Using proprioceptive information for the development of robot body representations

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Abstract—**As part of the attempt to improve a robot's flexibility and adaptation by adopting biologically inspired developmental methods, we trained a multilayer perceptron model (MLP) to develop body representations of a humanoid robot using proprioceptive and motor information. The information used were the left arm joint positions, the motor commands and the electric currents applied to these joints. By babbling its left arm, that is by executing a self-exploration behaviour, the robot gathered sensorimotor information for training the model. Once having learned the relation between these different modalities, the model can be used for running predictive processes. We present our first training results and discuss further research possibilities.**

I. Introduction

This project is part of an attempt to study and improve robot learning skills using developmental approaches inspired by psychology research [1]. This approach has the potential to allow more flexibility and adaptation in unexpected and uncertain environments [2]. Here, we focus on the development of body representations - the agent internal model of its own body parts' shape, orientation and movement. Such a model is required for executing certain motor actions such as touching and picking up different objects [3]. Although predefined models of the robot body are usually provided by the robot manufacturer (e.g. Aldebaran Nao, iCub), those are implemented explicitly and are incapable of being autonomously refined and of adapting to unexpected circumstances.

In infants, the process of acquiring body awareness involves active exploration of the sensorimotor space by babbling and self-touch [4]. Inspired by this developmental process, we applied similar mechanisms on the humanoid robot Nao. In particular, we equipped the robot with a mechanism for autonomously learning an internal body representation consisting of a mapping between different sensory and motor modalities. Our aim is to use the predictive capabilities provided by the model for detecting unexpected events, such as changes in the robot morphology or events from the external environment, based on the knowledge that the robot has about its own body. In this preliminary work, we present the learning of such a body representation and the predictive capabilities of the model.

As opposed to the iCub robot, the Nao robot does not have any "skin" sensors for touch recognition [5]. As an alternative, and inspired on the human proprioceptors which provide information from the human muscles [6], we adopted the available motor and current measurements from the robot joints. In mammals, such a proprioceptive information has a crucial part in the sensorimotor system and self perception development [7], [8].

Using an artificial neural network, the robot can develop and maintain an internal model that can also be used for recognising unexpected situations such as external stimuli or body changes. This knowledge can be encoded as a mapping between the different sensor modalities - the angle position of the joints measured from the proprioceptive sensor (in radians), the motor commands applied to the joints (in radians) and the electric current consumed by the joints (an absolute value in Ampere) [9].

The entire experiment was performed on the humanoid robot Nao manufactured by Aldebaran Robotics. We used it in real environments, as well as in a robot simulator - Cyberbotics Webots. In the experiment reported here, we used data recorded from the real robot. Training data was collected while the robot was performing a self-exploration behaviour of the left arm, namely random motor babbling. It was moving its five joints (presented in Figure 1) randomly, without any particular intention. In a preliminary experiment, we collected information from the two shoulder joints: "shoulder pitch" and "shoulder roll".

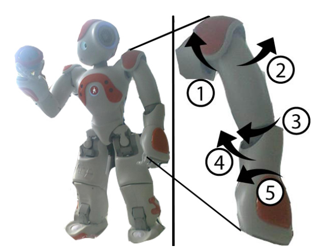

Fig. 1. The left hand joints of a Nao robot: shoulder pitch, shoulder roll, elbow yaw, elbow roll, wrist yaw. These joints allow the full motion of the robot's hand in space.

The data was then used to train an MLP model in a supervised manner using back-propagation. The MLP was constructed of a 4-node input layer, two hidden 6-node rectified linear layers and a sigmoidal output layer of 2 nodes, one for each target value. Perceived angle positions of the two shoulder joints and the motor commands applied to them were used as input (for a total of four variables) while the electric currents applied to the two joints were used as the output of the model.

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We tested the model on a second data set, recorded in the same way as for the training set, during babbling.

II. Preliminary results

The first step, presented in Figure 2, was the training of the MLP on a set that consists of 10500 samples (about 5 minutes of random motor babbling). The training was run for 1000 epochs to ensure convergence. During this process, we validated the performance of the model on a second set of 6000 samples (~3 minutes of random body babbling).

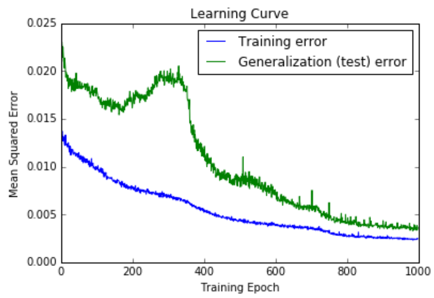

Fig. 2. The average training and test errors after each epoch of training. The curve shows signs of convergence as the change in the latest steps is small. The decaying generalisation error graph ensures us that the model is not overfitting the training samples, but rather relies on a true relation.

After training, we used the network to estimate again different parts of the validation session. These estimations are plotted in Figure 3 below the real current values.

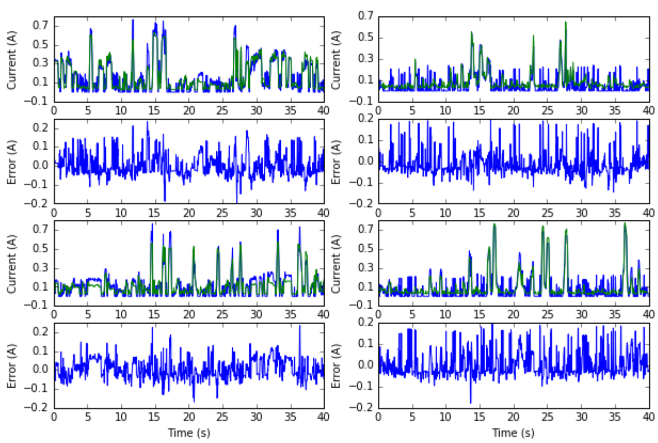

Fig. 3. Test estimation results. Every pair of plots shows an example of the real (Blue) and estimated (Green) current values above the prediction error along 40 seconds of left hand babbling. The plots on the left relate to the shoulder pitch joint and the plots on the right relate to the shoulder roll joint.

These preliminary results are promising. The MLP model seems to have learned how to use the joint sensor and actuator information to effectively estimate the current magnitude of new samples, especially the ones with high values.

III. Future work

So far we evaluated the likelihood of developing and maintaining a body representation of a Nao robot using the available proprioceptive information. After examining the preliminary results it seems plausible. Our next step will be to examine the model reaction to unexpected circumstances such as carrying weight on the babbling hand or colliding it with an obstacle. We expect to see an increase in the prediction error when encountering these unfamiliar situations. At the same time we would also like to include all the joints of the arm in the training and prediction tasks. We would also like to understand what information is actually used by the MLP for creating its predictions. for example, as shown in figure 4, the non-trivial relation between the sensor-actuator difference and the current seems to be averaged and learned by the model.

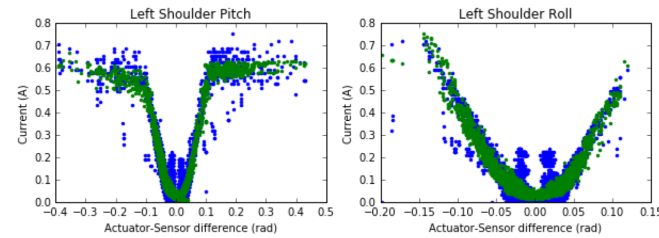

Fig. 4. The actual (Blue) and estimated (Green) current of each joint as a function of the actuator-sensor difference.

In the future, this learning process could include other modalities (e.g. visual) to develop more comprehensive body representations.

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