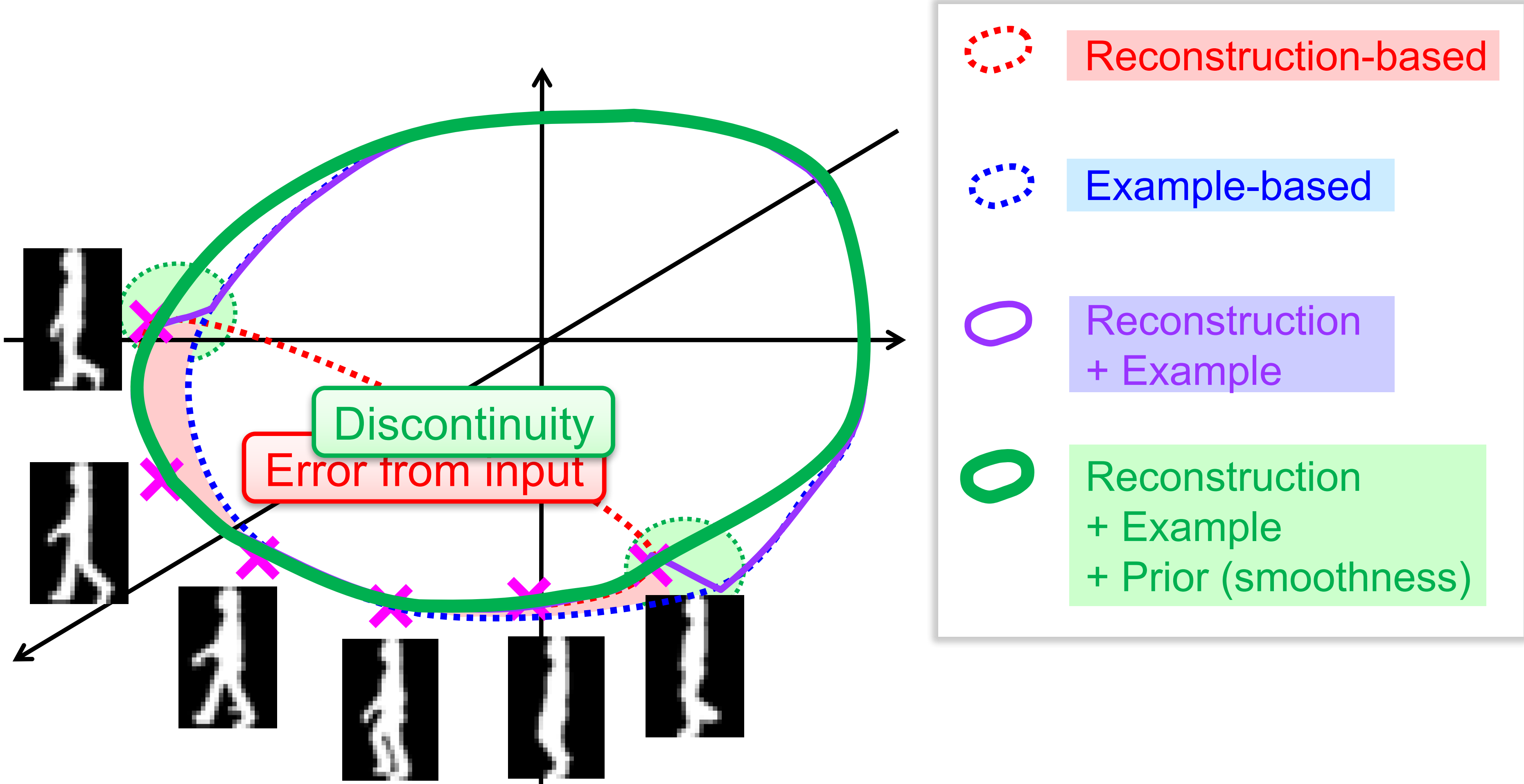


Unified approach to PTSR

[Akae et al. CVPR 2012]

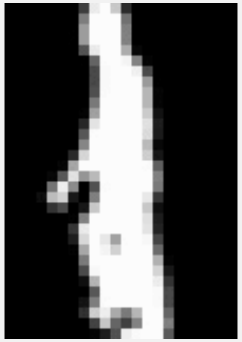
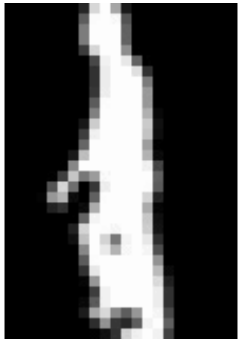
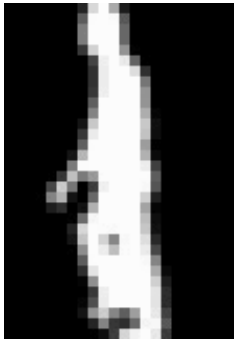
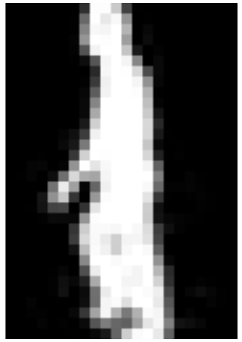


How does it work?

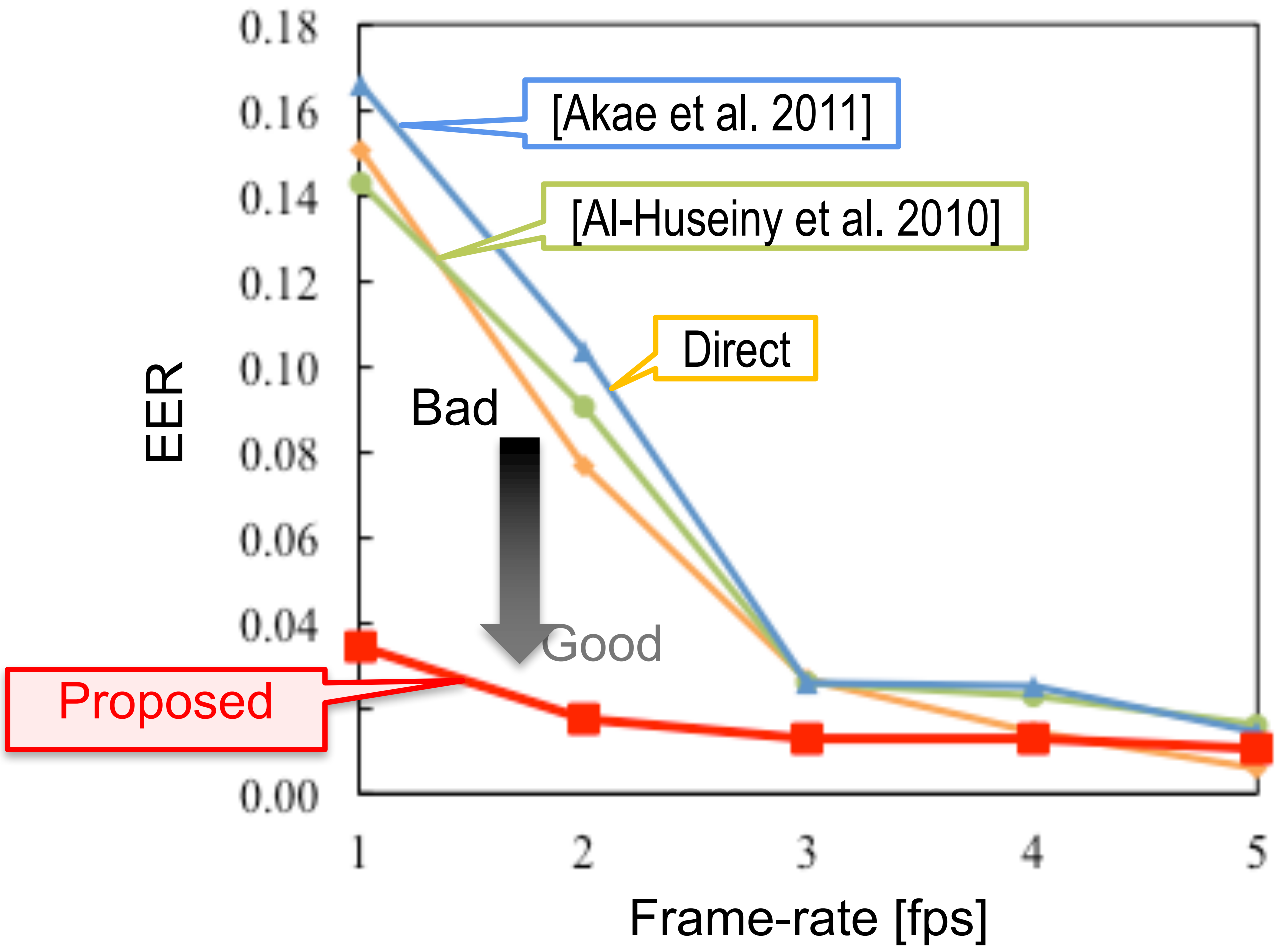


Solve by energy minimization framework

PTSR results -1 fps-

Frame-rate of input	Input	[Al-Huseiny et al. 2010]	[Akae et al. 2011]	Proposed
1 fps				

Performance evaluation: Verification



Gait based Age Estimation

Gait-based age estimation

- GPR (Gaussian Process Regression)

Input (Gait feature)

$\boldsymbol{x}_*$ 

Regressand (Age)

$$f_* \sim P(f \mid \boldsymbol{x}_*, D) = N(\mu_f, \sigma_f^2)$$

Output (Age)

$$y_* \sim P(y \mid \boldsymbol{x}^*, D) = N(\mu_y, \sigma_y^2)$$

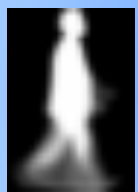
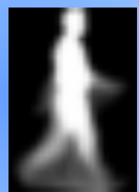
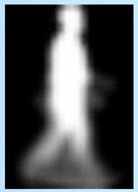
Regression parameter

θ

Observation noise

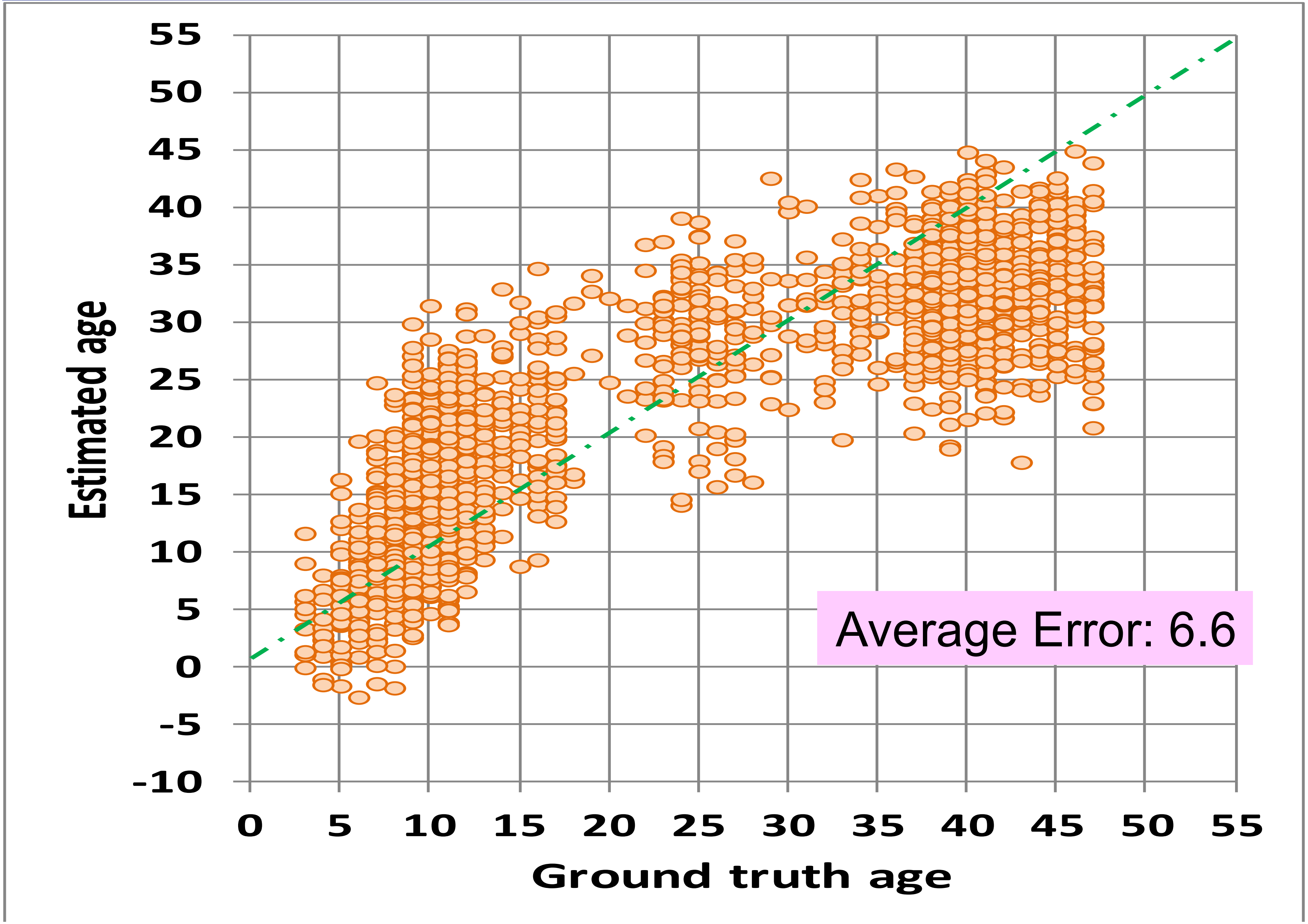
σ

Training set $\boldsymbol{D}$

Gait feature set X	$\boldsymbol{x}_1$ 	$\boldsymbol{x}_2$ 	…	$\boldsymbol{x}_N$ 
Age set $\boldsymbol{y}$	y_1	y_1	…	y_N

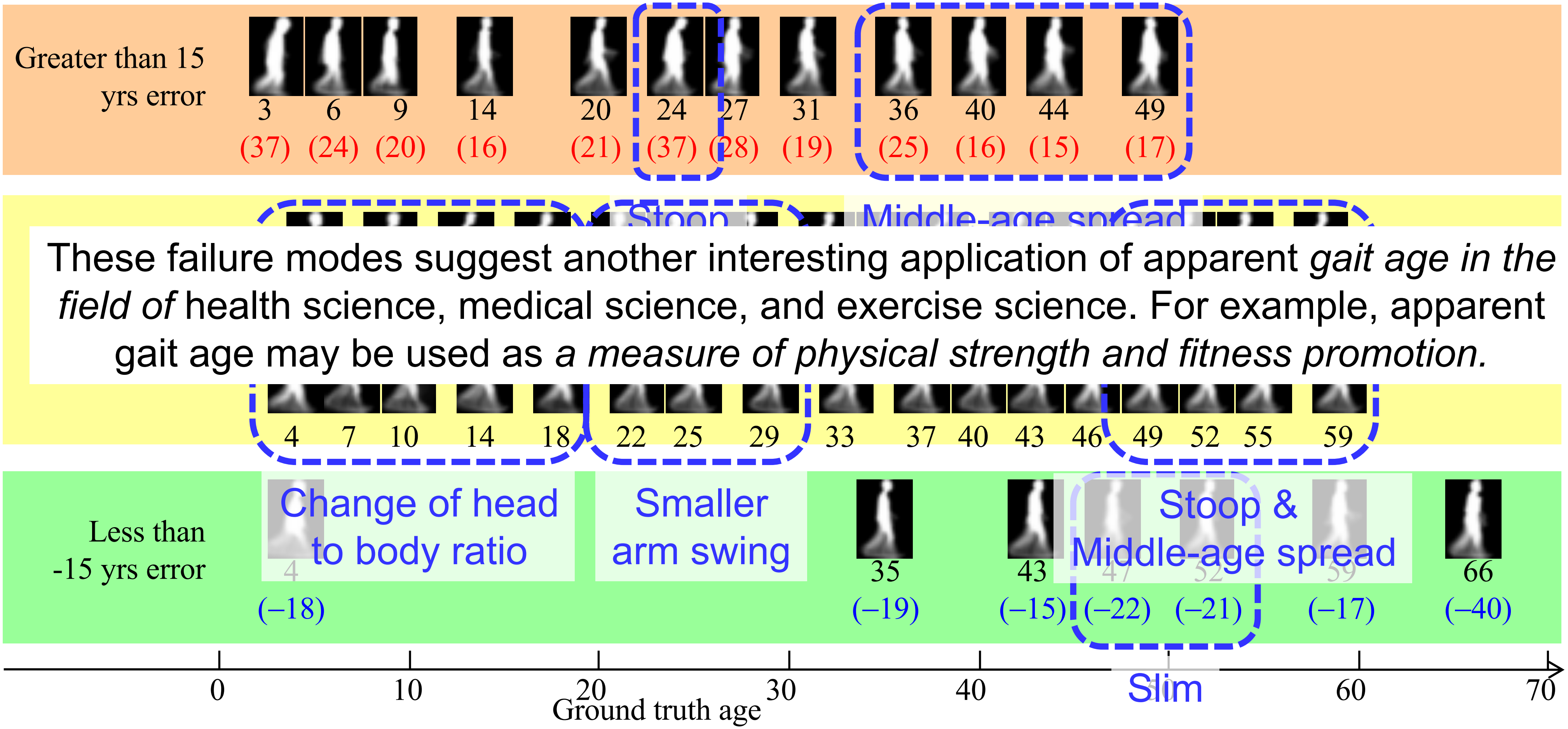
In Gaussian Process Regression framework, the regress and output are formulated as posterior given the input gait feature x_* and the training set D, and they are expressed as Gaussian distribution.

Phyisical Age Estimation



Experiments -Qualitative evaluation-

- Typical success and failure modes (male)



During growing process, we can see clear change of head to body ratio.

Human gait pattern includes

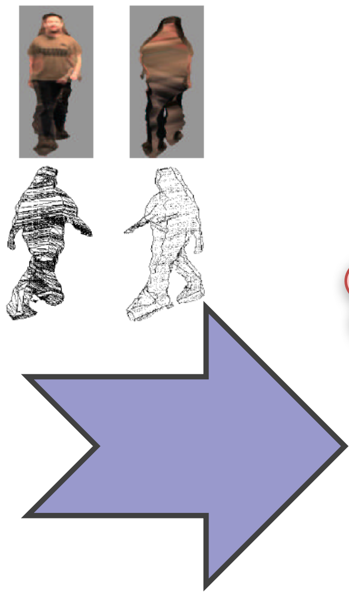
Personality, Age, Gender

Emotion, The state of mind

Human intention, Scene

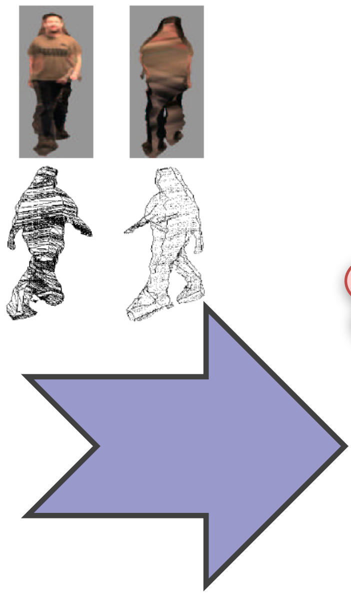
Human physical/mental condition

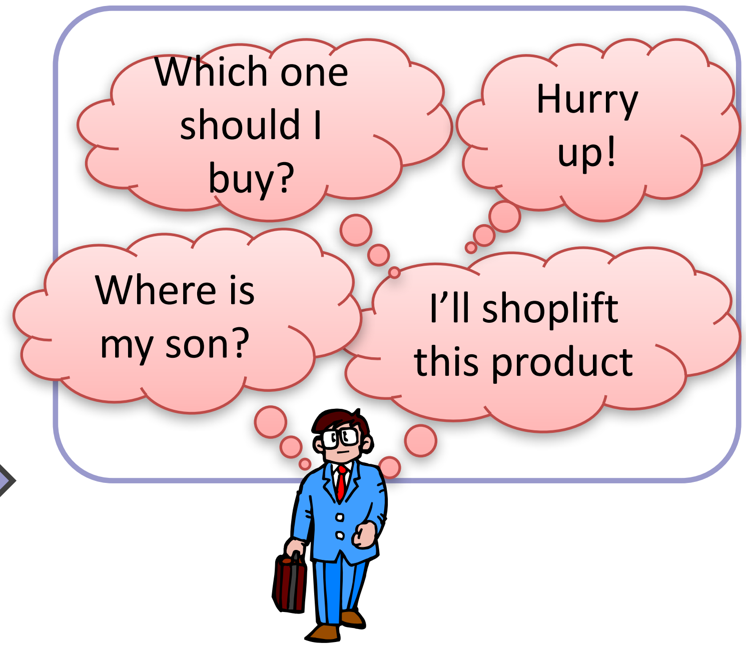
Human relationships, Surrounding people



Behavior Understanding based on Intention-Gait Model

The main purpose of this project is
to develop technology for understanding
human physical/mental condition, **human intention**, **human relationship** from the **gait.**





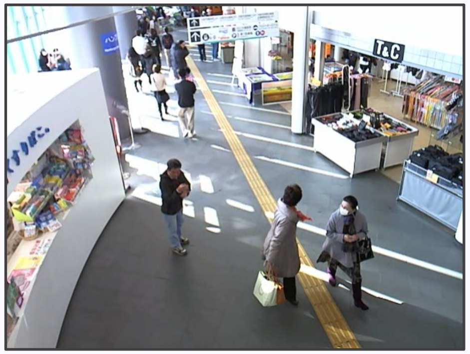
Behavior Understanding based on Intention-Gait Model

Individual Gaze & Walking Trajectory	*Group Interaction*	**Walking Ability**

Safety & Security

Detection of petty crimes (Shoplifting, etc.)

Commercial use



Estimation of group attributes, statuses and rules

Elderly support

Estimation of phycial/cognitive function

Relational analysis between gait and attention

Human Vision group
@Tohoku Univ.

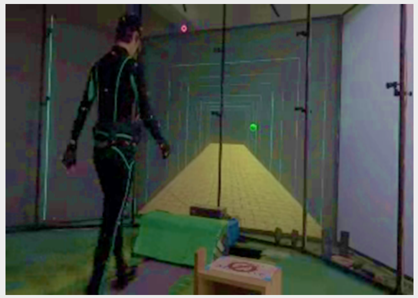
Attention

Saliency map → Saliency based Gaze distribution model

Gaze probability distribution

Body parts based Gaze distribution model

Head/Torso orientation



Gait-Head/Torso orientation model

Input data sequence

Computer Vision group
@Osaka Univ.

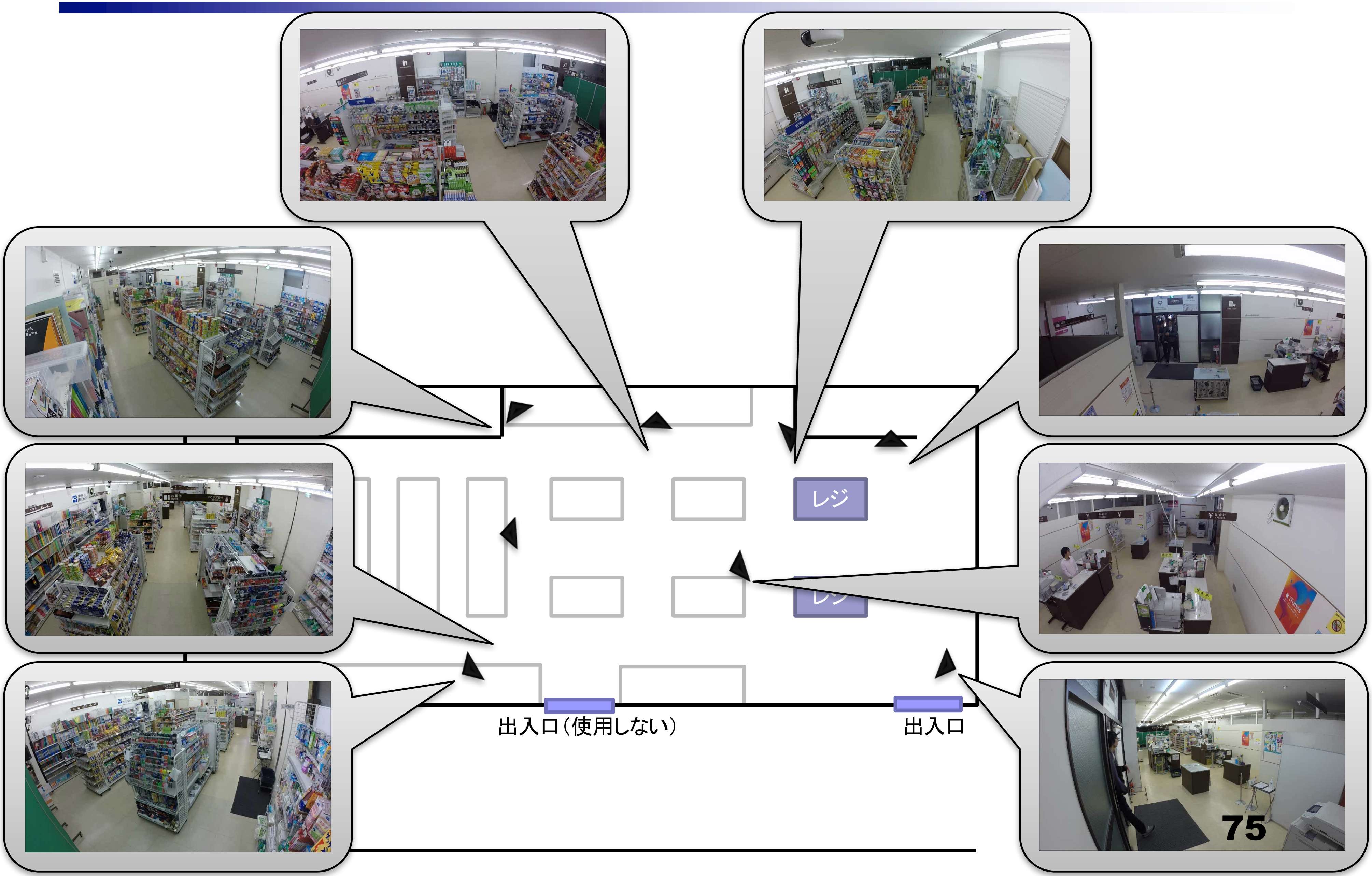
Experimental settings (Participant)

Wearable camera (GoPro)

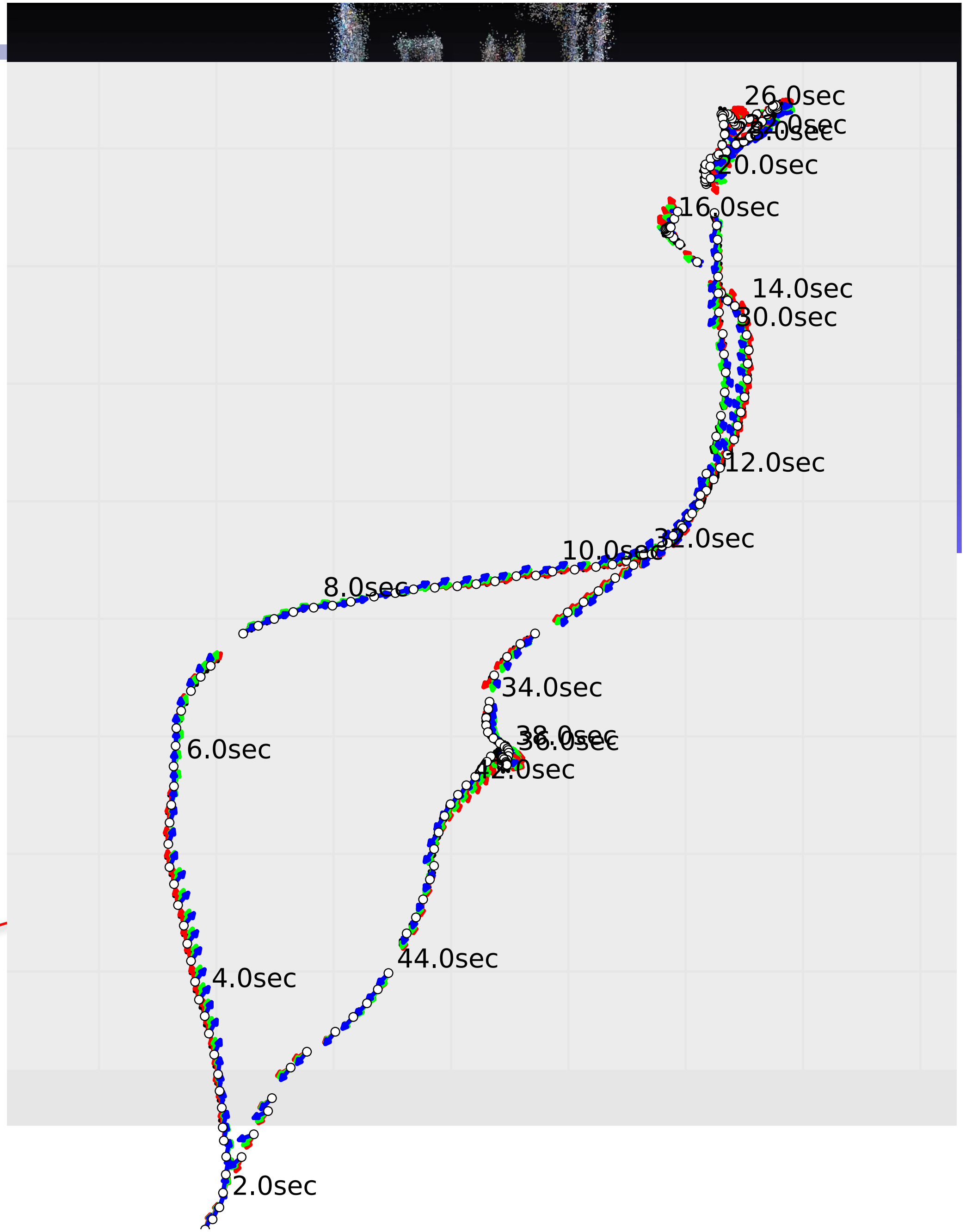
Gaze tracker (EMR-9)

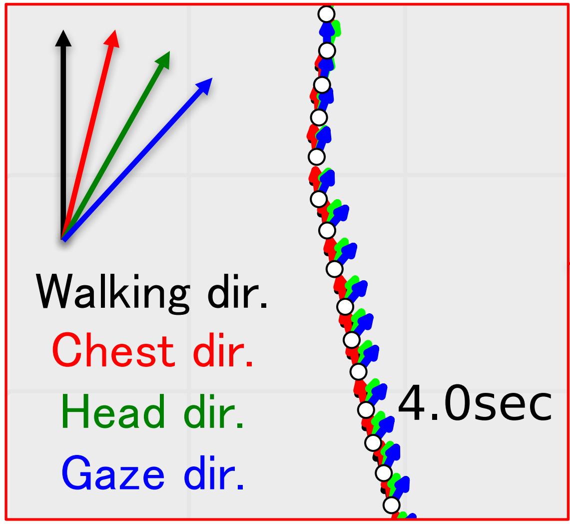
Wearable camera (GoPro)

Experimental settings (Environment)



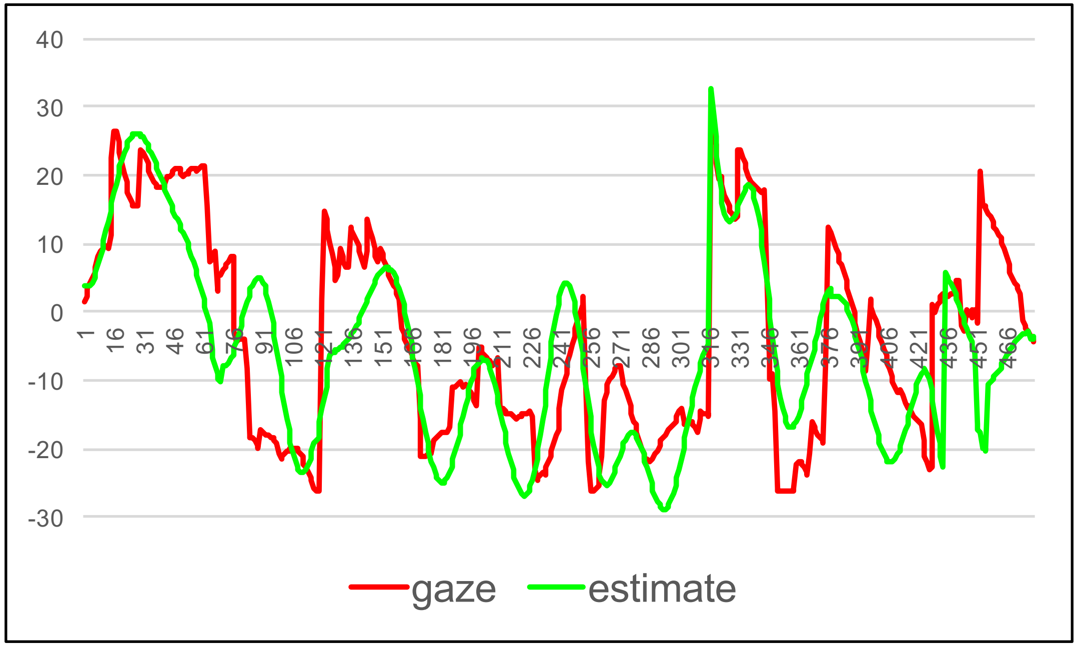
Chest, head, gaze direction acquisition by SfM





Gaze estimation result

- Our proposed method estimates gaze direction from the following observation:
  - Chest position/direction
  - Head position/direction



Walking Ability

Elderly support

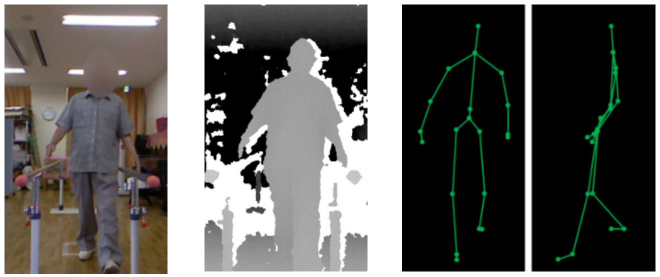
Estimation of phycial/cognitive function

Gait Analysis for Elderly Care

(2010-2015) Behavior Understanding Based on Intention-Gait Model supported by JST-CREST

How to evaluate the cognitive function?

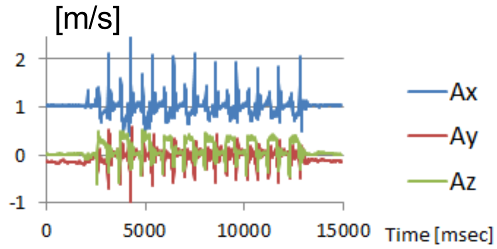
Camera (Kinect)



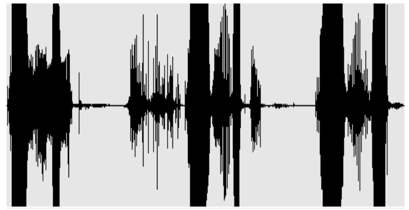
Color Depth Skeleton

Collect subject's motion

Smartphone with microphone)



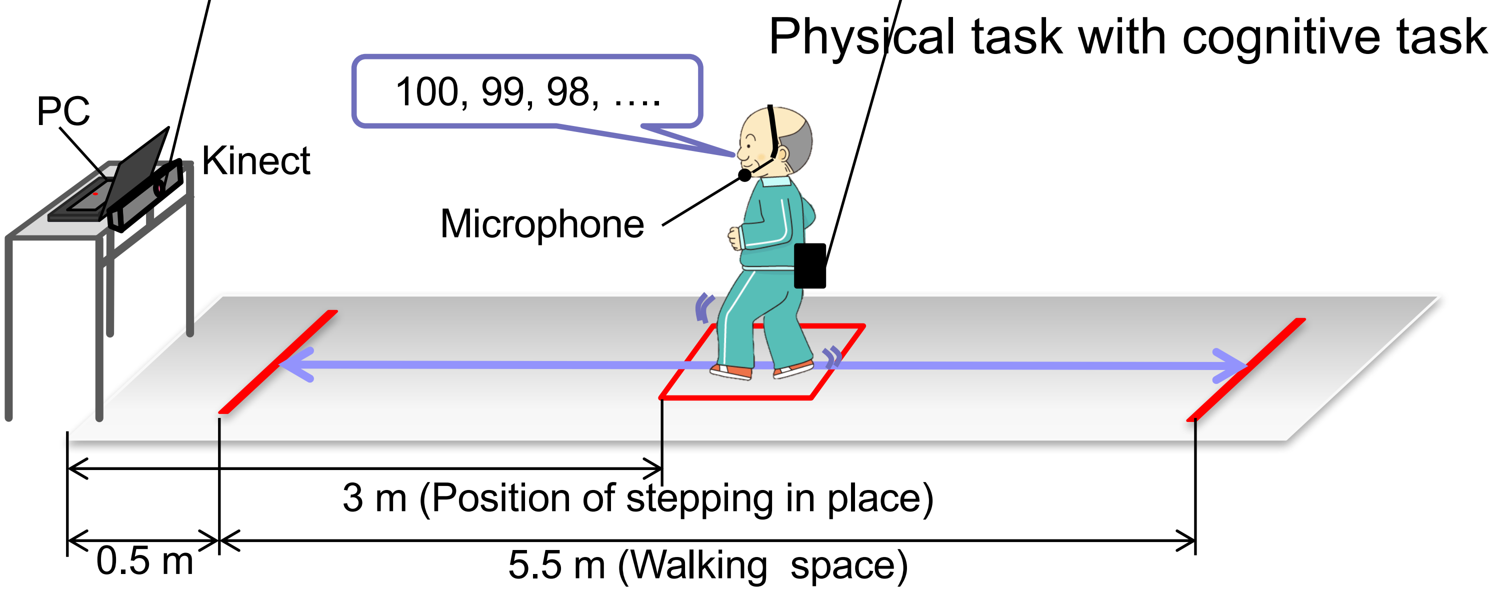
Acceleration



Voice

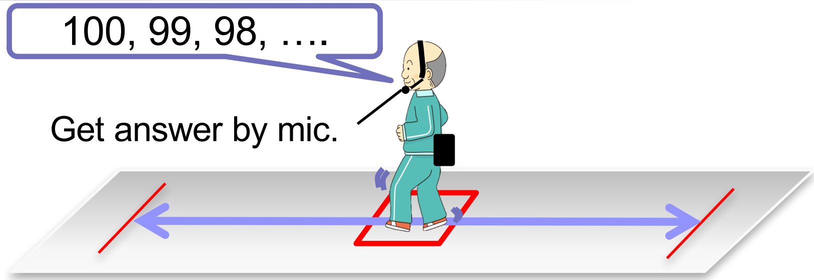
Collect subject's motion
(heel strike timing)

Collect subject's
cognitive task answer

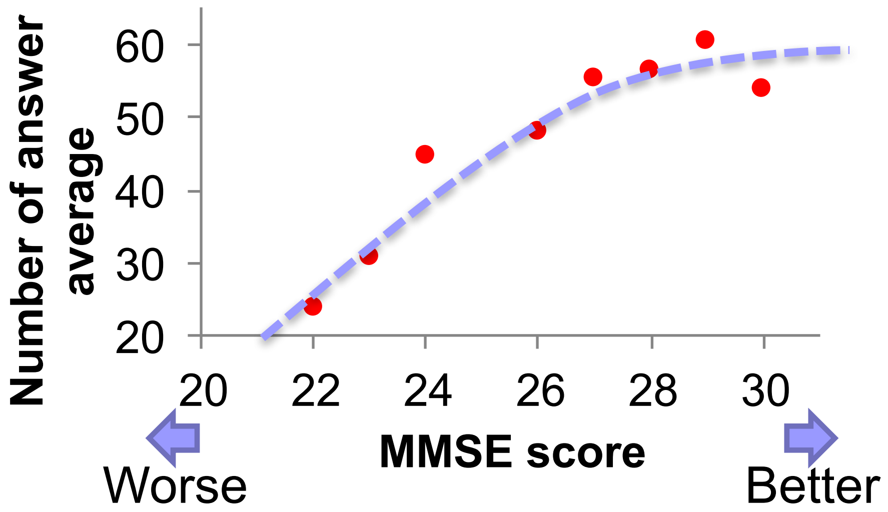


Result (cognitive function): Subject answer

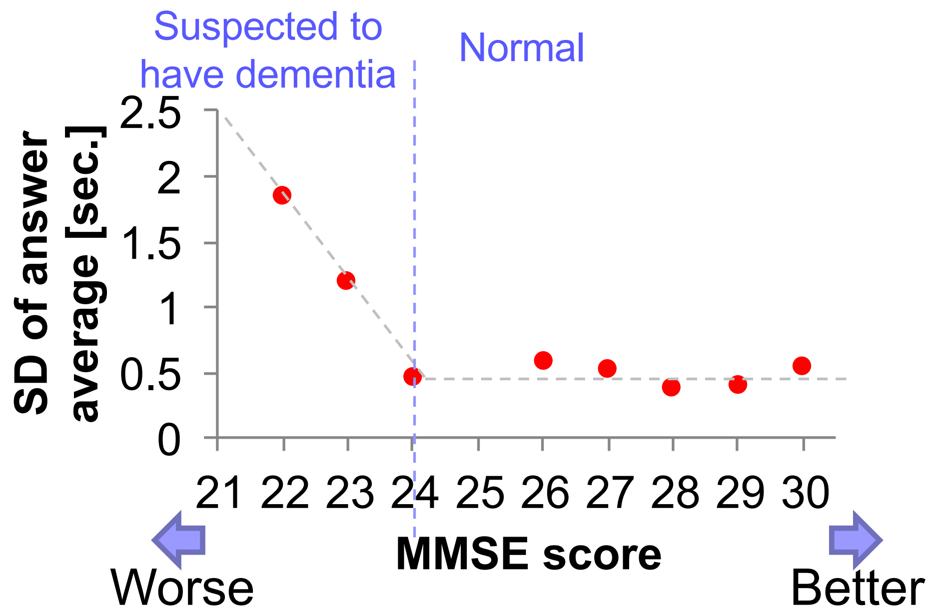
Dual task:
Walking with countdown from 100



“MMSE score” vs. “Number of answers”



“MMSE score” vs. “Standard deviation of answer”



Gait Analysis for Innovative Entertainment

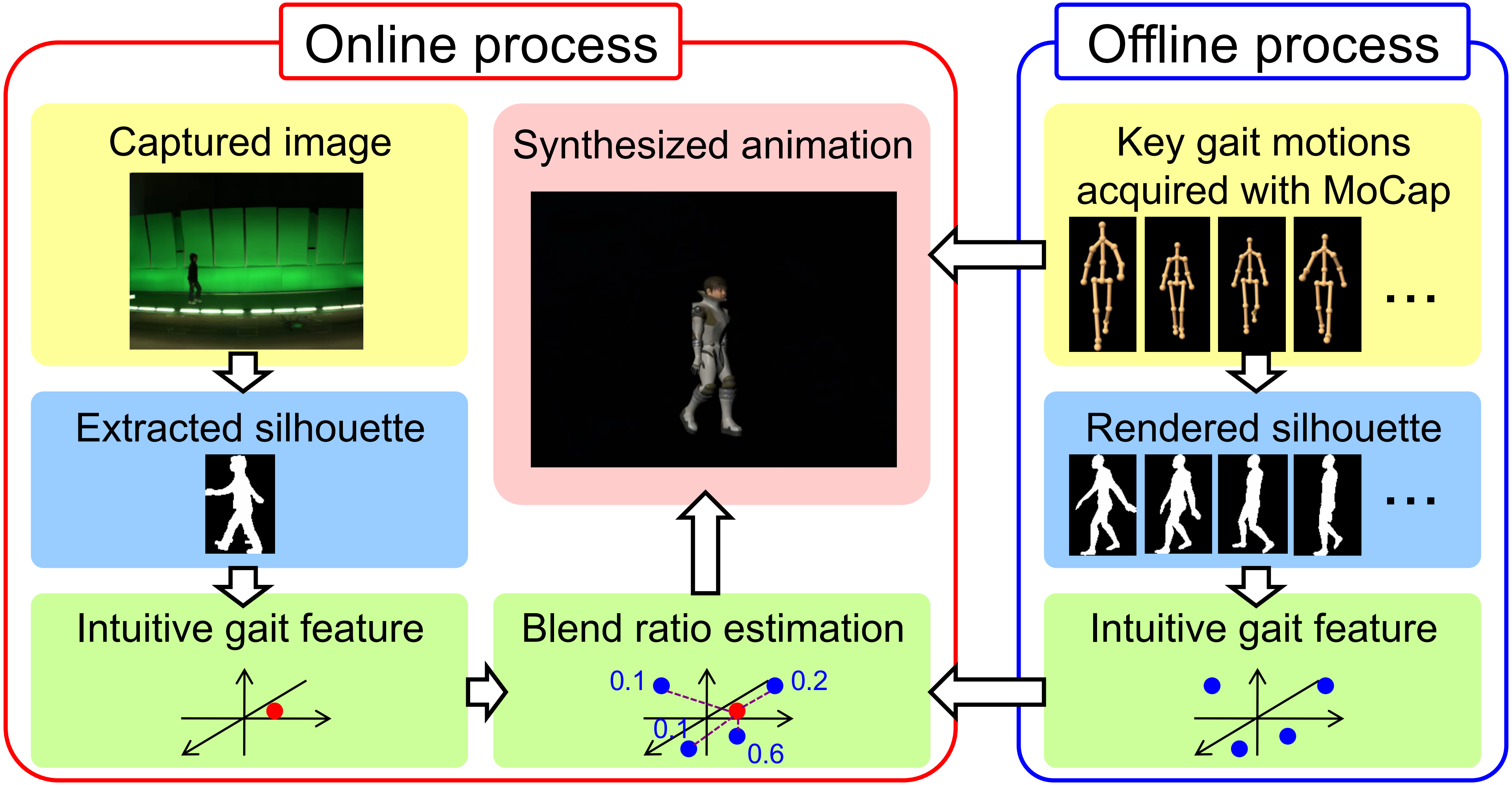
Dive Into the Movie

"Dive into the Movie (DIM)" is a name of project to aim to realize a world innovative entertainment system which can provide an immersion experience into the story by giving a chance to audience to share an impression with his family or friends by watching a movie in which all audience can participate in the story as movie casts.

To realize this system, we are trying to model and capture the personal characteristics instantly and precisely in face, body, gait, hair and voice.

Collaborated with
Waseda University (Prof. Morishima)
Advanced Telecommunications Research Institute International (ATR). (Dr Nakamura, NAIST)

Online measurement of intuitive gait feature for digital entertainment [3][4]



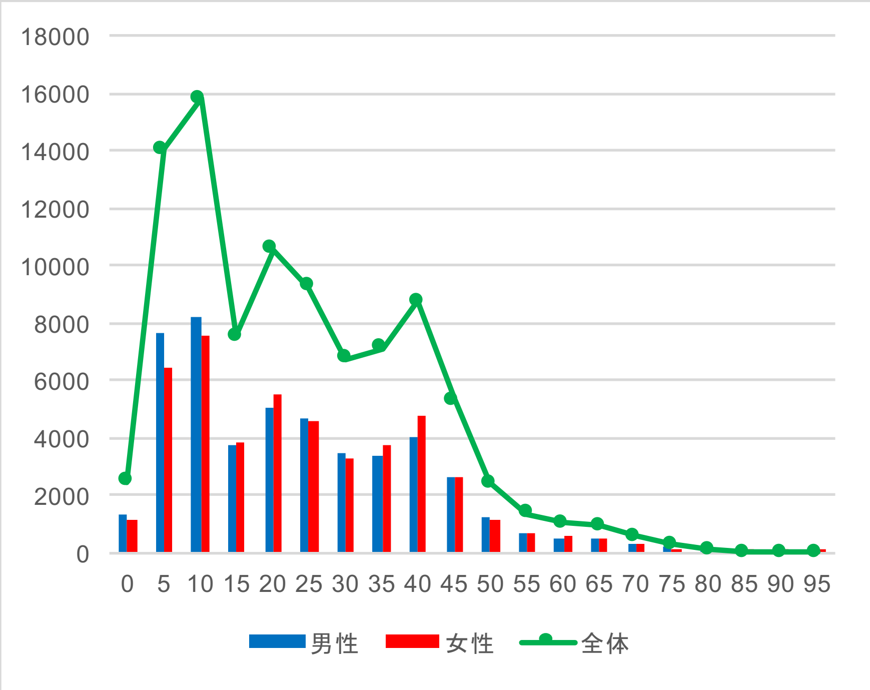
[3] M. Okumura, Y. Makihara, S. Nakamura, S. Morishima, and Y. Yagi, ``The Online Gait Measurement for the Audience-Participant Digital Entertainment,'' Proc. of Invited Workshop on Vision Based Human Modeling and Synthesis in Motion and Expression, No. 5, pp. 1-10, Xi'an, China, Sep. 2009.
[4] Y. Makihara, M. Okumura, Y. Yagi, and S. Morishima, ``The Online Gait Measurement for Characteristic Gait Animation Synthesis,'' Proc. of Human Computer Interaction International 2011, Virtual and Mixed Reality - New Trends, vol. 6773, pp.325--334, Springer, Orlando, FL, USA, Jul. 2011.

Public Gait Database

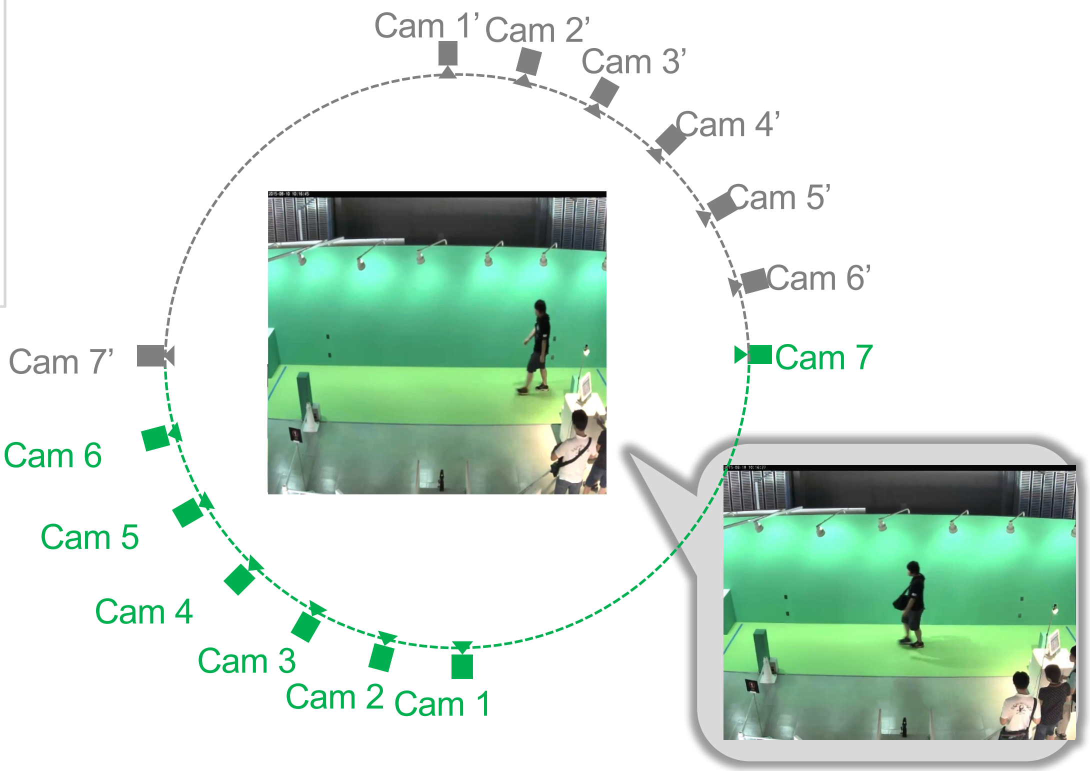
http://www.am.sanken.osaka-u.ac.jp/BiometricDB/index.html

- *The OU-ISIR Gait Database*
  - *Treadmill Dataset*
  - *Large Population Dataset*
  - *Speed Transition Dataset*
  - *Inertial Sensor Dataset*
  - *Similar Actions Inertial Dataset*
- *The OU-ISIR Biometric Score Database*

New Gait Database (Closed)



95109 subjects



THANKS FOR YOUR ATTENTION

Yasushi YAGI

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URL: http://www.am.sanken.osaka-u.ac.jp/