An Evaluation Framework and Database for MoCap-Based Gait Recognition Methods

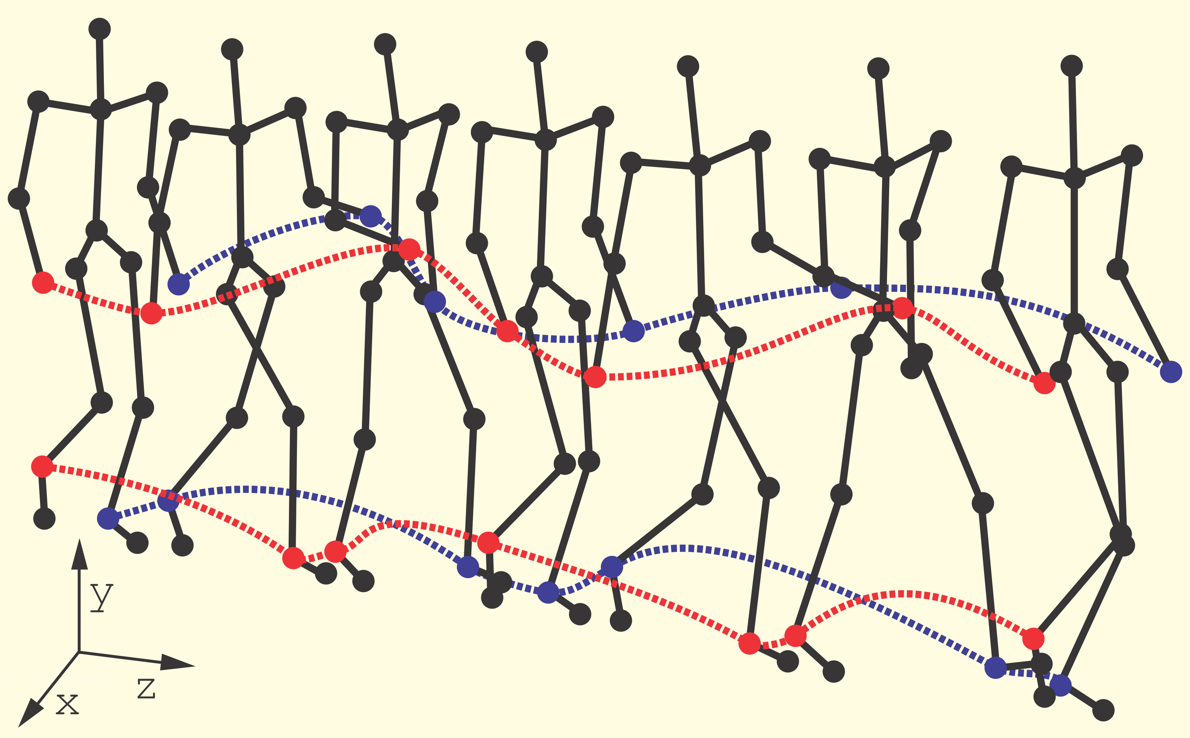
Michal Balazia · Petr Sojka

Masaryk University, Faculty of Informatics, Botanická 68a, 602 00 Brno, Czech Republic

https://gait.fi.muni.cz

Motion Capture Data

Motion capture (MoCap) technology provides video clips of individuals walking which contain **structural motion data**. The format keeps an overall structure of the human body and holds estimated **3D positions** of major anatomical landmarks as the person moves. These MoCap data can be collected online by a system of multiple cameras (Vicon) or a depth camera (Microsoft Kinect). To visualize the MoCap data, a simplified **stick figure** representing the human skeleton (graph of joints and bones) can be recovered from body point spatial coordinates in time. Recent rapid improvement in MoCap sensor accuracy has brought affordable MoCap technology to assist **human identification** in such applications as access control and video surveillance.



Our Contribution

As a contribution to reproducible research, this paper presents a framework and a database to improve the development, evaluation and comparison of methods for gait recognition from MoCap Data. The **evaluation framework** provides implementation details and source codes of state-of-the-art gait features extraction methods. It includes a description and source codes of a mechanism for evaluating four class separability coefficients of feature space and four rank-based classifier performance metrics. This framework also contains a tool for learning a custom classifier and for classifying a custom query on a custom gallery. We provide the **evaluation database** along with source codes for its extraction from the general CMU MoCap database.

Databases

Data in the standard ASF/AMC format was obtained from the Carnegie Mellon University Graphics Lab and is referred to as the **CMU MoCap database**. It is a well-known and recognized benchmark database of structural human motion data. Our extracted database contains only gait cycles (motions holding two steps) and is **normalized** with respect to a person's position, walk direction and skeleton. First, an exemplary gait cycle was identified, and clean gait cycles were then filtered out using a threshold for their Dynamic Time Warping distance on bone rotations in time. Setting the distance threshold too high might also qualify sub-motions that do not resemble gait cycles. Seven **new databases** of various sizes have been extracted:

distance threshold	# identities	# gait cycles
56.3	2	35
59.4	4	67
63.3	8	130
73.7	16	302
173.3	32	2,047
302	**54**	**3,843**
495.3	64	5,923

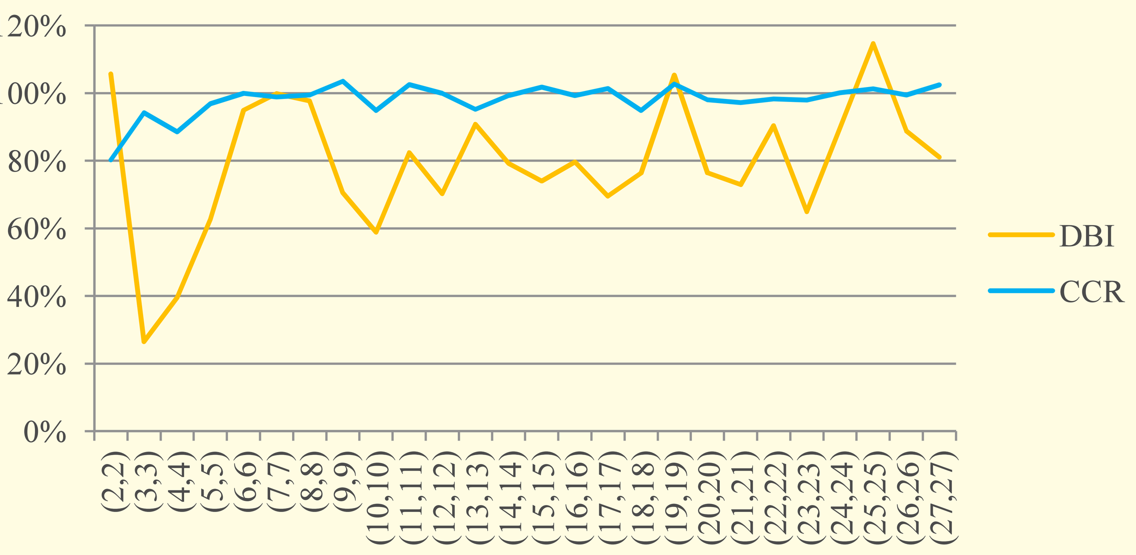
Classification

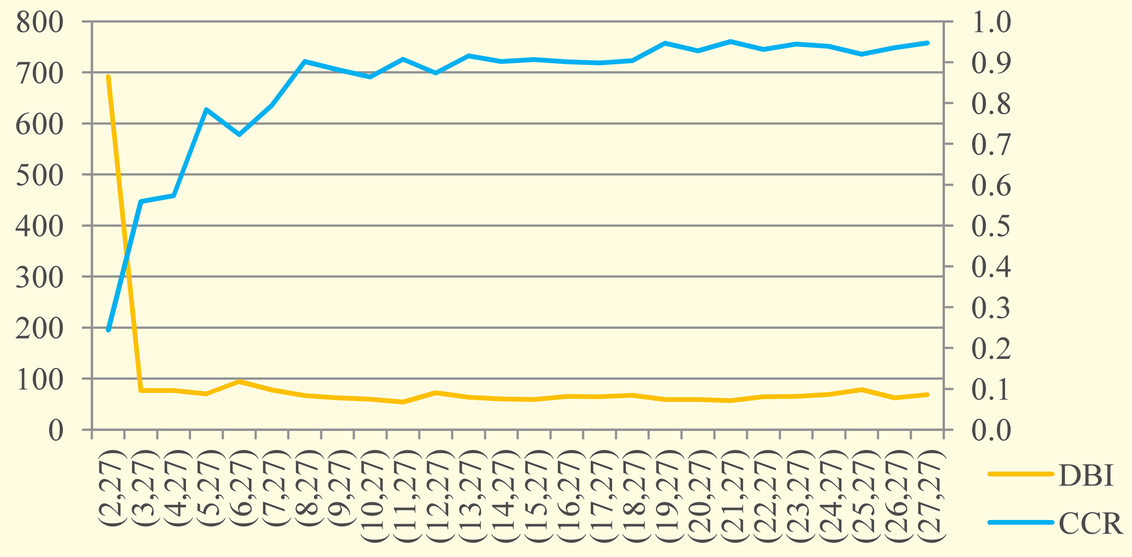
The framework enables **learning classifiers** of implemented methods on any given database.

A learned classifier can be used to **perform classification** of a custom query on a custom gallery.

Walker-Independent Features

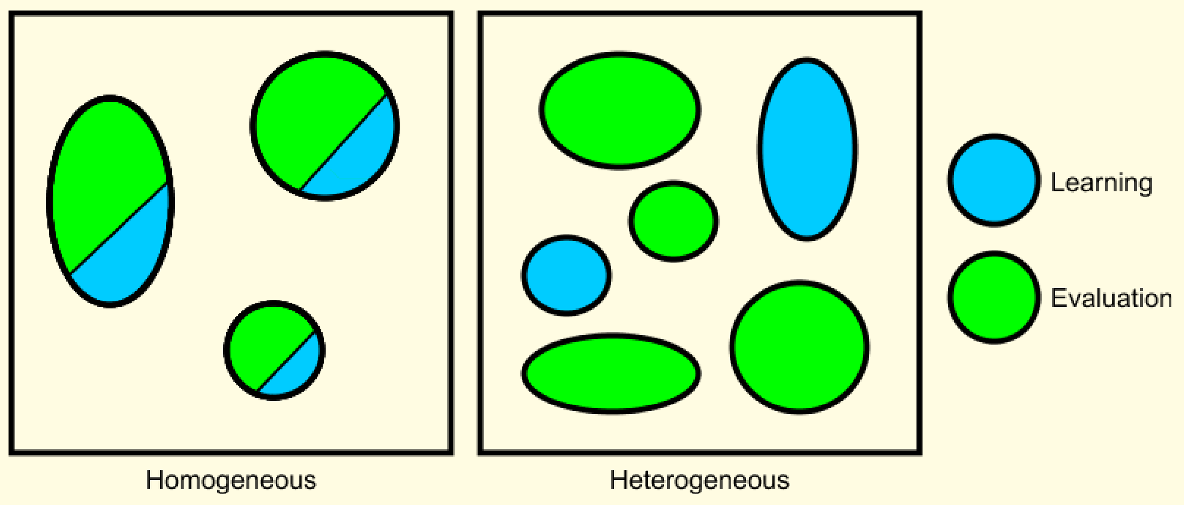
The heterogeneous set-up has the form (C_L, C_E) specifying how many learning and how many evaluation identity classes are randomly selected. Evaluations on the 302 database of the MMC method on joint coordinates **compare the set-ups** and show how performance in the heterogeneous set-up improves with an increasing number of learning identities.



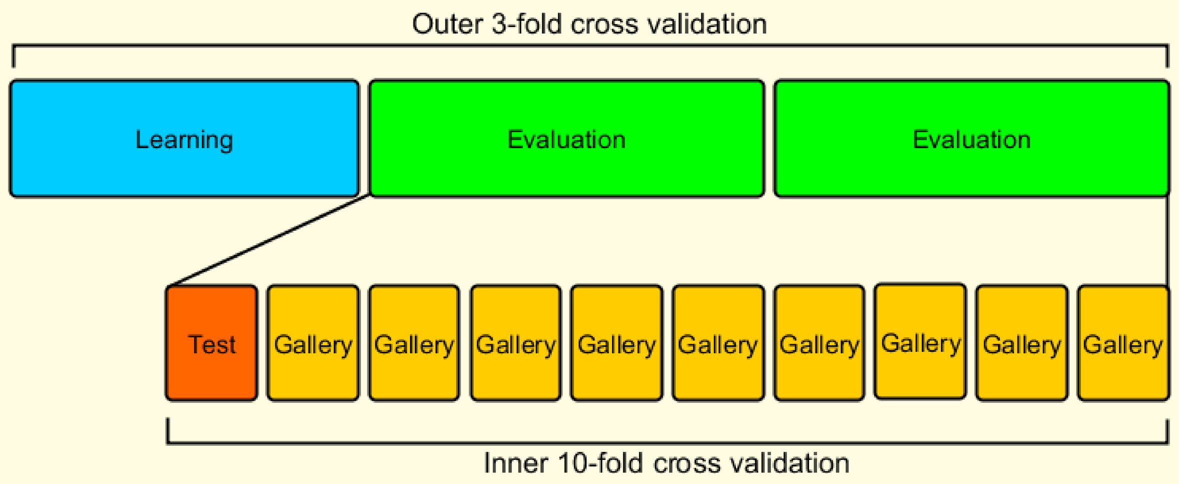


Evaluation Mechanism

We introduce two set-up concepts of data separation into a learning part $\mathcal{G}_L = \{(\mathbf{g}_n, \ell_n)\}_{n=1}^{N_L}$ of C_L identity classes and an evaluation part $\mathcal{G}_E = \{(\mathbf{g}_n, \ell_n)\}_{n=1}^{N_E}$ of C_E identity classes: **homogeneous** and **heterogeneous**. The homogeneous set-up learns the transformation matrix on $^1/_3$ samples of C_L identities and is evaluated on templates derived from other $^2/_3$ samples of the same $C_E = C_L$ identities. The heterogeneous set-up learns gait features on all samples in C_L identities and is evaluated on all templates derived from other C_E identities.



In the homogeneous set-up, all results are estimated with the **nested cross-validation** that involves the outer 3-fold cross-validation loop where templates in one fold are used for learning the features and templates in the remaining two folds for evaluation. In the heterogeneous set-up, the learning and evaluation parts are selected at random based on given C_L and C_E. For both set-ups, feature space is first evaluated on class separability coefficients. Evaluation of classification based metrics advances to the inner 10-fold cross-validation loop taking one dis-labeled fold as testing set and rest as gallery.



Class separability coefficients:

- Davies-Bouldin Index (DBI)
- Dunn Index (DI)
- Silhouette Coefficient (SC)
- Fisher's Discriminant Ratio (FDR)

Classification based metrics:

- Cumulative Match Characteristic
- False Accept Rate / False Reject Rate
- Receiver Operating Characteristic (ROC)
- Recall / Precision Rate
- Correct Classification Rate (CCR)
- Equal Error Rate (EER)
- Area Under ROC Curve (AUC)
- Mean Average Precision (MAP)

Implemented Methods and Results

We implemented **gait feature extraction methods** of 13 other researchers. The following table lists all 20 implemented methods including the ones based on learning gait features by the Maximum Margin Criterion (MMC) and by a combination of Principal Component Analysis and Linear Discriminant Analysis (PCALDA) introduced in our previous research. We also include the random classifier that operates on no features and the baseline classifier based on raw data compared with Dynamic Time Warping. Raw data are in the form of bone rotations (BR) and joint coordinates (JC). The table contains **results** for all single-number evaluation metrics, along with the Distance Computation Time (DCT) and Template Dimension (TD). Evaluations are performed with the homogeneous set-up and on the 302 database.

	class separability coefficients				classification based metrics				scalability	
method	DBI	DI	SC	FDR	CCR	EER	AUC	MAP	DCT	TD
Ahmed	216.2	0.842	−0.246	0.954	0.657	0.38	0.659	0.165	0.01	24
Ali	501.5	0.26	−0.463	1.175	0.225	0.384	0.679	0.111	0.01	2
Andersson	142.3	1.297	−0.102	1.127	0.84	0.343	0.715	0.251	0.01	68
Ball	161	1.458	−0.163	1.117	0.75	0.346	0.711	0.231	0.01	18
Dikovski	144.5	1.817	−0.135	**1.227**	0.881	0.363	0.695	0.254	0.01	71
Gavrilova	185.8	1.708	−0.164	0.77	0.891	0.374	0.677	0.254	44.78	5,254
Jiang	206.6	1.802	−0.249	0.85	0.811	0.395	0.657	0.242	8.17	584
Krzeszowski	154.1	1.982	−0.147	0.874	0.915	0.392	0.662	0.275	35.32	3,795
Kumar	**118.6**	1.618	−0.086	1.09	0.801	0.459	0.631	0.217	7.87	13,950
Kwolek	150.9	1.348	−0.084	1.175	0.896	0.358	0.723	0.323	0.06	660
Preis	1,980.6	0.055	−0.512	1.067	0.143	0.401	0.626	0.067	0.01	13
Sedmidubsky	398.1	1.35	−0.425	0.811	0.543	0.388	0.657	0.149	5.79	292
Sinha	214.8	1.112	−0.215	1.101	0.674	0.356	0.697	0.191	0.01	45
$\_\mathrm{MMC}_{BR}$	154.2	1.638	**0.062**	1.173	0.925	**0.297**	**0.748**	0.353	0.01	53
$\_\mathrm{MMC}_{JC}$	130.3	1.891	0.051	1.106	0.918	0.378	0.721	0.315	0.01	51
$\_\mathrm{PCALDA}_{BR}$	182	1.596	−0.015	0.984	0.918	0.361	0.695	0.276	0.01	54
$\_\mathrm{PCALDA}_{JC}$	174.4	1.309	−0.091	0.827	0.863	0.44	0.643	0.201	0.01	54
_Random	6,628.8	0.003	−0.355	0.977	0.042	0.5	0.5	0.058	**0**	**0**
$\_\mathrm{Raw}_{BR}$	163.7	**2.092**	0.011	0.948	**0.966**	0.315	0.743	**0.358**	70.27	8,229
$\_\mathrm{Raw}_{JC}$	155.1	1.954	−0.12	0.897	0.926	0.377	0.679	0.283	160.64	13,574

Acknowledgements

Balazia, M. and Sojka, P.: **Walker-Independent Features for Gait Recognition from Motion Capture Data**, In: IAPR Structural and Syntactic Pattern Recognition and Statistical Techniques in Pattern Recognition, Springer LNCS, 2016.

Balazia, M. and Sojka, P.: **Learning Robust Features for Gait Recognition by Maximum Margin Criterion**, In: 23rd IEEE/IAPR International Conference on Pattern Recognition, IEEE, 2016.

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