Human Gait Analysis

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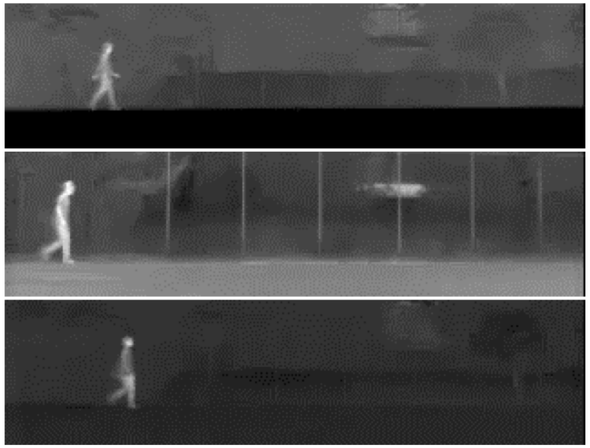
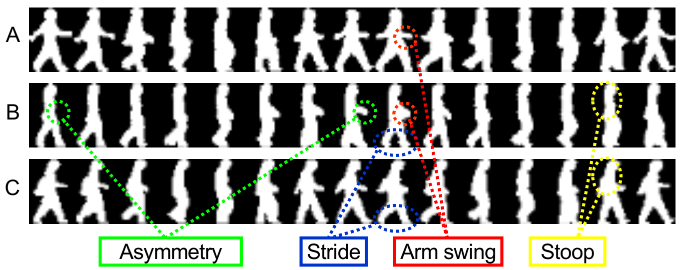
Human gait -Personality- Identity -



Human gait -Personality-



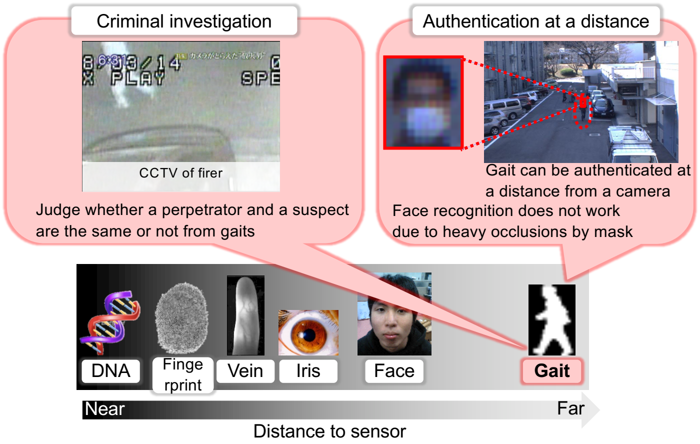
Gait recognition: Person authentication from gait personalities

Example of practical use (1)

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

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

Advantage of gait recognition



Today's topics

- Gait identification & gait verification
- What is the difficulty for applying gait to wide-area surveillance ?
  - The difference of the observation direction
  - Occlusion in crowd scene
  - Speed change
  - The difference of clothes
  - Low sampling rate
- Age estimation
- Gait analysis for innovative entertainment

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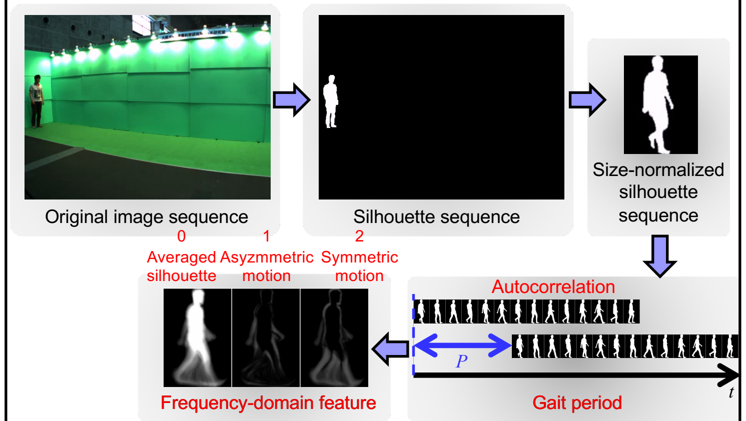
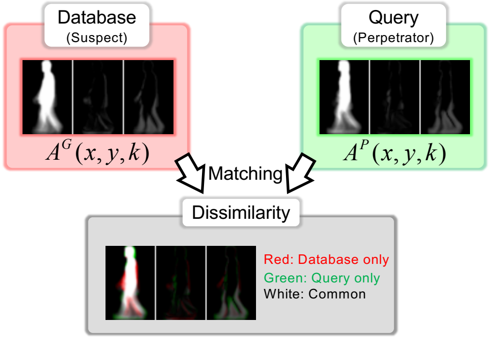
Gait identification & gait verification

Gait feature extraction



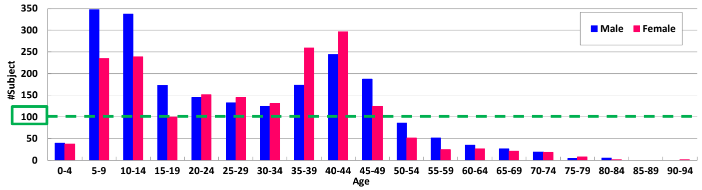
Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, and Y. Yagi, ``Gait Recognition Using a View Transformation Model in the Frequency Domain,'' 9th European Conf. on Computer Vision, Vol. 3, pp. 151-163, 2006.

Dissimilarity: Single feature



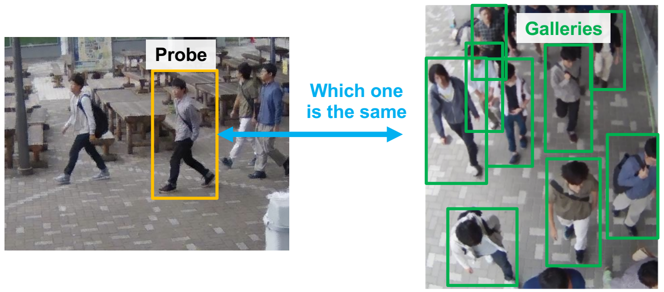
$$t = \sqrt{\sum_{x,y,k} \left(A^G(x,y,k) - A^P(x,y,k)\right)^2}$$

Database: OU-LP



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

Identification (1:N matching)

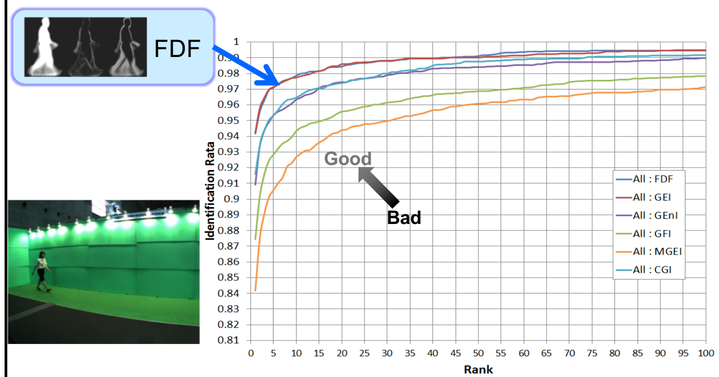


Applications

- Person re-identification
- ID-less access control

Performance evaluation: identification

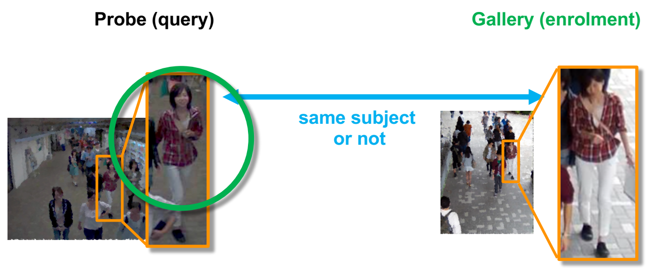
[Iwama et al. IFS 2012]



Cumulative matching characteristics (CMC) curve

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

Verification (1:1 matching)



Applications

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

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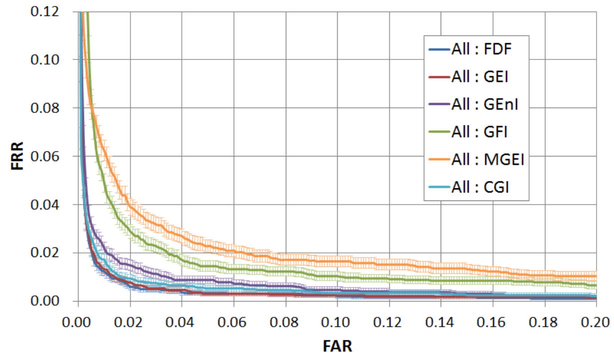
Performance evaluation: verification



EER: 1.15%

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World first packaged gait verification system for criminal investigation

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- What is the difficulty for applying gait to wide-area surveillance ?
  - □ The difference of the observation direction ECCV2006
  - □ Occlusion in crowd scene
  - □ Speed difference
  - □ The difference of clothes
  - □ Low sampling rate
- Age estimation
- Gait analysis for innovative entertainment

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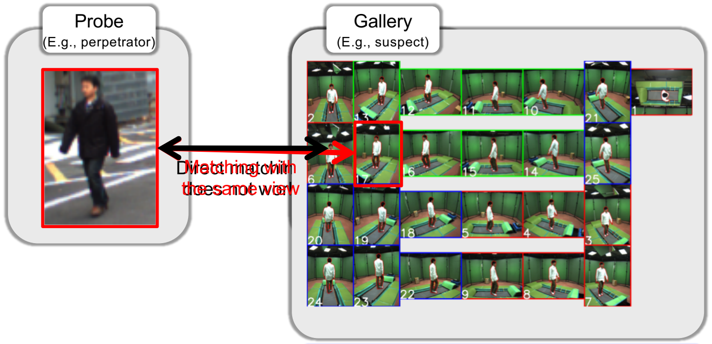
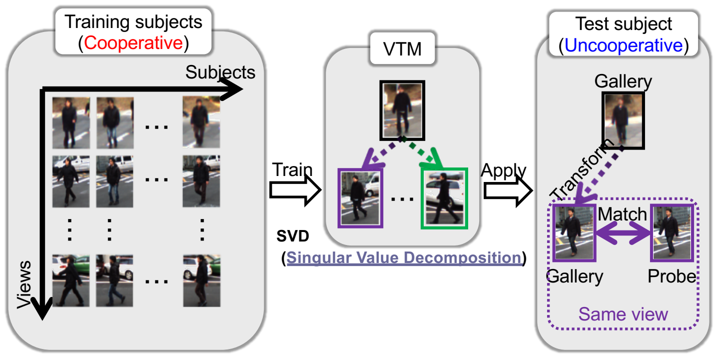
Challenge -View differences-



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

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

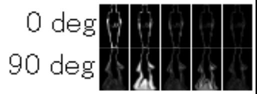
- Gait feature for mth subject from θ_i view

$$a^m_{\theta_i} = P_{\theta_i} v^m$$

View transformation

- From a single reference θ_j to θ_i

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

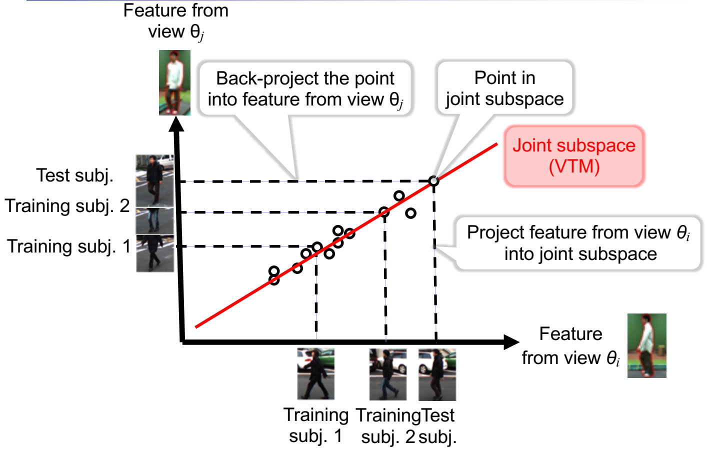


  - Orthogonal motion to reference θ_j is degenerated

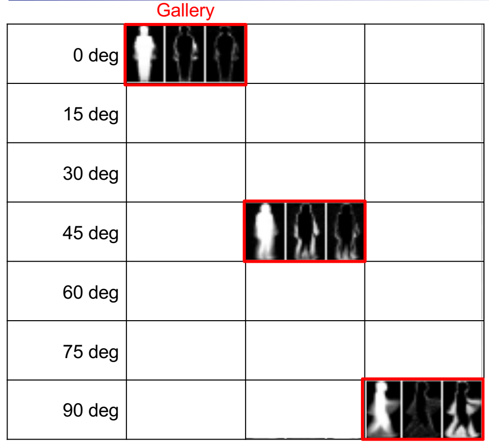
- From multiple references $\{\theta_j(1), \ldots, \theta_j(k)\}$ to θ_i

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

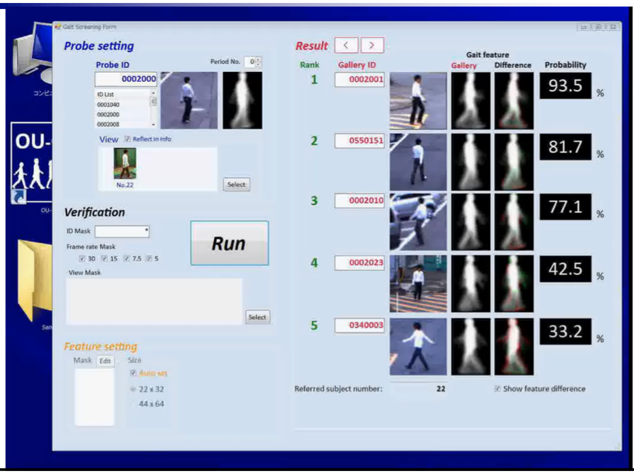
How does it work?



Transformation results



Example of batch verification



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- What is the difficulty for applying gait to wide-area surveillance ?
  - The difference of the observation direction
  - Occlusion in crowd scene ICB2015
  - Speed difference
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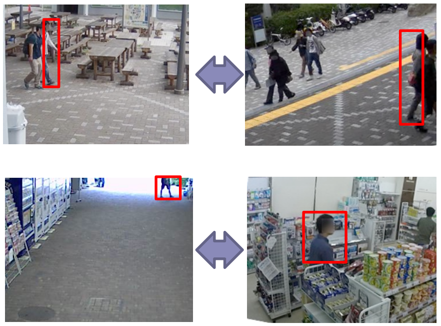
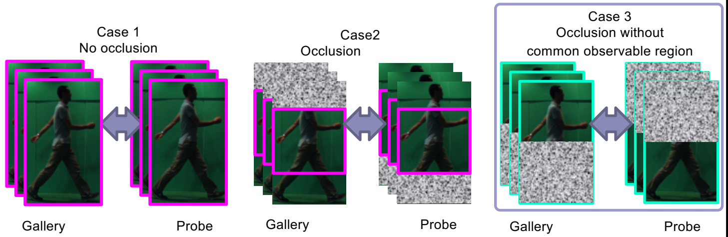
Actual situation of observed gait in surveillance



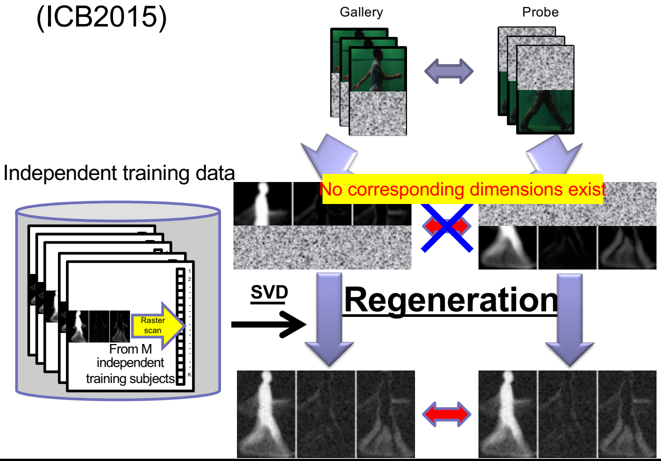
Challenge: Serious occlusion



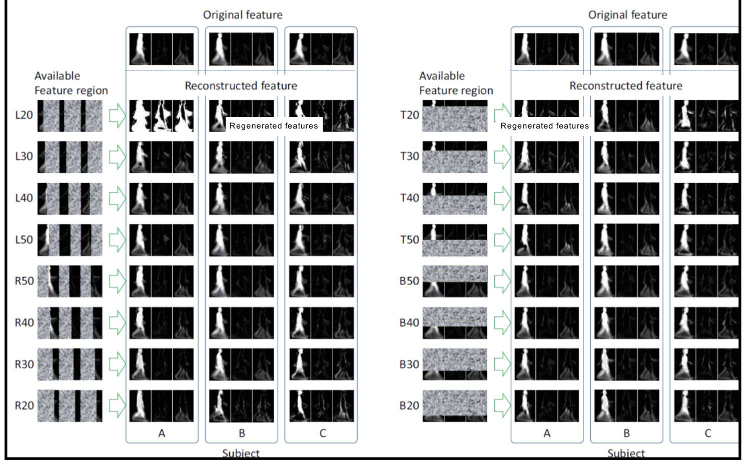
- Common observable regions (COR) are used for recognition
- Direct comparisons are impossible in case 3
  because any common region cannot be observed

Gait regeneration for recognition

(ICB2015)

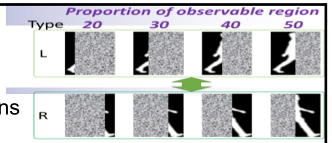


Experiment : Regenerated gait



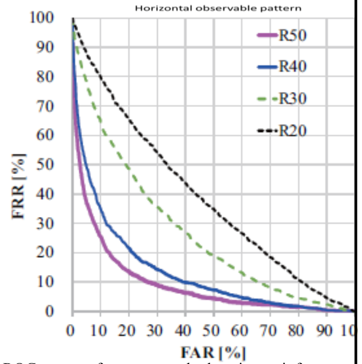
Experiment

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

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  - Speed difference ACCV2016
  - The difference of clothes
  - Low sampling rate
- Age estimation
- Gait analysis for innovative entertainment

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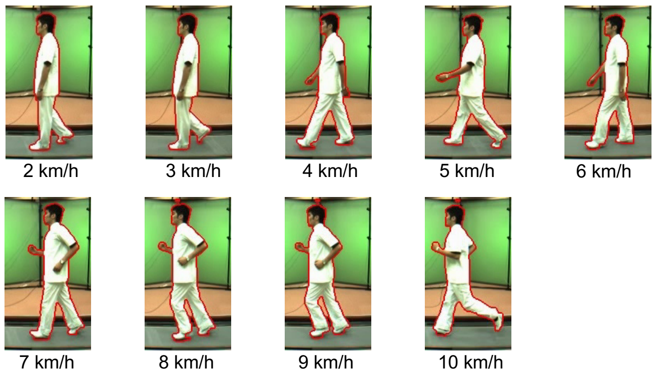
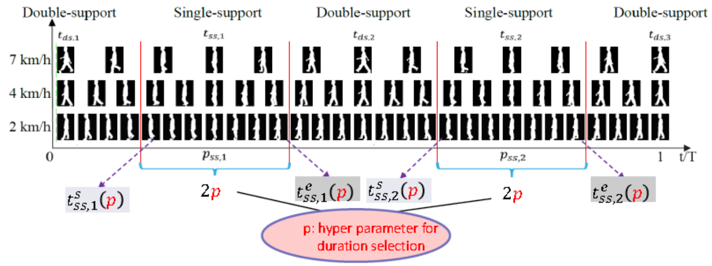
Challenge -Speed difference-



Single-Support GEI (SSGEI)

- Aggregate multiple frames of optimal duration around single-support phase.

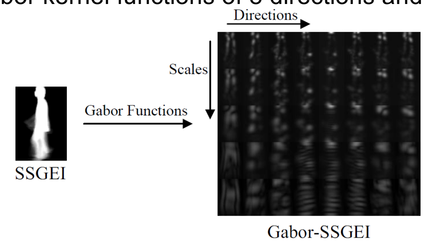


- Representation:

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

Post-process

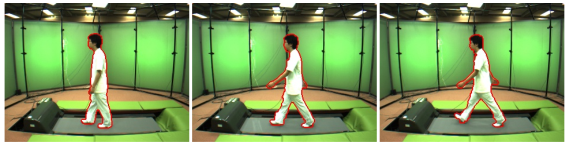
- Gabor filtering [Tao et al. 2007]
  - Gabor kernel functions of 8 directions and 5 scales.



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

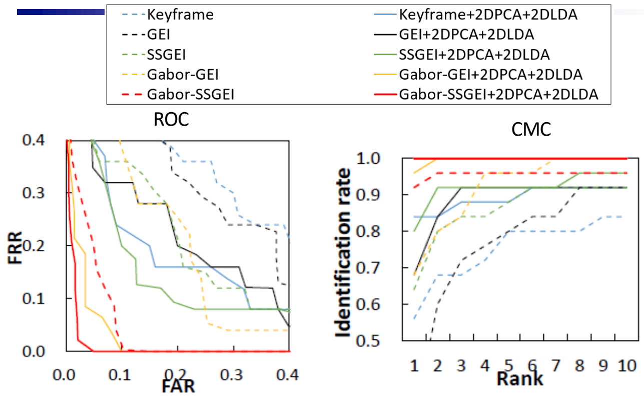
Experiments: dataset 1

- **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.

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  - The difference of clothes — ACCV2016
  - Low sampling rate
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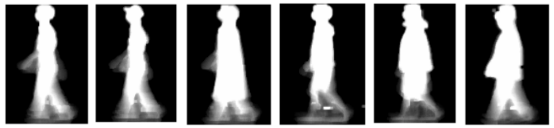
Background

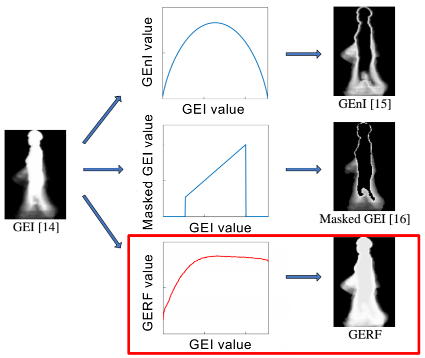
- Gait recognition
  - Pros:
    - Availability at a distance for an uncooperative subject (c.f. face, iris)
  - Cons:
    - Accuracy drop due to many covariates (e.g., clothing, view, speed)



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

Objective

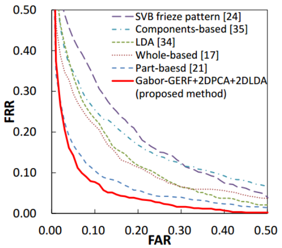
- Transform GEI into more discriminative feature under clothes variation



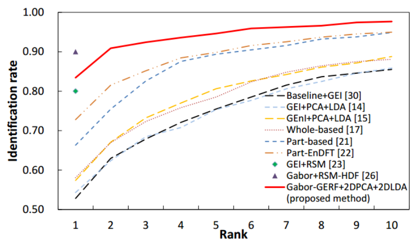
A sort of gait energy transformation process via a gait energy response function (GERF)

Comparison with state-of-the-arts methods

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

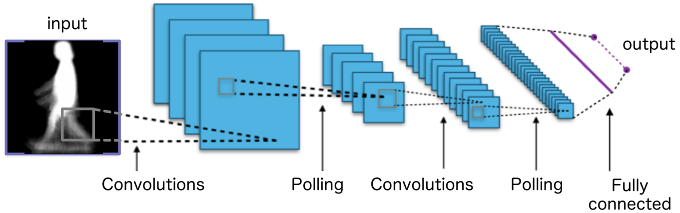


ROC curves



CMC curves

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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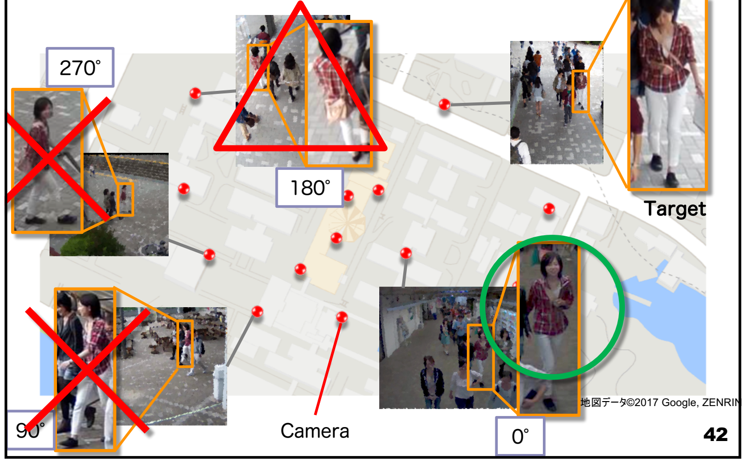
VTM based approach

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



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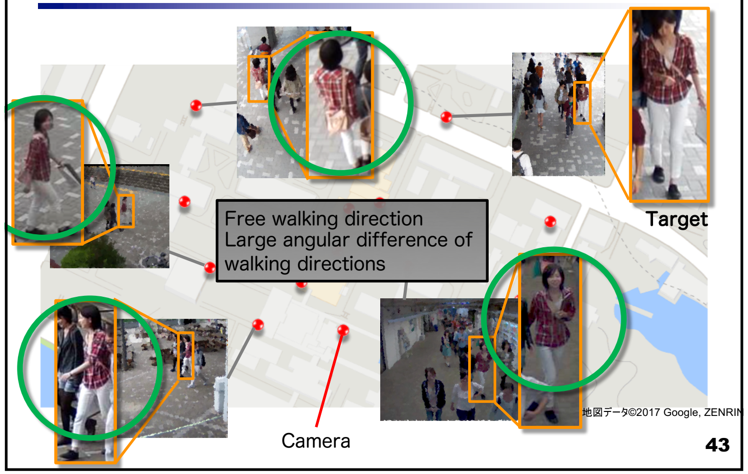
CNN based Cross View Approach



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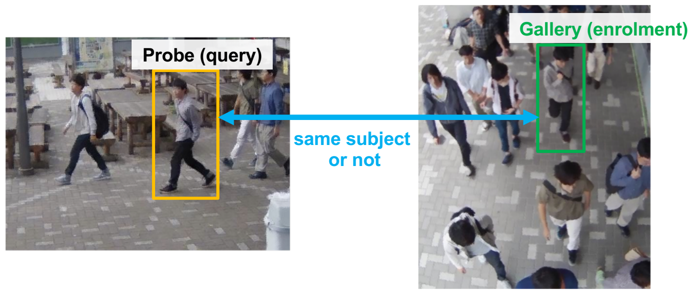
Verification (1:1 matching)



Applications

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

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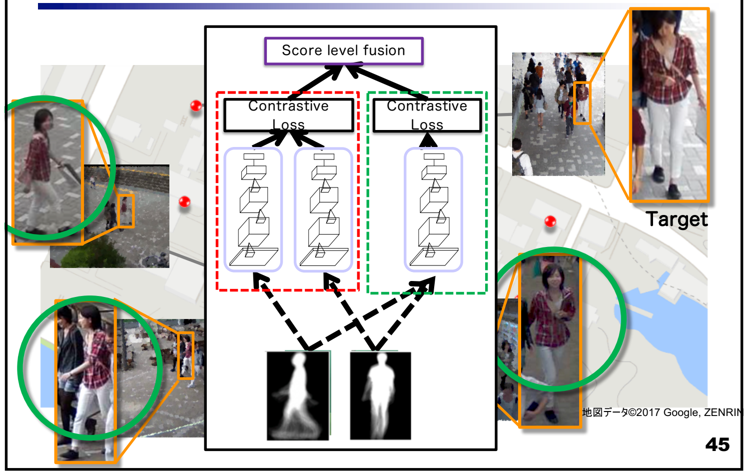
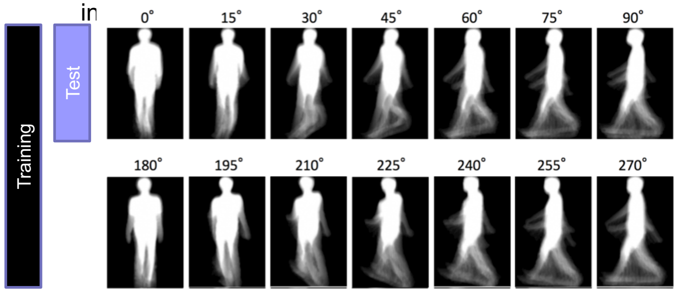
CNN based Cross View Approach



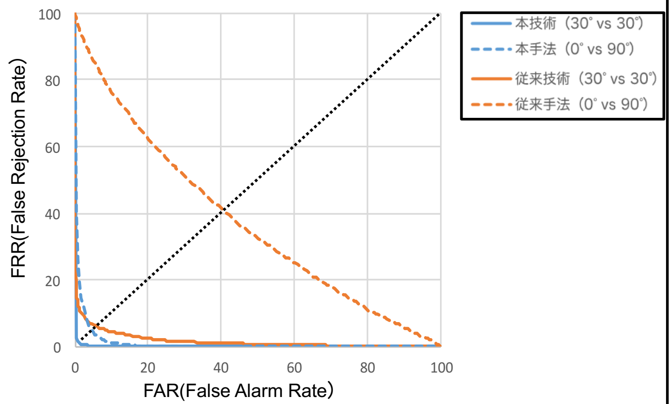
Gait database

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

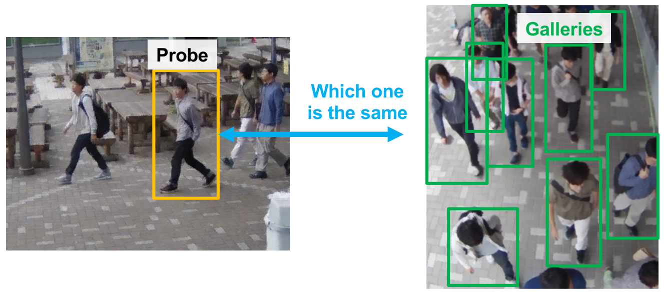
- Gait feature: GEI (Gait energy image)
- #Subjects: about 10,000 (training : testing = 1 : 1)
- View variation: 14 views（0-90°, 180-270°, 15° - in



ROC curve of new combined CNN model



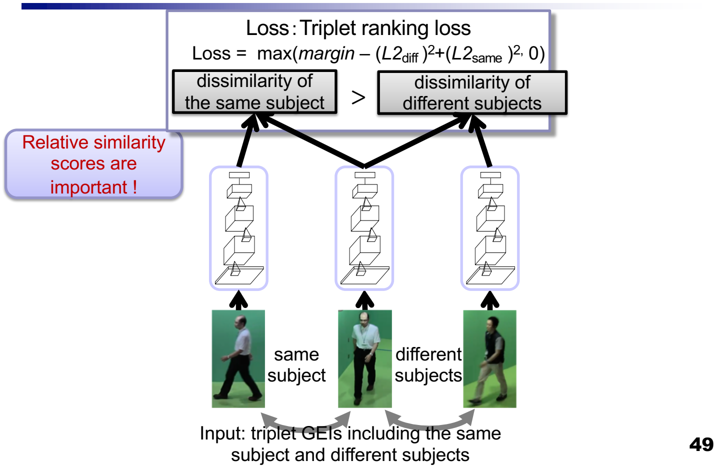
Identification (1:N matching)



Applications

- Person re-identification
- ID-less access control

Network architecture for identification



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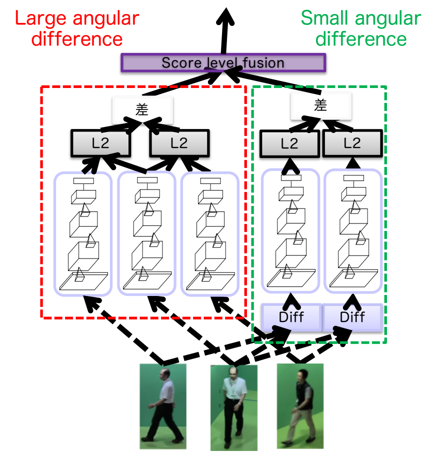
CNN based gait identification



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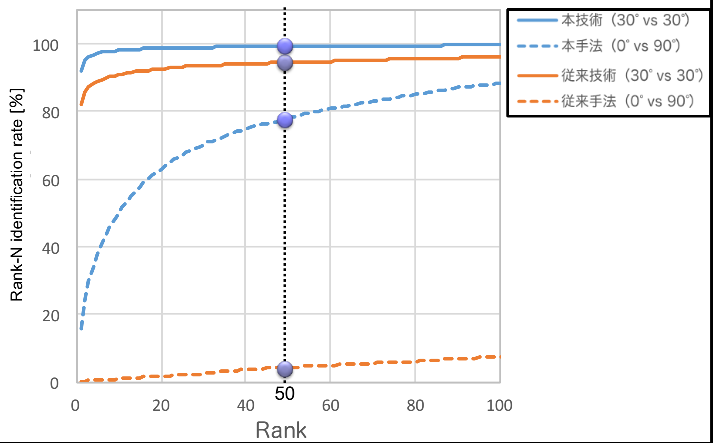
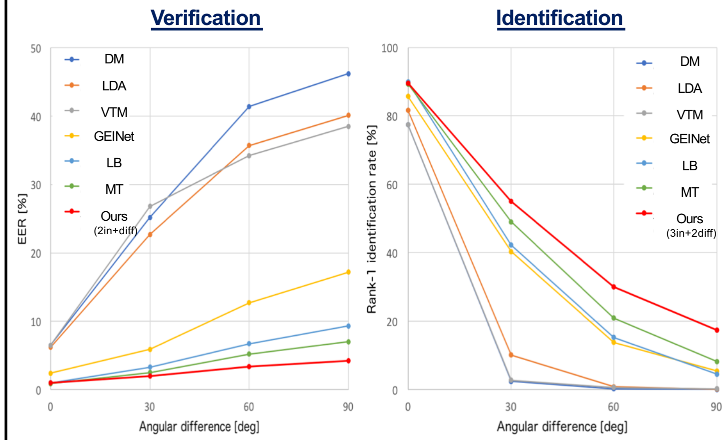
Rank-N identification rate（Subject about 5,000）



Comparison with benchmarks



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- What is the difficulty for applying gait to wide-area surveillance ?
  - The difference of the observation direction
  - Occlusion in crowd scene
  - Speed difference
  - The difference of clothes & carrying status Trans. IFS2019
  - Low sampling rate
- Age estimation
- Gait analysis for innovative entertainment

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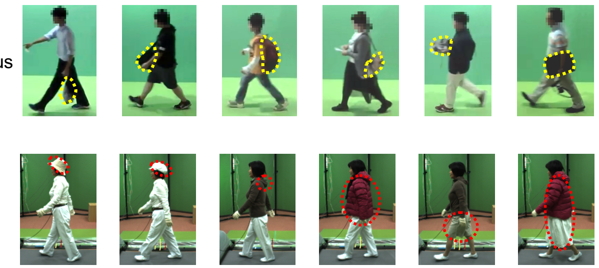
Joint Intensity Transformer Network for Gait Recognition against Clothing and Carrying status

- Carrying status and clothing appear in various spatial positions
  - Only spatial metric learning is insufficient

Carrying status

Clothing



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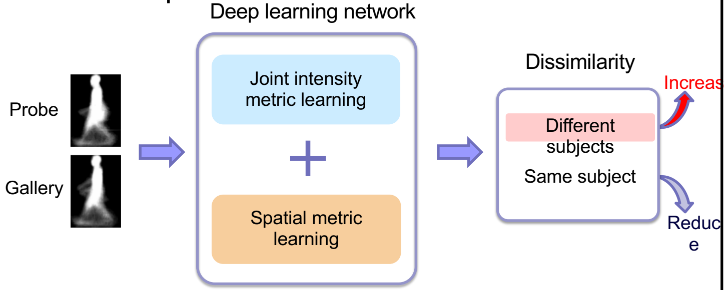
Objective

- Extend joint intensity and spatial metric learning method using deep learning-based techniques



X. Li, Y. Makihara, C. Xu, Y. Yagi, M. Ren, ``Joint Intensity Transformer Network for Gait Recognition Robust against Clothing and Carrying status,'' IEEE Transactions on Information Forensics and Security, Vol. 14, No. 12, pp. 3102-3115, Dec. 2019. [open access]

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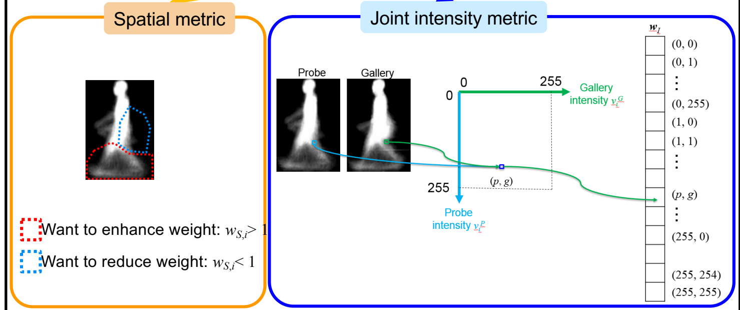
Joint intensity and spatial metric learning [Makihara et al. 2017]

- General dissimilarity measure

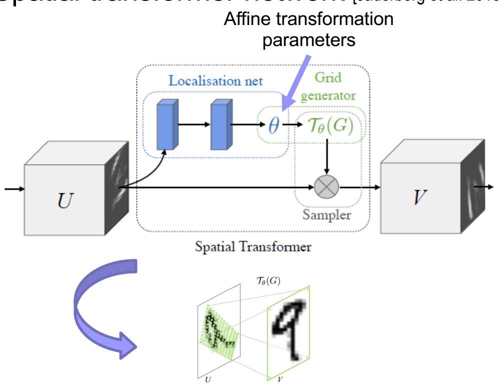
$$D(\mathbf{v}^P,\mathbf{v}^G)=\sum_{i=1}^{N_S} w_{S,i}\,\eta(v_i^P,v_i^G)$$

N_S: #Pixels
i: Position index



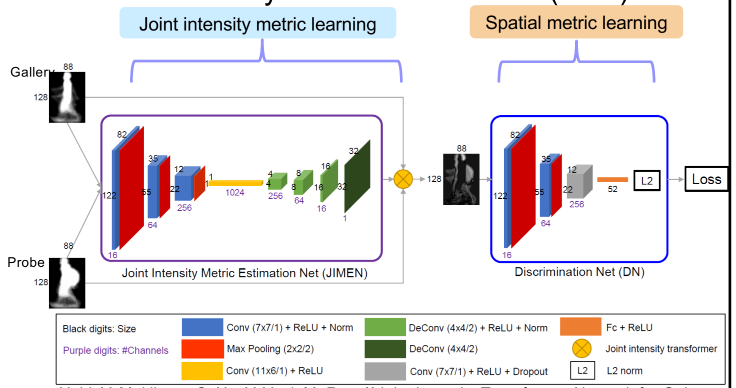
Inspiration

- Spatial transformer network [Jaderberg et al. 2015]



Proposed method

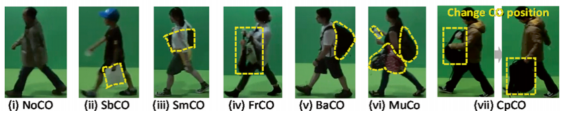
- Joint intensity transformer network (JITN)



X. Li, Y. Makihara, C. Xu, Y. Yagi, M. Ren, ``Joint Intensity Transformer Network for Gait Recognition Robust against Clothing and Carrying status," IEEE Transactions on Information Forensics and Security, Vol. 14, No. 12, pp. 3102-3115, Dec. 2019. [open access]

Databases

- OU-LP-Bag
  - The largest dataset with carried objects
  - Total 62,528 subjects with seven carrying status labels
  - Every subject has two sequences (w/ and w/o bag)
  - Cooperative and uncooperative setting



- OU-LP-Bag β
  - Total 2,070 subjects (1,034 for training, 1,036 for test)
  - Every subject has two sequences (w/ and w/o bag)
- OUTD-B
  - Total 68 subjects (20 for training, 48 for test)
  - The largest combination of clothing, at most 32

Comparison on OU-LP-Bag

	Cooperative setting		Uncooperative setting	
Methods	Rank1 [%]	EER [%]	Rank1 [%]	EER [%]
DM	17.74	18.46	15.90	29.89
GEI w/ LDA	40.79	7.35	31.44	14.40
GEI w/ RSVM	24.66	9.58	18.28	14.69
GERF	38.48	7.97	31.24	11.35
GEINet	22.26	11.29	18.52	14.68
SIAME	49.80	2.17	50.27	2.22
LB	74.39	1.68	70.53	1.66
2diff / diff	73.14	1.36	72.75	1.35
Proposed method	74.44	1.25	74.03	1.25

Today's topics

- ~~Gait identification & gait verification~~
- What is the difficulty for applying gait to wide-area surveillance ?
  - The difference of the observation direction
  - Occlusion in crowd scene
  - Speed difference
  - The difference of clothes & carrying status
  - Low sampling rate CVPR2012
- Age estimation
- Gait analysis for innovative entertainment

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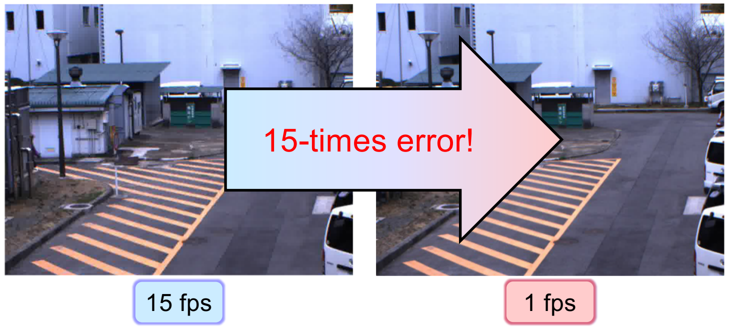
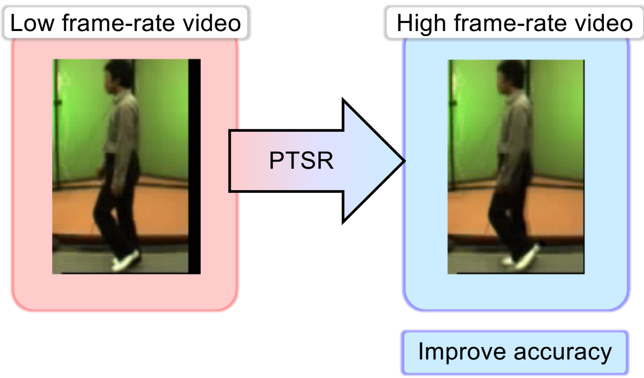
Challenge -Low frame-rate-



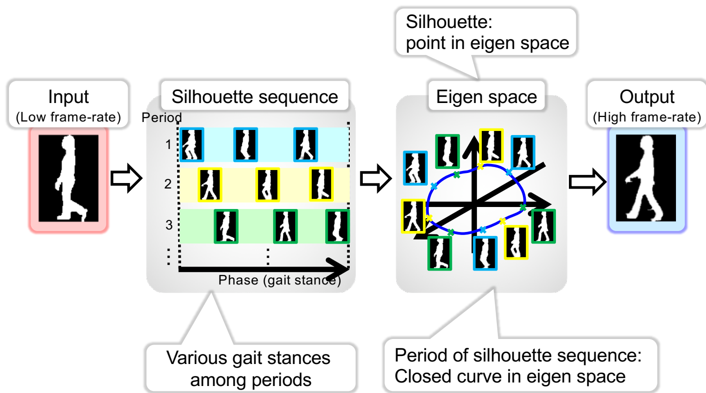
Solution

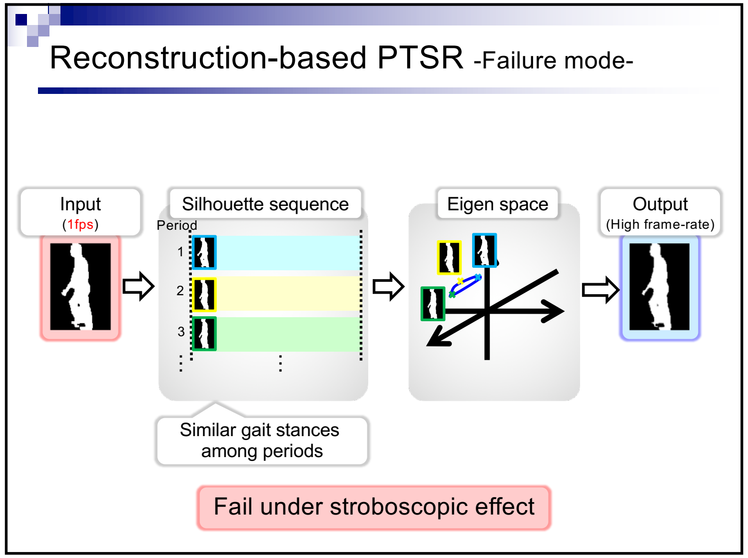
- Periodic Temporal Super Resolution (PTSR)

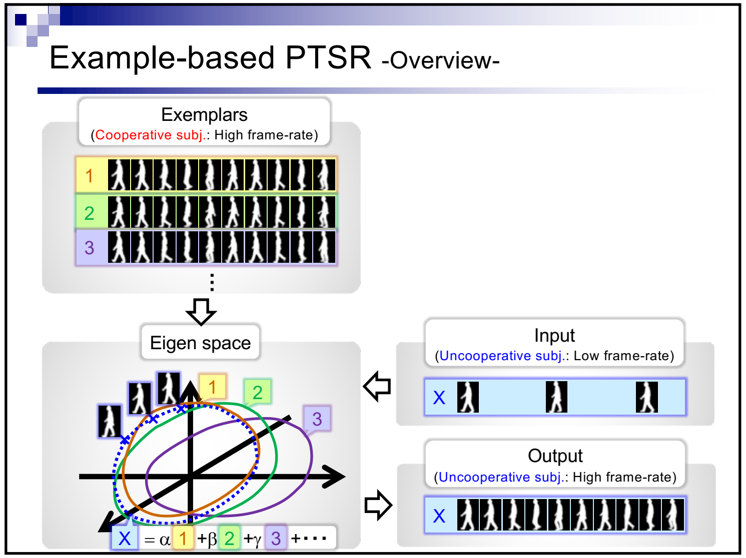


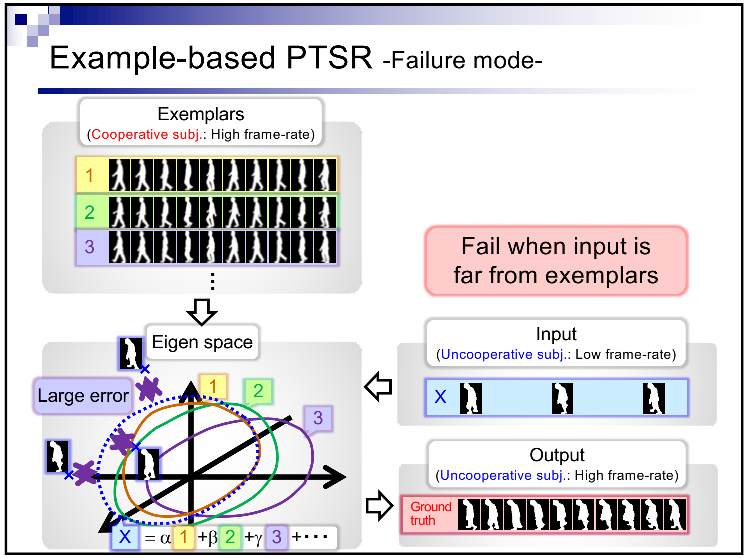
Reconstruction-based PTSR

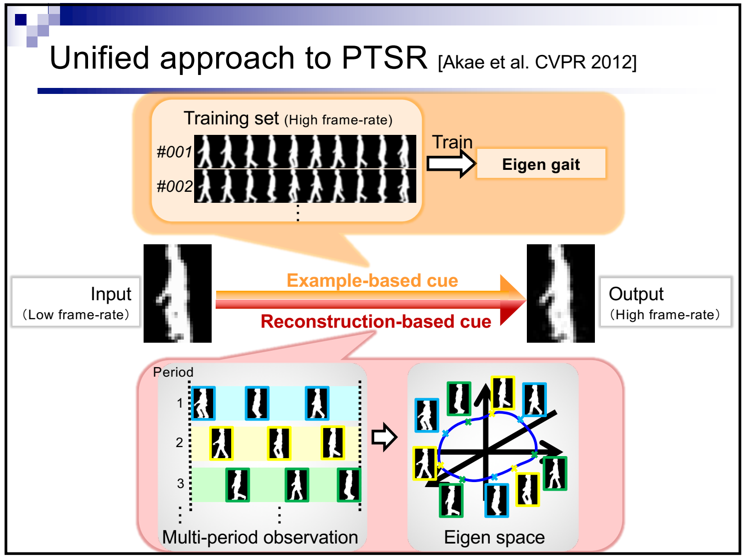
-Overview- [Makihara et al. ACCV 2010]



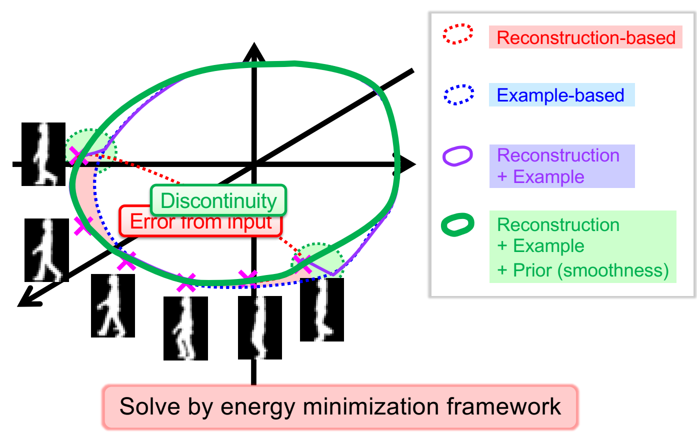

Reconstruction-based PTSR -Failure mode-
Input
(1fps)
Silhouette sequence
Period
1
2
3
Eigen space
Output
(High frame-rate)
Similar gait stances
among periods
Fail under stroboscopic effect


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 = α 1 +β 2 +γ 3 +・・・

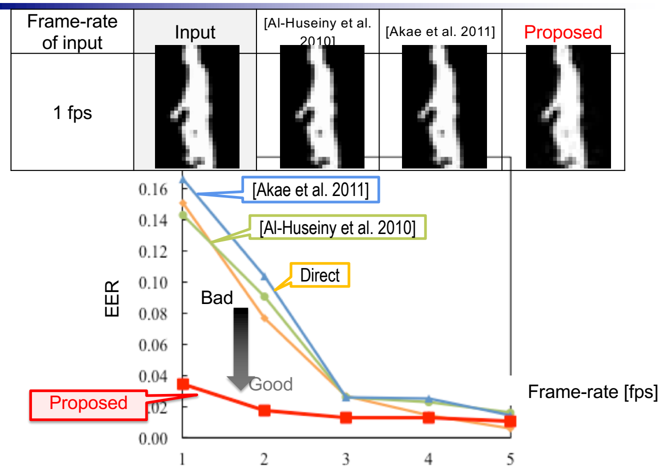

Example-based PTSR -Failure mode-
Exemplars
(Cooperative subj.: High frame-rate)
1
2
3
Fail when input is
far from exemplars
Eigen space
Large error
Input
(Uncooperative subj.: Low frame-rate)
X
Output
(Uncooperative subj.: High frame-rate)
Ground
truth
X = α 1 +β 2 +γ 3 +・・・


Unified approach to PTSR [Akae et al. CVPR 2012]
Training set (High frame-rate)
#001
#002
Train
Eigen gait
Input
(Low frame-rate)
Example-based cue
Reconstruction-based cue
Output
(High frame-rate)
Period
1
2
3
Multi-period observation
Eigen space

How does it work?



PTSR results -1 fps-



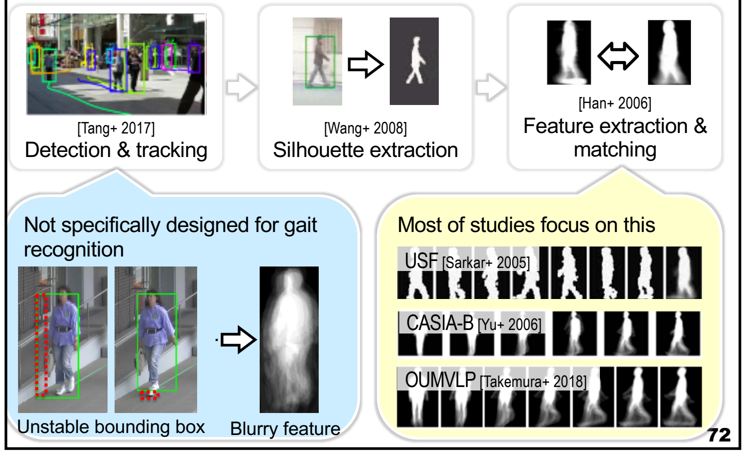
The 9th IEEE International Conference on Biometrics: Theory, Applications, and Systems (BTAS 2018), Oct. 23rd, 2018

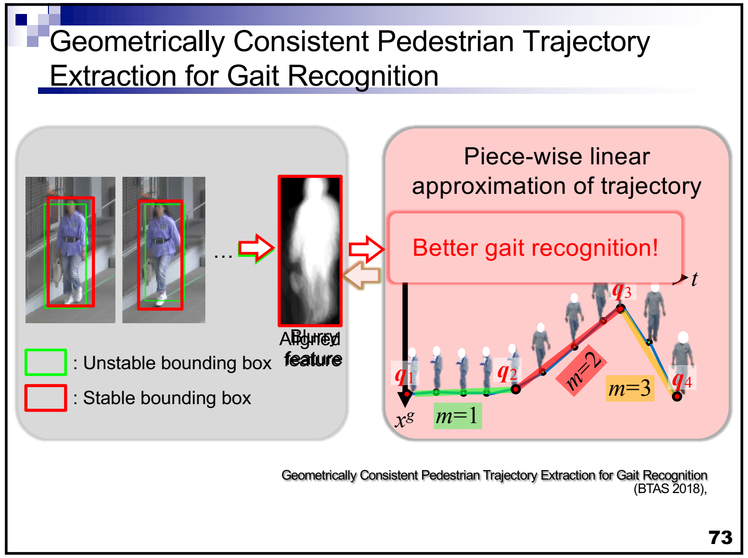
Geometrically Consistent Pedestrian Trajectory Extraction for Gait Recognition

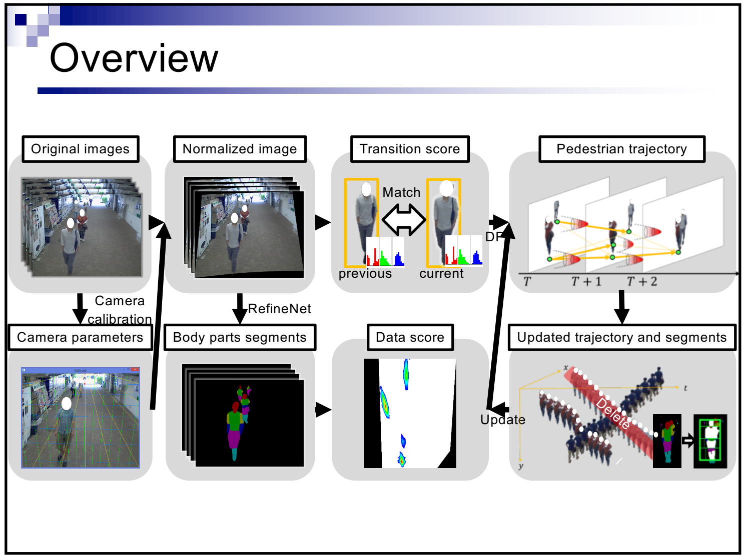
Yasushi Makihara, Gakuto Ogi, Yasushi Yagi

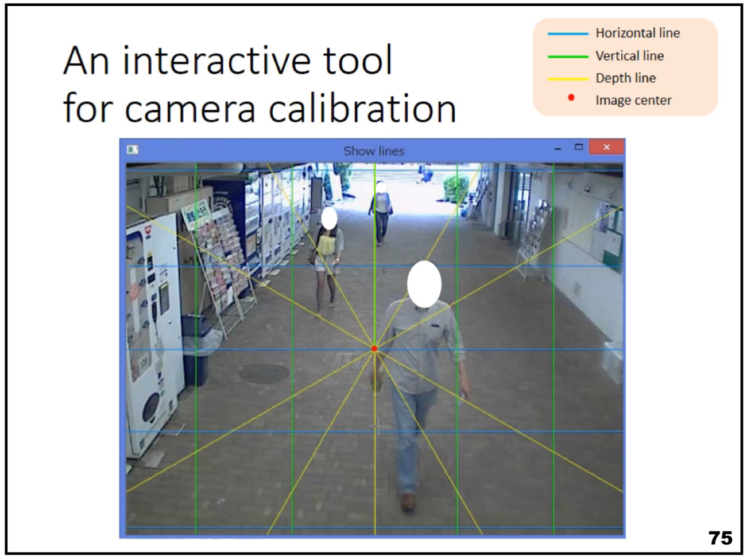
The Institute of Scientific and Industrial Research, Osaka University, Japan

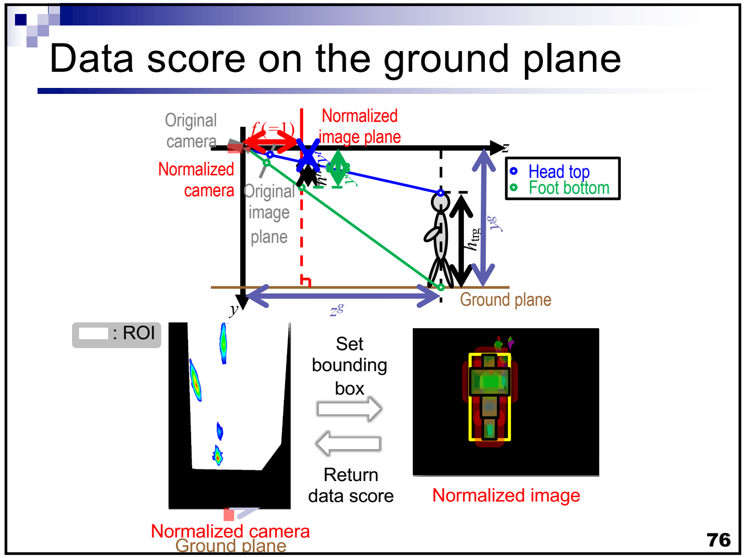
Gait recognition process




Geometrically Consistent Pedestrian Trajectory Extraction for Gait Recognition
Piece-wise linear approximation of trajectory
Better gait recognition!
: Unstable bounding box
: Stable bounding box
Blurred / Aligned feature
m=1
m=2
m=3
Geometrically Consistent Pedestrian Trajectory Extraction for Gait Recognition (BTAS 2018),
73


Overview
Original images
Normalized image
Transition score
Pedestrian trajectory
Match
previous
current
DP
Camera calibration
RefineNet
Camera parameters
Body parts segments
Data score
Updated trajectory and segments
Update
Delete


An interactive tool for camera calibration
Horizontal line
Vertical line
Depth line
Image center
Show lines
75


Data score on the ground plane
Original camera
Normalized image plane
Normalized camera
Original image plane
Head top
Foot bottom
Ground plane
: ROI
Set bounding box
Return data score
Normalized image
Normalized camera
Ground plane
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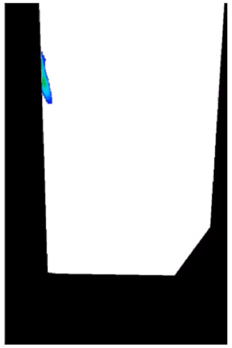
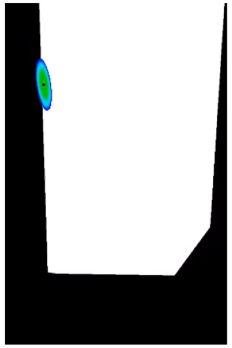
Data score

Normalized image



Data score w/o quadratic approximation



Data score w/ quadratic approximation

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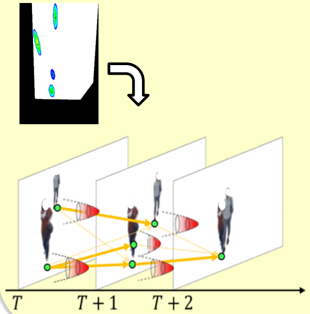
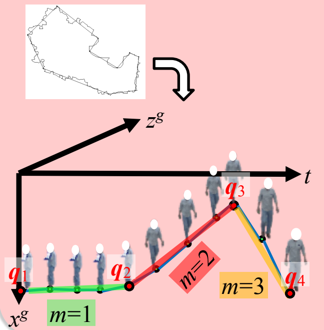
Pedestrian trajectory by DPs

Analytical DP by quadratic approximation for efficiency [Uchida+ 2010]



DP-based piece-wise linear approximation for stable trajectory [Kolesnikov+ 2003]



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Detection and tracking results

[Dollar+ 2014] for detection
[Milan+ 2015] for tracking

Proposed method

Proposed method extracts more stable bounding boxes.

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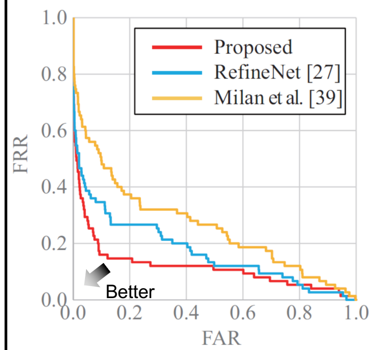
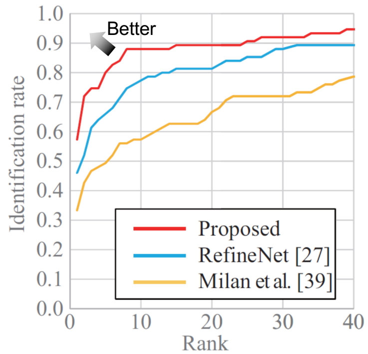
Gait recognition results



ROC curve



CMC curve

Proposed method achieved higher accuracy.

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Today's topics

- Gait identification & gait verification
- What is the difficulty for applying gait to wide-area surveillance ?
  - The difference of the observation direction
  - Occlusion in crowd scene
  - Speed difference
  - The difference of clothes & carrying status
  - Low sampling rate
- Age estimation AIU2018
- Gait analysis for innovative entertainment

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Gait-based age estimation (AIU2018 Dec. 3rd, 2018)

A. Sakata, Y. Makihara, N. Takemura, D. Muramatsu, Y. Yagi, ``Gait-based Age Estimation using a DenseNet," Prof. of the Int. Workshop on Attention/Intention Understanding (AIU 2018), pp. 55-63, Dec. 2018.

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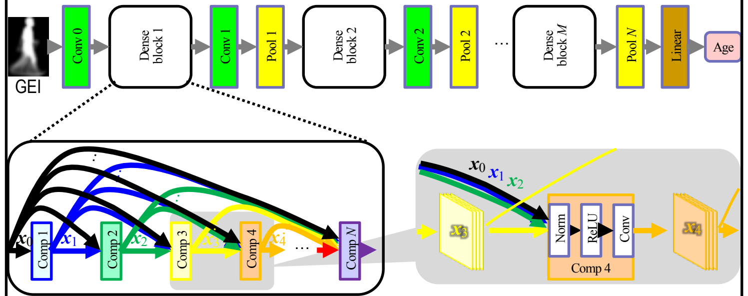
Network architecture

- Densely connected convolutional network (DenseNet) [Huang+ 2017]
  - State-of-the-art performance in many computer vision tasks
  - Utilize skip connection from all preceding layers



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Experiments: Data set

- The OU-ISIR Gait Database, Large Population Dataset with Age (OULP-Age) [Xu+ 2017]
  - 63,846 subjects (31,093 males and 32,753 females)
  - Age range: 2 to 90 years old
  - Protocol
    - Training set : 31,923 subjects Testing set: 31,923 subjects

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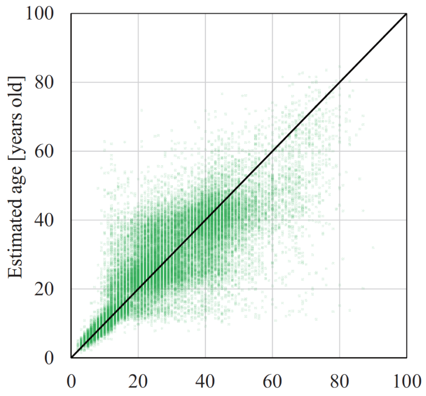
Experiments: Scatter plots



Experiments: Mean absolute error

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|\hat{l}_k^t - l_k^t\right|$$

#Test samples

Estimated age

Ground truth age

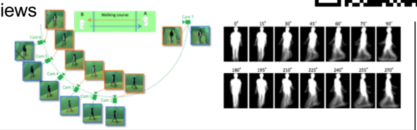
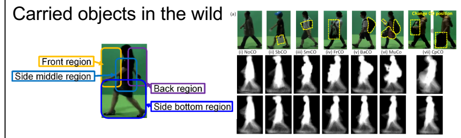
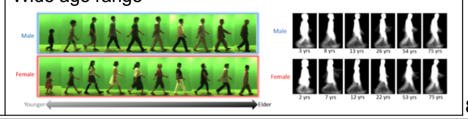
		MAE [years]
Non-deep learning	MLG	10.98
	GPR (K=10)	8.83
	GPR (K=100)	7.94
	GPR (K=1000)	7.3
	SVR (linear)	8.73
	SVR (Gaussian)	7.66
	OPLDA	8.45
	OPMFA	9.08
	AGDMLR	6.78
Deep learning	GEINet	6.22
	DenseNet	5.79

Better

List of representative gait databases (DBs)

Name	#Subjects	#Sequences	Covariates	#Viewpoints	Indoor (I) / Outdoor (O)
CMU MoBo	25	600	✔	6	I (Treadmill)
Georgia Tech	15	268	✔	-	O
	18	20	✔	-	-
HID-UMD	25	100		1	O
	55	222	✔	2	O
SOTON Small Database	12	-	✔	3	I
SOTON Large Database	115	2,128	✔	2	I/O
SOTON Multimodal	>300	>5,000	✔	12	I
SOTON Temporal	25	2,280	✔	12	I
USF HumanID	122	1,870	✔	2	O
CASIA A	20	240	✔	3	I
CASIA B	124	13,640	✔	11	I
CASIA C	153	1,530	✔	1	O
CASIA D	88	2640	✔	1	O
OU-ISIR, Treadmill A	34	612	✔	1	I (Treadmill)
OU-ISIR, Treadmill B	68	2,764	✔	1	I (Treadmill)
OU-ISIR, Treadmill C	200	200	✔	25	I (Treadmill)
OU-ISIR, Treadmill D	185	370		1	I (Treadmill)
OU-ISIR, LP	4,007	7,842		2	I
OU-ISIR, LP-Age	63,846	63,846	✔	1	I
OU-ISIR, LP-Bag	62,528	178,018	✔	1	I
OU-ISIR, MVLP	10,307	277,358		14	I
TUM-IITKGP	35	850	✔	1	O
TUM-GAID	305	3,370	✔	1	O
WOSG	155	684	✔	8	O

Ad: World's largest gait database

Data set	#Subjects	Covariates
OUMVLP [Takemura+ 2017]	10,307	14 views 
OULP-Bag [Uddin + 2018]	62,528	Carried objects in the wild 
OULP-Age [Xu+ 2018]	63,846	Wide age range 

OU-ISIR 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 (4,016 subjects)*
  - *Large Population Multi-view Population Dataset* (*10,307* subjects)
  - *Large Population Dataset with Bag* (62,528 subjects)
  - *Large Population Dataset with Age* (63,846 subjects)
  - *Inertial Sensor Dataset*
  - *Similar Actions Inertial Dataset*
- *The OU-ISIR Biometric Score Database*

ICB2019 Competition:
"Wearable Sensor-based Gait Challenge: Age and Gender"
http://www.am.sanken.osaka-u.ac.jp/GAG2019/

Please note that each corresponding signed release agreement is required to get the access to each dataset, i.e., required release agreements are different among datasets

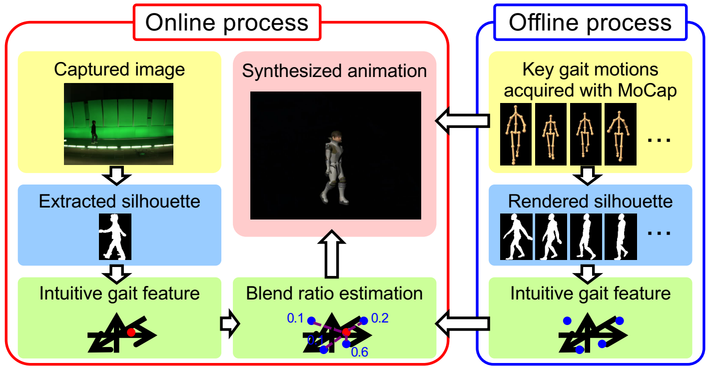
Dive Into the Movie

"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.

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  - Dr. Chunsheng Hua
  - Dr. Al Mansur
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  - Dr. Rasyid Aqmar
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  - Mr. Yusuke Fujihara
  - Ms. Betria Silvana Rossa
  - Mr. Ryo Kawai
  - Mr. Yuma Higashiyama
  - Mr. Ruochen Liao
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  - Mr. Takuhiro Kimura
  - Mr. Jaemin Son
  - Mr. Xiang Li
  - Ms. Chi Xu

THANKS FOR YOUR ATTENTION

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