Gait Recognition through MPCA plus LDA

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Outline

- Motivation
- Overview of the proposed method
- MPCA framework
- Gait recognition through MPCA+LDA
- Experimental results
- Conclusions

Motivation

- Gait recognition: human identification at a distance in surveillance/monitoring apps
- Gait (silhouette) sequences: multi-dimensional (tensor) objects
- Dimensionality reduction/feature extraction
  - PCA: vectorization, break correlation/structure
  - Directly on tensor representation?
- Objective: direct tensor feature extraction

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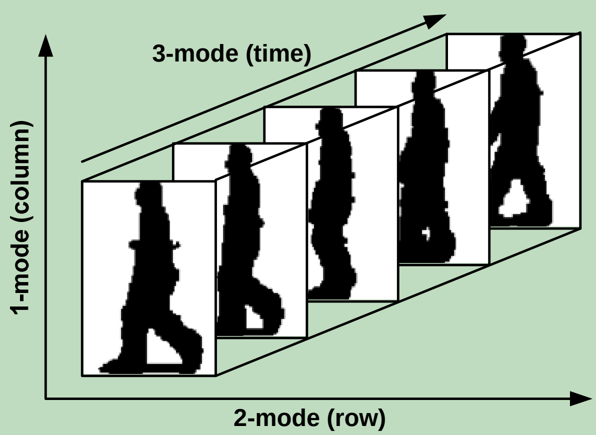
Gait sequence as tensor object



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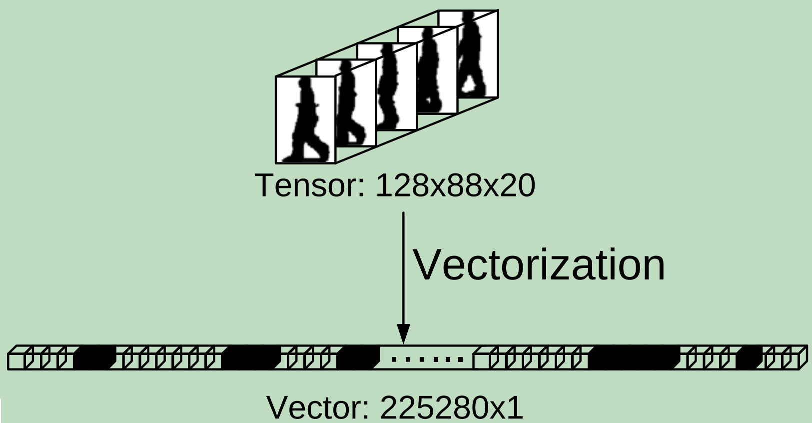
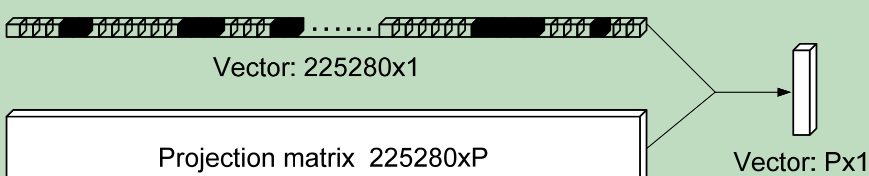
To apply PCA and/or LDA



Linear projection



- Very high dimensionality
- Correlation and structure are broken

Overview of the proposed method

- Input: gait sequences as tensors
- Algorithm: feature extraction from tensors using multilinear projection
- Output: features extracted from gait sequences in their natural representation as tensors.

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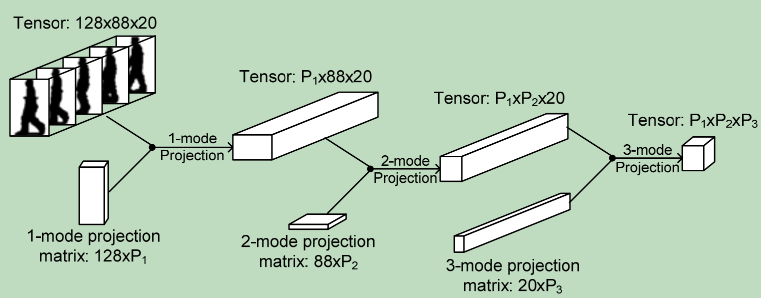
Multilinear projection



- Operations on lower dimensionality
- Original correlation and structure are preserved

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The MPCA framework

- Input: *M* training gait samples
  $\mathcal{X}_m \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}, m = 1, \ldots, M$
- Output: multilinear transformation
  $\{\tilde{\mathbf{U}}^{(n)} \in \mathbb{R}^{I_n \times P_n}, n = 1, \ldots, N\}$
- Objective: the projection
  $\mathcal{Y}_m = \mathcal{X}_m \times_1 \tilde{\mathbf{U}}^{(1)^T} \times_2 \tilde{\mathbf{U}}^{(2)^T} \ldots \times_N \tilde{\mathbf{U}}^{(N)^T}$
  captures most of the variations

Definition of tensor variations

Definition 1 *Let* $\{\mathcal{A}_m, m = 1, \ldots, M\}$ *be a set of* M *gait samples in* $\mathbb{R}^{I_1} \otimes \mathbb{R}^{I_2} \ldots \otimes \mathbb{R}^{I_N}$. *The total scatter of these samples is defined as:* $\Psi_{\mathcal{A}} = \sum_{m=1}^{M} \| \mathcal{A}_m - \bar{\mathcal{A}} \|_F^2$, *where* $\bar{\mathcal{A}}$ *is the mean sample calculated as* $\bar{\mathcal{A}} = \frac{1}{M} \sum_{m=1}^{M} \mathcal{A}_m$.

Objective function

$$\{\tilde{\mathbf{U}}^{(n)}, n = 1, ..., N\} = \arg \max_{\tilde{\mathbf{U}}^{(1)}, \tilde{\mathbf{U}}^{(2)}, ..., \tilde{\mathbf{U}}^{(N)}} \Psi_{\mathcal{Y}}$$

- No known optimal solution to simultaneously optimize the *N* matrices
- Solution – Part I:
  - Decompose into *N* optimization subproblem
  - Find each $\tilde{\mathbf{U}}^{(n)}$ maximizing the scatter in each *n*-mode vector subspace

Solution – Part II

Theorem. *Let* $\{\tilde{\mathbf{U}}^{(n)}, n = 1, ..., N\}$ *be the solution to the objective function. Then, for given* $\tilde{\mathbf{U}}^{(1)}, ..., \tilde{\mathbf{U}}^{(n-1)}, \tilde{\mathbf{U}}^{(n+1)}, ..., \tilde{\mathbf{U}}^{(N)}$, *the matrix* $\tilde{\mathbf{U}}^{(n)}$ *consists of the* P_n *eigenvectors corresponding to the largest* P_n *eigenvalues of the matrix*

$$\Phi^{(n)} = \sum_{m=1}^{M} \left(\mathbf{X}_{m(n)} - \bar{\mathbf{X}}_{(n)}\right) \cdot \tilde{\mathbf{U}}_{\Phi^{(n)}} \cdot \tilde{\mathbf{U}}_{\Phi^{(n)}}^{T} \cdot \left(\mathbf{X}_{m(n)} - \bar{\mathbf{X}}_{(n)}\right)^{T},$$

$$\tilde{\mathbf{U}}_{\Phi^{(n)}} = \left(\tilde{\mathbf{U}}^{(n+1)} \otimes ... \otimes \tilde{\mathbf{U}}^{(N)} \otimes \tilde{\mathbf{U}}^{(1)} \otimes ... \tilde{\mathbf{U}}^{(n-1)}\right).$$

Solution – Part III

- $\tilde{\mathbf{U}}_{\Phi^{(n)}} \cdot \tilde{\mathbf{U}}^T_{\Phi^{(n)}}$ depends on $\tilde{\mathbf{U}}^{(1)}, \ldots, \tilde{\mathbf{U}}^{(n-1)}, \tilde{\mathbf{U}}^{(n+1)}, \ldots, \tilde{\mathbf{U}}^{(N)}$.
- Optimization of one projection matrix in one mode depends on the projection matrices in all the other modes
- No closed form solution and an iterative solution is introduced.

The (iterative) MPCA algorithm

- Initialize projection matrices and determine the subspace dimensionality if not given
- Compute projection matrices one mode by one mode fixing projections in all other modes
- Repeat until convergence

Initialization and termination

- Initialization: full projection truncation (FPT)
  - Full projection: $P_n = I_n$ for $n = 1, \ldots, N$, $\mathbf{U}_{\Phi^{(n)}} \cdot \mathbf{U}_{\Phi^{(n)}}^T$ is an identity matrix.
  - Eigentensor: $\tilde{\mathcal{U}}_{p_1 p_2 \ldots p_N} = \tilde{\mathbf{u}}_{p_1}^{(1)} \circ \tilde{\mathbf{u}}_{p_2}^{(2)} \circ \ldots \circ \tilde{\mathbf{u}}_{p_N}^{(N)}$
  - FPT: Keeping the first P_n columns of the full projection matrix $\tilde{\mathbf{U}}^{(n)}$ in *n*-mode for all *n.*
- Termination: $(\Psi_{\mathcal{Y}_k} - \Psi_{\mathcal{Y}_{k-1}}) < \eta$

Subspace dimensionality determination

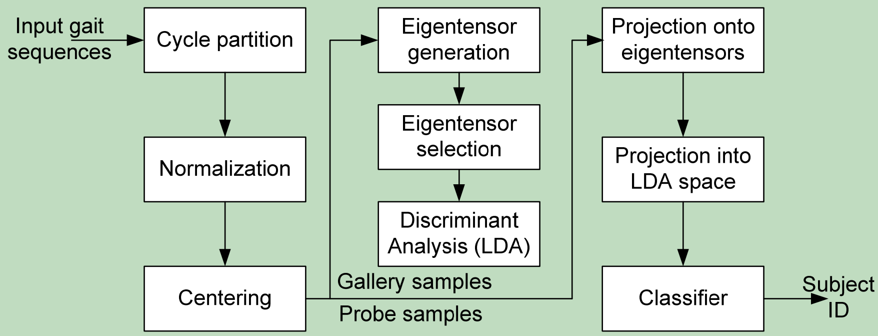
- Ratio of variations kept in the *n*-mode

$$Q^{(n)} = \frac{\sum_{i_n=1}^{P_n} \lambda_{i_n}^{(n)*}}{\sum_{i_n=1}^{I_n} \lambda_{i_n}^{(n)*}}$$

- Keep the first P_n eigentensors in *n*-mode so that

$$Q^{(1)} = Q^{(2)} = \ldots = Q^{(N)} = Q$$

MPCA plus LDA for gait recognition



Gait recognition using MPCA+LDA

- Gait samples: half gait cycles, partitioned through number of foreground pixels
- Normalization: spatial and temporal interpolation
- Eigentensor selection by class discriminability

$$\Gamma_{p_1 p_2 \cdots p_N} = \frac{\sum_{c=1}^{C} N_c \cdot \left[\bar{\mathcal{Y}}_c(p_1, p_2, \ldots, p_N) - \bar{\mathcal{Y}}(p_1, p_2, \ldots, p_N)\right]^2}{\sum_{m=1}^{M} \left[\mathcal{Y}_m(p_1, p_2, \ldots, p_N) - \bar{\mathcal{Y}}_{c_m}(p_1, p_2, \ldots, p_N)\right]^2}$$

Experimental data

- USF HumanID "Gait Challenge" data sets v.1.7
  - Different conditions: walking surfaces, shoe types and viewing angles
  - 71 subjects in gallery set: 731 gait samples
  - Seven probe sets
  - Gait sample size: $128 \times 88 \times 20$

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Parameters

- Q=97, 92% of the total variations kept
- Number of eigenvectors kept in each mode: $P_1 = 61, P_2 = 42, P_3 = 17$
- Number of EigenTensors selected :

$$H_{\mathbf{y}} = 170$$

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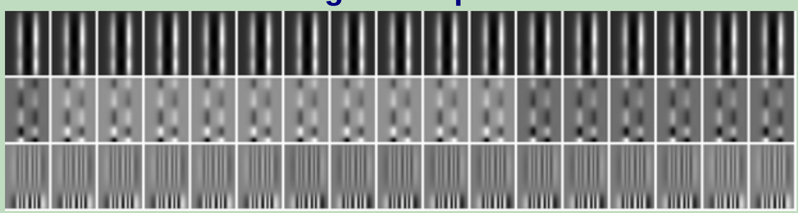
Examples of gait sample and EigenTensorGait (unfolded)

A gait sample

Mean gait sample



Three EigenTensorGaits

Similarity measure

- Feature $\mathbf{z}$ with subject *c*:

$$S(\mathbf{z}, c) = -\min_{n_c} d(\mathbf{z}, \mathbf{z}_{n_c})$$

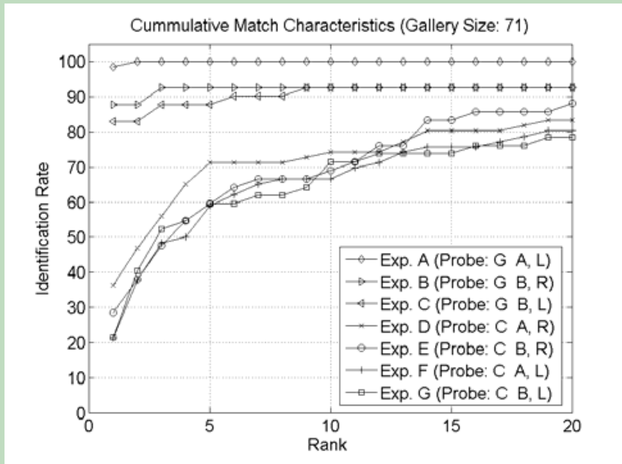
- Mahalanobis+angle distance measure

$$d(\mathbf{a}, \mathbf{b}) = \frac{\sum_{h_z=1}^{H_z} \mathbf{a}(h_z) \cdot \mathbf{b}(h_z)}{\sqrt{\lambda_{h_z} \sum_{h_z=1}^{H_z} \mathbf{a}(h_z)^2 \sum_{h_z=1}^{H_z} \mathbf{b}(h_z)^2}}$$

- Probe sequence *p* with a gallery sequence *g*

$$S(p, g) = \frac{1}{N_p} \sum_{n_p=1}^{N_p} S(\mathbf{z}_{n_p}, g) + \frac{1}{N_g} \sum_{n_g=1}^{N_g} S(\mathbf{z}_{n_g}, p)$$

CMC Curves



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Rank 1 comparison

Probe	BL	HMM	LTN	GEI	MPCA-HT	MPCA+LDA
A(GAL)	79	99	94	**100**	94	99
B(GBR)	66	**89**	83	85	76	88
C(GBL)	56	78	78	80	66	**83**
D(CAR)	29	35	33	30	27	**36**
E(CBR)	24	29	24	33	**36**	29
F(CAL)	**30**	18	17	21	15	21
G(CBL)	10	24	21	**29**	19	21
Mean	42	53	53	**54**	48	**54**

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Rank 5 comparison

Probe	BL	HMM	LTN	GEI	MPCA-HT	MPCA+LDA
A(GAL)	96	**100**	99	**100**	99	**100**
B(GBR)	81	90	85	85	83	**93**
C(GBL)	76	**90**	83	88	81	88
D(CAR)	61	65	65	55	64	**71**
E(CBR)	55	65	**67**	55	52	60
F(CAL)	46	**60**	58	41	53	59
G(CBL)	33	50	48	48	48	**60**
Mean	64	74	72	67	68	**76**

Conclusions

- MPCA framework: multilinear projection for tensors capturing most variations
- LDA on selected eigentensors for recognition
- Results: outperform state-of-the-art gait recognition algorithms
- Future work: extension to other tensor objects and development of other tensor subspace algorithms

Acknowledgement

- Thank Prof. Sarkar from the University of South Florida (USF) for providing the Gait Challenge data sets.

Back up slides

Notations and basics

- Vector: lowercase boldface $\mathbf{x}$
- Matrix: uppercase boldface $\mathbf{U}$
- Tensor: calligraphic letter $\mathcal{A}$
- *n*-mode product: $\mathcal{A} \times_n \mathbf{U}$

$$(\mathcal{A} \times_n \mathbf{U})(i_1, \ldots, i_{n-1}, j_n, i_{n+1}, \ldots, i_N) = \sum_{i_n} \mathcal{A}(i_1, \ldots, i_N) \cdot \mathbf{U}(j_n, i_n)$$

- Scalar product: $< \mathcal{A}, \mathcal{B} >$

$$< \mathcal{A}, \mathcal{B} > = \sum_{i_1} \sum_{i_2} \ldots \sum_{i_N} \mathcal{A}(i_1, i_2, \ldots, i_N) \cdot \mathcal{B}(i_1, i_2, \ldots, i_N)$$

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Notations and basics

- Frobenius norm: $\| \mathcal{A} \|_F = \sqrt{< \mathcal{A}, \mathcal{A} >}$
- Outer product: $\mathcal{A} = \mathbf{u}^{(1)} \circ \mathbf{u}^{(2)} \circ \ldots \circ \mathbf{u}^{(N)}$

$$\mathcal{A}(i_1, i_2, \ldots, i_N) = \mathbf{u}^{(1)}(i_1) \cdot \mathbf{u}^{(2)}(i_2) \cdot \ldots \cdot \mathbf{u}^{(N)}(i_N)$$

- *n*-mode unfolding:

$$\mathbf{A}_{(n)} \in \mathbb{R}^{I_n \times (I_1 \times \ldots \times I_{n-1} \times I_{n+1} \times \ldots \times I_N)}$$

  - Column vectors of $\mathbf{A}_{(n)}$ are *n*-mode vectors of $\mathcal{A}$

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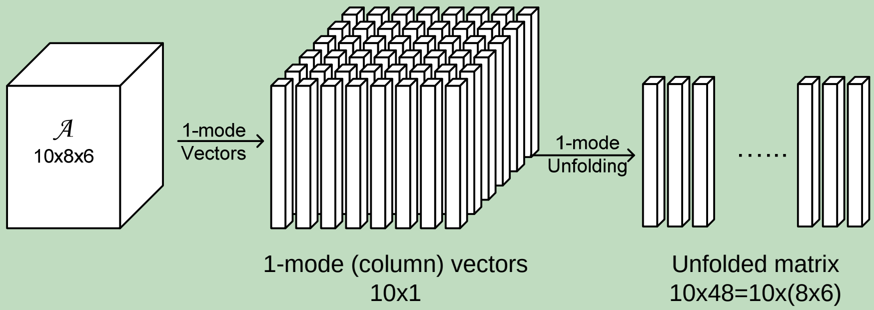
Unfolding into matrices



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Notations and basics

- Tensor decomposition (Tucker's model)

$$\mathcal{A} = \mathcal{S} \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)} \times \dots \times_N \mathbf{U}^{(N)}$$

  - $\mathbf{U}^{(n)} = \left(\mathbf{u}_1^{(n)} \mathbf{u}_2^{(n)} \dots \mathbf{u}_{I_n}^{(n)}\right)$ is an orthogonal matrix
  - $\mathcal{S} = \mathcal{A} \times_1 \mathbf{U}^{(1)^T} \times_2 \mathbf{U}^{(2)^T} \dots \times_N \mathbf{U}^{(N)^T}$

- Equivalent form (sum of rank-1 tensors):

$$\mathcal{A} = \sum_{i_1=1}^{I_1} \dots \sum_{i_N=1}^{I_N} \mathcal{S}(i_1, \dots, i_N) \mathbf{u}_{i_1}^{(1)} \circ \dots \circ \mathbf{u}_{i_N}^{(N)}$$

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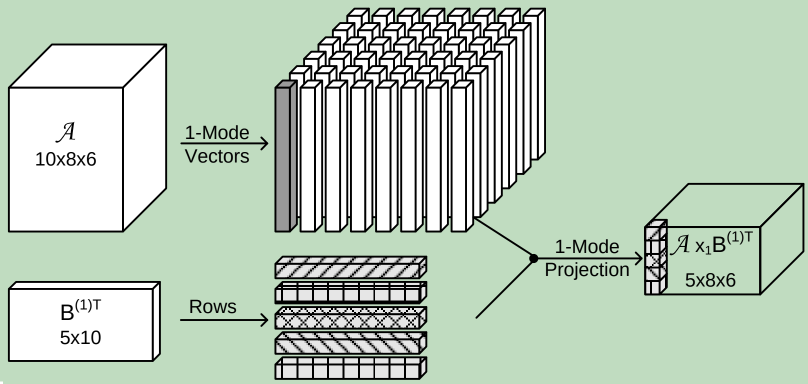
Multilinear projection in one mode



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