Learning to Jump with a Musculoskeletal Robot using a Sparse Coding of Activation

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***Abstract*— We propose a novel learning method called "Sparse Coding of Activation" that allows an efficient search for a near-optimal solution. With previous learning algorithms, the number of required trials has been too large for real multi-DoF robots to acquire. The sparse coding method constructs a compressed representation of the activation pattern which is sent to the motor system. The learning system evaluates the resulting behavior of the motor system. Thus complex properties of the motor system including actuator, skeleton, and environment are involved in the activation patterns. In the present paper, we use the SCA (Sparse Coding of Activation) method to learn motions for a musculoskeletal robot. We describe a series of experiments in which the robot attempts to learn jumping and landing. The result shows that jumping and landing on the level ground is acquired within 150 trials (about 30 minutes).**

I. Introduction

Autonomous learning is a very attractive way to approach the problem of robot control. Through the training process, the robot can acquire movements that are well adapted to the uncertain, fluctuating environment. In addition, it does not always require an explicit representation or a precise model of the system.

Motor learning has been successfully implemented for many low-dimensional and quasi-static problems. There are many studies of theoretical models for motor control learning [1][2]. Though in theory the technique of reinforcement learning is a general approach to learning control policies, in practice innovations are necessary for practical systems. The multi-DoF motion requires large amount of exploration in the iterative framework. Most previous examples of motor learning for multi-DoF robots require prior knowledge [3][4][5].

In this paper, we propose a new learning method called "Sparse Coding of Activation". The principle of sparse coding has been discussed in the biological area[6]. The sparse coding method has the potential to provide an efficient means of motor learning. We use the method to learn jumping and landing of a legged musculoskeletal robot "Mowgli2".

II. Learning with the Sparse Coding of Activation

A. Sparse Coding of Activation

We propose the framework of learning with a "Sparse Coding of Activation"(Fig.2). The SCA (Sparse Coding of Activation) is a method using the activation pattern, which is an abstract representation of the motion as opposed to a high-dimensional desired target state. The patterns are generated by the combination of the appropriate basis functions under the constraint of sparseness.

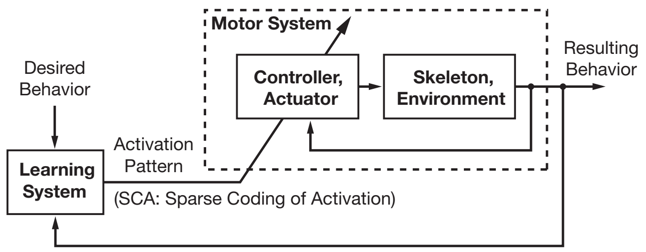

Fig. 2. The framework of the learning with the Sparse Coding of Activation

B. Evaluation and Optimization

We employ the mixture of random exploration and improved hill-climbing search as the optimization technique for the learning. The system finds the best pattern with the hill-climbing search start with the pattern which is obtained from previous random exploration.

In the phase of hill-climbing search, the system generate the subsequent pattern ($\boldsymbol{x}_{best} + \Delta\boldsymbol{x}$) using previous best parameter $\boldsymbol{x}_{best}$ and perturbation $\Delta\boldsymbol{x}$. The system decides to accept or reject the tested activation pattern by applying an evaluation function to the resulting behavior. In addition, the system stochastically validates the pattern by retry. This validation procedure ensures that bad evaluations, which occur often in the uncertain real world, are experimentally corrected.

C. Implementation for the Musculoskeletal Robot

There are several possible representations for the SCA (Sparse Coding of Activation). Here, we use a simple step function as a basis function defined by the following equation.

$$f(t) = \begin{cases} a & (0 \leq t \leq T) \\ 0 & (t < 0, t > T) \end{cases} \tag{1}$$

The activation pattern is divided to n phases, and T_n is a duration time of each phase (Fig.3).

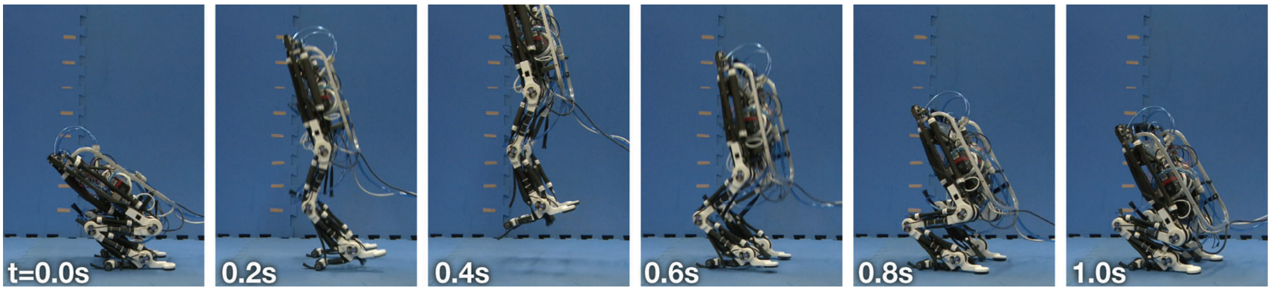

Fig. 1. The acquired motion of jumping and landing on level ground.

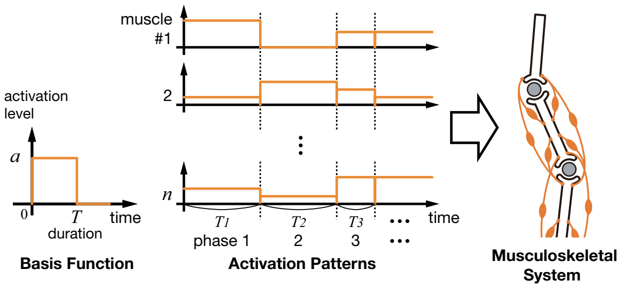

Fig. 3. Sparse Coding of Activation using step function.

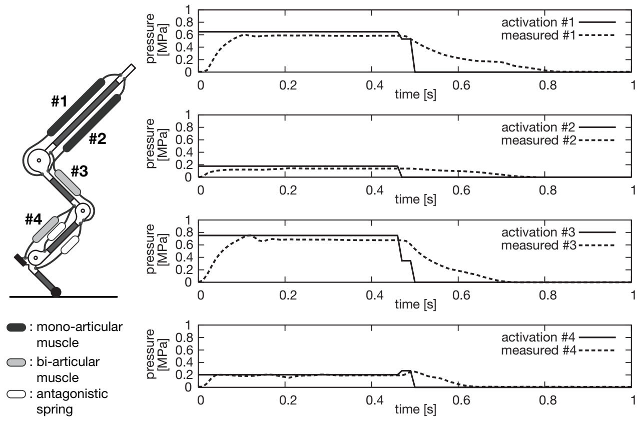

Fig. 4. The acquired activation pattern and measured pressure.

III. Mowgli 2: Musculoskeletal Legged Robot

We developed a bipedal robot with an artificial musculoskeletal system[7]. The robot weighs about 3 kg, is 0.84 m body height with the legs extended, and has 8 pneumatic muscles and 4 passive springs for 6 DoF legs. A leg has 3 degrees of freedom, one for each joint (hip, knee, and ankle).

Several proportional pressure control valves and a CPU board are mounted on the robot. For the purposes of the learning experiment, which requires several hours, electrical power and compressed air is supplied from external equipment. The robot has an orientation sensor, a potentiometer on each joint, a pressure sensor on each muscle, and a touch switch on one foot.

IV. Experiments and Results

We apply the method to a planar jumping with 4 muscle groups. The left leg and right leg receive same activation. The parameters to be learned consist of continuous values of air pressure and duration time for each phase. The number of phases of activation pattern is set to 2. We conducted three learning sessions which includes 100 or 150 trials including 50 random exploration trials. The evaluation function is a linear combination of maximum height and the similarity between the observed position at the end of the movement to the desired squatting position. The activation patterns are valued for each jumping trials.

The vertical jumping was acquired in all of these 3 sessions. Learning time for one search session was about 30 minutes. The snapshots of the motion which was acquired in the 3rd session are shown in Fig.1. Fig.4 shows time series data of muscle activation pattern and measured air pressure.

The acquired activation pattern shows that flexor muscle #2 is suppressed. The direction of the jumping is regulated by the fine difference of the activation level of each muscle.

V. Conclusion

In this research, we apply the "Sparse Coding of Activation" for the jumping and landing movements with the legged musculoskeletal robot. The result shows that vertical jumping motion is acquired with only 150 trials despite the dynamic task involving a highly nonlinear pneumatic system.

The experiment described here employs the step function as the basis function, and the duration of each phase is the same for each muscle group. For future work, we will generate activation patterns from a mixture of prepared step functions, and allow disjoint muscle activation times.

References

[1] S. Schaal, Learning Robot Control, In Arbib MA (ed) The handbook of brain theory and neural networks, 2nd Edition, pp.983–987, MIT Press, 2002.

[2] M. I. Jordan, Computational aspects of motor control and motor learning, In H. Heuer, & S. W. Keele (Eds.), Handbook of perception and action, New York: Academic Press, 1996.

[3] H. Benbrahim and J. Franklin, Biped dynamic walking using reinforcement learning, *Robotics and Autonomous Systems Journal*, Vol.22, No.3, pp.283-302, 1997.

[4] C. Sabourin, O. Bruneau, Robustness of the dynamic walk of a biped robot subjected to disturbing external forces by using CMAC neural networks, *Robotics and Autonomous Systems*, Vol.51, Issues 2-3, pp.81–99, 2005.

[5] Jun Morimoto and Kenji Doya, Acquisition of stand-up behavior by a real robot using hierarchical reinforcement learning, *Robotics and Autonomous Systems*, Vol. 36, pp. 37–51, 2001.

[6] B. A. Olshausen and D. J. Field, Sparse coding of. sensory inputs, *Current Opinion in Neurobiology*, Vol.14, No.4, pp.481–487, 2004.

[7] Ryuma Niiyama, Akihiko Nagakubo and Yasuo Kuniyoshi, Mowgli: A Bipedal Jumping and Landing Robot with an Artificial Musculoskeletal System, *Proc. of the 2007 IEEE International Conference on Robotics and Automation (ICRA 2007)*, pp.2546–2551, 2007.