Random Movement Strategies in Self-Exploration for a Humanoid Robot

Guido Schillaci
Cognitive Robotics Group,
Department of Computer Science,
Humboldt-University Berlin, Germany
guido.schillaci@informatik.hu-berlin.de

Verena V. Hafner
Cognitive Robotics Group,
Department of Computer Science,
Humboldt-University Berlin, Germany
hafner@informatik.hu-berlin.de

***Abstract*—Motor Babbling has been identified as a self-exploring behaviour adopted by infants and is fundamental for the development of more complex behaviours, self-awareness and social interaction skills. Here, we adopt this paradigm for the learning strategies of a humanoid robot that maps its random arm movements with its head movements, determined by the perception of its own body. Finally, we analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed.**

I. Introduction

Embodied agents, humans, other animals as well as robots, can generate useful sensory stimulations by interacting with the environment. Their actions change the environment and what they perceive from it; on the other hand, what they perceive influences their actions consequently. This is known as sensorimotor coordination[1].

The discovery of mirror neurons demonstrates how closely cognitive concepts and sensorimotor activity are coupled in the human brain. Mirror neurons are thought to play a fundamental role in social cognition and in understanding behaviours and intentions of others[2]. Supporters of this theory claim that, somehow, we are able to predict what a demonstrator is doing, because some areas in the brain, including the mirror system, internally simulate aspects of the sensorimotor loop in learning and planning. We understand an observed behaviour as we compare a simulated execution of it with a set of motion primitives we have in our memory. But, how much do perceptual abilities require motor skills? In order to imitate a demonstrator, an observer has to recognize the action, but in order to recognize the action the observer must be able to perform the action. This tricky question can be answered if we look at the development as an incremental process: infants learn an ability on top of other abilities already present[1]. Body babbling observed in infants has been classified by Meltzoff and Moore[3] as a mechanism that provides experience for mapping movements to the resulting body configurations.

Such a sensorimotor stage, where infants explore the environment in terms of the physical actions they can perform, inspired several robotics studies. In [4], the role of exploration is to gather evidence to form and test models. In [5], Demiris et al. propose a way for combining knowledge through exploration and knowledge from others, through the creation and use of mirror neuron inspired internal models. Saegusa et al., in [6], consider motor-babbling-based sensorimotor learning as an effective method to autonomously develop an internal model of the own body and the environment using multiple sensorial modalities.

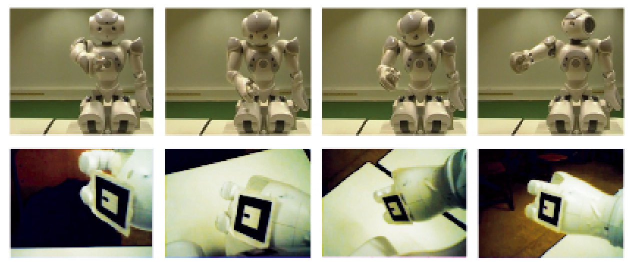

Fig. 1. A typical babbling sequence using the Nao platform. In the lower part, the corresponding frames grabbed by the onboard camera (note that the camera is placed below the fake eyes).

Here, we adopt motor babbling for the learning strategies of a humanoid robot that maps its random arm movements with its head movements, determined by the perception of its own body. We also analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed.

II. Learning through self-exploration

We implemented learning through self-exploration on a humanoid platform[1] whose dimensions resemble those of a child, actually simulating the real visual input perceived by a young human subject (see Figure 1).

During the learning process, the robot performs random arm movements and tries to estimate the position of its end-effector (the hand, where a marker is placed on), analysing the frames grabbed from its head camera. We implemented an attentive system composed by two modules: marker detection[2] and motion detection. When a marker is detected, the head of the robot is rotated in order to focus on it, and the current configuration of the joint angles of the arm and of the neck

[1]NAO robot from Aldebaran. We adopted the NAO-TH framework (http://www.naoteamhumboldt.de)

[2]We use the ARToolkit for detecting markers (http://www.hitl.washington.edu/artoolkit).

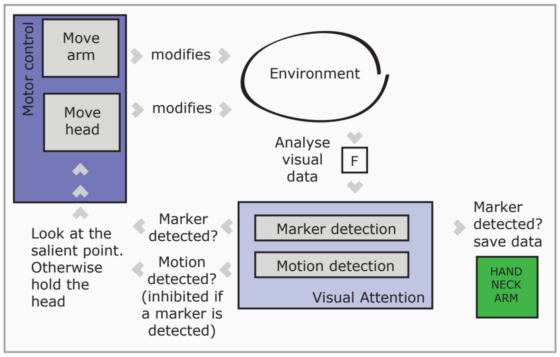

Fig. 2. Learning Algorithm. The marker detection module inhibits the motion detection module, giving a higher saliency to the hand of the robot.

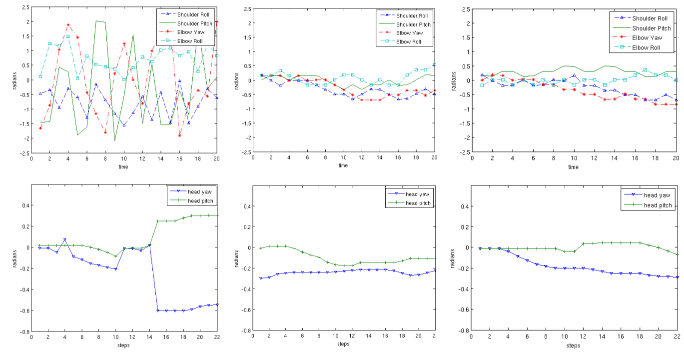

Fig. 3. In the upper part of the figure, typical values of the joints angles of the arm for each strategy (PR, RW, IRW) are shown. The lower part shows the values of the joint angles of the neck.

are stored and coupled with the estimated 3D position of the marker (representing the hand). Due to the limited opening angle of the camera and the robot's short arms (like a child), for most of the time the robot has to rotate its head searching for the marker. The motion detection module is used in order to find the moving arm. Frame by frame, when the head is not moving, the optical flow between the current frame and the previous one is computed. The magnitude of the optical flow is fed into the CAMShift algorithm to find the centroid of the fastest moving area of the video to look at. Figure 2 shows the scheme of the learning algorithm.

III. Preliminary Results

The preliminary results we present here refer to three different types of movement strategies for motor babbling: Purely Random (PR), Random Walk (RW) and Inertial Random Walk (IRW)[3]. Figure 3 shows typical trajectories of the arm joints and of the neck joints for each type of babbling. PR generates sparse commands in the action space and the long jumps in the joints space often increase the probability to lose the sight of the hand. Even if IRW is the strategy that better resembles human motion, up to now RW seems to be the best strategy in terms of learning speed, as depicted in Table I[4]. IRW seems to perform worse than RW due to its tendency to follow the motion inertia towards areas wherein the hand is partially occluded by the shoulder of the robot. The last row of Table I represents, for each strategy, the maximum jump in degrees that a random movement can perform[5].

[3]In PR, random values are sampled from a uniform distribution over the range of each joint of the arm; in RW, random steps (increase/hold/decrease the joint by *angle-step*) are sampled from a uniform distribution; in IRW, random steps are sampled from a non-uniform distribution, where the previous performed step has a higher probability to be sampled. The babbling is performed on 4-DoF of the Nao arm: two each for shoulder and elbow.

[4]Low detecting rates depends on a high probability that movements go outside the field of view of the camera, and on the time needed to find again the arm by moving the head.

[5]The ranges are (in degrees): ShoulderPitch, from -120 to 120; ShoulderRoll, from -95 to 0; ElbowRoll from 0 to 90; ElbowYaw from -120 to 120. In RW and IRW, only a maximum step of 10 degrees is allowed for each joint. The maximum speed of the total movement (sum of all the joints) is 20 degrees per second for all strategies.

TABLE I
Preliminary Results

	PR	RW	IRW
Detections per sec.	1.04	4.63	2.63
Max jump in deg.	665	40	40

IV. Future Work

The collected data could be used for generating unexplored movement and for reaching unexplored positions in the action space. Imitation of hand trajectories of a skilled agent could be done through a mapping of the proprioceptive and external data. Behaviours could be modelled by mapping regions of the action space with the states of a discrete Hidden Markov Model. Learning performance could be improved using a head equipped with two pan-tilt mechanisms to reproduce both neck movements and saccades. These learned skills are the prerequisites for imitation learning in human-robot interaction.

Acknowledgment

This work has been financed by the EU funded Initial Training Network (ITN) in the Marie-Curie People Programme (FP7): INTRO (INTeractive RObotics research network).

References

[1] R. Pfeifer and J. Bongard, "How the body shapes the way we think: A new view of intelligence." *The MIT Press*, Nov. 2006.

[2] V. Gallese, "Before and below theory of mind: embodied simulation and the neural correlates of social cognition." *Phil. Trans. of the Royal Society B*, vol. 362, no. 1480, pp. 659–669, Apr. 2007.

[3] A. N. Meltzoff and M. K. Moore, "Explaining facial imitation: a theoretical model." *Early Development and Parenting*, vol. 6, pp. 179–192, 1997.

[4] A. Dearden, "Developmental learning of internal models for robotics. phd thesis." pp. 20–22, 2008.

[5] Y. Demiris and A. Dearden, "From motor babbling to hierarchical learning by imitation: a robot developmental pathway." *Proceedings of the Fifth International Workshop on Epigenetic Robotics Modeling Cognitive Development in Robotic Systems (2010)*, vol. 123.

[6] R. Saegusa, G. Metta, G. Sandini, and S. Sakka., "Active motor babbling for sensorimotor learning," *IEEE International Conference on Robotics and Biomimetics*, pp. 794–799, Feb. 2008.