Lecture Notes on Data Engineering and Communications Technologies 94

Isaac Woungang
Sanjay Kumar Dhurandher *Editors*

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Preface

The last decade has witnessed tremendous advances in computing and networking technologies, with the appearance of new paradigms such as Internet of Things (IoT) and cloud computing, which have led to advances in wireless and intelligent systems for communications. Undoubtedly, these technological advances help improve many facets of human lives, for instance, through better healthcare delivery, faster and more reliable communications, significant gains in productivity, to name a few. At the same time, the associated increasing demand for a flexible and cheap infrastructure for collecting and monitoring real-world data nearly everywhere and every time, coupled with the above-mentioned integration of wireless mobile systems and network computing, raises new challenges with respect to the dependability of integrated applications and the intelligence-driven security threats against the platforms supporting these applications. The WIDECOM conference is a conference series that provides a venue for researchers and practitioners to present, learn, and discuss recent advances in new dependability paradigms, design, and performance of dependable network computing and mobile systems, as well as issues related to the security of these systems.

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Chapter 1
Adaptive System for Object Detection and Picking Based on Efficient Convolutional Neural Networks

Hwang-Cheng Wang, Wei-Zhi Chen, Yan-Long Huang, and Jia-Jun Zhuang

1.1 Introduction

This work aims to improve environmental cleanliness by constructing an adaptive object detection and recognition system. The system is composed of the following main components:

Robotic arm control: The control mechanism directs a multi-axis robotic arm to precisely pick up garbage and moves it into a bin at the back of the robot.

Positioning and path planning: In the outdoors, GPS is used to obtain position information and guides the robot. In indoor areas or areas where satellite signals cannot be received, paths are planned through machine motion trajectories and perimeter sensors.

Automatic patrol: After identifying the location of garbage, the robot automatically navigates to the target.

Database management: The database increases data management efficiency so that relevant parties can easily query the operation data. Moreover, through big data analysis, the main distribution area of garbage can be used to determine the best movement path.

Remote monitoring, control, and security: Through the technology of Internet of Things, it is possible to control and monitor the operation of the robot. Under special conditions, such as rain, large garbage that cannot be transported, or threat to the robot, suitable information will be sent to the operator.

The overall system architecture is shown in Fig. 1.1.

The rest of the chapter is organized as follows. In Sect. 1.2, the motivation for the work is described. In Sect. 1.3, the design methodology is presented. In Sect. 1.4, the

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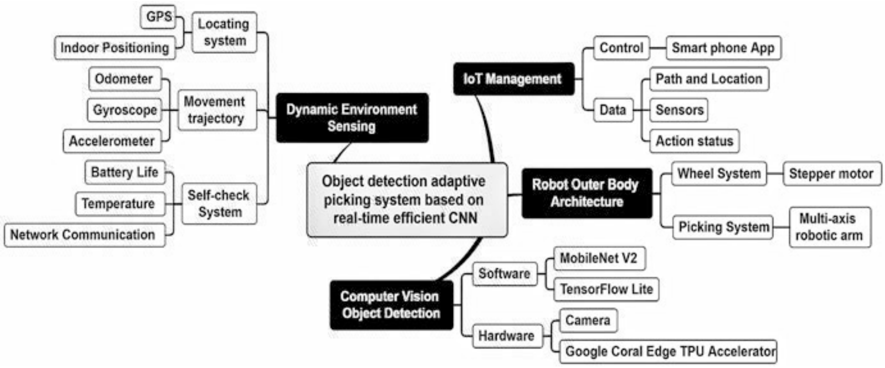

Fig. 1.1 System architecture

hardware and software implementation are discussed. In Sect. 1.5, the results and optimization of the proposed scheme are presented. Finally, Section 1.6 concludes the chapter and points to future work.

1.2 Motivation

This work was inspired by the innovative combination of technological advances to address a social issue. As the renowned economist John Galbraith eloquently put it, technology means the systematic application of scientific or other organized knowledge to practical tasks. There has been a flurry of new development in the areas of machine learning, wireless communication, and Internet of Things. The robot described in the chapter exploits machine learning to quickly identify common types of garbage that can be easily spotted on the street. It was trained using an efficient convolutional neural network. A camera mounted on the robot picks up images of objects on the street, and the robot will move toward an object if it is determined to be garbage. Various sensors embedded in the robot allow it to sense the surrounding area. Wireless communication is used to send signals among the components of the robot using a lightweight messaging protocol. The agile movement of the robot is enabled by inverse kinematic analysis. A robot operating system facilitates system integration which involves many hardware and software components. A number of measures have been taken to improve the dependability and robustness of the robot. Power consumption is an important design parameter. Innovative approaches have been adopted to reduce the power consumption to avoid the quick depletion of the battery that drives the robot. Finally, the design and implementation of the robot aim to improve environmental cleanness, which is vital to public hygiene.

1.3 Design Methodology

In order to reduce the cost of maintaining a clean environment and improve efficiency, we rely on the rapid development of image recognition and sorting technology in recent years and realize waste picking automation through image recognition and robotic arm. We exploit the classification and identification of garbage and integrate the robotic arm and wheel system to move swiftly to the target location. Through machine learning and big data analysis, we link computer vision and robot action to achieve intelligent autonomous garbage picking. Compared to the general sweeping robot, our design can handle a greater variety of garbage and can adapt to diverse terrains and environments.

Algorithm This work aims to recognize garbage, and we use a wide-angle lens as the main component for environmental image collection. In 2017, Google proposed MobilenetV1, which enabled CNNs to achieve higher accuracy with fewer computational resources through depthwise separable convolution. Based on MobilenetV1, Google proposed MobilenetV2 in 2018, which made CNNs more lightweight and achieved higher accuracy at the same time. Because of these, we adopted MobileNetV2 as the primary method to identify garbage.

This method can segment the image contents and mark them as individual objects and select and track specific objects, and finally assign appropriate labels to the computation results. Of course, the naming and rules of the tags can be decided and designed by the developer.

TPU In order to improve the performance of image recognition, we used Edge TPU Accelerator (Fig. 1.2) from Google as the processing core for real-time detection, together with the lightweight artificial intelligence framework TensorFlow Lite. TensorFlow Lite, a lightweight solution designed for mobile devices and embedded systems, can convert almost all the models trained in TensorFlow into TensorFlow Lite files (.tflite). The hardware and software eased the task of image detection.

Machine Learning and Visualization The machine learning was carried out on a Dell EMC PowerEdge R740 rackmount server with two Intel Xeon Gold 5218 (64-core processors) and two NVIDIA Quadro RTX™ 6000s to allow a large number of deep learning tasks to be performed more efficiently. The training also established checkpoints, which can be used to create a new set of tasks. The training also created checkpoints and visualized the training status through the TensorBoard streaming webpage (Fig. 1.3). The test results of image recognition are shown in Fig. 1.4.

Distance Sensor Optical sensors of reflective model and ultrasonic sensors were used to measure the distance.

We used the Adafruit VL53L0X time-of-flight distance sensor and HC-SR04 ultrasonic distance sensor to perform distance measurements and obtained the results in Table 1.1.

The optical distance sensor is more accurate than the ultrasonic counterpart and was used to measure the distance between an object and the lens. On the other

Fig. 1.2 Edge TPU accelerator

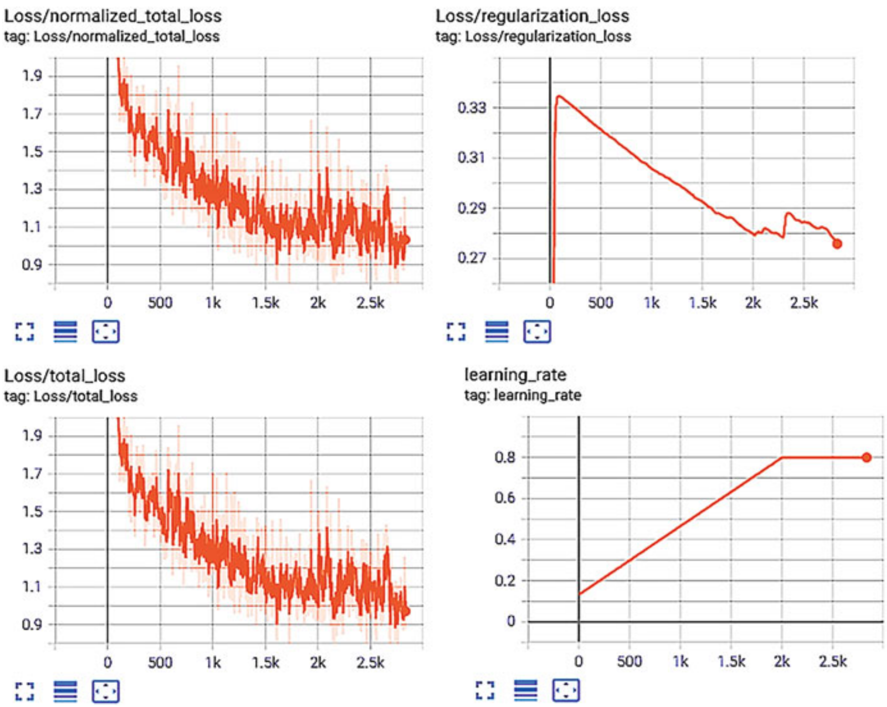

Fig. 1.3 Graphs showing the loss function and learning rate

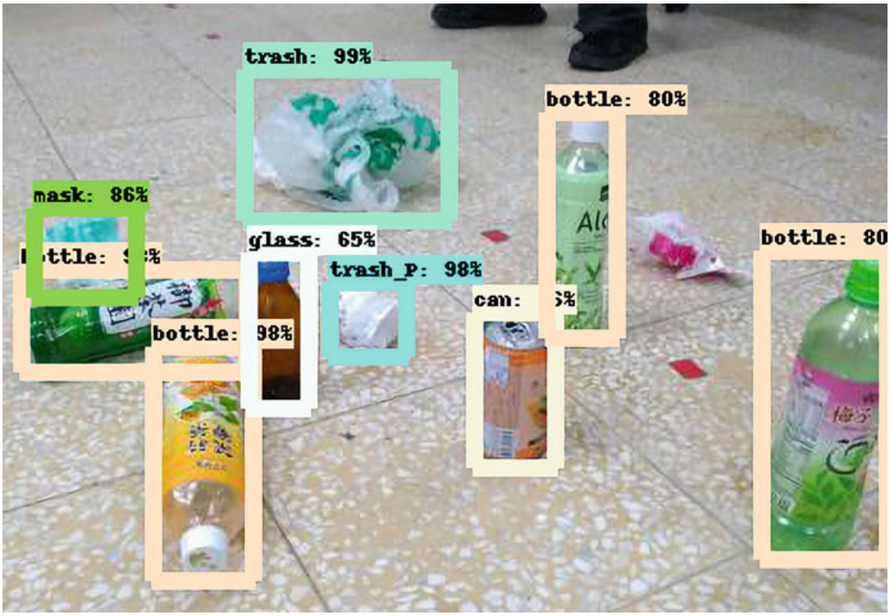

Fig. 1.4 Result of image detection

Table 1.1 Comparison of optical ranging and ultrasonic ranging modules

Module type	Optical (reflective model)	Ultrasonic
Representative module	VL53L0X	HC-SR04
Detectable target	Detection is affected by target materials/colors	Detection is unaffected by target materials/colors
Detecting distance	1000 mm max	4 m max
Accuracy	High	Low
Response speed	Fast	Slow
Dust/water	Affected	Unaffected
Measuring range	Small	Large

hand, the ultrasonic sensor has a broader coverage and was used for robot proximity sensing.

1.4 Hardware and Software Implementation

1.4.1 Integrated Development Environment

The Raspberry Pi development board was used to accommodate the components of the system. Image recognition constituted the core of the machine vision block.

The rest of the control, action block, and so on also needed to be incorporated into the overall architecture. A ROS development environment was built on top of the Ubuntu 20.04 system. The environment allowed the development and testing of individual functional blocks. The integration of the functional blocks is also easier and faster under ROS. In analogy to the human body, the system possessed the following functions:

Eye for image recognition: classification and recognition of targets through computer vision and machine learning.

Brain for environment integration: as the main control board connecting the hub of each block and the environment system mounted on it.

Hand for object picking: picking up the target by the robotic arm.

Feet for system mobility: moving along the path on wheels.

Ear for remote monitoring: receiving control and returning data through the Internet of Things technology.

Nerve for transmission of control signals: controlling various sensors, power management, etc.

The key components are described in the following.

Raspberry Pi The Raspberry Pi 4 Model B development platform is equipped with a quad-core 1.5 GHz ARM Cortex-A72 Broadcom BCM2711 processor, which provides excellent system control. It is fitted with HAT network power supply (PoE). Besides, it has 802.11 ac dual-band WiFi and Bluetooth 5.0 for wireless communication. In addition, it is lightweight and much cheaper than ordinary computers. It also supports many common I/Os.

Ubuntu In order to recognize objects of interest, the machine learning model needs to be trained. The pre-processing requires a development environment with different kits and compilers depending on the characteristics of the ported system. The environment for the training of the image recognition model is Ubuntu 20.04 operating system, which is the most widely used version of Linux at present. The Kernel Image generates smaller files according to different requirements, which is very beneficial for embedded products with hardware imitations.

ROS ROS is short for Robot Operating System developed from 2010 to now. Ubuntu 20.04 uses the 13th release of ROS Noetic Ninjemys, which is mainly responsible for connecting various components inside the robot for easy and fast connection. ROS supports many programming languages. The internal library tools of ROS also make maintenance easier. Overall, ROS is very suitable for large-scale real-time systems.

1.4.2 Data Preprocessing

The dataset contains five labels corresponding to bottles, masks, trash, glass, and cans in this work. Herein trash specifically refers to objects that are kneaded

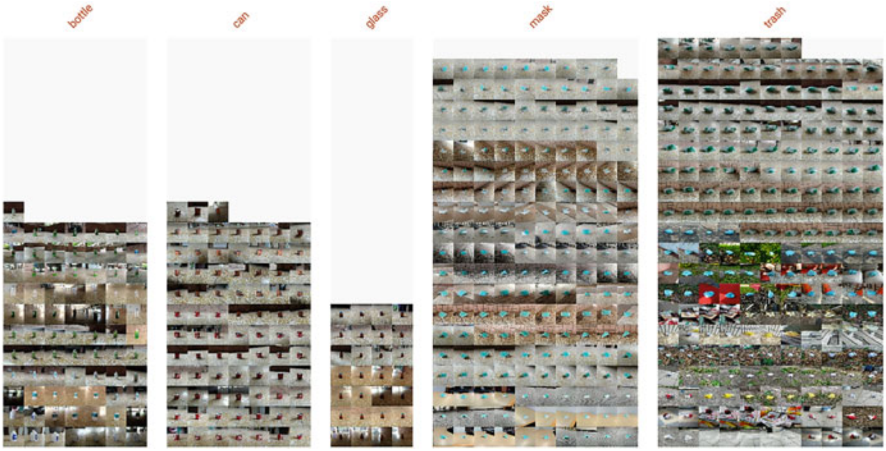

Fig. 1.5 Images used for training

into balls or objects with irregular shapes, such as plastic bags, crumpled paper, and paper balls. These are typically considered to be garbage and are frequently encountered in the surroundings. Figure 1.5 demonstrates part of the dataset.

We took about 3000 pictures of these objects by smartphone. Since the architecture of MobileNetV2 contains a fully convolution layer [1], it is reasonable to resize these images to 640 × 360 rather than a square. It helps retain more information from images. Moreover, the smaller size of images requires less computing time for training.

To ensure that the training and testing sets have approximately the same percentage of each target class sample in the dataset, we applied stratified sampling to split the data into a ratio of 8 to 2, which are the proportion of the training and testing sets. To avoid overfitting and to enhance the features of images of interest, we also made good use of OpenCV, which helped us create an augmented dataset. The augmentation consists of random Gaussian blur of between 0 and 0.75 pixels, salt and pepper noise applied to 5% of the pixels, and random exposure adjustment between −17% and +17% [2–4].

A desirable feature of the model is its scalability. If one needs to increase the recognition targets, one only needs to expand the dataset and retrain the model.

1.4.3 Remote Monitoring

Mobile Device Applications Nowadays, smartphones are ubiquitous and have excellent connection and control capabilities. With the appropriate APP installed, they can support the remote operation of the database and robot. Android Studio was used for the development of the APP. Users employed the APP to control the