First Steps Towards the Development of the Sense of Object Permanence in Robots.

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***Abstract*— Evidence in developmental studies showed that infants, around the age of three months, are already able to represent and to reason about hidden objects [1].**

We investigate the development of the sense of object permanence in robots. In the preliminary experiment presented here, a humanoid robot has to learn how the movements of its arms affect the visual detection of an object in the scene. The robot is holding a shield in its left hand, which can eventually hide the object from the visual input. As learning mechanism, we adopted a goal-directed exploration behaviour inspired on human development: the Intelligent Adaptive Curiosity (IAC) proposed by Oudeyer, Kaplan and Hafner [2]. We present an implementation of IAC on the humanoid robot Aldebaran Nao and we compare its performance with that of a random exploration strategy.

I. INTRODUCTION

Toddlers' capability to represent occluded objects is limited, compared to that of adults, suggesting that it must develop through infancy [1]. In this study, we investigate the development of the sense of object permanence in robots through exploratory behaviours. The role of exploration, play and curiosity is generally recognized by developmental psychologists and by biologists as of primary importance in the development of young children and other mammals [3].

Developmental theories usually identify a sequence of stages in infant development: in each step, only after certain cognitive and morphological structures are ready, the child can acquire a new skill. For example, children first learn how to crawl before they learn how to sit and, then, to walk [2]. Rehearsal of motor control through exploration behaviours has been observed already during pre-natal stages of development in foetuses [4] and continue after birth. Parents scaffold the environment and help the toddler's interaction with the world. Nonetheless the child's playing seems to be driven by an intrinsic motivation system which provides internal rewards during the experience [2].

Recently, interest on such behaviours has grown also in the robotics community. The challenge is to build robots with human-like capabilities of open-ended development through exploration and interaction behaviours [2]. An example of random exploration strategies, or *motor babbling*, in learning inverse and forward models in artificial agents has been presented by Demiris and Dearden [5]. However, random babbling has been shown to be inefficient, especially in presence of high-dimensional motor spaces. This motivated researchers in investigating intelligent exploration mechanisms. For example, Saegusa et al. [6] proposed an active motor babbling strategy for learning visuomotor coordination in a humanoid robot, where a confidence function worked as a memory of reliability for state prediction and control and was used in biasing the exploration strategy. Rolf et al. [7] presented an exploration behaviour based on goal-directed babbling for learning the inverse model of a complex robotic arm. Goal-directed exploration was shown to outperform random exploration strategies. Oudeyer et al. presented an implementation of an intrinsically motivated learning system, named *Intelligent Adaptive Curiosity* [2], where an internal reward reached by the act of playing was simulated and evaluated by the system in robot dogs (Sony AIBO).

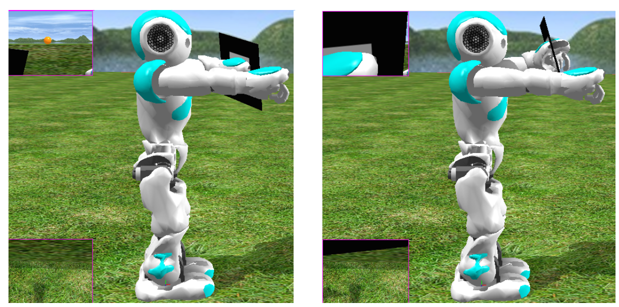

Fig. 1. Experimental setup in a simulator. The robot is holding a shield in its left hand and is facing an object. In the left image, the configuration of the robot's arm does not hide the orange ball situated in front of the robot (the visual input from the robot's top camera is visible in the upper left corner of the image). In the right image, the configuration of the arm results in a full occlusion of the object, as visible from the robot's top camera.

In this study, we investigate the role of exploratory behaviours in the development of the sense of object permanence in robots. Evidence in developmental studies showed that infants aged 3.5 months and older are already able to represent and to reason about hidden objects [1]. As a first step towards the development of such a skill, we created a simulated experimental setup where the task of the robot is to explore how the movements of its left arm affect the visual detection of an object in the scene. We adapted the efficient exploration behaviour provided by the Intelligent Adaptive Curiosity algorithm (described in the next section) proposed by Oudeyer, Kaplan and Hafner [2].

II. INTELLIGENT ADAPTIVE CURIOSITY (IAC)

An artificial agent can generate a rich set of sensorimotor information through self-exploration, which can be repre-

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sented as a vector of sensory values $S(t)$ and a vector of motor values $M(t)$, gathered at time t. IAC collects sensorimotor data into a sensorimotor space that is partitioned into regions. The partitioning is performed in a way that similar sensorimotor contexts belong to the same region. Each region R_i is characterized by its exclusive set of sensorimotor contexts $SM(t)$[1] and, in addition, by a learning machine, or *expert* E_i, which is trained with the sensorimotor contexts of its region. An expert is, in effect, an inference tool. It can be queried to infer a motor command $M(t)$ for reaching a desired sensory state $S(t+1)$ or to predict the sensory outcome $S'(t+1)$ of a desired action $M(t)$. Prediction errors can be computed as the distance between the predicted and the observed sensory outcomes.

A characteristic of the IAC framework is that each region in the sensorimotor space stores a list of experienced prediction errors, which is then used to evaluate the learning progress within the region. The learning progress is computed as the smoothed derivative of the error curve of E_i considering only the most recent samples. For exploration, IAC executes the action that has the highest expected learning progress.

III. The experiment

We created a simulated experimental setup where the task of the robot is to explore how the movements of its left arm affect the visual detection of an object in the scene[2]. The robot is holding a shield in its left hand, which can eventually hide the object from the visual input. The head posture is fixed to a configuration that already allows for the sight of the object (only one object is present in the scene), if no arm movements cross the field of view. A sensorimotor context consists of the following data:

- $S(t)$: ball detected, $b = 0, 1$ 4 joint angles $\alpha_i(t)$;
- $M(t)$: $\Delta\alpha_i$;
- $S(t+1)$: ball detected, $b = 0, 1$ 4 joint angles $\alpha_i(t+1)$

The range of the angles for the joints of the left arm was not restricted or normalized. The robot could move it's arm freely. The machine learning algorithm used for training the experts is based on a k-nearest neighbour algorithm ($k = 15$). A window of 40 samples was used for computing the first derivative of the prediction errors, which determined the learning progress of a region. For this reason, the initial 40 actions generated by the algorithm are chosen randomly. Afterwards, the algorithm executes the intelligent exploration behaviour by choosing the action for which the system expects the maximal learning progress. However, in 30% of the cases, actions were chosen randomly. The robot posture is set back to a starting position after each action is executed. All the relevant sensorimotor information are gathered at the end of the execution of each action. As expected, we observed the prediction error to decrease over time, as shown in Figure 2. In addition, we observed the prediction error of IAC to decrease faster than the prediction error of random motor babbling.

[1] $SM(t)$ denotes the sensorimotor context of the robot at time t, which includes both the sensory and the motor values gathered at time t.

[2] The algorithm has been implemented in Python v2.7 using the Aldebaran pyNaoqi SDK v1.14.5 for controlling the robot. The experiments have been run in the robot simulator Cyberbotics Webots v.7.4.0 (http://www.cyberbotics.com/overview)

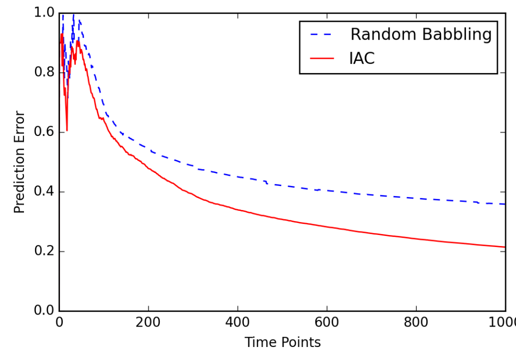

Fig. 2. The prediction error for one run for IAC compared to the prediction error for random babbling. The prediction error is calculated by computing the mean error of every region for every iteration and by averaging it over all the regions. The error is calculated using normalized euclidian distance.

IV. Conclusions

We showed how a humanoid robot can learn how the movements of its arms affect the visual detection of an object in the scene. In particular, we implemented an intelligent exploration behaviour based on intrinsic motivation, the *Intelligent Adaptive Curiosity* algorithm proposed by Oudeyer et al. [2], as a learning mechanism for the robot Nao, together with a comparison between IAC and random exploration strategies. This can be a preliminary study in the investigation of the development of the sense of object permanence in robots.

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