Prerequisites for Intuitive Interaction - on the example of Humanoid Motor Babbling

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***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. Exploring the possible space of movements and articulations is the first step towards social and intentional behaviours.**

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. In this paper, we analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed.

We believe that intuitive human-robot interaction requires physical and dynamic interaction and that creating a body map through learning is a major prereuisite.

I. Introduction

Researchers in Human-Robot Interaction are interested in developing models inspired by human cognitive processes, in particular such that they result in a natural interaction behaviour. Providing the robot with skills that let the interaction look clever and intuitive ensures a high level of satisfaction for the interacting person.

Cognitive robotics takes its inspiration from developmental studies in humans. Infants incrementally develop cognitive abilities through the interaction with the environment and with persons. 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].

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[2] 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 [3], the role of exploration is to gather evidence to form and test models. In [4], 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 [5], 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.

Exploring the possible space of movements and articulations is the first step towards more intentional behaviours, like exploring the world, wherein the agent wants to figure out how its actions change the state of the world. Socially speaking, an agent might be aware of itself, first, to be aware of the other as a being like the self with individual wants and intentions.

In the next section, we discuss the different prerequisites for intuitive interaction and how they could be implemented on a humanoid robot. We then adopt one of the major prerequisites for HRI - motor babbling and learning of a body map - 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 equip the robot with an elementary attentive system for perceiving its own body and for moving its head to focus on it. A self-exploring robot that can optimally adapt to the abilities of its own body in interaction with the environment, itself and others, could give a human the impression that it is intelligent, interested in something it would like to discover, driven by the curiosity of exploring its own movement. We analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed and how much energy they consume. We also implemented a simple algorithm for learning body maps through motor babbling. In the last section, we discuss how the results on motor babbling could influence future research aiming at intuitive human-robot interaction.

II. Prerequisites for Intuitive Human-Robot Interaction

What do we understand by intuitive interaction? This question is related to expectations of the human, but can also be described as an interaction that results in a satisfying experience for the human requiring a low cognitive load. It also means that the person does not have to learn a specific interaction protocol for the human-robot interaction, but that the robot adapts to the type of interaction initiated by the person. Intuitive interaction is still possible in case the human has no strong expectations on the robot, its capabilities, and reactions, but enters the interaction scenario with his or her expectations about interactions with other people, animals or even non-intentional agents or objects.

We have identified three different kinds of prerequisites for intuitive interaction:

a) *Physical prerequisites for intuitive interaction*. These are properties of the morphology, sensors types, and appearance of the robot. End-effectors with a large number of degrees of freedom, and a variety of sensors, ideally similar to those of a human, would facilitate the interaction and increase the interaction experience for the user. The properties of the environment or of the user interfaces also seem to be of importance when used as tools for interacting with robots (see for example [6]).

b) *Representation of self and other*. In [7], the authors claim that perspective taking and Theory of Mind skills are crucial for engaging in sensible short time interaction. For implementing such abilities, the robot must be aware of its own body and abilities. A prerequisite for HRI is, thus, the ability to build a body map, which can be done through body babbling, through interaction with the world or through interaction with others. Meltzoff et al. demonstrated in [2] that body babbling provides experience mapping movements to the resulting body configurations. Hafner et al., in [8], argued that self-other distinction is crucial for the development of sophisticated forms of social interaction and proposed a unified representation of a body schema in order to solve the body correspondence problem. Self-other representation is also necessary for simulating the action of the interacting partner through perspective taking.

c) *Social skills and expectations*. When interacting, the robot and the human constitute a dynamic system [9]. Each agent might be able to predict and react to the actions and intentions of the other, often without any verbal communication. Developmental research supports the idea that actions are learnt incrementally and one of the most powerful social skill to do that is imitation. A robot might be able to learn by imitation and to generalize the learned behaviours in different environments and situations. Adapting to physical and social circumstances is a fundamental prerequisite for HRI. Without any doubt, moreover, a robot able to express emotions enhances naturalness of human-robot interaction [10].

We chose to investigate one of those prerequisites of intuitive interaction - representation of self and others - through body babbling.

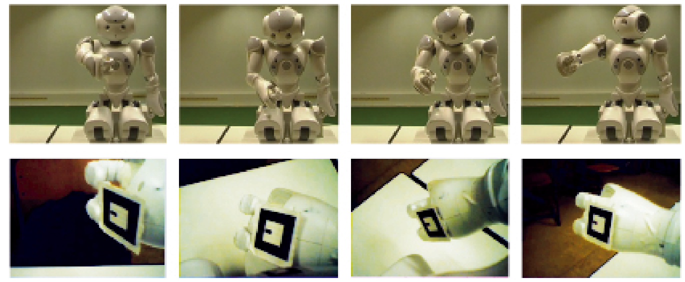

Fig. 1. A typical babbling sequence using the Nao platform. In the lower part are the corresponding frames grabbed by the onboard camera (note that the camera is placed below the fake eyes of the Nao).

III. Motor Babbling in a Humanoid Robot

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 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.

IV. Random Movement Strategies

The 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).

The babbling is performed on 4-DoF of the Nao arm: two each for shoulder and elbow. 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; IRW is a kind of smooth random walk algorithm which simulates the inertia that a moving mass has when it changes the direction of the motion. Instant by instant, a random step is sampled from a uniform distribution, as in RW, and a small amount of

[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).

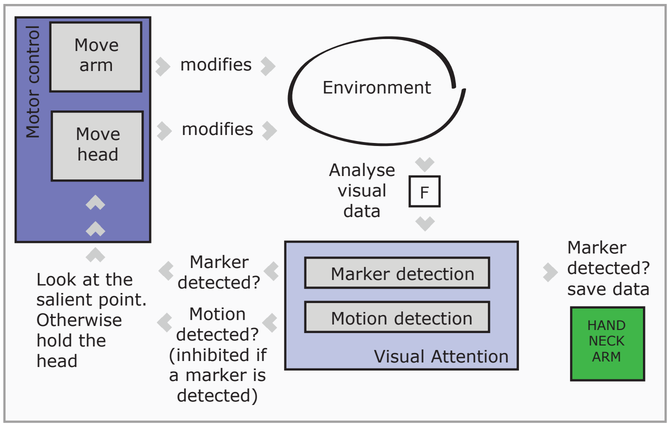

Fig. 2. Learning Algorithm. The marker detection module inhibits the motion detection module, giving a higher saliency to the hand of the robot.

the previous step is added to the current one, simulating the fact that the change of direction is not immediate, as the mass tends to follow the past movement by inertia.

V. Motor Babbling Results

We simulated each strategy for 8 minutes. Figure 3 shows typical trajectories of the arm joints and of the neck joints for each type of babbling. PR generates sparse random commands in the action space; even if it can be thought as a good strategy able to explore uniformly the action space, the long jumps in the arm joints configuration very often increase the probability to lose the sight of the hand. This results in a very time consuming strategy with a low marker detection rate. Table I shows some results for each strategy. Low detecting rates depend 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.

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. 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[3].

We also measured the sum of all the distances (in degrees) covered by each joint for each strategy during a certain amount of time, and compared these values between the three strategies. We used this measurement as an estimate of energy consumption. In simulation, IRW seems to be the cheapest strategy. Consider, for a moment, that the arm is moving toward a given direction. If a new control command is generated toward the opposite direction of the current motion, the simulated inertial strategy will not change instantaneously the direction. Instead, it would lower the speed, first, and then change direction. Going directly on the other direction (as RW might do), would consume more energy. Due to its fast changes of direction and movements, PR seems to be the worst strategy, again.

[3]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.

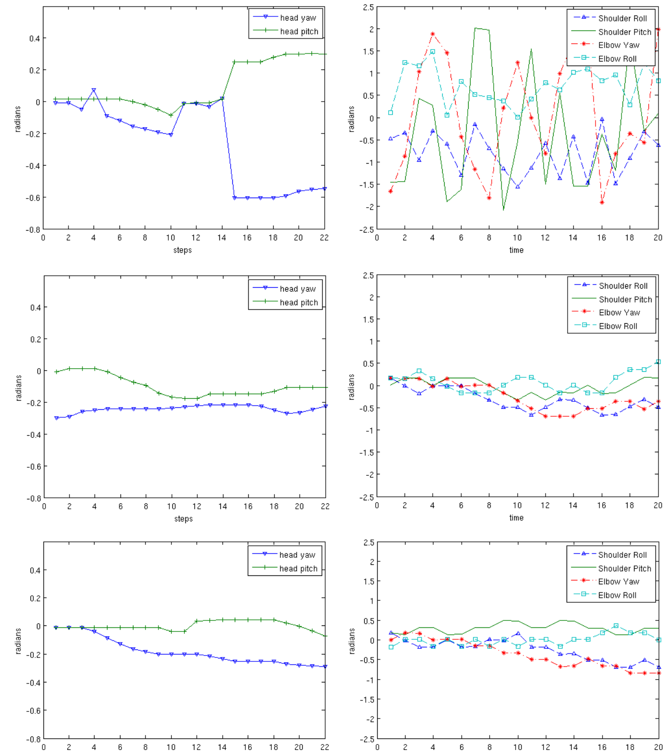

Fig. 3. In the left column of the figure, typical values of the joints angles of the neck for each strategy (PR, RW, IRW) are shown. The right column shows the values of the joint angles of the arm.

The sum of the distances is an estimate of energy consumption but, on the other hand, will give us the same amount of energy spent for a continues movement from 0 to 40 and a movement going from 0 to 20 and then back to 0, for instance. For that reason, we also measured the electric current applied to each servo and compared the averages of the total current applied to all the motor between the three strategies.

We also considered the two servos of the neck (which move accordingly to the attention system), measuring again the distance (in degrees) covered by all the joints, (inclusive the neck ones) for both energy measurements.

All the results confirm that PR is the worst babbling strategy in learning a mapping between the joints configuration of the neck and that of the arm, because of the low marker detection rate and of the high energy dissipation.

Analysing qualitatively the expectation of a human observer on the sensorimotor coordination skills of the robot, it can be noted that PR has also a significantly low rating. The robot is most of the time babbling and searching for the marker, due to the often long jump between an arm movement and the next one. RW and IRW have a higher rating.

TABLE I
DETECTION RATES FOR THE DIFFERENT STRATEGIES

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

TABLE II
ENERGY CONSUMPTION ANALYSIS

		PR	RW	IRW
Simulation	Distance Covered			
	PR	1.000	0.696	0.616
	RW	1.436	1.000	0.885
	IRW	1.622	1.130	1.000
Real Robot	Electric Current			
	PR	1.000	0.752	0.766
	RW	1.330	1.000	1.018
	IRW	1.306	0.982	1.000

VI. LEARNING BODY MAPS THROUGH BODY BABBLING

Learning the mapping between the proprioceptive sensory data and the visual acquired information does not consist only in collecting the data through body babbling. The knowledge base represented by the set of stored vectors $[markerPosition; neckConfiguration; armConfiguration]$ can be used for inferring data given some evidences. For example, given a point in the hand's action space, a learned body map can be used to predict the neck's and arm's configurations which let the visually detected marker (representing the hand) be as close as possible to the desired point.

In this work, a mapping between the proprioceptive data, represented by the 6D vector $[neckConfiguration; armConfiguration]$[4], and the external data, represented by the (x, y) image coordinates of the marker placed on the hand of the robot, has been used to perform a simpler forward prediction: given a configuration of the neck and arm joints, infers where the position of the hand will be (here: the coordinates of the marker, if detected, in the image).

Given a query (neck and arm joints), we used a k-Nearest Neighbours algorithm to find the k closest vectors in the knowledge base (using the OpenCV's FLANN library). For each vector, the elements related to the marker position are extracted. The prediction of the outcome is computed as the mean of these values. A control command is then applied to each joint both of the neck and of the arm, as the mean of the relative elements of the k vectors. This algorithm has been adapted from [11], [12]. For each prediction, the error is measured as the distance between the predicted point in the image and the detected (if any) marker position resulting from the applied control command.

Preliminary results on the prediction performance have been collected from babbling samples using the RW and IRW random movement strategies. A knowledge base has been created from a session of RW babbling, resulting in 662 samples. Test data were extracted from the babbling with a probability of 0.05 from the knowledge base (resulting in 27 samples). Given a frame of 320×240 pixels, the average distance between the centre of the detected marker and the predicted position of the marker has been measured as 15.29 pixels, using $k = 5$ in the k-NN algorithm.

A learned body maps using IRW babbling has also been tested. With 548 samples in the KB and $k = 5$, 25 testing predictions (extracted as before from the collected set) gave an average error of 21.74 pixels.

It has to be noted, also, that during motor babbling the robot attempts to follow the hand with its gaze, trying to maintain the marker close to the centre of the image. This means that the knowledge base is dense around the centre of the image (approximatively an ellipse whose axes are $2/3$ of the image's width and height) and sparse at the edges of the image, resulting in better predictions when the arm's and neck's query configuration is close to those stored configurations resulting in a marker position around the centre of the image. This leads to a more exact prediction when the marker is in the center of the visual field.

VII. FUTURE WORK ON BODY BABBLING

In this work, we analysed three random movement strategies in self-exploration for a humanoid robot. However, further interesting strategies could be introduced.

Infants, for the essence of play, engage in particular activities for their own sake. This suggests the existence of a kind of intrinsic motivation system [11] which provides internal rewards during these play experiences. In [13], the authors show a curiosity-driven robot which explores its environment in search of new things to learn: the robot gets bored with situations that are already familiar, and also avoids situations which are too difficult.

However, establishing which is the best random movement strategy is not the only aim of our work.

Imitation of hand trajectories of a skilled agent could be done through a mapping of the proprioceptive and external data. Behaviours, or motion trajectories, could be modelled by mapping regions of the action space with the states of a discrete probabilistic model[14], [15].

Learning performance could be improved using a head equipped with a pan-tilt camera mechanism to reproduce both neck movements and saccades. These learned skills are the prerequisites for imitation learning in human-robot interaction.

Moreover, the simple adopted attentive system is the precursor for a more complex system able to detect faces and eye-gaze directions. Studies on the development of cognitive functions in infants (i.e., Baron-Cohen[16]) identify this set of skills as necessary for the acquisition of complex social behaviour, like joint attention. These abilities are fundamental in the simulation theory of mind reading and compose part of the so called Theory of Mind, that is that set of skills necessary for understanding behaviours and intentions of others. A

[4] 2 DoF for the neck and 4 DoF for the arm.

very interesting robotic example is the system developed by Scassellati [17] in an embodied theory of mind architecture for a humanoid robot.

VIII. Discussion

We showed and analysed three different random movement strategies for generating control commands for the arm of a humanoid robot and we showed how sensorimotor coordination can be performed using a simple attentive mechanism which drives the robot's head movements to focus its gaze towards the moving hand. We used a simple technique for learning the mapping between different sensory modalities and we equipped the robot with predicting abilities of sensory consequences (the position of a marker placed on the hand of the robot) from control commands applied to its neck and its arm.

Possessing a body map allows the robot to become aware of itself. Self-awareness is a prerequisite for a robot interacting in an intuitive way with a person We discussed how body maps are important for a robot for having an intuitive human-robot interaction and we demonstrated how body maps can be learnt through body babbling. A robot behaving as self-aware can increase the success in fulfilling the expectations of the interacting partner.

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