Emergent locomotion patterns of soft-bodied robots with information maximization

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1 Introduction

The ability to adaptively move in complex environment is a key skills for robots as well as animals. It is now increasingly recognized the essential contribution of bodies to such adaptive skills by saving computational resources in nervous system. Recently, soft-bodied robots have been developed and have performed complex and adaptive motor behaviors by exploiting physical properties of their bodies. For example, a soft robot consisting of only elastomeric polymers achieves navigation of a difficult obstacle [1]. Although accumulating studies have shown that soft-bodied robots are useful for producing adaptive locomotion, almost all of these robots are controlled by hand tuning or simple cyclic input [2]. This is partially because soft-bodied robots have hysteresis and/or non-linear properties.

In contrast, there are many studies about design and control methods of locomotor behaviors for rigid-bodied robots. A special attention has been focused on the central pattern generators (CPGs), i.e. neural circuits capable of generating coordinated rhythmic motor patterns and many researchers have applied them into robots. For instance, the dog-like Tekken series accomplish stable locomotion using couplings between CPGs and sensory feedbacks [3] whereas the salamander robot autonomously modulate locomotor patterns from walking to swimming according to change in environment [4]. However, online generation of substantially new locomotor behaviors is difficult because CPGs require much time to adjust parameters. On the other hand, there are several studies focusing on online motor generations in a self-explorative manner, for examples, by exploiting the chaotic properties [5] or maximizing predictive information [6]. Especially, approach with maximizing information has been shown usefulness for complex system with non-linear and hysteresis.

In this paper, we applied control based on information maximization to soft-bodied robots. We examine whether this information-based control can be applied using computer simulations and robot experiments.

2 Methods & Materials

To achieve emergent exploration of locomotion patterns for soft robots, we developed a robot control system with

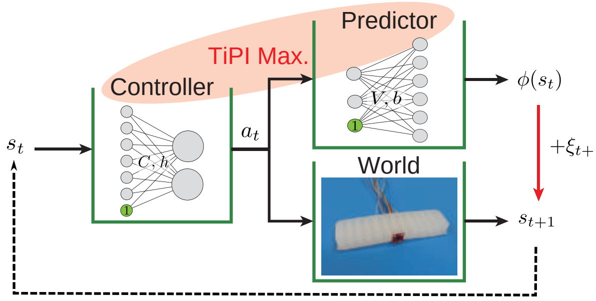

Figure 1: System diagram.

a mechanism of information measure maximization (Fig. 1). We employ an algorithm which maximizes mutual information between the past and the future of sensory time-series data. The system is connected to the robot with sufficient number of sensors so that the whole system can form sensory-motor loop for emergent behaviors.

2.1 Controller for Generating Motions

We chose a time-local predictive information (TiPI) [7] as the information measure for the emergent exploration. The TiPI increases entropy of sensory time-series data and makes the successive time steps more dependent. This means that the robot is controlled to obtain various sensor values while improving prediction. In consequence of this mechanism, the system is suited for the self-organized exploration of numerous motions.

TiPI is defined as conditioned mutual information as

$$I^{\tau}(S_{t+1};S_t) := I(S_{t+1};S_t|s_{t-\tau}) \tag{1}$$

where S_t is the probability density distribution at step t and $\tau = 1$. In order to obtain the probability density distribution S_{t+1} and S_t, we used the s_{t+1} and s_t that is predicted based on s_{t-1} and including a Gaussian noise. The control system consists of a sensory-motor map and a predictor whose parameters are updated according to the maximization of TiPI with gradient method. The sensory-motor mapping K and the predictor ϕ are defined as

$$a_{t+1} = K(s_t) = g(Cs_t + h) \tag{2}$$
$$\hat{s}_{t+1} = \phi(a_t) = Ta_t + b \tag{3}$$

where the vector s_t is sensor value, vector a_t is motor command, matrices C, T and vectors h, b are the parameters

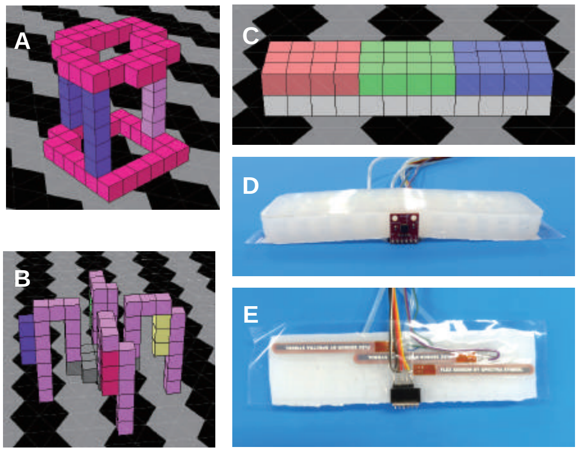

Figure 2: Overview of all tested robot system. (A) Non bioinspired robot, (B) Legged robot. (C) Inchworm like robot. (D, E) Developed soft-body robot made of silicon rubber with one acceleration sensor (D) and three bend sensors (E).

updated according to TiPI maximization and g is a mapping that satisfies $g_i(z) = \tanh(z_i)$. Further details are on [7]. We used sensors that can reflect the gross state of the robot, such as velocity sensor and acceleration sensor. All of the actuators work to increase the entropy of the sensors so that the system can generate systemic coordinated motions.

2.2 Soft Robots

We use a voxel-based physical simulator VoxCAD for modeling soft robots [8]. The model in the VoxCAD is represented by a set of passive and active voxels with configurable material properties. We can control the inflation and deflation of a group of voxels by changing the natural length of the sides. For the experiments, we made a three soft robot models: a non bio-inspired robot, a legged robot, and an inchworm like robot (Fig. 2 (A) (B) (C)). The robots consist of 62, 73, and 72 voxels, respectively. We use different material properties for different colored group of voxels. For example in the inchworm like robot, the top layer is consists of three cells that is independently controlled as an actuator. The lower layer is made of deformable but passive material. The control system receives both motor outputs and sensory inputs from the robot. The motor outputs of the robot models are sizes of each cell. The sensory inputs are three-axis acceleration of the center of gravity and the strains of each cell. Control interval is 2,000 ms.

We also developed a real soft-bodied robot made of silicone rubber. The shape followed the inchworm-like soft robot in the simulation (Fig. 2 (D) (E)). We implement deformable voxels by pneumatic inflation. Since the robot is a single piece of silicone rubber, we change the material properties by embedding a sheet of cloth for the passive layer. The lower surface of the robot is covered with plastic sheet to prevent from sticking on the floor. Thus, the motion capability is similar to the soft robot in simulation. We controlled the flow of air by a small electric pump and solenoid valves.

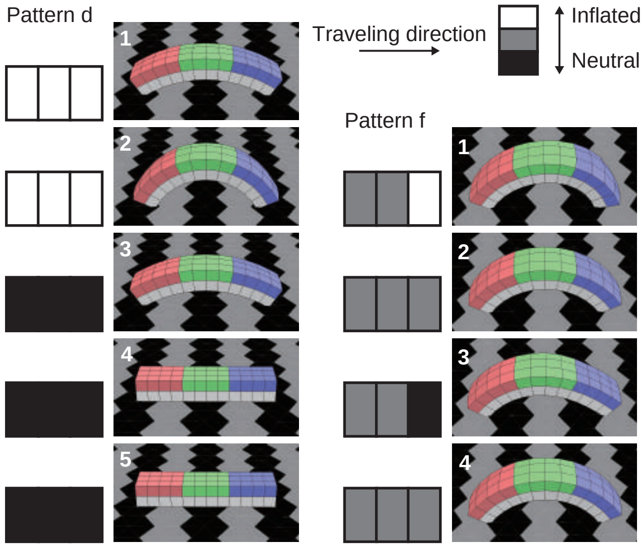

Figure 3: Examples of generated patterns.

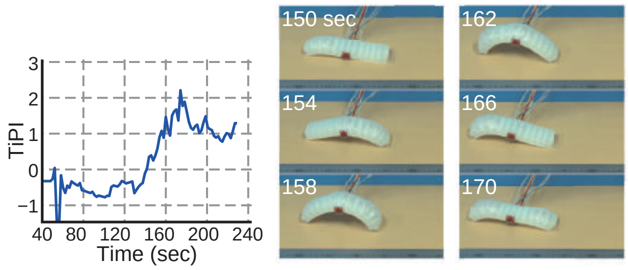

Figure 4: Time evolution of TiPI and locomotion patterns in the experiment of developed soft-body robot.

The motor outputs are calculated sizes of each cell. The sensory inputs are obtained from an acceleration sensor on the center, and bending sensors on the lower surface. Control interval is 2,000 ms.

3 Experiments & Results

In order to examine the proposed control method that is based on the maximization of TiPI, we conducted computer simulations and robot experiments. We applied TiPI maximization to the several robot models and recorded the emergent motions. Then, extracted periodic motions were analyzed in terms of mean travel distances and mutual information.

3.1 Soft Robot Simulation

In the simulation, we put the inchworm like robot on the level ground. The robot has three segments with volumetric deformation and an elastic backing structure. All the emergent periodic motions are extracted from a total of 400 sec (200 control steps) exploration. We observed six periodic motions that were repeated more than one time (Fig. 3). Their cycle were from three to eleven steps. 4 patterns out of six can travel in a certain direction and others stay in the

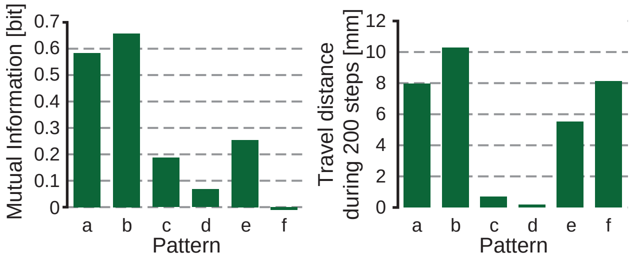

Figure 5: Mutual information and travel distance of each pattern in simulation of VoxCAD.

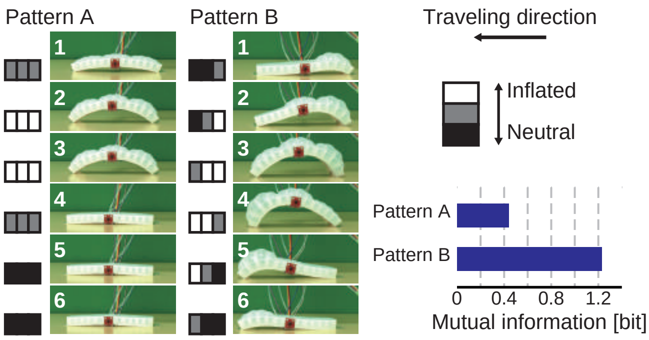

Figure 6: Relationship between motor patterns and mutual information.

same place. We also observed that the control method can discover both symmetric motions with synchronous deformation in all active segments, and asymmetric motions with wavelike deformation.

3.2 Soft-bodied Real Robot

We conducted the same experiment with the silicone-based real robot. We put the robot on the level ground same as the simulation. The robot is driven by pneumatic deformation via cables. The experiment was conducted for 300 sec (150 control steps). The control system could discover three patterns of periodic motions with increase of TiPI (Fig. 4). The results show that the control method is applicable to real robot that has nonlinear deformations.

3.3 Analysis of Locomotion with Mutual Information

We compared the emerged six patterns in the simulation experiment in terms of the travel distances and the mutual information between sensory inputs and motor outputs. We found that the motion patterns with large mutual information have large mean travel distance though the converse is not true (Fig. 5). This result suggests that information maximization of sensory-motor information can be useful for the exploration of the locomotion patterns. We conducted the same analysis on the measurement of the real robot experiment. We used manually designed two motion patterns: travels in specific direction, and stays in one place. As a result, the pattern with large traveling has higher mutual information than the one that stays, which is consistent with the result of the simulation (Fig. 6).

4 Discussion

In our computer simulations and robot experiments, soft-bodied robots produced several locomotor patterns in a self-organized fashion. Our results suggest that maximization of predictivee information can be used in soft robots for online generation of adaptive locomotor behaviors. In addition, we analyzed the relationship between mutual information and traveling distance and then suggest that maximization of sensory-motor information can lead to producing of locomotion with no any external information such as traveling distance.

In future works, we will investigate the relationship between morphology of robot bodies and emergent locomotion patterns in more detail. Furthermore, because information maximization have been discussed the relationship with animals' learning, for example Hebbian plasticity [7], we will compare the process that animals learn locomotor behaviors.

Acknowledgements

This work has been supported in part by JSPS Grant-in-Aid for Scientific Research(A) 26240039.

References

[1] Shepherd, R. F. *et al.*, "Multigait soft robot," *Proc Natl Acad Sci USA*, vol. 108, no. 51, pp. 20 400–20 403, 2011.

[2] Seok, S. *et al.*, "Peristaltic locomotion with antagonistic actuators in soft robotics," in *IEEE Int Conf Robot Autom*, 2010, pp. 1228–1233.

[3] Fukuoka, Y. *et al.*, "Adaptive dynamic walking of a quadruped robot 'Tekken' on irregular terrain using a neural system model," in *IEEE Int Conf Robot Autom*, vol. 2, 2003, pp. 2037–2042.

[4] Ijspeert, A. J. *et al.*, "From swimming to walking with a salamander robot driven by a spinal cord model," *Science*, vol. 315, no. 5817, pp. 1416–1420, 2007.

[5] Yamada, Y. *et al.*, "Neural-body coupling for emergent locomotion: A musculoskeletal quadruped robot with spinobulbar model," in *IEEE Int Conf Robot Syst*, 2011, pp. 1499–1506.

[6] Martius, G. *et al.*, "Self-exploration of the stumpy robot with predictive information maximization," in *From Animals to Animats 13*, ser. Lecture Notes in Computer Science, del Pobil, A. *et al.*, Eds. Springer International Publishing, 2014, vol. 8575, pp. 32–42.

[7] Martius, G., Der, R., and Ay, N., "Information driven self-organization of complex robotic behaviors," *PLoS One*, vol. 8, no. 5, p. e63400, 2013.

[8] Hiller, J. D. and Lipson, H., "Dynamic simulation of soft heterogeneous objects," *CoRR*, vol. abs/1212.2845, 2012.