Sensorimotor Loop Simulations as a Prerequisite for Imitation. Experiments with a Humanoid Robot

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Introduction

Developmental Robotics is a recent interdisciplinary field involving robotics, cognitive science, developmental psychology and neuroscience which aims at building robots capable of learning and interacting like humans do and, at the same time, providing a test platform for the theories of neuroscientists and of developmental and cognitive scientists.

We as humans, are able to understand the motor actions of an interacting individual thanks to social skills that let us empathize with a demonstrator and simulate its behaviour. This hypothesis has been supported by the neuroscientific discovery of the **Mirror Neurons System**, which is thought to be involved in internal simulations of the sensorimotor loop.

In this work we focus on **imitation** as a learning mechanism for robots and in particular on the role sensorimotor loop simulations play in **action recognition** and **action execu-**

Internal Simulations of the Sensorimotor Loop

There is evidence that the primitive exploratory actions of human infants come from random acts known as **body babbling**. Using such a non-social learning behaviour, newborns acquire the capability to understand how their movements affect their perception of the environment. This capability is gradually reinforced and extended through social learning.
The 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 of our body, e.g. where an object can be reached. A proposed mechanism to code these schemes are internal models [2, 3, 4, 7].

In this work we investigate the capabilities of two such models. First, we look at a forward model which is an internal model that incorporates knowledge about sensory changes produced by self-generated actions of an agent. Forward models (or predictors) present the causal relation between actions and their consequences.
Secondly, we investigate inverse models (or controllers) which perform the opposite transformation providing a system with the necessary motor command to go from a current sensory situation to a desired one. 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 of these pairs is more plausible in the given context.

We tested this hypothesis on a humanoid robot (Aldebaran Nao), which was programmed for learning autonomously, through body babbling, a couple of predictor-controller pairs for reaching positions in space with its two arms [6]. In order to have a set of different possibilities for action selection, we extended the left arm of the robot with a tool, which significantly modifies the working space of the arms [1, 5].
The system successfully learns and predicts the causal relationship between the motor commands applied to the robot's arms and neck with the visual perception of its moving hands.
Running internal simulations of reaching actions with both arms, allows the robot to choose which is the best arm to use for reaching an object before executing the action (Fig. 1,2,3,4).

The same paradigm can be applied in action recognition (Fig. 5, 6). Internal simulation of

Figure 1.
Body Babbling for learning the sensorimotor schemes that code for the capabilities of the arms.

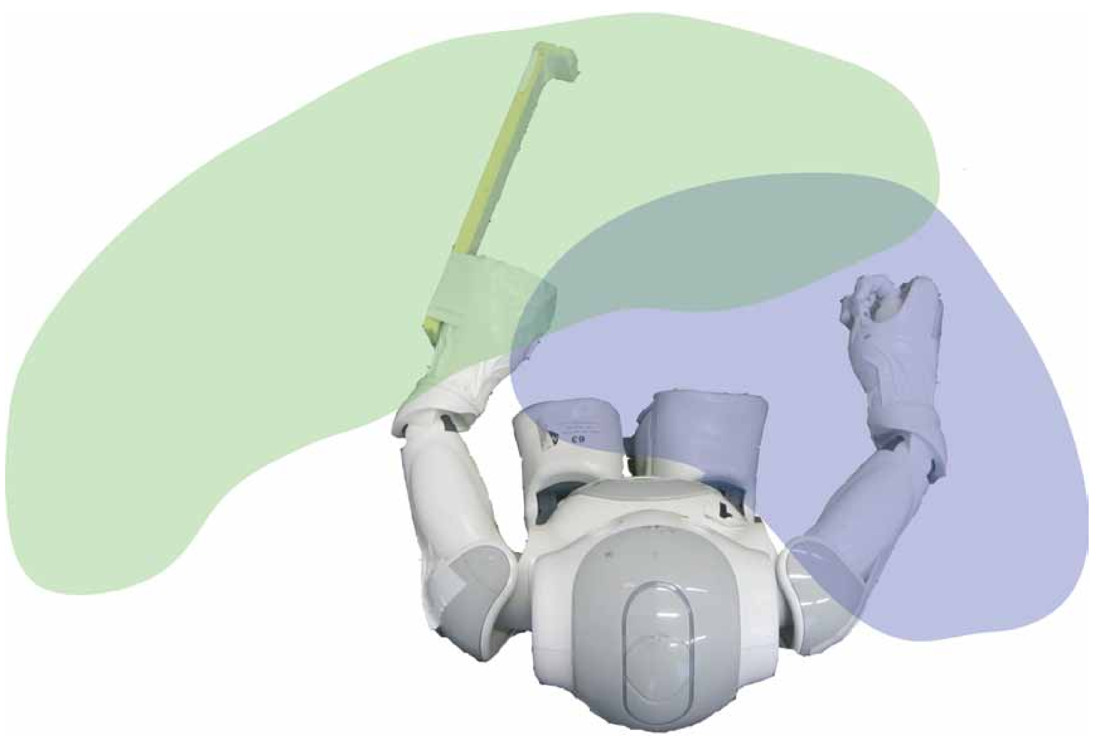

Figure 2.
Top-down view of the Nao with an illustration of the reachable space for each end-effector.

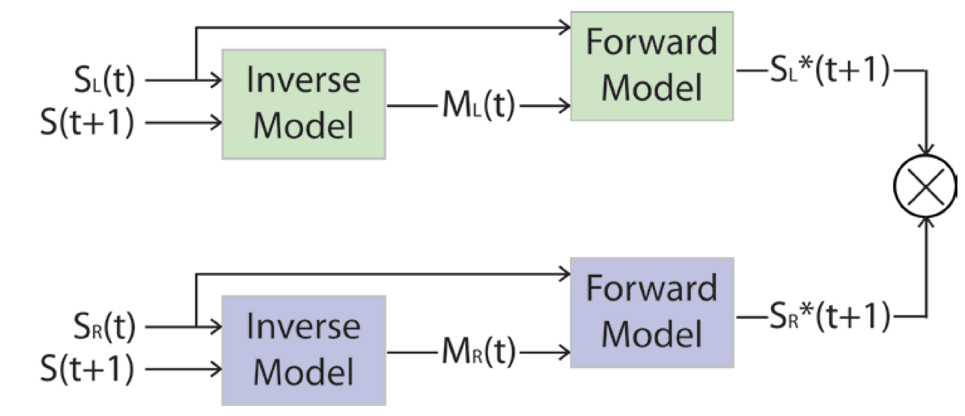

Figure 3.
Two Controller-Predictor pairs.
Given the current sensory situation, composed by the coordinates of the hands, S(t), and the coordinates of the goal position, S(t+1), the controller for each arm proposes a motor command M(t). These M(t) and the current sensory situation are passed to each of the forward models which in turn predicts a next possible sensory situation. These predicted hand positions are compared with the desired one and the pair with less error is selected for actual execution, namely moving the corresponding arm.

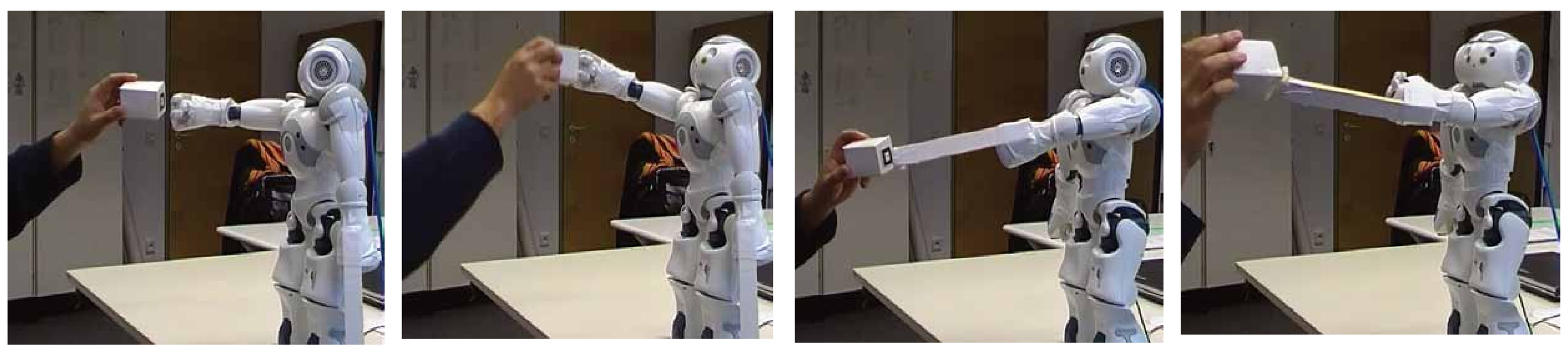

Figure 4.
Action execution demonstration using the controller-predictor pairs from Figure 3.

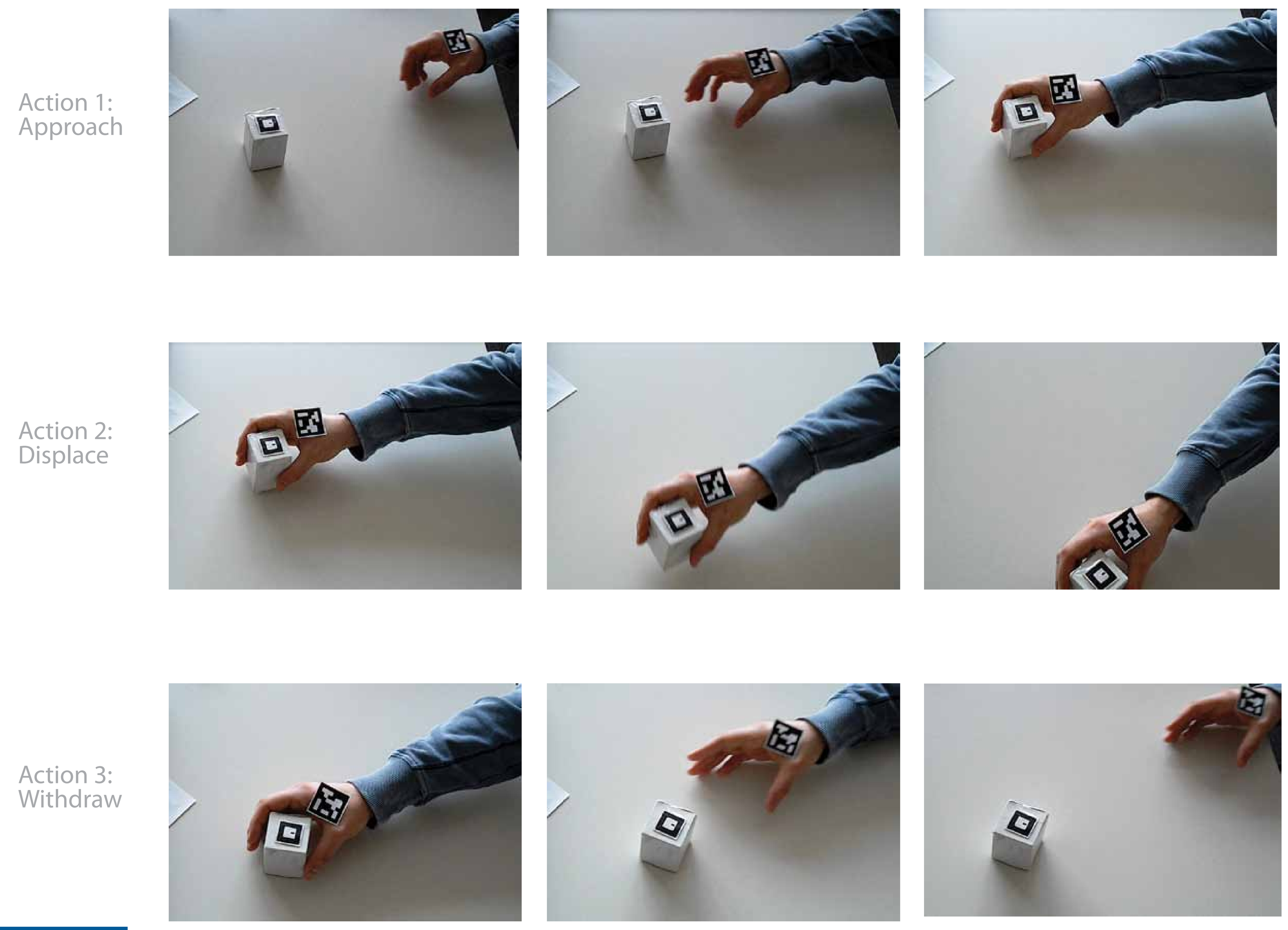

Figure 5.
Test actions for the experiments on action recognition. Features are extracted from videos of three actions for learning controller-predictor pairs as in the action execution example. A different controller-predictor pair is associated with each action.

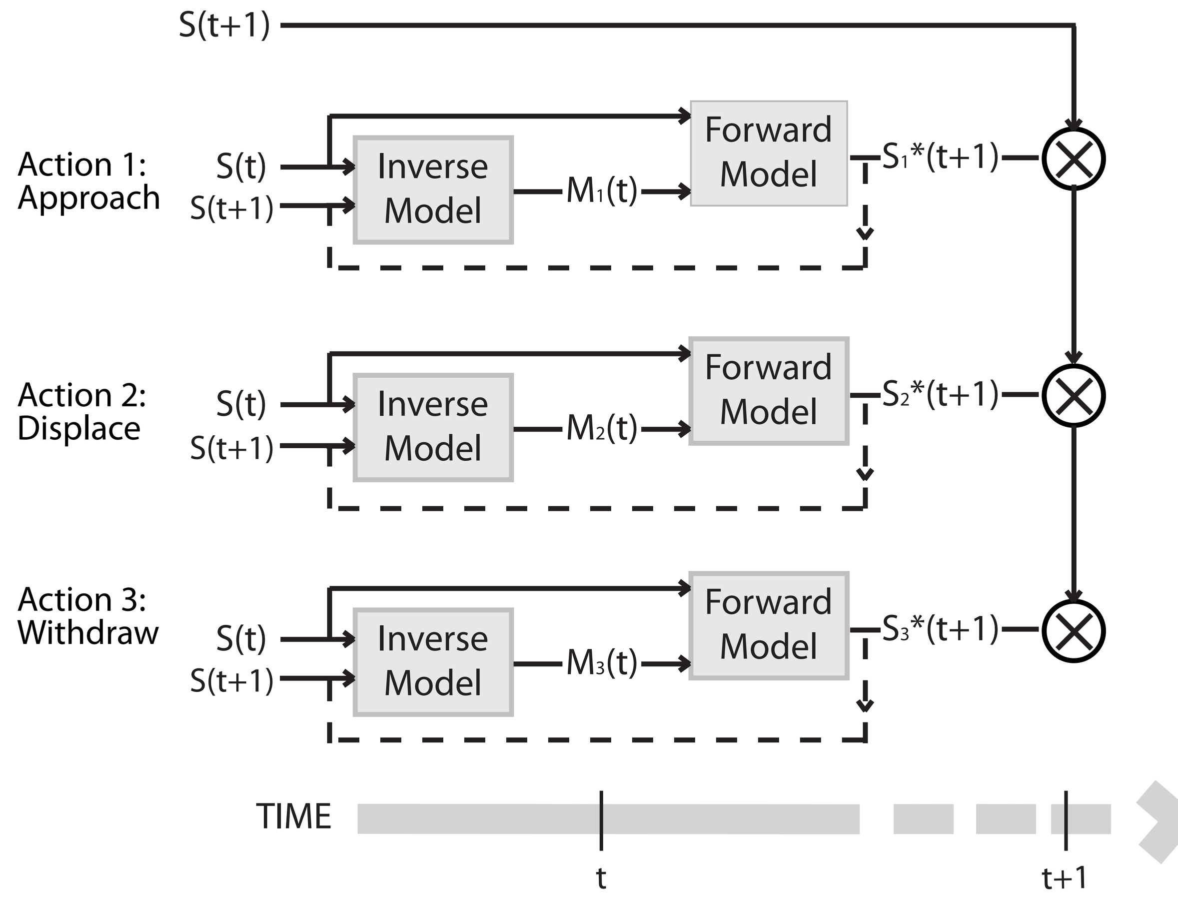

Figure 6.
Behaviour recognition mechanism with three predictor-controller pairs. Each of these pairs is associated with an action. Only one time slice is represented. In the behaviour recognition case, S(t) and S(t+1) code for the states of the observed demonstration. The sensory situation S(t) is composed by variables representing the relations between the position of the hand of the demonstrator and the position of the object. The motor command M(t) is represented by the translation to be applied to the hand.

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References

[1] K. O'Regan, L. Rat-Fischer and J. Fagard. Mechanisms leading to tool use: A longitudinal study in human infants. Frontiers in Computational Neuroscience,2011
[2] A. Dearden. Developmental learning of internal models for robotics. PhD thesis, Imperial College London, 2008.
[3] M. Haruno, D. M. Wolpert, and M. Kawato. Mosaic model for sensorimotor learning and control. Neural Computation, 13, 2001.
[4] M. I. Jordan and D. E. Rumelhart. Forward models: Supervised learning with a distal teacher. cognitive science, 16:307,1992.
[5] A. Maravita and A. Iriki. Tools for the body (schema). Trends in Cognitive Science, 2004.
[6] G. Schillaci, V.V. Hafner, B. Lara, Coupled Inverse-Forward Models for Action Execution Leading to Tool-Use in a Humanoid Robot. To appear in Proc. of the Human-Robot Interaction 2012 conf. (HRI2012)
[7] D. M. Wolpert, K. Doya, and M. Kawato. A unifying computational framework for motor control and social interaction. Phil. Trans. of the Royal Soc. of London. Series B: Biol. Sc., 358(1431), March 2003.