You Are How You Walk: Gait Recognition from Motion Capture Data

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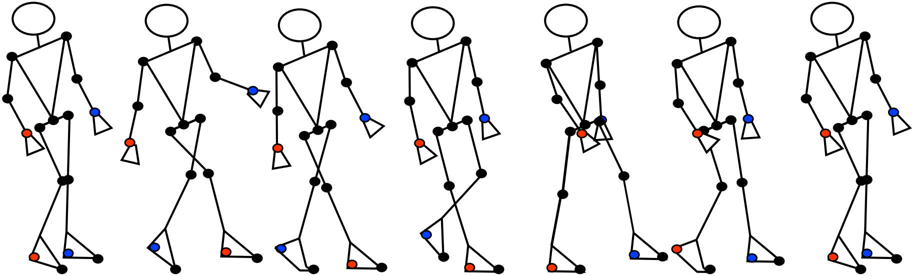
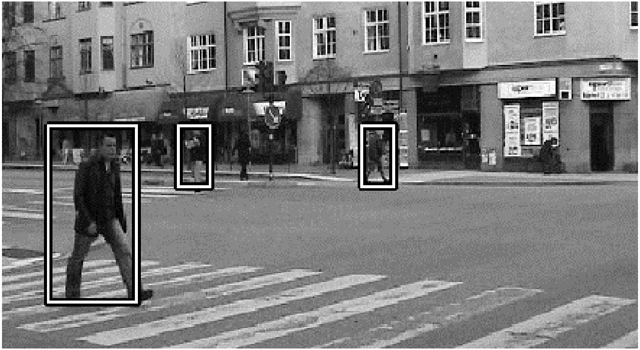
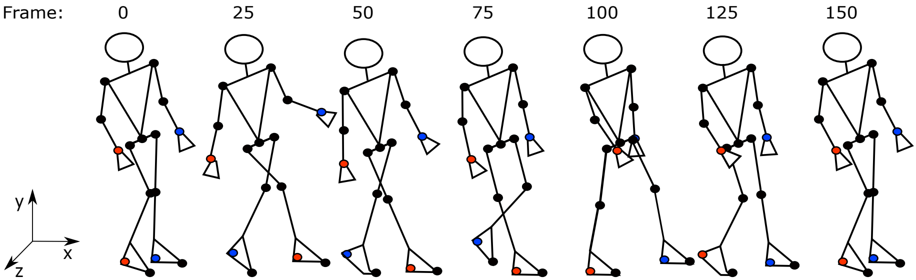


Human Identification by Gait



- Data captured by a system of multiple cameras or a depth camera
- Large tracking space
- Multiple samples of a single walker
- High variance in encounter conditions
- Database of large amount of biometric samples
- Identification in real time

Motion Capture Data (MoCap)



- Structural motion data
- Skeleton of joints and bones
- Data = 3D positions of joints in time.
- Can be collected by a system of multiple cameras (Vicon) or a depth camera (Microsoft Kinect)

Raw MoCap Gait Data

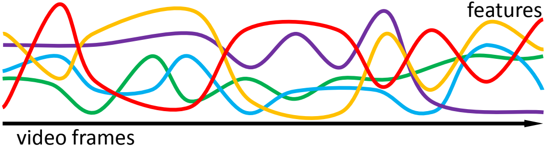
- Model of human body has J **joints**
- Measured gait cycle has **length** of T video frames
- Raw MoCap **gait sample** is a tensor

$$\mathbf{g} = \begin{bmatrix} \gamma_1(1) & \cdots & \gamma_1(T) \\ \vdots & \ddots & \vdots \\ \gamma_J(T) & \cdots & \gamma_J(T) \end{bmatrix}$$

- $\gamma_j(t) \in \mathbb{R}^3$ are **3D coordinates** of $j \in \{1, \ldots, J\}$ at $t \in \{1, \ldots, T\}$
- Dimensionality $3JT$
- **Sample space** $\{\mathbf{g}\}$

Geometric Features

- Examples of geometric gait features:
  - joint angles (angle in shoulder-elbow-wrist)
  - inter-joint distances (feet distance)
  - joint velocity or acceleration
  - areas of joint polygons (upper body span)
  - ...



- Examples of distance functions:
  - Dynamic Time Warping
  - Minkowski distances
  - ...

Linearly Learned Latent Features

- Labeled learning sample space $\{(\mathbf{g}_n, \ell_n)\}_{n=1}^{N_L}$
- ℓ_n is a label of one of the **identity classes** $\{\mathcal{I}_c\}_{c=1}^{C_L}$
- $\mathcal{I}_c$ has a priori probability p_c
- Consider an **optimization criterion** $\mathcal{J}$

- Feature extraction is given by a **feature matrix** $\boldsymbol{\Phi} \in \mathbb{R}^{D \times \widehat{D}}$
- D-dimensional sample space $\{\mathbf{g}_n\}_{n=1}^{N}$
- $\widehat{D}$-dimensional **feature space** $\{\widehat{\mathbf{g}}_n\}_{n=1}^{N}$

- Transform gait samples $\mathbf{g}_n$ into **gait templates** $\widehat{\mathbf{g}}_n = \boldsymbol{\Phi}^\top \mathbf{g}_n$
- Examples of distance functions:
  - Mahalanobis distance
  - Minkowski distances
  - ...

Learning by MMC

- Optimize **class separability** of the feature space
- **Margin** of two classes is the Euclidean distance of their means μ_c minus both their variances $\mathbf{\Sigma}_c$
- **Maximum Margin Criterion** used by the Support Vector Machines

$$\mathcal{J} = \frac{1}{2} \sum_{c,c'=1}^{C_L} p_c p_{c'} \left((\mu_c - \mu_{c'})^\top (\mu_c - \mu_{c'}) - \operatorname{tr}(\mathbf{\Sigma}_c + \mathbf{\Sigma}_{c'}) \right)$$
$$= \ldots = \operatorname{tr}(\mathbf{\Sigma}_\mathrm{B} - \mathbf{\Sigma}_\mathrm{W})$$

- Between-class scatter matrix $\mathbf{\Sigma}_\mathrm{B}$, within-class scatter matrix $\mathbf{\Sigma}_\mathrm{W}$
- Criterion for a feature matrix $\mathbf{\Phi}$

$$\mathcal{J}(\mathbf{\Phi}) = \operatorname{tr}\left(\mathbf{\Phi}^\top (\mathbf{\Sigma}_\mathrm{B} - \mathbf{\Sigma}_\mathrm{W}) \mathbf{\Phi} \right)$$

- Solution: solve the **generalized eigenvalue problem**

$$(\mathbf{\Sigma}_\mathrm{B} - \mathbf{\Sigma}_\mathrm{W}) \mathbf{\Phi} = \mathbf{\Lambda} \mathbf{\Phi}$$

- **Mahalanobis distance** function on templates

Learning by PCA+LDA

- 2-stage feature extraction technique
- **Principal Component Analysis** and **Linear Discriminant Analysis**
- Total scatter matrix $\boldsymbol{\Sigma}_{\mathrm{T}} = \boldsymbol{\Sigma}_{\mathrm{B}} + \boldsymbol{\Sigma}_{\mathrm{W}}$
- Criterion for a feature matrix $\boldsymbol{\Phi}_{\mathrm{LDA}}$

$$\mathcal{J}\left(\boldsymbol{\Phi}_{\mathrm{PCA}}\right) = \mathrm{tr}\left(\boldsymbol{\Phi}_{\mathrm{PCA}}^{\top} \boldsymbol{\Sigma}_{\mathrm{T}} \boldsymbol{\Phi}_{\mathrm{PCA}}\right)$$

$$\mathcal{J}\left(\boldsymbol{\Phi}_{\mathrm{LDA}}\right) = \mathrm{tr}\left(\frac{\boldsymbol{\Phi}_{\mathrm{LDA}}^{\top} \boldsymbol{\Phi}_{\mathrm{PCA}}^{\top} \boldsymbol{\Sigma}_{\mathrm{B}} \boldsymbol{\Phi}_{\mathrm{PCA}} \boldsymbol{\Phi}_{\mathrm{LDA}}}{\boldsymbol{\Phi}_{\mathrm{LDA}}^{\top} \boldsymbol{\Phi}_{\mathrm{PCA}}^{\top} \boldsymbol{\Sigma}_{\mathrm{W}} \boldsymbol{\Phi}_{\mathrm{PCA}} \boldsymbol{\Phi}_{\mathrm{LDA}}}\right)$$

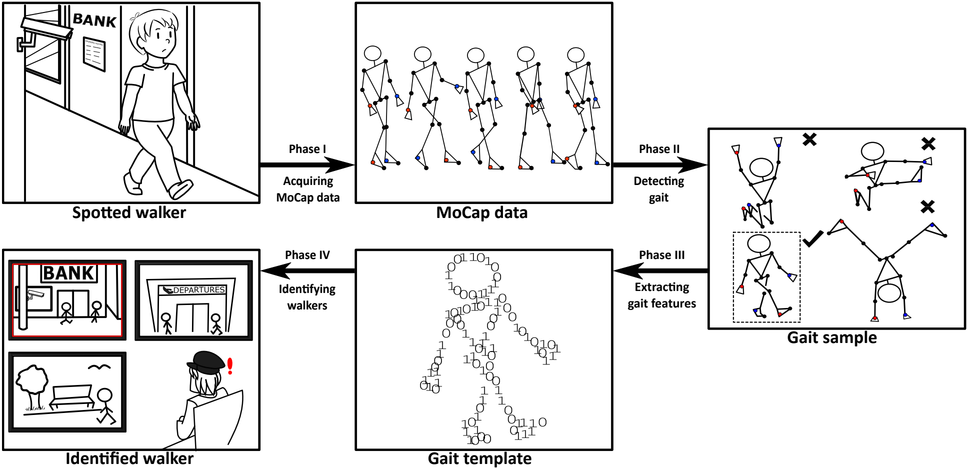
- Solution: solve the **generalized eigenvalue problems**

$$\boldsymbol{\Sigma}_{\mathrm{T}} \boldsymbol{\Phi}_{\mathrm{PCA}} = \boldsymbol{\Lambda} \boldsymbol{\Phi}_{\mathrm{PCA}}$$

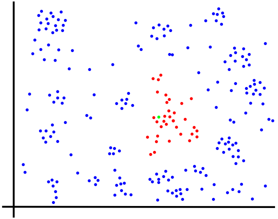
$$\left(\boldsymbol{\Phi}_{\mathrm{PCA}}^{\top} \boldsymbol{\Sigma}_{\mathrm{W}} \boldsymbol{\Phi}_{\mathrm{PCA}}\right)^{-1} \left(\boldsymbol{\Phi}_{\mathrm{PCA}}^{\top} \boldsymbol{\Sigma}_{\mathrm{B}} \boldsymbol{\Phi}_{\mathrm{PCA}}\right) \boldsymbol{\Phi}_{\mathrm{LDA}} = \boldsymbol{\Lambda} \boldsymbol{\Phi}_{\mathrm{LDA}}$$

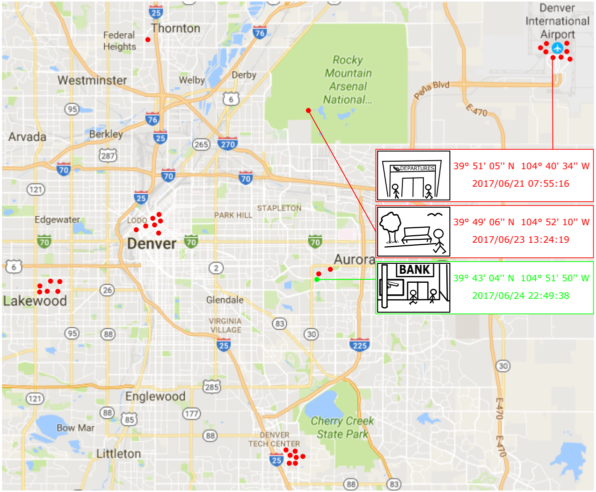
- **Mahalanobis distance** function on templates

Identity Classification Pipeline

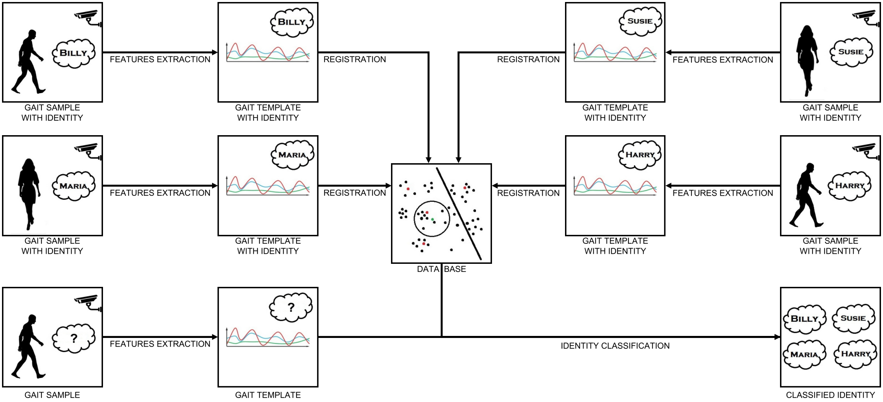


Identity Classification Pipeline



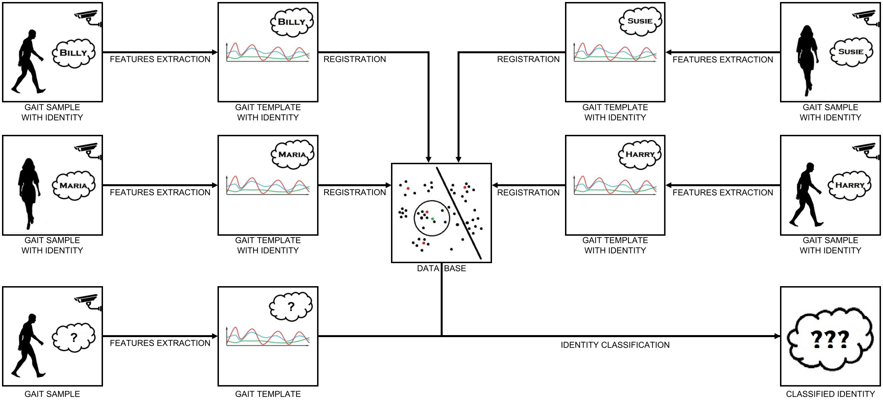


The Classification Problem



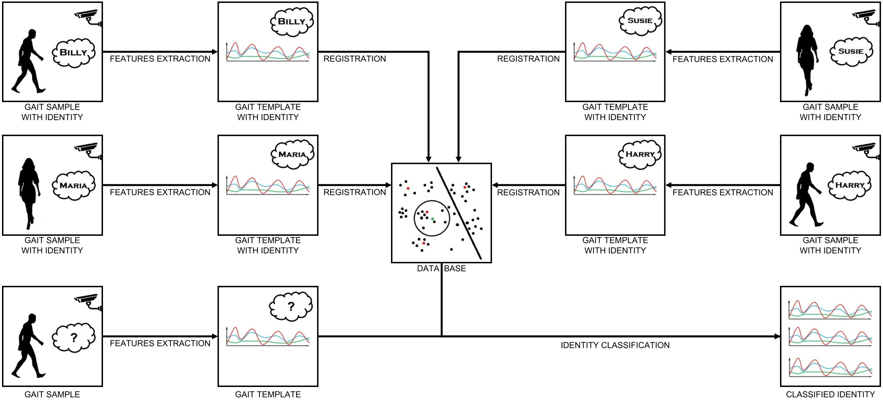
Identity: Label of a registered identity class.

But In Video Surveillance Environment ...

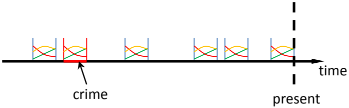


How can we represent the identity in video surveillance environment?

The Class Discovery Problem



Identity: Content of a discovered identity class = movement history.



You are how you walk.

Universal Gait Features

- Data need to be acquired without walker's consent
- New identities can appear on the fly
- Labels for all encountered people may not always be available

- **Universal gait features** – features of a high power in recognizing all people and not only those they were learned on
- We learn the universal gait features by MMC or by PCA+LDA on an **auxiliary dataset**
- The dataset is assumed to be rich on **covariate conditions** – aspects of walk people differ in
- These features create an **unsupervised environment** particularly suitable for **uncooperative person identification**

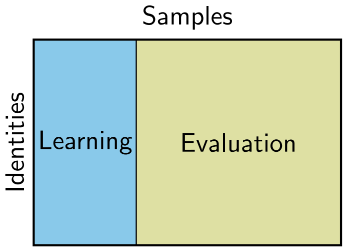
Evaluation: Database

- ASF/AMC format of MoCap data
- **CMU MoCap database** obtained from the CMU Graphics Lab
- Extracted database contains only gait cycles (motions of two steps)
- **Normalization**: position, walk direction and skeleton
- 7 extracted databases:

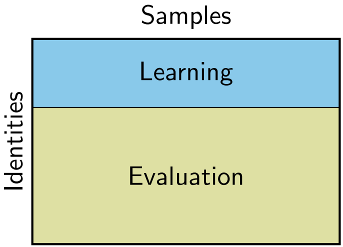
# identities	# gait cycles
2	35
4	67
8	130
16	302
32	2,047
54	**3,843**
64	**5,923**

Evaluation: Data Separation

- Data separation

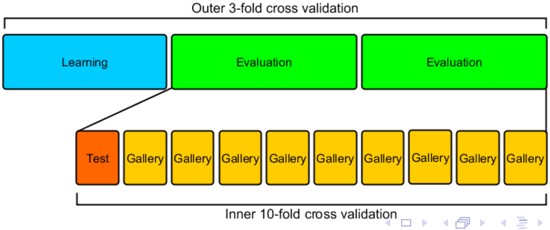


Normal evaluation



Cross-identity evaluation

- Evaluation of classification estimated by **nested cross-validation**



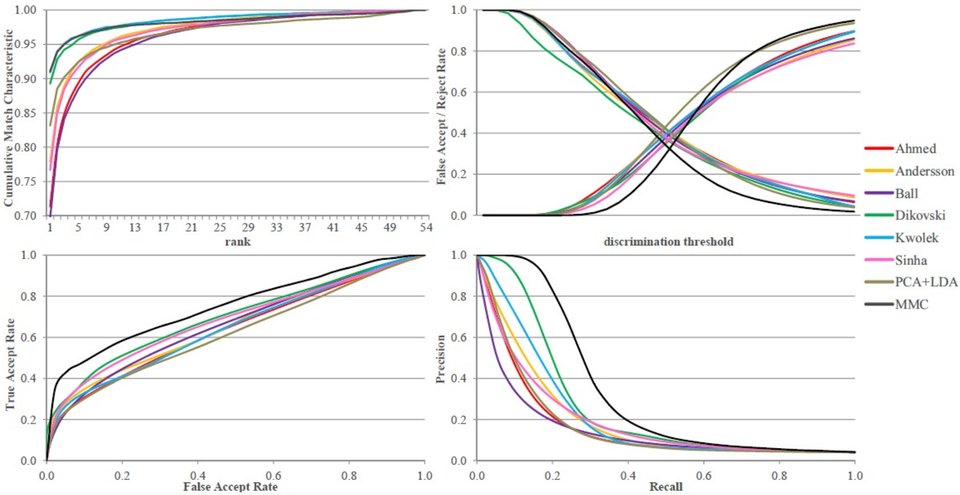
Evaluation: Metrics

- **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 / 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)

Evaluation: Results

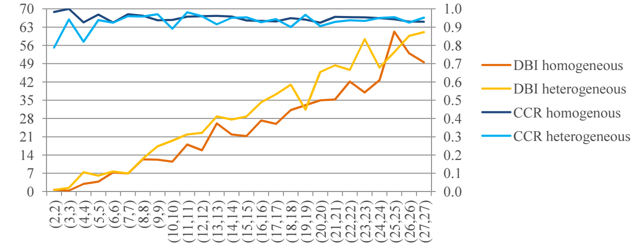
	class separability coefficients				classification based metrics				scalability	
method	DBI	DI	SC	FDR	CCR	EER	AUC	MAP	DCT	TD
Ahmed	216.2	0.842	−0.246	0.954	0.657	0.38	0.659	0.165	**0.01**	24
Ali	501.5	0.26	−0.463	**1.175**	0.225	0.384	0.679	0.111	**0.01**	**2**
Andersson	**142.3**	1.297	−0.102	1.127	0.84	**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
_MMC$_{BR}$	154.2	1.638	**0.062**	**1.173**	**0.925**	**0.297**	**0.748**	**0.353**	**0.01**	53
_MMC$_{JC}$	**130.3**	1.891	**0.051**	1.106	0.918	0.378	0.721	0.315	**0.01**	51
_PCALDA$_{BR}$	182	1.596	−0.015	0.984	0.918	0.361	0.695	0.276	**0.01**	54
_PCALDA$_{JC}$	174.4	1.309	−0.091	0.827	0.863	0.44	0.643	0.201	**0.01**	54
_Random					0.042					**0**
_Raw$_{BR}$	163.7	**2.092**	**0.011**	0.948	**0.966**	**0.315**	**0.743**	**0.358**	70.27	8,229
_Raw$_{JC}$	155.1	**1.954**	−0.12	0.897	**0.926**	0.377	0.679	0.283	160.64	13,574

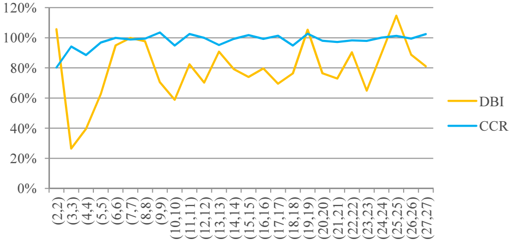
Evaluation: Results



Evaluation: Results

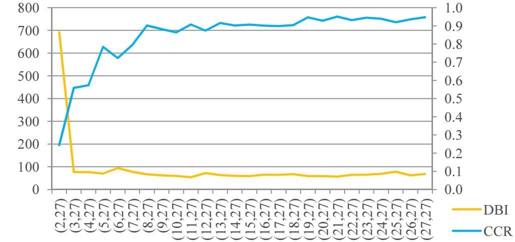
- Homogeneous set-up with $C_L = C_E \in \{2, \ldots, 27\}$
- Heterogeneous set-up with $C_L = C_E \in \{2, \ldots, 27\}$

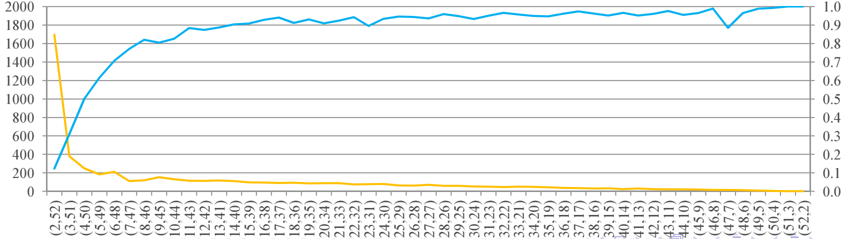




Evaluation: Results

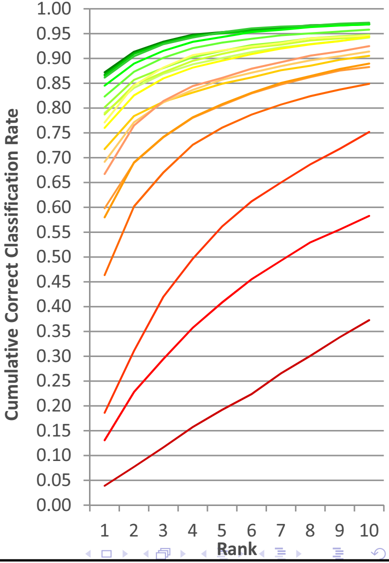
- Heterogeneous set-up with $C_L \in \{2, \dots, 27\}$ and $C_E = 27$
- Heterogeneous set-up with $C_L \in \{2, \dots, 52\}$ and $C_E = 54 - C_L$



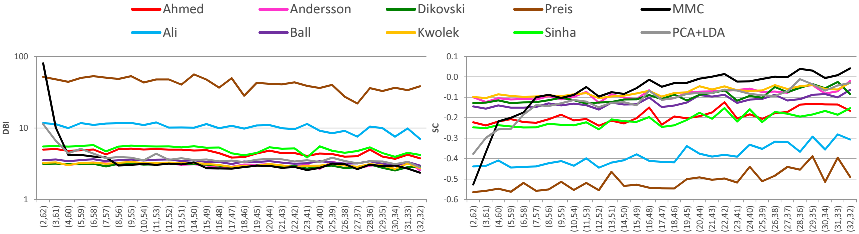


Evaluation: Results

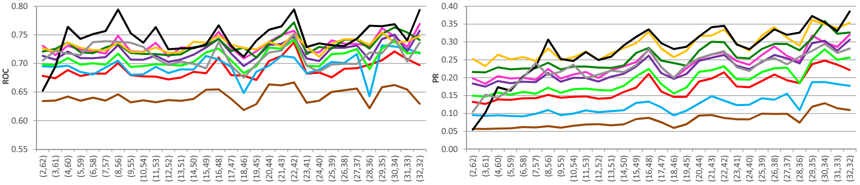
method	CCR	EER	AUC	MAP	CMC
$\mathrm{Raw}_{\mathrm{JC}}$	0.872	0.321	0.731	0.317	
$\mathrm{MMC}_{\mathrm{BR}}$	0.868	0.305	0.739	0.332	
$\mathrm{Raw}_{\mathrm{BR}}$	0.867	0.333	0.701	0.259	
$\mathrm{MMC}_{\mathrm{JC}}$	0.861	0.325	0.72	0.309	
$\mathrm{PCA{+}LDA}_{\mathrm{BR}}$	0.845	0.335	0.682	0.247	
KwolekB	0.823	0.367	0.711	0.296	
KrzeszowskiT	0.802	0.348	0.717	0.273	
$\mathrm{PCA{+}LDA}_{\mathrm{JC}}$	0.79	0.417	0.634	0.189	
DikovskiB	0.787	0.376	0.679	0.227	
AhmedF	0.771	0.371	0.664	0.22	
AnderssonVO	0.76	0.352	0.703	0.228	
NareshKumarMS	0.717	0.459	0.613	0.19	
JiangS	0.692	0.407	0.637	0.204	
BallA	0.667	0.356	0.698	0.207	
SinhaA	0.598	0.362	0.69	0.176	
AhmedM	0.58	0.392	0.646	0.145	
SedmidubskyJ	0.464	0.394	0.65	0.138	
AliS	0.186	0.394	0.662	0.096	
PreisJ	0.131	0.407	0.618	0.066	
Random	0.039				



Evaluation: Results

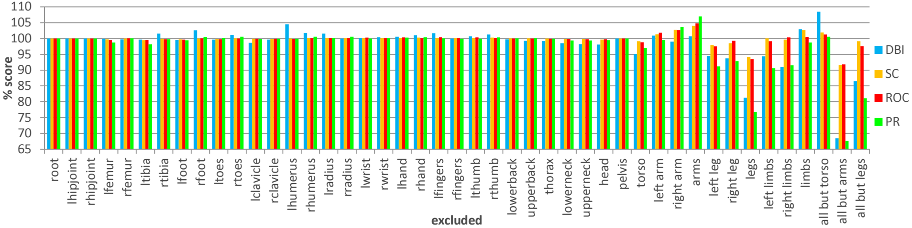


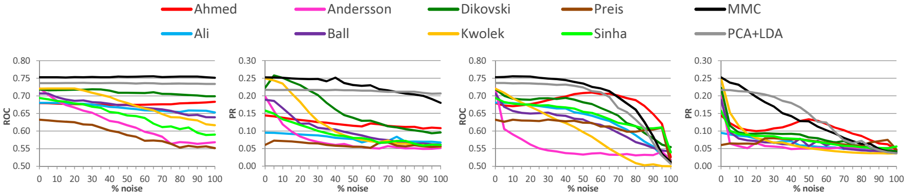
(a) DBI (b) SC



(c) AUC (d) MAP

Evaluation: Results





Evaluation Framework and Database

- Available online at `https://gait.fi.muni.cz`

- Database extraction drive
- Implementations of all 20 methods
- Classifier learning and classification mechanism
- Evaluation mechanism and 12 performance metrics

Summary

- Universal gait features learned on an auxiliary dataset
- Our approach based on MMC and PCA+LDA
- Broad evaluation on normal and cross-identity setups
- MMC learned on 17 identities recognizes 37 identities with 95% CCR
- MMC learned yet on 7 identities best recognizes 57 identities
- Evaluation framework and database

https://gait.fi.muni.cz

Thank you for attention.
Questions?