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Wiping 3D-Objects with Various Shapes by Robot using Deep Learning

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1. Background

Recently, robots are expected to help our daily works. We pay particular attention to wiping. In our daily life, there are many variations in the shape of objects, it is hard to make models and attach labels for each of objects. We adopt machine learning method to robot control system, which has high generalization ability and adaptability to the environment.

2. Previous studies and purpose of this study

Leidner et al. develop a system for a robot to wipe a desk according to the computational model. This research is limited to operate in certain environment [1]. Cauli et al. let a robot generate the wipe motion to clean the dirt on the specific table by using deep learning method. But this research is unable to wipe the Three-dimensional object [2]. Adachi et al. add force feedbacks when robot touches the object which shown that the success rate of the operation can be improved. However, they do not use the vision data so that there is no variation in the target position [3].

In this research, we propose a learning model for wiping 3D-object tasks according to the shape of objects without computational model using force feedback from touching object and image information. Finally, the robot can generate a suitable wiping motion according to the shape of the object.

3. Method

We use the direct teach method to let the robot experience wiping actions. The direct teach method is the way to move robot's arm directly by experimenter's guidance. We collect the training data by replaying the movement from direct teach. The reason that we use the replay data is not to influence the vision and force feedback by experimenter. Then, collected data is trained by two deep learning modules to generate the wipe motion by robot-self. Finally, we evaluate the wipe-motion generation and generalization ability using untrained objects.

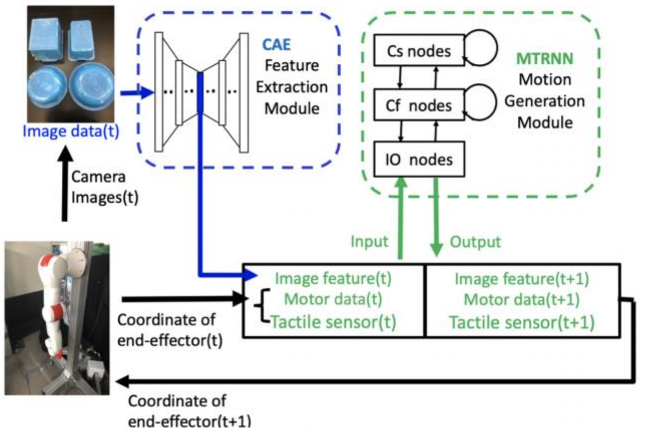

Fig.1.The proposed learning model

4. Proposed deep learning model

We propose a learning model, which consists of two parts shown in figure.1: Convolutional Auto-Encoder (CAE) [4], and Multiple Timescales Recurrent Neural Network (MTRNN) [5].

4.1 CAE

CAE has an hourglass-like structure that can learn to make the output data same as input data. In this way, the image can be compressed and the features of objects and robot arms can be extracted from the intermediate layer as low-dimensional "image features".

4.2 MTRNN

MTRNN has fast context (Cf) and slow context (Cs) nodes with different time constants. Especially, Cs nodes which have large time constants can acquire the useful information for the sequential data. At this time, the motions need to be adjusted according to the shape of objects. Thus, we can evaluate whether the robot recognize the shape of objects by analyzing the internal state of Cs layer.

MTRNN can learn to predict the next state from current state.

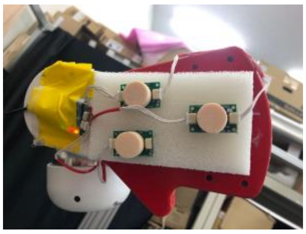

Fig.2 Tactile sensors.

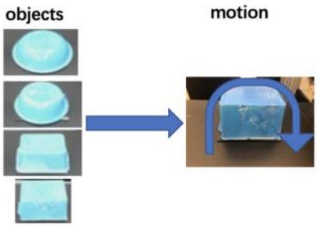

Fig.3 Objects and motion

Therefore, the robot can obtain the ability to generate the suitable motion according to the shape of object.

5. Experiment setup

In this research, we use robot called Twendy-2 Arm developed by Tokyo Robotics co. ltd, which has 7 degree of freedom. The camera is set outside, in front of the robot. Three tactile sensors are attached to a sponge which is stuck to the hand of the robot arm shown in the figure 2.

We show the task setting in figure 3. We prepare four different shape objects for training. The wiping action is set as starting from the left side of the object to the upper, then wipe till to another side, and then from the upper to the bottom.

Recorded data includes robot arm joint angle (7 dim), tactile data (3 sensors x 4 dim) and image features from camera (15 dim). We take total of 24 (4 objects x 6 times) time-series data.

6. Result

Fig.4 shows the results of principal component analysis (PCA) of internal state of Cs layers. In this research, we use the 20th step of Cs nodes for analyzing because which is the timing to just start touching the object. We confirmed that wipe motion according to shape of object were self-organized.

As shown in the Fig.5, using the untrained 3D-object, the robot can generate wipe motion without human assistance.

7. Conclusion and future work

In this research we propose a deep learning model that can wipe the 3-D objects according to the shape of objects without computation model and assistance from human. And the robot can generate the wipe motion on untrained object.

In future work, we suppose to update the learning model that can not only wiping the 3D-objects but also can recognize and wipe the dirt on the objects.

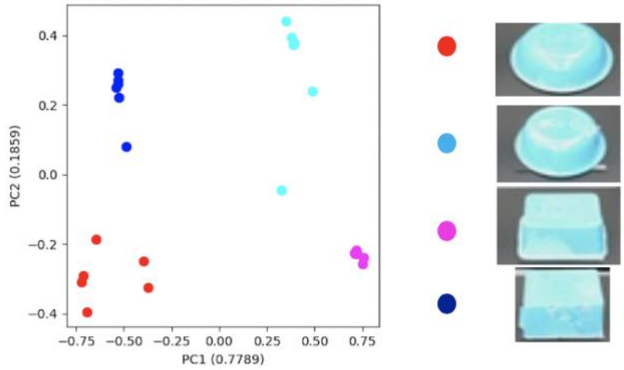

Fig.4 Internal state of CS layer

Fig.5 Images of wiping the untrained object from camera

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