Internal Simulation of the Sensorimotor Loop in Action Execution and Recognition

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Introduction

The idea that "Thinking is restrained speaking or acting" anticipated the idea that behaviours can be simulated in our brain. Three basic assumptions are made:

- Simulation of actions. Motor structures are activated resembling the activity of action execution without producing any movement.
- Simulation of perception. We are capable to image perceiving something, without any external stimulus.
- Anticipation. A simulated action can produce perceptual activity that resembles the activity that would have occurred if the action had really been performed.

Recent theories suggest that activity in motor structures, when initiating an action, can occur while its execution is suppressed by the primary motor cortex. Furthermore, internal simulations of the sensorimotor loop seem to play an important role not only in action execution but also in action recognition. Both of these are basic prerequisites for the imitation of an observed action. We as humans, are able to understand the motor actions of an interacting individual thanks to the social skills that allow us to empathize with the demonstrator and simulate its behaviour. This hypotesis is now supported by the neuroscientific discovery of Mirror Neurons System, which is thought to be involved in internal simulations of the sensorimotor loop in learning and planning.

Internal simulation in action execution

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.

We investigated the capabilities of two such models. First, we looked 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 investigated 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 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 the space with its two arms. 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 arm.

The system successfully learned and predicted the causal relationships between the motor commands applied to its 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 (see Figure 4).

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







Figure 2.

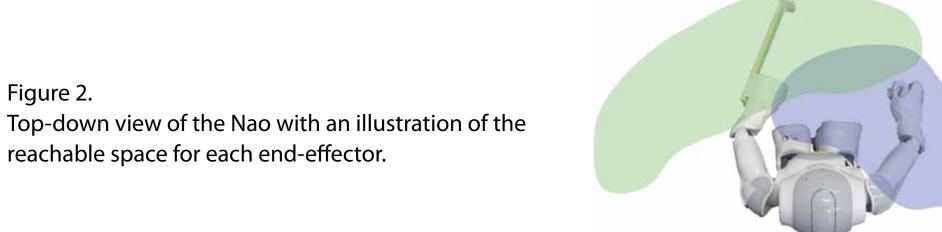


Figure 3. Two Controller-Predictor pairs.

Given the current sensory situation, composed by the coordinates of the hands (St) and the coordinates of the goal position (St+1), the controller for each arm proposes a motor command (Mt). This Mt and the current sensory situation are passed to each of the forward models which in turn predicts a next possible sensory situation. This 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.

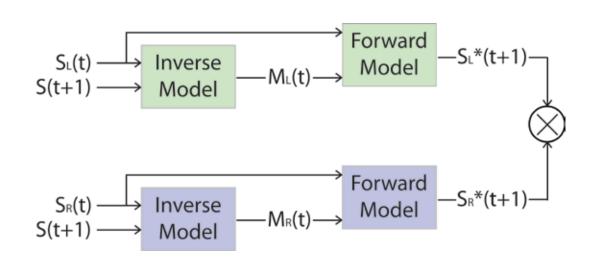
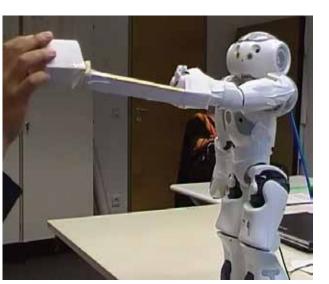


Figure 4. Action execution demonstration.









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INTRO

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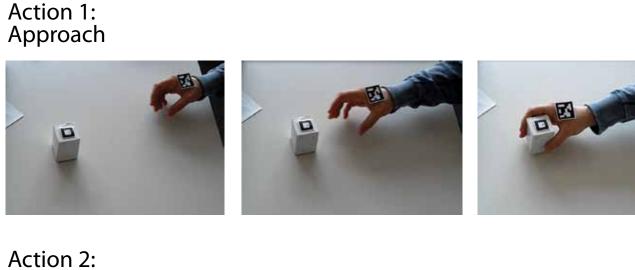
Internal simulation in action recognition

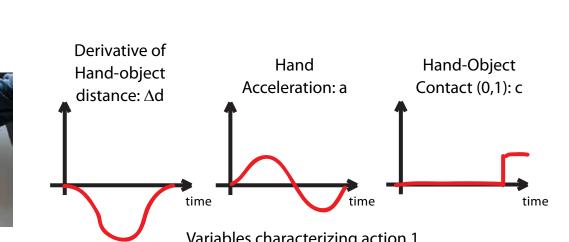
Several mirror system inspired architectures have been designed, with the aim of using internal models in robotics to produce simple movements or behaviours as well as to understand them when produced by others.

By means of modularity multiple paired inverse-forward models (one for each known action) can act in parallel. The perceived state and, if exists, a desired goal are sent to all the inverse models, resulting in a generation of multiple motor commands (efference copies) which are sent to their respective forward models. Each forward model simulates the sensory consequences of the control created by its coupled inverse model; then each sensorymotor consequence is compared with the actual demonstrator state. The inverse model with higher confidence (less distance with the demonstration) is selected as the estimate of the demonstrator's behaviour (when observing behaviours) or for control generation (when reproducing behaviours).

Using this approach we model a system which can recognize actions performed on objects by a demonstrator. The actions are described by the behaviour of different variables that characterize the relations between the position of the hand of the demonstrator and the position of the object.

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

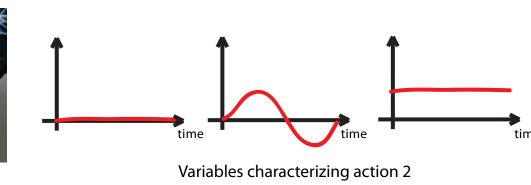




Displace







Withdraw

Action 3:





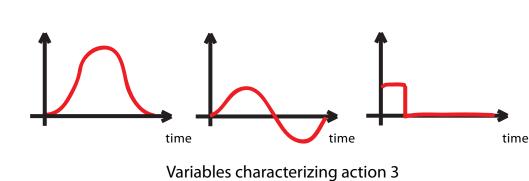


Figure 6. Recursive simulation of the sensorimotor loop for one action. The sensory situation S(t) is composed by

variables: Δd , a, c. The motor command M(t) is represented by the translation $(\Delta x, \Delta y, \Delta z)$ to be applied to the hand.

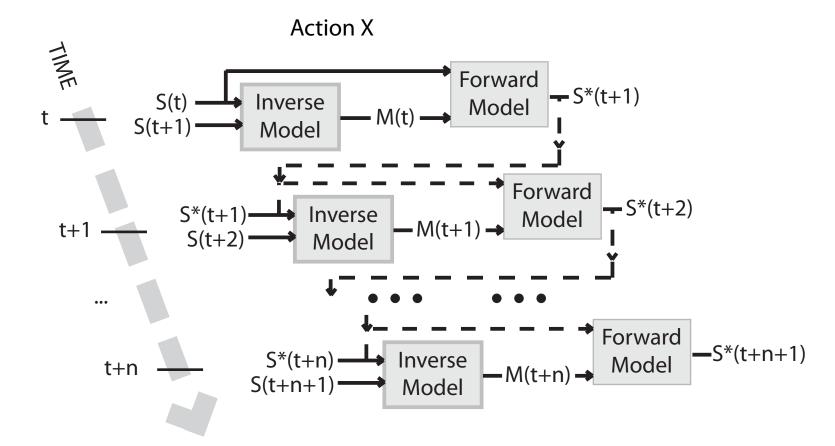


Figure 7. Behaviour recognition mechanism with three predictor-controller pairs. Each of these pairs is associated to an action. Only one time slice is represented. In the behaviour recognition case, S(t) and S(t+1) code for the states of the observed demonstration

