Curiosity-Driven Development of Tool Use Precursors

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Abstract

This is the abstract.

Keywords: curiosity-driven learning; tool use; goal babbling; overlapping waves;

Introduction

Development of tool use (Guerin, Kruger, & Kraft, 2013), precursors of tool use: behavior without objects, behavior with one object, interaction of objects. Grounding of representation and planning based on a large amount of experiences. Seemless progression between the successives phases as overlapping waves. Ongoing process of upgrading representations. Developmental trajectories.

Curiosity studies in developmental psychology (Kidd, Piantadosi, & Aslin, 2012) (Gottlieb, Oudeyer, Lopes, & Baranes, 2013)

Curiosity-driven modelling work, emergence of developmental trajectories. (Oudeyer, Kaplan, & Hafner, 2007) (Oudeyer, 2007) (Csikszentmihalyi, 1990) (Schmidhuber, 1991) (Santucci, Baldassarre, & Mirolli, 2013) (Cangelosi et al., 2010) (Oudeyer & Smith, 2014)

IAC series of architectures and Explauto framework: previous experiments. (Moulin-Frier, Nguyen, & Oudeyer, 2014) (Moulin-Frier, Rouanet, Oudeyer, & others, 2014) (Baranes & Oudeyer, 2010) (Baranes & Oudeyer, 2009) (Baranes & Oudeyer, 2013)

Representations in explauto and other models (Mugan & Kuipers, 2009a) (Metzen & Kirchner, 2013) (Sutton et al., 2011) (Mugan & Kuipers, 2009b) (Vigorito & Barto, 2010) (Sutton, Precup, & Singh, 1999)

Other related work (Ugur, Nagai, Sahin, & Oztop, 2015) (Schmerling, Schillaci, & Hafner, 2015)

More details on experiments (Ijspeert, Nakanishi, Hoffmann, Pastor, & Schaal, 2013)

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Methods

Environment

We simulate a 2D robotic arm using tools to move an object into different boxes in the environment. In each trial, we execute a motor command given by the agent, we evaluate its consequences on the sensory dimensions and we give him this sensory feedback. 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.

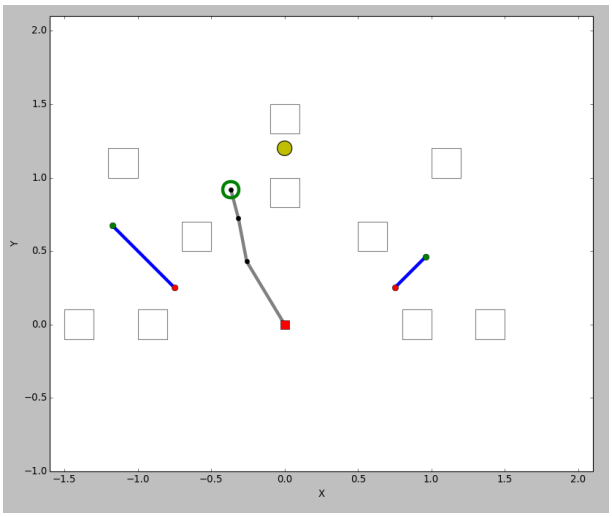

Figure 1: Play Environment

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 π *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.

Motor control We use Dynamical Movement Primitive (Ijspeert et al., 2013) 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 degrees-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 duration. The weights are bounded in the interval $[-200, 200]$ (mapped to the standard interval $[-1, 1]$) which allow each joint to fairly cover the 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 which are represented by the motor space $M = [-1, 1]^{12}$.

Objects and tools A yellow sphere can be moved into one of the 4 fixed squared boxes. The initial position of the sphere is $(0, 1.2)$ and is thus unreachable directly with the gripper. One of two sticks can be grasped in order to reach the object. A small stick of length 0.3 is located on the right of the arm, with initial position $(0.75, 0.25)$ and initial angle $\frac{\pi}{4}$ from the horizontal line. A long stick of length 0.6 is located on the left of the arm, with initial position $(-0.75, 0.25)$ and initial angle $\frac{3\pi}{4}$ from the horizontal line as in Fig. 1. If the gripper closes near the end of one of the sticks (closer than 0.1), it is considered grasped and will follow the gripper's position and the angle of the arm's last part until the gripper opens. Similarly, if the other end of a stick reaches the sphere (within 0.1), the object will follow the end of the stick. Ten boxes have identifiers 1 to 10 and are static at positions $(-1.4, 0)$, $(-1.1, 1.1)$, $(0, 1.4)$, $(1.1, 1.1)$, $(1.4, 0)$, $(-0.9, 0)$, $(-0.6, 0.6)$, $(0, 0.9)$, $(0.6, 0.6)$ and $(0.9, 0)$ and have size 0.2. The first five boxes can only be reached with the long stick, and the other five can be reached by the two sticks. At the end of the trial, the object is considered to be in one of the box if its center is in the box.

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, the trajectory of the end of the sticks, the end position of the object, and whether the object is in each box. The trajectory of the hand and of the end point of the sticks are represented by sequences of x and y positions at different time points: steps 12, 25, 37 during the movement of 50 steps (6D for the hand and for each stick). Similarly, the trajectory of the gripper is a sequence of 1 or -1 depending whether the gripper is open or closed (3D). The agent receives the identifier of the reached box if one of them has been reached, 0 otherwise. He also gets the minimal distance of the object (at the end of the movement) to the center a box, even if none have been reached. The sensory information thus contains 9 values for the trajectory of the hand and gripper (S_{Hand}), 6 for the trajectory of the end of each stick (S_{Stick_1} and S_{Stick_2}), 2 for the end position of the object (S_{Object}) and 2 for the boxes (S_{Boxes}). The sensory space has a total of 25 dimensions.

Learning architectures

Explauto framework (Moulin-Frier, Rouanet, et al., 2014)

Goal Babbling

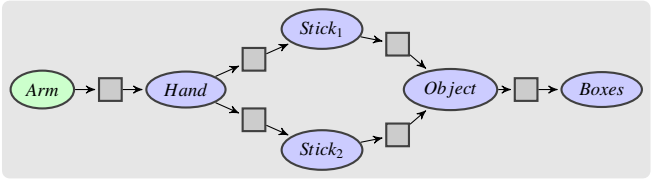

Figure 2: Hierarchy of sensorimotor models

SAGG-RIAC (Baranes & Oudeyer, 2013)

Flat architecture

Hierarchical architecture We present here an architecture that represents sensorimotor information with a hierarchical structure in Fig. 2.

Only the motor module (mod1) adds exploration noise ($\sigma = 0.02$) even in hierarchical architecture. That was the key to have more efficient hierarchical exploration. Indeed, if all modules successively add exploration noise, few iterations succeed in touching the object. Alternatively, if the exploration noise is reduced, exploration is less efficient as in NN only the motor module will finally apply noise on known motor commands. With regression instead of NN, noise can instead be put only on the babbling module.

Experiments

NN, 100 iterations of Motor babbling and then 300000 iterations of the condition

Conditions

- H0-MB: Random Motor Babbling
- H0-GB: Random Goal Babbling with a flat architecture learning

$$M \rightarrow S_{Hand} \times S_{Stick_1} \times S_{Stick_2} \times S_{Object} \times S_{Boxes}$$

- H0-TR: The same architecture but with active goal babbling (my version of SAGG-RIAC)
- H1: Hierarchical architecture with Random Goal Babbling in each module, and choice of module that babbles based on interest (ε-prop: probabilities proportional to interest but with $\varepsilon = 10\%$ of random choice). Choice of tool to use based on the maximum interest of the two modules that learn from the spaces of the tools to the object space, around the goal object point (competence progress on the k=10 NN).
- H1-GR: same as H1 but the choice of module to babble is ε-greedy with $\varepsilon = 0.1$
- H1-CL: same as H1 but the choice of the tool to use is based on the maximum competence around the goal object point (competence of the NN)

Measures Exploration of the different sensory spaces (number of reached cells in a discretization of the space divided by number of cells).

Results

Discussion

H0 vs H1

H1 vs H1-GR

H1 vs H1-CL

Acknowledgments

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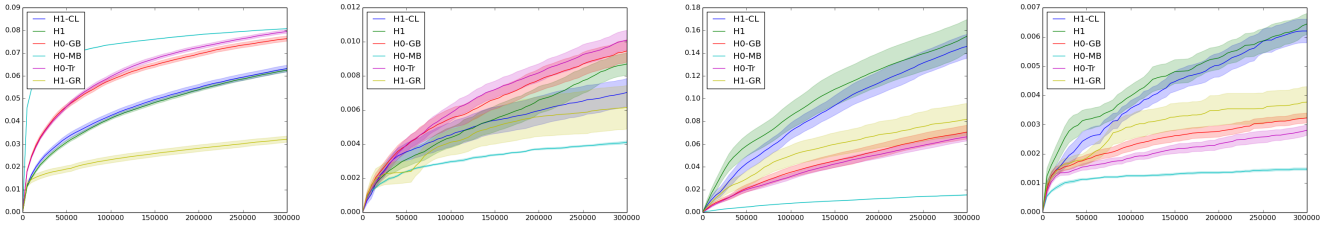
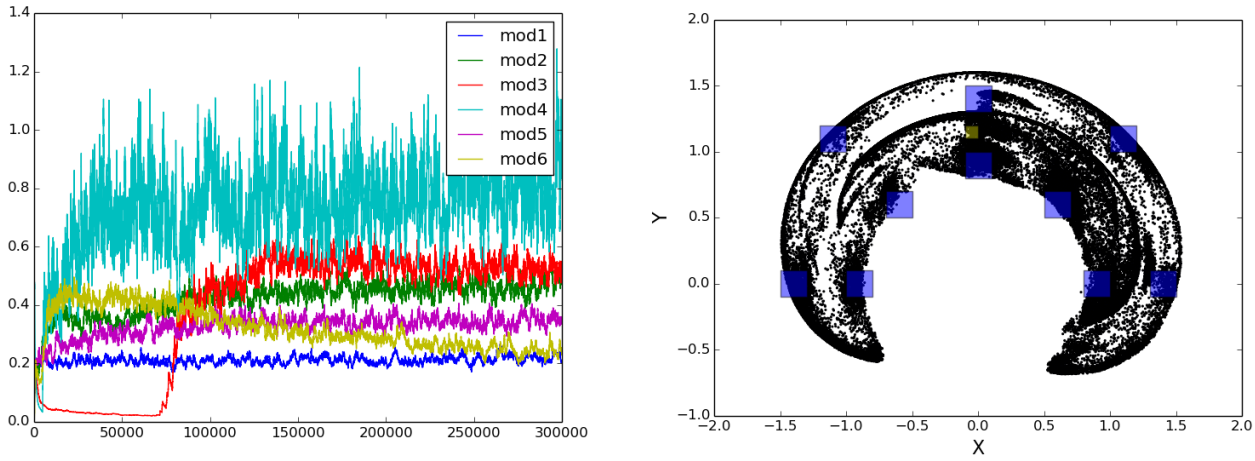


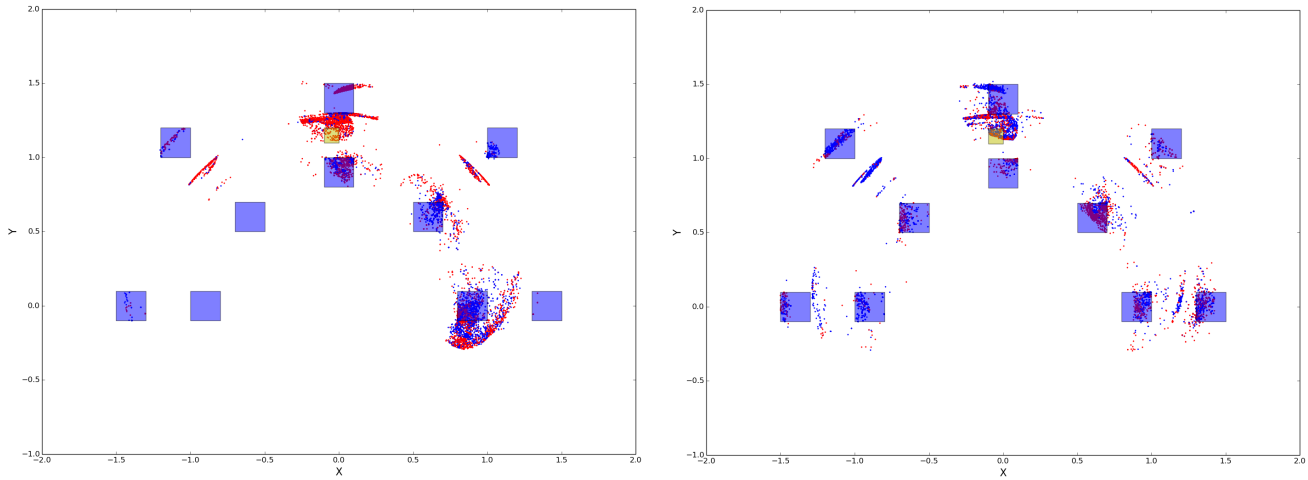
(a) Hand (b) Tool (c) Object (d) Box

Figure 3: Exploration of sensory spaces.



(a) (b)

Figure 4: Condition H1. (a) Interests of each module. (b) Exploration of the object space: each dot is one point reached with the object at the end of one movement.



(a) H1 (b) H1-CL

Figure 5: Chosen tool depending on object goal position. Blue points: long stick choice. Red points: small stick choice.