

# Is That Me? Sensorimotor Learning and Self-Other Distinction in Robotics

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**Abstract**—In order to have robots interact with other agents, it is important that they are able to recognize their own actions. The research reported here relates to the use of internal models for self-other distinction. We demonstrate how a humanoid robot, which acquires a sensorimotor scheme through self-exploration, can produce and predict simple trajectories that have particular characteristics. Comparing these predictions to incoming sensory information provides the robot with a basic tool for distinguishing between self and other.

**Keywords**—Internal simulations; inverse and forward models; self-advantage; self-other distinction; sensorimotor learning.

## I. INTRODUCTION

Distinguishing between self and other is a cognitive ability that requires a basic understanding of our self and how we interact with the world. To achieve this, we seem to rely on very finely tuned models of our motor capabilities. These models are involved in the control of our actions as well as in the prediction of the sensory consequences these have on our bodies and the environment [1]. These predictions are what is thought to underly our sense of ownership, and thereby provides us with a means to recognize when actions are performed by others [2].

The visual system, which is of particular interest here, has been shown to be very sensitive to biological motion [3]. Even when presented with point-light displays of human movement for which bodily form information is essentially absent, people can still rely on the available kinematic information to successfully track the motion [4], predict its outcome [5], or even recognize who produced it [6]. Such effects generally lead to a so-called *self-advantage*: Performance is better when perceiving one's own movements.

Human biological motion has specific properties that makes it different from other types of motion [3]. For example, when people move their hands from one point to another, they often follow a straight line with a bell-shaped velocity profile, characterized by an initial acceleration phase followed by a somewhat longer deceleration phase [7]. Another well-known property of human action is that movement velocity systematically varies with movement curvature, such that we typically slow down as curvature increases [8].

Perfect candidates to encode such properties are Inverse-Forward Models pairs. These pairs form multi-modal sensory

associations between sensory situations and motor commands. An inverse model is a controller that suggests a motor command to bring a system from a given sensory state to a desired sensory state. In contrast, a forward model predicts a sensory state given the current sensory state and a motor command.

We use these internal model pairs to code the movements performed by a Nao humanoid robot [9]. The research reported here is based on the use of such models for self-other distinction. We believe that in order to have robots interact with other agents, it is important that they first be able to recognize their own actions.

## II. EXPERIMENTS

In order to learn the internal model shown in figure 1 we let the robot perform random body babbling. This babbling is performed in the joint space of the robot's arm. For every movement, we record the 3D-coordinates of the end position of the arm. The babbling training session resulted in 41,502 collected samples.

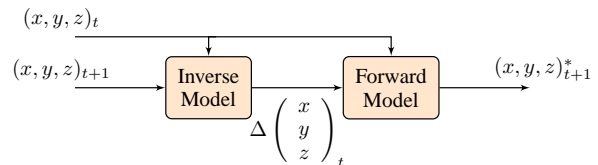


Fig. 1: Internal model pair

Each model is coded as a Multi-Layer Perceptron network. For the inverse model the sensory situation  $S_t$  is the position of the end-effector at time  $t$  and the goal position  $S_{t+1}$  is the coordinate at  $t + 1$ .

The output of the inverse model is the necessary change in 3D coordinates to go from  $S_t$  to  $S_{t+1}$ . The suggested motor command  $M_t$  and the current sensory situation  $S_t$  are used as input to the forward model, which in turn predicts the resulting sensory situation <sup>1</sup>.

<sup>1</sup>The forward and inverse models have been coded as MLPs with 6 input neurons, 10 neurons in the hidden layer, and 3 output neurons. During training, the epsilon threshold term criteria was reached after 18 iterations for the forward model and after 154 iterations for the inverse model. Training term criteria: MaxIteration=5000; Epsilon= 0.00001; Activation function = Symmetrical Sigmoid; Training algorithm = BackPropagation.

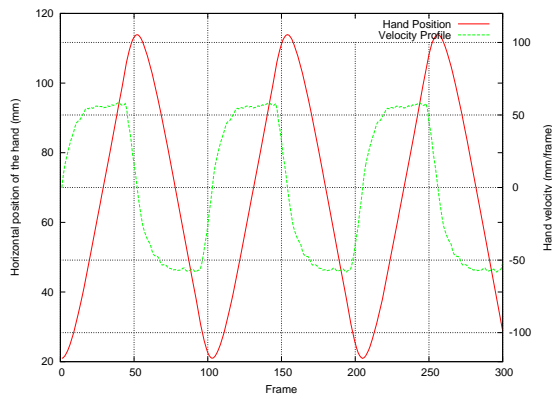


Fig. 2: Nao: hand trajectory (red line) and corresponding velocity profile (green line).

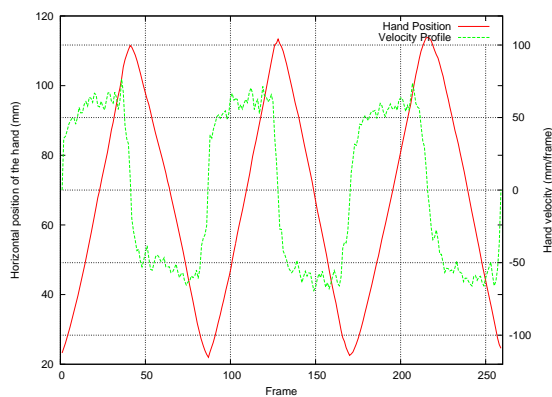


Fig. 3: Puma: hand trajectory (red line) and corresponding velocity profile (green line).

Figures 2 and 3 show the execution of a number of controlled back and forth movements (along the  $X$ -axis) by the Nao and another robot, viz. a Puma. As can be seen, these movements have distinctive trajectories (red lines) and velocity profiles (green lines) and we relied on internal simulations to distinguish between these two types of movements. Figure 4 shows two frames of the experimental setup.

Simulations of the sensorimotor loop were run by feeding the internal models with the sensory states taken from the two

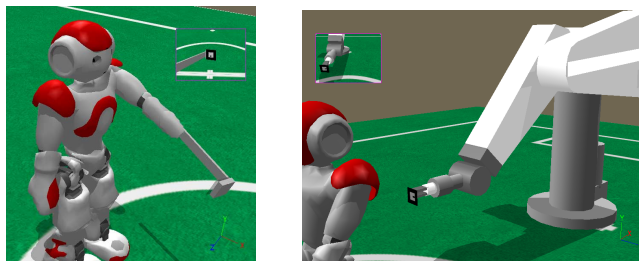


Fig. 4: Experimental Setup: both the babbling training session for data collection and the testing session were run in the Webots robot simulator.

trajectories (Nao, Puma). Frame by frame, prediction errors were computed as the euclidean distance between the actual hand positions and the predicted ones. The prediction errors at each frame over 3 movement cycles were submitted to a two-tailed independent-samples  $t$  test, which yielded a significant effect,  $t(563) = 4.55$ ,  $p < .001$ . This result reflects that the mean prediction error for the Nao profile ( $31.19mm$ ) was smaller than for the Puma ( $35.74mm$ ) profile and is consistent with the self-advantage typically observed in prediction [5] and recognition [6] experiments involving humans.

### III. CONCLUSIONS

In order to have robots interact with other agents, it is important for them to be able to first take ownership of their own actions. We demonstrated how sensorimotor schemes acquired through self-exploration can be used as a basis for distinguishing between the self and other. In particular, the errors that arise from predicting observed actions with one's own sensorimotor system could be used for self-other distinction in robotics. An interesting challenge for future research will be to establish what aspects of movement (e.g., form, velocity, or perhaps the relationship between the two) is being learned by the Nao and how this ultimately leads to a better prediction of its own movements.

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