

# Object Recognition Using Flexible Tactile Sensor

SHOSHI TOKUNO<sup>1,a)</sup> YUICHIRO TANAKA<sup>1,2</sup> TAKUMI KAWASETSU<sup>3</sup> KOH HOSODA<sup>3</sup> HAKARU TAMUKOH<sup>1</sup>

**Abstract:** We propose an object recognition system based on tactile information obtained from a tactile sensor. Our tactile sensor is made of flexible materials and composed of three parts: silicon rubber, liquid metal, and a coil printed on a circuit board. The sensor is mounted on a robot hand to acquire the tactile information of grasped objects. The tactile information for object classification is learned by an echo state network (ESN). The tactile time series data acquired by the tactile sensor are fed into the ESN for training and classification. To determine whether the system can classify two objects with different hardness levels and two objects with similar colors which cannot be classified by an image recognition system, we conducted two experiments. The classification accuracy of two objects with different hardness levels was 90%, and that of two objects with similar colors was 100%.

**Keywords:** Flexible tactile sensor, Echo state network, Object recognition

## 1. Introduction

The development of home service robots has been attracting attention due to the declining birthrate and aging population. Home service robots are expected to have useful functions for living with humans, such as cleaning up rooms. Object recognition is necessary to achieve these functions. In general, object recognition is performed with a camera. However, as shown in Fig. 1, misrecognition may occur depending on the surrounding environment and the color of the object when we use an image recognition system. To solve this problem, information other than images must be added to the recognition system.

In this study, we use tactile information obtained from flexible tactile sensors. The use of flexible materials makes tactile sensors possible to measure various shaped objects and to reduce the risk of damage to the grasped object. We propose an object recognition system using a robot hand with a flexible tactile sensor proposed by Hamaguchi et al [1].

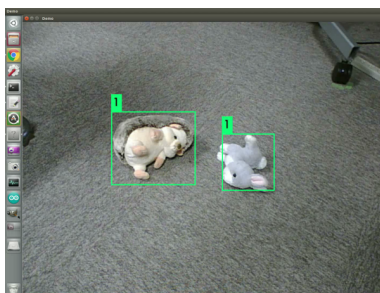


Fig. 1: Result of image recognition system that was recognized the hedgehog as the rabbit

## 2. Flexible Tactile Sensor

This section describes the flexible tactile sensor used in the present study. Fig. 2 shows the structure and working principle of the flexible tactile sensor. The sensor consists of three parts: silicon rubber, liquid metal, and a coil printed on a circuit board. When a force is applied to the contact reservoir, liquid metal is swept away and the detection reservoir expands. As the applied force increases, more liquid metal is poured over the coil and the coil inductance decreases. Therefore, the applied force can be determined by monitoring the change in the coil inductance. In this study, we mount the flexible tactile sensors on a robot hand of a TOYOTA Human Support Robot (HSR) [2]. The flexible tactile sensor on the robot hand is shown in Fig. 3.

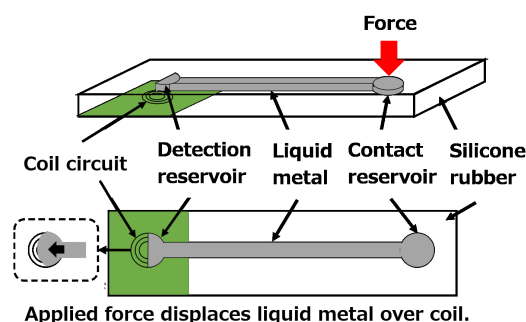


Fig. 2: Structure and working principle of the flexible tactile sensor

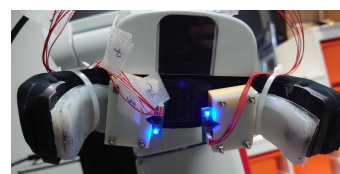


Fig. 3: Flexible tactile sensor on the robot hand

<sup>1</sup> Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-ku, Kitakyushu, Fukuoka, Japan

<sup>2</sup> Research Fellow of Japan Society for the Promotion of Science

<sup>3</sup> Osaka University, 1-3 Machikaneyamacho, Toyonaka, Osaka, Japan

<sup>a)</sup> tokuno.syoshi525@mail.kyutech.jp

### 3. Object Recognition System

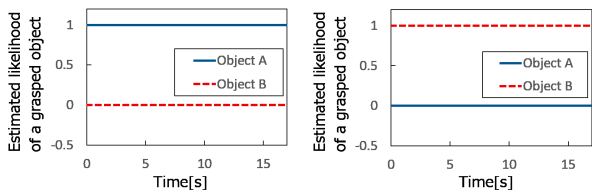
This section introduces our object recognition system using the flexible tactile sensor. The tactile information for object classification is learned by an echo state network (ESN) [3], a type of reservoir computing [4]. The computational cost of the ESN is lower than that of recurrent neural networks that update all weights using backpropagation through time because the ESN only updates output weights. Our proposed system has a training mode and an inference mode. In training mode, the tactile data are fed to the ESN. After feeding the tactile data, the optimized output weights are computed by ridge regression. The supervised signals for two-object classification are shown in Fig. 4. In inference mode, the ESN is fed test data and predicts the grasped object. The estimated likelihood of a grasped object is defined as the time average of the ESN output. An example of the inference mode is shown in Fig. 5.

### 4. Experiment

The experiments were conducted on the objects shown in Fig. 6. In this experiment, we prepared an input data that was the time series data where the robot repeated grasping and releasing the object five times. The torque of the robot hand during grasping was 0.1 N. For each object, we prepared five training data and 20 test data.

#### 4.1 Classification of two objects with different hardness levels

We used two objects with different hardness levels in this ex-



(a) Supervised signal of object A (b) Supervised signal of object B  
Fig. 4: Examples of supervised signals for classifying two objects

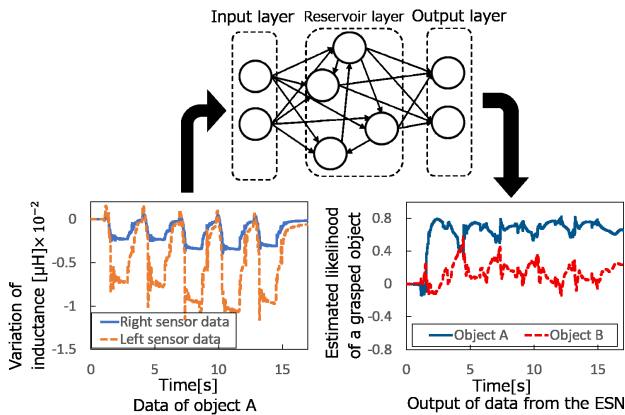


Fig. 5: Example of inference mode



(a) Can (b) Sponge (c) Hedgehog (d) Rabbit

Fig. 6: Grasped objects in the experiments

Table 1: Result for using can and sponge

	Can	Sponge
Result	17/20	20/20

Table 2: Result for using hedgehog and rabbit

	Hedgehog	Rabbit
Result	20/20	20/20

periment shown in Figs. 6(a) and 6(b). The results are shown in Table 1. 17 out of 20 test data of the can were successfully classified and all test data of the sponge were successfully classified. Three test data of the can were unsuccessfully classified because some sensor data of can were similar to those of sponge due to the way of grasping. The sensor data in this experiment was obtained by grasping from one direction. To overcome this problem, we consider to increase the number of tactile sensors because we can get more detailed sensor data.

#### 4.2 Classification of two objects with similar colors

We used two objects with similar colors in this experiment shown Figs. 6(c) and 6(d). The results of using these objects are shown in Table 2. All test data of both the hedgehog and the rabbit were successfully classified. That is, our proposed system can classify grasped objects with similar colors.

### 5. Conclusion

We proposed a grasping object recognition system using flexible tactile sensors.

In future work, we will consider combining tactile recognition with image recognition. We will also consider mounting a soft robot hand on a home service robot for object recognition because tactile sensors are compatible with soft robot hands constructed from flexible materials.

**Acknowledgments** This research is based on results obtained from a project commissioned by the New Energy and Industrial Technology Development Organization (NEDO).

### References

- [1] S. Hamaguchi, T. Kawasetsu, T. Horii, H. Ishihara, R. Niiyama, K. Hosoda and M. Asada : Soft Inductive Tactile Sensor Using Flow-Channel Enclosing Liquid Metal, IEEE Robotics and Automation Letters, vol. 5, no. 3, pp. 4028-4034 (2020).
- [2] T. Yamamoto, K. Terada, A. Ochiai, F. Saito, Y. Asahara and K. Murase : Development of Human Support Robot as the research platform of a domestic mobile manipulator, ROBOMECH Journal, vol. 6, no. 1 (2019).
- [3] H. Jaeger : The “echo state” approach to analysing and training recurrent neural networks-with an erratum note, Bonn, Germany: German National Research Center for Information Technology GMD Technical Report, vol. 148, no. 34 (2001).
- [4] M. Lukoševičius and H. Jaeger : Reservoir computing approaches to recurrent neural network training, Computer Science Review, vol. 3, no. 3, pp. 127-149 (2009).