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CREATION OF RANDOM DOT TYPE CONTACT SENSOR AND ESTIMATION OF PRESSURE DISTRIBUTION BY CONVOLUTIONAL NEURAL NETWORK

Takuya Takahashi[1], Pornthep Sarakon[1], Hideaki Kawano[1]
Kazuhiro Shimonomura[2] and Hideaki Orii[3]

[1]Faculty of Engineering
Kyusyu Institute of Technology
1-1, Sensui-cho, Tobata-ku, Kitakyusyu 804-8550, Japan
kawano@ecs.kyutech.ac.jp

[2]Department of Robotics
College of Science and Engineering
Ritsumeikan University
1-1-1 Nojihigashi, Kusatsu, Shiga 525-8577, Japan

[3]Faculty of Engineering
Fukuoka University
8-19-1, Nanakuma, Jonan-ku, Fukuoka 814-0180, Japan
oriih@fukuoka-u.ac.jp

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Abstract. *There are dangerous tasks in the factory production process. Therefore, industrial robots are used. However, it is a reality that even either an injury or death is caused by an accident. Currently, contact-type sensors for directly pressing an object on a sensor unit have been developed. This sensor can recognize the direction of pressure or force applied to the object and the hardness of the object. By using the contact sensor, it is possible to grasp everything like a person. However, it cannot know at what position of the sensor how much pressure is applied. In this study, we developed a random dot type contact sensor that can estimate the pressure distribution. The heat map of pressure distribution was created using Convolutional Neural Network (CNN) for the change image of the taken sensor part.*

Keywords: Contact sensor, CNN, Pressure sensor, Robot arm, Pressure distribution

1. **Introduction.** There are dangerous tasks in the factory production process. Therefore, industrial robots are used. However, it is a reality that even either injury or death is caused by an accident. The main cause of the accident is that a person gets caught in a machine or accidentally touches a hot object. Therefore, an automatic robot arm is necessary. It is also important to improve the performance of the robot arm. Conventionally, it has been common to operate a robot arm based on information such as the position and shape of an object using a camera. However, it is not possible to extract pressure information applied to the sensor. Currently, we develop contact-type sensors for directly pressing an object on a sensor unit developed. This sensor can recognize the direction of pressure or force applied to the object and the hardness of the object. By using the contact sensor, it is possible to grasp everything like a person. However, it cannot know at what position of the sensor how much pressure is applied. In this study, we developed a sensor that can estimate the pressure distribution. This sensor has a two-stage structure of white gel and transparent gel. A black particulate marker is placed between the gels. This sensor is called a random dot type contact sensor. An object is pressed against this

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random dot type contact sensor, and the changed image is taken with a USB camera. Moreover, the heat map of pressure distribution was created using Convolutional Neural Network (CNN) for the change of the sensor part photographed with the USB camera.

2. **Related Work.** There are diverse object recognition studies using tactile sensor [1,2]. In addition, methods have also been proposed that use spatio-temporal data to classify objects [3-5]. There are several studies developing a new sensor. Chuang et al. presented a high resolution shape recognition based on an ultrasonic tactile sensor [6]. Liu et al. presented by using Joint Kernel Sparse Coding (JKSC), they were able to distinguish not only spatial feature but material texture also roughness [7-10]. There is also a sensor that uses a camera to obtain touch information. It is a study using a sensor with a marker in place, called "gelsight" [11]. This sensor and three color light sources are used to detect the depth map of the touched object. It also detects the direction of the force applied to the sensor. The depth map is created using a method called photometric stereo method. The photometrics method uses a fixed camera and multiple light sources to perform 3D shape recognition of the target object. The direction of the force applied to the sensor is identified by measuring where the marker at the fixed position has moved. However, we do not know the position of the object. This study also estimates tactile characteristics from vision with unsupervised learning [12]. The degree of tactile characteristics is estimated from the image. You can see the texture of the object. In this paper, we developed a sensor to estimate pressure distribution.

3. **Proposed Methods.** We randomly made contact sensors interspersed with particulate markers. Section 3.1 explains the random dot tactile contact sensor created in this study. This tactile sensor is made of transparent gel and white gel. Therefore, background information can be blocked, making it less susceptible to light effects. An object is pressed against the sensor to capture a change image. There is a marker between the gels, and the marker fluctuates by pressing an object against this sensor. We took this change image. The change image was analyzed by CNN to estimate the pressure distribution. The input image is a sensor change image. The teacher data prepared the array corresponding to the input image. Input another prepared test image to the learned model. The estimated pressure distribution of the output was compared with the ideal pressure distribution created in advance.

3.1. **Random dot type contact sensor.** The description and preparation procedure of the random dot type contact sensor are shown below. The sensor was made of soft gel. The structure of the sensor is a two-layer structure. The first layer used a cloudy gel to block background information. The second layer used a clear gel. This is to capture the change of the first layer with the USB camera. A black particulate marker was randomly placed between the first and second layers. Since white gel appears, it is a sensor that easily changes RGB. This black particulate marker changes by pressing the object. As the pressure is applied, the black particles move away. The place where the force is applied changes as it is. Both position information and pressure can be measured. The change image is taken under a certain pressure. The composition of the sensor is shown in Figure 1. The actual sensor is shown in Figure 2.

3.2. **Creating data sets.** As an input image, an image is 1600×1200 that sensor was taken with a USB camera and cropped into 1100×1100. The image is resized to 150×150. An example of the input image is shown in Figure 3. Describe the procedure for creating teacher data. The teacher data prepares an array of pressure distributions corresponding to the input image. Acquire the coordinates of the entire object to be pressed in advance. Next, get the center coordinates when pressing the object. From these two coordinates, the coordinates where pressure is applied are calculated. The values of the coordinates

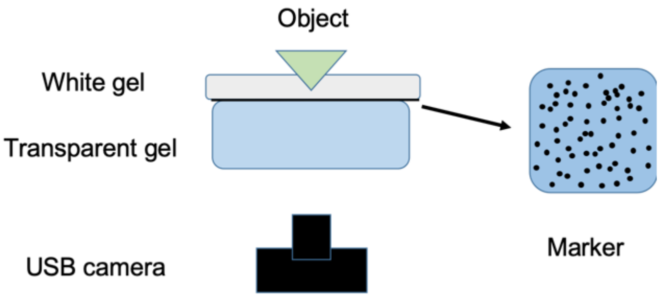

FIGURE 1. Sensor structure

FIGURE 2. Actual sensor

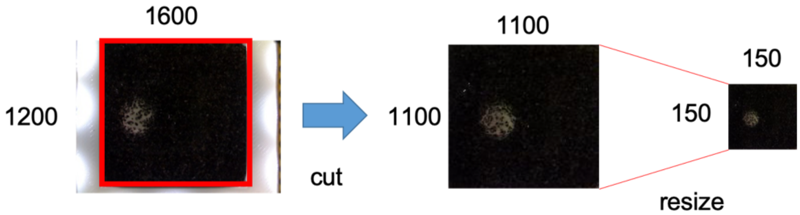

FIGURE 3. Resized input image

were expressed as a 50×50 array. The unit of pressure is g/cm^2. The sensor is made of soft gel. Therefore, the portion where the object is not in contact is also deformed. So we used an average value filter. The average value filter is a filter that smoothes an image to remove noise. The average of pixel values in the vicinity of the target pixel is calculated. Then, the pixel value is updated. The size of the mean filter was 3×3 and the coefficient was 1. A description of the mean filter is shown in Figure 4.

4. **Experiments.** We study using CNN in this research. The structure of CNN is seven layers in the convolutional layer, five layers in the deconvoluted layer, and two layers in the total bonding layer. Figure 5 shows the structure of CNN. It is common for CNN learning to reduce the features of the input image. However, position information is important for the estimation of pressure distribution. So we added a deconvoluted layer. Location information can be reflected more.

4.1. **Experiment settings.** The pressure distribution was estimated using the CNN model for the change image captured by the sensor. We used pressured images of circles, squares and rectangles for learning. The learning was performed with the number of captured images increased to 10,400. The test stage used the image which was not used for learning. We also tested objects that did not use for mapping. Input the image to the learned model. The estimated pressure distribution is output. An ideal pressure

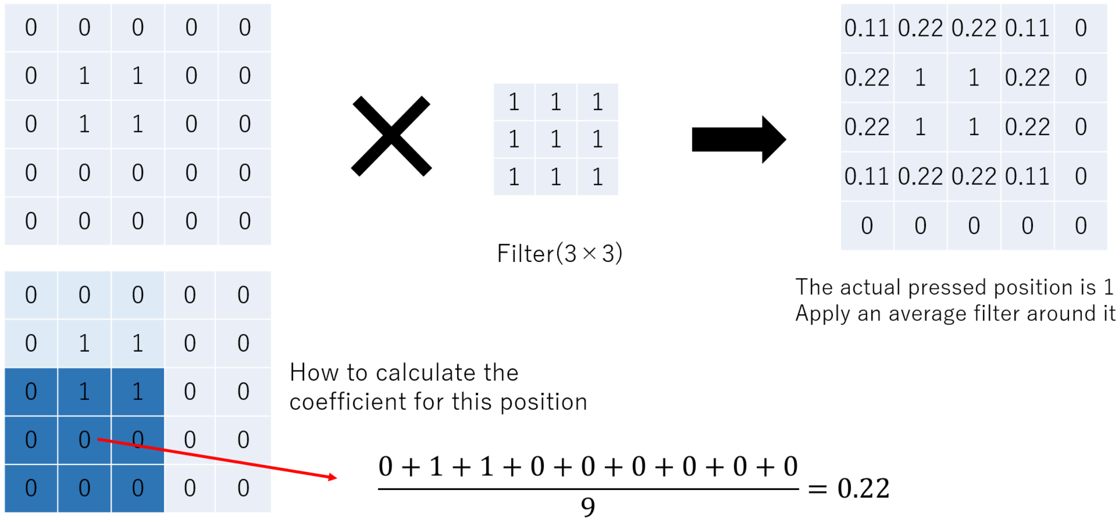

FIGURE 4. Average value filter. Overwrite if the value is larger than the original array.

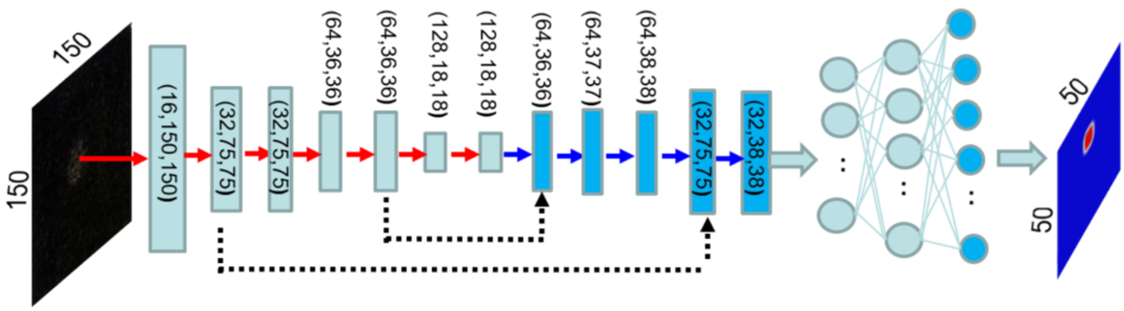

FIGURE 5. CNN structure

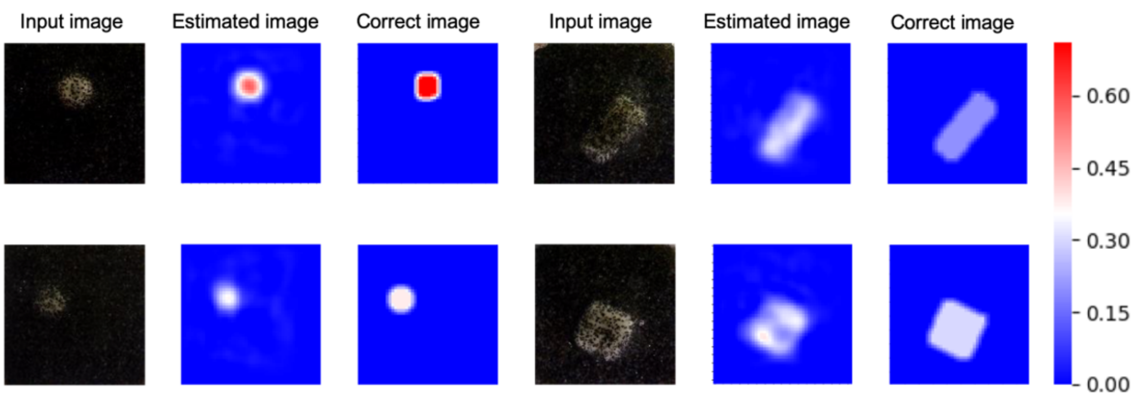

FIGURE 6. (color online) Object used for learning

distribution was prepared in advance and compared. We also created a heat map for comparison. The pressure values were expressed as color change.

4.2. **Experiment results.** In the test, images of the object used for learning and the object used for testing were prepared respectively. The results are shown in Figures 6 and 7. The position information and pressure value are quantitatively evaluated by the estimated pressure distribution. 21 images of an object used for learning and 18 images of a different object used for testing are randomly selected. And we put out the average value of each. In the evaluation of position information, the barycentric coordinates are obtained from the obtained x-coordinate and y-coordinate pressure values. Then, the error

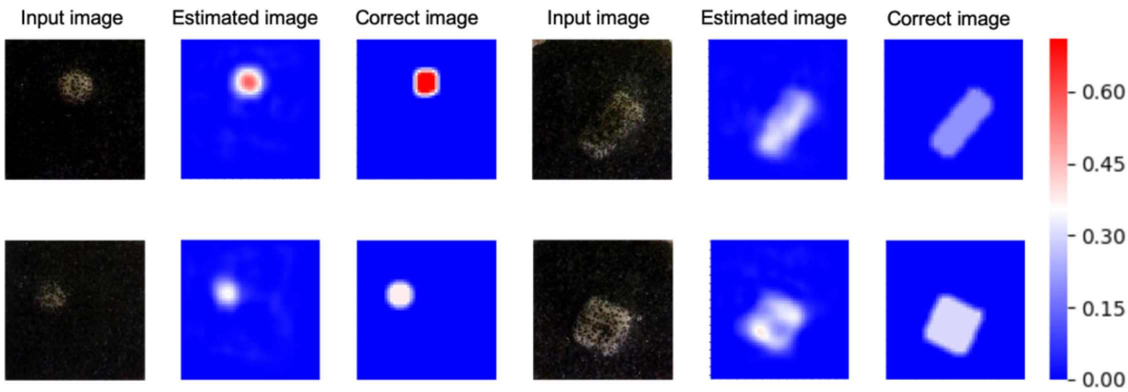

Figure 7. (color online) Object not used for learning

Table 1. Positional error

	x-coordinate error (pixel)	y-coordinate error (pixel)
Object used for learning	12	11
Object not used for learning	10	12

Table 2. Pressure error

	RMSE (N/m^2)
Object used for learning	1.04×10^{-3}
Object not used for learning	1.36×10^{-3}

is calculated by comparison with the barycentric coordinates of the pressure distribution of the correct answer. The results are shown in Table 1. The error is expressed in pixel units. The error of pressure used the Root Mean Square Error (RMSE). Images were randomly selected and averaged. The results are shown in Table 2. The results show that it is possible to estimate the pressure distribution using a random dot contact sensor. The correct image was assumed to be uniformly pressured when the object was touched. A uniform value can be confirmed on the heat map at the contact portion. However, the estimated image does not have a uniform distribution at the contact portion. This is due to the fact that the amount of markers has become uneven at the time of sensor creation. Also, there may be a problem when shooting. That is, when applying force to an object, the force is not applied exactly in the middle of the object. If you deviate from the middle, it will not follow the correct coordinates. Further, since the number of images is mechanically increased, it is considered that the cause is that the number of original images is small.

5. **Conclusions.** In this study, we made a random dot contact sensor. The pressure distribution was estimated using the created sensor. As a result, it was possible to confirm the change in pressure applied to the object. Moreover, the estimation model of pressure distribution was able to be built using CNN. However, from the estimation results, there is no uniform distribution at the contact area. The position was a little error. In the future, it is necessary to create a sensor that is easy to understand change. Also, when applying force to an object, the force is not applied exactly in the middle of the object. If you deviate from the middle, it will not follow the correct coordinates. Further, since the number of images is mechanically increased, it is considered that the cause is that the number of original images is small.

REFERENCES

[1] T. Matsubara, K. Shibata and K. Sugimoto, Active touch point selection with travel cost in tactile exploration for fast shape estimation of unknown objects, *International Conference of Advanced Intelligent Mechatronics (AIM)*, pp.1115-1120, 2016.

[2] G. Vezzani, N. Jamali, U. Pattacini, G. Battistelli, L. Chisci and L. Natale, A novel Bayesian filtering approach to tactile object recognition, *International Conference of Humanoid Robots (Humanoids)*, IEEE-RAS, pp.256-263, 2016.

[3] H .Yang, F. Sun, W. Huang, L. Cao and B. Fang, Tactile sequence based object categorization: A bag of features modeled by linear dynamic system with symmetric transition matrix, *International Joint Conference of Neural Networks (IJCNN)*, pp.5218-5225, 2016.

[4] M. Madry, L. Bo, D. Kragic and D. Fox, ST-HMP: Unsupervised spatio-temporal feature learning for tactile data, *International Conference on Robotics and Automation (ICRA)*, pp.2262-2269, 2014.

[5] L. Cao, R. Kotagiri, F. Sun, H. Li, W. Huang and Z. M. M. Aye, Efficient spatio-temporal tactile object recognition with randomized tiling convolutional networks in a hierarchical fusion strategy, *Proc. of AAAI National Conf. Artif. Intell.*, pp.3337-3345, 2016.

[6] C. H. Chuang, H. K. Weng, J. W. Chen and M. O. Shaikh, Ultrasonic tactile sensor integrated with TFT array for force feedback and shape recognition, *International Conference of Advanced Intelligent Mechatronics (AIM)*, pp.348-355, 2018.

[7] H. Liu, D. Guo and F. Sun, Object recognition using tactile measurements: Kernel sparse coding methods, *IEEE Trans. Instrumentation and Measurement*, vol.65, no.3, pp.656-665, 2018.

[8] H. Liu, Y. Yu, F. Sun and J. Gu, Visual-tactile fusion for object recognition, *IEEE Trans. Automation Science and Engineering*, vol.14, no.2, pp.996-1008, 2018.

[9] H. Liu, J. Qin, F. Sun and D. Guo, Extreme kernel sparse learning for tactile object recognition, *IEEE Trans. Cybernetics*, vol.47, no.12, pp.4509-4520, 2018.

[10] H. Liu, Y. Wu, F. Sun and D. Guo, Recent progress on tactile object recognition, *International Journal of Advanced Robotic Systems*, vol.14, no.4, 2018.

[11] W. Yuan, C. Zhu, A. Owens, M. A. Srinivasan and E. H. Adelson, Shape-independent hardness estimation using deep learning and a GelSight tactile sensor, *MDPI*, 2018.

[12] K. Takahashi and J. Tan, Deep visuo-tactile learning: Estimation of tactile properties from images, *International Conference on Robotics and Automation (ICRA)*, 2019.