Coupled Inverse-Forward Models for Action Execution Leading to Tool-Use in a Humanoid Robot

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ABSTRACT

We propose a computational model based on inverse-forward model pairs for the simulation and execution of actions. The models are implemented on a humanoid robot and are used to control reaching actions with the arms. In the experimental setup a tool has been attached to the left arm of the robot extending its covered action space. The preliminary investigations carried out aim at studying how the use of tools modifies the body scheme of the robot. The system performs action simulations before the actual executions. For each of the arms, predicted end-effector positions are compared with the desired one and the internal pair presenting the lowest error is selected for action execution. This allows the robot to decide on performing an action either with its hand alone or with the one with the attached tool.

Categories and Subject Descriptors

I.2.6 [**Computing Methodologies**]: Artificial Intelligence—*Learning*

General Terms

Theory, Experimentation

Keywords

Internal models, inverse and forward models, action simulation, tool-use

1. INTRODUCTION

In this paper, we present preliminary results on a computational model for action execution. This model will be extended to implement action recognition. The Nao humanoid from Aldebaran has been adopted as robot platform. Internal models are used for predicting the end position of both arms. An extension tool is attached to the left hand of the robot to emphasize the power of predictor-controller pairs in selecting the best arm for action execution.

We understand the physical world according to our own experience. The faculties, capabilities and skills to dynamically interact with the world, which as adult humans we posses, emerge through a long process of tuning and rehearsing of *sensori-motor schemes*. A very important example is the acquisition of the sensori-motor schemes that code for the capabilities and reaches of our body. This set of schemes provides us with a notion which we exploit in order to perform tasks such as throwing, reaching and grasping, which have helped us through our development as a species. A proposed mechanism to code these schemes are internal models. In this work we investigate the capabilities of forward and inverse models.

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 characteristic of natural systems [4]. 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}. Much research has been done on computational forward models for action preparation and movement, with highly functional models that account, for example, for hand trajectory planning [3].

In cognitive robotics, an interesting implementation is presented by Dearden [2] where a robot learns a forward model that successfully imitates actions presented to its visual system, learning from a social context using a forward-inverse model pair.

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}). Theories on how the human Central Nervous System (CNS) manages sensorimotor control suggest that a modular approach is implemented in the brain. Predictor-controller pairs, modelling different goal-directed actions, are run in parallel for assessing which one is more plausible in the given context. In [7], Wolpert suggested coupled inverse and forward models for action execution and recognition.

Tool use is an important skill that is acquired during early childhood in humans and requires several cognitive abilities related to sensorimotor interaction. Bril et al.[1] consider tool-use as an instance of a goal-directed action. Tool-use requires both an action and a cognition component. Maravita and Iriki [5] propose that we hold an adaptive body map comprising body posture and shape. They suggest that

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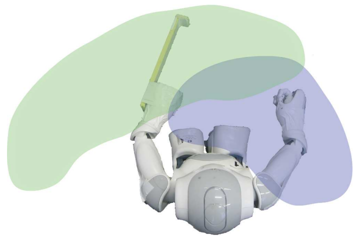

Figure 1: Top-down view of the Nao with an illustration of the reachability space for each end-effector.

the body schema is extended temporarily with the tools we are using ("as if our own effector (e.g. the hand) were elongated to the tip of the tool"). From this perspective, the extended arm experiment on the robot can be seen as the body of the robot being temporarily extended by a suitable tool for a specific task (namely reaching an object).

2. PRELIMINARY RESULTS

We implemented a system for generating reaching commands towards given points in the space. Figure 1 illustrates how different the action spaces of both arms can be, if the robot is provided with an extension tool on its left arm. While far-away positions can be reached with the left extended end-effector, other positions (like the ones close to the chest) are only reachable with the right arm. A forward-inverse model pair has been learned for each arm of the robot (see Figure 1) using a motor babbling mechanism previously implemented [6]. A k-Nearest Neighbours based algorithm has been adopted, together with the knowledge bases (one for each arm) collected during babbling, as the inference algorithm for both inverse and forward models.

Before executing the necessary motor command to reach a position, an internal simulation shown in Fig. 2 is run as follows: find the motor command M_t which given the sensory situation S_t, composed by the current coordinates of the arms, brings the system to the desired sensory situation S_{t+1}, composed by the coordinates of the goal position. This process is performed by a learned inverse model of each arm. Use the predicted motor command and the current sensory situation to find the next sensory situation. Again, this process is performed by a forward model of each arm. Predicted end-effector positions are compared with the desired one and the forward-inverse model pair with less error is selected for actual execution, namely moving the corresponding arm. Figure 3 shows the errors of both pairs when presented with different end positions estimated from a marker.

3. FUTURE WORK

These preliminary results make only use of one-step predictions, future work will include the use of the predicted sensory situation as input back to the system in what can be seen as long-term predictions. Internal models will also be used for goal-directed action recognition. Experiments on human-robot interaction will be performed for investigating whether a robot can direct user's action (like with pointing to an object) and how robot expectations on user reactions can be modelled as a prior distribution on the coupled inverse-forward models.

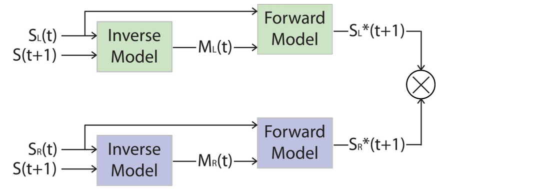

Figure 2: Inverse (controller) - forward (predictor) model pairs. $S_L(t)$ and $S_R(t)$ are the (x, y, z) coordinates of each end-effector at time t; $S(t+1)$ is the desired position to reach; $S^*_L(t+1)$ and $S^*_R(t+1)$ are the predicted final positions for each end-effector; $M_L(t)$ and $M_R(t)$ are the predictions of the motor configurations for reaching $S(t+1)$ from $S_L(t)$ and $S_R(t)$, respectively.

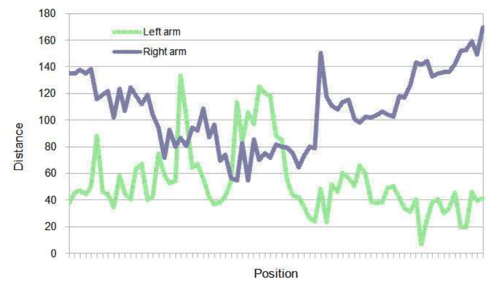

Figure 3: Distance between the predictions of end-effector position and the desired point.

Future work will also consider an active choice between several tools for a given task, and will include additional actions apart from reaching an object.

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