Learn to Grasp Utilizing Anthropomorphic Fingertips together with a Vision Sensor

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***Abstract*— A robot should have softness and many sensors to manipulate an object dexterously and to adapt various environments. However, many existing schemes that a designer calibrates the sensor output to the world coordinate frame are difficult to adapt for such the robot. This paper proposes a learning mechanism for a robot hand which consists of anthropomorphic fingertips. The sensor for the fingertip is difficult to calibrate because the sensor receptors are embedded randomly in the soft material. The effectiveness of the proposed mechanism is demonstrated by an experiment that the robot picks up an unknown weight object.**

***Index Terms*— grasping, object manipulation, distributed sensor, soft finger, anthropomorphic finger**

I. Introduction

Many existing control schemes for the robot hand are designed with respect to the world coordinate frame, and outputs of the sensors are calibrated with the frame by the designer [1], [2], [3]. These robots achieve a given task by using models of the robot and the object described with the frame. Therefore, the robot and the object have to be simple enough to be easily modeled by simple calibration. For this purpose, the designer has to place the sensor in the exact position and orientation. However, the robot using the scheme can not adapt to unknown environments which the designer did not suppose. Furthermore, the robot using the scheme is affected by calibration errors and disturbances.

If the sensor placement for the robot is fully controlled, it may not be able to sense the information that is essential for the task but that the designer has not expected. Therefore, dexterity of the existing robot is not sufficient because of lack of sensing ability. One way to avoid such designer's bias and limitation of sensing is to embed as many receptors as possible into the robot randomly. Our previous work [4] show that the soft fingertip which contains many tactile receptors has high sensing ability. However, the robot which has softness and many sensors is difficult to calibrate the sensors and to build a controller. Therefore, the task and the sensor output must be represented in a sensor space which is defined by the robot's self.

In [5], the output of the vision and force sensor were represented in the sensor space of the robot, and the robot achieved manipulating an object. Hosoda et al. [6] produced an anthropomorphic fingertip whose tactile receptors are randomly distributed in and on the soft material. Furthermore, a neural network for the representation of slippage utilizing the anthropomorphic fingertip and a vision sensor was proposed. The context of the given task is, however, not considered in the mechanism. Additionally, Hakozaki el al. [7] proposed artificial skin in which many tactile receptors are embedded randomly, what they call telemetric skin. However, they proposed only the structure and did not propose the control architecture to utilize it. Yamada et al. [8] proposed a soft finger whose tactile receptors are embedded regularly, and which can grasp the unknown weight and a friction coefficient object by detecting the incipient slippage. However, the designer decided the mechanisms for detecting the incipient slippage and for controlling the grasping force.

This paper proposes a learning mechanism to utilize the anthropomorphic fingertips through a task context, that is, a grasping task, together with a vision sensor. The mechanism finds the correlation between the output of the vision and the tactile sensors, and realizes grasping. Experimental results to pick up an object are shown to demonstrate the effectiveness of the proposed mechanism.

The remainder of this paper is organized as follows. First, the design of the anthropomorphic soft fingertip is introduced. The fingertip consists of two silicone rubber layers of different hardness containing two kinds of randomly distributed receptors. Then, the learning mechanism for grasping is proposed. It learns the correlation among the output of the sensors and a motor command by Hebbian learning. Finally, experimental results are shown to validate capability of the proposed mechanism.

II. Anthropomorphic soft fingertip

Fig. 1 shows a cross sectional view of the developed anthropomorphic soft fingertip. The fingertip has two layers made of the different hardness of silicone rubber: the outer layer is harder than the inner layer. A rod is inserted at the

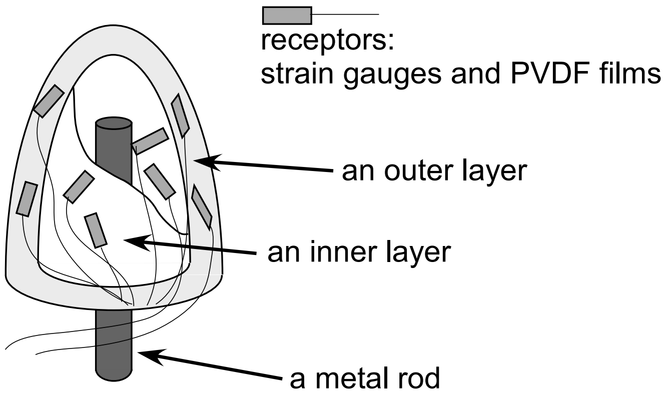

Fig. 1. A cross sectional view of the developed anthropomorphic fingertip

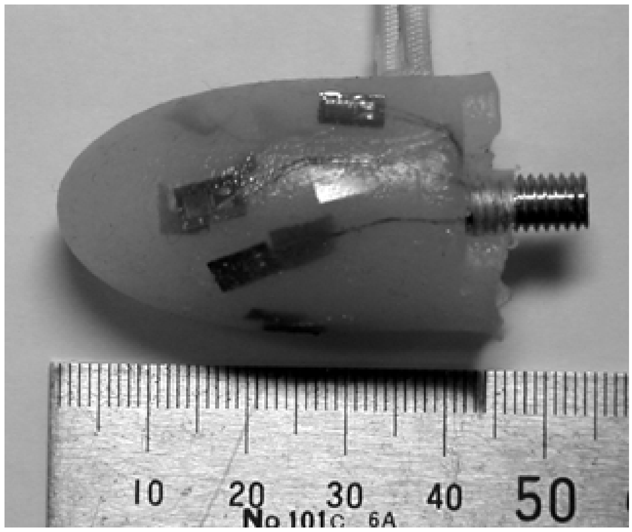

Fig. 2. A photo of the anthropomorphic soft fingertip

center of the fingertip to play a role of a bone. Strain gauges and PVDF (polyvinylidene fluoride) films that sense strain and velocity of strain are embedded in both layers as tactile receptors. A developed soft fingertip is shown in Fig. 2. Its diameter and length are 25 mm and 55 mm, respectively. The fingertip has twenty-four receptors; six strain gauges and six PVDF films are embedded in the inner layer, and also the same number of the strain gauges and the PVDF films are embedded in the outer layer.

Since the receptors are embedded randomly, the same kind of receptors embedded in the different positions may sense different kinds of tactile information. A strain gauge embedded near the surface of the skin is expected to sense the local static strain between the skin and the object surface whereas the strain gauge embedded near the rod is expected to sense the total force exerted on the finger and is expected to be insensitive to the local texture of the object. A PVDF film is expected to sense the strain velocity, which means that it is more sensitive to the transient or small strain (or stick slip) than the strain gauge. The silicone rubber between two PVDF films is expected to act like a low-pass filter; therefore, the difference between the signals is expected to represent the local stick slip phenomena. Additionally, our previous work [4] shows that the fingertip has high sensing ability by discriminating between the objects.

III. Learning mechanism for grasping

The calibration for the anthropomorphic fingertip is difficult because the fingertip is made of soft material and contains randomly distributed tactile receptors. Therefore, the robot has to learn the meaning of the sensor output instead of the calibration.

In this paper, the robot hand with a vision sensor iterates picking up an object, and learns the correlation among the tactile sensors, the vision sensor, and a motor command. From this learning, the robot acquires behavior for picking up the object by minimum grasping force. Experimental conditions for the learning mechanism are as follows: 1) weight and a friction coefficient of the object are unknown, 2) the grasping force is increased or decreased discretely by a sign of the controller output, and 3) the vision sensor observes motion between the object and the robot, then it outputs three states: “picking up success”, “stopping the robot hand”, and “picking up failure.”

Fig. 3 shows a block diagram of a control system for the robot. Details of neural networks which consists of a sensor network and a motor network are shown in Fig. 4. The sensor network learns the correlation between the output of the tactile sensor and the vision sensor, and outputs a state of the grasping object. The motor network converts the output of the sensor network to the motor command.

Details of the sensor network in Fig.4 is as follows. The sensor network learns the correlation between the output of the vision and the tactile sensor by Hebbian learning. The output of each strain gauge is normalized by the maximum value over time and is given to the strain gauge node s_n. s_n ranges from -1 to 1. Furthermore, the output of each PVDF film is also normalized by the maximum value over time, and the value of 1 or 0 are given to the PVDF film node p_k if the normalized value is over or under a threshold, respectively. The values of -1, 0, and 1 are given to the vision node v and denote “picking up failure”, “stopping the robot hand”, and “picking up success”, respectively. The output of the sensor network is calculated by following equations.

$$S^p = \sum_k p_k w_k^p + v \qquad (1)$$

$$S^s = \sum_n s_n w_n^s + S^p \qquad (2)$$

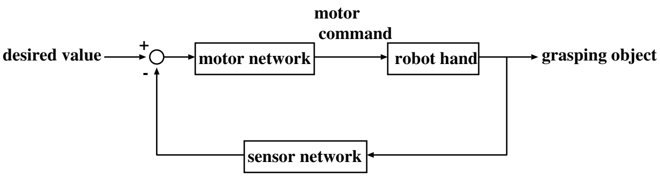

Fig. 3. A block diagram of robot hand controller

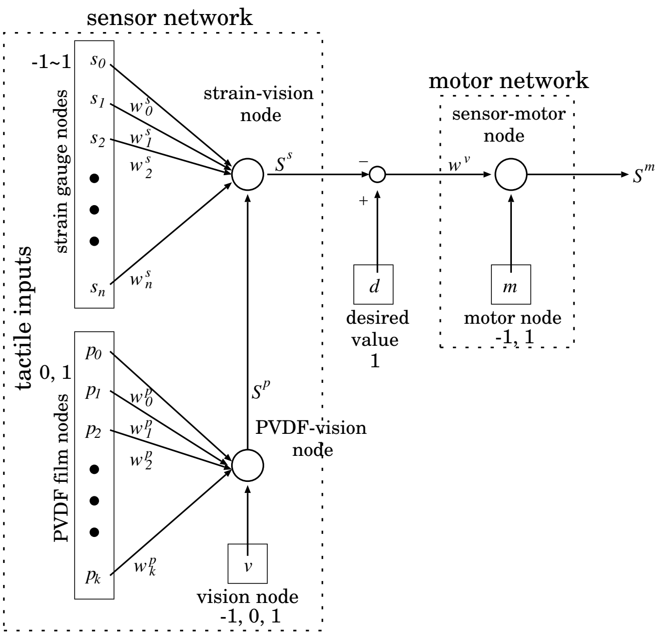

Fig. 4. A neural network for grasping behavior

where, w_k^p denotes the connection weight between the PVDF film node and the vision node, and w_n^s denotes the connection weight between the strain gauge node and the PVDF–vision node. The initial value of w_k^p and w_n^s are set to zero. The connection weights of the sensor network are updated by following equations.

$$S^a = \sum_n s_n^a w_n^s \tag{3}$$

$$\Delta w_k^p = \alpha \, p_k \, v \tag{4}$$

$$\Delta w_n^s = \beta \, s_n \, S^p (1 - S^a) \tag{5}$$

where, α and β denote learning rates. By (4), the PVDF–vision node learns the correlation between the output of the PVDF film and the vision sensor when the fingertip slips on the object because the PVDF film responds to velocity of strain. In (3), s_n^a is the value of the strain gauge node at instant of picking up the object, and w_n^s is the current connection weight. The connection weight w_n^s is updated that S^a approximates 1 in (5). In the equation, the constant value of 1 is the same value as the PVDF–vision node S^p when the robot achieves picking up the object. Therefore, the strain–vision node learns minimum grasping force for picking up the object by (3) and (5). Thus, the tactile sensors play the same role as the vision sensor by using this neural network. Additionally, after the learning, the sensor network outputs the value of 1 when the robot achieves picking up the object. When the grasping force is insufficient, the network outputs less than 1.

The motor network in Fig.4 learns the correlation between the output of the sensor network S^s and the motor command m by Hebbian learning. Thus, the network outputs the motor command for controlling the grasping force by subtracting S^s from the desired value d. The desired value d is the same value as the strain-vision node S^s when the robot achieves picking up the object: the value of d equals 1. The motor command m denotes increasing or decreasing the grasping force, and the value of -1 or 1 are given to m. This value is given at learning phase only, and the value equals 0 at after learning. An output of this network S^m is calculated by a following equation.

$$S^m = (d - S^s) w^v + m \tag{6}$$

where, w^v denotes the connection weight between the output of the sensor network and the motor node. The initial value of w^v is set to zero. The connection weight of the motor network is updated by a following equation.

$$\Delta w^v = \gamma \, S^s \, m \tag{7}$$

where, γ denotes a learning rate. Consequently, the robot acquires grasping behavior that adapts to slippage by using the sensor network and the motor network.

IV. Experiment

To demonstrate capability of the proposed learning mechanism, an experiment that the robot picks up an object is shown. The object is a plastic cup that its weight and a friction coefficient are unknown. The robot autonomously acquires a motor command and the minimum grasping force to pick up the object. Furthermore, the experiment shows that the robot can deal with the heavier object by adapting to slippage.

A. Experimental equipment

Fig. 5 and 6 show an experimental equipment. The developed fingertips are mounted at the end of a robot hand that has 4 DOFs by two fingers (Fig. 5). However, the hand is used for 1 DOF gripper because the experiment demonstrates controlling the grasping force. Additionally, because of limit of the number of A/D converter channels, the tactile receptors in one side fingertip are used for the tactile sensor. The output of the strain gauges and the PVDF films are amplified and fed to a host computer via an A/D converter. A robot hand system contains the robot hand, a robot arm, and a video

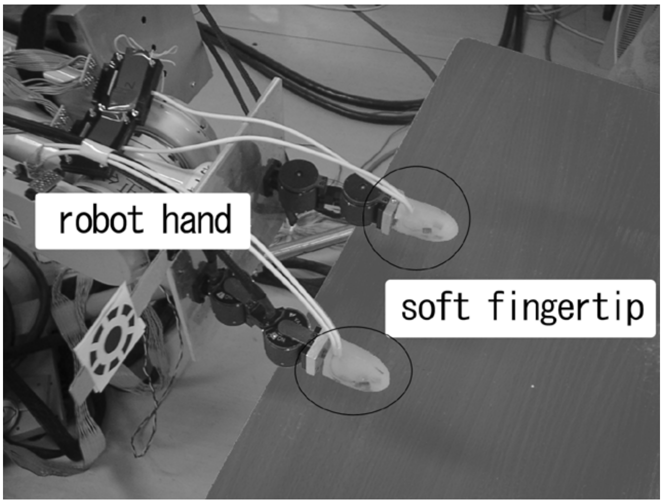

Fig. 5. The anthropomorphic fingertips are mounted at end of robot fingers.

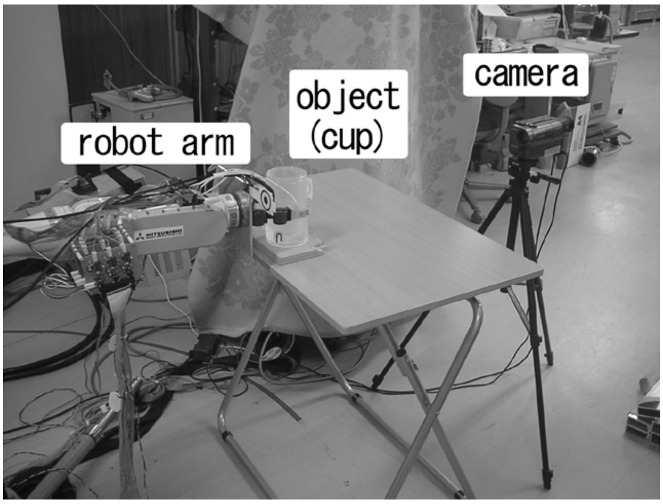

Fig. 6. A robot system consists of a robot arm, a robot hand with anthropomorphic fingertips, and a video camera.

camera (Fig. 6). The object is picked up by the robot arm, and the camera observes the motion between the object and the arm.

An example of the output of the vision and the tactile sensor when the robot hand picks up the object is shown in Fig. 7. These curves in the figure are part of the output of the tactile sensors that respond largely to a contact. In the example experiment, the grasping force and the robot arm are controlled by a designer. The experimental procedure consists of two phases. First, the robot hand is moved to a lower position of the object. In this phase, the fingertips do not touch the object. Then, the object is picked up by increasing the grasping force and moving the robot hand to the upper position.

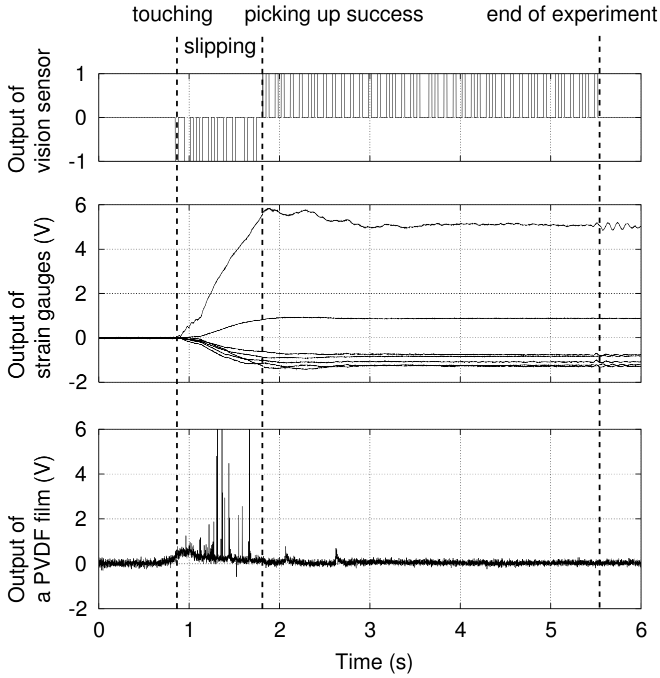

Fig. 7. An example of sensor output when the fingertip picks up the object

In Fig. 7, the fingertip does not touch the object at the beginning of the experiment, and the robot hand starts moving to the upper position when the fingertip touches the object. The fingertip touches the object at about 0.9 s. Until about 1.8 s, the fingertip slips on the surface of the object because the grasping force is insufficient. Then, the grasping force becomes sufficient, and the object is picked up until about 5.6 s. This figure shows three characteristics of the sensors: 1) the vision sensor outputs states of the grasping object, 2) the strain gauge responds to grasping force, and 3) the PVDF film responds to transition of strain such as an instant of contact or slippage.

B. Learning procedure

The developed fingertip has twelve strain gauges and the same number of the PVDF films. However, some suitable receptors to achieve the task are selected by the designer: the strain gauges that maximum output is more than 1.5 V are selected, and the PVDF film #3 which largely responds to slippage is selected.

The learning procedure consists of three phases.

1) The robot hand is located at a bottom of the object. At this time, the fingertips do not touch the object.
2) The grasping force is increased, and the robot hand moves to the upper position. In this learning phase, the grasping force is increased regardless of the output of the motor network S^m.
3) The connection weights are updated by the output of

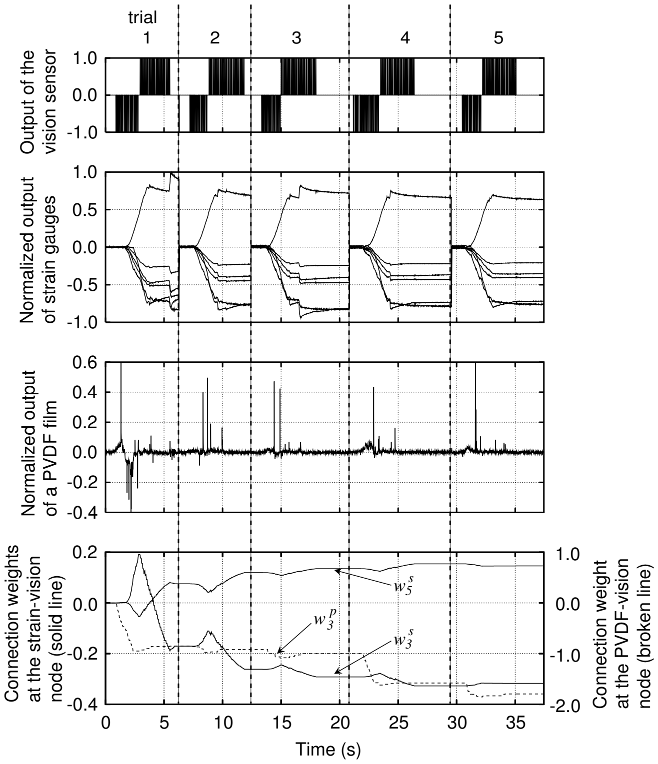

Fig. 8. Time courses of the sensor output and the connection weights at learning phase

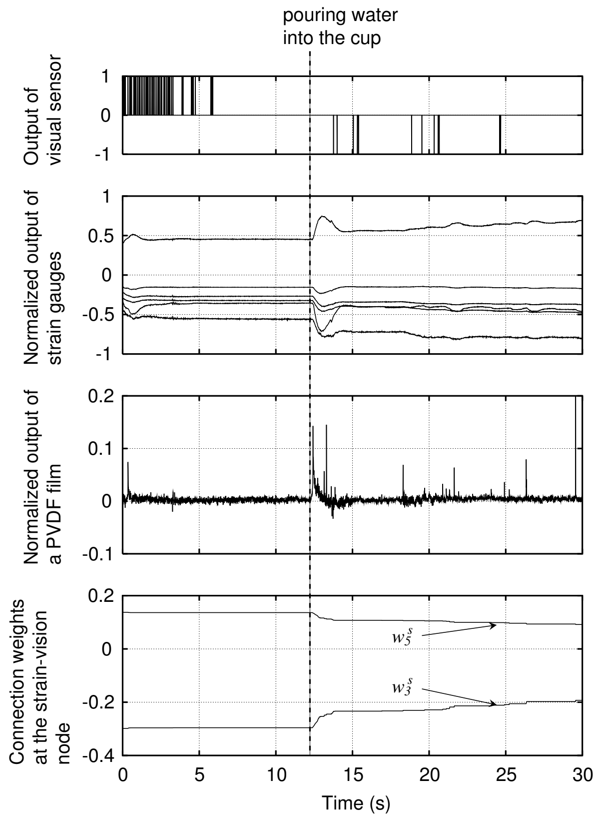

Fig. 9. Time courses of the sensor output and the connection weights at after learning

the tactile sensors, the vision sensor, and the motor command.

4) The above three phases are iterated.

Additionally, the robot arm is controlled by the designer. The connection weights w_n^s, w_k^p, and w^v are reinforced by this procedure, then the neural network acquires the grasping force control to pick up the object. At the phase 2), the grasping force is increased regardless of the output of the motor network S^m. The reason is that the output of the motor network equals 0 at the beginning of the learning because the initial connection weights equal 0, then the grasping force does not increase. Therefore, to begin updating the connection weights, the motor command except the value of 0 is needed. Additionally, because of the linear structure, the neural network can output the motor command for decreasing the grasping force even if the network learned a situation of increasing the grasping force only.

Fig. 8 shows time courses of the sensor output and some connection weights at the learning phase. The robot does not pick up the object while the vision sensor outputs the negative value. In this state, the fingertip slips on the surface of the object because of the insufficient grasping force. When the grasping force becomes sufficient, the robot picks up the object, and the vision sensor outputs the positive value. Therefore, the strain–vision node learns minimum grasping force by (5). On the other hand, the large signal of the PVDF film occurs when the vision sensor outputs the negative value, and the PVDF film does not output the large signal when the vision sensor outputs the positive value. Therefore, the PVDF–vision node learns slippage by (4).

Because of linear structure, the network can not learn the exclusive state that the robot fails and succeeds in picking up the object. Therefore, in the bottom of Fig. 8, the connection weights w_3^s and w_5^s at first trial are not stable by the output of the vision sensor. However, the connection weights are expected to converge because the learning at the failing in picking up the object is almost ignored. The reasons why the learning is almost ignored are as follows: 1) the number of learning at succeeding in picking up the object is more than failing in picking up one, 2) the updating value Δw_n^s in (5) at failing in picking up the object is small because the output of the strain gauge is small by the insufficient grasping force, and 3) the updating value Δw_n^s becomes small step by step because $(1 - S^a)$ in (5) is approximated 0 by updating the connection weights w_n^s. Therefore, the connection weights of the strain–vision node w_n^s are converged after some trials. In the figure, the connection weights are converged by five trials.

C. Picking up the object at after learning

An experiment demonstrates that the robot hand using the learned neural network can pick up a cup as the object by minimum grasping force, and that the robot can deal with the heavier object. The procedure of this experiment is the same as the procedure in the learning phase excluding that the fingertip touches the object at the beginning of the experiment. Furthermore, the vision sensor node v equals 0 at any time to demonstrate that the tactile sensors play a role of the vision sensor. However, the output of the vision sensor is recorded for analyzing experimental data. Additionally, the motor command node m also equals 0. Note that the connection weights w_n^s are updated by the output of the strain gauge nodes and the PVDF film nodes even if the vision node equals 0.

Fig. 9 shows time courses of the output of the vision sensor, the strain gauges, the PVDF film, and the connection weights w_n^s. From this figure, the output of each strain gauge until 12 s is smaller than the learning phase's output in Fig. 8. In other words, the robot grasps the object by small force. Then, the weight of the object becomes heavy by pouring water into the cup at 12 to 14 s. The PVDF film outputs large signal at this time because of impact of pouring water. After pouring water, the slippage between the cup and the fingertip occurs because of the insufficient grasping force. The PVDF film responds to the slippage, and the PVDF–vision node outputs the state of the picking up failure even if the vision node equals 0. It means that the PVDF film plays a role of the vision sensor. Then, the connection weights w_n^s are updated by only the output of the tactile sensors. Consequently, the slippage between the fingertip and the object is stopped by increasing the grasping force. This result shows that the robot can adapt to heavier weight by the proposed mechanism.

V. Discussion and Future Works

In this paper, the learning mechanism for the fingertip which has the randomly distributed receptors was proposed. The learning mechanism was to find the correlation among the output of the sensors and the motor command, and to realize the grasping. The experiment to demonstrate the ability of the mechanism showed that the robot can pick up the unknown weight object through learning, and can deal with the heavier object.

The tactile sensor of the anthropomorphic fingertip is similar to human tactile organ which sense various contact conditions. The receptors of the tactile organ can sense different properties because of the dynamics of the body where the receptor is embedded even if the receptors have similar response characteristic. These receptors can sense contact force, slippage, or vibration that are meaningful contact information to achieve dexterous manipulation [9], [10]. Therefore, we expect that the robot hand can manipulate the object dexterously by utilizing the anthropomorphic fingertip even if the experimental result in this paper only shows the control of grasping force.

Although the anthropomorphic fingertip has twenty-four tactile receptors, in the experiment, some suitable receptors to achieve the task are selected by the designer. The autonomous robot has to select suitable receptors by itself. The experiment shows that the robot controls grasping force only. The robot has to achieve complex tasks to demonstrate the capability of the fingertip. Additionally, the fingertip can not discriminate between the contact and the slippage because the PVDF film senses the velocity of strain. These are future works.

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