Biologically Inspired Control of a Simulated Octopus Arm via Recurrent Neural Networks

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ABSTRACT

The aim of this study is to explore a control architecture that can control a soft and flexible octopus-like arm for an object reaching task. Inspired by the division of functionality between the central and peripheral nervous systems of a real octopus, we discuss that the important factor of the control is not to regulate the arm muscles one by one but rather to control them globally with appropriate timing, and we propose an architecture equipped with a recurrent neural network (RNN). By setting the task environment for the reaching behavior, and training the network with an incremental learning strategy, we evaluate whether the network is then able to achieve the reaching behavior or not. As a result, we show that the RNN can successfully achieve the reaching behavior, exploiting the physical dynamics of the arm due to the timing-based control.

Categories and Subject Descriptors

I.2.11 [Distributed Artificial Intelligence]: Intelligent agents

General Terms

Design

Keywords

Soft Robotics, Recurrent Neural Network, Octopus

1. INTRODUCTION

How does an octopus control its soft and flexible body? An octopus has hyper-redundant limbs with a virtually infinite number of degrees of freedoms (DOFs), and its movements are significantly sophisticated [1]. From the conventional control perspective, its method of controlling movement is outstanding and far-reaching. Therefore, it has been an excellent test case to learn how to control a flexible and soft body [4].

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In a real octopus, it is well known that simplification strategies have evolved to reduce the number of control parameters in the movement of its flexible arms. That is, the functionality is divided between the central nervous system (CNS) and the peripheral nervous system (PNS). Taking the reaching behavior as an example, it consists of a bend propagation along the arm toward the tip in a highly stereotypical and invariant way. The bend is always created on the dorsal side of the arm as the ventral side of the arm approaches the object. It is well studied that the CNS only sends an initiation command to the PNS; therefore, almost all the required control of the arm muscles in the reaching behavior is handled by the PNS [3]. Accordingly, several studies have intensively focused on the role of the PNS in the reaching behavior [5, 6].

In this study, we focus on not only the role of the PNS, but also the coordination between the CNS and the PNS. This raises a new challenge. Indeed, due to this control scheme, the CNS does not have to control the movement of the muscles one by one, and the PNS mainly drives the behavior. On the other hand, because of this division of functionality, the following questions remain unaddressed. How can the CNS recognize when to apply the command to the PNS? How can the CNS wait for the bend propagation to be completed while the PNS is activated? These questions suggest that we need to consider an additional important factor in the control, which is timing.

2. MODEL AND RESULTS

A dynamical systems approach is suitable in realizing the timing-based control. As such, the control architecture is based on a recurrent neural network (RNN), in combination with a feed forward network (FFN) (Fig. 1 (b)). The main body of the RNN controls the angle of the arm base and the timing to send a signal to the low-level control (PNS). The accompanying network decides the power of the signal and the angle that is required to achieve the reaching behavior. In order to determine the performance of the networks, we established the reaching tasks by using a physical simulator of the octopus arm (Fig. 1 (a)). As revealed in octopus biology, the octopus starts to create a bend on the dorsal side of its arm and, through the bend propagation, its arm

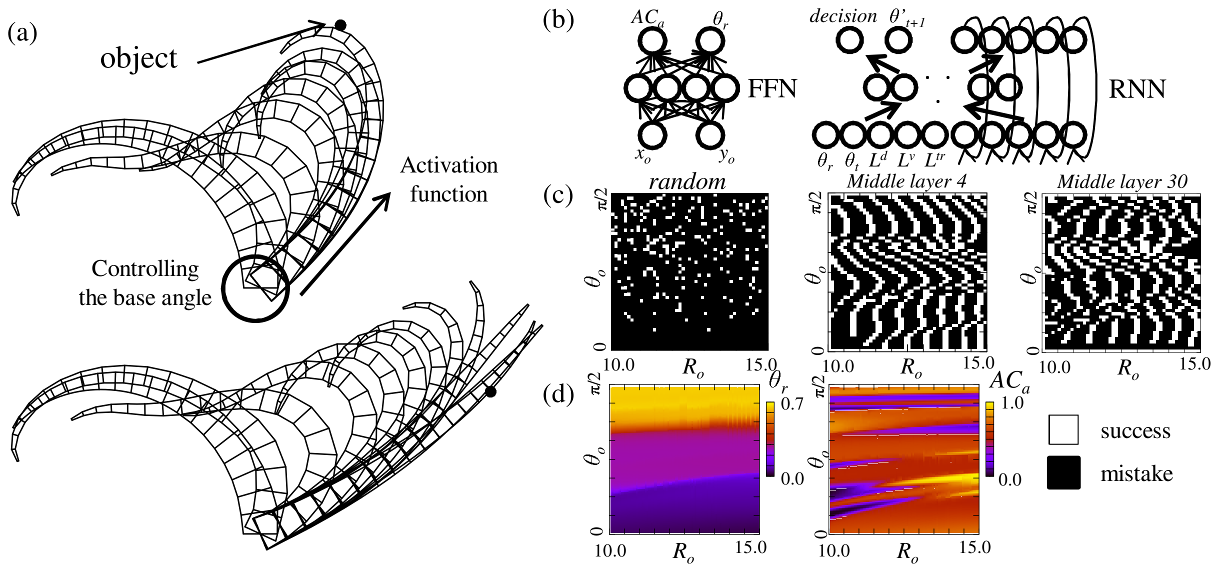

Figure 1: (a) Examples of the arm dynamics during the reaching behavior controlled by the networks. (b) Dual network used in this study. The RNN takes proprioceptive inputs (L^d, L^v, L^{tr} : the lengths of the muscles (springs) of the most proximal compartment of the arm), the current base angle (θ_t), and the required base angle (θ_r), and outputs the base angle of the next timestep (θ'_{t+1}) and a decision neuron. If the value of the decision neuron goes over 0.5, then the FFN is used. By regulating the value of the decision neuron, the RNN can achieve a timing-based control. The FFN regulates the required base angle and the parameter for the activation function, $a(t,i) = AC_a \cdot \frac{1}{2}\{1 + \tanh[\beta(\frac{t}{\tau} - i + i_0)]\}$, which represents the PNS, accordingly to the position of the object, $(x_o, y_o) = (R_o \cos\theta_o, R_o \sin\theta_o)$. (c) Success plots of the reaching behavior according to the position of the object. The left figure shows when AC_a and θ_r are set to random. The middle and right figures show when they are controlled by our trained networks. We varied the number of nodes of the middle layer of the FFN from 4 to 30 and observed its performances. In each case, the success rates were around 40% and were significantly higher than the control condition. (d) The plots show the outputs of the FFN (middle layer 30) for θ_r (left) and AC_a (right) according to $R_o - \theta_o$. For θ_r, we can clearly see the gradation corresponding to the θ_o.

approaches the object from the ventral side. The important point here is the time it takes for the bend to form. Usually, to handle these time lags, they are predefined as a default setting or additional stimuli are sent to externally signal the time lag. However, our aim is to autonomously control the time lag in the network.

In order to achieve the reaching behavior toward the object, the networks are required to exploit the physical dynamics of the arm [2]. For the training of the networks we applied an incremental learning strategy. Unlike the conventional supervised learning case, we do not predefine the learning sets, but rather collect the learning sets by actually running the arm. As a result, networks that can successfully achieve the reaching behavior have been developed (Fig. 1 (a)). We found that networks are regulating the time lag by using the relaxation dynamics to the point attractor, and autonomously switching the point attractors to regulate the base angle of the arm in the internal dynamics. Also, the performance of the reaching behavior seems to depend on the location of the object; this means that the networks are successfully recognizing the dynamics of the arm (Fig. 1 (c) (d)). We will present, in detail, the overall model settings, the mechanism of internal dynamics that was developed to realize the time lag, and the performance of the reaching behavior.

3. ACKNOWLEDGMENTS

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