Object Classification with a Robot Gripper equipped with Force Sensitive Fingertips using Convolutional Neural Networks

Christoph Uhrhan[1], Philipp Triebold[1] and Orion Franz Lorenz Salas[2]

[1]Furtwangen University
{uc,philipp.triebold}@hs-furtwangen.de
[2]Frickly Systems GmbH
info@frickly.systems

Abstract. In this paper we present a solution for the identification and classification of grasped objects with an electrical robot gripper with force sensor arrays in its fingertips. The solution is based on a convolutional neural network (CNN). The CNN is trained with relatively few examples but gives already reasonable results. Objects to be detected are of geometrical shape like ring, pen, sphere. The challenges in such applications are the generation of random training data and interfaces between the different components such as gripper, sensor array fingertips and robot. The trained CNN is ported to a Raspberry Pi for real-time execution and communication between the gripper and the robot.

Keywords: force sensing robot gripper; convolutional neural network, object classification; bin picking.

1 Introduction

The flexibility of robots depends not at least on the flexibility of the robot gripper. Beside versatile finger kinematics [1] universal grippers need appropriate sensors to interact with the environment. The mostly used sensors are cameras to detect the correct grasp position [2], [3], [4]. As more sophisticated the gripper become as more time consuming is the classical programming of grasping procedures. Several approaches are proposed using Artificial Intelligence to learn the correct grasping [5], [6]. Standard electrical grippers offer already the possibility to adjust and measure position and the applied force of the finger. Additional sensitive fingertips with a force sensor array give additional information about the location size and shape of the grasped object.

Nevertheless, the interpretation of this additional information is not always unique and/or difficult to program. [7] presents two approaches to determine the elasticity of the grasp object using force sensing in the fingertips. The following presented approach interprets fingertip force sensor data to classify objects by its shape using convolutional neural networks (CNN). This reduces the programming effort to identify specific objects. This approach is a contribution to make fingertip sensors easier to use in industrial robot applications, for example for bin picking applications.

2 Experimental Setup

The base of our experiments is the electrical gripper WSG50 from Weiss Robotics (Figure 1) equipped with forces sensor matrix in the fingertips.

Fig. 1. Electrical Gripper from Weiss Robotics

2.1 Fingertip Sensor

The fingertip sensor provides a force distribution over the fingertip area (Figure 2). The output is a 6 x 14 matrix with force/pressure values in the range of 20 to 250 kPa for each force pixel with a pixel size of 3.4 x 3.4 mm².

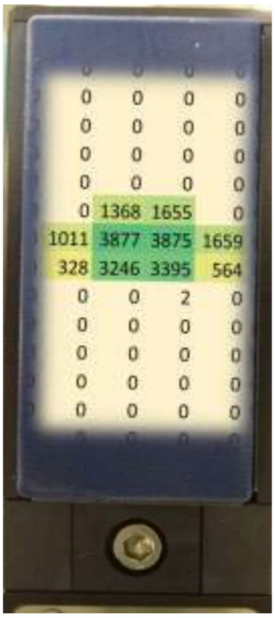

Fig. 2. Sensor-Array in the Fingertips

2.2 Data Organisation

To make the handling of the sensor data more universal, the two arrays of the fingers are put together to one matrix which represents the force distribution of both finger matrices in a 6 x 28 matrix (Figure 3). Like this the data can easily be used within Python and the Keras library.

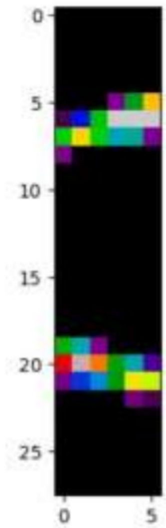

Fig. 3. Combined Sensor-Data-Array from 2 Fingers

2.3 Data Generation

A big challenge to use Neural Networks is the generation of sufficient data sets. In this approach we used an automated randomized grasping sequence where the objects are swinging between the fingertips and the gripper closes randomly (Figure 4). Additionaly the length of the pendulum has been varied. Like this about 950 data sets has been generated per object. The selected objects are shown in Figure 5.

Fig. 4. Setup for the data generation

Fig. 5. Objects to be identified

3 Object Classification using Convolutional Neural Networks

Convolutional Neural Networks (CNN) has been selected because these are known that they need relative few training data sets for the classification. Several convolutional neural network structures have been tested from very simple one to more advanced ones [8].

3.1 Simple CNN with 2 Convolutional Layers

The first approach was a very simple CNN with 2 convolutional layers and 1 max pooling layer only. With this first reference approach an accuracy of 50% could be achieved. This value could be optimized by manually eliminating obvious wrong training data sets, e. g. where the objects has only touched very few force pixels. Like this the accuracy could be increased to 87% already.

3.2 Improved CNN

To further increase the accuracy, several CNN has been implemented and tested. The final CNN has 21 layers and 11.779 parameters (Table 1). This network achieved an accuracy of 98,65% for the test data and 99,47% for the training data. This is a quite good result for only less than 1000 training sets. The forecast of the network shows the confusion matrix in Table 2.

Using the test data sets the network did only one wrong forecast. One pen has been classified as a ring. The reason of the miss-interpreted set shows Figure 6. For a bigger ring the image is very similar to a pen which is slightly inclined within in the grippers.

Table 1. Final CNN structure

Layer Type	Result Values/Dimensions	No. of Parameters
Input	-	-
Convolutional 2D	(None, 358, 78, 10)	280
Convolutional 2D	(None, 368, 76, 10)	910
MaxPoolling2D	(None, 178, 38, 10)	0
Dropout	(None, 178, 38, 10)	0
Convolutional 2D	(None, 176, 36, 10)	910
Convolutional 2D	(None, 174, 34, 10)	910
MaxPoolling2D	(None, 78, 17, 10)	0
Dropout	(None, 78, 17, 10)	0
Convolutional 2D	(None, 85, 15, 10)	910
Convolutional 2D	(None, 83, 13, 10)	910
MaxPoolling2D	(None, 41, 6, 10)	0
Dropout	(None, 41, 6, 10)	0
Convolutional 2D	(None, 39, 4, 10)	910
Convolutional 2D	(None, 37, 2, 10)	910
MaxPoolling2D	(None, 18, 1, 10)	0
Dropout	(None, 18, 1, 10)	0
Flatten	(None, 180)	0
Dense	(None, 64)	11584
Dense	(None, 3)	195
Output	(1)	-

Table 2. Confusion Matrix

	Forecast of the Network		
Correct Value	**Sphere**	**Ring**	**Pen**
Sphere	60	0	0
Ring	0	80	1
Pen	0	0	41

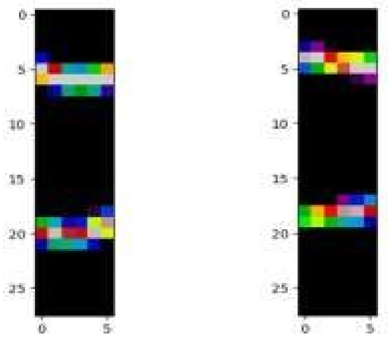

Fig. 6. Comparison ring (left) vs. pen (right)

4 Real-Time Robot Setup

The data generation and training of the network has been done on a standard computer with a NVIDIA GPU. For the final robot application, the trained network has been ported to a Raspberry Pi. The Raspberry Pi functions as the interface between the gripper and a robot (Universal Robot UR5). On the one hand the basic functions of the gripper WSG50 should be made accessible to the UR5 robot. On the other hand, the sensor data, read from the gripper fingers, should be evaluated and the grasped object classified (Figure 7). To reach both goals an interface between the robot and the gripper is made using a Raspberry Pi. The Raspberry Pi communicates with the gripper over TCP/IP and with the robot over Modbus TCP.

Additional to the communication between the components the Raspberry Pi should do the analysis of the sensor data, means the trained CNN should be executed on the Raspberry Pi itself. A special function has been implemented that reads and classifies the data from the gripper fingers. This classification is done with the Tensorflow-Lite module. The trained model file has then just to be stored on Raspberry Pi.

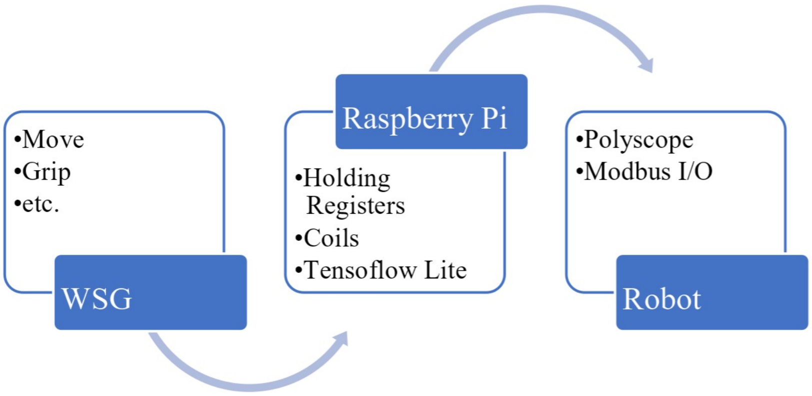

Fig. 7. Communication between Gripper, Raspberry Pi and Robot

5 Conclusion

In this paper we present a solution for the identification and classification of grasped objects with an electrical gripper with force sensor arrays in its fingertips. The solution is based on a convolutional neural network (CNN). The CNN is trained with relatively few examples but gives already reasonable results. Objects to be detected are of geometrical shape like ring, pen, sphere. The challenges in such applications are the generation of random training data and interfaces between the different components such as gripper, sensor array fingertips and robot. The trained CNN has been ported to a Raspberry Pi for real-time execution and communication between the gripper and the robot.

Further research will be to use the finger positions and motor currents of the gripper additionally to the force sensor matrix to expand the data sets. Like this even more details of the grasped object should be trainable. In combination with a classical approach to detect the object location (position and orientation) inside the gripper which uses the centre of gravity and axis of inertia [9], the grasped objects can not only be classified but be moved by the robot the goal position with the required orientation.

With these approaches, new solutions for the bin-picking-problem without camera or with cameras with less resolution might be possible.

References

1. Tadaaki Hasegawa, et. al: Powerful and Dexterous Multi-Finger Hand Using Dynamical Pulley Mechanism, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
2. Xinghao Zhu, et. al.: Learn to Grasp with Less Supervision: A Data-Efficient Maximum Likelihood Grasp Sampling Loss, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022

3. Xibai Lou, Yang Yang, Changhyun Choi: Learning Object Relations with Graph Neural Networks for Target-Driven Grasping in Dense Clutter, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
4. Mayer, V., et. al.: FFHNet: Generating Multi-Fingered Robotic Grasps for Unknown Objects in Real-Time, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
5. Xinghao Zhu, et. al.: Learn to Grasp with Less Supervision: A Data-Efficient Maximum Likelihood Grasp Sampling Loss, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
6. Xibai Lou, Yang Yang, Changhyun Choi: Learning Object Relations with Graph Neural Networks for Target-Driven Grasping in Dense Clutter, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
7. Gabler, V., Huber, G., Wollherr, D.: A Force-Sensitive Grasping Controller Using Tactile Gripper Fingers and an Industrial Position-Controlled Robot, 39th IEEE International Conference on Robotics and Automation, ICRA 2022, 23-27 May 2022
8. Lorenz Salas, F.: Verbesserung des SMARTGRIPPERs im Robotik Labor mit Fokus auf Automatisierung, Bachelor-Thesis, Fakultät Wirtschaftsingenieurwesen, Hochschule Furtwangen, Wintersemester 2020/21
9. Schmidt, Ch.: Intelligentes Greifen für flexible Roboteranwendungen, Bachelor-Thesis, Fakultät Wirtschaftsingenieurwesen, Hochschule Furtwangen, Wintersemester 2017/18