Learning to Recognize Parallel Combinations of Human Motion Primitives with Linguistic Descriptions using Non-Negative Matrix Factorization

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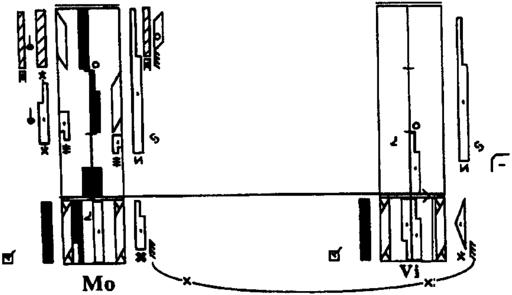
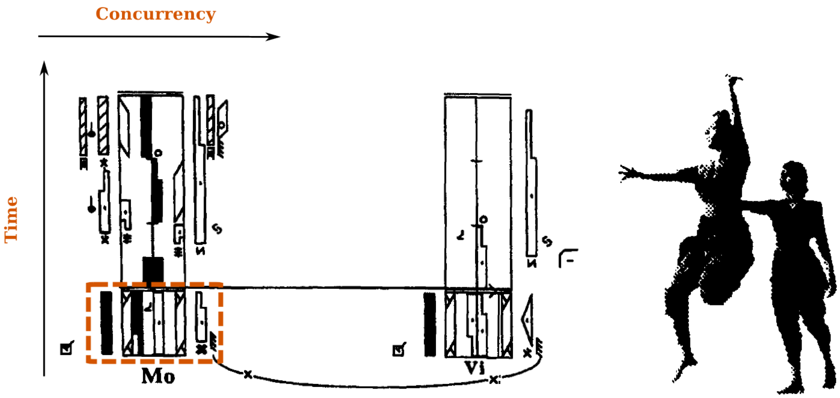
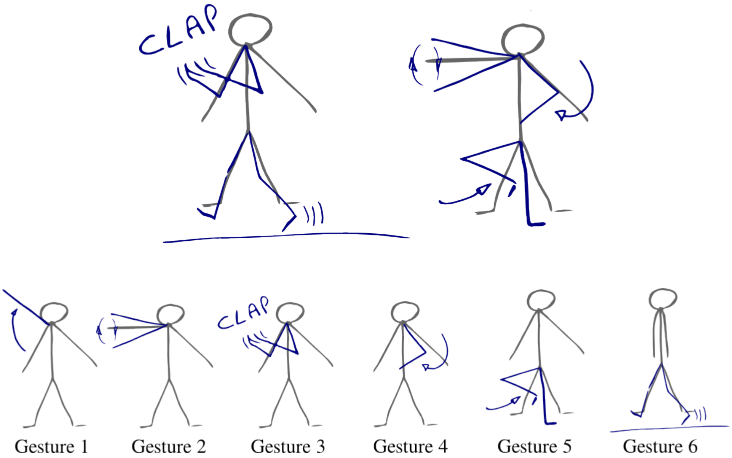
Motions and behaviors are complex

Picture: `http://www.hongkiat.com/`

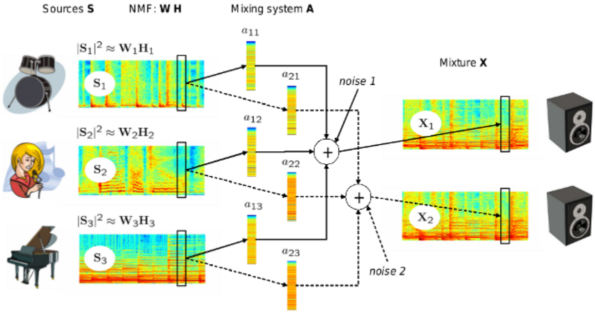

Mo
Vi


Concurrency
Time
Mo
Vi

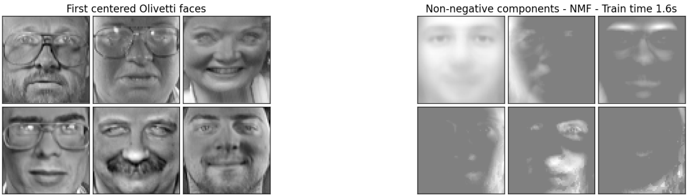


Learn a dictionary of **primitive motion** to explain/represent complex behaviors.

Dictionary learning in other fields



(Source http://perso.telecom-paristech.fr/˜fevotte/)



(Source Scikit-learn documentation)

An ambiguous problem

- invariances in the decomposition,
- levels of decomposition,
- real ambiguity in the behavior (e.g. cultural, contextual),
- ...

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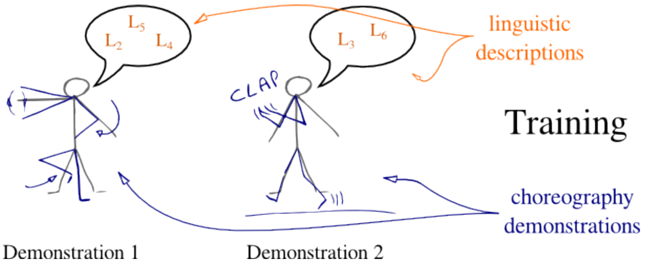
Heuristics to guide the dictionary learning:

- **structural**

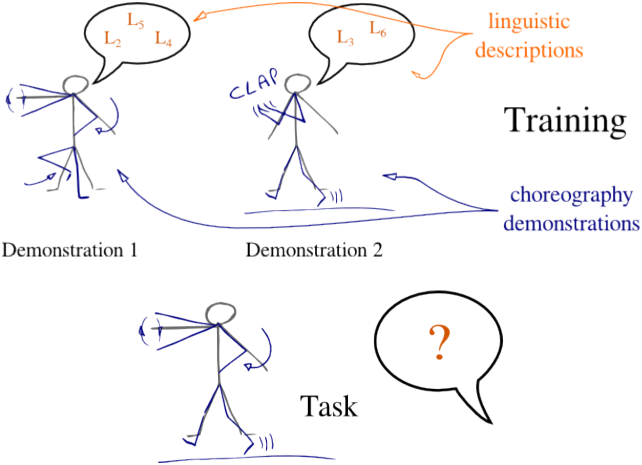
  non-negativity
- **social and multimodal**

  decomposition shaped by linguistic modality (also models **language grounding**)

Learning setup



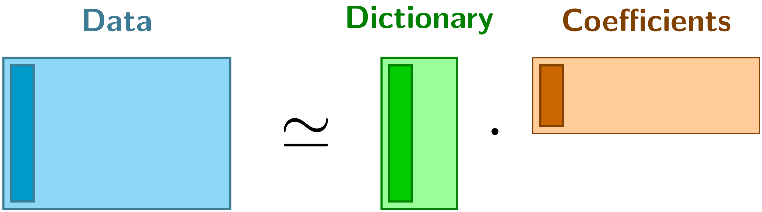
Learning setup



This setup is symetric to [Driesen et al., 2009].

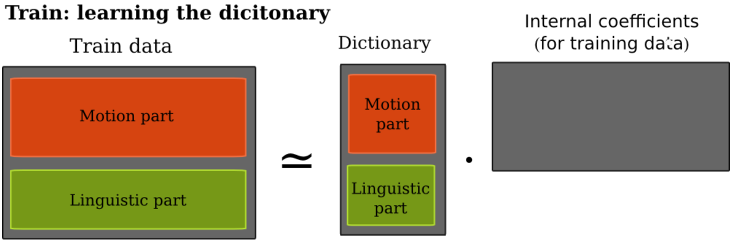
Non-negative matrix factorization (NMF)

The big picture:

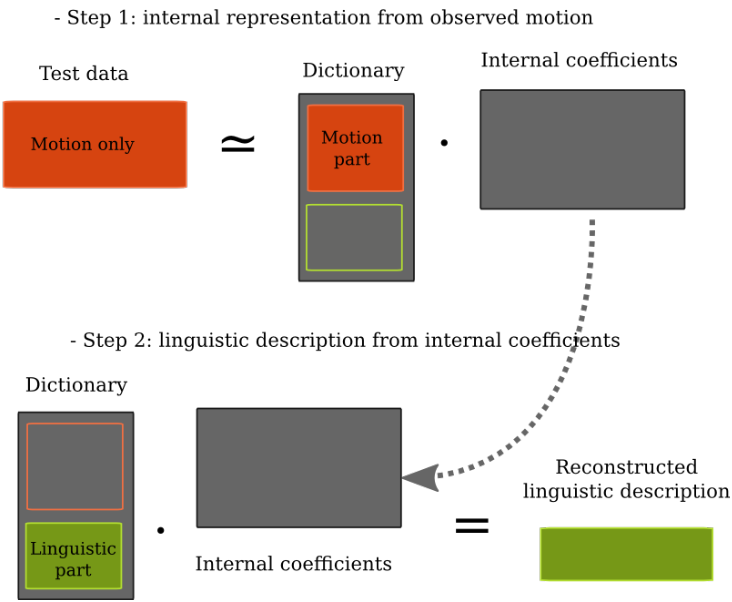


NMF for multimodal data

[Driesen et al., 2009, Mangin & Oudeyer, 2012b]



Test: producing linguistic data from demonstrated motions



Data representation

Motion features

moving skeleton (from Kinect)

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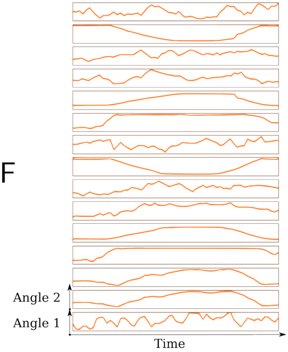
moving skeleton (from Kinect)

$\longrightarrow$ angles and angle velocities for each DOF



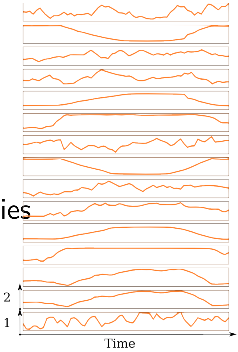
Data representation

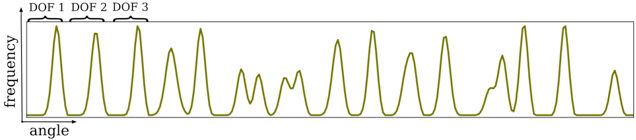
Motion features

moving skeleton (from Kinect)

$\longrightarrow$ angles and angle velocities for each DOF

$\longrightarrow$ histograms of positions or position-velocities





Data representation

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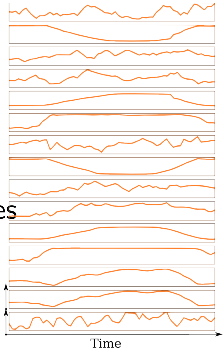
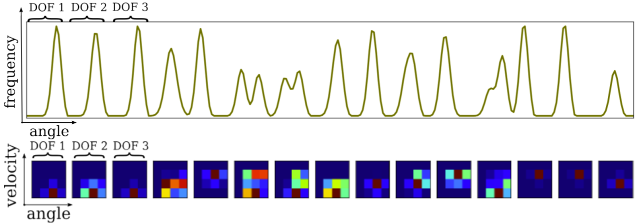
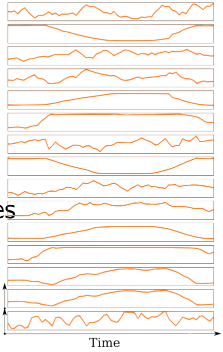
⟶ angles and angle velocities for each DOF

⟶ histograms of positions or position-velocities





Data representation



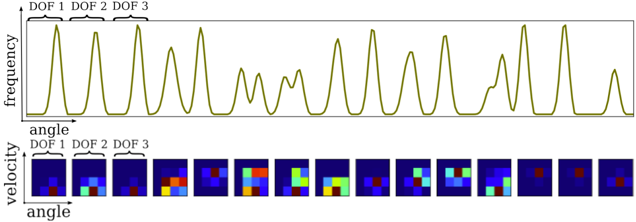
Motion features

moving skeleton (from Kinect)

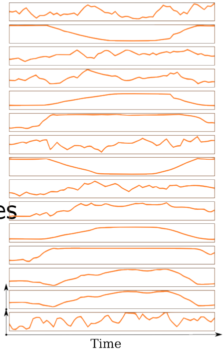
⟶ angles and angle velocities for each DOF

⟶ histograms of positions or position-velocities

⟶ flattened in a non-negative vector



Data representation



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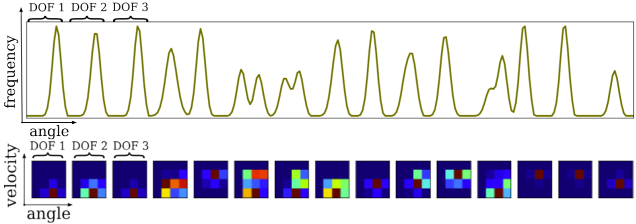


Language representation

$[0, 0, 1, 0, 0, 0, 0, 0, 1, 0] \quad \longrightarrow$ symbols 2 and 8

The choreography dataset

Available online:

http://flowers.inria.fr/choreography_database.html

3 separate sets of examples:

- **primitive:** only one primitive motion demonstrated in each example

  (**326** examples, **47** primitive motions)

- **mixed small:** complex choreographies

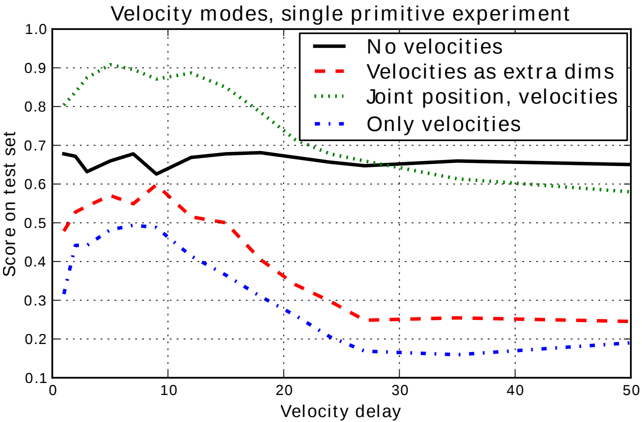
  (**137** examples, **16** primitive motions)

- **mixed full:** complex choreographies

  (**277** examples, **47** primitive motions)

Evaluation on classification

(only one primitive motion at a time)



Evaluation on reconstruction of multiple labels

(reconstructed description is thresholded and compared to human annotations)

	l_{full}
17 labels (SVM, linear)	0.818
17 labels (NMF, Frobenius)	0.854
17 labels (NMF, DKL)	0.789
47 labels (SVM, linear)	0.422
47 labels (NMF, Frobenius)	0.625
47 labels (NMF, DKL)	0.574

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47 labels (NMF, Frobenius)	0.625
47 labels (NMF, DKL)	0.574

Results for unobserved combinations

	l_{full}
17 labels (NMF, Frobenius)	0.568
17 labels (SVM, linear)	0.667
47 labels (NMF, Frobenius)	0.406
47 labels (SVM, linear)	0.206

Extensions

- **Other constraints** (sparsity, etc.)
- **Going to real language** (merge with [Driesen et al., 2009])
- **Learn position in time**
- **Other motion representations (towards imitation):** models of activities as combination of potential functions [Mangin & Oudeyer, 2012a]

Thank you!

Bibliography

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In *to appear in third International Workshop on Human Behavior Understanding*, number 3 Vilamoura, Algarve (Portugal).

Mangin, O. & Oudeyer, P.-Y. (2012b).
Learning to recognize parallel combinations of human motion primitives with linguistic descriptions using non-negative matrix factorization.
In *to appear in International Conference on Intelligent Robots and Systems (IROS 2012)* Vilamoura, Algarve (Portugal): IEEE/RSJ.

Evaluation on reconstruction of multiple labels

(reconstructed description is thresholded and compared to human annotations)

	l_{full}	$l_{\text{given number}}$
17 labels (SVM, linear)	0.818	-
17 labels (NMF, Frobenius)	0.854	0.971
17 labels (NMF, DKL)	0.789	0.905
47 labels (SVM, linear)	0.422	-
47 labels (NMF, Frobenius)	0.625	0.755
47 labels (NMF, DKL)	0.574	0.679

Results for unobserved combinations

	l_{full}	$l_{\text{given number}}$
17 labels (NMF, Frobenius)	0.568	0.800
17 labels (SVM, linear)	0.667	-
47 labels (NMF, Frobenius)	0.406	0.653
47 labels (SVM, linear)	0.206	-