I Know How I Would Do It.
Internal Simulations of Sensorimotor Experience.

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***Abstract*—This paper suggests the adoption of internal models for coding sensorimotor schemes. The reported experiments demonstrate how the simulation and predictive capabilities supplied by internal models can provide a robot with important cognitive tools, from behaviour selection and recognition to the recognition of the authorship of an action. In the context of active learning in robotics, internal simulation mechanisms can play an important role. For example, their predictive capabilities could allow for more efficient exploration behaviours. Analysing the prediction error of simulated movements could drive an artificial agent towards unexplored or poorly explored regions of its actions space.**

I. INTRODUCTION

Theories of grounded and embodied cognition focus on the role of the body of an agent for the acquisition of knowledge [1]. In particular, grounded cognition theories consider internal simulations of the sensorimotor experience, or re-enactments of experienced perceptual, motor and introspective states, as important mental activities which could account for the offline characteristics of cognition.

In the quest of implementing internal simulation mechanisms, forward and inverse models have been proposed [2][3]. A forward model is an internal model which incorporates knowledge about sensory changes produced by self-generated actions of an agent. Given a sensory situation S_t and a motor command M_t (intended or actual action), the forward model predicts the next sensory situation S_{t+1}. While forward models (or predictors) present the causal relation between actions and their consequences, inverse models (or controllers) perform the opposite transformation providing a system with the necessary motor command M_t to go from a current sensory situation S_t to a desired one S_{t+1}.

Forward models were first proposed in the control literature as means to overcome problems such as the delay of feedback on standard control strategies and the presence of noise, both also characteristic of natural systems [4]. In the cognitive sciences, such mechanisms have been suggested for modelling several behaviours, ranging from the cancellation of the tickling sensation [5] to the accounting for schizophrenia [6]. The main idea stems from the relevance of the prediction of the consequences of self-produced actions: we are better in predicting the outcomes of our motor commands than the ones of other agents [7].

The recent discovery of mirror neurons in the central nervous system also supports the general idea of internal simulations. The mirror neuron system is thought to be involved in internal simulations of the sensorimotor loop in learning and planning, as it has been found that neurons in this area show activation both when an individual performs a specific action and when the individual observes the same action performed by a demonstrator (for a recent review, see [8]). It seems that an observer understands a demonstrated behaviour comparing a simulated execution of it with a set of primitives stored in its memory.

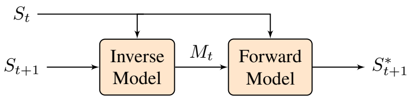

Fig. 1. Inverse-Forward Model pair. Simulating the outcome of a sensorimotor behaviour consists of two steps. First, the inverse model predicts the motor command necessary to reach a desired sensory situation, according to the sensorimotor behaviour it is coding. Then, an efferent copy of this command is sent to the coupled forward model, for anticipating the sensory situation which would have resulted from the application of that motor command.

In the philosophy and cognitive science literature, the mechanism of mental simulation is often referred as *mental imagery*. This phenomenon has been defined as a quasi-perceptual experience which resembles perceptual experience but occurs in absence of external stimuli [9]) and it is thought also to influence movement execution and the acquisition and refinement of motor skills [10]. For example, mental training (that is, the practice of using motor imagery for enhancing motor performances) has become a popular method for professional athletes and for the rehabilitation in patients affected by cerebral lesions. In [11], a model of a robot controller was presented that allows an artificial agent to autonomously improve its sensorimotor skills. This was achieved by generating additional imaginary examples that can be used by the controller itself to improve the performance through a simulated mental training.

In the context of active learning in robotics, internal simulation mechanisms can play an important role. For example, such predictive capability could allow for more efficient exploration behaviours. Analysing the prediction error of simulated movements could drive an artificial agent towards unexplored or poorly explored regions of its actions space. The internal models proposed here will be used to enhance the pre-defined motion primitives as have been used in previous work in the playground experiment [12]. There, the action selection and exploration was based on a curiosity-driven method.

In this context, forward and inverse models (Figure 1) become central players, as they naturally fuse together sensory and motor information, providing agents with multimodal representations [13]. Due to their functioning, these models allot agents with internal simulations, anticipation and predictive capabilities.

Here, we present several robotics experiments in which we adopted the internal models paradigm. We strongly believe that research on grounded cognition, internal models and internal simulations needs to be pushed forward, if we want robots to naturally interact with the environment and with other agents.

II. EXPERIMENTS

Sensorimotor learning is fundamental for the development of cognition. Here, we present experiments in which a humanoid robot (Nao from Aldebaran) learned sensorimotor behaviours by self-exploring its action space or by observing a skilled demonstrator. Representing such sensorimotor schemes as internal models provided the robotic agent with internal simulations and predictive capabilities, which we tested in experiments on behaviour selection, human behaviour recognition and self-other distinction. The main idea behind such experiments was that prediction errors can be used for selecting the best strategies to adopt for reaching a desired goal or for classifying observed behaviours.

In [14], a mechanism for behaviour selection has been implemented using internal simulations. We programmed a Nao robot for learning a repertoire of behaviours by self-exploration, namely motor babbling. The learning session consisted in the robot collecting and mapping sensory (estimated position of its hand) and motor information (command sent to the joints of the corresponding arm) while performing random movements. For each arm, a sensorimotor scheme has been coded as an inverse - forward model. For emphasizing the difference between the two sensorimotor schemes, one of the arm was extended with a tool, changing its original action space. Figure 2 shows a top-down view of the action spaces explored during babbling, with and without the extension tool. Simulations of the sensorimotor loop have been used for selecting the best strategy from the action repertoire for reaching a desired goal, namely selecting the arm resulting in the smallest hand-target distance. Internal simulations for each of the sensorimotor behaviours (left arm, with or without tool, or right arm) are performed before executing the actual motor command. The predicted outcome is compared with the desired goal (an object handed to the robot by the user) and prediction errors are used for selecting the best arm to use (e.g. the one with or without a tool).

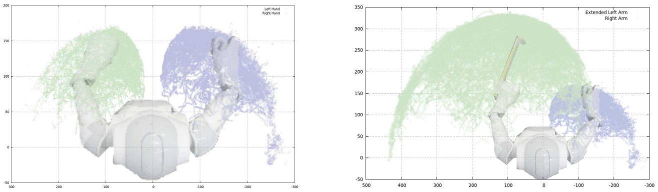

Fig. 2. Reachable spaces for the hands of the Nao, with or without the extension tool on the left arm.

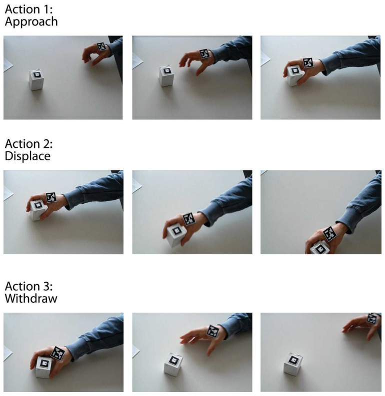

Fig. 3. Typical frames of approach and displace actions.

The same paradigm has been adopted for human behaviour understanding. During action demonstration, like in Figure 3, the observed sensory situation is compared with the ones predicted by simulating each known sensorimotor scheme stored in the action repertoire. Prediction errors are then used for behaviour classification and for target object identification [14]. In a recent experiment, we trained the models using data taken from the observation of self-produced actions, instead of using data taken from the observation of a human demonstrator, as reported in [14]. Prediction errors are then used for classifying sequences of three different actions, resulting in a correct classification rate of 78.40% of the observed frames, against 89.45% reached with training the models with data taken from human demonstrations. It is plausible that the

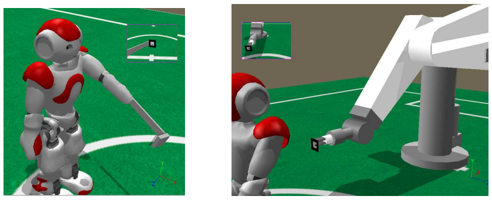

Fig. 4. Self-other distinction experiment: Nao observing itself performing a controlled trajectory and observing a Puma robot performing a similar trajectory. An inverse-forward model has been trained with data taken from self-exploration. Prediction errors coming from the simulations of both the observed trajectories are statistically significantly different ($p < 0.001$). With the prediction error of the NAO observing itself being lower than when observing the PUMA robot.

non-ownership of the observed action affects the prediction performances, this was confirmed by the results of an experiment on self-other distinction[15]. In this, we demonstrated how a humanoid robot which acquires a sensorimotor scheme through self-exploration, performs simple trajectories that hold intrinsic and constant characteristics related to the internal dynamics. The NAO-specific dynamics are clearly present when analysing the velocity profile of the agent. Comparison of these characteristics provides the agents with a basic tool for distinguishing between self and others (see Figure 4).

III. CONCLUSION

We strongly support the use of internal models for encoding sensorimotor schemes. We demonstrated how their simulation and predictive capabilities can provide a robot with important cognitive tools. We would like to push forward the investigation on these types of models, which we believe have not been fully studied and their capabilities not properly exploited in the context of active learning and exploration in robotics.

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