Research on Visual Algorithm of Road Garbage Based on Intelligent Control of Road Sweeper

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Abstract. In order to reduce drivers’ labor intensity during the operation of road sweeper, the development of road operation feature recognition algorithm based on visual perception technology is of great significance, especially in the intelligent control of the cleaning devices and the improvement of energy saving effect. This paper summarizes the development status and trends of road sweepers in domestic and foreign, proposes intelligent road sweeper operation power control system, and designs key technologies. Taking the type of garbage and the coverage of garbage as the target of feature recognition, the corresponding visual perception and recognition algorithm was developed, and the algorithm was tested and analysed. The recognition rate and recognition effect reached the expected.

1. Introduction
At present, with the development of artificial intelligence, more and more mechanical equipment tends to be automated and intelligent. However, the road sweeping vehicles used at this stage need manual operation, the level of intelligence is low. And the operators need high-intensity labor. With the improvement of living environment and sanitation requirements, the cleaning work of urban pavement requires the development of mechanical operation with high cleaning efficiency and good effect from the traditional low-efficiency manual cleaning operation.

Now the road sweeper is mainly a traditional fuel road sweeper that integrates sweeping and garbage collection. It has large fuel consumption and large energy loss. New energy sweepers can achieve environmental protection and low energy consumption. Compared with fuel cleaning vehicles, the cost of use is reduced by 50\%-80\% [1]. So domestic and foreign companies are committed to using new energy sweepers instead of traditional fuel sweepers to reduce fuel consumption. At the same time, China is also vigorously promoting the development of new energy road sweepers, especially the pure electric road sweepers [2]. However, the new energy road sweeper cannot reduce the unnecessary energy loss generated during the operation. In order to fundamentally reduce the unnecessary energy loss, the technical optimization of the road sweeper in the future must be closer to the intelligence and informationization. However, unmanned sweepers are mainly used in closed or semi-enclosed scenes such as parks, communities, and plazas. There are still many shortcomings in driverless technology. It takes a long time to popularize or even replace the manual driving sweeper.

From this point of view, the optimization of road sweepers at this stage can not only focus on unmanned driving, but should focus on the application of intelligent technology to reduce energy loss. That is, to be able to detect and provide optimal actuator power selection in real time according to specific operating conditions. It achieves semi-automation of road sweepers. This paper intends to apply image recognition technology to urban road sweepers, and proposes a waste type recognition algorithm based on Faster-RCNN model and an algorithm for road waste coverage. Based on these
two algorithms, the garbage on the road surface is identified, and the cleaning gear of the cleaning device is controlled, thereby reducing the working intensity of the sanitation workers, realizing effective energy-saving automatic cleaning, and improving driving safety.

2. Intelligent Control of the Cleaning Mechanism

2.1. Intelligent Operation Power Control System
In order to achieve the purpose of intelligently selecting the position of the road sweeper, on the basis of the traditional road sweeper power control device, add the camera, the vehicle-level industrial computer Nuvo-5095GC, the vehicle DC power supply and the cleaning device integrated controller to build the intelligence power control system: The camera is connected to the industrial computer through the GigE interface. The vehicle DC power supply supplies power to the vehicle industrial computer and camera respectively. The vehicle-mounted industrial computer is connected to the built-in integrated controller through the CAN interface. The cleaning unit integrated controller is connected to the sweeping disk, fan and high pressure water pump via a digital I/O interface. As shown in Figure 1.

![Diagram](Image)

**Figure 1.** The power control system of intelligent road sweeper operation

Through the intelligent operation power control system, the industrial computer can receive the road garbage distribution status information from the camera and make a decision, and send the decision information to the cleaning device integrated controller through the CAN interface, which can the selection of the operating gear positions of each actuator. As shown in Figure 2. Therefore, intelligent decision-making can be used to replace the traditional road sweeper driver decision-making, so as to achieve high accuracy and low energy consumption.
2.2. Intelligent Operation Power Control System

The working conditions of urban road sweepers are more complicated. There are various kinds of garbage such as confetti, peel, leaves, plastic bags, etc on the urban road, as shown in Figure 3.

Road sweepers need to sweep and recycle road waste through sweepings and wind turbines. Tests show that when the types of garbage are different, the minimum required sweeping position and minimum fan position are different. Therefore, when intelligently selecting the road sweeper gear position, the type of road waste should be taken as the main factor.

At the same time, if the type of road waste is single, the number of garbage is proportional to the power of the actuator. The larger the ground area of a single type of garbage requires the actuator power (gear position) to increase. Therefore, the ratio of the ground area (coverage ratio) of a single type of garbage is selected as the main factor affecting the selection of the working gear.

3. Visual Perception Algorithm

3.1. Identification of Garbage Type Algorithm

This paper identifies the types of waste based on the Faster-RCNN model. Faster-RCNN is a new target detection method [3]. Based on Fast-RCNN, a regional proposals network (RPN) is designed to generate the region proposals. It shares the convolution feature of the full map with the detection
network, which greatly reduces the time to generate the proposed area, and at the same time produces higher quality region proposals [4]. Structurally, Faster-RCNN has integrated feature extraction, proposal extraction, bounding box regression, and classification into a single network. Most of its predictions are done using the GPU, which makes the overall performance greatly improved, especially in terms of detection speed [5].

Its flow chart is shown in Figure 4.

![Faster-RCNN flow chart](image)

**Figure 4.** Faster-RCNN flow chart

Next, take photos of the road garbage, and use the image annotation tool LabelImg to mark the image and select ground truth. The completed image can be used to create a sample library for model training. The sample library picture is shown in Figure 4. 15000 images were selected as the training validation set and test set, and 1000 images were used as incremental test sets, which can improve the generalization ability of garbage detection. After repeated iterations of 150,000 times, the value of the loss function is close to 0 and it does not change with the increase of the number of times. At this time, the final learning model is obtained.

3.2. Garbage Coverage Algorithm
The garbage coverage calculation flow chart is shown in Figure 5.

![Garbage coverage calculation flow chart](image)

**Figure 5.** Garbage coverage calculation flow chart

The HSV colour space algorithm is used to remove the shadow of the garbage. Because the HSV colour space uses colour information of hue (H), saturation (S) and Value (V). This method is very
similar to the human visual perception method. So it can more accurately reflect the moving target and
the information of shadow’s color and grayscale [6].

Next, the image is divided into blocks. In this paper, the original image is divided by 6×8. Each
sub-block is processed on the basis of image segmentation. The sample segmentation is shown in
Figure 6.

![Figure 6. Image segmentation](image)

Gaussian denoising is performed on each sub-block image, which can protect image detail, texture
and edges [7]. After the noise is removed, the Sobel operator is used to detect the edge of the image to
distinguish the foreground and background of the image. It also has a smoothing effect on the noise
and can eliminate the influence of noise.

Calculate the horizontal and vertical edge gradients of the image separately:

\[
G = \left( G_x^2 + G_y^2 \right)^{1/2}
\]

(1)

\[
\theta = \arctan \left( \frac{G_y}{G_x} \right)
\]

(2)

\[
G_x = \begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix} * A ,
G_y = \begin{bmatrix}
1 & 2 & 1 \\
0 & 0 & 0 \\
1 & 2 & -1
\end{bmatrix} * A
\]

(3)

In the formula, \( G_x \) represents the image gradient detected by horizontal. \( G_y \) represents the image
gradient detected by vertical. \( A \) represents the original image. \( G \) \( \theta \) represent the gradient size and
the gradient direction of each block.

Further, based on the edge detection, the Otsu algorithm is used to determine the optimal threshold.
And the foreground and the background of the image are distinguished according to the optimal
threshold [8].

\[
f(i, j) = \begin{cases}
1, & F(i, j) > T \\
0, & \text{else}
\end{cases}
\]

(4)

\( F(i, j) \) is the gray value of the image. \( f(i, j) \) is the gray value distinguish the foreground and
background. And \( T \) is the calculated optimal threshold.

At this point, the image segmentation work has been completed. In order to remove the incoherent
points in the segmented image, we need to morphologically depict the image and take a closing
operation. That is, first dilate and then erode.
Figure 7. Process diagram

The binary image after morphological characterization is traversed, and the number of pixel points in each small block is counted, so that the coverage rate of the garbage can be quantitatively evaluated.

\[
P_{ij} = \frac{\sum_{x=1}^{X} \sum_{y=1}^{Y} (H_{XY}/255)}{XY} \tag{5}
\]

\(P_{ij}\) represents the grading index. \(H_{XY}\) represents the pixel value of the sub-block. \(i\) and \(j\) represent the \(i\)-th row and the \(j\)-th column of the sub-block in the original picture. \(XY\) represent the resolution horizontal and vertical values of the sub-block.

\[
I_{ij} = \begin{cases} 
0 & 0 \leq P_{ij} < 0.02 & P_{ij} \geq 0.5 \\
1 & 0.02 \leq P_{ij} < 0.1 \\
2 & 0.1 \leq P_{ij} < 0.2 \\
3 & 0.2 \leq P_{ij} < 0.3 \\
4 & 0.3 \leq P_{ij} < 0.4 \\
5 & 0.4 \leq P_{ij} < 0.5 
\end{cases} \tag{6}
\]

Each sub-block is graded that we can obtain its quantized value. Thereby we can obtain a garbage distribution matrix of the original image. The corresponding number represents the rating of the amount of garbage. Based on the garbage distribution feature matrix, the feature weight method is used to obtain the target road condition garbage coverage.

\[
FL_{dd} = \sum_{i=1}^{8} \sum_{j=1}^{6} w_{ij} I_{ij} \tag{7}
\]

\(FL_{dd}\) represents road garbage coverage. \(w_{ij}\) represents the feature weight matrix, which is determined by the distribution law of road garbage characteristics and is used to adjust the sub-block confidence. Through the calculation of coverage rate, it is possible to accurately select the appropriate cleaning gear for the quantity of garbage to achieve the energy saving effect.

4. Identification Effect and Result Analysis

4.1. Identification Effect and Analysis of Garbage Species

The training and testing of this experiment are carried out on the Ubuntu16.04 system, and the training is based on the Faster-RCNN algorithm. The test results are shown in Figure 8. It can be seen from the figure that the detection rate of the garbage with obvious characteristics such as cigarette case, plastic bag, paper towel and banana peel is relatively high. After calculation, the detection rate can reach over
95%. For objects with many changes in features such as stones, the detection rate is slightly lower. The detection rate of garbage in the distant photos is also low. The detection of these objects with more characteristic changes requires further research.

Figure 8. Detected image

4.2. Identification Effect and Analysis of Garbage Coverage
Import the image of road garbage, divide it into 6×8 blocks. The image is processed, and then the white pixels in the figure are traversed to obtain a garbage coverage distribution matrix, as shown in Figure 9. It can be seen from the above that after the morphological portrayal, the edge features of the object are basically similar to the original image, which can be used to calculate the garbage coverage.

Figure 9. Coverage matrix acquisition

5. Conclusion
In this study, the image recognition technology was applied to the cleaning vehicle, and the intelligent control of the cleaning operation mechanism was discussed. At the same time, the algorithm was developed for the identification of garbage species and the identification of a single type of garbage
coverage. Subsequent algorithmic fusion of species identification and coverage identification will be performed to accurately control the gear selection of the cleaning device mechanism.

6. Acknowledgments
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7. References
[1] Li Z 2016 Technique Development Trend of New Energy Environmental Sanitation Vehicle Construction Machinery Technology & Management Vol 29 pp57-59.
[2] Ai HJ 2018 J. Internal Combustion Engine & Parts Vol3 pp237-238.
[3] Ren S, He K, Girshick R & Sun J 2017 Faster r-cnn: towards real-time object detection with region proposal networks. IEEE Transactions on Pattern Analysis & Machine Intelligence Vol 39(6) pp1137-49.
[4] Wang X, Shrivastava A & Gupta A 2017 a-fast-rcnn: hard positive generation via adversary for object detection 2017 IEEE conference on computer vision and pattern recognition (cvpr) pp3039-3048.
[5] Hosu, Ionel-Alexandru & Rebedea T 2016 Playing atari games with deep reinforcement learning and human checkpoint replay.
[6] Gao DX, Cao JT, Li P 2014 Study and application of removing the shadow based on the HSV color space Electronic Design Engineering Vol22(13) pp65-68.
[7] Zhang K, Chen Y, Chen Y, Meng D & Zhang L 2016 Beyond a gaussian denoiser: residual learning of deep cnn for image denoising IEEE Transactions on Image Processing Vol26(7) pp 3142-55.
[8] Zhou C, Tian L, Zhao H & Zhao K 2015 A method of Two-Dimensional Otsu image threshold segmentation based on improved Firefly Algorithm 2015 IEEE International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER).