Dynamic Motion Learning for a Flexible-Joint Robot using Active-Passive Motor Babbling

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1. INTRODUCTION

Dynamic motion taking advantage of inertia with a flexible-joint robot is useful for energy efficiency and rapid motions. However, it is difficult to control flexible joints considering the complexity of their dynamics.

To overcome the problem in past studies, oscillator [1], attractor [2], and search tree [3] methods have been explored. Attractors and oscillators force trajectories to return to the pre-designed trajectories when any deviation occurs, while the search tree finds sub-optimal motion. These methods have three limitations: (1) Generate only designed motion; (2) require all robot model information; and (3) take time to search. To overcome these problems, we use recurrent neural network (RNN) and motor babbling to acquire body dynamics, forward inverse model [4]. RNNs can learn various motions and therefore, robots will be able to acquire body dynamics with motor babbling. Motor babbling is defined as the movement that infants use to acquire their own body model [5]. RNNs can also generate associative motions, which do not take time to search. In our previous research [4], a robot performed simple motions using motor babbling to acquire body dynamics with RNN. However, to generate more complex motions, it is necessary to learn specific movements. It would take a long time to learn such specific tasks with neural networks. Therefore, we propose a method where the robot learns specific tasks after the robot performs pre-training with motor babbling to acquire body dynamics. To acquire body dynamics (natural dynamics) with a flexible-joint robot, we also target the type of motions used in motor babbling.

2. MOTOR BABBLING FOR MOTION LEARNING

In this section, we describe the method for dynamic motion learning for a flexible joint. To realize this, we undertake following approach.

- A robot learns motor babbling to acquire body dynamics during pre-training, then learns the target task motions
- The robot performs several types of motion in motor babbling to acquire body dynamics with flexible-joint efficiently.

2.1 Pre-training with Motor Babbling

First, the robot learns motor babbling with RNN to acquire body dynamics in pre-training. To learn body dynamics, we implemented a type of RNN, Multiple Time-scales RNN (MTRNN) proposed by Yamashita and Tani [6]. MTRNN can predict and generate the next state from the current state. Next, the robot learns the target tasks with the acquired body dynamics.

If a robot has redundant flexible joints, there are numerous possible motion patterns. During motor babbling, the robot learns frequently occurring motions caused by the bodily constrains. This will generate limited number of motion patterns. After the robot acquires its body dynamics from motor babbling, the robot modifies the acquired body dynamics to specific target tasks, instead of directly learning the tasks. The acquired body dynamics are reused when the robot learns other task. Therefore, motor babbling would still be efficient even if it takes time to learn the body dynamics.

2.2 Types of Motion for Motor Babbling

We classify the motion into two types: (1) passive motion; and (2) active motion. During passive motion, the robot operates under inertia without torque input. During active motion, the robot generates torque to perform the motion. A flexible joint is characterised with damping, spring, and friction properties. Under these conditions, it is assumed that the torque exerted by the robot itself affect the motion intricately. This makes it difficult to acquire body dynamics. By contrast, it is easy to learn body dynamics from passive motion. From active motion, the robot learns how to exert torque.

3. EXPERIMENT SETUP

To evaluate our method, we built a humanoid robot model with the OpenHRP3 robotics simulator. The model's size and DOFs were based on the humanoid robot ACTROID. Seven DOFs of the right arm with flexible joint were used.

The robot performed motor babbling for 3 [s], 30 steps. The first five steps were active motion and the last 25 steps were passive motion. As target tasks, the robot performed crank turning and door opening and closing. The robot turns the crank for 10 cycles in

48.95 [s], 979 steps, and open and close the door for 30 cycles in 66.95[s], 1339 steps. The robot's joint angles, angular velocity, joint torque, and arm tip positions were used to train the MTRNN.

4. RESULTS and DISCUSSION

Fig. 1 shows the number of learning iterations of MTRNN required to correctly generate the target tasks. Each experiment was conducted five times with different MTRNN initial parameters. In crank turning, the active-passive babbling method resulted in a reduction of 73.3% and 65.1% in terms of learning cycles compared with direct learning task and active motor babbling. In door opening/closing, a reduction of 82.2% and 66.7% in terms of learning cycles compared with random babbling. There was no significant difference using t-test between active motor babbling and active-passive motor babbling in terms of door opening/closing because two out of five of the neural networks failed to generate motion correctly and variance was large in active motor babbling. We suspect that this is because the robot does not have experience of passive motion. As a result, the robot could not learn the correct motions. Fig. 2 shows the motion of the tasks to generate the motion of crank turning and door opening/closing. Even if the number of iterations is small when compared with direct learning tasks and active motor babbling, the robot generates motion with the same performance. Therefore, we can say that motion generation using inertia is effective when the flexible-joint robot learns the motion considering dynamics.

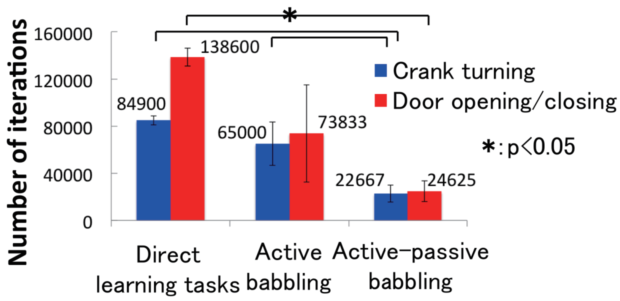

Fig. 1 Learning cycle of crank turning and door opening/closing

5. CONCLUSION

We proposed a method for dynamic motion learning with a flexible-joint robot using motor babbling. First, a robot learns simple motions via motor babbling to acquire body dynamics by RNN. Next, the robot performs additional learning for a target task with the acquired body dynamics. By classifying the motions used in motor babbling into two, passive and active motion, it was possible to learn tasks more efficiently.

In future work, we plan to conduct experiments with real robot, e.g. ACTROID and/or PR2.

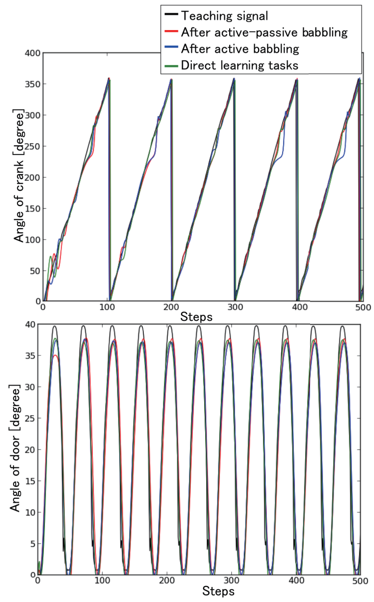

Fig. 2 Generated motion of crank turning and door opening/closing

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