Human Gait Analysis

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Human gait -Attribute-

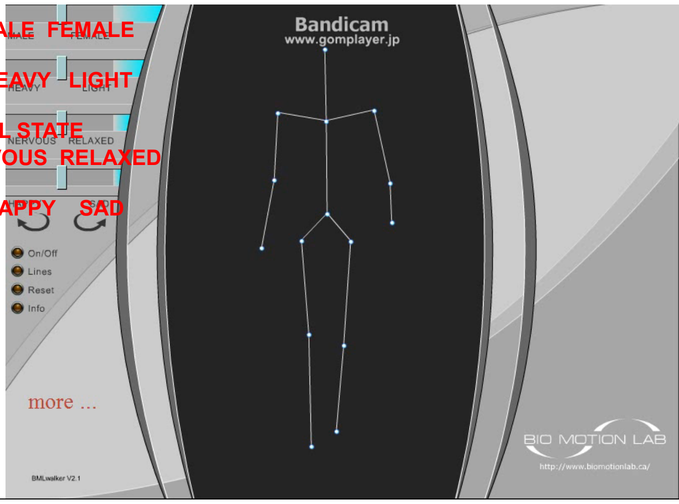
- Biological Motion Lab. Queen's University
  - http://www.biomotionlab.ca/Demos/BMLwalker.html

SEX: MALE FEMALE

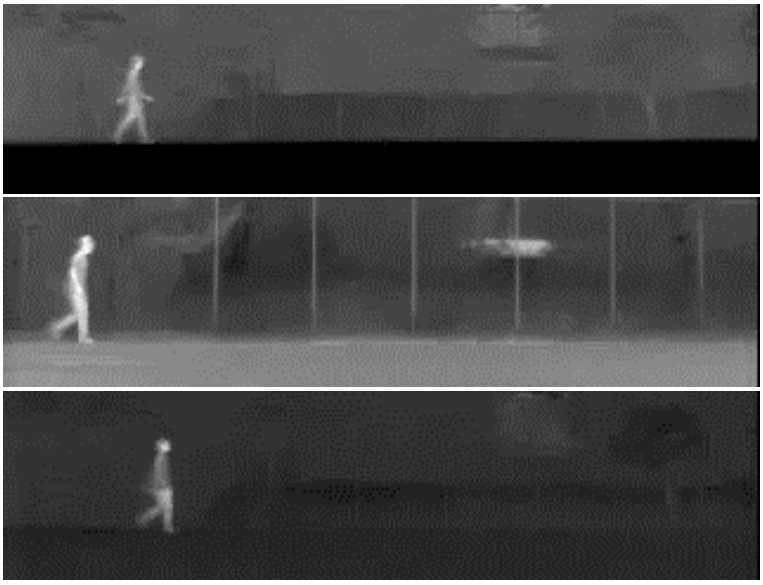
WEIGHT: HEAVY LIGHT

EMOTIONAL STATE
NERVOUS RELAXED

HAPPY SAD

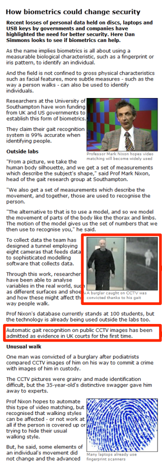


Human gait -Personality- Identity -



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)

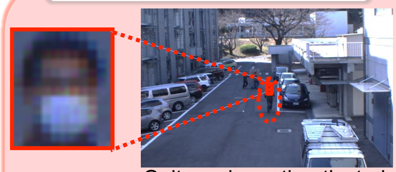
Advantage of gait recognition

Criminal investigation

CCTV of firer

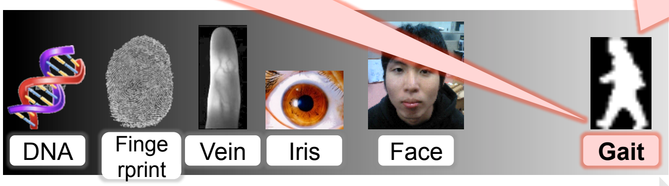
Judge whether a perpetrator and a suspect are the same or not from gaits

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

Today's topics

- Gait identification & verification
- What is the difficulty for applying gait recognition to wide-area surveillance ?
  - The difference of the observation direction
  - Speed change
  - The difference of clothes
  - Low sampling rate
  - Occlusion in crowd scene
- Gait Analysis for Innovative Entertainment

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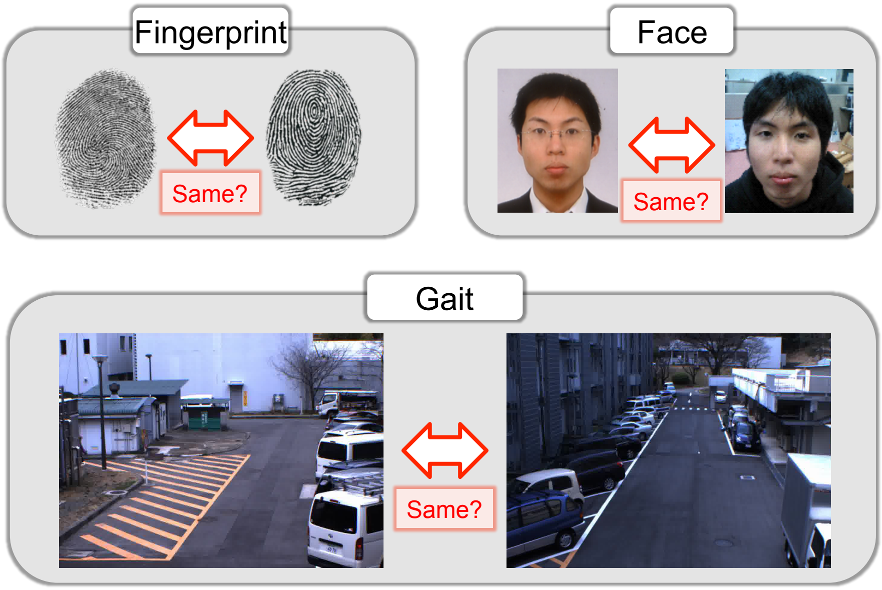
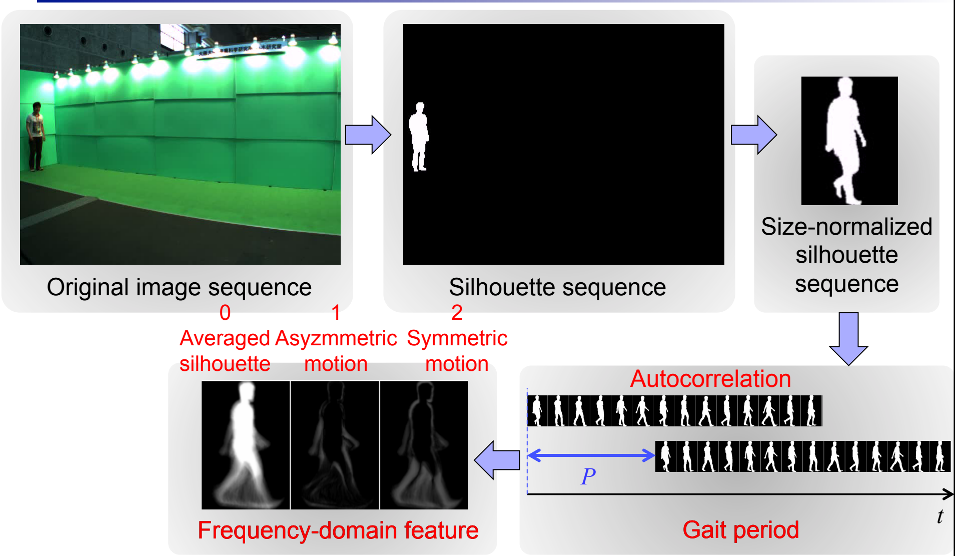
Gait identification & gait verification

Person authentication by biometrics

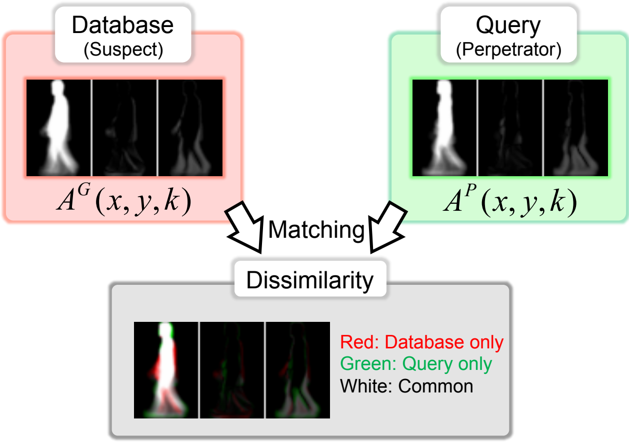


Gait feature extraction



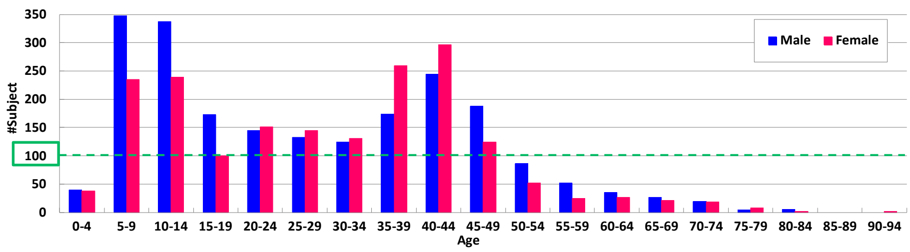
Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, and Y. Yagi, ``Gait Recognition Using a View Transformation Model in the Frequency Domain,'' 9th European Conf. on Computer Vision, Vol. 3, pp. 151-163, 2006.

Dissimilarity: Single feature



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

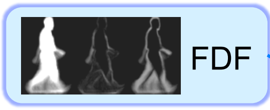
Database: OU-LP

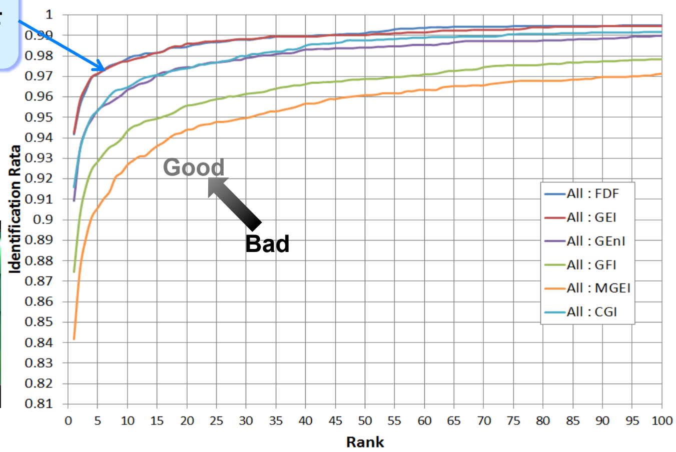


The world largest database with 4,007 subjects (Male: 2,135, Female: 1,872)

Performance evaluation: identification

[Iwama et al. IFS 2012]

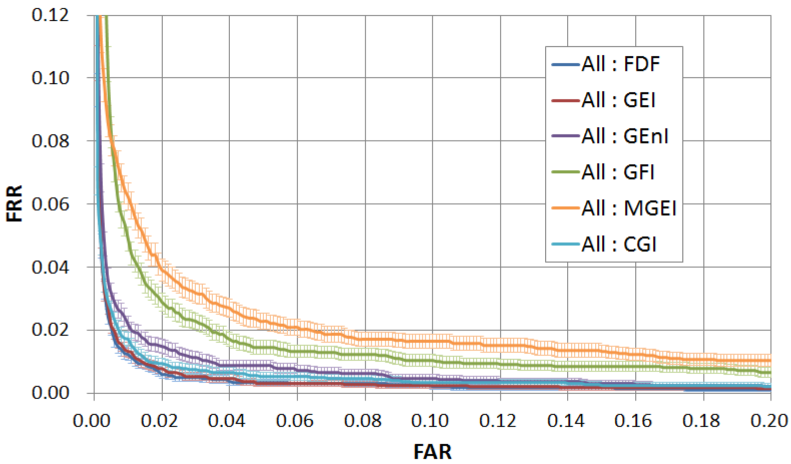




Cumulative matching characteristics (CMC) curve

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

Performance evaluation: verification



EER: 1.15%

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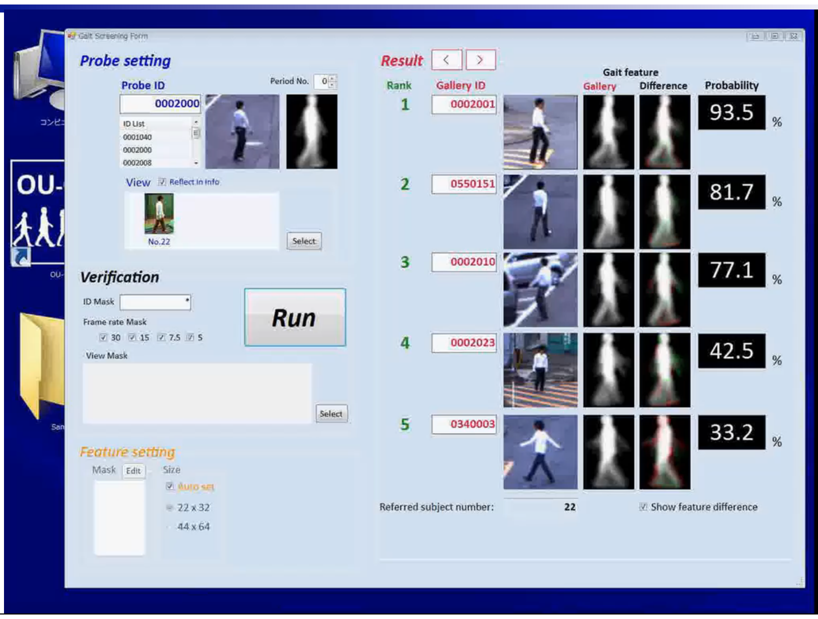
World first packaged gait verification system for criminal investigation

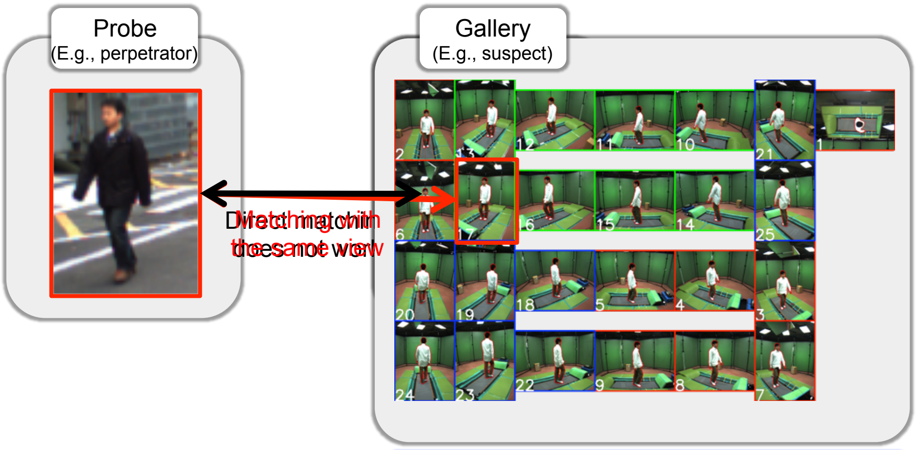
Example of batch verification



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

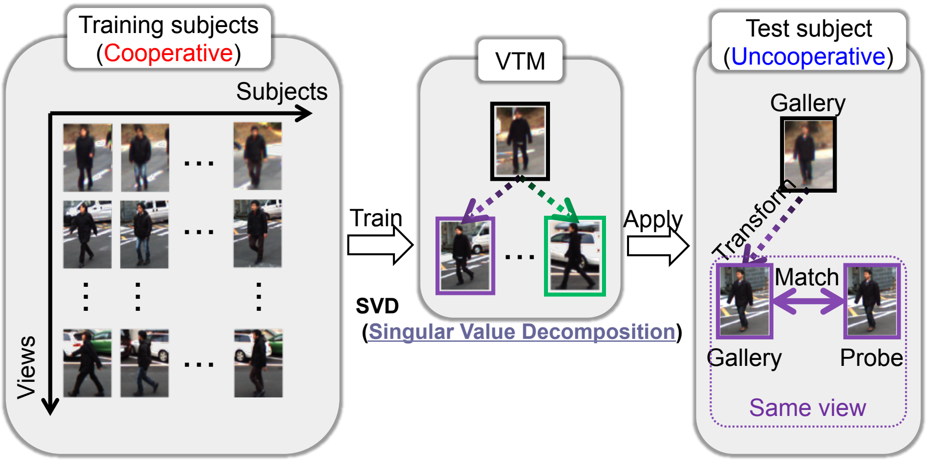
Challenge -View differences-



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

$$
\begin{array}{c} \text{individual} \\ \overbrace{\begin{bmatrix} \boldsymbol{a}_{\theta_1}^1 & \boldsymbol{a}_{\theta_1}^2 & \cdots & \boldsymbol{a}_{\theta_1}^M \\ \boldsymbol{a}_{\theta_2}^1 & \boldsymbol{a}_{\theta_2}^2 & \cdots & \boldsymbol{a}_{\theta_2}^M \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{a}_{\theta_K}^1 & \boldsymbol{a}_{\theta_K}^2 & \cdots & \boldsymbol{a}_{\theta_K}^M \end{bmatrix}} \\ \text{Training data matrix} \end{array} = USV^T = \underbrace{\begin{bmatrix} P_{\theta_1} \\ P_{\theta_2} \\ \vdots \\ P_{\theta_K} \end{bmatrix}}_{\text{Transformation matrix to each view}} \underbrace{\begin{bmatrix} \boldsymbol{v}^1 & \boldsymbol{v}^2 & \cdots & \boldsymbol{v}^M \end{bmatrix}}_{\text{View-independent individual vector}}
$$

view

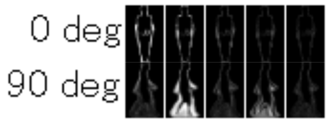
- Gait feature for mth subject from θ_i view

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

View transformation

- From a single reference θ_j to θ_i

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

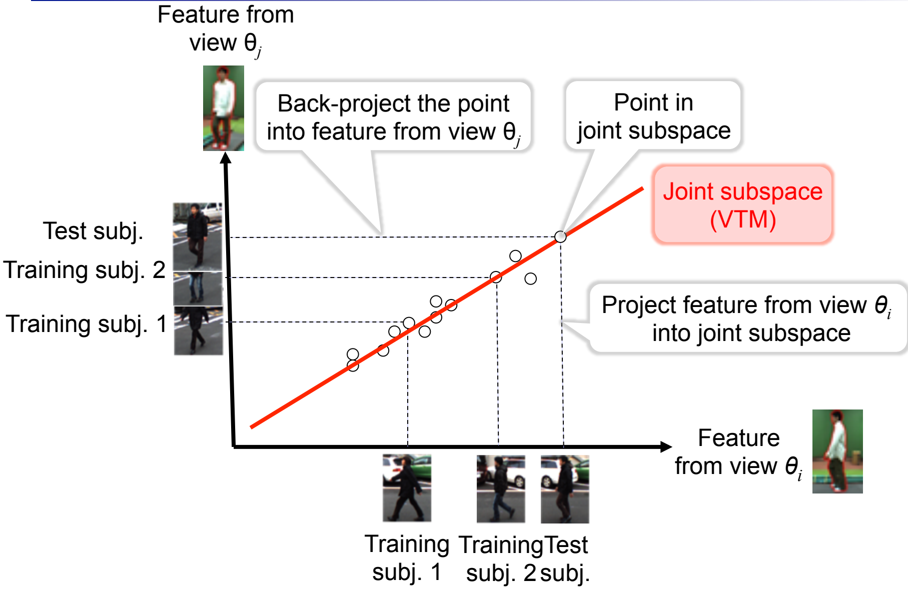


  - Orthogonal motion to reference θ_j is degenerated

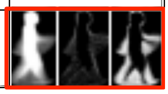
- From multiple references $\{\theta_j(1),\ldots,\theta_j(k)\}$ to θ_i

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

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
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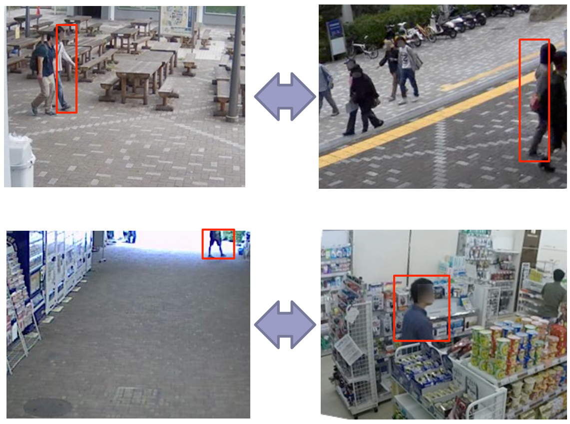
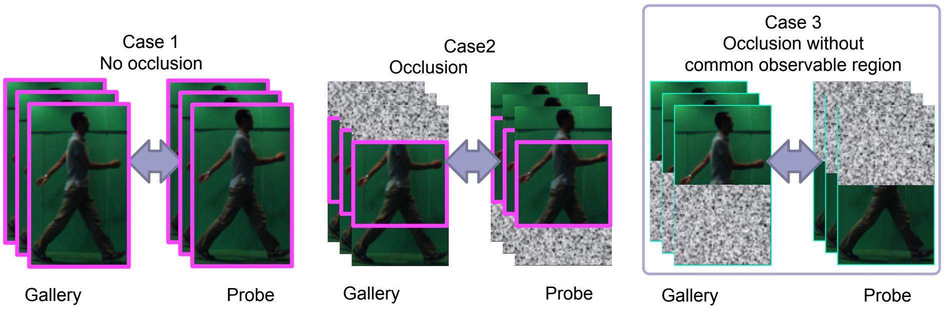
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene
  - ICB2015

Actual situation of observed gait in surveillance



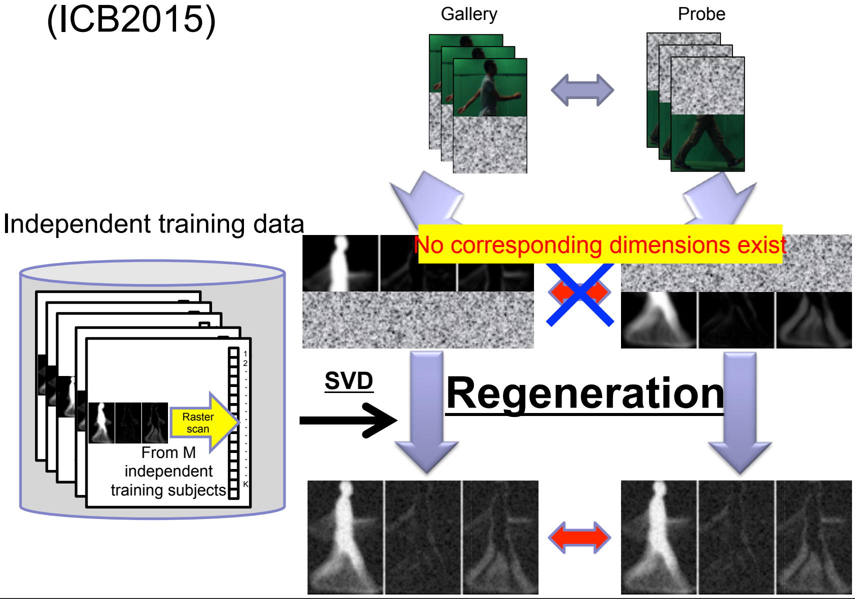
Challenge: Serious occlusion



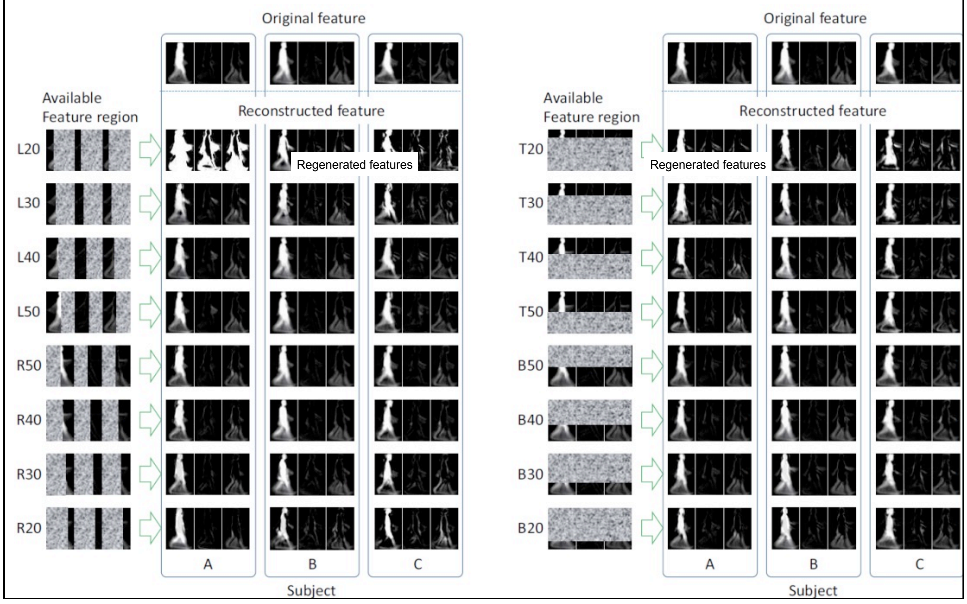
- Common observable regions (COR) are used for recognition
- Direct comparisons are impossible in case 3
  because any common region cannot be observed

Gait regeneration for recognition

(ICB2015)

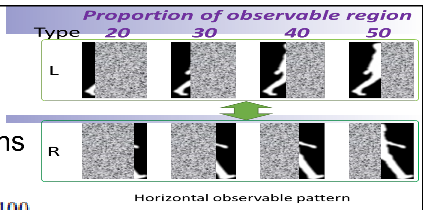


Experiment : Regenerated gait



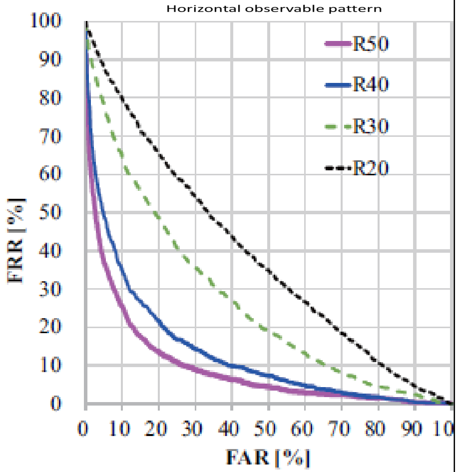
Experiment

Results with horizontal observable patterns



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 ?

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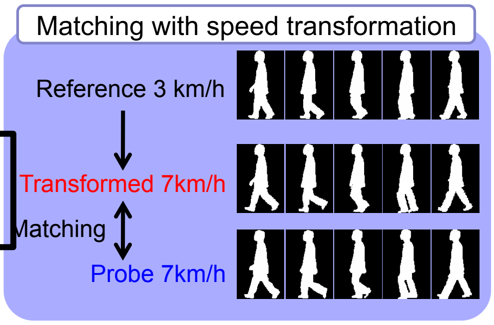
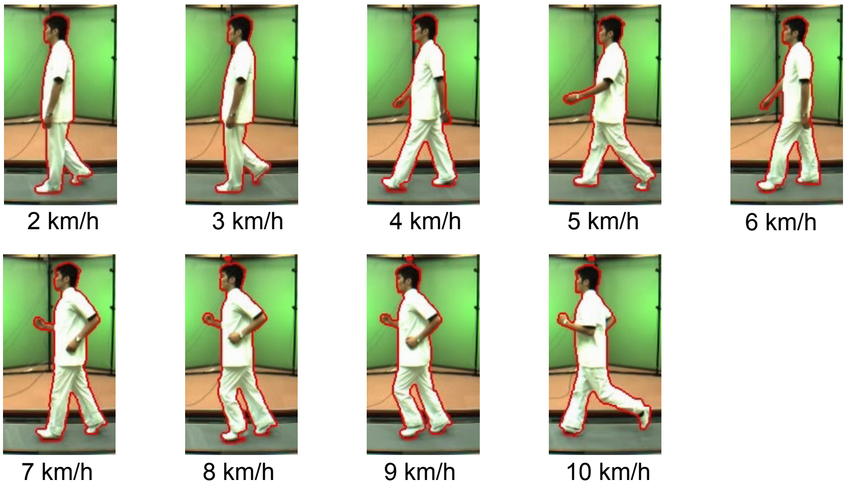


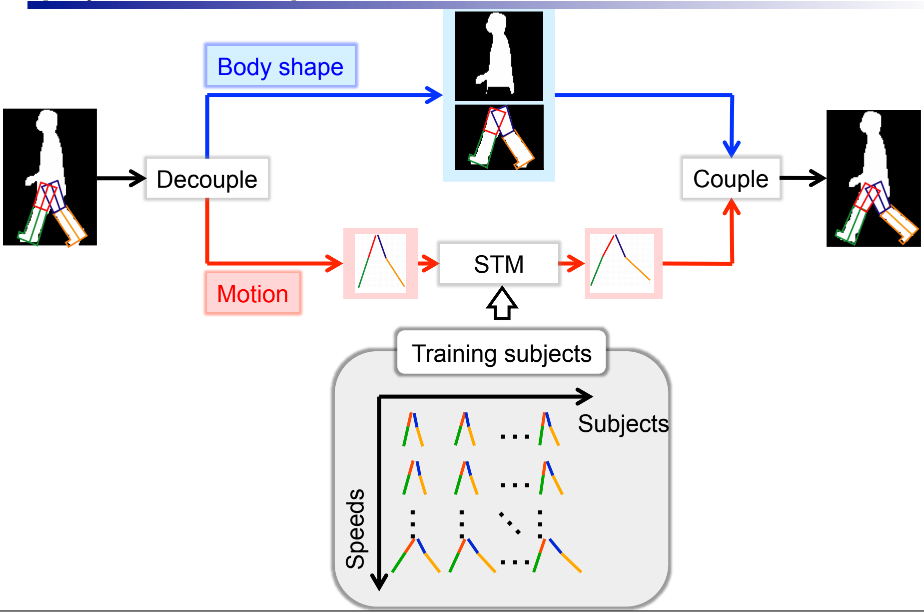
Speed transformation model

Challenge -Speed difference-

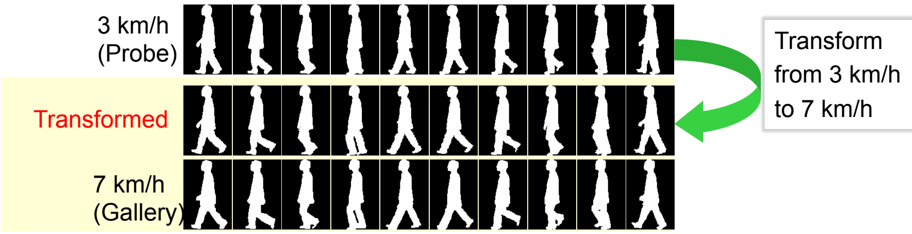


Speed transformation model (STM)

[Tsuji et al. CVPR 2010]

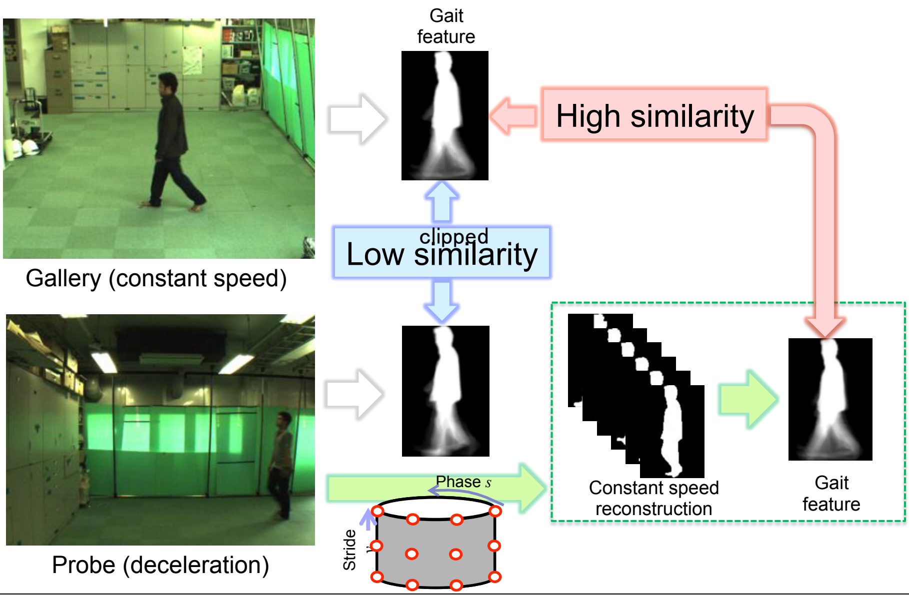


Transformation results



Extension to speed transition

[Mansur et al. CVPR 2014]

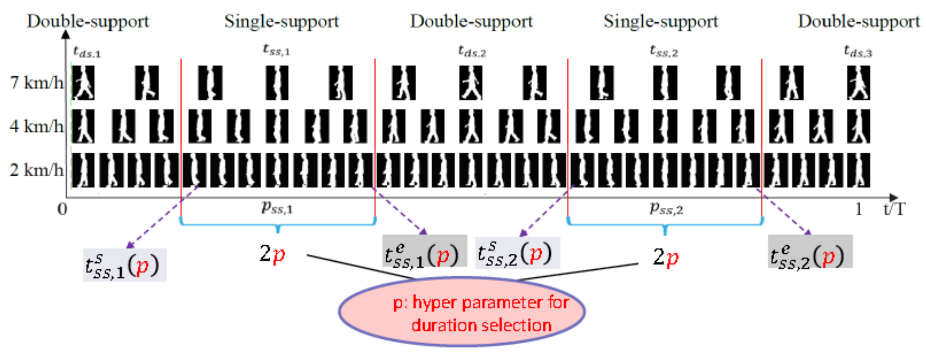


Speed Invariance vs. Stability: Cross-Speed Gait Recognition using Single-Support Gait Energy Image

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.

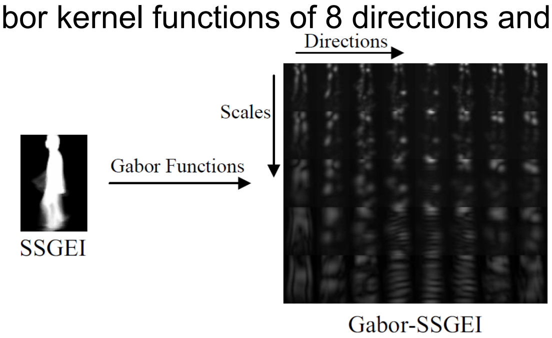


- Representation:

$$S(x,y;p) = \frac{1}{2}\sum_{k=1}^{2}\frac{1}{t^{e}_{ss,k}(p) - t^{s}_{ss,k}(p) + 1}\sum_{t=t^{s}_{ss,k}(p)}^{t^{e}_{ss,k}(p)} I(x,y,t), \qquad (0 < p \le 1/4).$$

Post-process

- Gabor filtering [Tao et al. 2007]
  - Gabor kernel functions of 8 directions and 5 scales.



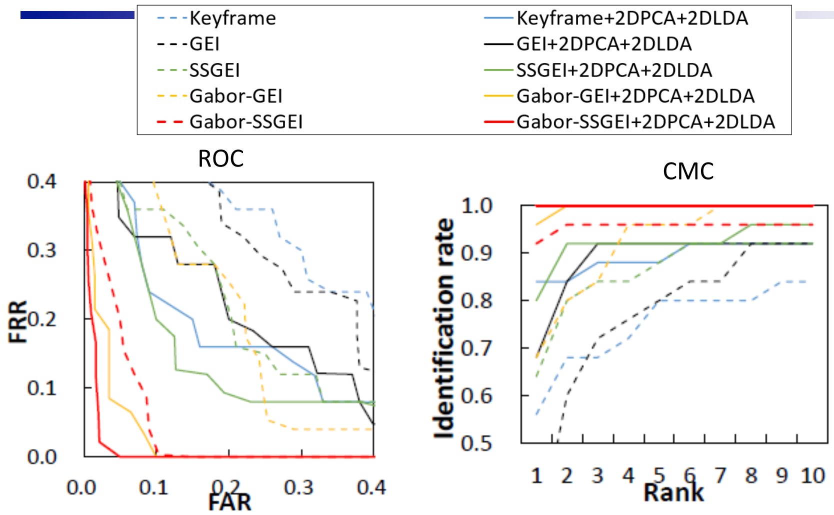
- Metric Learning
  - 2DPCA [Yang et al. 2004]: Reduce feature dimension.
  - 2DLDA [Li et al. 2005]: Achieve optimal discrimination capability.

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: 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.

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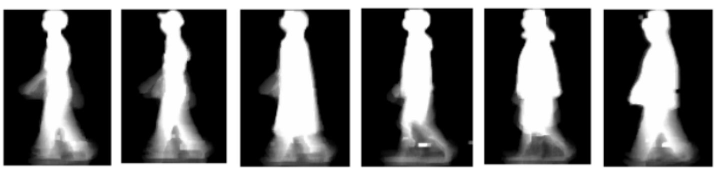
Gait energy response function for clothes-invariant gait recognition

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:

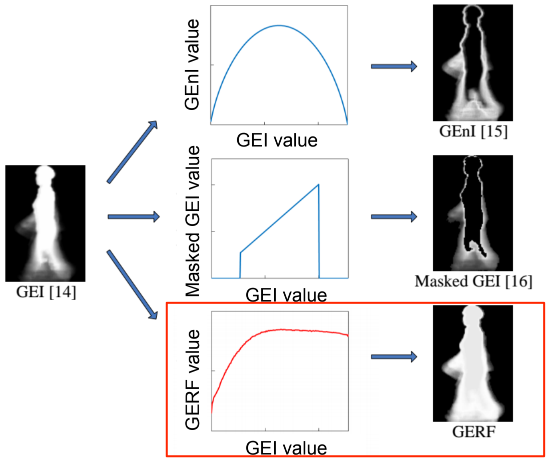
ew,



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

Objective

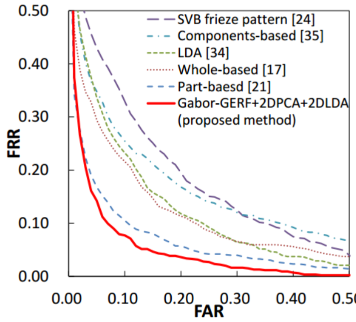
- Transform GEI into more discriminative feature under clothes variation



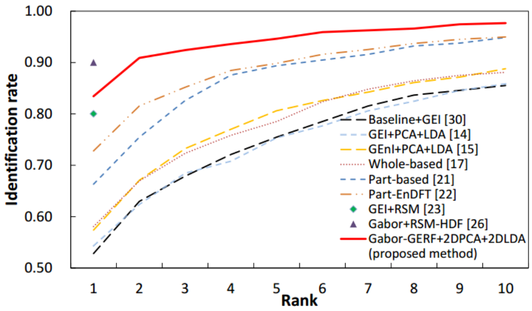
A sort of gait energy transformation process via a gait energy response function (GERF)

Comparison with state-of-the-arts methods

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



ROC curves



CMC curves

Appropriate Network Architecture According to a Situation for CNN-based Cross-view Gait Recognition

Noriko Takemura (Osaka Univ.), Yasushi Makihara (Osaka Univ.),
Daigo Muramatsu (Osaka Univ.), Tomio Echigo (OECU),
Yasushi Yagi (Osaka Univ.)

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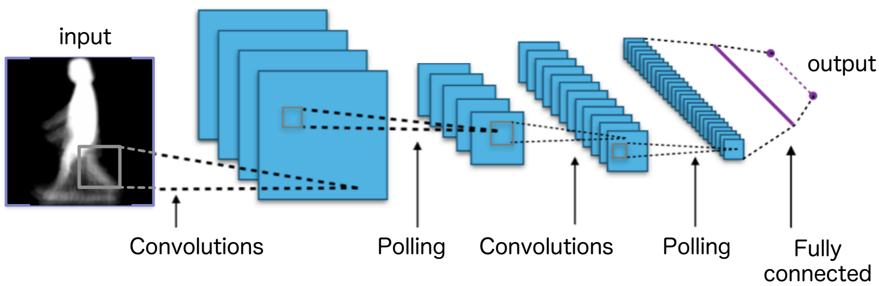
CNN-based discriminative approach

Convolutional Neural Network (CNN)-based gait recognition



- CNN-based methods have achieved state-of-the-art performance.
- Network architectures can be designed flexibly.

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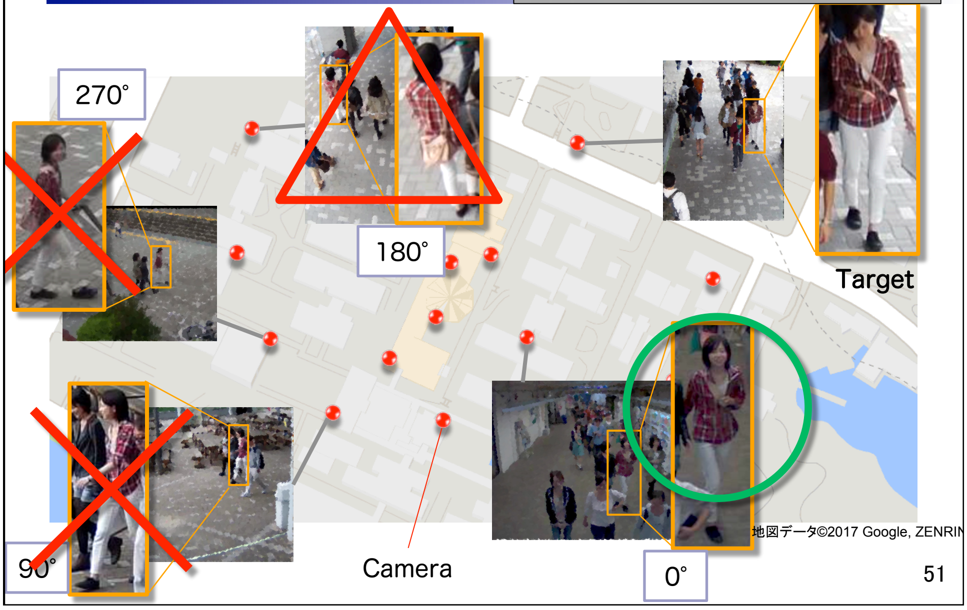
VTM based approach

- Walking direction is given
- Limitation of an angular difference of walking directions



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CNN based Cross View Approach

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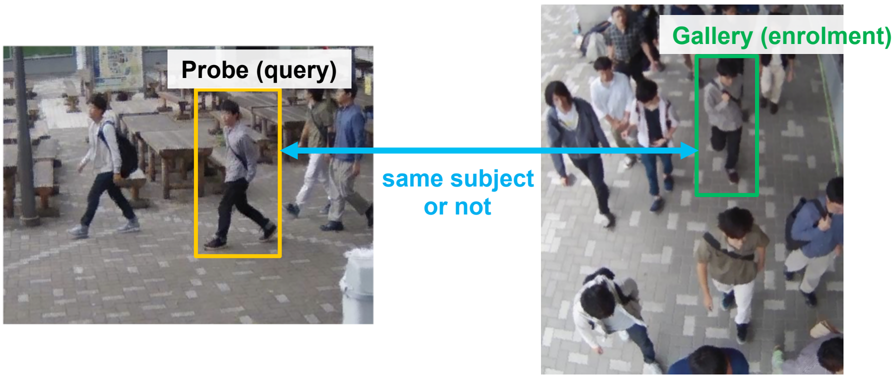
Verification (1:1 matching)

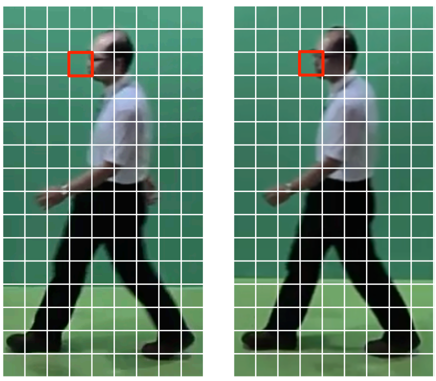


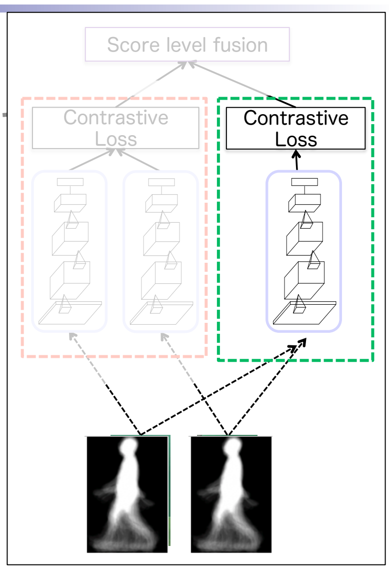
Applications

- Matching a perpetrator and suspect for a criminal investigation.
- Detecting a specific person at border control.

6

In case of small angular difference





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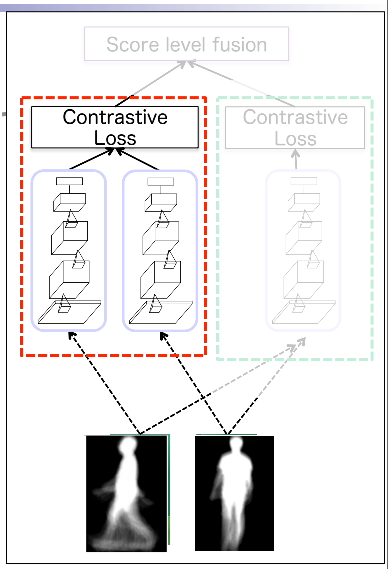
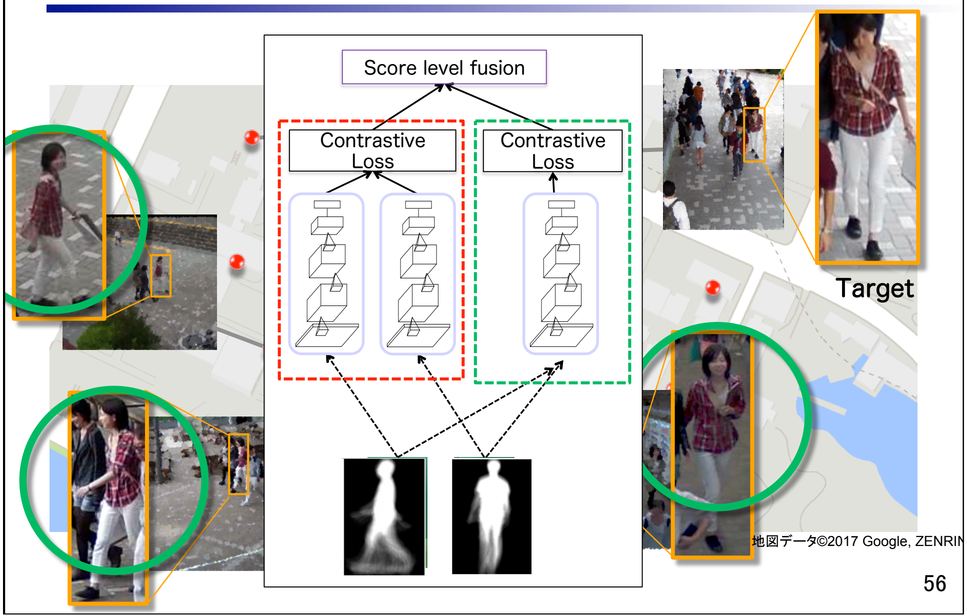
In case of large angular difference



55

CNN based Cross View Approach



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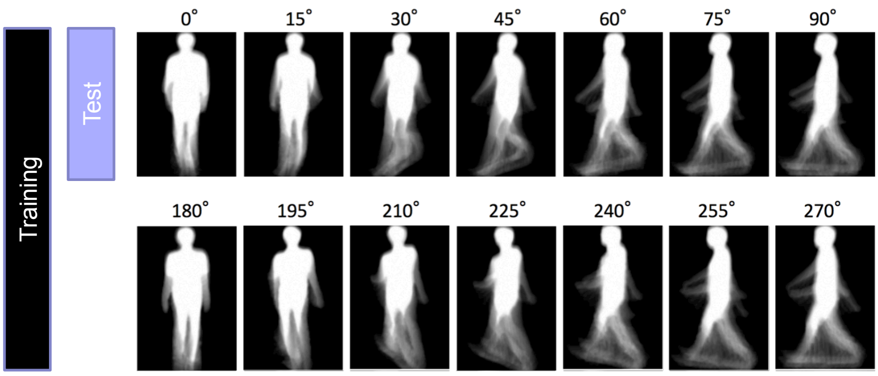
Gait database

OU-MVLP（OU-ISIR Multi-View Large Population）

- □ Gait feature: GEI (Gait energy image)
- □ #Subjects：about 10,000 (training : testing = 1 : 1)
- □ View variation：14 views（0-90°，180-270°，15°-intervals）



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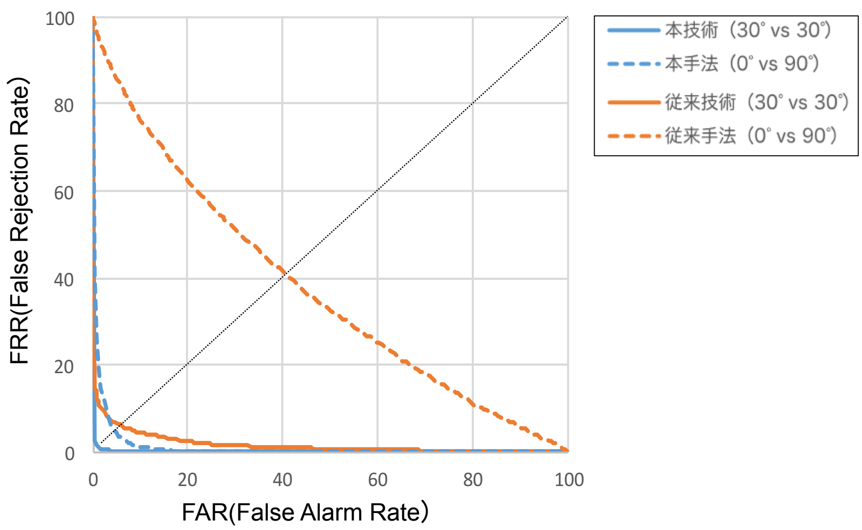
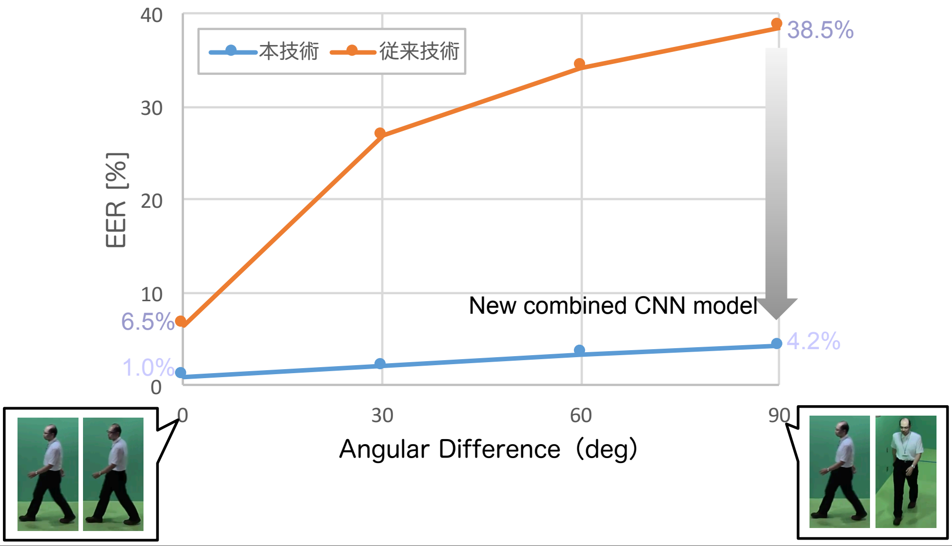
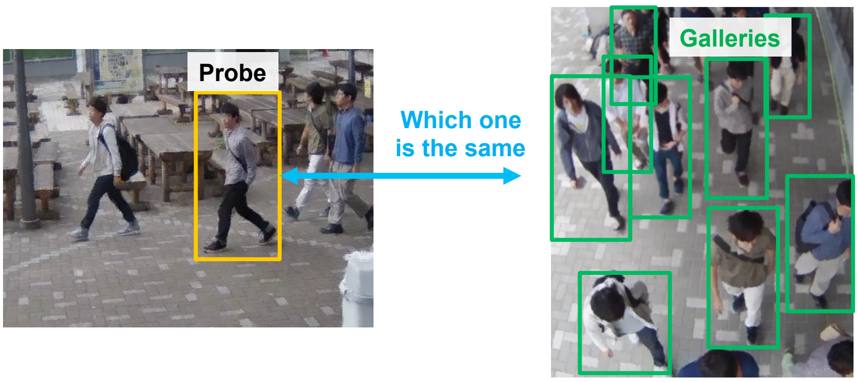
ROC curve of new combined CNN model



Equal Error Rate of new combined CNN model



Identification (1:N matching)

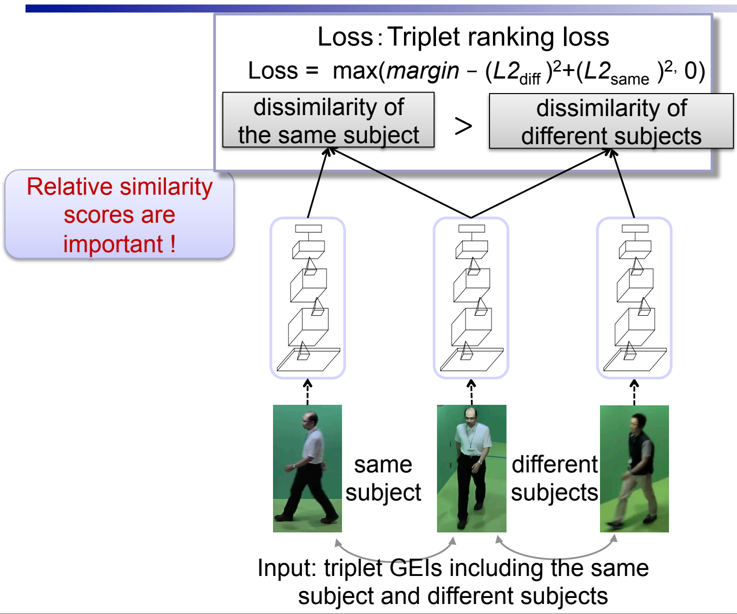


Applications

- Person re-identification
- ID-less access control

8

Network architecture for identification



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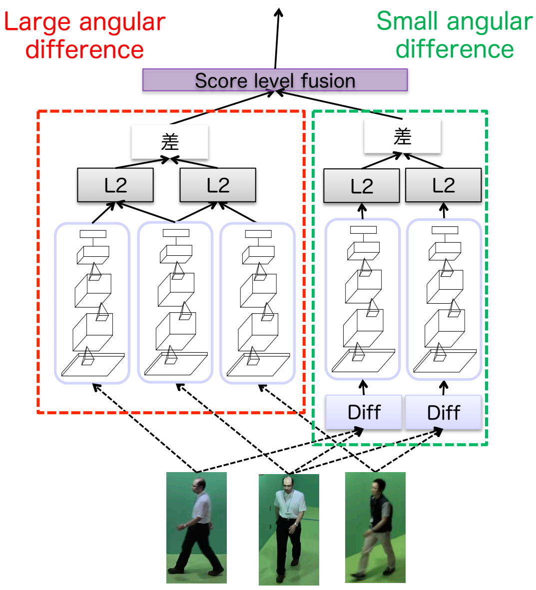
CNN based gait identification



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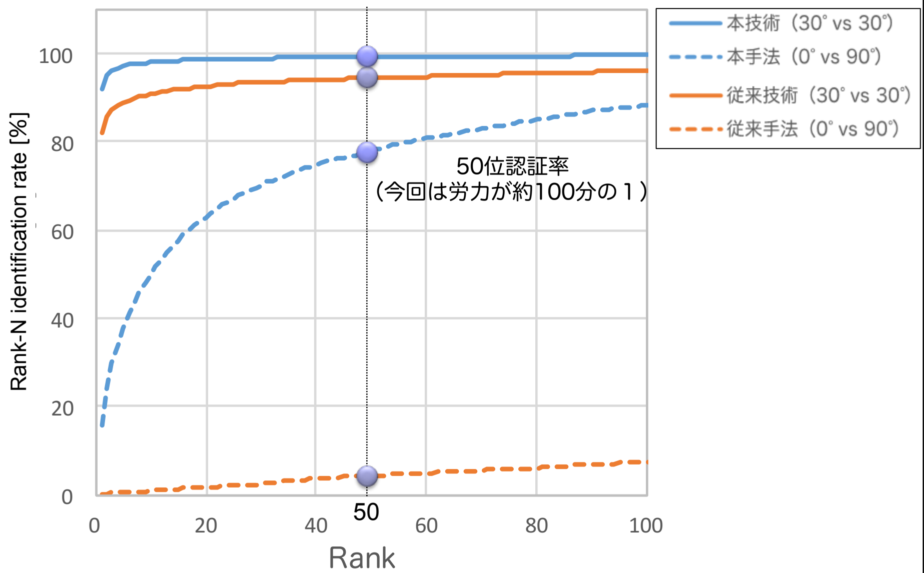
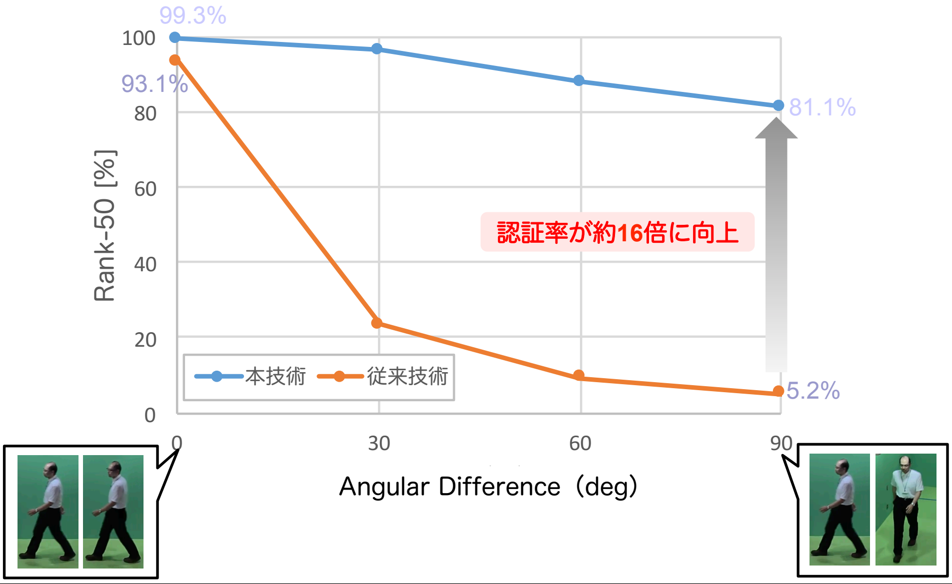
Rank-N identification rate（Subject about 5,000）



Rank-N identification rate（Subject about 5,000）



Benchmarks

- Direct matching
  - DM (L2 distance of two GEIs as the dissimilarity)
- Generative approach
  - VTM (View transformation model) [ECCV2006]
- Discriminative approach
  - LDA (Linear discriminant analysis) [ICB2014]
- CNN-based discriminative approach
  - GEINet [IEICE2016]
  - MT (Mid-level@Top) [TPAMI2016]
  - LB (Local@Bottom) [TPAMI2016]

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Evaluation criteria

- For verification

  Equal error rate (EER)

  EER of false acceptance rates (FARs) and false rejection rates (FRRs) .

- For identification

  Rank-1 identification rate

  Rate of hitting the best matching as the correct matching.

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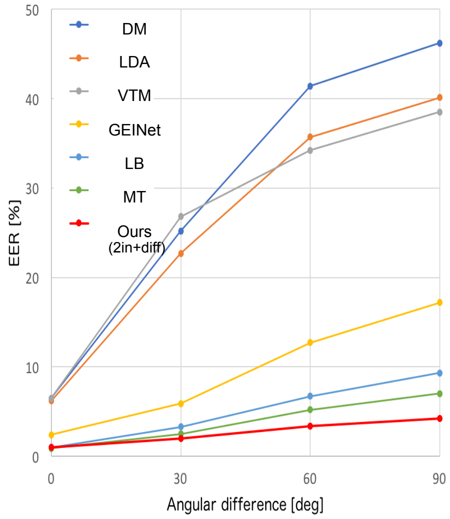
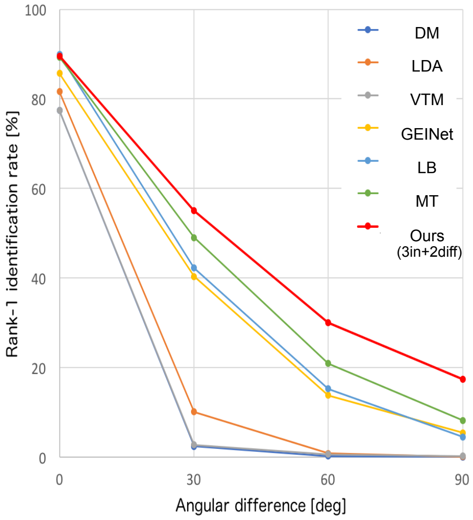
Comparison with benchmarks

Verification



Identification



N. Takemura, Y. Makihara, D. Muramatsu, T. Echigo and Y. Yagi,

"On Input/Output Architectures for Convolutional Neural Network-Based Cross-View Gait Recognition,"

IEEE Transactions on Circuits and Systems for Video Technology (Early access)

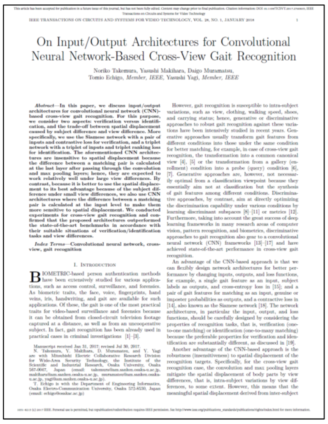

On Input/Output Architectures for Convolutional Neural Network-Based Cross-View Gait Recognition

TABLE III: Recognition accuracy comparing our methods with the benchmarks using OU-ISIR LP.

(a) Rank-1 identification rates (%)

	Angular difference			
	0	10	20	30
DM	91.5	49.5	11.2	2.8
LDA	97.8	97.1	93.4	82.9
VTM	91.5	64.0	37.2	20.5
GEINet	96.5	95.8	92.5	84.9
Wu [14]	98.9	95.5	92.4	85.3
2in	97.9	97.6	95.6	92.0
3in	98.5	98.2	96.4	92.3
diff	98.7	98.5	97.2	94.7
2diff	99.1	99.0	98.0	95.1
2in+diff	**99.3**	**99.2**	**98.6**	**96.9**
3in+2diff	**99.2**	**99.2**	**98.6**	**97.0**

(b) EERs (%)

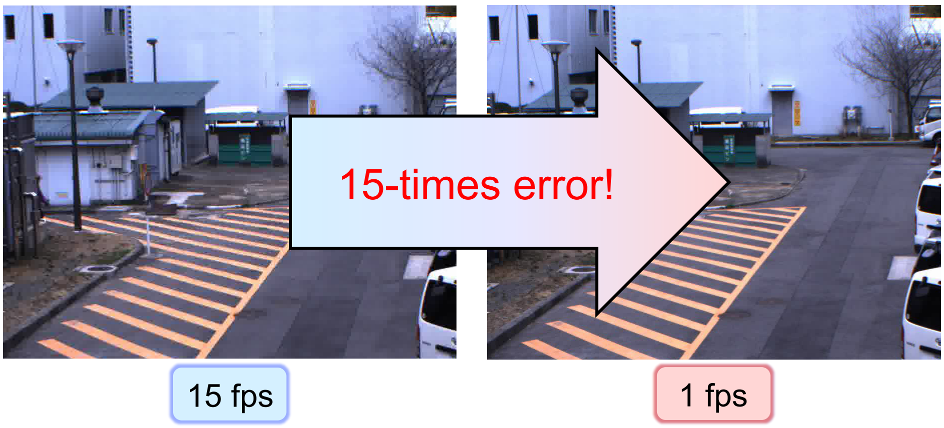
	Angular difference			
	0	10	20	30
DM	4.3	8.4	20.2	31.3
LDA	2.1	2.5	3.7	5.7
VTM	4.3	10.5	14.8	18.9
GEINet	1.9	2.1	3.0	4.9
Wu [14]	-	-	-	-
2in	0.3	0.3	0.5	0.7
3in	0.7	0.8	1.0	1.4
diff	**0.3**	**0.3**	**0.4**	**0.7**
2diff	1.8	2.0	2.7	3.9
2in+diff	**0.2**	**0.2**	**0.2**	**0.4**
3in+2diff	1.0	1.1	1.4	1.9

Wu [14]: Fusion method using 8 different CNNs including LB and MT.

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

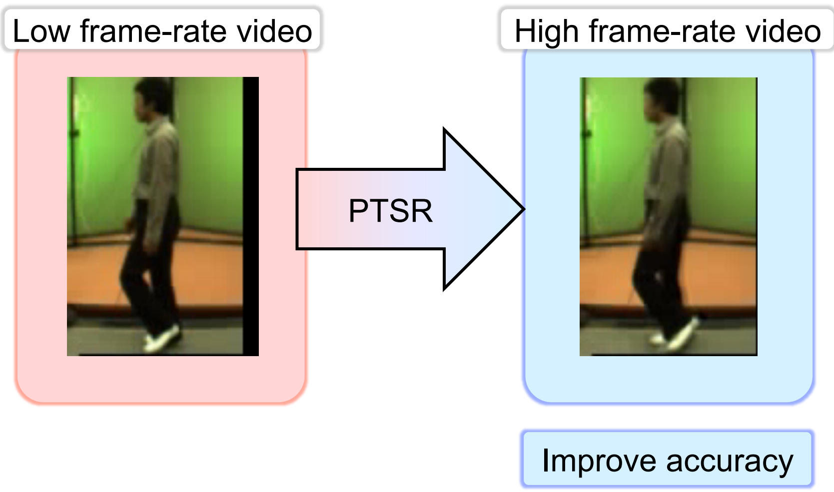
- The difference of the observation direction
  - ECCV2006
- Speed change CVPR2010
- The difference of clothes
  - Pattern Recognition 2010
- The difference of shoes
- Low sampling rate
  - ACCV2010, IJCB2011,
  - CVPR2012
- Occlusion in crowd scene
  - ICB2015

Challenge -Low frame-rate-

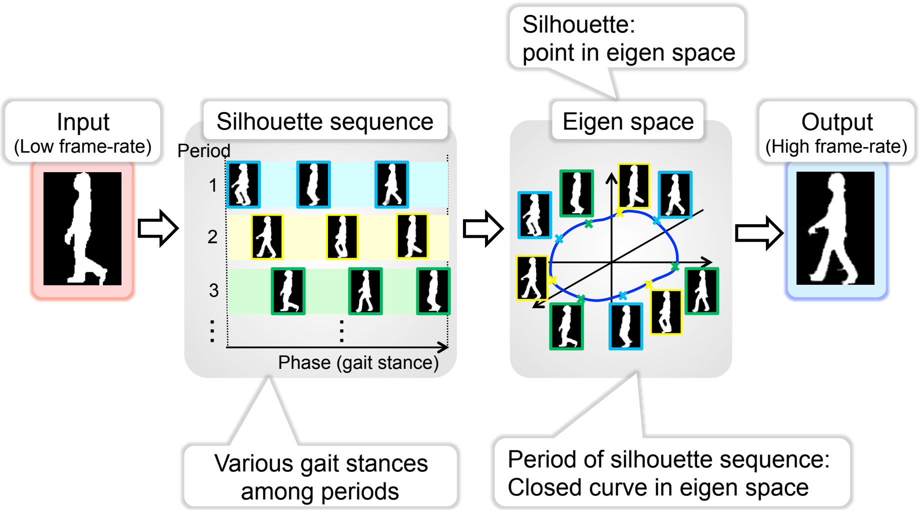


Solution

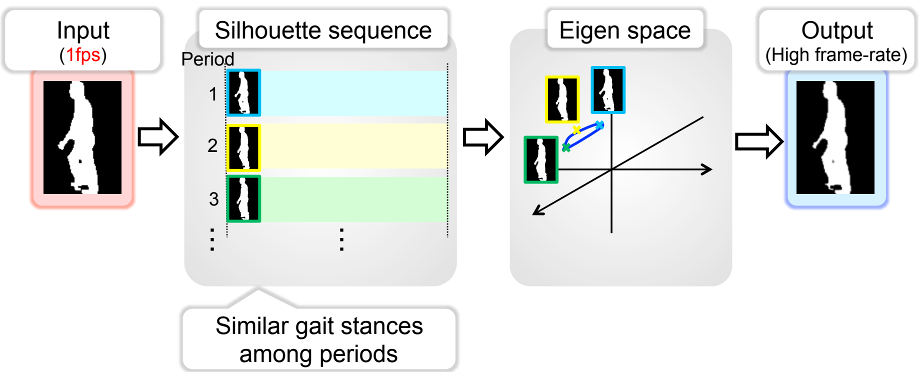
- Periodic Temporal Super Resolution (PTSR)



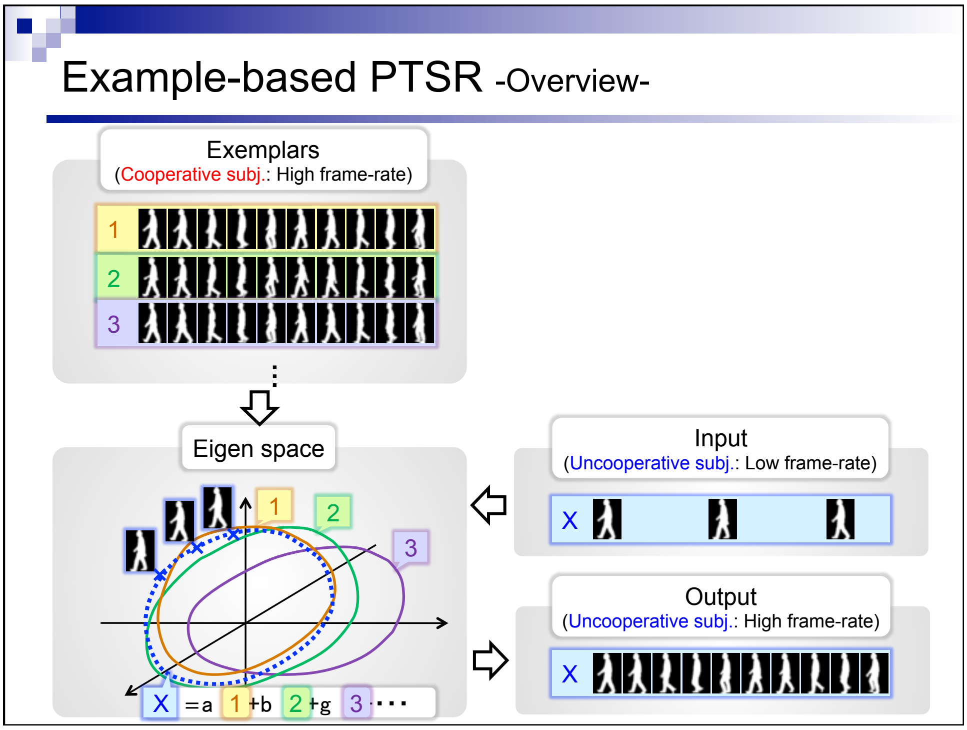
Reconstruction-based PTSR -Overview- [Makihara et al. ACCV 2010]

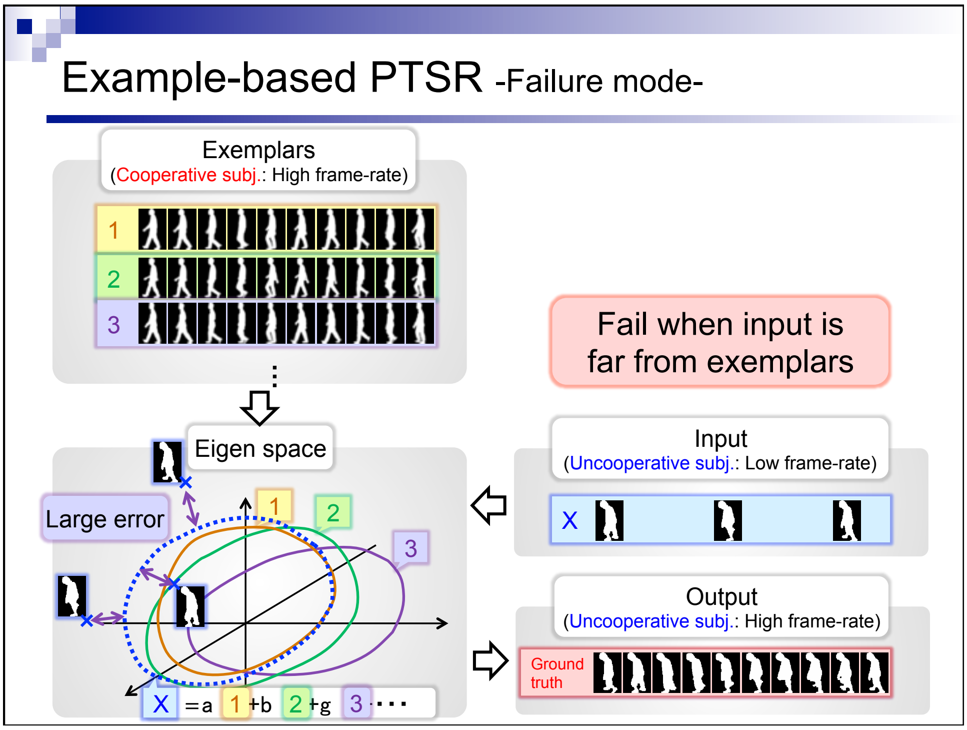


Reconstruction-based PTSR -Failure mode-

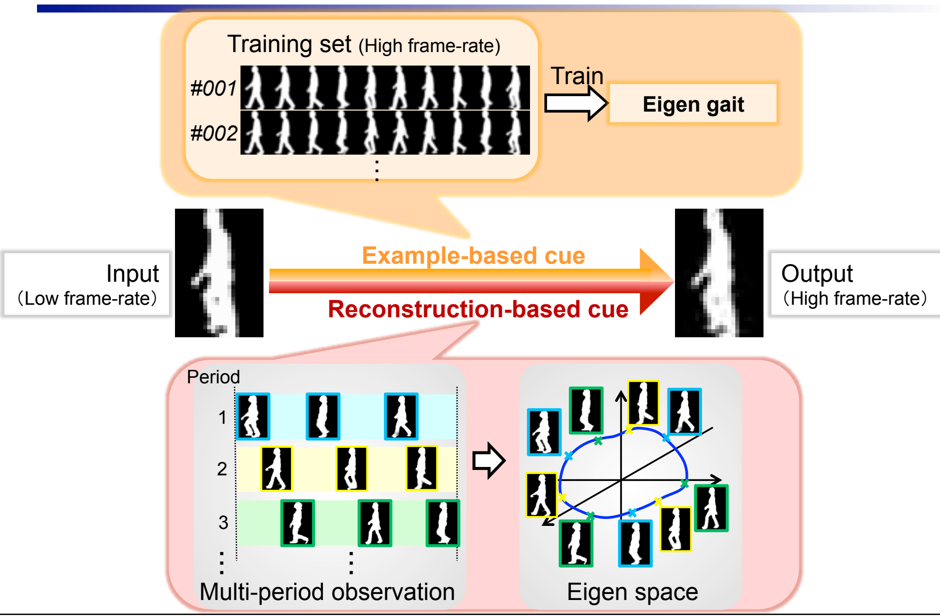


Fail under stroboscopic effect

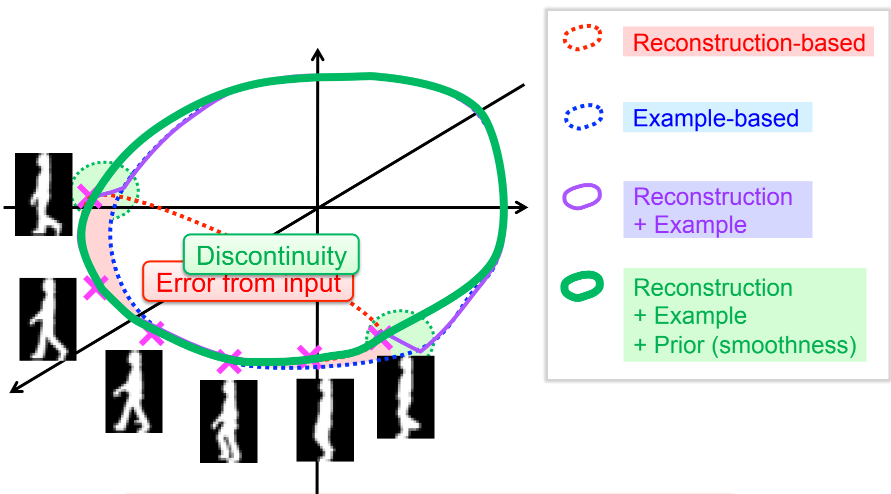

Example-based PTSR -Overview-
Exemplars
(Cooperative subj.: High frame-rate)
1
2
3
Eigen space
Input
(Uncooperative subj.: Low frame-rate)
X
Output
(Uncooperative subj.: High frame-rate)
X
X =a 1 +b 2 +g 3 ···


Example-based PTSR -Failure mode-
Exemplars
(Cooperative subj.: High frame-rate)
1
2
3
Fail when input is far from exemplars
Eigen space
Large error
Input
(Uncooperative subj.: Low frame-rate)
X
Output
(Uncooperative subj.: High frame-rate)
Ground truth
X =a 1 +b 2 +g 3 ···

Unified approach to PTSR [Akae et al. CVPR 2012]

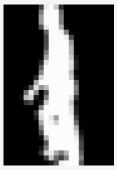
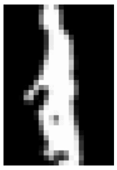
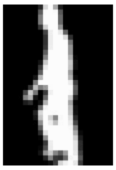
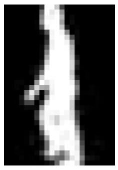


How does it work?

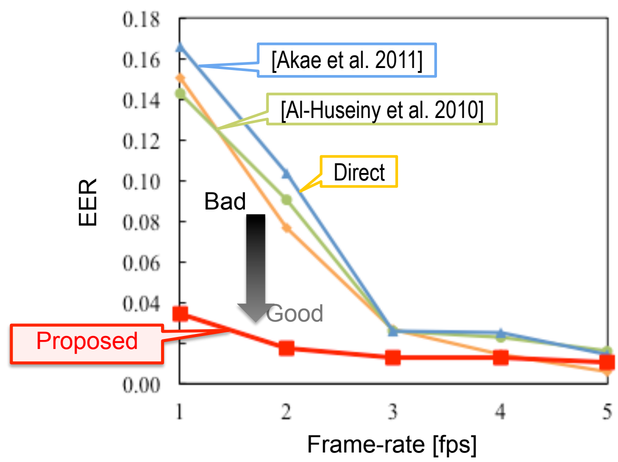


Solve by energy minimization framework

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 Analysis for Innovative Entertainment

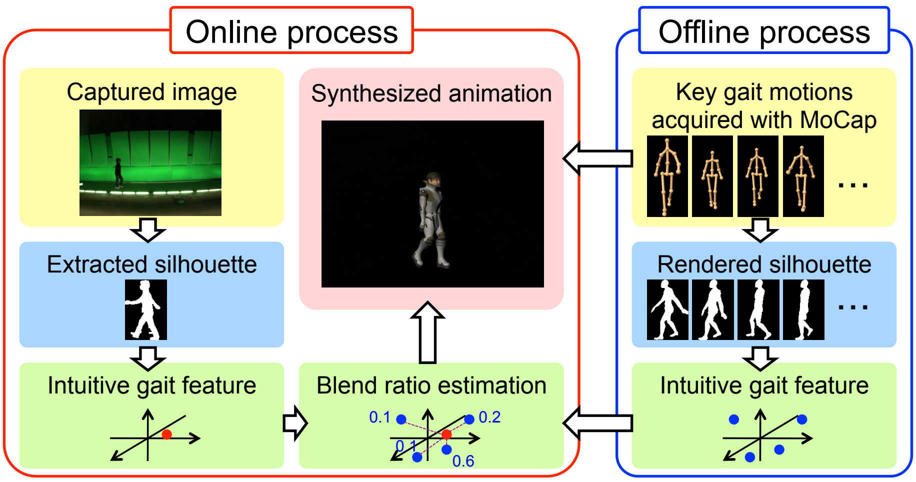
Dive Into the Movie

"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]



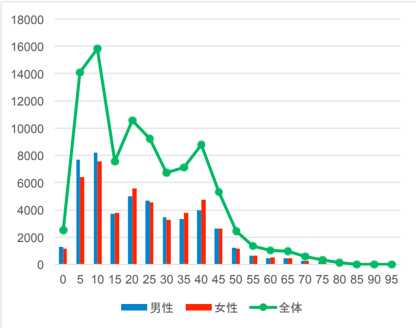
[3] M. Okumura, Y. Makihara, S. Nakamura, S. Morishima, and Y. Yagi, ``The Online Gait Measurement for the Audience-Participant Digital Entertainment," Proc. of Invited Workshop on Vision Based Human Modeling and Synthesis in Motion and Expression, No. 5, pp. 1-10, Xi'an, China, Sep. 2009.
[4] Y. Makihara, 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

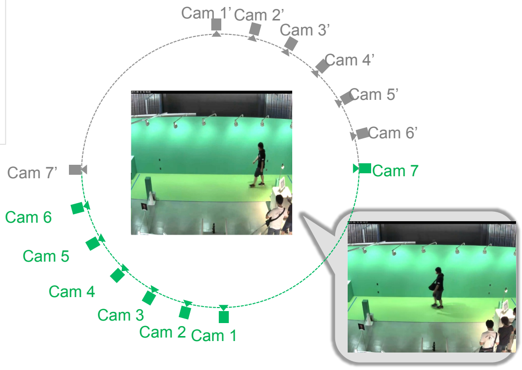
http://www.am.sanken.osaka-u.ac.jp/BiometricDB/index.html

- *The OU-ISIR Gait Database*
  - *Treadmill Dataset*
    - **dataset A -Speed variation-**
    - **dataset B -Clothes variation-**
    - **dataset C -view variation-**
    - **dataset D -Gait fluctuation-**
  - *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

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