# Difference of Gaussian like feature enhances object classification accuracy in magnetorheological elastomer-gel tactile sensor

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***Abstract*— This paper reports an object classification method based on tactile information obtained by a magnetorheological elastomer-gel tactile sensor that we have been proposing. We hypothesize that the characteristic spatial response of our sensor contributes to classify objects because its spatial response is a difference of Gaussian (DoG), which is a edge enhancement filter. We compared the accuracy of classification between sensor outputs with the DoG like spatial response and without it (simple Gaussian like response). Our experimental result shows that the accuracy is higher in DoG like spatial response in most cases, and it supports our hypothesis.**

## I. INTRODUCTION

Object classification is a crucial task for robots to handle various objects in dexterous. Various classification methods based on tactile information have been reported, and many of them extract feature vectors by using software filters or analytical algorithms from raw sensory signals [1-3]. In contrast, a magnetic flexible tactile sensor we have been developed [4] has a potential to partly reduce these processing costs because its spatial response is not a commonly seen Gaussian-like one but a difference of Gaussian (DoG)-like one, which is known to work as a edge enhancement filter. However, we should verify whether such a characteristic spatial response increase object classification accuracy.

In this study, therefore, the accuracy of object classification for nine different object cases with support vector machines was compared between two spatial response settings, which are a DoG-like one and Gaussian-like one.

## II. OBJECT CLASSIFICATION METHOD

### A. *Magnetorheological Elastomer-Gel Tactile Sensor*

Fig. 1 shows the appearance and structure of the minimum setup of the proposed tactile sensor [4]. The sensor consists of a flexible dual-layer elastomer (W 150mm x L 150mm x H 12mm) and a printed circuit board holding a magnet and a magnetic sensor. The upper layer of the elastomer is magnetorheological elastomer that contains high magnetic permeability particles (e.g. iron powder) and the lower one is non-magnetic elastomer. This sensor detects applied contact loads as changes of the magnetic flux distribution.

We found the proposed sensor has a bipolar spatial response, and the spatial response can be modeled by a difference of Gaussian function, which is a famous edge enhancement filter. Fig. 2 shows the spatial response of the sensor obtained by applying 5-mm depth directional deformation with a cylindrical indenter having 10-mm diameter.

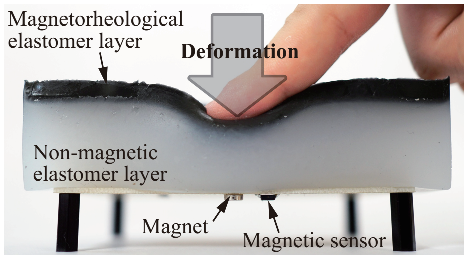


Fig. 1. Appearance and structure of the proposed tactile sensor that can detect applied depth directional deformation as a change of magnetic field.

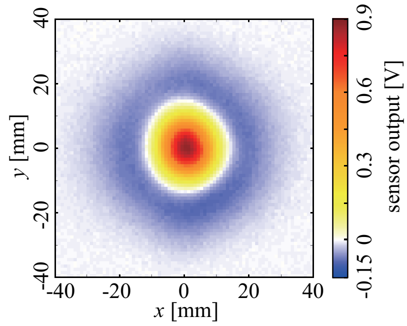


Fig. 2. Difference of Gaussian like spatial response of the proposed sensor with one magnet located at the origin.

The sensor has a positive response area around the magnet (approx. within 30 mm diameter) and a negative area (within 70 mm diameter) outside the positive area.

Although we used one pair of a magnet and a magnetic sensor as shown in Fig. 1 in previous works, we used four pairs of a magnet surrounded by four magnetic sensors to obtain richer tactile information as shown in Fig. 3. These four magnets were located at each edge of a 30 mm grid, i.e. positive response areas for these magnets were contiguous.

### B. *Experimental setup and conditions*

Fig. 4 (a) shows the experimental setup, and Fig. 4(b) illustrates bottom shapes of objects and their indexes for classification. These objects were attached to a three axis robot stage (IAI corp., TTA-C3-WA-30-25-10, positioning accuracy: 20 $\mu$m), and the stage automatically pressed the objects at the center of the grid of magnets against the sensor with 5 mm depth. The sensor outputs were measured 100 times for each case.

To evaluate the classification ability of our sensor, we set nine objects in three levels of classification difficulty:

1) **Shape classification with small objects (cases 1-3).** 10 mm size indenters with square, circle, and triangle bottoms were prepared as difficult cases. Contact areas of these indenters for the sensor overlapped with the negative areas of sensors' outputs (i.e., outside of any positive areas).

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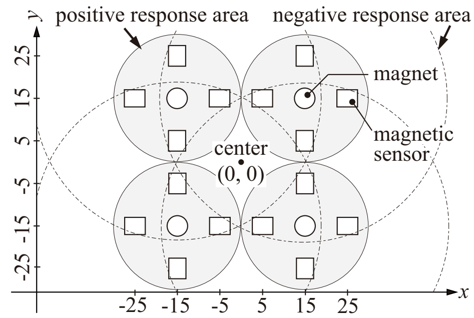


Fig. 3. Arrangement of 4 magnets and 16 magnetic sensors on $x$-$y$ plane.

2) **Shape classification with middle-size objects (cases 4-6).** 20 mm size indenters with square, circle, and triangle bottoms were prepared as standard cases. Contact areas of these indenters cover several positive and negative areas only inside the grid of magnets.
3) **Orientation classification with a long object (cases 7-9).** A indenter having rectangular bottom with 10 mm width and 60 mm length was prepared as easy cases. The indenter was pressed onto the sensor surface in different angles against the $x$-axis in each case (0, 45, and 90 deg. for the objects 7, 8, and 9, respectively). Contact areas in these cases cover several positive and negative areas inside and outside the grid of magnets.

### *C. Object classification algorithm*

In order to classify various shape objects based on tactile information, we employ a support vector machine that was implemented with LIBSVM (https://www.csie.ntu.edu.tw/˜cjlin/libsvm/) as C-SVM with a RBF kernel. The parameters of SVM were set as follows: $\sigma$ = 1/9, $C$ = 1, and eps = 0.001. Input features for the SVM were a set of sensor output voltages of 16 magnetic sensors and the task of the SVM was to distinguish the contact object from other eight objects. To investigate whether and how the DoG like feature of the sensor contributes to increase the classification accuracy, we compared the performances between two settings of the input features: The first one (DoG setting) contains negative values of the sensor outputs by using DoG like outputs as they are. The second one (Gaussian setting) contains only the positive values by cutting out the negative values.

## III. RESULTS AND DISCUSSIONS

Table 1 (a) and (b) summarize the confusion matrices of classification accuracy in the DoG setting and the Gaussian setting, respectively. The correct answer rates are highlighted with black background. In the easy cases 7-9, the accuracies were 100% in the whole case. In the standard cases 4-6, the accuracies were higher in the DoG setting than in the Gaussian setting, and they were over 80%. In the difficult cases 2 and 3, the accuracies were higher in the DoG setting and they were over 30%. In the case 1, the accuracy was lower in the DoG setting.

Thus, in most cases, the DoG setting increased accuracy, and the each accuracy exhibits over 80% in standard and easy cases. This indicates our sensor has a fine classification ability if contact objects cover several positive response areas. In contrast, the accuracy was appear to be decreased by the DoG setting in the case 1. This should be considered as the result that the DoG setting increased the accuracies in the case 2 and 3. We can find the classification tendency toward the case 1, e.g., the case 3 and 5 were misclassified as the case 1 over 75% cases in the Gaussian setting.

Our results show that DoG feature of our sensor improved the object classification ability and suggested the accuracy was over 80% if the objects covered several positive and negative response areas. This suggest that the DoG feature contributes the classification tasks. Further experiments are required to conclude this hypothesis and to understand the mechanism of the accuracy improvement.

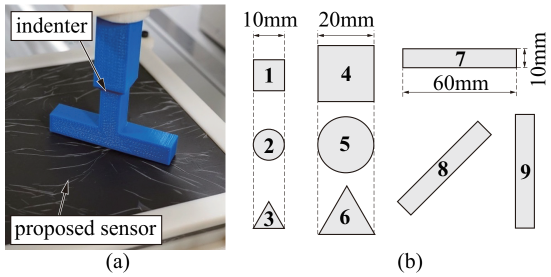


Fig. 4. Experimental setup. Nine types of objects were pressed onto the sensor surface with 5 mm depth. (a) Appearance of the setup. (b) Bottom shape of the nine objects used in this study. Objects 7, 8, and 9 had the same rectangular shape but different angles against the $x$-axis.

TABLE I

(a) Confusion matrix in the DoG setting.

| case numbers | difficult case | | | standard case | | | easy case | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | 64 | 27 | 5 | 0 | 0 | 4 | 0 | 0 | 0 |
| 2 | 41 | 51 | 7 | 0 | 0 | 1 | 0 | 0 | 0 |
| 3 | 32 | 38 | 30 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 99 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 96 | 4 | 0 | 0 | 0 |
| 6 | 15 | 3 | 1 | 0 | 1 | 80 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |

(b) Confusion matrix in the Gaussian setting.

| case numbers | difficult case | | | standard case | | | easy case | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | 84 | 9 | 2 | 0 | 0 | 5 | 0 | 0 | 0 |
| 2 | 80 | 13 | 3 | 0 | 1 | 3 | 0 | 0 | 0 |
| 3 | 75 | 12 | 9 | 0 | 1 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 96 | 4 | 0 | 0 | 0 | 0 |
| 5 | 16 | 11 | 0 | 2 | 46 | 25 | 0 | 0 | 0 |
| 6 | 65 | 6 | 0 | 0 | 2 | 27 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |

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