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WASTE CLASSIFICATION TECHNOLOGY OF MANIPULATOR BASED ON CANNY EDGE-DETECTION OPTIMIZATION ALGORITHM

Yang Li and Songting Zhan*

College of Science
Liaoning University of Technology
No. 169, Shiying Street, Guta District, Jinzhou 121001, P. R. China
ly18841615758@163.com; *Corresponding author: zhansongting978@163.com

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Abstract. *With the rapid development and application of artificial intelligence technology, waste classification using manipulator has become the future development direction. In this paper, we study a mechanical arm waste classification technology based on the Canny edge-detection optimization algorithm. On the 6-DOF manipulator platform, the spatial coordinates of the target object are obtained by real-time camera data acquisition and image processing. The rotation of each servo is made to reach the target point, so that the manipulator can grasp and classify the objects accurately. Meanwhile, the technology can also be used in the field of express logistics classification.*

Keywords: Canny edge-detection, Waste sorting, Mechanical arm, Gaussian filtering, Double threshold detection

1. **Introduction.** Edge-detection is a basic tool which is often used in visual recognition, and common edge-detection algorithms include LOG operator, Canny operator, etc. Canny operator can better protect the edge and display the continuity of image edge, but it is more sensitive to noise. If the traditional Canny edge-detection algorithm is used to extract the edge information, the image will be too smooth, which not only reduces the accuracy of extracting local information, but also cannot filter the noise well, and the obtained edge information will contain false edges. In order to reduce noise, Zhang et al. [1] used automatic anisotropic Gauss check image smoothing to reduce noise and optimize Canny edge-detection algorithm.

A manipulator is an automatic manipulator which can imitate some functional movements of the human arm and realize the functions of grasping and carrying according to the fixed instructions [11]. Since the manipulator has strong flexibility and stability, it is usually used in industrial manufacturing, space exploration, medical treatment and other fields, especially in recent years widely used in waste classification. The Magpie system, invented in the UK, automatically and quickly classifies waste [2]. Moreover, ABB company has developed a fast positioning and grasping manipulator based on visual integration, which is characterized by high precision, high stability, high moving speed and high flexibility [3]. Currently, we can identify the rubbish such as beverage bottles, banana peels, cans, and waste paper in the mechanical field of vision [4], the accuracy rate reaches 80%, and the success rate of picking up by the mechanical arm reaches 80%. However, in the case of obstacles, shadows or moving objects, the waste classification accuracy of the system needs to be improved [5].

Currently, among the edge-detection methods in use, the Canny edge-detection algorithm is one of the strictly defined methods that can provide good and reliable detection. It is one of the most popular algorithms for edge-detection because it meets the three

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criteria for edge-detection and has the advantage of being simple to implement. The problem of capturing the edges of the image is solved by the mechanical arm.

Based on the above analysis, this paper proposes a garbage classification technology using manipulator based on Canny edge-detection optimization algorithm. Some details of the image can be saved by the optimization algorithm, but also can be connected to make the overall sense effect better, the detected edge is clearer, and can solve the problem of manipulator capturing the image edge [10].

This paper firstly expounds the design steps of the Canny edge-detection optimization algorithm technology, and then applies the algorithm to the robotic arm, simulates the positioning and grasping process through experiments, obtains the experimental results, and finally analyzes.

2. Key Technologies and Principles.

The steps of Canny edge-detection optimization algorithm are as follows:

1) Gaussian filter is selected for filtering, so that the processed image can be smooth, so as to achieve noise filtering;
2) Calculate gradient strength and orientation per pixel;
3) The non-maximum method is used to suppress the clutter caused by edge-detection;
4) Double threshold detection is used to identify actual and hidden edges;
5) The aim of edge-detection is achieved by suppressing isolated weak edges.

In the last step, the method of suppressing isolated weak edges is used to achieve the goal of edge extraction, thus achieving better edge extraction effect.

2.1. Gaussian filtering smoothing.

Gaussian filtering is a method of weighted average for images. The values of each pixel are obtained by weighted average of itself and other pixels in other regions. In this method, the image data is transformed into energy, and the noise belongs to the high frequency part. The effect of noise on the signal can be reduced by smoothing. Edge-detection can maximize the effect of reducing the impact of noise on experimental data. Through some operations, we can filter out the impact of these noises and prevent error detection. The image processed for smoothing needs convolution, and the object of convolution is Gaussian filter and the image itself. The image can be smoothed by convolution, and the influence of edge detector noise can be greatly reduced. Set the size of the Gaussian filter core to $(2k+1) \times (2k+1)$. Then the following formula can be generated:

$$H_{ij} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(i-(k+1))^2 + (j-(k+1))^2}{2\sigma^2}\right); \quad 1 \le i, j \le (2k+1) \tag{1}$$

where σ is a standard deviation, and here $\sigma = 1.4$. One example of Gaussian convolution nuclei of size 3×3 is shown in Formula (2):

$$H = \begin{bmatrix} 0.0924 & 0.1192 & 0.0924 \\ 0.1192 & 0.1538 & 0.1192 \\ 0.0924 & 0.1192 & 0.0924 \end{bmatrix} \tag{2}$$

a-i are the waveform points of all pixels, where e is the pixel to filter out the waveform, h_{11}-h_{33} belong to the H matrix. After Gaussian filtering, the luminance value of e can be expressed as Formula (3):

$$\begin{aligned} e = H * A &= \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} * \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \\ &= sum\left(\begin{bmatrix} a \times h_{11} & b \times h_{12} & c \times h_{13} \\ d \times h_{21} & e \times h_{22} & f \times h_{23} \\ g \times h_{31} & h \times h_{32} & i \times h_{33} \end{bmatrix}\right) \end{aligned} \tag{3}$$

Choosing the parameters of Gaussian convolution kernel can directly affect the efficiency of Canny detector. By comparison, 5×5 Gaussian convolution kernel is selected to avoid positioning error of edge-detection at the same time.

2.2. **Calculation of gradient direction and intensity.** The edge of the image can be aimed at any azimuth, so Canny edge-detection algorithm generally adopts four operators, which can detect the vertical, horizontal and diagonal edges of the image, respectively. By using vertical and horizontal operators representing edge-detection, such as horizontal G_x and vertical G_y, the first derivative value can be obtained, and the direction θ and gradient G of pixel can be deduced.

$$G = \sqrt{G_x^2 + G_y^2}, \quad \theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{4}$$

where G represents gradient intensity, G_x represents gradient amplitude in x direction; G_y represents the magnitude of the gradient in the y direction, and θ represents the direction of the pixel point. The arctan is the inverse tangent function that we are going to use in this formula. Sobel operators in the x and y directions can be expressed as

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{5}$$

S_x represents the Sobel operator in the x direction, which can be used to detect the direction with the edge direction of y. S_y represents the Sobel operator in the y direction, which can be used to detect the direction with the edge direction of x.

2.3. **Non-maximum suppression.** Non-maximum suppression is a kind of edge thinning technology, which is also an edge sparsity technology, and an edge technology that can realize "thin" edges. After processing some image-related operations, such as gradient calculation, when gradient value is only used, the extracted contour is still relatively fuzzy. In order to suppress all gradient values except the local maximum to 0, the following non-maximum suppression method can be adopted, and the specific steps are as follows.

1) The gradient intensity contained in the current pixel is compared with the gradient intensity contained in the two pixels along the positive and negative gradient directions.

2) Compare the gradient intensity of the current pixel with other two pixels at the same time. If it is found that the current pixel reaches the maximum, the current pixel can be saved and can be used as an edge point; if it is found that the current pixel does not reach the maximum, the current pixel will be suppressed.

2.4. **Double threshold detection.** The remaining pixels allow the actual edges to be more accurately described. However, some edge pixels are due to noise and color changes. When these stray responses to be processed appear, in the image edge processing, it is necessary to use the weak gradient value to process, and retain some edge pixels with the characteristics of high gradient value. To achieve this, high and low thresholds are typically used for processing. When the gradient value of edge pixel is higher than the previously set high threshold, it is defined as strong edge pixel. When the gradient value of edge pixel is lower than the previously set high threshold and greater than the previously set low threshold, it is defined as weak edge pixel. If the gradient of an edge pixel is less than the low threshold originally set, the pixel will be suppressed. The content of the input image determines the selection of the threshold.

2.5. **Inhibitory isolation of low threshold points.** After the above steps have been processed, the pixels that are currently identified as strong edges are edges. However, because weak edge pixels can be extracted from real edges and generated by noise or color changes, there are some controversies about weak edge pixels. In order to obtain more accurate data, it is necessary to suppress the latter. Edge pixels connected to strong edge pixels are usually caused by real edge weak edge pixels, but they are not connected in response to noise. In order to further track the connection, it is necessary to see the weak edge pixels and their adjacent eight pixels. When only one of the eight pixels is required by the rule to belong to strong edge pixels, then the weak edge points will be saved and be at the real edge.

3. Algorithm Design and Implementation.

3.1. **Hardware options.** In this paper, a 6-DOF mechanical arm composed of six rotating joints is selected. The 6-DOF mechanical arm is very similar to the human arm in structure and performs most of the operator's instructions well. The dofbot expansion board is selected as the main control expansion board, and the operating voltage of the steering gear controller is 6.0∼7.4 V, so as to facilitate the connection of sensors and other modules. Figure 1 illustrates the mechanical arm vision hardware system designed in this paper.

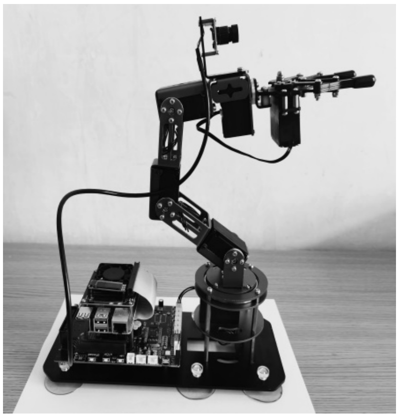


FIGURE 1. Hardware system for mechanical arm vision

3.2. **Mechanical arm grasping process.** Firstly, the object to be grasped was identified and its coordinates were obtained. Secondly, the rotation angle of each steering gear was calculated through inverse kinematics, and then the attitude of the end-effector of the manipulator was determined according to the demand. Finally, each steering gear was controlled to reach the target point after grasping. However, according to the state of the target, the attitude of the end-effector of the manipulator can be adjusted, and its state can be horizontal, vertical, side, etc. When facing different types of target, the attitude of the manipulator should be adjusted according to its position characteristics. For example, when grasping an easy-open can in the vertical state, the end actuator should be held sideways [6]. In this system, the mechanical arm has to grasp the item according to the specific position of the item for which it can provide coordinates. Based on the coordinates of the target item, we know the position and orientation of the end-effector of the mechanical arm, and by using an inverse kinematic algorithm we are able to calculate the angle of each mechanical arm joint [7]. The D-H method [8] is then used to model the mechanical arm, assigning a reference coordinate system to each joint, and then the total transformation matrix of the arm is obtained by a flush transformation, and finally the angle of each robot arm joint is obtained by inverse solution.

3.3. **Positioning fetching.**

1) Object positioning calculation in the field of vision

When the camera sees the ground from the robot arm, the widest field of vision is 45° squints. At this point, the box below the field of vision is trapezoid-like. Through perspective transformation, the four sides of the box are transformed into the four sides of the image. The distance between the center of the object and the center of the image in the visual field $(640, 480)$ is proportional to the distance between the center of the object and the center of the square $(160, 160)$.

2) Inverse solution angle adjustment

After obtaining the positioning of the object in the base coordinate system, inverse kinematics can be used to calculate the angle of rotation of each joint of the manipulator in the specified attitude. The range of motion of the manipulator's joint is 0°∼180°, and the negative angle value cannot be reached. If the inverse solution crosses the boundary with negative values, it needs to be adjusted appropriately [9].

3.4. **Clamping jaw calculation.** As it is usually necessary to use different end-effectors depending on the use scenario, the kinematic inverse solution is generally obtained for the end position of the robot arm, not the end of the end-effector (gripper jaws, suction cups, etc.).

The coordinate system of the base plate is called the base coordinate system, the red, green and blue coordinate system at the jaws is the end coordinate system and the jaws are the end-effectors. The kinematic inverse solution is where the end coordinate system arrives, not the position picked up by the jaws. Before the inverse solution can be found, information on the position of the end coordinate system arrival (i.e., the positional information of the end coordinate system) needs to be obtained.

1) To find the angle of offset, the tangent (y/x) of an angle is known and the value in radians of that angle.

2) Find the length of the projection of the gripper jaws on the hypotenuse, corresponding to the xy-plane.

3) Find the length of the projection of the mechanical arm into the xy-plane (excluding the gripping jaw portion), corresponding to the distance shown in Figure 2, excluding the red portion.

4) Find the end position (excluding the gripper jaws), corresponding to the x, y coordinates as shown in the figure.

5) The final step is to find the z-axis coordinates.

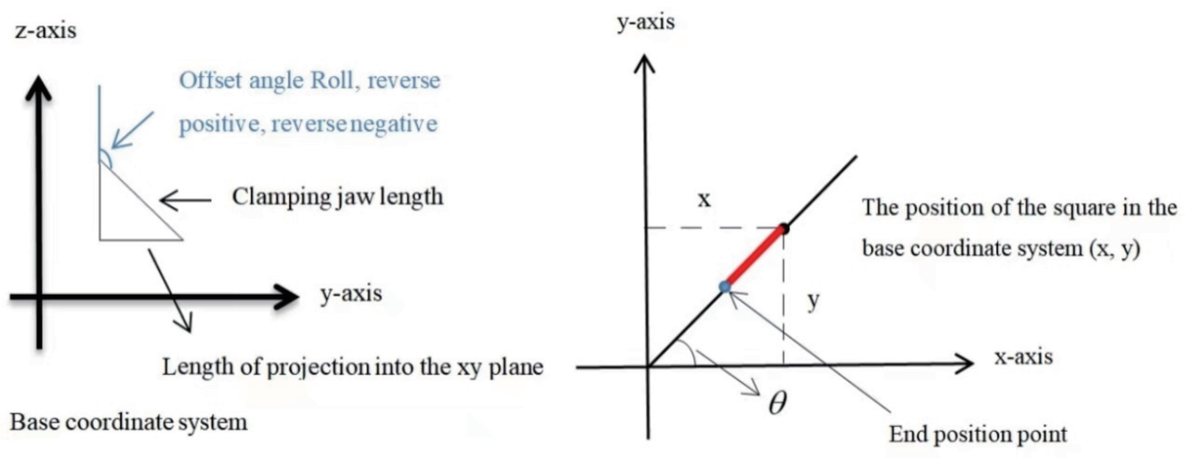


Figure 2. Square location

4. Experimental Results and Analysis. The rotation matrix between the target pose and the initial pose in the camera coordinate system can be calculated to provide real-time target position and pose data for the mechanical arm to grasp. The overall programming flow chart is shown in Figure 3.

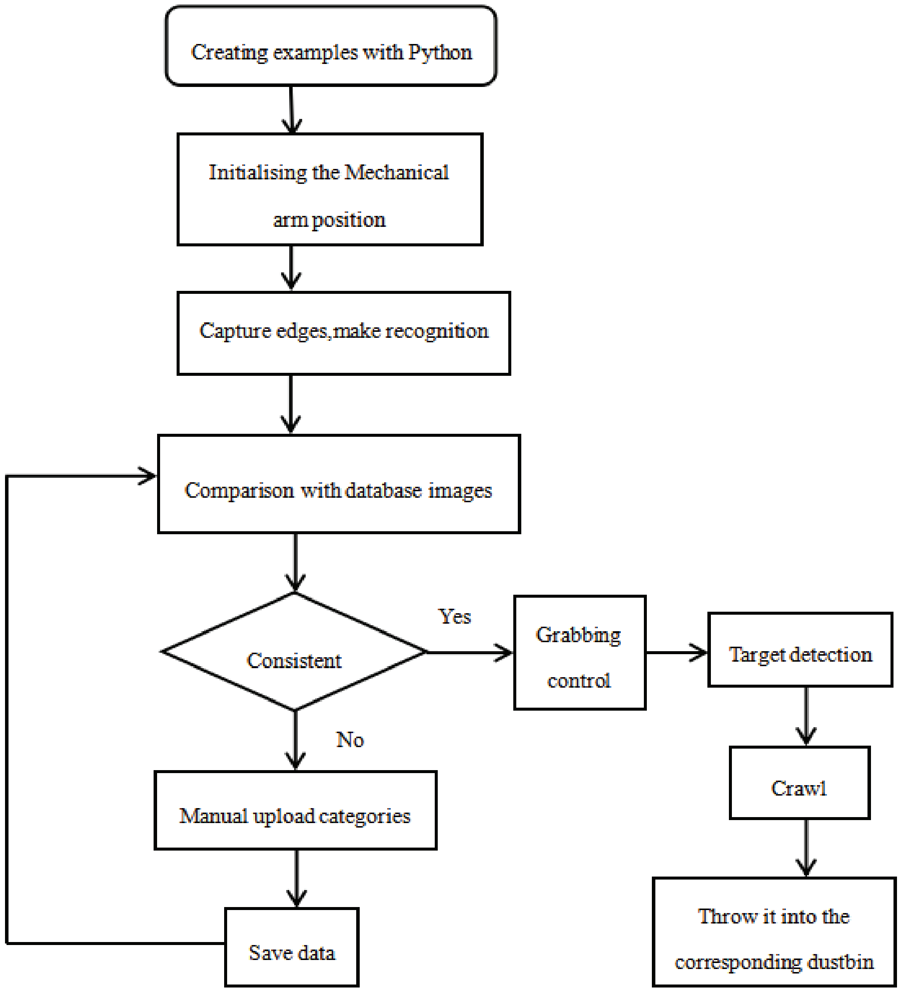


FIGURE 3. Flow chart of the program design

The mechanical arm system used in this paper is based on the Qt Creater platform, design the UI interface and use the Python language to write functions related to the host computer programming software.

Considering that the existing mechanical arms do not yet support the completion of complete gripping control experiments, the testing of target item gripping and classification was chosen to be carried out in a controlled indoor environment in order to verify the effectiveness of the algorithm. Experiments were conducted to test the overall performance of the algorithm by moving the camera in each direction to simulate the information read by the camera in different position states of the mechanical arm.

Four different types of waste are first placed in the target detection area, then the camera of the robot arm detects the target and identifies the type and name of each type of waste, displays the detection screen through the jupyterlab interface, and finally clicks on the "grap" button in the view to pick up and accurately sort the different types of waste. The waste sorting recognition interface is shown in Figure 4.

The experimental results of the test crawl to sort four different types of waste are shown in Figure 5.

The experimental results show that the algorithm is effective in grasping and classifying in all directions, and the data error in estimating the coordinates of the target object in all directions can be controlled within a small range, so that the mechanical arm can complete the grasping and classification work better, which verifies the effectiveness of the technique.

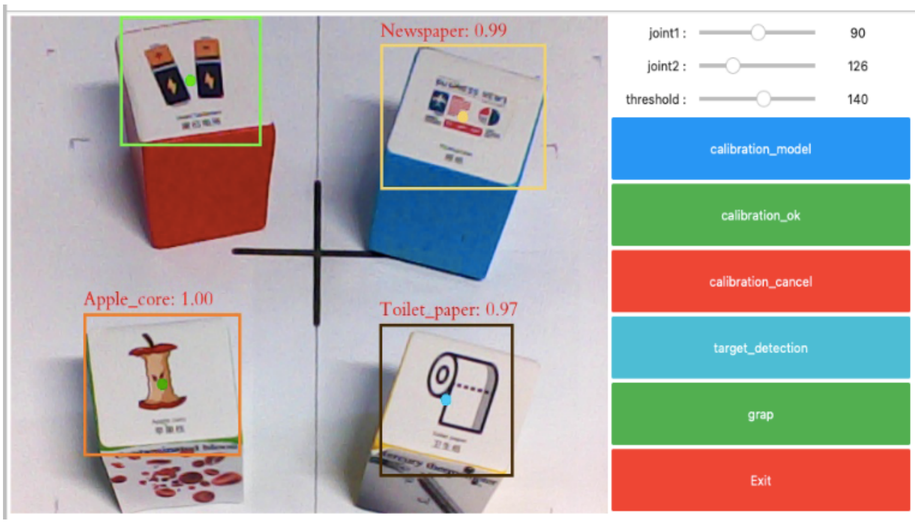
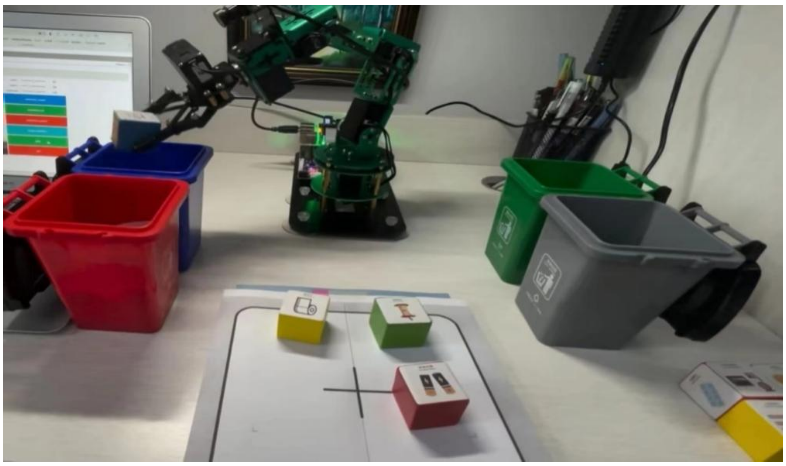


FIGURE 4. Waste sorting recognition interface

(a) Crawling process



(b) Category placement

FIGURE 5. Grabbing and sorting four different types of waste

5. **Conclusions.** Against the backdrop of the rapid development of domestic mechanical arms, with the artificial intelligence development of vision systems, their image recognition ability has progressed by leaps and bounds. In particular, the edge feature of an image is an important feature of an image, and is one of the important foundations of digital image processing, pattern recognition and computational vision. This paper proposes a technique for rubbish classification using a mechanical arm based on an optimised Canny edge-detection algorithm, which can effectively solve situations such as unclear or distorted recognized images. As people's lives become increasingly fast-paced, the amount of waste generated by urban dwellers also increases dramatically. The mechanical arm replaces manual sorting to improve sorting accuracy, allows continuous work throughout the day and protects workers' health. When the robotic arm faces the lamination and accumulation of garbage, it should be considered as a further research direction to identify and grasp with a better angle and more accurately by using the proposed methods [12,13].

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