Valuation of climbing activities

using

Multi-Scale Jensen-Shannon Neighbour Embedding

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ECML 2015, September 7-11, Porto

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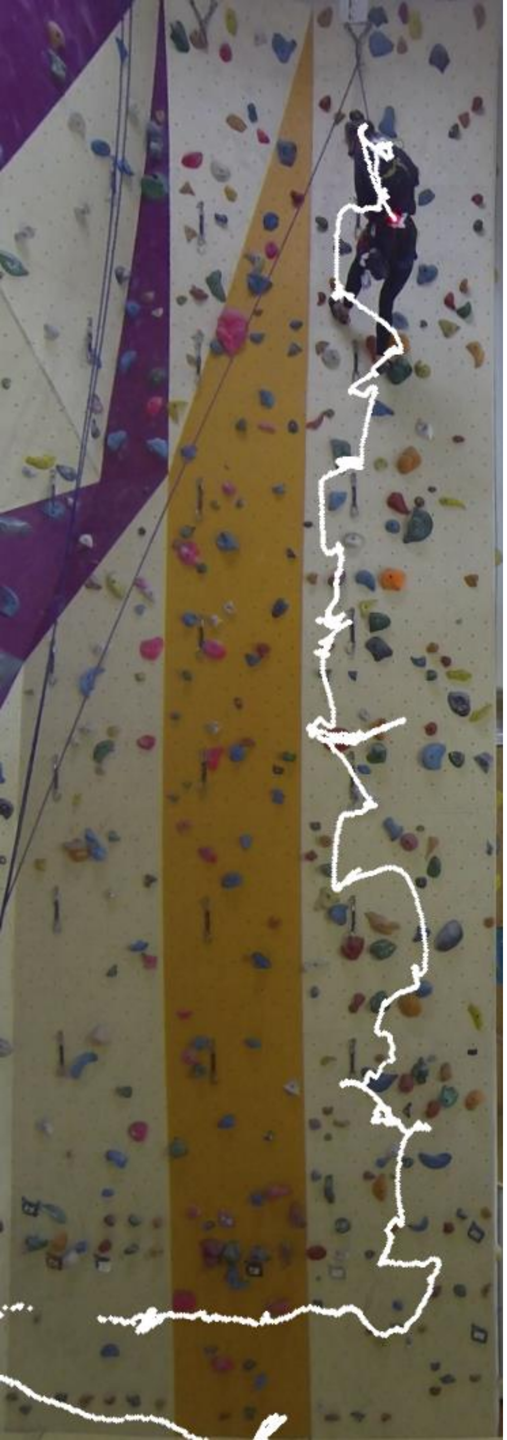
What is the role of technique variations in learning design for practising?

Can technique variations, induced by different practising environments, improve the performance in yet other environments (transfer learning)?

How can we help the performer transfer this techniques to other environments?



Context of this study

- Past coordination studies focus on articulations seen as oscillators, most of them are limited to two limbs

Objectives

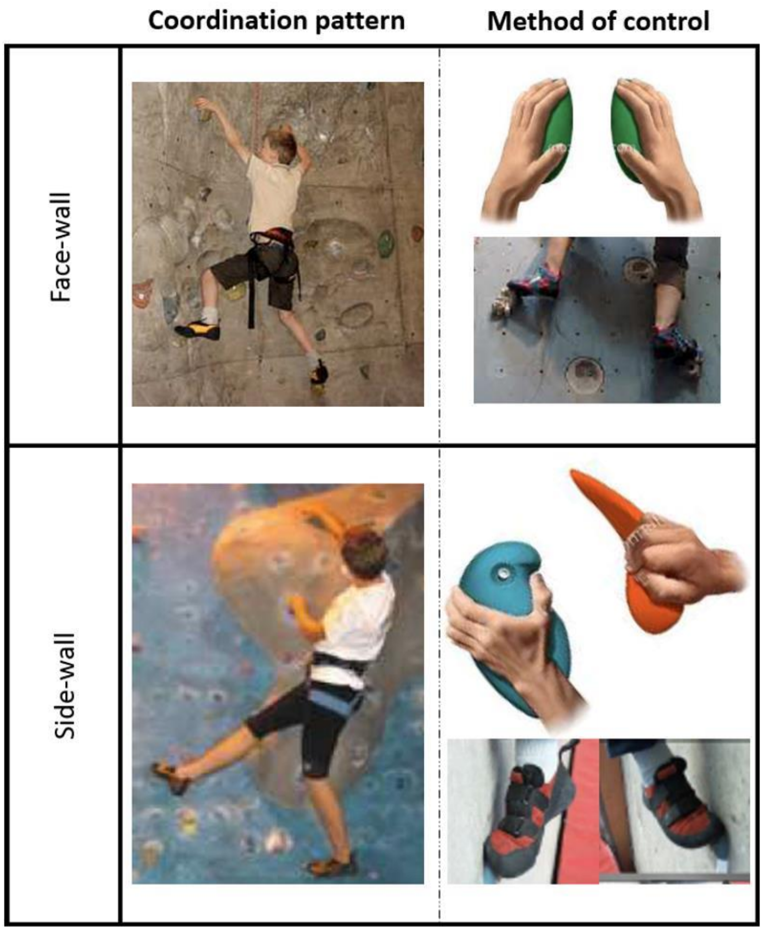
- Propose a ML framework to study the full body coordination
- Relate the results to climbing fluency (performance measure)

Predominant coordination patterns

Two global patterns of climbing can be distinguished :

- **Face-wall**
  (Beginers and experts)

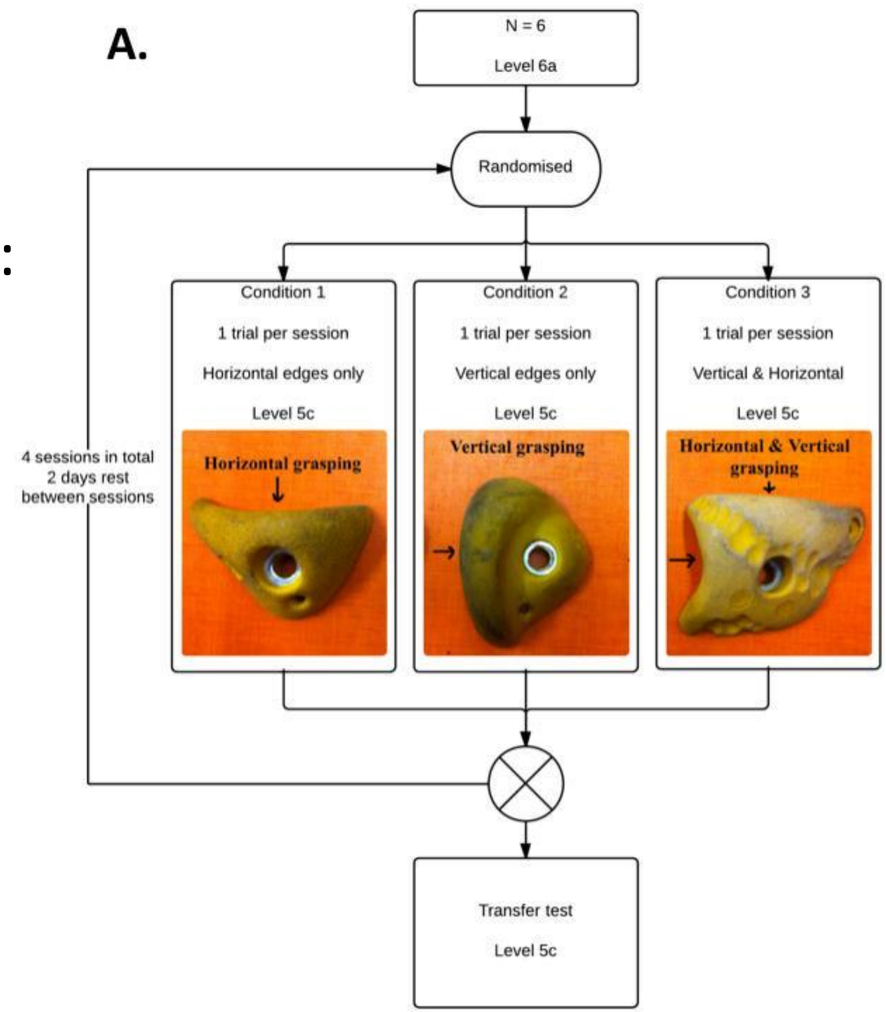
- **Side-wall**
  (Experts)



Experimentation

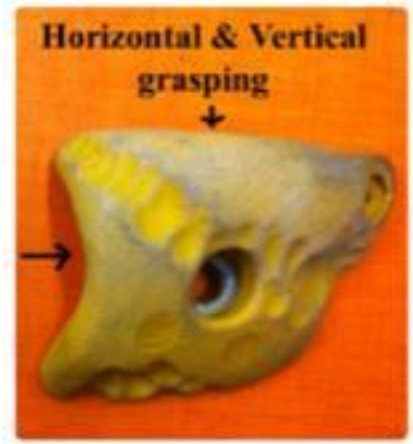
- 14 climbers
- 4 sessions
- Same 3 paths, climbed in random order at each session:
  - Horizontal holds (Face-wall induced)
  - Vertical holds (Side-wall induced)
  - Horizontal + Vertical holds (Neutral)

- And new path, *Transfer route*, at the last fourth session



Route Design

Horizontal	Vertical	Both
Face-wall	Side-wall	Neutral

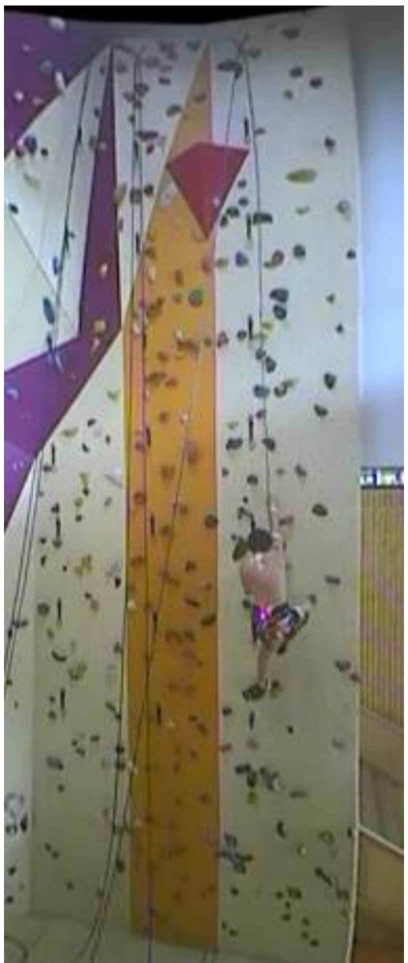


Common features:

- Set to 5c
- 10.3m high
- 20 hand-holds

Route Design

Horizontal	Vertical	Both
Face-wall	Side-wall	Neutral



Recorded signals
during climbers' activities

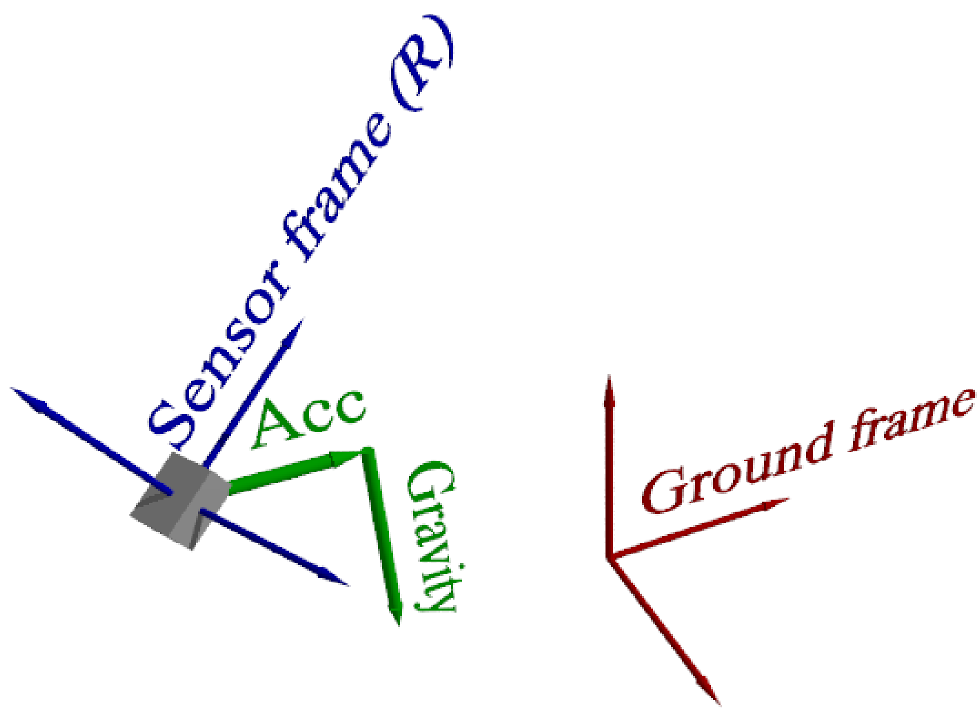
Inertial measurement unit

- MotionPod3, Movea, Grenoble, France
- For each of the 4 limbs and hip:
  - Accelerometer (Acc)
  - Angular speed (Gyr)
  - Magnetometer (Mag)
- Sensor positions:

Recorded signals

during climbers' activities

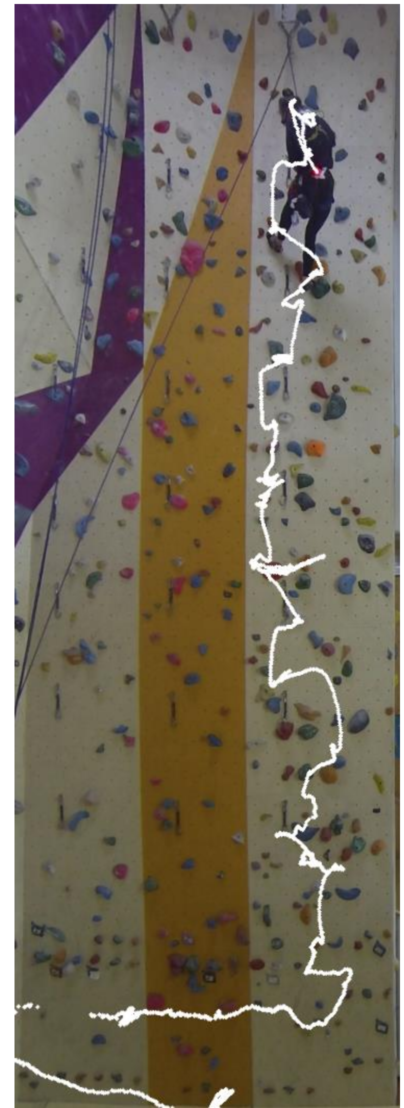
Transformed into 3D orientation
with complementary filters



Recorded signals

during climbers' activities

Videos for human annotation and possible future tracking



Measure of climbing smoothness: *Jerk*

Trajectory duration

$$J_x = \frac{T^5}{(\Delta x)^2} \int_0^T \left\| \frac{d^3 x}{dt^3}(s) \right\|^2 ds,$$

Pelvis position

Trajectory length

Variation of acceleration

The jerk

- is an indicator of climbing fluency
- has good correlation with climbing fluency/efficiency, but can not be linked to inter-limb coordination
  Seifert, L., Orth, D., Boulanger, J., Dovgalecs, V., Hérault, R., Davids, K.
  Climbing skill and complexity of climbing wall design: assessment of jerk as a novel indicator of performance fluency.
  Journal of applied biomechanics 30(5), 619–625 (2014)
- *does* fulfill *not* the need of an interpretable indicator
  (in terms of inter-limb coordination to help the performer)

Proposed alternative processing

- Looking for *inter-limb coordination patterns*
- Signal segmentation into
  4 high-level behavioral states

  Jérémie Boulanger, Ludovic Seifert, Romain Hérault, Jean-Francois Coeurjolly.
  Automatic sensor-based detection and classification of climbing activities,
  arXiv:1508.04153, in revision for IEEE Sensors Journal

- Extraction of 3D orientation statistics
  (geodesic mean and variance) for each state
  + state distribution
  + state transition probabilities
- Dimension reduction and clustering
- Comparison to jerk

Signal segmentation

Limb/hip level

- Using accelero and gyro signal with a CUSUM method, limb signals are segmented into 4 activities:
  - *Immobility*
    When a limb is detected as being immobile
  - *Exploration*
    All movements except the last one before traction. An example is the case when the climber is trying several holds before choosing the one he will be using for traction
  - *Change*
    The last movement before traction, or the final change in hold (or change in limb orientation on the same hold) before being used
  - *Use*
    When a limb is moving during traction

Signal segmentation

Full body level

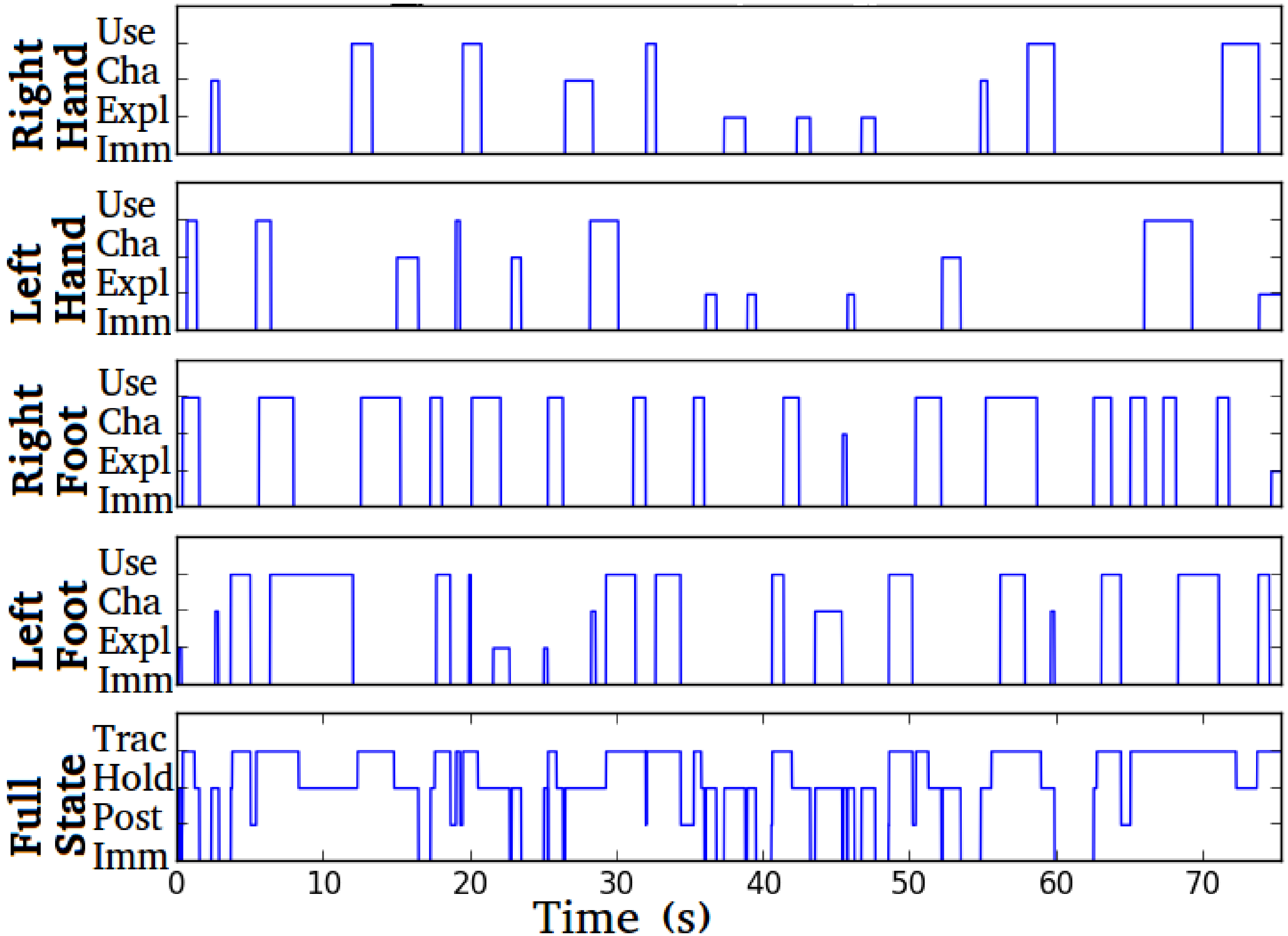
Using all the 4 limb + hip segmentations,
a full body state is computed:

- *Immobility*
  All limbs are immobile and the pelvis is immobile
- *Postural Regulation*
  All limbs are immobile and the pelvis is moving
- *Hold interaction*
  At least one limb is moving and the pelvis is immobile
- *Traction*
  At least one limb is moving and the pelvis is moving

Signal segmentation

Example

Segmentation on each limb + full-body state



Features extracted from signals

For each climb:

- 20 rotation means (4 states, 5 sensors, each in R^{3x3})
- 20 rotation variances (20 reals)
- State distribution (4 reals)
- State transition matrix (16 reals)

220 continuous features by climb,
with latent manifolds

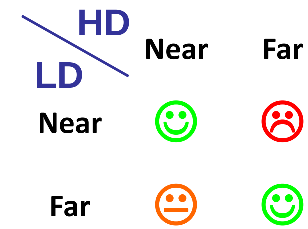
➔ **Weighted mixture of geodesic distances**

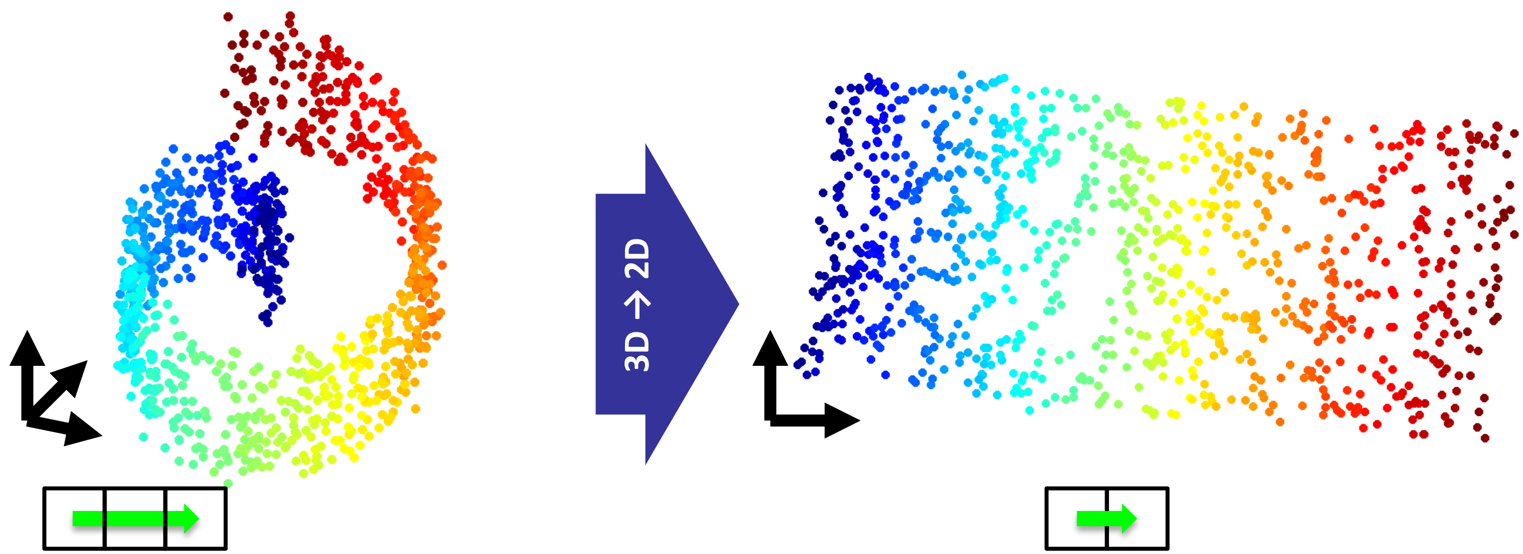
➔ **Dimensionality reduction (DR)**

Dimensionality reduction

(a.k.a. (NL)DR, manifold learning, embedding, projection, …)

- Aims at representing high-dimensional (HD) data in low-dimensional (LD) spaces, while preserving structure
- Can be
  - Linear/nonlinear
  - Parametric/non-parametric
  - Supervised/semi-supervised/unsupervised



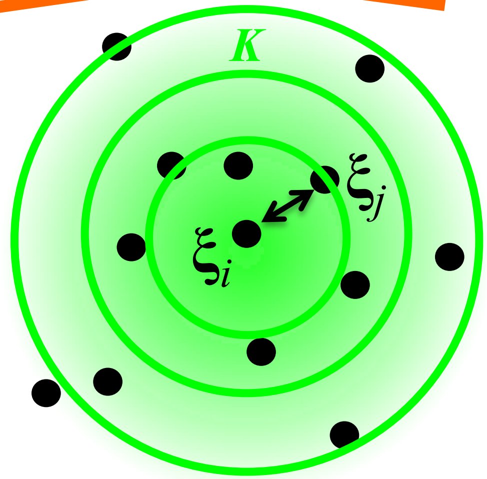


$\mathbf{\Xi} = [\boldsymbol{\xi}_i]_{1 \leq i \leq N}$ $\quad$ $\mathbf{X} = [\mathbf{x}_i]_{1 \leq i \leq N}$

Student *t*-distributed

Stochastic neighbour embedding

1. Choose size K of neighbourhoods in HD space



$$\delta_{ij} = \|\boldsymbol{\xi}_i - \boldsymbol{\xi}_j\|_2$$

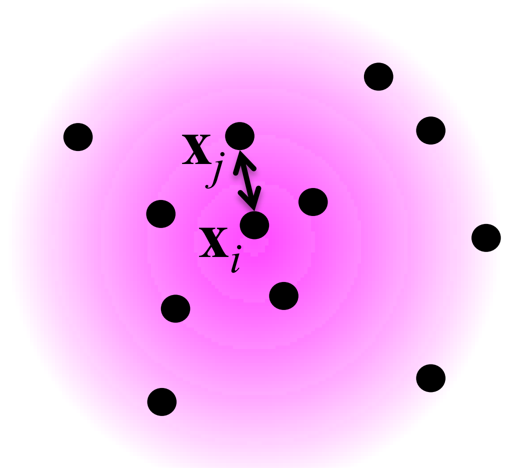
NeRV

Ms. JSE

mixtures of

5. Minimise KL divergences (for all *i*)

$$D_{\mathrm{KL}}(\boldsymbol{\sigma}_i \| \mathbf{s}_i) = \sum_{j=1}^{N} \sigma_{ij} \log(\sigma_{ij}/s_{ij})$$



$$d_{ij} = \|\mathbf{x}_i - \mathbf{x}_j\|_2$$

2. Convert hard neighbourhoods into soft ones

$$\sigma_{ij} = \frac{\exp(-\delta_{ij}^2/(2\lambda_i^2))}{\sum_{k,k\neq i} \exp(-\delta_{ik}^2/(2\lambda_i^2))}$$

3. Adjust all bandwidths (same entropies for all *i*)

$$\log(K) = -\sum_{j=1}^{N} \sigma_{ij} \log \sigma_{ij}$$

4. Define soft neighbourhoods in LD space

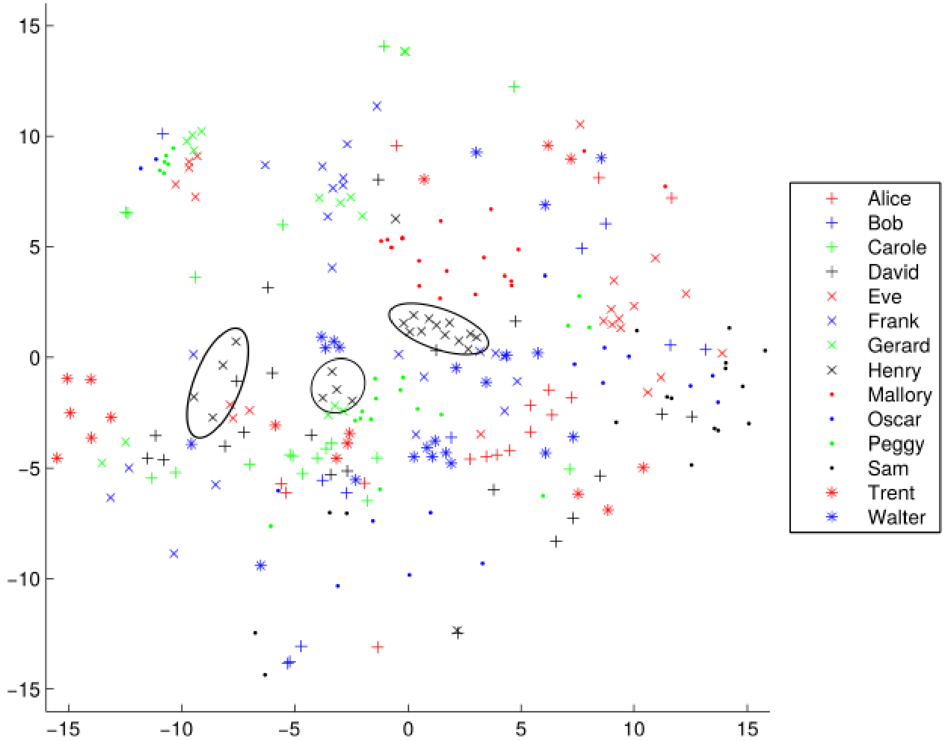
$$s_{ij} = \frac{\exp(-d_{ij}^2/2)}{\sum_{k,k\neq i} \exp(-d_{ik}^2/2)}$$

(with unit bandwidths)

$$s_{ij} = \frac{(1+d_{ij}^2)^{-1}}{\sum_{k,l,k\neq l}(1+d_{kl}^2)^{-1}}$$

Results

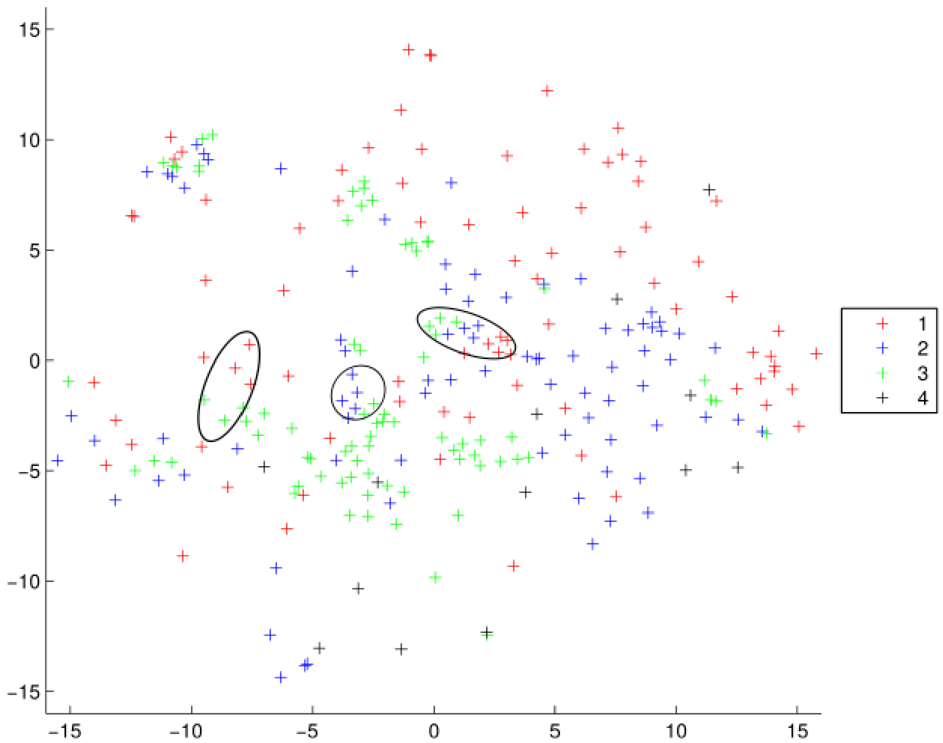
DR with Ms.JSE



Projection with climber labelling

Results

DR with Ms.JSE



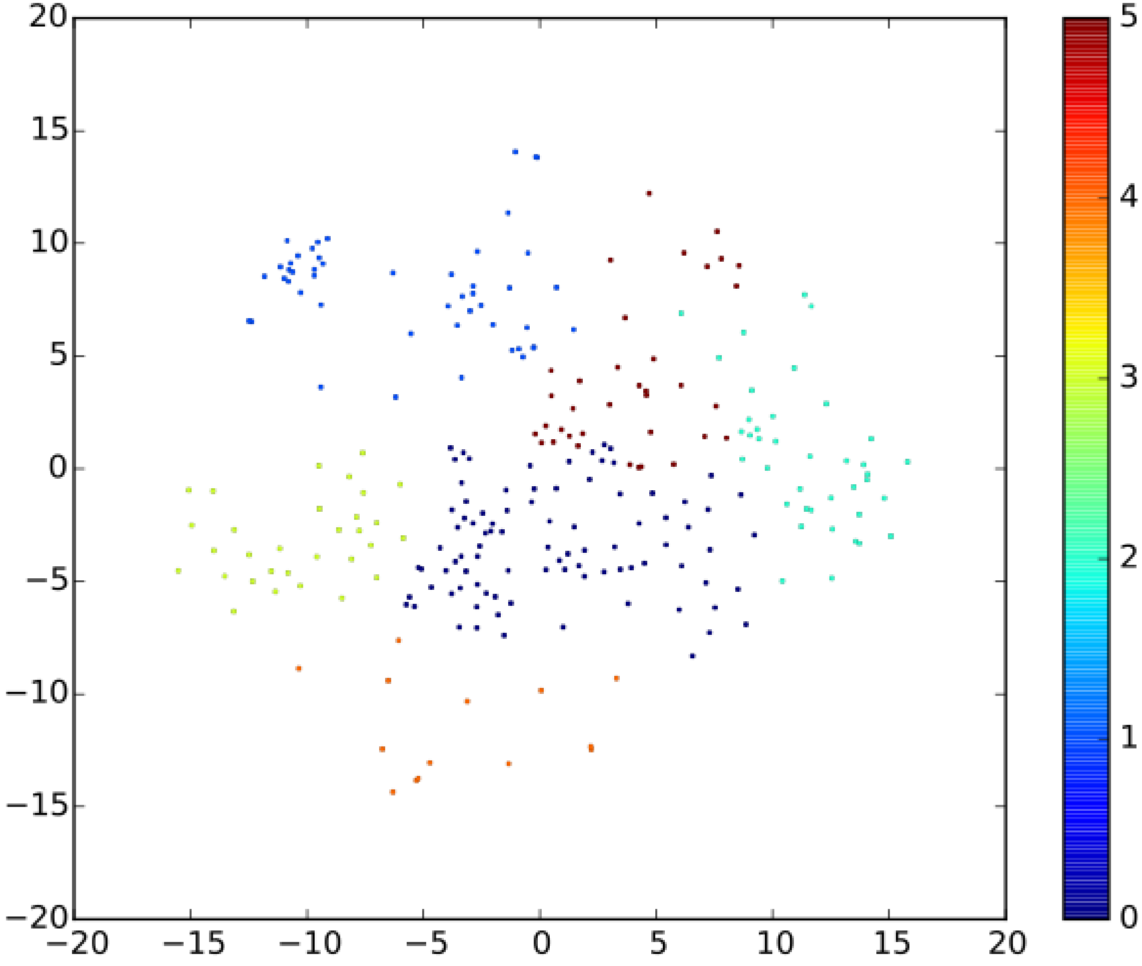
Same projection with path labelling

Observations

- For a particular climber, multiple clusters appears
- Clusters are not necessarily linked to a path effect (*Henry* example)
- **Are climbers' clusters linked to a time effect (learning effect) ?**

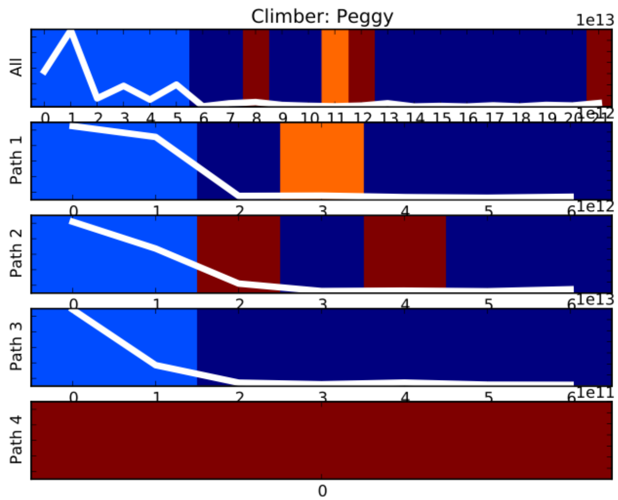
Results

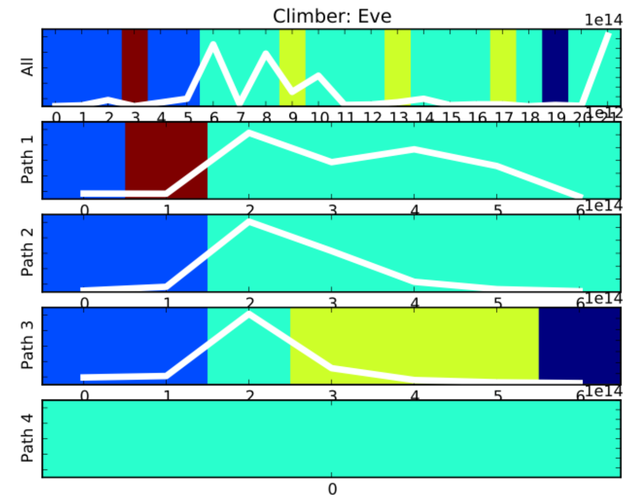
Hierarchical clustering (BIC: 6 clusters)

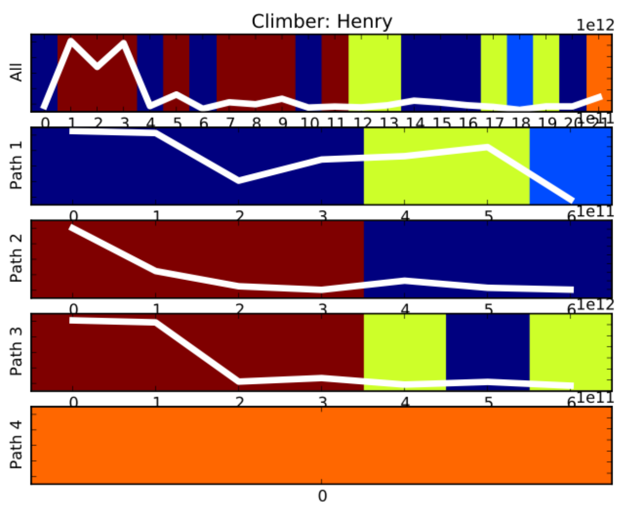


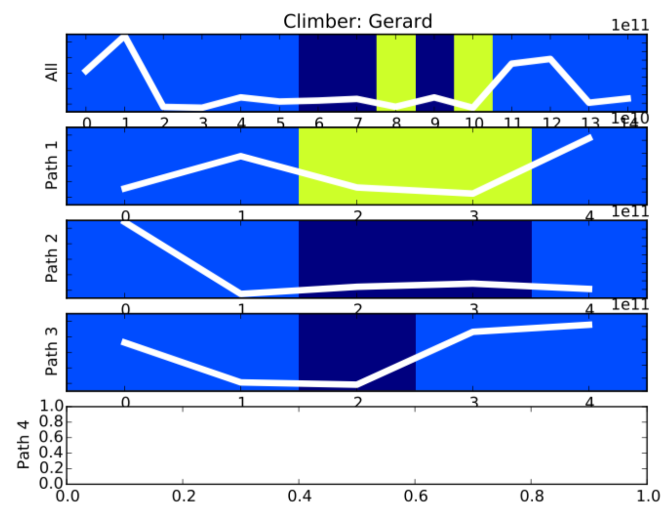
Results

Temporal representation of clusters









Colours: clusters; white curves: jerk (the lower the jerk, the better the fluency)

Conclusions

– The clusters are correlated to fluency
– Compared to the jerk, a cluster can be linked to 3D orientations (one orientation per high-level state)
  ➔ **Improved interpretability**

Perspectives

– An example per climb
  ➔ an example per signal segment
– Looking at patterns on 3 first paths that lead to better performance on the 4th path (transfer learning)