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Learning of Motor Control from Motor Babbling ⋆

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Abstract: Human intelligence is deeply dependent on its physical embodiment, and its development requires interaction between its own body and surrounding environment. However, it is still an open problem that how we can integrate the lower level motor control and a higher level symbol manipulation system. One of our research goals is to make a computational model of human intelligence from the motor control to the higher level symbol manipulation. To this end, we propose a robot motor control learning as the first step in this paper. The method is based on HMMs (Hidden Markov Models). The robot moves its arm randomly by changing torques of joint angles and obtains the pose of its arm. The HMM uses state space for representing the relationship between joint torques and pose of the arm by segmenting the obtained sensory-motor information autonomously. The robot can gradually learn to move its arm to a specific position by planning the torque sequence using the learned model. Moreover, we also discuss a future plan for the ultimate goal. We are planning to probabilistically integrate the proposed motor control HMM and the language acquisition model, which has already been proposed by the authors. In this paper, we describe an overview of the integrated model with some important building blocks for our future plan.

Keywords: Motor control, motor babbling, sensorimotor learning, language acquisition.

1. INTRODUCTION

Recently, artificial intelligence using deep neural networks is growing very rapidly and achieved very high performance in many recognition tasks. For example, convolution neural networks (CNN) Krizhevsky et al. (2012) show almost same performance to the human vision. The CNNs sometimes even outperform the human vision in specific tasks. Deep reinforce learning (or deep Q-network) has been proven to be able to outperform human skills for many video games through learning by trial and error Mnih et al. (2013, 2015).

On the other hand, human intelligence basically depends on embodiment and the interaction of man with his environment is indispensable to intellectual development. Levine *et al.* investigate intelligence based on the interaction between embodiment and environments through the reinforcement learning of the sensorimotor system. They showed that the robot can learn meaningful actions such as assembling airplane of toys Levine et al. (2015). However, the implementation of such a high level intelligence starting form the self body control to very high level cognition is very hard and is still an open problem Taniguchi et al. (2015).

The ultimate goal of this research is to realize and understand the intelligence achieving intellectual actions and language understanding by constructing a model of intelligence, which develops from the body control to symbol manipulation. In this paper we focus especially on the acquisition of self motor control through the interaction between a robot and environment, which is a very basic part toward the ultimate goal. Here we aim at constructing an algorithm that incrementally learns motor control through motor babbling like babies based on the sensorimotor learning. This paper examines the use of hidden Markov models for the motor learning. The idea is that the robot moves its own arm randomly, which is the motor babbling, and then the trajectories and joint torques are segmented and represented using the state-space. The robot can use the state-space model to calculate a torque sequence for moving its arm from current pose to a goal by estimating the most likely state sequence.

Such a probabilistic modeling of motor control has an advantage for probabilistically integrating it with our proposed language acquisition model, which uses Bayesian modeling Attamimi et al. (2015), in order to achieve the above mentioned ultimate goal. Furthermore, we can apply the idea of reinforcement learning Nagai et al. (2015, 2016) for constructing a human-like higher level intelligence, where the robot starts learning its motor control from scratch and then gradually acquires language, symbol manipulation and so on. This paper also discusses the integration of multi-layered multimodal LDA (mMLDA) and reinforcement learning for implementing a whole intelligent system based on the proposed motor control learning.

Some researchers have proposed sensorimotor learning using the motor babbling in the literature Demiris et al. (2005); Saegusa et al. (2008); Nishide et al. (2008); Yamada et al. (2015). However, no effort can be found to examine extending such a learning to language acquisition to the best our knowledge. On the other hand, Takano *et*

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al. proposed a probabilistic model which connects physical body motions and language bidirectionally Takano et al. (2015). Although it is a promising and interesting model, they do not consider incremental learning such that the robot is proactive in learning the motor control from scratch and gradually reaches to the high level intelligence such as language and symbol manipulation.

2. LEARNING OF MOTOR CONTROL USING HMM

This section describes the proposed method for learning of motor control by structuring the data obtained through motor babbling.

2.1 Learning

The multimodal hidden Markov model (multimodal HMM) is utilized for the proposed method as a state emits multiple information such as joint torques and the pose of the arm. We take 2-step learning procedures; 1) each observation (modality) is modeled by a different HMM independently, and then 2) states of all HMMs are merged so that all combination of different states are represented by a single merged HMM. This procedure makes it possible for the model to represent all significant boundaries of all state-space. Moreover, the number of states is relatively easy to decide.

2.2 Estimation of state sequence

Once the HMM has been trained, the robot is able to calculate torque sequence which moves the arm from the current position to a goal. The Viterbi algorithm, which is a dynamic programming algorithm, is used for finding the most likely state sequence $[s_0,\ s_1,\ \cdots,\ s_N]$ that maximizes the following equation.

$$P(s_0, s_1, \cdots, s_N | \boldsymbol{X}_s, \boldsymbol{X}_g) \propto P(\boldsymbol{X}_s | s_0) P(\boldsymbol{X}_g | s_N) \prod_{t=1}^{N-1} P(s_t | s_{t-1}), \quad (1)$$

where $\boldsymbol{X}_s$, $\boldsymbol{X}_g$ and N represent the current pose, the goal pose and the number of steps, respectively.

3. EXPERIMENT

Experiments on the learning and the arm path planning have been carried out using the robot platform “Baxter” from rethink robotics. As shown in Fig. 1, Baxter has two arms with 7 degrees of freedom. One of them is used in our experiment. We decided a start position P_0 and eight goal positions $P_1,\ P_2,\ \cdots,\ P_8$. The robot moves its arm starting from P_0 to one of eight goals many times as the motor babbling. During the motor babbling, the poses and all joint torques are recorded in order to train the proposed HMM.

Initially, there were two independent HMMs. One is the HMM that models joint torques and the other HMM is for modeling the position of the end effector. Each HMM has nine states. Then two HMMs were merged resulting in the HMM with 52 states. Figure 2 illustrates joint torques, which are compressed by PCA. Figure 3 represents positions of the end effector (training samples), which are colored according to their states.

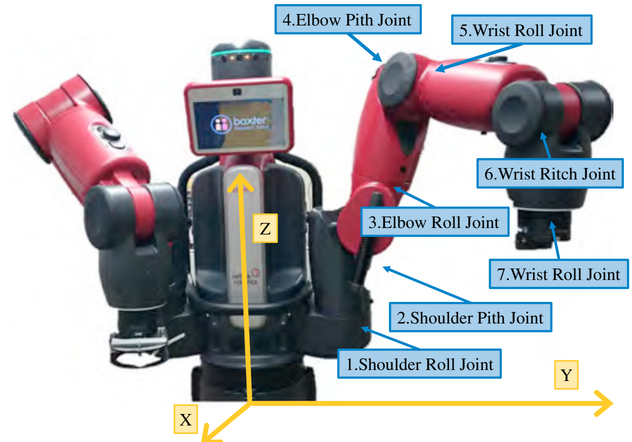

Fig. 1. The robot platform “Baxter”.

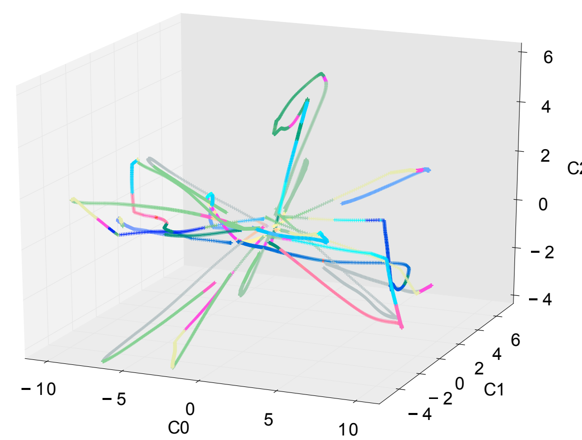

Fig. 2. Torque space compressed by PCA.

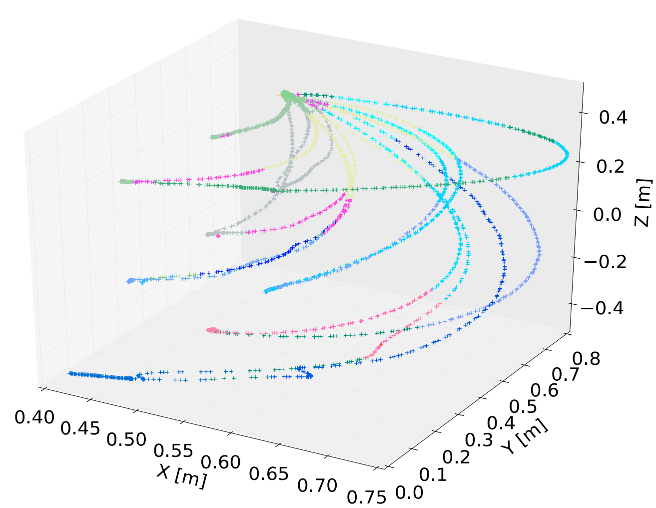

Fig. 3. Positions of end effector.