

Key point selection and clustering of swimmer coordination through Sparse Fisher-EM

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Abstract. To answer the existence of optimal swimmer learning/teaching strategies, this work introduces a two-level clustering in order to analyze temporal dynamics of motor learning in breaststroke swimming. Each level have been performed through Sparse Fisher-EM, a unsupervised framework which can be applied efficiently on large and correlated datasets. The induced sparsity selects key points of the coordination phase without any prior knowledge.

Keywords: Clustering, Variable selection, Temporal dynamics of motor learning, Sparse Fisher-EM

1 Introduction

The development of Dynamical Systems Theory [1] in understanding motor learning has increased the interest of sports scientists in focusing on temporal dynamics of human motor behavior. Broadly speaking, the investigation of motor learning traditionally implied the assessment of both a pre-learning behavior and a post-learning behavior [2], but the deep understanding of the process of motor learning requires a continuous and long term assessment of the behavior rather than previous traditional discrete assessments. Indeed, such a continuous assessment of behavioral data enables to investigate the nature of the learning process and might highlight the paramount role played by motor variability in optimizing learning [2].

From a theoretical point of view, motor learning is viewed as a process involving active exploration of a so-called perceptual-motor workspace which is learner dependent and defines all the motor possibilities available to him. Few studies have already highlighted this exploratory behavior during learning a ski

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simulator task [3] or a soccer kicking task [4]. These authors showed that learners exhibited different qualitative motor organizations during skill acquisition. Nevertheless, these princeps studies mainly focused on a static analysis, defining the different behaviors exhibited during learning. As a matter of fact, a major interest in the field of motor learning resides in the definition of different pathways of learning, namely different possible learning strategies [5]. Such an interest in investigating the existence of different "routes of learning" needs to focus on a dynamical analysis, namely the analysis of the successions of different behaviors. An unanswered question to date concerns the existence of optimal learning strategies (i.e. strategies that would appear more effective). Thus, the discovery of optimal learning strategies could have a huge impact on the pedagogical approach of practitioners.

The article will describe at first the context of the research insisting on the way data have been collected, what are the long-term expectations in sport science field and what are the short term locks in machine learning field. Then we will give a brief view of the Fisher-EM algorithm [6] which is an unsupervised learning method used in this work. In the end, preliminary results of the data clustering will be analyzed.

2 Context of the Research

2.1 Previous work

In breaststroke swimming, achieving high performance requires a particular management of both arm and leg movements, in order to maximize propulsive effectiveness and optimize the glide and recovery times [7]. Therefore, expertise in breaststroke is defined by adopting a precise coordination pattern between arms and legs (i.e. a specific spatial and temporal relationship between elbow and knee oscillations). Indeed, when knees are flexing, elbows should be fully extended (180°), whereas knees should be fully extended (180°) when elbows are flexing, in order to ensure a hydrodynamic position of the non-propulsive limbs when the first pair of limbs is actually propulsive [8, 9].

Based on this context, the breaststroke swimming task was deemed as suitable in investigating the dynamics of learning, mainly as it implies at a macroscopic scale the acquisition of an expert arm-leg coordination that can be easily assessed. However, the investigation of potential differences in learning strategies required a continuous movement assessment. In that sense, the use of motion sensors allowed a fast, accurate and cycle per cycle movement assessment.

Previously, two analysis methods were used in the cycle per cycle study of motor learning. A previous study [3] highlighted the unstable character of the transition between novice and expert, but not really an exploration as experimental setup assumes that novices left their initial behavior to adopt the expert one. Therefore, no search strategies were really investigated. In order to overcome this issue, [4] used a cluster analysis (Hierarchical Cluster Analysis) in their experiment on football kicking and highlighted different behaviors used

by each participant during learning to kick a ball. The authors therefore linked these different behaviors to a search strategy. However, the cluster analysis was performed individually and there was no comparison done between the learners (e.g. did they use identical behaviors?), it implied only few participants (i.e. four learners), it was performed only with 120 kicks per learner (i.e. 10 kicks per session during 12 sessions) and like the previous study of [3] it only defined the behavior from a static point of view (i.e. defining what behavior was adopted).

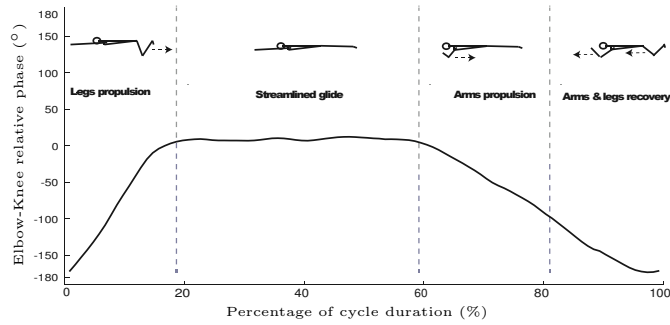


Fig. 1: A typical continuous relative phase between the knee and the elbow

2.2 Data collection

For this study, 26 novices were involved in 16 lessons of breaststroke swimming, with two sessions per week for a total duration of two months. The general goal of learning for all the 26 swimmers was to increase the distance per stroke, while maintaining the speed stable. Then the 26 learners were divided into four different groups, each group receiving a different instruction during the learning process: 1) Control group (N=7): This group received only the general goal of learning, increase the distance per stroke 2) Analogy group (N=7): In addition to the general goal of learning, this group received a single additional instruction: "glide two seconds with your arms outstretched" 3) Pacer group (N=6): In addition to the general goal of learning, this group had to follow an auditory metronome trying to perform one cycle every single auditory signal. The frequency of the metronome was decreased every two sessions, in order to promote a decrease in the stroke frequency of the learners that should lead to an increase in the distance per stroke 4) Prescription group (N=6): In addition to the general goal of learning, this group received multiple additional instructions: "keep your arms outstretched forward when you extend your legs; then glide with your arms and legs outstretched; then keep your legs outstretched when you flex your arms; recover both arms and legs together". These different instructions were supposed to have a specific impact on the learning strategies of the learners.

Each learner performed 10 trials of 25-m swim during each session, with 1 x 25-m consisting approximatively in 8 recorded cycles (one cycle correspond to the period between two successive maximal knee flexion). During every learning session, all learners were equipped with small motion sensors on both arms and legs (3-D gyroscopes, 3-D magnetometers, 3-D accelerometers) including a data logger and recording elbow and knee angles at a frequency of 200 Hz. Following the literature in coordination dynamics [1], the coordination between elbow and knee was defined by the continuous relative phase between these two oscillators [10], considering elbows and knees as acting like individual pendulums [7]. A value of relative phase close to -180° or 180° defined an anti-phase relationship (i.e. opposite movements of knee and elbow) while a value close to 0° defined an in-phase mode of coordination (i.e. identical movements of knee and elbow); here, each cycle will be described by a time series of 100 normalized values of continuous relative phase between the knee and the elbow (Fig. 1).

To sum-up, we have recorded 4160 trials ($26 \text{ swimmers} \times 16 \text{ sessions} \times 10 \text{ trials}$) and there is an average of 8 cycles per trials. Thus, the dataset is composed by 33280 cycles, each cycle is represented by 100 continuous relative phase samples.

2.3 Study expectations

From a sport sciences point of view, the specific aims of the study were twofold: – Assessing the dynamics of learning: In other words, the aim was to assess not only the different behaviors used during learning but also the transitions between these behaviors, that is the potential search strategy exhibited by learners (e.g. they used preferably behavior n° 1 then n° 4, then n° 3 ...). – Assessing the impact of different learning conditions on the dynamics of learning: In other words, the aim was to investigate the possible existence of different behaviors exhibited by the learners regarding their learning condition, as well as the possible existence of different search strategy exhibited by the different groups.

A last point in this experiment was the possibility to transfer the results of the analysis towards practical application or guidelines for teachers. From a pedagogical point of view, it appeared difficult to teach novice swimmers by giving instruction on the arm-leg coordination during all the cycle and the definition of key points within the entire cycle reflects a paramount aspect for teaching. Indeed, a strong literature in sports pedagogy highlights the role played by attentional focalization during motor learning, as a focalization on a key point of the swimming cycle may be highly beneficial in seeking to reorganize the entire arm-leg coordination [11]. A third aim of this study was then to define highly discriminative key points within the swimming cycle and that might be the target of the instruction in order to orient the attention of learners.

From a machine learning point of view, there are two locks to tackle: 1) Each cycle is described by 100 features which are highly correlated due to the fact that they are samples of the relative phase which is a continuous time signal. Nevertheless, we don't want to bias the study by preprocessing the data, a transformation like filters, wavelet transform or sample selection that will embedded

our a priori knowledge. 2) The number of cycles are not equal on all the trials, that is why a trial can not be directly described by a fixed number of features.

Those two problems were address by 1) using a clustering by Fisher-EM [6] that also performs dimension reduction and features selection, 2) doing a two stage clustering: on cycles then on trials; a procedure similar to *Bags of words* to have fixed size features on trial.

3 Fisher-EM Algorithm

A clustering can be derived from a mixture of Gaussians generative model. A Gaussian, which is parameterized by a covariance matrix and a mean in the observation space, represents a cluster. An observation is labeled according to its ownership (likelihood ratio) to each Gaussian. Knowing the number of clusters, the mixture and Gaussian parameters are learned from the observation data through an Expectation-Maximization (EM) algorithm.

The Fisher-EM algorithm [6] is based on the same principles but the mixture of Gaussians does not lie directly on the observation space but on a lower dimension latent space. This latent space is chosen to maximize the Fisher criterion between clusters and thus be discriminative and its dimension is bounded by the number of clusters. This reduction of dimension leads to more efficient computation on medium to large datasets (here 33280 examples by 100 features) as operations can be held in the smaller latent space.

3.1 Generative Model

We consider that the n observations y_1, y_2, \dots, y_n are realizations of a random vector $Y \in \mathbb{R}^p$. We want to cluster these observations into K groups. For each observation y_i , a variable $z_i \in Z = \{1, \dots, K\}$ indicates which cluster its belong to. This clustering will be decided upon a generative model, namely a mixture of K Gaussians which lies in a discriminative latent space $X \in \mathbb{R}^d$ where $d \leq K - 1$.

This latent space is linked to the observation space through a linear transformation,

$$Y = UX + \epsilon \quad , \quad (1)$$

where $U \in \mathbb{R}^{p \times d}$ and $U^t U = Id(d)$ where $Id(d)$ is the identity matrix of size d , i.e. U is an orthogonal matrix and ϵ non-discriminative noise.

Let be $W = [U, V] \in \mathbb{R}^{p \times p}$ such that $W^t W = Id(p)$. V is the orthogonal complement of U . Thus, a projection $U^t y$ of an observation y from space Y of dimension p , lies on the latent discriminative subspace X of dimension d and the projection $V^t y_i$ lies on the non-discriminative complement subspace of dimension $p - d$.

Conditionally to $Z = k$, random variables X and Y are assumed to be Gaussian, $X_{|Z=k} \sim \mathcal{N}(\mu_k, \Sigma_k)$, and $Y_{|Z=k} \sim \mathcal{N}(m_k, S_k)$, where $\mu_k \in \mathbb{R}^d$, $\Sigma_k \in \mathbb{R}^{d \times d}$, $m_k \in \mathbb{R}^p$ and $S_k \in \mathbb{R}^{p \times p}$.

With the help of equation 1, we can deduce parameters of the distribution $Y_{|Z=k}$ in the observation space from the parameters of the distribution $X_{|Z=k}$

in the latent space, $m_k = U\mu_k$ and $S_k = U\Sigma_kU^t + \Psi$, where $\Psi \in \mathbb{R}^{p \times p}$ is the covariance matrix of ϵ which is assumed to follow a 0-centered Gaussian distribution. To ensure that ϵ represents non-discriminative noise, we will impose that the covariance of ϵ , Ψ , projected into the discriminative space is null, i.e. $U\Psi U^t = \mathbf{0}(d)$, and that Ψ projected into the non-discriminative subspace is diagonal, i.e. $V\Psi V^t = \beta Id(p-d)$. Thus,

$$W^t S_k W = \begin{pmatrix} \Sigma_k & \mathbf{0} \\ \mathbf{0} & \beta_k Id(p-d) \end{pmatrix}. \quad (2)$$

All the Gaussian distributions are mixed together, the density of the generative model is given by $f(y) = \sum_{k=1}^K \pi_k \phi(y; m_k, S_k)$ where π_k are mixing proportion and m_k, S_k are deduced from $\{U, \beta, \mu_k, \Sigma_k\}$.

Finally, the model is parameterized by: $-U$ the projection from discriminative subspace to observation space, $-\beta_k$ variance of ϵ in the non-discriminative subspace, $-\pi_k$ the mixing parameter, $-$ and Gaussian parameter $\{\mu_k, \Sigma_k\}$, where the 3 last parameters are repeated by the number of Gaussians.

Model variations, that lead to reduced numbers of parameters, can be achieved by enforcing shared covariances β and/or Σ between Gaussians, diagonalization of the covariance Σ without or with constant diagonal, and combination of these enforcements.

3.2 Parameter estimation

The iterative Expectation-Maximization (EM) algorithm can be extended by a Fisher Step (*F-Step*) in-between the *E-Step* and the *M-Step* where the latent discriminative subspace is computed [6]. The Fisher criterion computed at the *F-Step* is used as a stopping criterion. Convergences properties can be found in [12].

E-Step In this step, for each observation i , its posterior probability to each cluster k is computed by

$$o_{ik} \leftarrow \frac{\pi_k \phi(y_i, \hat{\theta}_k)}{\sum_{l=1}^K \pi_l \phi(y_i, \hat{\theta}_l)},$$

where $\hat{\theta}_k = \{U, \beta, \mu_k, \Sigma_k\}$. From these probabilities, each observation can be given to a cluster by $z_i = \arg \max_k o_{ik}$.

F-Step The projection matrix U is computed such that Fisher's criterion is maximized in the latent space,

$$U \leftarrow \underset{U}{\arg \max} \underset{w.r.t.}{\text{trace}} \left((U^t S U)^{-1} U^t S_B U \right), \quad U^t U = Id(d)$$

where S is the variance of the whole dataset and $S_B = \frac{1}{n} \sum_{k=1}^K n_k (m_k - \bar{y})(m_k - \bar{y})^t$ where $n_k = \sum_i o_{ik}$ and \bar{y} the mean of the dataset.

M-Step Knowing the posterior probabilities o_{ik} and the projection matrix U , we compute the new Gaussian parameters by maximizing the likelihood of the observations,

$$\hat{\pi}_k \leftarrow \frac{n_k}{n}, \quad \hat{\mu}_k \leftarrow \frac{1}{n_k} \sum_{i=1}^n o_{ik} U^t y_i, \quad \hat{\Sigma}_k \leftarrow U^t C_k U, \quad \hat{\beta}_k \leftarrow \frac{\text{trace}(C_k) - \sum_{j=1}^d u_j^t C_k u_j}{p - d},$$

where u_j is the j -th column of U and $C_k = \frac{1}{n_k} \sum_{i=1}^n o_{ik} (y_i - m_k)(y_i - m_k)^t$ the empirical covariance matrix of the cluster k .

3.3 Sparse version

Yet, the use of latent space introduces dimension reduction and computation efficiency. Nevertheless the back-projection from the latent space to the observation space can involve all the original features. To do feature selection, the projection matrix U has to be sparse. [13] proposed 3 methods to enforce sparsity: 1) After a standard F-step, compute a sparse approximation of U independently of the Fisher criterion, 2) Compute the projection with a modified Fisher criterion with a L_1 penalty on U , 3) Compute U from the Fisher criterion using a penalized SVD algorithm.

4 Application to swimmer coordination

The clustering is done in two steps: 1) A clustering on cycle data. Here an observation is just one swimming cycle. This clustering has two purposes, a) give a label to each cycle b) select which phase samples over the 100 are informative through sparsity. 2) A clustering on trials. Each trial can be described now by a sequence of cycle labels learned at the first step. Features for this clustering consist in the transition matrix of the sequence with its diagonal put to zero. The number of cluster is chosen by analysis of the Bayesian information criterion (BIC).

For the first clustering level, analysis of the BIC (Tab. 1) highlights the existence of 11 clusters within the whole set of data. The mean coordination of these clusters are represented at Figure 2a. This result advocates for qualitative reorganizations of motor behavior during motor learning, as each learner visited between 9 and 11 different clusters during their sessions. For instance, the mean and standard deviation of one cluster (n°8) is presented in Figure 2b.

In order to differentiate the effect of the different instructions on the learning process, Table 2 shows the distribution of each emerging cluster across the different learning conditions. Interestingly, the use of different additional instructions led to the exhibition of different preferred patterns of coordination. For instance, the group who received an analogy exhibited preferably clusters 3, 7, 8 and 9, whereas clusters 2, 4 and 10 were inhibited. In the meantime, the use of the prescriptive instruction preferably led to the use of cluster 5 and inhibited the use of clusters 2, 6 and 10. This result is a key point of the experiment, validating

the possibility of guiding the exploration during learning and by extension the result of the learning process with using different types of instructions during the practice.

On Figure 2c, we have superimposed a typical coordination curve and, in gray bars, the back-projection of latent space into observation space to see induced sparsity from the first level. The height of a bar at a feature $i \in [1 \dots p]$ is proportional to $\sum_{j=1}^d |U_{ij}|$. A null value shows that the corresponding feature is not involved in the projection to the latent space, i.e. it is not selected by the F-Step or it is squeezed by the sparsity; therefore it can be considered not relevant to build the clusters. Interestingly, only key points of the movement have high values, thus the Fisher-Em algorithm is able to select key points without any prior knowledge.

The second level of cluster analysis, based on the transition matrix during each trial showed the existence of six different clusters. More specifically, Figure 3 highlights the preferred transitions exhibited by each emerging cluster. Interestingly, the group who showed the highest number of preferred transition (i.e. cluster 6) was associated with the learning group that did not receive any instruction. In that sense, this second level of cluster analysis allowed to highlight the use of temporary additional information during learning in order to modify the learning search strategy, namely by impacting the preferred transitions.

5 Perspectives

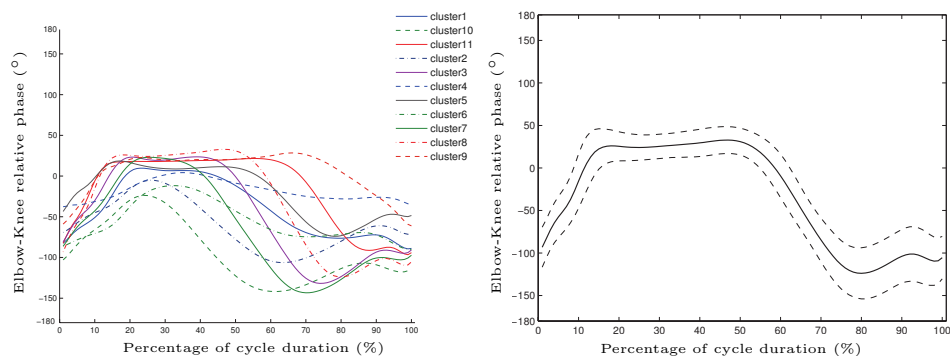
These preliminary experiments show that we can apply efficiently the Fisher-EM clustering on highly correlated features. Interestingly, the induced sparsity corresponds to key points of the coordination phase. Now, a qualitative work needs to be undertaken to qualify clusters of trials in term of learning condition and learning dynamics.

Table 1: Analysis of the BIC for the first level showing a plateau at 11 clusters

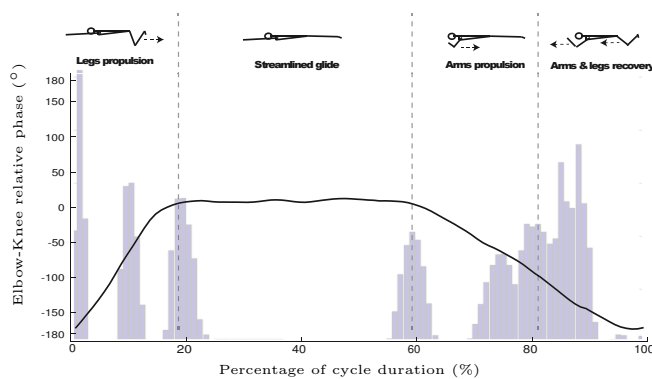
Number of clusters	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
BIC value ($\times 10^7$)	-1.23	-1.21	-1.18	-1.18	-1.15	-1.14	-1.13	-1.11	-1.08	-1.04	-1.05	-1.05	-1.07	-1.04	-1.04	-1.05

Table 2: Distribution (in %) of each cluster according to learning conditions

Cluster	Control	Analogy	Pacer	Prescription	Total	Cluster	Control	Analogy	Pacer	Prescription	Total
1	24.62	35.15	14.39	25.84	100	7	23.12	39.03	17.25	20.60	100
2	47.85	7.16	28.77	16.22	100	8	16.72	46.56	17.41	19.31	100
3	17.60	45.59	12.07	24.74	100	9	14.69	41.91	18.04	25.36	100
4	61.18	4.59	10.98	23.26	100	10	27.81	5.95	64.36	1.87	100
5	28.73	25.73	1.86	43.69	100	11	19.46	26.18	26.34	28.01	100
6	44.25	16.70	23.95	15.09	100						



a) Mean patterns of coordination for each cluster b) Mean pattern for cluster 8 (black line), standard deviation (dotted line)



c) A typical coordination and superimposed induced sparsity

Fig. 2: First clustering level

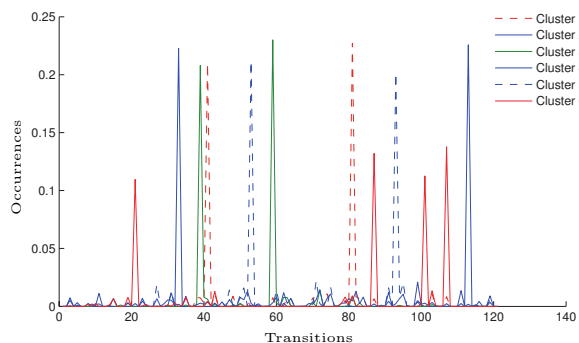


Fig. 3: Mean patterns of possible transitions within a trial for the 2nd level clustering, please note that there are $121 = 11 \times 11$ possible transitions as there is 11 clusters at first level

References

1. Scott Kelso, J.: *Dynamic Patterns: the self-organization of brain and behavior*. MIT Press (1995)
2. Müller, H., Sternad, D.: Decomposition of variability in the execution of goal-oriented tasks: Three components of skill improvement. *Journal of Experimental Psychology: Human Perception and Performance* **30**(1) (2004) 212–233
3. Nourrit, D., Delignières, D., Caillou, N., Deschamps, T., Lauriot, B.: On discontinuities in motor learning: A longitudinal study of complex skill acquisition on a ski-simulator. *Journal of Motor Behavior* **35**(2) (2003) 151–170
4. Chow, J.Y., Davids, K., Button, C., Rein, R.: Dynamics of movement patterning in learning a discrete multiarticular action. *Motor Control* **12**(3) (2008) 219–240
5. Gel'fand, I.M., Tsetlin, M.L.: Some methods of control for complex systems. *Russian Mathematical Survey* **17** (1962) 95–116
6. Bouveyron, C., Brunet, C.: Simultaneous model-based clustering and visualization in the fisher discriminative subspace. *Statistics and Computing* **22**(1) (2012) 301–324
7. Seifert, L., Leblanc, H., Chollet, D., Delignières, D.: Inter-limb coordination in swimming: Effect of speed and skill level. *Human Movement Science* **29**(1) (2010) 103–113
8. Seifert, L., Chollet, D.: A new index of flat breaststroke propulsion: A comparison of elite men and women. *Journal of Sports Sciences* **23** (March 2005) 309–320
9. Tagaki, H.: Differences in stroke phases, arm-leg coordination and velocity fluctuation due to event, gender and performance level in breaststroke. *Sports Biomechanics* **3** (2004) 15–27
10. Hamill, J., Haddad, J.M., McDermott, W.J.: Issues in quantifying variability from a dynamical systems perspective. *Journal of Applied Biomechanics* **16** (2000) 407–418
11. Komar, J., Chow, J.Y., Chollet, D., Seifert, L.: Effect of analogy instruction on learning a complex motor skill. *Journal of Applied Sport Psychology* (in press)
12. Bouveyron, C., Brunet, C.: Theoretical and practical considerations on the convergence properties of the Fisher-EM algorithm. *J. Multivariate Analysis* **109** (2012) 29–41
13. Bouveyron, C., Brunet, C.: Discriminative variable selection for clustering with the sparse Fisher-EM algorithm. Technical report, <http://hal.archives-ouvertes.fr/hal-00685183>