Unsupervised learning of simultaneous motor primitives through imitation

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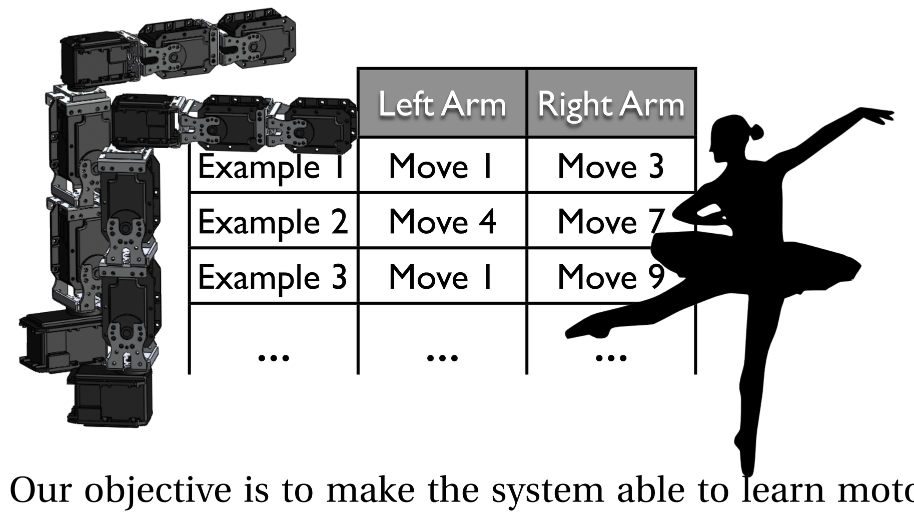
Learning skills in a life long perspective happens gradually, in a cumulative manner and with increasing complexity. It is therefore required to be able to decompose complex skills as combinations of simpler ones.

Motor primitives have been introduced as a form of elementary building blocks for more complex motor control and skills, that can both be found in biological and robotic systems, and can be either innate or acquired [1]. Combinations of skills may take different form, such as using different basic skills in **sequence**, in **alternative** contextual situations, or **simultaneously** with eventual competition or subordination.

Methods for discovery and learning of such motor primitives, from sequential and alternative (expert-like) combinations [2, 3, 4, 5] have already been developed in robotic contexts. However, these works does not allow a robotic system to learn simultaneously active primitives from demonstrations, which is the problem we are interested in.

1 . Experimental setup



	Left Arm	Right Arm
Example 1	Move 1	Move 3
Example 2	Move 4	Move 7
Example 3	Move 1	Move 9
...	...	...

We are interested in learning motor primitives that are happening simultaneously in demonstrations.

Such a situation is present in dancing movements: **choregraphies** are composed of elementary postures and transitions that happen independently on different limbs.

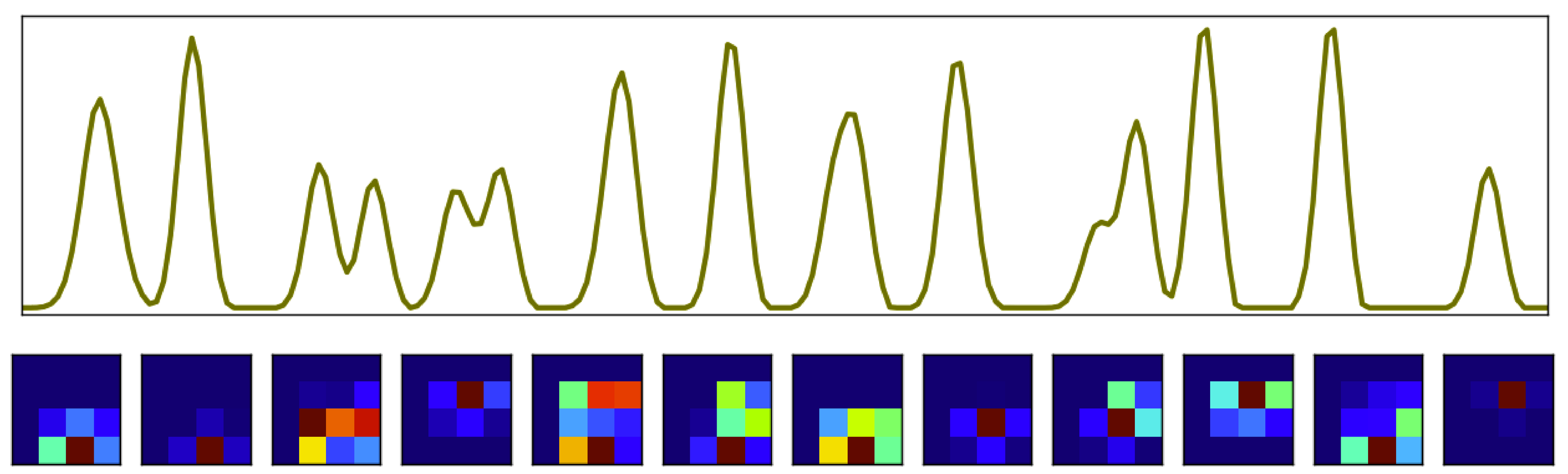
We consider a simple **robotic dancer**, composed of two 6-DOFs arms, and two sets of movements, associated respectively to left and right arm.
We provide the system with demonstrations each composed of one left arm movement and one right arm movement, executed simultaneously.

Our objective is to make the system able to learn motor primitives, and use them to represent demonstrations as pairs of learned primitives, instead of learning each particular demonstration in a flat manner. For a sufficient number or primitives, the former achieves better **compression** and allow better re-usability than the latter.

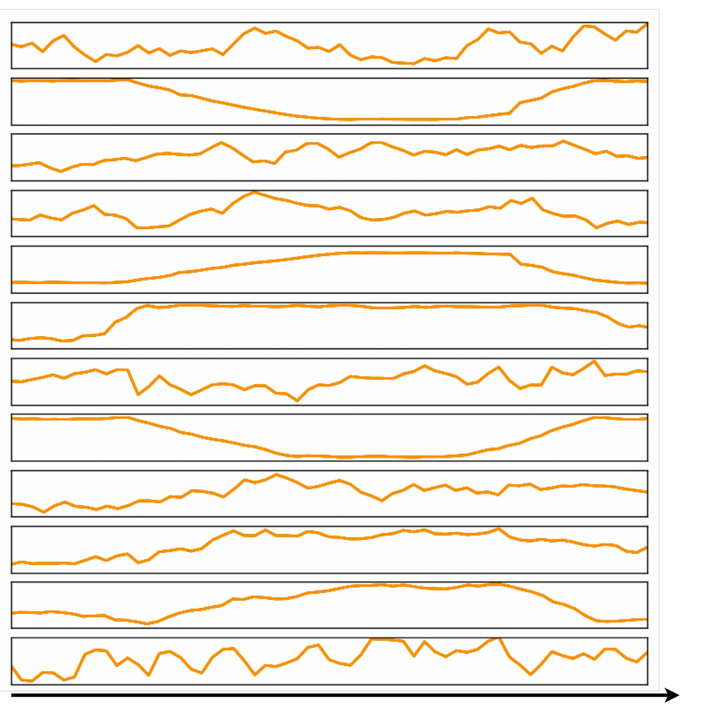
2 . Data acquisition and representation

The robotic system is provided with **kinesthetic demonstratrations**, from which motor positions are recorded. Each demonstration is then represented as a sequence of motor position.

Several alternative histogram-like transformations of the data are likely to be used: **position histograms**, **velocity histograms**, **joint position-velocity histograms**.



Top: histogram of positions, Bottom: hitogram of joint positions and velocities



Sequence of motor positions

3 . Discovering motor primitives by Non-Negative Matrix Factorization

Non-negative matrix factorization (NMF) is an efficient technique to discover non-negative components of a signal in an unsupervised scenario.

NMF takes as input a data matrix X of dimension $n \times p$ where n is the number of demonstrations, and p the dimension of our features space (here the sum of resolution of histograms).
Given a parameter k, NMF yields two non-negative matrices H and W, of dimension respectively $n \times k$ and $k \times p$.

$$X \simeq H \cdot W$$

Lines of W, called **atoms**, provide a basis of prototypical elements of the data, that is to say some kind of motor primitives. The coefficients of H are then interpreted as the degree of activity of those primitives in the demonstrations.

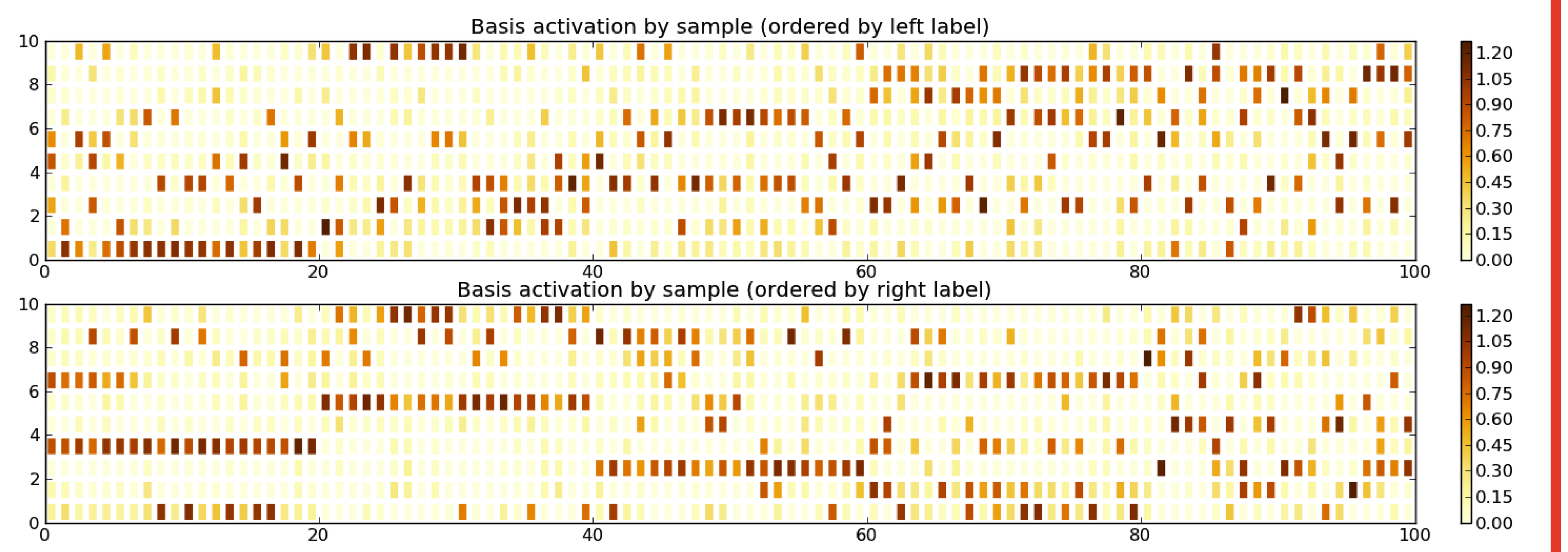
4 . Preliminary results

In the presented experiment, 10 different movements (5 for each arm) are considered. Each one of the 100 demonstrations is a combination of two movements: one on each arm. In the following qualitative results the system is given the total number of primitives and achieves compression of the histogram data as the superposition of 10 primitives (which are atoms from NMF).

Activity coefficients of the learned motor primitives are displayed below. Lines correspond to primitives, columns to demonstrations.

Both graphics represent the same data, but demonstrations are ordered differently. The first one is ordered according to left movement label, the second one by right movement labels. Thus in the top graph, groups of 10 columns contains the same left arm movement.

Horizontal blocks of dark coefficients corresponding to a given movement indicates that one learned primitive is describing well this movement.



5 . Conclusion

This preliminary experiment is to take as a proof of concept for the use of histogram like representations coupled with matrix factorization to discover simultaneous motor primitives.

However, the presented results only are qualitative. In order to obtain quantitative evaluation of this approach, it is important to evaluate the system on some precise task. The authors are currently studying such an evaluation on both a classification task, and joint motor-learning.

References

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