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Original Article

An Autonomous Trash Cleaning Robot

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Abstract - *Object detection is one of the fundamental tasks in computer vision. A common paradigm to address this problem is to train object detectors that operate on a sub-image and apply these detectors in an exhaustive manner across all locations and scales. The exhaustive search through all possible locations and scales poses a computational challenge. The main objective of this work is to design an autonomous trash-cleaning robot that can be operated in a remote place. The primary action in many repetitive tasks is picking up objects and moving them to other locations. This robot was designed as a fetching robot. It was to come with a set of objects that it was designed to detect and segregate into biodegradable and non-biodegradable, and it can collect these items from the environment when there are placed at random. Experimental results show that the proposed work can provide improved results than the existing machine learning algorithms.*

Keywords - *Autonomous, Deep learning, Image processing, Neural network, Robot.*

1. Introduction

Manual garbage pickup and cleaning is a tedious process, and an autonomous robot can be a potential candidate for this application. Autonomous floor-cleaning, aquatic cleaning, wall cleaning, and rubbish-collecting robots have been developed for years, while autonomous cleaning robot that can operate on seashores still remains a challenging task due to a lack of garbage recognition ability. Motivated by the garbage collection robot working on the beach, this paper aims to develop a robot that can automatically identify the garbage and pick it up. As a key component of such robots, automatic trash detection algorithms use You Only Look Once (YOLO). In contrast, a web camera can be preferable for object detection because it provides much more information. Besides, deep neural networks have been applied with great success to the detection, segmentation, and recognition of objects in images. Therefore we employ a Convolutional Neural Network (CNN) for recognizing and locating the garbage in images captured by a web camera equipped on the robot.

Moreover, the network can also be used to detect and segment the ground, which is useful for obstacle avoidance. Besides these key components, the robot presented in this paper provides basic functions such as path planning, obstacle avoidance, localization, and environment perception. Moreover, the requirement of distinguishing between garbage and non-garbage for selecting the navigational goal makes it more challenging.

2. Related Works

In [1], authors proposed a Region Proposal Network (RPN) that shares full-image convolutional features with the detection network. An RPN is a fully convolutional network that simultaneously predicts object bounds at each position. RPNs are trained end-to-end to generate high-quality region proposals, which Fast R-CNN uses for detection. With an alternating optimization, RPN and Fast RCNN can be trained to share convolutional features. The authors in[2] presented a residual learning framework to ease the training of networks that are substantially deeper, and they reformulated the layers as learning residual functions with reference to the layer inputs instead of learning unreferenced functions. In [3], the authors proposed a CNN architecture that integrates semantic part detection and abstraction for fine-grained classification. Their proposed network includes two sub-networks, one for detection and one for recognition. The detection sub-network has a top-down proposal method to generate small semantic part candidates for detection. The authors in [4] proposed a method for object recognition from RGB-D data. They introduced a multimodal neural network architecture for RGB-D object recognition. In [5], the authors presented a comparative study of two competing features for the task of finding correspondence points in consecutive image frames.

Numerous methods are used to make a garbage-collecting robot. As a solution to manual primary-way disposal, a cost-effective garbage cleaning robot was developed, and that is named “Thooyan.” This system consists of a very simple but highly efficient mechanism. The main components consist of a rotating brush assembly (rake), a unique tilting wedge, a conveyor system, and a garbage collection unit. The robot is programmed in a certain pattern to navigate automatically and detect obstacles to move in a free path. If encountered by a moving obstacle, the robot is programmed to pause for a duration of 50sec and then send again to move, or it will take a turn off 180 degrees. A solar panel is provided for partial charging of the battery. Since the robot uses a conveyor belt, the cost of the whole system will be more which adds a limitation to the system. But it gave an idea or advantage to using solar panels, which in turn helps to reduce power consumption. This robot is a small step to change the manual waste collection and ensures the safety of sanitary workers. Many research works deal with the cleaning robot for swimming pools, the house, and domestic stairs. However, the cleaning robot for the beach is not much discussed. Therefore this work deals with developing a prototype garbage collection robot on the beach.

3. Proposed Work

The object recognition problem can be defined as a labeling problem based on known object models. Formally, given an image containing one or more objects of interest (and background) and a set of labels corresponding to a set of models known to the system, the system should assign correct labels to regions, or a set of regions, in the image. The object recognition problem is strongly coupled to the segmentation problem. Segmentation cannot be done without at least a partial recognition of objects. It is known that without segmentation, object recognition is not possible. All object recognition systems use explicit or implicit models and employ feature detectors based on these object models. The hypothesis formation and verification components vary in importance in different object recognition approaches.

Some systems use only hypothesis formation and then select the object with the highest likelihood as the correct object. Pattern classification approaches are a good example of this approach. On the other hand, many artificial intelligence systems rely little on hypothesis formation and do more work in the verification phases. An object recognition system must select appropriate tools and techniques for the steps discussed above. Many factors must be considered in selecting appropriate methods for a particular application. An object-centered representation uses the description of objects in a coordinate system attached to objects. This description is usually based on features or descriptions of objects. Object-centered representations are independent of the camera parameters and location. Thus, to make them useful for object recognition, the representation should have enough information to produce object images or object features in images for a known camera and viewpoint. This requirement suggests that object-centered representations should capture aspects of the geometry of objects explicitly. Finally, implement a neural network classification algorithm to classify the object. The backpropagation neural network algorithm can be implemented, providing recognition results with improved accuracy.

4. Methodology

At first, images are captured using the real-time camera module, and the image is processed. Image segmentation is typically done to locate objects and boundaries in images. The Raspberry Pi camera board plugs directly into the CSI connector on the raspberry pi. It can deliver a crystal clear 5 MP resolution image. After locating the trashes, they are collected using the robotic arm, and the garbage is segregated as biodegradable and non-biodegradable. Separation is done using the image processing technique. There are two main parts to this work. They are the motor driver part and image processing part motor driver part which includes a robotic arm that behaves as a slave to the master circuit, which includes raspberry pi, where the image processing program is executed. The instructions are sent serially from raspberry pi to Arduino to control the robot's operation.

Algorithm

Step 1: Start and initialize the camera
Step 2: Detection of object
Step 3: Calculating the coordinates of the object and setting the arm
Step 4: Object is picked and classified as biodegradable and non-biodegradable
Step 5: Placed in the respective bin

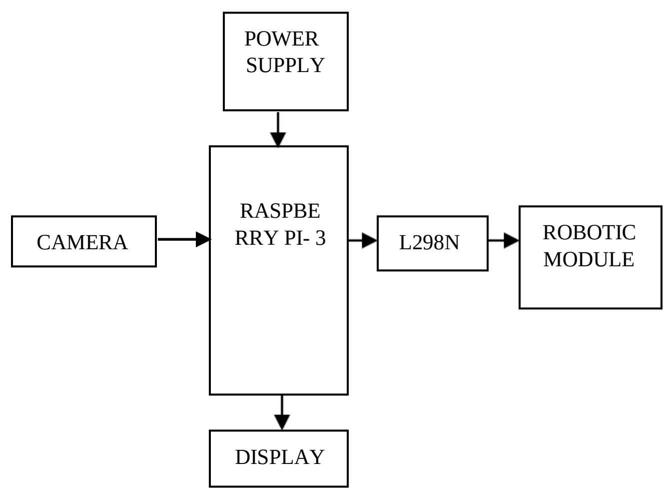

Fig. 1 Block diagram of trash cleaning robot

The Raspberry Pi 3 Model B is the third generation Raspberry Pi. This powerful credit-card-sized single-board computer can be used for many applications and supersedes the original Raspberry Pi Model B+ and Raspberry Pi 2 Model B. It adds wireless LAN & Bluetooth connectivity making it the ideal solution for powerful connected designs. The Raspberry Pi Camera Board plugs directly into the CSI connector on the Raspberry Pi. It is able to deliver a crystal clear 5MP resolution image or 720p HD video recording at 30fps. The sensor itself has a native resolution of 5 megapixels and has a fixed focus lens onboard. In terms of still images, the camera is capable of 1200-pixel static images and also supports 720 at 30fps, 720p at 60fps, and 640x480p 60/90 video recording. L293D is a typical Motor driver or Motor Driver IC, which allows the DC motor to drive in either direction. L293D is a 16-pin IC that can control a set of two DC motors simultaneously in any direction.

5. Conclusion

Object detection is a computer technology related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class. Object Recognition is a technology in the field of computer vision. It is considered one of the most difficult and challenging tasks in computer vision. This work successfully separates different objects or garbage using image processing techniques into degradable and non-degradable. There are two main parts in this work as motor drive part and the image processing part. The motor drive part includes a robotic arm that behaves as a slave to the master circuit, which includes raspberry pi, where the image processing program is executed, and the instructions are sent serially from raspberry pi to Arduino to control the robot's operation. At the prediction time, our model generates scores for the object's presence in a particular category. It makes predictions with a Single network evaluation. Here object detection is a regression problem to spatially separated bounding boxes and associated class probabilities. The tracking of multiple objects in a single image can be implemented using the segmentation of images. Segmentation is the process of partitioning a digital image into multiple segments. More precisely, image segmentation is a process of assigning a label to every pixel in an image. The container's position can be made autonomous, and the coverage area can be expanded as a future job.

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