Learning a high diversity of object manipulations through an evolutionary-based babbling

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I. Introduction

During the last years different robots have arrived to the domestic environment. Service robots, as Roomba[1], are able to clean both the floors and carpets of a house, for example. Its success mainly stems from the fact that it does not interact with objects. It just needs to move around in a room while avoiding obstacles to fulfill its mission. To be able to perform more complex tasks in our environment, a robot should be able to identify our everyday life objects and know what to do with them: it needs to know their affordances. Developmental robotics [1] proposes to make robots learn by themselves such affordances through a dedicated exploration step, similar to the *body babbling* [2] performed by infants.

Previous works explored the environment based on the concept of intrinsic motivations [3]. The Intelligent Adaptive Curiosity [4] relies on predictive models of action results and focuses the babbling on actions associated to predictive models whose learning progress is maximal. The Novelty-driven Evolutionary Babbling [5] looks for behaviours generating novel perceptions. Novelty Search [6] is used in this work to generate trajectories to be executed by the end-effector of the robot, focusing on those that modify the scene, i.e. those moving one or more objects without the need to provide the robot with the notion of what an object actually is [5].

In this work and to discover object affordances, we propose an approach to generate large sets of diverse behaviours involving interactions with the target object. No primitive behaviour is provided. The proposed babbling relies on the detection of the position of the object and tries to generate, thanks to robot arm movements, as many different object positions as possible. The proposed approach discovers how to grasp, push and throw objects at different locations, which are behaviours that are usually difficult to generate without prior information about the dynamics of the robot and of the objects.

II. Method and results

To generate a diversity of arm trajectories of interest for object manipulation while exploring an environment, we utilize an evolutionary algorithm called Multi-dimensional Archive of Phenotypic Elites (MAP-Elites) [7], [8]. This algorithm defines

[1] http://www.irobot.fr/

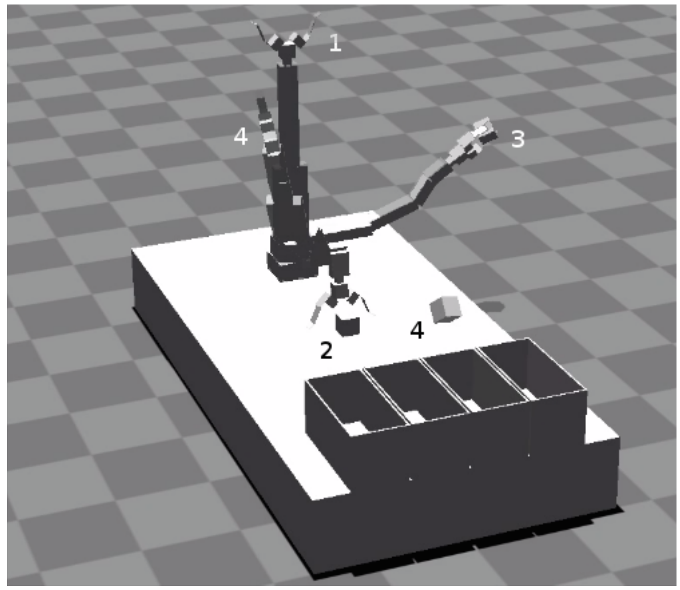

Fig. 1. Example of a trajectory to launch the cube into a basket: (1) the robotic arm is in its initial position, (2) the arm gets close to the cube, (3) the arm gets the ball and moves to a new position, and (4) the arm launches the cube to the basket and reaches the final position.

a multi-dimensional grid (called map) that it will try to fill. Each dimension corresponds to a behaviour descriptor. The dimensions are discretized and each 'cell' in this map contains at most one controller (e.g., a trajectory): the controller that generates a behaviour fitting with the behaviour descriptor value of the cell and having the best performance according to a user defined fitness function. Controllers are randomly generated at first. They are then evaluated to see where they fit in the map. If the corresponding cell is empty, they are added to the map; otherwise, only the best performing controllers among those in the cells and the new ones are kept in the map. New individuals are generated thanks to a mutation operator and likewise added to the map if the corresponding cell is empty or if they behave better. See [8] for more details. Finally, the algorithm returns the highest performing solution for each encountered behaviour descriptor value.

We have defined an experiment to evaluate the performance of MAP-Elites for an object babbling purpose. The evaluated scenario is composed of a table, a small cube and four baskets

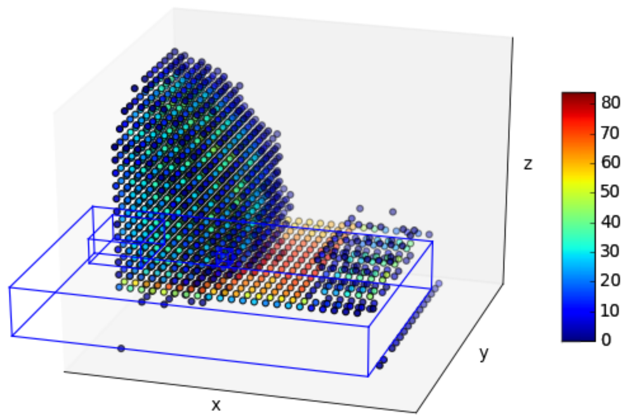

Fig. 2. Results obtained after the execution of the MAP-Elites algorithm. The big blue box represents the table, the medium one the robotic arm, and the small one the initial position of cube. Each point represents a final position reached by the small cube after the execution of a trajectory. The color of each point corresponds to the number of different ways to reach each position.

(Figure 1). The goal is to discover what the robot can do with the small cube and in particular what displacement of the object it can perform, without providing it with pushing or grasping primitives. The proposed behaviour descriptors are: x, y, z, Δx, Δy and Δz; where x, y and z are the final position of the cube after each movement, and Δx, Δy and Δz define, for each dimension, the difference between the two most extreme positions of the cube during its movement (for example, $\Delta x = x_{max} - x_{min}$). These 3 additional dimensions allow the algorithm to get different ways of putting the cube at a particular position. The performance comparison is based on the total torque required to perform the cube displacement (to be minimized). During the experiment both the arm and the cube are reinitialized to their initial positions after the execution of a movement.

The simulated robot arm is based on the features of a Crustcrawler Pro-Series robotic arm[2]. A controller represents a trajectory, initially composed of one end position of the arm. A dedicated mutation operator can add intermediate positions to create more complex trajectories. A position is defined by seven values related to the six joint values composing the arm, and another value related to the opening of the gripper in between positions.

The results obtained are depicted in Figure 2. Most of the discretized positions on the table have been reached by the cube, including positions within the four baskets (95.2% of the 352 cells located on the table are filled). Other positions over the table have been also reached while the gripper held the cube in the air. MAP-Elites thus revealed to be able to launch the cube into the baskets, as exemplified by the trajectory plotted on Figure 1. This result implies for the robot to grasp the object, to lift it and to launch it towards the basket, which requires to move towards the cube and open the gripper at the right moment. MAP-Elites has then been able to generate a diverse repertoire of trajectories putting the cube in many different positions, including positions requiring a non-trivial sequence of cube manipulations without any primitive behaviour. More than 60,000 behaviours have been autonomously found by the algorithm after 1.6 millions of evaluations. These data could actually be used to automatically design primitive behaviours on which a physical robot can rely on or to extract higher level information about the object affordances. An online video showing several executions of the experiment is available at https://youtu.be/FSn_YeAiHAs. We are currently working on the transfer of the behaviours generated in simulation on the real robot arm, notably with the transferability approach [9].

III. Acknowledgements

This research is sponsored in part by the DREAM project[3]. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 640891. This work was performed within the Labex SMART (ANR-11-LABX-65) supported by French state funds managed by the ANR within the Investissements d'Avenir programme under reference ANR-11-IDEX-0004-02. This work has been funded by a DGA/UPMC scholarship for Antoine Cully.

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[2] http://www.crustcrawler.com/

[3] http://www.robotsthatdream.eu/