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Kinesthetic Sensing Exploiting the Active Interaction between the Environment and an Ostrich-Neck-inspired Manipulator

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1 Introduction

1.1 "RobOstrich" manipulator

Ostriches skillfully use their long, slender, flexible necks as manipulators. The animal trunk is a compliant, multi-linked structure ("flexible structure") and driven by an underactuated tendon-driven system ("tendon driven"). Many researchers have developed animal-trunk-inspired manipulators in order to introduce animal dexterity into manipulators. However, they suffer from difficulties in modeling and in achieving dexterity and structural stability [1]. These issues are affected by scaling effects with respect to mass and size. To address these issues, we have developed a manipulator: "RobOstrich manipulator" (short for *Robotic ostrich*), which was inspired by the ostrich, the largest species of birds (Fig. 1). Experiments with the RobOstrich manipulator have shown that morphology, such as muscle arrangement and joint range of motion, can solve the above three issues in tendon-driven flexible manipulators [1].

1.2 Kinesthetic sensing through a flexible body

Kinesthetic sensing is touch sensing by receptors embedded in muscle and tendon. Animals achieve diverse touch sensing by combining this kinesthetic sensing with the touch sensing on the skin's surface (cutaneous sensing) [2]. Kinesthetic sensing via the sensation of muscles, which includes active interaction with the environment, such as shaking or banging is called "dynamic touch" [3]. The robotic arm in [3] can classify the category of the object it is shaking using kinesthetic sensing. This classification is possible because the body's flexibility allows the inertial forces of the shaken object to propagate through the body and change the internal pressure of the pneumatic artificial muscles. Although this study investigates differences in classification performance based on vibration frequency, direction of shaking, and other factors, the benefit of using kinesthetic sensing is still debatable.

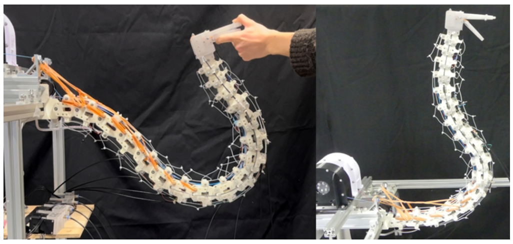

Figure 1: Images of RobOstrich manipulator

One example of the dynamic interaction with the environment in ostrich neck movements is the instantaneous and repetitive ground-collision picking behavior. In this behavior, the ostrich's eyes are closed, which suggests that they do not use their vision. In addition, the kiwi, which is another member of the order Ratitae, uses touch sensing while pecking to detect prey hidden in the soil [4]. To achieve this touch sensing without vision, the densely-populated receptors in their beaks provide keen cutaneous sensation. On the other hand, the bird's neck is a sophisticated kinesthetic sensor with receptors for stabilizing posture during flight or while running [5]. In this paper, we examine the advantages of proprioceptors (joint angle sensors) in the neck for touch sensing in the pecking movement using the RobOstrich manipulator.

2 Classification by physical reservoir computing

First, inspired by kiwi feeding behavior, we define the classification task, which uses proprioceptors to classify the depth of rigid plates buried in soft material. As shown in Fig. 2(a), a joint angle sensor is attached to each joint, and a pressure sensor is attached to the tip of the beak. Sensing with proprioceptors requires learning because there is no one-to-one correspondence between the necessary information and the receptors. Therefore, we regard the RobOstrich manipulator as a physical reservoir and solve this classifica-

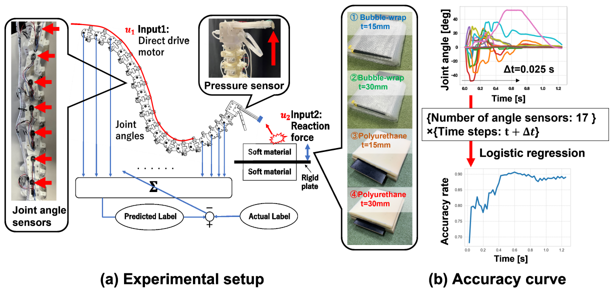

Figure 2: Classification task and its learning method

tion problem [6]. In order to quantitatively evaluate the performance of the RobOstrich manipulator as a physical reservoir, we used logistic regression to classify the time series of joint angles during the pecking movement and calculated the accuracy rate. Here, the time steps used for classification are increased to obtain the accuracy curve: the change in accuracy over time (Fig. 2(b)).

3 Evaluation of classification performance

In this section, we show the performance of a four-class classification via kinesthetic sensing. Each class differs in terms of the material or the depth at which the rigid plates are buried. Fig. 3(a) shows the behavior of the head in this task. Fig. 3(b) shows the time series of the mean values and standard deviations of the joint angles for three joints in one cycle of pecking movements during five trials of ten cycles each. This figure indicates that the trajectories of the joint angles (at the head, middle, and root joints) are different for each object. In other words, each joint may have the ability to identify an object. Fig. 3(c) here shows the accuracy for the four-class classification using the time series for each joint. From this graph, two facts are evident:

1. For each joint, classification with a single angle sensor has a higher accuracy rate than classification with a single pressure sensor.
2. Using all joints simultaneously results in the highest accuracy rate for the four-class classification.

We consider that reflecting information about the collision in more joints allows for higher-performance classification.

4 Advantages of kinesthetic sensing

This section demonstrates the advantages of kinesthetic sensing with flexible manipulators. Fig. 4 compares the time series of the mean values of the accuracy rate between the case using the joint angle sensor and the case using the pressure sensor during five trials of ten cycles each. We can see that while the accuracy rate increases only at the moment of collision when using the pressure sensor, it increases before and after the collision when using the joint angle sensor and finally exceeds the accuracy rate of the pressure sensor. We consider this may be because of the residual effects of the previous cycle's pecking behavior. In other words, it is possible to memorize information about collisions as behavior, and this memory can lead to more accurate touch sensation.

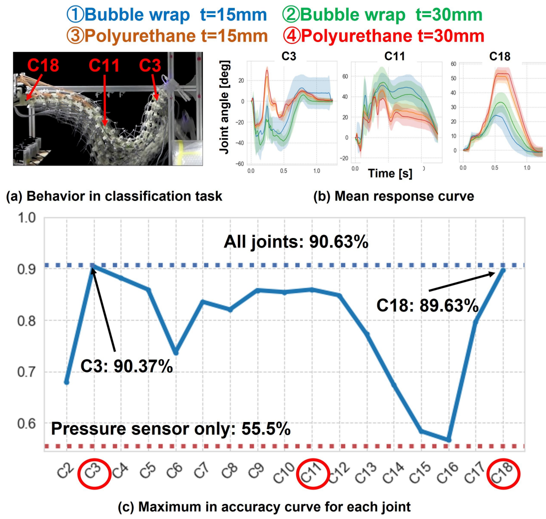

Figure 3: Classification performance

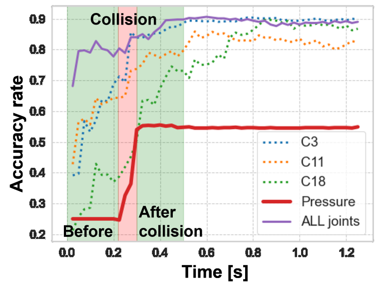

Figure 4: Comparison of accuracy curve

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