Contributions to Gait Recognition Using Multiple-Views

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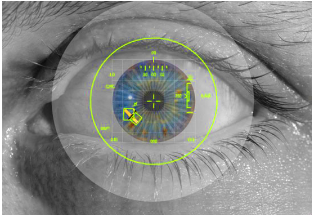
Introduction
Gait recognition

Gait as a biometric feature for identification.

- Each individual describes an unique gait pattern.
- It can operate at a distance and can be applied discreetly without needing the active participation of the subject.



Outline

Introduction

Aplications

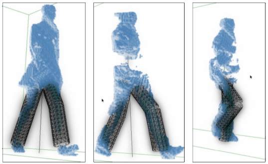
- Smart video surveillance where subjects do not know they are being monitored.
- Access control in special or restricted areas:
  - Military bases.
  - Governmental facilities.
  - Vault door at bank offices.
  - Medical isolation zones.

Outline

State of Art
Classification

Classification:

- Model-based approaches.
- Model-free approaches.



State of Art
Classification

Classification:

- Model-based approaches.
- Model-free approaches.

Covariate conditions:

- Clothing.
- Camera viewpoint.
  - Trajectory of motion.
- Load carrying.
- Walking speed.

State of Art
Classification

Classification:

- Model-based approaches.
- Model-free approaches.

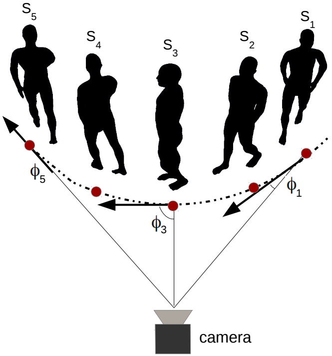
- View-dependent approaches.
- View-independent approaches.

Covariate conditions:

- Clothing.
- Camera viewpoint.
  - Trajectory of motion.
- Load carrying.
- Walking speed.

State of Art

The influence of a curved path on the silhouette appearance



In a curved path, the observation angle between the walking direction of the subject and optical axis of the camera is gradually changed, which affects the silhouette appearance.

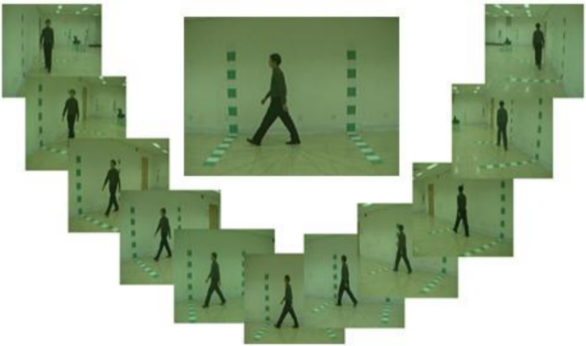
Outline

Aim of this work

- Obtaining multi-view and view-independent algorithms to recognize people independently of the trajectory of motion.
- 3D reconstructions.
    - Aligned along the way.
    - New 3D gait descriptors.

Outline

Gait databases

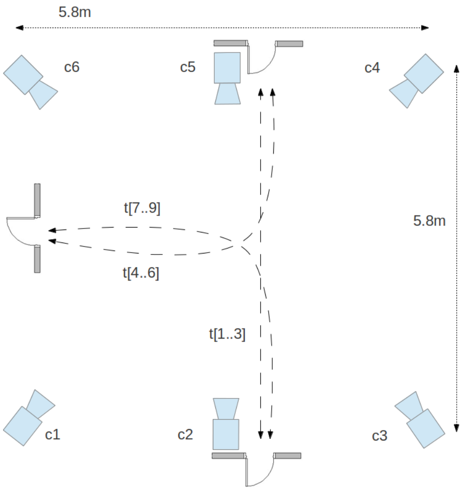


CASIA Gait Database B and CMU Motion of Body, MoBo.

AVA Multi-View Dataset for Gait Recognition (AVAMVG)
Features

- 20 subjects.
- 10 gait sequences for each subject.
- Curved and straight trajectories.
  - Three straight trajectories.
  - Six curved trajectories.
- 6 IEEE 1394 calibrate cameras, at a height of 2.3m.
- $4:3$, 640×480, 25Hz.

AVA Multi-View Dataset for Gait Recognition (AVAMVG)
Workspace setup



AVA Multi-View Dataset for Gait Recognition (AVAMVG)
Samples

Samples of AVAMVG. People walking in different directions, from multiple points of view.

Outline

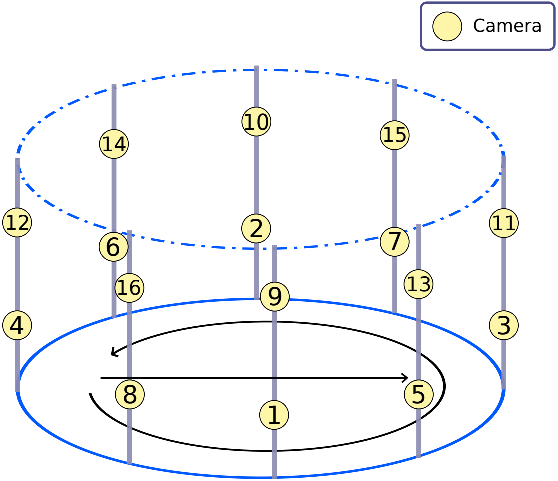
Kyushu University 4D Gait Database (KY4D)

Features

- 42 subjects.
- 6 gait sequences for each subject.
- Curved and straight trajectories.
  - Four straight trajectories.
  - Two curved trajectories.
- 16 calibrated cameras.
- 1032×776.
- 3D models are also available.

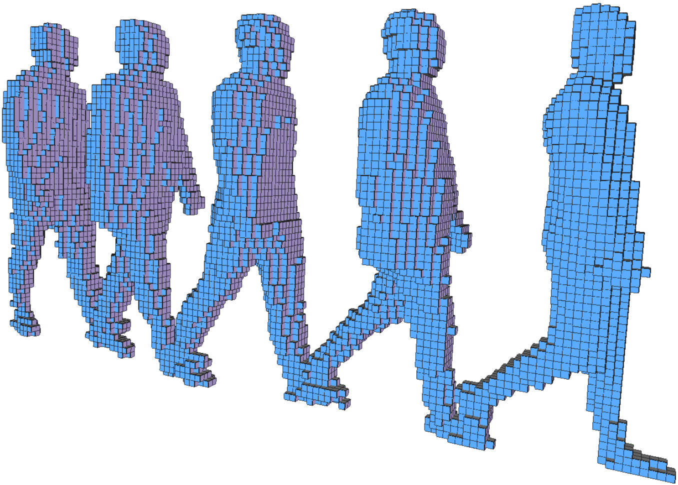
Kyushu University 4D Gait Database (KY4D)

Experimental setup



Outline

3D sequence



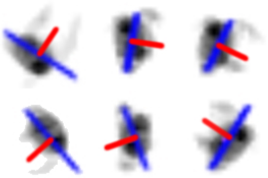
Example of reconstructed gait sequence, where each cube represents a voxel.

Voxel size: $0.000027\mathrm{m}^3$

Gait alignment

$$\vec{v}_t = p_t - p_{t-1} \qquad (1)$$

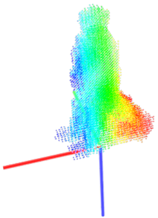
$$\alpha_t = \arctan \frac{v_{t_y}}{v_{t_x}} \qquad (2)$$



Displacement vector (red line) and principal axis (blue line).

- The alignment is used to achieve the independence which refers to the trajectory. This mechanism allow the individual to walk freely in the scene.

Gait alignment



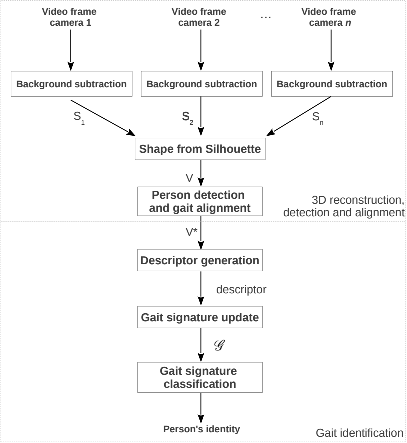
Aligned sequence

Displacement vector (red line) and principal axis (blue line).

- The alignment is used to achieve the independence which refers to the trajectory. This mechanism allow the individual to walk freely in the scene.

Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions

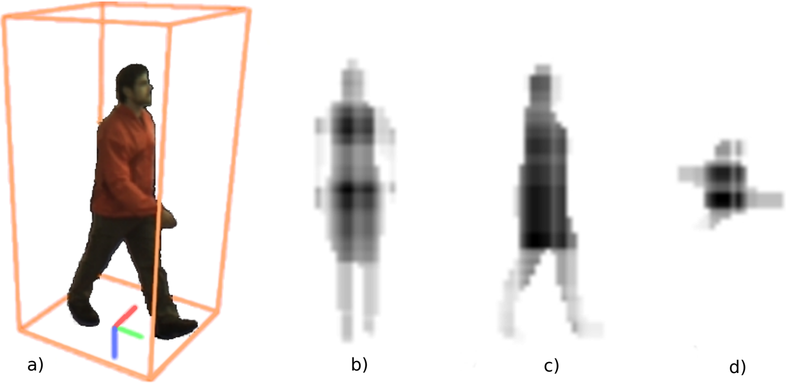
D. López-Fernández, F.J Madrid-Cuevas, A. Carmona-Poyato, M.J. Marín-Jiménez, R. Muñoz-Salinas, and R. Medina-Carnicer. Viewpoint-independent gait recognition through morphological descriptions of 3d human reconstructions. Image and Vision Computing, 48-49:1-13, 2016. ISSN 0262-8856. doi: 10.1016/j.imavis.2016.01.003



Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions

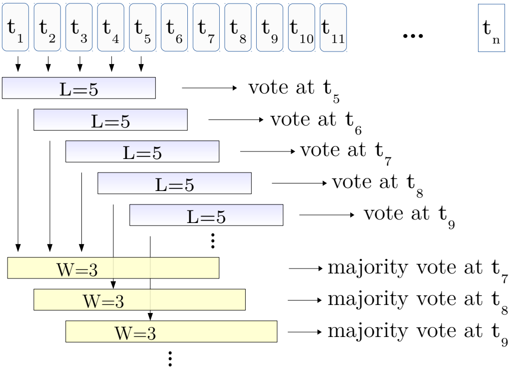
- A new gait descriptor is proposed, called Cover by Cubes (CC).
  - Represents the union of all cubes of maximum size that can fit in a human volume.
  - The elements of the set overlap each other, introducing redundancy (i.e. robustness).
  - Each element (cube) of CC(V^*) covers at least one voxel that belongs to no other cube.
  - The union of all cubes reconstructs the volume V so that no information is ever lost.
- We also propose CRP descriptor, based on computing the CR descriptor on the front, side, and top projections of the gait volume.

Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions



Cover by Rectangles descriptors computed on the front (b), side (c), and top (d) view projections of a 3D volume reconstruction (a).

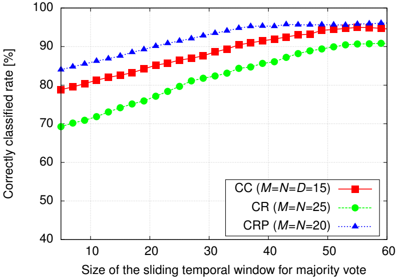
Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions



Sliding temporal window for majority voting.

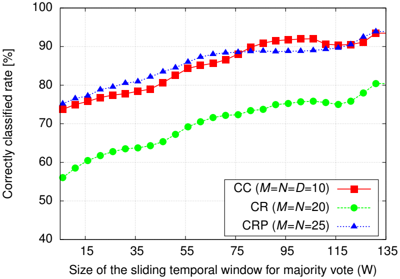
Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions

Results on **AVAMVG**:



CCR for different lengths of the sliding temporal window for majority voting.

Results on **KY4D**:



CCR for different lengths of the sliding temporal window for majority voting.

Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions

Correct classification rate on **AVAMVG**. Each column corresponds to a test trajectory, using the remaining trajectories as training set.

Method	Tr. 1	Tr. 2	Tr. 3	Tr. 4	Tr. 5	Tr. 6	Tr. 7	Tr. 8	Tr. 9	Mean
CRP	100%	88%	100%	99.3%	99.2%	97.7%	96.2%	84.8%	100%	**96.1%**
CC	100%	96%	75.5%	98.6%	87.8%	99.1%	99.5%	94%	100%	**94.5%**
Seely *et al.*	90%	80%	94.7%	90%	60%	100%	80%	84.2%	90%	85.4%
Ariyanto *et al.*	55%	45%	52.6%	45%	26.3%	35%	35%	31.5%	40%	40.6%

CRP: M=N=20, W=60. CC: M=N=D=15, W=60.

Correct classification rate on **KY4D**.

Method	Tr. 1	Tr. 2	Tr. 3	Tr. 4	Tr. 5	Tr. 6	Mean
CRP	92.6%	100%	100%	97.5%	84.9%	87.8%	**93.8%**
CC	97.5%	97.5%	95.1%	97.5%	82.9%	90%	**93.4%**
Seely *et al.*	95.1%	100%	97.5%	100%	68.2%	72.5%	88.8%
Ariyanto *et al.*	41.4%	41.4%	43.9%	53.6%	19.5%	17.5%	36.2%

CRP: M=N=25, W=135. CC: M=N=D=10, W=135.

Entropy Volumes for Viewpoint Independent Gait Recognition

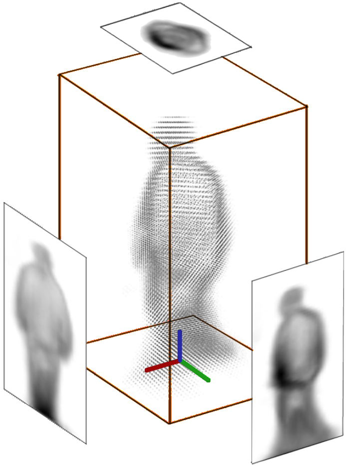
D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, and R. Medina-Carnicer. Entropy volumes for viewpoint-independent gait recognition. Machine Vision and Applications, 26(7):1079–1094, 2015. ISSN 1432-1769. doi: 10.1007/s00138-015-0707-9

- This approach focuses on capturing 3D dynamic information of walking humans through the concept of entropy.
  - A new descriptor, called Gait Entropy Volume (GEnV) is computed over aligned gait volumes.
  - We propose early fusion of marginal distributions of the GEnV as gait features.

$$\mathrm{GEnV}(x, y, z) = m\left(\sum_{k \in \{0,1\}} p_k(x, y, z) \mathrm{e}^{(1 - p_k(x,y,z))} - 1\right), \tag{3}$$

where x, y and z are the voxel coordinates, m is a normalizing constant defined as $m = 1/(e^{1-1/2} - 1)$, and p_k is the probability of voxel occupation.

Entropy Volumes for Viewpoint Independent Gait Recognition



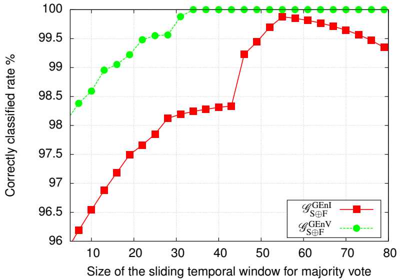
3D representation of GEnV computed over L 3D-reconstructed and aligned volumes of an individual. Voxels are represented as points. Intensity on gray level represent the entropy value corresponding to that voxel. Marginal distributions of GEnV are also shown.

Entropy Volumes for Viewpoint Independent Gait Recognition

Results on **AVAMVG**:

Signature	PCA	PCA+LDA	ϵ
$\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}}$	97.94	**97.95**	0.95
$\mathscr{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{F}}$	96.82	95.44	0.85
$\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{T}}$	96.51	95.99	0.95
$\mathscr{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{T}}$	96.03	94.63	0.80
$\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{F}\oplus\mathrm{T}}$	92.74	92.82	0.99
$\mathscr{G}^{\mathrm{GEnI}}_{\mathrm{F}\oplus\mathrm{T}}$	90.04	90.27	0.90
$\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}\oplus\mathrm{T}}$	97.20	97.16	0.95
$\mathscr{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{F}\oplus\mathrm{T}}$	97.52	97.29	0.90

Comparative results (CCR) obtained with combined GEnV signatures and combined GEnI signatures. $W = 1$.



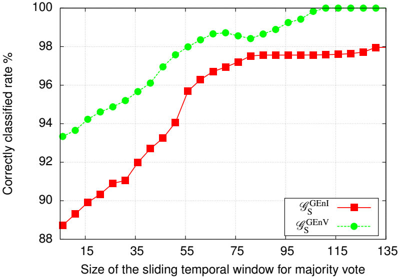
Performance of $\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}}$ and $\mathscr{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{F}}$ for different lengths of the majority voting window.

Entropy Volumes for Viewpoint Independent Gait Recognition

Results on **KY4D**:

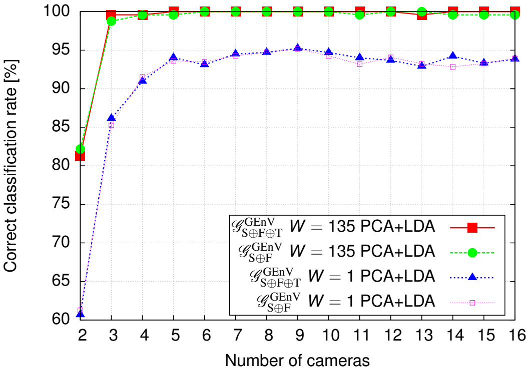
Signature	PCA	PCA+LDA	ϵ
$\mathcal{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}}$	94.23	94.04	0.95
$\mathcal{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{F}}$	92.40	91.18	0.90
$\mathcal{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{T}}$	94.34	93.76	0.95
$\mathcal{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{T}}$	93.91	92.18	0.90
$\mathcal{G}^{\mathrm{GEnV}}_{\mathrm{F}\oplus\mathrm{T}}$	90.62	89.47	0.99
$\mathcal{G}^{\mathrm{GEnI}}_{\mathrm{F}\oplus\mathrm{T}}$	87.58	86.12	0.95
$\mathcal{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}\oplus\mathrm{T}}$	95.00	**95.13**	0.95
$\mathcal{G}^{\mathrm{GEnI}}_{\mathrm{S}\oplus\mathrm{F}\oplus\mathrm{T}}$	94.28	93.17	0.90

Comparative results (CCR) obtained with combined GEnV signatures and combined GEnI signatures. $W = 1$.



Performance of $\mathcal{G}^{\mathrm{GEnV}}_{\mathrm{S}}$ and $\mathcal{G}^{\mathrm{GEnI}}_{\mathrm{S}}$ for different lengths of the majority voting window.

Entropy Volumes for Viewpoint Independent Gait Recognition



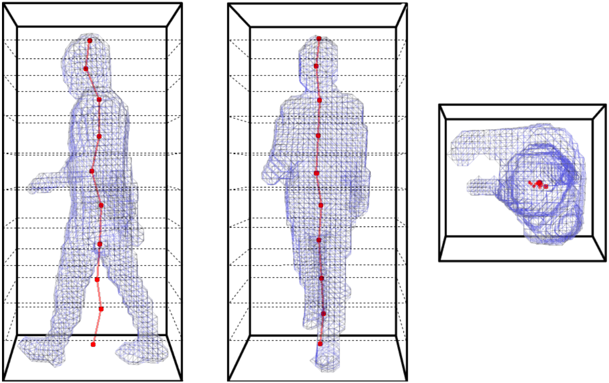
Performance of $\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}}$ and $\mathscr{G}^{\mathrm{GEnV}}_{\mathrm{S}\oplus\mathrm{F}\oplus\mathrm{T}}$ on **KY4D** database for an increasing number of cameras.

Outline

Rotation-Invariant Gait Descriptor for Multi-View Recognition

D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, and R. Medina-Carnicer. A new approach for multi-view gait recognition on unconstrained paths. Journal of Visual Communication and Image Representation, 38:396 – 406, 2016. ISSN 1047-3203. doi: 10.1016/j.jvcir.2016.03.020.

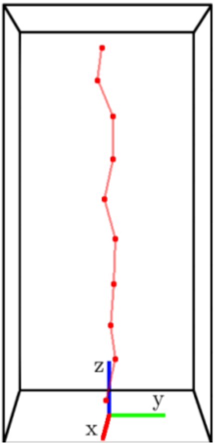
- This method uses 3D human reconstructions to extract gait features which are invariant to rotation changes.



Rotation-Invariant Gait Descriptor for Multi-View Recognition
Descriptor generation

- β_h is the acute angle between the normal vector to the floor plane ($\vec{Z} = (0, 0, 1)$) and the vector joining each pair of consecutive centroids.
- for each instant t, our descriptor is a tuple of angular measurements that we define as

$$D_{H,t} = (\beta_{(0,t)}, \beta_{(1,t)}, ..., \beta_{(H-2,t)}). \qquad (4)$$



Rotation-Invariant Gait Descriptor for Multi-View Recognition
Descriptor generation

- Coarse-to-fine refinement.
  - Number of levels:

$$0 < l \leqslant \lfloor \log_2 H \rfloor, \tag{5}$$

  - We concatenate the level descriptors to represent our coarse-to-fine descriptor:

$$\mathscr{D}_{(l,t)} = (D_{(2,t)}, D_{(2^2,t)}, ..., D_{(2^l,t)}). \tag{6}$$

Rotation-Invariant Gait Descriptor for Multi-View Recognition

Signature update

- The signature $\mathscr{G}$ is defined on a sliding temporal window of size L:

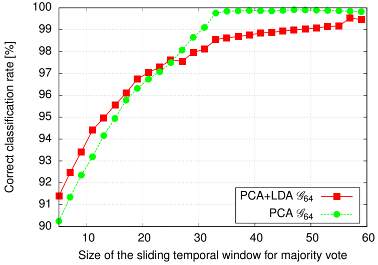
$$\mathscr{G}_{(l,t)} = \left(\mathscr{D}_{(l,t-L+1)}, \ldots, \mathscr{D}_{(l,t-1)}, \mathscr{D}_{(l,t)}\right), \quad (7)$$

Rotation-Invariant Gait Descriptor for Multi-View Recognition

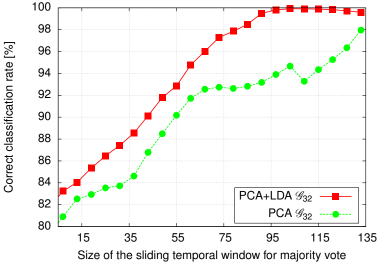
	AVAMVG		KY4D	
l	PCA	PCA+LDA	PCA	PCA+LDA
1	8.19	N.A	12.13	N.A
2	45.25	41.64	57.25	N.A
3	68.83	59.71	74.84	73.16
4	82.28	80.59	85.03	85.38
5	87.11	86.89	**87.40**	**89.52**
6	**87.88**	**89.13**	86.59	88.72

Correct classification rate [%] for both **AVAMVG** and **KY4D** datasets and several values for the parameter l. We use a k-fold cross-validation strategy, where k corresponds to the number of trajectories. The size of the sliding temporal window for majority voting is set to $W = 1$.

Rotation-Invariant Gait Descriptor for Multi-View Recognition



Performance of our descriptor on the **AVAMVG** database for different lengths of the majority voting window.



Performance of our descriptor on the **KY4D** database for different lengths of the majority voting window.

Rotation-Invariant Gait Descriptor for Multi-View Recognition

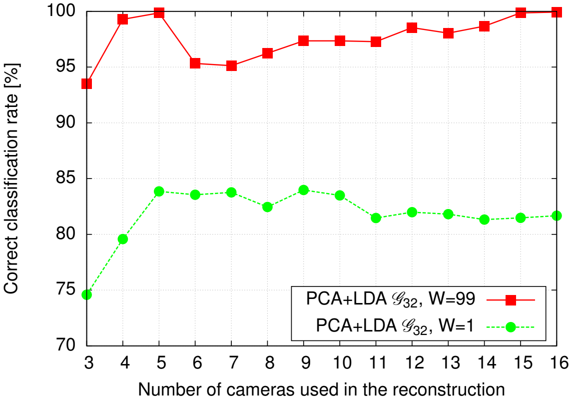
Method	Training trajectories	t4	t7	AVG
$\mathscr{G}_{64}$, W=57, PCA+LDA	straight {t1,t2,t3}	90.69	96.57	**93.63**
$\mathscr{G}_{64}$, W=30, PCA+LDA	straight {t1,t2,t3}	89.85	94.26	**92.05**
Castro *et al.*	straight {t1,t2,t3}	85.00	95.00	90.00
Seely *et al.*	straight {t1,t2,t3}	55.00	70.00	62.50
Iwashita *et al.*	straight {t1,t2,t3}	35.14	37.71	36.42

Correct classification rate [%] on **AVAMVG** gait dataset. Each row corresponds to a different method. The second column indicates the training trajectory. The third and fourth columns indicate the tested trajectory.

Method	Training trajectories	Curve 1	Curve 2	AVG
$\mathscr{G}_{64}$, W=130, PCA+LDA	straight {1,2,3,4}	68.29	77.50	**72.89**
$\mathscr{G}_{64}$, W=20, PCA+LDA	straight {1,2,3,4}	63.16	73.53	**68.34**
Iwashita *et al.*	straight {1,2,3,4}	61.90	71.40	66.65
Castro *et al.*	straight {1,2,3,4}	58.50	61.00	59.75
Seely *et al.*	straight {1,2,3,4}	19.51	35.00	27.25

Correct classification rate [%] on **KY4D** gait dataset. Each row corresponds to a different method. The second column indicates the training trajectory. The third and fourth columns indicate the tested trajectory.

Rotation-Invariant Gait Descriptor for Multi-View Recognition



Performance of our descriptor on **KY4D** database for an increasing number of cameras.

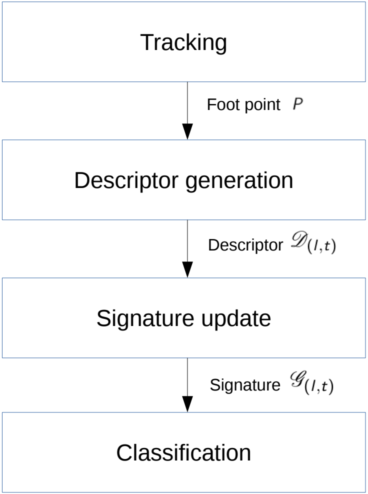
Outline

Multi-view gait recognition on curved trajectories

D. López-Fernández, F. J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, and R. Medina-Carnicer.: Multi-view gait recognition on curved trajectories. In Proceedings of the 9th International Conference on Distributed Smart Camera (ICDSC '15). ACM, New York, NY, USA, 116-121. DOI: 10.1145/2789116.2789122.

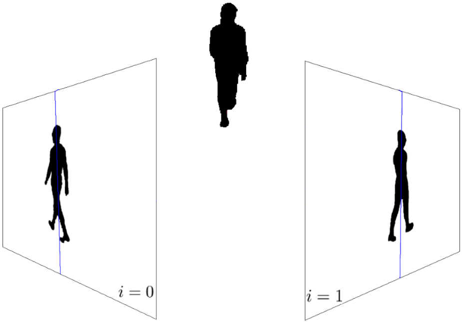
- A method to recognize walking humans regardless direction changes on curved trajectories.
- Our approach aims to extract 3D dynamical information of gait that is invariant under rotation.
  - Without using 3D reconstructions.

Multi-view gait recognition on curved trajectories
Framework



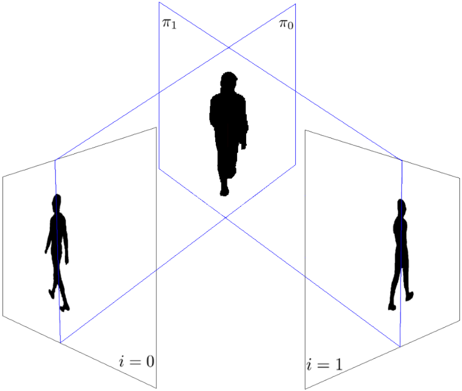
Multi-view gait recognition on curved trajectories
Tracking

- We extract the principal axis of the silhouette for each camera *i* by Principal Component Analysis (PCA).



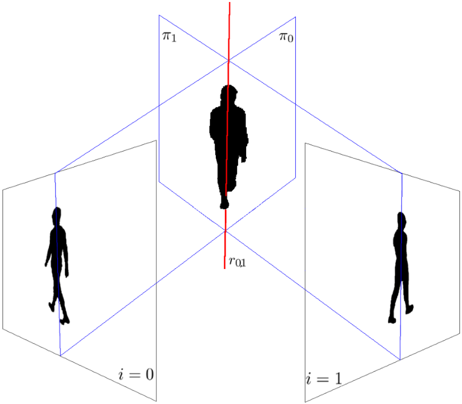
Multi-view gait recognition on curved trajectories
Tracking

- For each view *i*, this line is back-projected in order to get the plane $\pi_i \in \{\pi_0, \pi_1, ..., \pi_{N-1}\}$.



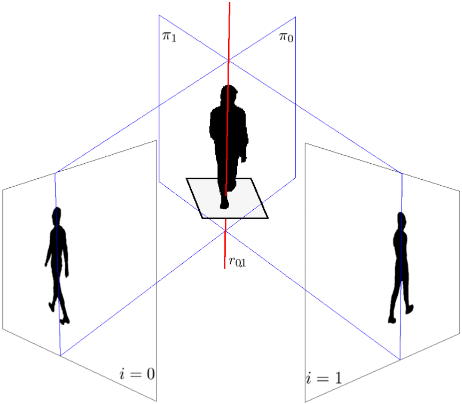
Multi-view gait recognition on curved trajectories
Tracking

- $r_{i,j}$ is the intersection line between the planes π_i and π_j, where $0 \leqslant i < N$ y $0 \leqslant j < N$.



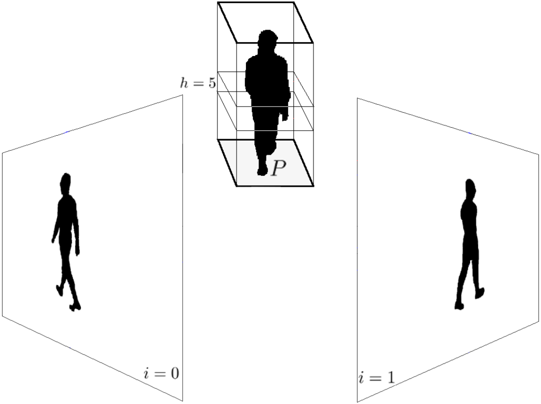
Multi-view gait recognition on curved trajectories
Tracking

- Candidate foot points are obtained by intersecting each line $r_{i,j}$ with the floor plane.



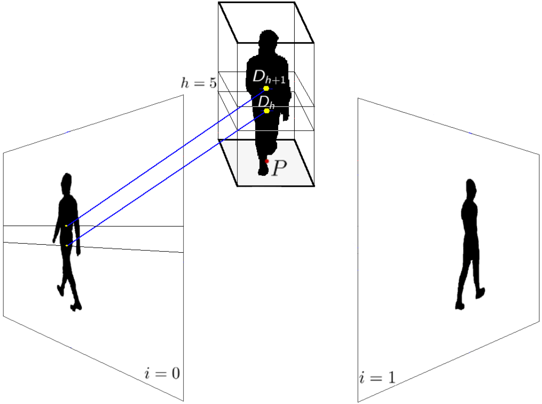
Multi-view gait recognition on curved trajectories
Descriptor generation

- Given a foot point $P : (P_x, P_y, 0)$, the 3D scene is vertically divided into $H \in \mathbb{N}^+$ parts of slices.



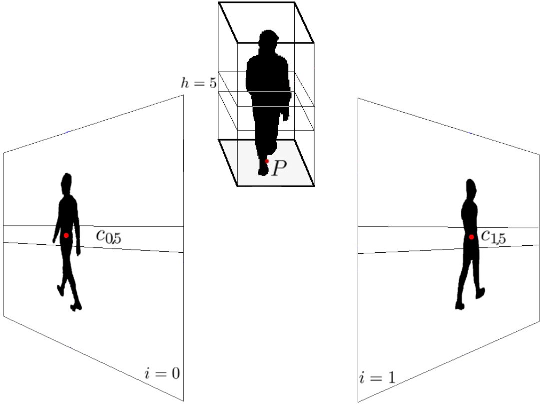
Multi-view gait recognition on curved trajectories
Descriptor generation

- We compute the bounding box enclosing the projections of the 3D points $D_h = (P_x, P_y, h\frac{Z}{H})$ and $D_{h+1} = (P_x, P_y, (h+1)\frac{Z}{H})$.



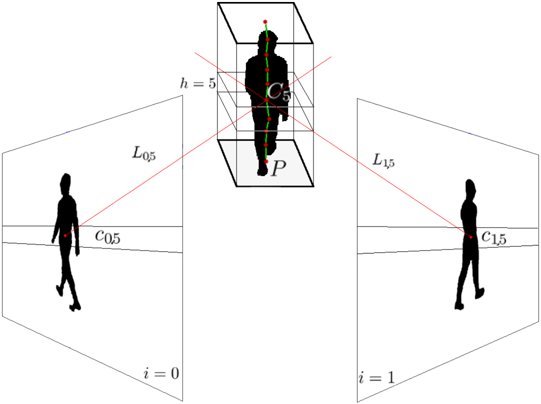
Multi-view gait recognition on curved trajectories
Descriptor generation

- The 2D centroid of the silhouette within the bounding box is computed for each camera view.



Multi-view gait recognition on curved trajectories
Descriptor generation

- We backproject the ray $L_{i,h}$ passing through the 2D centroid $c_{i,h}$ in order to obtain an approximation of the 3D centroid C_h of the slice h in the scene.



Multi-view gait recognition on curved trajectories

What level of refinement for our coarse-to-fine gait descriptor is required?

l	PCA	PCA+LDA
1 (2 slices)	5.99	N.A
2 (4 slices)	31.54	32.92
3 (8 slices)	56.98	56.38
4 (16 slices)	74.75	74.68
5 (32 slices)	80.21	**81.40**
6 (64 slices)	79.56	80.69

Correct classification rate [%] on the lower set of cameras for several values of the parameter l. The size of the sliding temporal window for majority voting is set to $W = 1$. Best result is marked in bold.

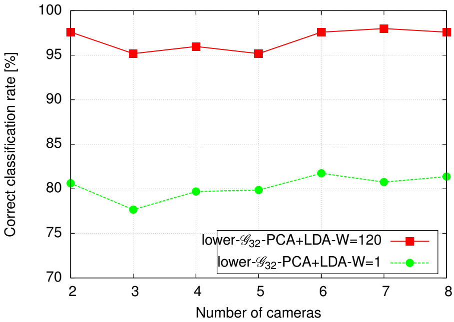
Multi-view gait recognition on curved trajectories

	Straight paths				Curved paths		
Experiment	t1	t2	t3	t4	t5	t6	AVG
upper-$\mathscr{G}_{32}$-PCA-W=1	44.63	51.80	46.78	48.13	28.74	58.45	46.42
upper-$\mathscr{G}_{32}$-PCA-W=120	70.73	78.04	82.92	87.80	54.34	85.00	76.47
upper-$\mathscr{G}_{32}$-PCA+LDA-W=1	49.85	57.07	51.12	52.68	29.70	56.05	$49,41$
upper-$\mathscr{G}_{32}$-PCA+LDA-W=120	80.48	80.48	90.24	82.92	52.17	72.50	$76,46$
lower-$\mathscr{G}_{32}$-PCA-W=1	84.86	87.73	88.97	89.49	52.24	78.02	80.21
lower-$\mathscr{G}_{32}$-PCA-W=120	95.12	100	100	100	**97.82**	**100**	**98.82**
lower-$\mathscr{G}_{32}$-PCA+LDA-W=1	88.24	89.82	89.10	90.30	52.42	78.52	81.40
lower-$\mathscr{G}_{32}$-PCA+LDA-W=120	**97.56**	**100**	**100**	**100**	91.30	97.50	97.72

Correct classification rate on **KY4D** [%]. Each column corresponds to a test trajectory, using the remaining trajectories as training set. Each row corresponds to a different configuration of the gait descriptor. Each entry contains the percentage of correct recognition for each tuple trajectory-setup.

Multi-view gait recognition on curved trajectories

How many cameras are needed to achieve good performance?



Performance of our descriptor for an increasing number of cameras.

Conclusions and main contributions

- We have develop new 3D gait recognition methods able to identify people independently of the trajectory of motion, tackling such a main goal from the standpoint of 3D reconstructions.
    - 3D sequences of walking people could be aligned along their way.
    - The use of volumetric reconstructions allowed more information to be analysed in contrast 2D based methods.

Future work

- New unconstrained gait recognition methods, i.e. without camera calibration on single-view datasets.
- Occlusion handling.
- The design of methods to address other covariate conditions, such as clothing and load or bag carrying.

Publications
International journals

- D. López-Fernández, F.J Madrid-Cuevas, A. Carmona-Poyato, M.J. Marín-Jiménez, R. Muñoz-Salinas, R. Medina-Carnicer.: Viewpoint-Independent Gait Recognition through Morphological Descriptions of 3D Human Reconstructions. Image and Vision Computing. 2016. ISSN: 0262-8856. DOI: 10.1016/j.imavis.2016.01.003
- D. López Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, R. Medina-Carnicer.: Entropy volumes for viewpoint-independent gait recognition. Machine Vision and Applications, vol 26, no. 7-8, pp. 1079-1094. 2015. ISSN: 0932-8092. DOI: 10.1007/s00138-015-0707-9
- D. López-Fernández, F.J Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, R. Medina-Carnicer.: A new approach for multi-view gait recognition on unconstrained paths. Journal of Visual Communication and Image Representation. 2016. ISSN: 1047-3203. DOI: 10.1016/j.jvcir.2016.03.020

Publications

Conference proceedings

- D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, M.J. Marín-Jiménez, R. Muñoz-Salinas.: The AVA Multi-View Dataset for Gait Recognition (AVAMVG). In: 2nd Workshop Activity Monitoring by Multiple Distributed Sensing, AMMDS. ICPR 2014, Lecture Notes in Computer Science, vol. 8703. pp. 26-39. Springer Berlin Heidelberg (2014). DOI: 10.1007/978-3-319-13323-2_3.
- D. López-Fernández, F. J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, and R. Medina-Carnicer.: Multi-view gait recognition on curved trajectories. In Proceedings of the 9th International Conference on Distributed Smart Camera (ICDSC '15). ACM, New York, NY, USA, 116-121. DOI: 10.1145/2789116.2789122.

Questions time