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Development and Testing of Garbage Detection for Autonomous Robots in Outdoor Environments

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***Abstract*— In Japan, there is a growing concern about labor shortages due to the declining birthrate and aging population, and there are high expectations for robots to help solve such social problems and create industries. However, due to the prohibition of public road tests in Japan, there are few examples of actual applications of robots. Therefore, considerations and problems in the practical application of robots are still unclear.**

In this paper, by focusing on the implementation of garbage collection technology, we have developed an autonomous garbage collection robot using deep learning. In addition, we have verified the usefulness of our garbage detection technology in outdoor environments by conducting actual demonstrations at HANEDA INNOVATION CITY, which is a large-scale commercial and business complex belonged private property, Utsunomiya University, and Nakanoshima Challenge 2019, which is a field of demonstration experiment in the outdoor environment.

Our garbage detector was designed to detect cans, plastic bottles, and lunch boxes automatically. Through experiments on test data and outdoor experiments in the real-world, we have confirmed that our detector has a 95.6% Precision and 96.8% Recall. Comparisons to other state-of-the-art detectors are also presented.

I. INTRODUCTION

In Japan, there is a growing concern about labor shortages due to the declining birthrate and aging population, and there are high expectations for robots to help solve such social problems and create industries. Littering of garbage in Japan has become one of the social issues, and urgent action is needed due to serious environmental pollution and damage to the landscape. Therefore, we focus on the implementation of an autonomous mobile robot equipped with automatic garbage collection technology.

In recent years, there has been a lot of research on object detection using deep learning, such as YOLO (You only look once [1]), and the technology in this field has made significant progress over the years. It is expected to be applied to autonomous mobile robots. However, due to the prohibition of public road tests in Japan, there are few examples of actual applications of robots. Therefore, considerations and problems in the practical application of robots are still unclear.

On the other hand, real-time processing is required for the real-world tasks. A high-performance GPU can be used for the tasks that require immediacy. However, it cannot be installed in autonomous mobile robots with limited computational resources and power. Hence, autonomous mobile robots are required to use a low-cost system, and conducting demonstration experiments is necessary to see if the system can be implemented.

In such a background, there are the real-world demonstration sites such as HANEDA INNOVATION CITY, and demonstration experiments such as Nakanoshima Challenge. HANEDA INNOVATION CITY is a large-scale commercial and business complex located in the vicinity of Haneda Airport. There is a place for the implementation of the latest technology, such as robotics. Nakanoshima Challenge, on the other hand, is a challenge aimed at improving the technology of autonomous mobile robots on the promenade in Osaka and has been held since 2018 as a demonstration experiment in the real-world environment. The challenge aims to introduce an automated garbage collection robot at the 2025 Osaka Expo in Osaka, Japan. In the garbage detection challenge, the staff of Nakanoshima Challenge is set a challenge to determine the type of garbage by submitting three types of garbage (cans, plastic bottles, and lunch boxes) to the robot's camera.

In this paper, we have developed an autonomous garbage collection robot and verified the usefulness of our garbage detection technology in outdoor environments by conducting actual demonstrations at HANEDA INNOVATION CITY, Utsunomiya University, and Nakanoshima Challenge 2019. Our contributions are summarized as follows:

- We have developed an autonomous garbage collection robot that can detect three types of garbage (cans, plastic bottles, and lunch boxes) automatically.
- Training data for three types of garbage detectors are designed. Cans, plastic bottles, and lunch boxes can be detected.
- We have verified the usefulness of our garbage detection technology in outdoor environments by conducting actual demonstrations at HANEDA INNOVATION CITY, Utsunomiya University, and Nakanoshima Challenge 2019.
- We have performed comparative experiments using our detector with other object detection algorithms.

II. RELATED WORKS

In recent years, it has become mainstream to use deep learning for object detection. This is because deep learning has high accuracy compared with methods such as SVM [2], AdaBoost [3, 4], HOG [5], and Haar-like [6]. Moreover, the algorithm enables users to detect objects they want to.

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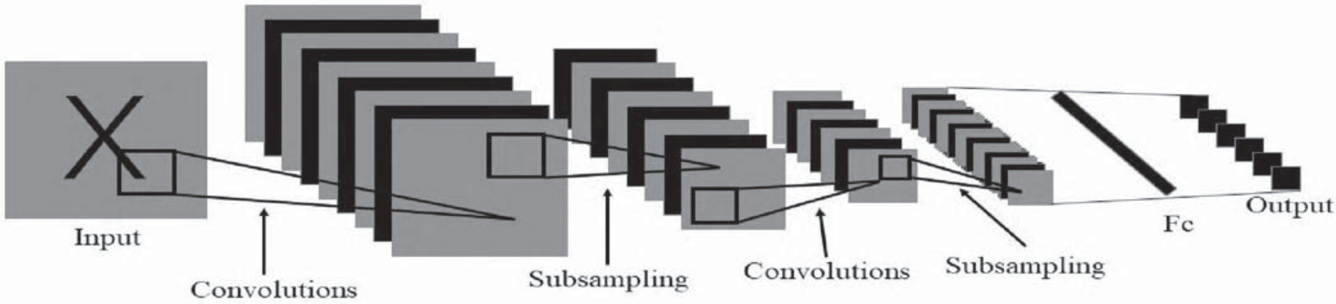


Fig. 1. Architecture of a Convolutional Neural Network.

A general convolutional neural network (CNN [7]) used for object detection with deep learning is a model of receptive fields in the human visual cortex and is an algorithm often used for image recognition. The network model is shown in Fig. 1. The network is composed of input layers, convolutional layers, pooling layers, fully connected layers, and output layers, and is characterized by a structure in which convolutional layers and pooling layers are alternately connected. Other than this structure, it has the same structure as the deep neural network described above. The convolutional layer extracts local features of the input image in the front stage and combines the features of the front stage in the rear stage to perform global feature extraction. The processing performed at this time is similar to the convolution of filters in general image processing, and feature extraction is performed by blurring the image or emphasizing edges. In the first convolutional layer, convolution processing is performed on the input image, the activation function is applied to this result, and the value is used as the feature map. Then, from the convolutional layers on and after the second layer, the convolution processing is performed by inputting the feature map of the previous layer.

As a result, the pooling layer that combines the features of the previous stage and can perform global feature extraction is placed after the convolutional layer, and the feature map output from the convolutional layer is reduced. consequently, local features can be grouped together, and invariance with respect to minute position changes of features in the image is realized. There are several methods for this pooling, such as maximum value pooling, average value pooling, and Lp pooling. Maximum value pooling is a method that is often used and outputs the maximum value in the region of interest. The average value pooling outputs the average value in the attention area. Lp pooling emphasizes the central value in the region of interest and outputs it. In the pooling layer, weights that change with learning do not exist, and activation functions are generally not applied. The parameters that make up the CNN are the value of the weight filter of the convolutional layer, the connection weight of the fully connected layer, and the bias. These perform learning by the error backpropagation method as in deep neural networks.

YOLOv2 [8], which is a kind of object detection algorithm, extracts feature maps using Fully Convolutional Network (FCN). In this detector model, all layers are convolutional layers and are propagated to the output layer while retaining the position information of the feature map. The output is divided into n $\times$ n grids depending on the size of the input image, each with multiple bounding boxes. Since each of the bounding boxes has a probability of the existence of an object called reliability and a conditional probability of what it is, the region estimation and classification of images are simultaneously performed in one network. This enables rapid object detection.

Fast R-CNN [9] and Faster R-CNN [10], which are conventional object detection methods using deep learning, have high processing costs and a high-performance GPU is indispensable for use in tasks that require immediacy. Therefore, these methods are not suitable for mobile robots with limited computational resources and power.

SSD [11] and DSSD [12] are other methods using the same single shot detector as YOLO. YOLO is, however, faster in detection FPS than SSD and DSSD.

YOLOv2 is a method suitable for mobile robots because it can be applied with edge devices that consume less power. In this paper, we have verified the usefulness of this system by introducing YOLOv2 in developing an automatic garbage collection robot.

III. Garbage Collection Robot

A. Hardware

This paper describes the development of an autonomous garbage collection robot, SARA, which is developed in our laboratory. Fig. 2 shows an image of SARA. SARA is designed for the purpose of transporting objects and people to realize a robot that can coexist with humans.

Its size is 0.70 m, depth = 1.19 m, and height = 0.68 m. its weights are 99.2 kg. SARA uses cameras C920 x 3 (Logicool). NVIDIA Jetson TX1 is used as the computational processor for deep learning, and the Jetson TX1 is not directly connected to the C920. It is connected to the PC. The camera images are sequentially saved in a specific folder on the PC, and the images are transferred between the PC and the Jetson TX1 by synchronizing the folder with the folder on the Jetson TX1. In this case, the image file format saved on the PC is ppm. However, it is converted to jpg to speed up the image transfer. Our detector detects using the image.

Fig. 2. SARA.

Fig. 3. Training data examples.

The detection results obtained by this method are transferred to the PC, and the robot's motion is determined based on the results. Besides, there are some problems to be solved for object detection in the real world, such as out-of-focus and blurred images caused by raindrops adhering to the camera in rainy weather, and whiteout against the light. Therefore, a shade is attached to the upper part of the body to protect it from rain and sun.

B. Detection Methods

In developing our garbage detection technology, we get data, train a detector, conduct demonstration experiments, and reflect the analysis in the framework appropriately.

In the garbage detection challenge, a staff of Nakanoshima Challenge shows three types of garbage: cans, plastic bottles, and lunch boxes on the robot's camera, and the robot has to detect them correctly. In this paper, as a first step towards the implementation of an autonomous garbage collection robot, we have developed a specification to detect the types of garbage showed by people to achieve the garbage detection challenge of Nakanoshima Challenge 2019.

We obtain cans, plastic bottles, and lunch boxes images with different backgrounds and sunshine conditions at Utsunomiya University. we take images of garbage with the Nakanoshima Challenge logo for each class, since the detection challenge is to detect garbage with the logo In Nakanoshima Challenge 2019. Besides, if only the garbage with the logo is used as training data, there is a possibility not to determine the type of garbage by overfitting the logo, hence the garbage of each class without the Nakanoshima Challenge logo is also used.

C920 is used as the camera for taking images with 320x240 resolution. An example of the training data is shown in Fig. 3. Each class is obtained from various angles under sunny, cloudy ambient light, or room light. Images used in the training data is cans (1335 images), plastic bottles (880 images), and lunch boxes (901 images), for a total of 3116 images. Since the misdetection of cans often occurs, we increase the number of can images compared to other classes. The annotations required for training with YOLOv2 include the name of the target object (can, PET, lunchbox), and the location information of the target. Our method is implemented under Darknet (a C-based deep learning implementation framework [13]). The training is carried out on a workstation with NVIDIA GEFORCE GTX 1080 Ti GPU, CUDA 8.0. We have developed a garbage detector by training 30000 iterations with 32 batch sizes.

IV. Experiments

We have developed an autonomous garbage collection robot using the method described in Section III and conducted demonstration experiments at Haneda Innovation City, Utsunomiya University, and Nakanoshima challenge 2019.

To evaluate the performance of our developed detectors, Precision, Recall, and Accuracy are used. With Precision, Recall, and Accuracy defined as

$$Precision = \frac{TP}{TP \cup FP}, \; Recall = \frac{TP}{TP \cup FN} \tag{1}$$

$$Accuracy = \frac{TP}{TP \cup FP \cup FN} \tag{2}$$

TP (True Positive) is the number of objects correctly classified by the detector. FP (False Positive) is the number of objects incorrectly classified as different objects by the detector. And, FN (False Negative) is the number of objects unclassified as the objects exist by the detector.

One target is prepared for each piece of test data. If a target and background are detected incorrectly, FP is counted for each box, and FN is counted if the target cannot be detected.

A. Experiments in HANEDA INNOVATION CITY

1) Conditions: HANEDA INNOVATION CITY is a large-scale commercial and business complex located in the vicinity of Haneda Airport. Since HANEDA INNOVATION CITY is private property, robots can be tested without special permission. Therefore, we obtain images of the site using SARA, and verify whether our garbage detector we have developed can be applied to the robot.

We validate our detector using test data. The test data is taken with the Nakanoshima Challenge logo in HANEDA INNOVATION CITY and Nakanoshima Challenge 2019. Images used in the test data is cans (200 images), plastic bottles (200 images), and lunch boxes (200 images), for a total of 600 images. In this experiment, we use three types of label names: "can", "PET", and "lunchbox".

TABLE I
DETECTION RESULTS ON TEST DATA
(NVIDIA GEFORCE GTX 1080 TI GPU).

Methods	Backbone	Input size	FPS	P/R/A*[%]
YOLOv2	Darknet-19	416x416	114	92.9/89.9/84.5

P: Precision, R: Recall, A: Accuracy

TABLE II
DETECTION RESULTS WITH YOLOV2.

name	TP	FP	FN	P/R/A*[%]
can	155	21	24	88.0/86.6/77.5
PET	166	14	21	92.7/88.7/83.0
lunch box	186	3	11	98.4/94.4/93.0

P: Precision, R: Recall, A: Accuracy

2) Results: Table I and II show the detection results. An example of the detected image is shown in Fig. 4. From the result of Table I, Precision of all classes is 92.9% and Recall is 89.9%. Fig. 4 shows that there is no large deviation in the detection position. Besides, it is possible to detect the target where a part of that is hidden while being held by the hand. The confidence score of each class is approximately 90%. However, from the results in Table II, it can be seen that Precision of can is low (88.0%) compared to the others. As shown in Fig. 5, there is misdetection and undetected of garbage that is oblique and is only partially visible. Especially concerning cans, cans are often detected as plastic bottles.

3) Discussions: Precision and Recall of cans are lower than the other garbage because the part where a can is visible becomes extremely small depending on the angle and position of the garbage, and the correct feature quantity could not be extracted. As for three types of garbage, the accuracy is low when the angle is oblique and only a part of the garbage is visible. Therefore, we need to use such images that cause false detection as the training data.

On the other hand, there is little possibility to continue erroneous detection because Precision of our detector in various environments is approximately 90%. Therefore, we consider that it is possible to prevent erroneous detection with a system that uses multiple detection results from the camera.

B. Experiments in Utsunomiya University

1) Conditions: We evaluate the real-world autonomous robot equipped with our detector for outdoor use. Experiments are conducted in various outdoor locations at Utsunomiya University under sunny and non-backlit conditions. To reproduce Nakanoshima Challenge, we pause the robot when it reaches the detection area and detects the garbage. Three types of garbage, cans, plastic bottles, and lunch boxes are used. When the robot detects the garbage, it tells the name of the detected target by voice. The order of presentation is randomized If all three types are detected, we define it as a success. If the detection result is not communicated within 20 seconds for each type, we define it as a failure. Six sets of these are performed with and without a logo, and its usefulness in outdoor conditions are evaluated.

2) Results: Fig. 6 and 7 show the actual detection results. By changing the specifications to use multiple images, it is possible to detect with Accuracy 100% under both experimental conditions with and without the Nakanoshima logo. The garbage without the Nakanoshima Challenge logo is also detected correctly, and the confidence score for both is approximately 90%. We also confirm that our detector processes in real-time. Regarding the processing speed using Jetson TX1, the processing speed is 3 FPS at normal times and approximately 6 FPS at max performance using Jetson_clocks. On the other hand, among plastic bottles without logos, the ones with labels up to the bottom are sometimes erroneously detected as cans. However, in Nakanoshima Challenge, such a plastic bottle is not used in this experiment because the Nakanoshima logo is attached to Nakanoshima challenge 2019.

3) Discussions: In this experiment, we do not use plastic bottles with a label on the bottom. However, it is necessary to be able to detect such plastic bottles when considering actual social implementation. Therefore, it is necessary to use such kinds of garbage as training data.

(a)can (b)PET (c)lunchbox

Fig. 4. Detection examples on test data.

(a)can (b)PET (c)lunchbox

Fig. 5. failure detection examples on test data.

(a)can (b)PET (c)lunchbox

Fig. 6. Qualitative results (with logo).

(a)can (b)PET (c)lunchbox

Fig. 7. Qualitative results (without logo).

Fig. 8. Nakanoshima challenge 2019 map[1].

(a)logo (b)garbage

Fig. 9. sample of garbage[1].

C. Experiments in Nakanoshima Challenge 2019

1) Conditions: Nakanoshima Challenge is aimed at the robotization of garbage collection with a view to real social problems. As a first step to the demonstration appeal at the Osaka Expo held in 2025, the challenges of outdoor garbage detection are being introduced in addition to the challenges of autonomous movement. Nakanoshima Challenge 2019 is scheduled to run twice in July and once in September for a total of three experimental days. The actual run is scheduled in September. In the garbage detection challenge, the robot is first stopped in the two garbage detection areas designated on the course shown in Fig. 8. After that, the type of garbage with the Nakanoshima Challenge logo presented by the staff is detected. Fig. 9 shows examples of logos and garbage used in Nakanoshima Challenge 2019. There are three types of garbage: a 350 ml can, a 500 ml plastic bottle, and a lunch box, which are presented in any order. Each of the garbage must be detected within 20 seconds. After identifying the three types, it is necessary to return to autonomous movement. However, teams that are difficult to return are allowed to resume running manually in Nakanoshima Challenge 2019.

It was cloudy with occasional rain in the first and second experimental days. It was cloudy on the third experimental day and on the day of the actual run.

2) Results: As a result of detecting garbage in the first and second experimental runs in July of Nakanoshima Challenge 2019, we can detect garbage accurately in area 2. In area 1, however, misdetection of cans and plastic bottles occur at first. We are faced with the following two problems when starting the garbage detection challenge:

- Undetected of plastic bottles (transparent material) due to changing background.

[1]Nakanoshima Challenge 2019 manual ver.1.06.pdf

TABLE III
DETECTION RESULTS WITH VARIOUS OBJECT DETECTION ALGORITHMS (NVIDIA GEFORCE GTX 1080 TI GPU).

Methods	Backbone	Input size	FPS	P/R/A*[%]
YOLOv2	Darknet-19	416x416	114	95.6/96.8/93.0
YOLOv3	Darknet-53	416x416	54	96.5/96.7/90.7
SSD	VGG-16	300x300	42	96.0/95.7/93.2
DSSD	ResNet-101	320x320	33	97.3/98.8/97.8
Faster R-CNN	VGG-16	600x600	21	90.0/98.1/95.7

P: Precision, R: Recall, A: Accuracy

TABLE IV
DETECTION RESULTS WITH YOLOv2.

name	TP	FP	FN	P/R/A*[%]
can	170	18	13	90.4/92.9/85.0
PET	199	0	1	100.0/99.5/99.5
lunch box	189	7	4	96.4/97.9/94.5

P: Precision, R: Recall, A: Accuracy

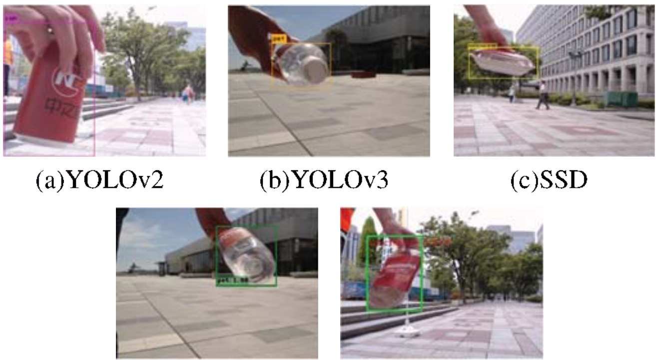
- Misdetection of cans and plastic bottles due to having similar features.

These problems are considered to be caused by differences in sunshine conditions and background. Besides, the similarity of the outer diameter of cans and plastic bottles caused a problem that each object is an error detected. In particular, cans are often detected as plastic bottles. Therefore, we modify the training data in Section III. As a result, in the third experimental day and the actual runs, we are able to detect all three types of garbage in two garbage detection areas. The confidence score of each class is also 90%. Some of the garbage are not captured with the camera in its entirety. However, these are also detected correctly. The detection of garbage in Nakanoshima Challenge 2019 is stable by using multiple image detection results. We have demonstrated the usefulness of our garbage detection system in outdoor environments in which people live.

V. COMPARISONS

A. Conditions

We perform additional training on our garbage detector developed in this paper. We then compare it with other object detection algorithms to see if it can be adapted to other algorithms other than YOLOv2 and to verify what kind of differences occur. The training data are created in addition to the data in Section III. From the experimental results on test data, we find that some garbage is not detected or is falsely detected because the angle of the image is oblique. Therefore, such images are combined with the previous training data, and a total of 3799 training data are trained: cans (1555 images), plastic bottles (1116 images), and lunch boxes (1128 images). Five object detection algorithms, YOLOv2, YOLOv3 [14], Faster R-CNN, SSD, and DSSD, are used in comparison experiments. YOLOv2 and YOLOv3 are implemented under Darknet. On the other hand, Faster R-CNN, SSD, and DSSD are implemented under PyTorch [15]. All experiments are carried out on a workstation with NVIDIA GEFORCE GTX 1080 Ti GPU, CUDA 8.0.



(a)YOLOv2 (b)YOLOv3 (c)SSD

(d)DSSD (e)Faster R-CNN

Fig. 10. detection examples.

(a)SSD (b)DSSD (c)Faster R-CNN

Fig. 11. Integration of detection results.

B. Results

The results of the detection are shown in Table III, IV. The results in Table III show that Precision and Recall are above 90% for all algorithms. Fig. 10 shows an example of the detected images. There is no large discrepancy in the detection position, and the detection of an object held by hand and partly hidden are also possible. After additional training of YOLOv2, the detection result is improved by 2.7% for Precision and 6.9% for Recall compared to our previous detector. Therefore, considering the results, for application on autonomous mobile robots, it is very effective to use such images that cause false detection as the training data. In particular, the detection results in Table IV show that the false detection of plastic bottles is eliminated and Precision is greatly improved. However, the number of false positives for lunch boxes increases by one case compared to our previous detector. The confidence score of YOLOv2 is approximately 90%, while the other algorithms are always 100%, confirming that the detection of garbage is stable. As for FPS, we have shown that YOLO is useful for the real-world tasks that require real-time performance.

C. Discussions

Examples of detection results for SSD, DSSD, and Faster R-CNN are shown in Fig. 11. In this figure, SSD mistakenly detects the staff's vest as a can and detects a lunch box as a plastic bottle in Nakanoshima Challenge 2019. However, other algorithms can correctly detect targets without any false positives. Therefore, we consider that the accuracy of object detection can be greatly improved by combining multiple detection results. If we use this method, it is also possible to determine which images are easy for the computer to detect, or to find out which objects are very difficult to.

VI. Conclusion

In this paper, to evaluate the usefulness of our garbage detection technology in outdoor environments, we have conducted actual demonstrations at various places such as Nakanoshima Challenge 2019. Through the experiments, three types of detectors, cans, plastic bottles, and lunch boxes, are created using deep learning. We have confirmed that it is possible to detect garbage with and without the Nakanoshima Challenge logo in real-time. We have then implemented our developed detector on an autonomous mobile robot and demonstrate that our garbage detection technology can be applied to the real-world tasks on an autonomous mobile robot by achieving the garbage detection challenge at Nakanoshima Challenge 2019.

In this paper, our detector can obtain high accuracy by increasing the number of cans compared to other classes. At that time, the number of data sets and the difference in the amount of each class is small. Therefore, no class imbalance issue occurred. However, it should be noted that increasing the number of datasets may cause class imbalance issues.

Besides, modified training is performed on our garbage detector, and the detection results are significantly improved. Other object detection algorithms are also trained. All of them achieve 90.0% or more in terms of Precision, Recall, and Accuracy.

In general, deep learning improves detection performance if there is a large amount of training data. However, the value of the image data has not been clarified. In this paper, we evaluate our detector through demonstration experiments and confirm that accuracy improvement can be achieved efficiently by adding data appropriately based on the analysis results.

In the future, we plan to increase the types of garbage that can be detected and to verify whether it is detectable or not.

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