Improving autonomous robot gripper position on lifting trash object based on Object Geometry Parameters and Centroid Modification

Emil Naf'an[1,2] and Riza Sulaiman[1] and Nazlena Mohamad Ali[1]

[1] Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia
[2] Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang, Padang 25221, Indonesia
riza@ukm.edu.my

Abstract. This study aims to improve the positioning accuracy of the gripper robot in lifting garbage objects. In general, the process of removing garbage objects only relies on the object's centroid. If the left and right sides of the centroid have the same parameters, then the lifting process usually goes well. If the object geometry parameters are different, then there is a possibility that the centroid point is in the 2D area, so that the robotic gripper cannot grip and lift the trash object. Likewise, if there is a difference in weight, the robot gripper will have difficulty lifting the object, because the object is one-sided. For this reason, the process of removing garbage objects needs to be improved by considering several parameters, not only the centeroid parameter. In this study, a method for lifting garbage objects is proposed based on several parameters, namely; geometry, centroid and garbage object type. The proposed method is called Object Geometry Parameters and Centroid Modification (OGP-CM). The test results show that the OGP-CM method is able to set the centroid position based on the geometric parameters and the type of trash. On the same object geometry, the improvement in accuracy is relatively low, ranging from 0.46% to 1.72%. A relatively high improvement in accuracy occurs for different object geometries, ranging from 11.54% to 13.09%. Thus the improvement of the position of the autonomous robot gripper in lifting objects using OGP-CM has been successfully carried out.

Keywords: Improving, Gripper Position, OGP-CM, Robot.

1 Introduction

Trash picking robot is a type of robot designed to assist in the process of collecting and transporting trash. These robots are usually equipped with navigation systems, sensors and manipulation devices to identify, collect and transport trash automatically (Kulshreshtha et al. 2021). Some examples of the use of trash collecting robots include; 1. Street Cleaning: Trash picking robots can be used to clean streets or public areas from trash. This robot can be configured to operate autonomously, recognizing and collecting trash scattered along the road. 2. Trash Collection in Public Places: Trash picking robots can be used in public places such as parks, parking lots, or shopping centers to collect trash thrown away by visitors. This robot can move automatically and collect trash around it. 3. Trash Collector in Industrial Environments: In industrial or factory environments, trash collector robots can be used to collect trash or trash in production areas. This robot can be equipped with sensors to identify certain types of trash or trash and move it to the appropriate disposal site. 4. Trash Collector in Offices or Households: Trash collector robots can also be used in offices or households to assist in daily trash collection. Robots can be programmed to follow specific routes and collect trash from bins at every point (Fang et al. 2023).

The use of trash picking robots has several benefits, such as increasing efficiency and cleanliness, reducing the need for human labor in the trash collection process, and reducing the potential risk or danger to workers (Kshirsagar et al. 2022). In addition, they can also be equipped with an automatic grouping or recycling system to separate trash based on its type. In the development of a trash collecting robot, several factors that need to be considered are the reliability of the navigation system, the ability to identify different types of trash, safety in interacting with humans or the surrounding environment, and efficiency in the process of collecting and transporting trash.

Along with the development of Artificial Intelligence (AI) technology, many researches on trash collecting robots also make use of AI. A widely used field of AI is deep learning, especially Convolutional Neural Networks (CNN). The following table summarizes some of the applications implemented over the past years regarding deep learning investigations (CNN) in trash management.

Table 1. Deep Learning Application in Trash Management, 2005–2022.

No.	Pengarang	Sumbangan	Deskripsi
1	(Fuchikawa et al. 2005)	Picking up trash using the Outdoor Service Robot	The robot only collects plastic trash in the form of PET bottles.
2	(Salvini et al. 2011)	Picking up trash using the *Dust Cart* robot.	This robot collects types of trash based on user input. After the user enters the type of trash, the robot opens the trash store according to the type of trash input.
3	(M. Yang & Thung 2016)	Trash classification using CNN.	The type of trash that can be identified is only up to 6 items of trash.
4	(Hulyalkar S., Deshpande R., Makode K. 2018)	SmartBin used CNN.	The type of trash that can be identified is only up to 4 items of trash, namely metal, glass, paper, and plastic.
5	(Salimi et al. 2019)	Trash classification using CNN on Trash Bin Robot.	After the robot sees trash, it makes a sound and invites people to come, collect

			the trash found by the robot, and throw it into the trash can attached to the robot.
6	(Adedeji & Wang 2019)	Trash classification using CNN.	The type of trash that can be identified is only up to 6 items of trash.
7	(Raza et al. 2021)	Trash classification using CNN.	Develop real-time trash detection using CCTV cameras. The type of trash that can be identified is only up to 8 items of trash.
8	(Funch et al. 2021)	Classification of metal and glass trash using CNN.	Develop a prototype to classify the presence of glass and metal in consumer trash bags.
9	(Longo et al. 2021)	Trash classification using CNN on Smart Trash Bin.	Developed a prototype of a smart trash can, able to classify trash with a hybrid sensor/image classification algorithm, as well as automatically separate different trash materials.
10	(Mao et al. 2021)	Trash classification using CNN.	The type of trash that can be identified is only up to 6 items of trash.
11	(Ren et al. 2021)	Beach trash classification using CNN.	The type of trash that can be identified is only up to 6 items of trash, namely: plastic, glass, paper, butt, metal, and wood.
12	(Yuan & Liu 2022)	Trash classification using CNN.	The type of trash that can be identified is only up to 6 items of trash, namely: metal, paper, plastic, cardboard, glass, and trash.
13	(Faisal et al. 2022)	Detection of plastic trash using Faster R-CNN.	Reduce plastic and bottle trash in the ocean with a case for Turtle conservation.
14	(Kshirsagar et al. 2022)	Trash classification using CNN and robotic techniques in trash material separation.	Developing a prototype of a Robot Arm that can grasp reusable trash.
15	(Rahman et al. 2022)	Trash classification using CNN.	Developed a TrashBin prototype for trash sorting. The type of trash that can be identified is only up to 6 items of trash, namely: cardboard, glass, metal, paper, plastic, trash.

Table 1 shows that CNNs are commonly used in trash classification studies. This is due to the relatively high success rate of trash identification. However, there is some research that combines CNN and sensors to verify this trash. In Table 1 some use ultrasonic sensors and range sensors in combination with CNN, but their use is only to detect the presence of objects in the designed system. Table 1 also has a prototype of a robot arm to collect trash. However, the robot does not yet have a LiDAR sensor that produces 2D and 3D shapes. So if the object is 2D, the robot gripper will not be able to hold the trash.

This research is focused on trash collection robots in the house compound. In order to collect trash, it is necessary to determine the accurate position of the gripper in lifting the trash object. Accurate gripper position affects the success of the object lifting process (Hernandez et al. 2023). In order for gripper placement to be achieved optimally, it is important to pay attention to the dimensions and characteristics of the object to be lifted, as well as consider factors such as weight distribution, gripper strength, and the capabilities of the robotic system used.

There are many techniques in determining the centroid, among others; methods of gravity, moment, thresholding, contour, area-based segmentation (Ni et al. 2022). However, if the object lifting process is based on the object's centroid only, then there are at least 3 possibilities that occur when the robot gripper tries to lift the trash object. This is illustrated in Figure 1, Figure 2 and Figure 3. In Figure 1, the trash object can be lifted properly. This is because the weight between the left and right sides of the object is relatively the same, so that the gripper can lift the object perfectly.

Fig. 1. The robotic gripper is capable of lifting trash object.

In figure 2, the trash object cannot be gripped by the gripper, because the centroid is located in a 2D position. As a result, the main objective, which is to remove the trash object, cannot be carried out.

Fig. 2. The robotic gripper is unable to grip or lift trash object.

In figure 3, the robotic gripper does not lift the object perfectly, due to the weight of the object not matching the centroid.

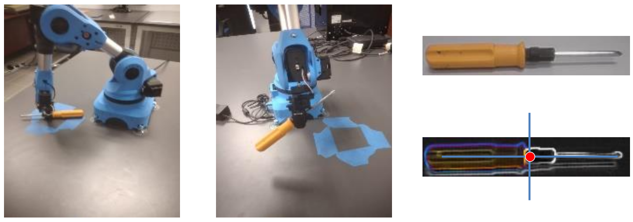

Fig. 3. Robotic grippers are not able to lift trash objects perfectly.

An example of an object being lifted is the screwdriver. In a screwdriver, if the centroid is made in the middle, then the weight between the two sides of the screwdriver is not the same. Because in the plastic package that holds the screwdriver there is iron for other types of screwdrivers. As a result, when lifting the screwdriver, the gripper cannot lift it perfectly. The two sides of the screwdriver are not parallel. One side of the screwdriver is down.

For this reason, the process of lifting trash objects needs to be improved by considering several parameters, not only the centeroid parameter. In this study, it is proposed to add parameters to achieve this improvement. Those parameters are object geometry and trash type.

2 Material and Methods

This study begins with the creation of an autonomous robot capable of identifying trash and navigating on the house compund. This has been done in previous research. The trash identification process has been successfully carried out in previous studies. The trash identification process has been successfully carried out in previous research (Naf'an et al. 2023). The method used is Sequential Camera LiDAR (SCL). In this method the process of identifying and classifying the types of trash uses the Convolutional Neural Network (CNN). This method also generates trash objects in 3D using the LiDAR sensor as a scanner. These two parameters become one of the references in lifting objects. Another parameter that is no less important is the determination of the centroid of the trash object. By obtaining the centroid of the trash object, the process of lifting the trash object is easier to do.

In this study, a method for lifting trash objects is proposed based on several parameters, namely; geometry, centroid and types of trash object. The proposed method is called Object Geometry Parameters and Centroid Modification (OGP-CM).

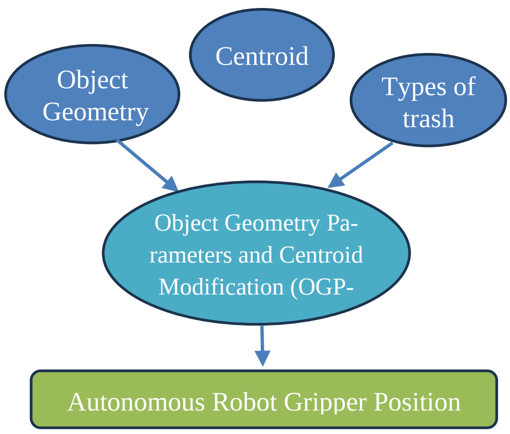

Fig. 4. Block Diagram of Proposed Method (OGP-CM).

The geometry of the object used is the 3D shape of the object. This shape is generated from detailed scanning by the LiDAR sensor on the Sequential Camera LiDAR (SCL) method (Naf'an et al. 2023). Likewise for the type of trash also obtained from the output of the SCL method (Naf'an et al. 2023).

3 Results and Discussion

3.1 Result of Type Trash

In previous study (Naf'an et al. 2023) a real-time identification test of 11 types of trash was carried out using four CNN architectures, namely AlexNet, VGG16, GoogleNet and ResNet18. The results of the trash identification are in table 2.

Table 2. The Average Accuracy of 11 types of Trash Using CNN Architectures.

No.	CNN Architecture	Accuracy
1	AlexNet	79.410
2	VGG16	86.588
3	GoogleNet	96.513
4	ResNet18	95.146

In table 2, it can be seen that the highest accuracy in trash identification was produced by GoogleNet, namely 96,513% and the lowest accuracy was produced by AlexNet, namely 79,410%.

3.2 Result of Geometry Trash Object

For object geometry, only the 3D shape of the trash object is required. This has been done in previous studies (Naf'an et al. 2023). Figure 5 shows the results of a detailed scan of one of the trash objects.

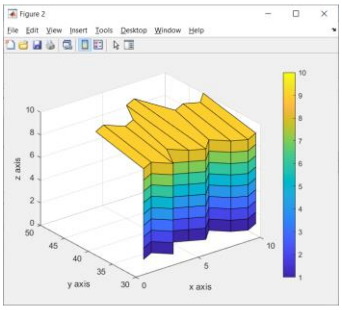

Fig. 5. Result of geometry trash object.

Figure 3 shows the 3D shape of the detected trash object. The more the amount of y-axis and z-axis data, the better the 3D shape of the trash object.

3.3 Result of Centroid

The results of centroid object can be seen in Figure 7. The left side is the 3D shape of the object, while the right side is the result of calculating the centroid area of trash object.

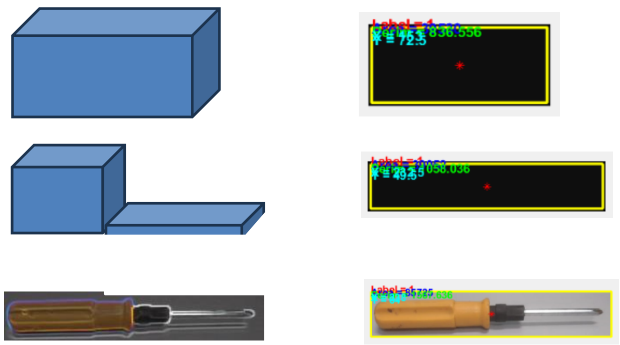

Fig. 6. Result of Centroid.

In Figure 6, it can be seen that the centeroid is marked with a red dot. Determination of the centroid using MATLAB software.

3.4 Result of Object Geometry Parameters and Centroid Modification (OGP-CM)

The test results from the OGP-CM can be seen in Figure 7, Figure 8 and Figure 9. In Figure 7, the trash object used has relatively the same two parameters between the left and right sides of the centroid These parameters include; trash object geometry, type of trash.

Fig. 7. Result of OGP-CM, trash object has the same parameters

In Figure 7, it can be seen that the gripper is right at the centeroid and trash objects can be lifted by the gripper perfectly. In figure 8, it can be seen that the centeroid is shifted to the side of the 3D object geometry. Calculation of the centeroid based on the geometry of the 3D object.

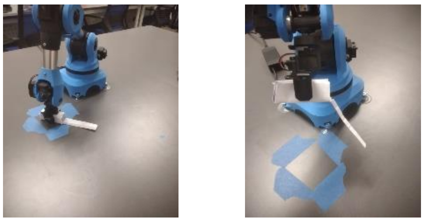

Fig. 8. Result of OGP-CM, trash objects has different geometry parameters

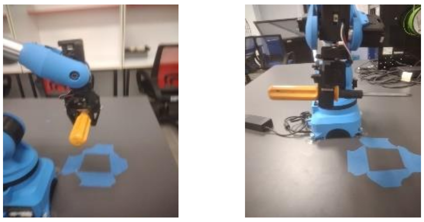

Fig. 9. Result of OGP-CM, trash objects has different type of trash parameters

In Figure 9, it can be seen that the centroid is shifted to the position of the screwdriver holder. The displacement of the centroid position is determined based on the type of trash object. This is because the whole trash object has geometry in 3D form.

Tests were carried out for 11 types of trash. Only 1 sample was taken from each trash. The accuracy value is taken from the position of the trash that is lifted by the robot gripper. If the position is flat, then the accuracy value is 100%. For every 1 degree change in tilt angle, this is assessed as a 1 percent reduction in the accuracy value. The test is only carried out when the robot gripper grips the object until the gripper rises approximately 20 cm from the robot's base. The robot gripper is given a delay of 10 seconds for accuracy measurement time. The accuracy of the gripper position is determined based on the gripper position error from the reference value. This error value is calculated as 1 percent per 2 mm error. The test results can be seen in table 3.

Table 3. The Comparison of positioning accuracy of robotic grippers in lifting trash with conventional and OGP-CM methods (Same Geometry Parameters)

No.	Type of trash	Geometry Parameters	Gripper Position (%)		Object Position (%)	
			Conventional	OGP-CM	Conventional	OGP-CM
1	Cardboard	Same	98	99	94	97
2	Food Packaging	Same	96	98	96	95
3	Fabric	Same	98	98	97	97
4	Fruit	Same	95	97	93	95
5	Glass	Same	84	85	83	89
6	Leaf	Same	96	98	97	94
7	Metal	Same	94	96	93	94
8	Paper	Same	97	98	96	95
9	Plastic	Same	92	98	90	93
10	Rubber	Same	95	95	93	90
11	Wood	Same	96	98	96	94
	Average		**94.64**	**96.36**	**93.45**	**93.91**

Table 4. The Comparison of positioning accuracy of robotic grippers in lifting trash with conventional and OGP-CM methods (Different Geometry Parameters)

No.	Type of trash	Geometry Parameters	Gripper Position (%)		Object Position (%)	
			Conventional	OGP-CM	Conventional	OGP-CM
1	Cardboard	Different	76	97	74	96
2	Food Packaging	Different	85	96	82	93
3	Fabric	Different	78	97	79	96
4	Fruit	Different	76	97	75	93
5	Glass	Different	76	83	78	86
6	Leaf	Different	85	95	87	93
7	Metal	Different	84	93	82	91
8	Paper	Different	84	97	82	93
9	Plastic	Different	82	97	81	92
10	Rubber	Different	90	95	85	88
11	Wood	Different	83	96	82	93
Average			**81.73**	**94.82**	**80.64**	**92.18**

In the geometry parameters there are the words 'Same' and 'Different'. The word 'Same' indicates that the geometry between the left and right sides of the center of mass is the same. While the word 'Different' indicates that the geometry between the left and right sides of the center of mass is different. With the OGP-CM method, the centroid value is shifted according to a predetermined value.

In table 3, the object geometry used is the same. The accuracy between conventional and OGP-CM is not much improved, only around 1.72% on the gripper position. While in the position of the object 0.46%. In table 4, the geometry of the objects used is different. There is a relatively large improvement in accuracy between conventional and OGP-CM, namely 13.09% in the gripper position. While in the position of the object 11.54%.

4 Conclusions

Improving the position of the autonomous robot gripper in lifting objects has been successfully carried out using the Object Geometry Parameters and Centroid Modification (OGP-CM) method. The test results show that the OGP-CM method is able to set the centroid position based on the geometric parameters and the type of trash. On the same object geometry, the improvement in accuracy is relatively low, ranging from 0.46% to 1.72%. A relatively high improvement in accuracy occurs for different object geometries, ranging from 11.54% to 13.09%.

The improvement in accuracy can be even higher if the gripper used is not a standard gripper. In the next research the ability of the gripper must be improved so that it can grip objects better. The gripper used should be adjusted to the object being lifted.

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