Curiosity-driven Exploration of Skill Hierarchies

Sébastien Forestier
INRIA Bordeaux Sud-Ouest
Bordeaux, France
Email: sebastien.forestier@inria.fr

Pierre-Yves Oudeyer
INRIA Bordeaux Sud-Ouest
Bordeaux, France
Email: pierre-yves.oudeyer@inria.fr

***Abstract*—The abstract goes here.**

I. Introduction

The study of the control of manipulation actions in humans has revealed a modular representation of actions either in the cerebral cortex and in the spinal cord with compositionality: an infinite number of movements can be expressed through combination of simple primitives, and generalization: certain neurons (higher in the hierarchy) can represent actions independently of the effectors used [1].

The same idea holds for language expressiveness which is based on syntactic hierarchical combinations on a vocabulary, that open infinite semantic possibilities. Greenfield has also argued that this parallel between manipulation and language compositionality can be found in the human ontegenic development with combinatorial steps for manipulation and syntax acquired approximately at the same period and in the same order [2]. Also, the author explains that the development of the neural substrates for language and tool use could be an ontogenic homology as first of all the same neural computations for hierarchical combinations and their semantics should take place for both modalities, and furthermore experiments with Broca's and Wernicke's aphasics show that hierarchical organization for language and manipulation is linked. Broca's aphasics, who have less syntactic organization of speech were shown to also have problems of representation of the hierarchical organization of constructions with blocks, whereas Wernicke's aphasics, whose syntax is normal but speech semantics is impaired, succeed in representing such objects hierarchies.

Functional MRI experiments by Higuchi et al. have shown that the human's neural substrates for tool use and language is indeed shared in the dorsal BA44 Broca's area [3], which gives evidence for the similar neural computations used. They furthermore argue that these results supports the hypothesis that tool use have appeared first in primate evolution in F5 area, and then the language has developed in humans reusing part of tool use and manipulation neural substrates in human's Broca area, homolog of primate's F5.

Like a developing child, a developmental robot will have to incrementally explore skills that add up to the hierarchy of previously learned skills throughout its life, with a constraint being the cost and time of experimentation. We will seek to define curiosity-driven hierarchical learning architectures that could reuse the sensorimotor contingencies previously learned and to combine them to explore more efficiently new complex sensorimotor models.

A. Goal of the study

- Exploring in a structured hierarchy is more efficient than directly from M to S.
- Which task should I explore now ?
- How to choose between different means to explore a given space ?
- How can high-level tasks guide the exploration of lower-level ones ?
- How can the system cope with perturbations on some of the forward models ?

B. Related work

[4], [5].

Different computational models have the possibility to learn skill hierarchies. In finite environments represented by a factored Markov Decision Process [6], an intrinsic motivation towards actions maximizing Dynamic Bayesian Networks' structure has been shown to allow the learning of the environment's structure.

In continuous environments but with discrete actions, Metzen et al. [7] use the framework of options [8] to learn skill hierarchies. An intrinsic motivation rewards positively the novelty of the states encountered and negatively the prediction error of the learned skill model.

The model from Fabisch et al. [9] learns in a setting with a discrete task space (called contexts). It uses an intrinsic motivation for learning progress, and a Multi-Armed Bandit algorithm (D-UCB) to choose on which context the agent should train for. The Upper Confidence Bound algorithm chooses between contexts given their estimated learning progress and the uncertainty of these estimations by picking the context with the maximum upper confidence bound. In other words, it maximizes the expected reward plus something related to the uncertainty associated with it, selecting either contexts with certain high rewards or ones with uncertain poor reward. This algorithm embeds directly a solution the exploration-exploitation trade-off problem as it represents the exploitation of knowledge by the expected progress and the exploration of other solutions by the uncertainty bonus. This algorithm supposes a stationary learning progress on each context so the authors use an adaptation (D-UCB, [10]) to encompass non-stationary learning progress.

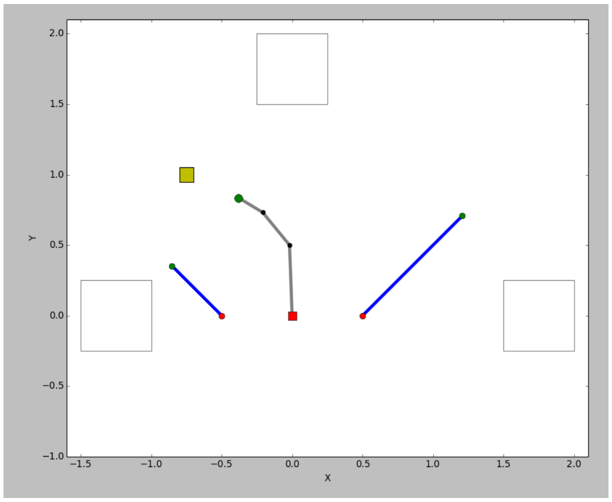


Fig. 1. Play Environment

In a fully continuous setting, Mugan et al. [11] have developed an algorithm that first learns a qualitative representation of environment states and actions in order to then learn the structure of Dynamic Bayesian Networks representing the temporal contingencies of those states and actions. In order to choose which action to practice, the authors use the IAC [12] where the agent is intrinsically motivated to choose actions that are estimated to yield high prediction error progress.

Here, we will rely more specifically on the SAGG-RIAC architecture [13]. This architecture learns a single mapping between continuous motor and sensori (or task) spaces with a competence-based intrinsic motivation. In our hierarchy of sensorimotor models, each model will be explored using the SAGG-RIAC procedure, but it could be replaced by another one without changing the mechanisms to learn the hierarchy that will be assessed.

II. Environment

We simulate a 2D robotic arm using tools to push an object in its environment with the help of an experienced pair. The agent can either try to push objects into boxes on its own, or produce a vocal signal that might engage the experienced pair to help move the object to reach a box.

The environment is designed such that each box is more easily reached by one different mean. Box 1 is best reached with the small stick, box 2 with the long stick, and box 3 with the small stick and the help of the pair.

An iteration consists of the evaluation of a motor command given by the agent which gives sensory information back to him, and finally the environment is resetted to its intial state.

The next sections precisely describe the different items of the environment and their interactions. See Fig. 1 for an exemple of the state of the environment.

A. Robotic arm

The 2D robotic arm has 3 joints plus a gripper located at the end-effector. Each joint can rotate from $-\pi\ rad$ to $\pi\ rad$ around its initial position, mapped to a standard interval of $[-1, 1]$. The length of the 3 parts of the arm are 0.5, 0.3 and 0.2 so the total length of the arm is 1 unit. The initial position of the arm is vertical with each joint at $0\ rad$ and its base is fixed at position $[0, 0]$. The gripper g has 2 possible positions: *open* ($g \geq 0$) and *closed* ($g < 0$) and its initial position is *open* (with $g = 0$). The robotic arm thus has 4 degrees of freedom represented by a vector in $[-1, 1]^4$. A trajectory of the arm will be represented as a sequence of such vectors.

B. Objects and tools

A yellow squared object can be moved into one of the 3 fixed squared boxes. The initial position of the yellow square is $(-0.75, 1)$ and is thus unreachable with directly with the gripper. One of 2 sticks can be grasped in order to reach the object. A small stick of length 0.5 is located on the left of the arm, with initial position $(-0.5, 0)$ and initial angle $\frac{3\pi}{4}$ from the horizontal line. A long stick of length $1.$ is located on the right of the arm, with initial position $(0.5, 0)$ and initial angle $\frac{\pi}{4}$ from the horizontal line as in Fig. 1.

If the gripper closes near the end of one of the sticks (closer than 0.2), it is considered grasped and will follow the gripper's position and the angle (with some noise) of the arm's last part until the gripper opens. The grasped stick will have its angle equal to arm's last part plus a gaussian noise (of size 0.02 for the small sitck and 0.1 for the long one), updated at each step of the movement.

Similarly, if the other end of a stick reaches the yellow squared object (within 0.25), the object will follow the end of the stick. Three boxes are fixed at positions $(-1.25, 0)$, $(0, 1.75)$ and $(-1.75, 0)$ and have size 0.5. At the end of the trial, the object is considered to be in one of the box if its center is in the box.

C. Help from an experienced pair

A pair sitting at the right of the robot will help him put the yellow square into the closer box. It will wait for the robot to move the object on its own, and if the robot also produces the good vocal signal, will move the object to the closest box.

However, as the long stick is long enough to reach the any of the 3 boxes but not the small one, the pair will help the robot only when it will use the small stick. Also, as the pair is sitting on the right side of the robot, it will be unable to help reach box 1 (on the left). The pair will help reach box 2 (on the front) but with a bad precision as it is far, and box 3 (on the right) with a good precision. The pair will put the object at the center of box 2 (with a gaussian noise of size 0.2 on x and y dimensions thus missing the box quite often), only if the object is located near box 2 at a distance from the base of the arm greater than $1.$ and an angle from the horizontal line between 45 and 105. If the angle is between -15 and 45, then the pair moves it towards the center of box 3 with a gaussian noise of size 0.05, thus rarely missing the box.

We simulate a simple vocal signal controled by pitch and intensity between -1 and 1. The pair will engage in helping the robot only if pitch and intensity were sufficiently high ($> 0.$).

D. Motor control

We use Dynamical Movement Primitive [14] to control the arm's movement as this framework permits the production of a diversity of arm's trajectories with few parameters. Each of the 4 arm's degree of freedom (DOF) is controlled by a DMP with a starting and a goal position equal to the rest position of the joint. Each DMP is parameterized by one weight on each of 3 basis functions whose centers are distributed homogeneously throughout the movement. The weights are bounded in the interval $[-200, 200]$ (mapped to the standard interval $[-1, 1]$) which allow each joint to cover its standard interval $[-1, 1]$ during the movement. Each DMP outputs a series of 50 positions that represents a sampling of the trajectory of one joint during the movement.

The arm's movement is thus parameterized by 12 weights, and the static vocal signal by 2 weights. Let M_a be the $12D$ space of arm's commands $[-1, 1]^{12}$, M_v be the $2D$ vocal space, and M the $14D$ global motor space.

E. Sensory feedback

At the end of the movement, the robot gets sensory feedback from the different items of the environment. It gets the trajectory of its hand and gripper, whether the vocal signal engaged the pair or not, the trajectory of the end of the sticks, the end position of the object, and whether the object is in each box and at which distance.

The trajectory of the hand and of the end point of the sticks is the sequence of x and y positions at different time points: steps 12, 25, 37 during the movement of 50 steps. The trajectory of the gripper is a sequence of 1 or -1 depending whether the gripper is open or not. The pair understanding of the vocal signal is represented as 1 if intensity and pitch were correct, -1 otherwise. For each box, the robot receives a 1 if the object was in the box, and 0 otherwise, plus the distance between the end position of the object and the center of the box.

The sensory information thus contains 6 dimensions for the trajectory of the hand, 1 for the pair help, 6 for the trajectory of the end of each stick, 2 for the end position of the object, and 2 for each box. The total sensory space has 44 dimensions.

III. Random Goal Babbling

IV. Hierarchically structured exploration

A. Experiment 1: Methods

- Idea: to compare our simplest algorithm (explore the module with higher progress) in a realistic setting (Hierarchy (a) of Fig. **??**) to the control condition where a sensorimotor model is learned directly from the whole motor space M to the whole sensori space S.
- Conditions: Hierarchy (a) vs $M \rightarrow S$, Motor Babbling vs SAGG-Random
- Features: MAB on all modules, NN, No TDD.
- Measures: exploration of intermediate spaces (hands, tools), exploration of top spaces (objects). Competence to reach random goals in reachable parts of intermediate and top spaces. Statistics on multiple runs to see regularity/diversity in developmental trajectories.

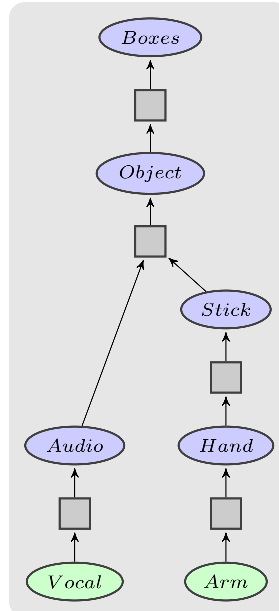


Fig. 2. H1

B. Experiment 1: Results

See Fig. 3, 4 and 5.

C. Experiment 1: Discussion

V. Choice of module to explore

A. Experiment 2: Methods

- Idea: to compare the different possibilities to choose the module to explore in the hierarchy: maximizing the progress, maximizing with a bias towards lower-level modules, or use ZPDES, with the same hierarchy (a) of Fig. **??**.
- Conditions: Random module, MAB on all modules, MAB with bias, ZPDES.
- Features: Hierarchy (a), SAGG-Random, NN, No TDD.
- Measures: exploration of intermediate spaces (hands, tools), exploration of top spaces (objects). Competence to reach random goals in reachable parts of intermediate and top spaces. Statistics on multiple runs to see regularity/diversity in developmental trajectories.

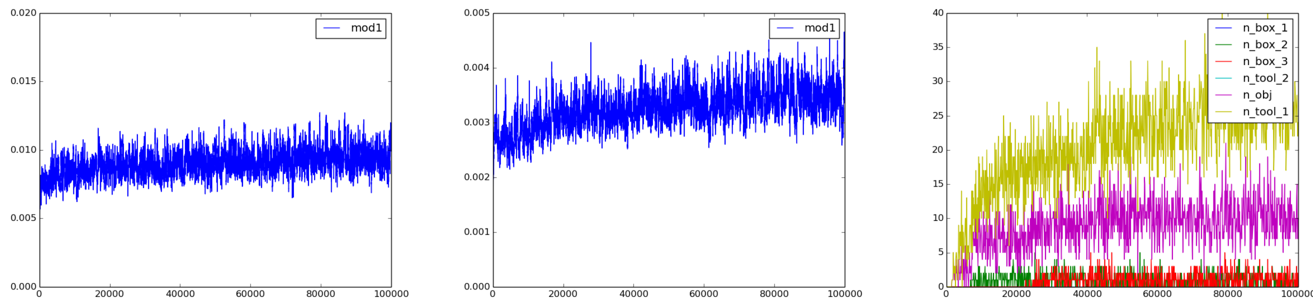
B. Experiment 2: Results

C. Experiment 2: Discussion

VI. Choice of tool to use

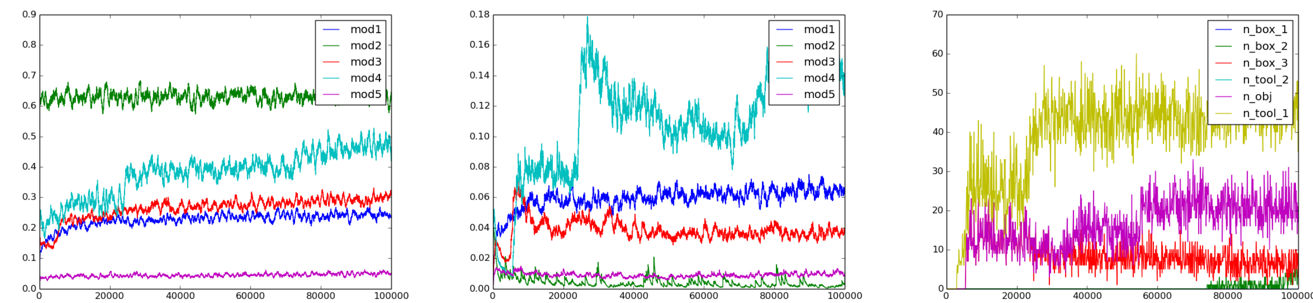
A. Experiment 3: Methods

- Idea: to explain how we can choose between different means (e.g. different tools) using the one with the maximal competence, or maximal progress. We can use the hierarchy (b) of Fig. **??**, in order to have 2 different tools to move the object.



(a) Competences (b) Interests (c) Events

Fig. 3. Competences, interests and events using H0 with Random Goal Babbling



(a) Competences (b) Interests (c) Events

Fig. 4. Competences, interests and events using H1 with Random Goal Babbling

- Conditions: maximize competence vs progress, noise on each tool, reachability (e.g. size) of each tool.
- Features: Hierarchy (b), MAB on all modules, SAGG-Random, NN, No TDD.
- Measures: exploration of intermediate spaces (hand, tools), exploration of top spaces (object). Competence to reach random goals in reachable parts of intermediate and top spaces. Statistics on multiple runs to see regularity/diversity in developmental trajectories.

B. *Experiment 3: Results*

C. *Experiment 3: Discussion*

VII. Top-Down Guidance

A. *Experiment 4: Methods*

- Idea: to compare different possibilities of Top-Down Guidance, with hierarchy (c) of Fig. **??** in order to have TD guidance at different levels: arm with one higher model, hand with 2 higher models, tool1 with one higher model, or tool2 with 2 higher models.
- Conditions: No TDD, Just add noise to motor command of each module (pb: interferes with competence estimation) vs explore n points and returns the best (warning: exponential) vs only one layer below the babbling module explores n points.
- Features: Hierarchy (c), MAB on all modules with bias (or no bias?), SAGG-Random, NN.
- Measures: exploration of intermediate spaces (hands, tools), exploration of top spaces (objects). Competence to reach random goals in reachable parts of intermediate and top spaces. Statistics on multiple runs to see regularity/diversity in developmental trajectories.

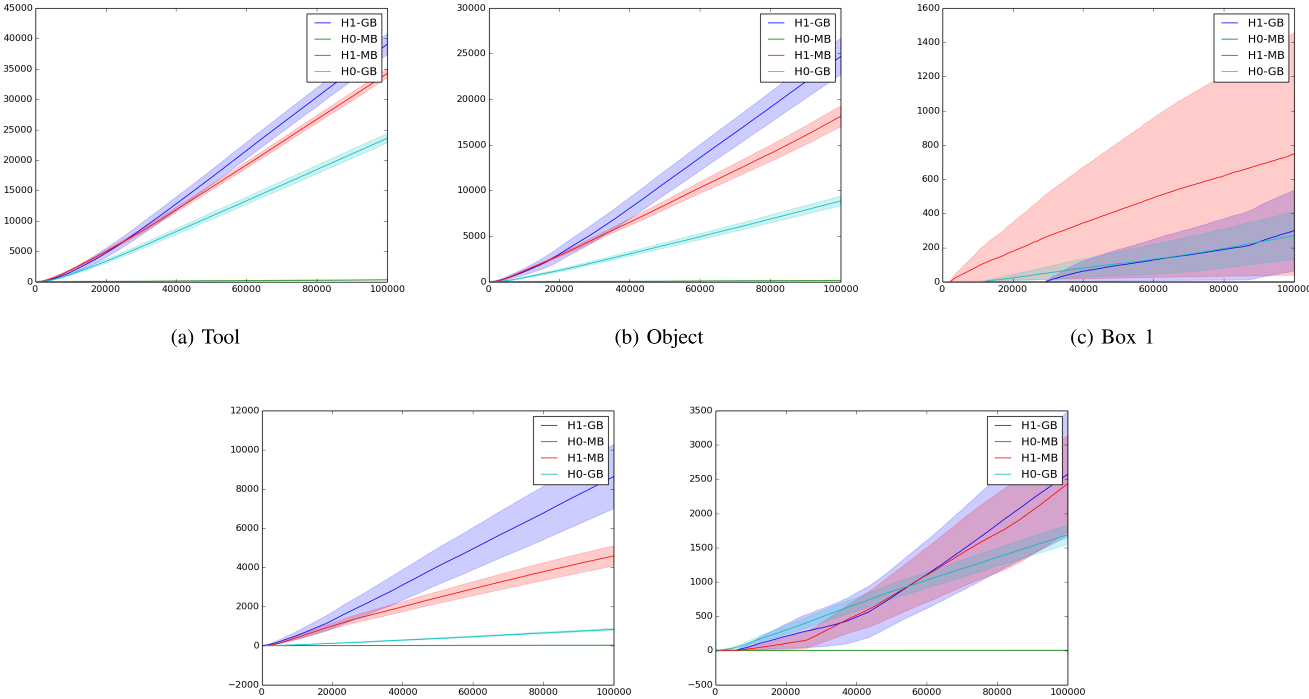
B. *Experiment 4: Results*

C. *Experiment 4: Discussion*

VIII. Robustness to perturbations

A. *Experiment 5: Methods*

- Idea: to apply perturbations to one of the possible forward models, either blocking, shifting or randomizing one dimension. We can use the hierarchy (d) of Fig. **??** in order to see an adaptation at 2 levels: the use of one hand to use one tool, the use of both tools to move the object even if only one is perturbated.
- Conditions: No perturbations, which model is perturbated (arm, tool), type of perturbation (blocking, shifting, random).
- Features: Hierarchy (d), MAB on all modules, SAGG-Random, NN, best TDD.
- Measures: exploration of intermediate spaces (hands, tools) and top spaces (objects) before and after pertur-



(a) Tool

(b) Object

(c) Box 1

(d) Box 2

(e) Box 3

Fig. 5. Number of touch of tool, object and boxes for each 100 iterations' bin.

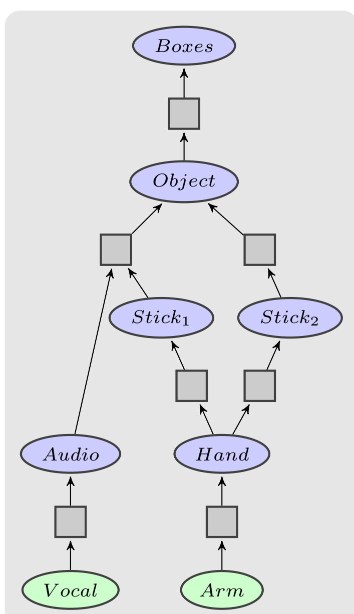


Fig. 6. H2

bations. Competence to reach random goals in reachable parts of intermediate and top spaces before and after perturbations. Statistics on multiple runs to see regularity/diversity in developmental trajectories.

B. Experiment 5: Results

C. Experiment 5: Discussion

IX. General Discussion

References

[1] A. Cangelosi, G. Metta, G. Sagerer, S. Nolfi, C. Nehaniv, K. Fischer, J. Tani, T. Belpaeme, G. Sandini, F. Nori *et al.*, "Integration of action and language knowledge: A roadmap for developmental robotics," *Autonomous Mental Development, IEEE Transactions on*, vol. 2, no. 3, pp. 167–195, 2010.

[2] P. M. Greenfield, "Language, tools and brain: The ontogeny and phylogeny of hierarchically organized sequential behavior," *Behavioral and Brain Sciences*, vol. 14, pp. 531–551, 12 1991.

[3] S. Higuchi, T. Chaminade, H. Imamizu, and M. Kawato, "Shared neural correlates for language and tool use in broca's area," *Neuroreport*, vol. 20, no. 15, pp. 1376–1381, 2009.

[4] E. Ugur and J. Piater, "Emergent structuring of interdependent affordance learning tasks," in *Development and Learning and Epigenetic Robotics (ICDL-Epirob), 2014 Joint IEEE International Conferences on*. IEEE, 2014, pp. 489–494.

[5] E. Ugur, Y. Nagai, E. Sahin, and E. Oztop, "Staged development of robot skills: Behavior formation, affordance learning and imitation with motionese," *Autonomous Mental Development, IEEE Transactions on*, vol. 7, no. 2, pp. 119–139, June 2015.

[6] C. M. Vigorito and A. G. Barto, "Intrinsically motivated hierarchical skill learning in structured environments," *Autonomous Mental Development, IEEE Transactions on*, vol. 2, no. 2, pp. 132–143, 2010.

[7] J. H. Metzen and F. Kirchner, "Incremental learning of skill collections based on intrinsic motivation," *Frontiers in Neurorobotics*, vol. 7, 2013.

[8] R. S. Sutton, D. Precup, and S. Singh, "Between mdps and semi-mdps: A framework for temporal abstraction in reinforcement learning," *Artificial intelligence*, vol. 112, no. 1, pp. 181–211, 1999.

[9] A. Fabisch and J. H. Metzen, "Active contextual policy search," *The Journal of Machine Learning Research*, vol. 15, no. 1, pp. 3371–3399, 2014.

[10] L. Kocsis and C. Szepesvári, "Discounted ucb." 2nd PASCAL Challenges Workshop, 2006.
[11] J. Mugan and B. Kuipers, "Autonomously learning an action hierarchy using a learned qualitative state representation," 2009.
[12] P.-Y. Oudeyer, F. Kaplan, and V. V. Hafner, "Intrinsic Motivation Systems for Autonomous Mental Development," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 2, pp. 265–286, Apr. 2007.
[13] A. Baranes and P.-Y. Oudeyer, "Active learning of inverse models with intrinsically motivated goal exploration in robots," *Robotics and Autonomous Systems*, vol. 61, no. 1, pp. 49–73, Jan. 2013.
[14] A. J. Ijspeert, J. Nakanishi, H. Hoffmann, P. Pastor, and S. Schaal, "Dynamical movement primitives: learning attractor models for motor behaviors," *Neural computation*, vol. 25, no. 2, pp. 328–373, 2013.