Smart Suitcase Implementation Using Fuzzy Logic and Deep Learning

KIM TIEN LY

School of Computer Science

University of Nottingham

UNITED KINGDOM

***Abstract*—This paper proposes a real-time control application using deep learning and fuzzy controller to create a smart suitcase. This device is a mobile robot that automatically follows its owner with the ability to avoid obstacles on its way. The deep learning model used in this project is based on the efficient technique and state-of-the-art object detection algorithm – Mobilenet-SSD convolutional neural network. The fuzzy logic controller with logical if-then rules forms an effective automatic control strategy. This paper presents a proof of concept illustrating the integration of fuzzy controller with real-time object detection and tracking using deep learning.**

Keywords—autonomous robot, mobile robot, deep learning, fuzzy controller, embedded system

I. INTRODUCTION

Machine learning for computer vision, especially convolutional neural networks have become popular for its diverse applications including face or object detection [1] [2], or even signal analysis [3]. Since AlexNet was released and won the ImageNet Challenge in 2012 [4], the general trend has been to make deeper and more complicated networks in order to achieve higher accuracy. However, these advances to improve accuracy are redetrimated in terms of size and speed. In 2017, Google has announced a class of efficient models called MobileNets for mobile and embedded vision applications. MobileNets are based on a streamlined architecture that uses Depthwise Separable Convolutions to build lightweight deep parameters that efficiently choose a tradeoff between latency and accuracy [4].

Fuzzy logic controller [5] allows flexible and optimal operation defining the rules to change vague explanations to obvious definitions. Fuzzy sets can be built from human experience and perception, which helps to deal with real-life situations. The vague boundaries enhance the ability to handle uncertainty in mobile robots, which makes fuzzy logic be widely implemented from daily products [6] to process industry [7] or decision making system [8].

Although deep learning techniques have long been applied in computer vision, robot vision has a specific challenge with real-time operation due to limited onboard resources. Similarly, fuzzy logic controller has been used in various robot applications, but only with basic automotive sensors for robots to compute immediate actions. This paper points out a clear approach to combine deep learning and fuzzy controller in an autonomous robot. The idea is to design a smart suitcase that can follow its user automatically in real-time, which gives the owner freedom to do another task when walking on an airport platform. This model is practically built and tested with the aim to contribute to develop devices for human utilities.

II. METHODS

A. Overview

A carry-on suitcase model is designed with four wheels, two of them are controlled by motors and the others are orientable. A Raspberry Pi 3 B+ is responsible for owner detection, which is a logo, for tracking. However, due to its limitation in real-time image processing, an Intel Movidius Neural Compute Stick is integrated with Raspberry Pi and an ARM STM32F407 microcontroller is used to control the robot to follow its owner and stimultaneously avoid obstacles, which are all other objects apart from the specified owner. SPI protocol is implemented for communication between them.

B. Raspberry Pi 3 B+

1) Training deep learning neural network model for object detection

Dataset is created using taken pictures of the specified logo with the help of data augmentation, which involves creating transformed versions of collected images using techniques such as flip, blur adding, rotation, image's characteristic adjustment, etc. Positions of the objects are labelled and saved as XML files in default PASCAL VOC format. Two classes are defined in order to classify the proposed object and background respectively. Cross-validation technique is applied in creating Lightning Memory-Mapped Database (LMDB). The training phase takes place on Google Colaboratory to make use of the computational power of GPU Tesla K40 supported by Google Corporation.

2) Tracking result transfer

SPI protocol is implemented for data transfer from Raspberry Pi to ARM, where Raspberry Pi is the master-side of the connection.

C. ARM

1) Fuzzy for owner following: takes the inputs from owner detecting result to compute two outputs for the difference in the two motors' PWM.

Input:

- Position error (ePosition): the difference between the center of the camera and the center of the detected frame. The purpose of this variable is to ensure that the owner is right in front of the suitcase.
- Distance error (eDistance): the difference between the height of the detected frame and the expected height. The purpose of this variable is to ensure a specific distance between the suitcase and its owner. Since there can be a lot of interference from

people passing by, using an ultrasonic sensor for distance measurement was crossed out.

Output: PWM difference value for each motor.

Rules: Fuzzy rules for owner following are defined in TABLE I.

TABLE I. Object following fuzzy rules for two motors. Noted abbreviations: negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), positive big (PB), low (LO), medium (ME), high (HI), negative (NE), positive (PO).

Right motor Left motor		ePosition				
		NB	NS	ZE	PS	PB
eDistance	NE	NS PB	ZE PM	PS PS	PM ZE	PB NS
	ZE	NM PM	NS PS	ZE ZE	PS NS	PM NM
	PO	NB PS	NM ZE	NS NS	ZE NM	PS NB

2) *Obstacle Avoidance*

a) *Sensors and algorithm*

The implemented algorithm is the bubble rebound algorithm [9]. Accordingly, robots require a ring of ultrasonic sensors covering a certain range returning results of detected objects on its way.

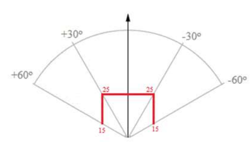


Fig. 1. Four ultrasonic sensors cover an angle of 120^0 with defined sensitivity bubble.

The robot is expected to move towards the area having the lowest density of obstacles [9].

b) Fuzzy for obstacle avoidance: takes the calculated angle from the bubble rebound algorithm together with current PWM of the two motors to compute two outputs for the difference in the two motors' PWM.

Input:

- Angle: the direction where the suitcase needs to follow to avoid obstacles.
- Current PWM: the current PWM on each motor.

Output: PWM difference value for each motor.

Rules: Fuzzy rules for obstacle avoidance are defined in TABLE II.

TABLE II. Obstacle avoidance fuzzy rules for two motors. Noted abbreviations: negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), positive big (PB), low (LO), medium (ME), high (HI) , negative (NE), positive (PO).

Right motor Left motor		Angle				
		NB	NS	ZE	PS	PB
Current_PWM	LO	NS PB	ZE PM	PS PS	PM ZE	PB NS
	ME	NM PM	NS PS	ZE ZE	PS NS	PM NM
	HI	NB PS	NM ZE	NS NS	ZE NM	PS NB

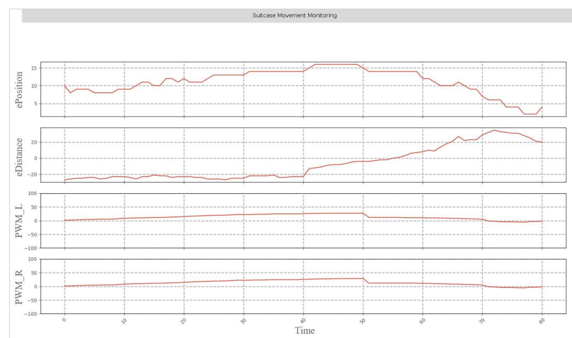
III. DISCUSSION

A. *Result*

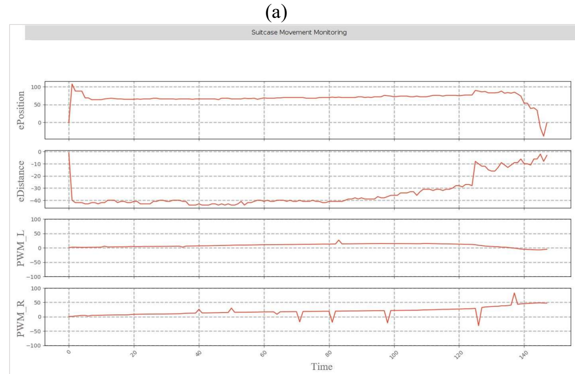
The autonomous suitcase is tested with both indoor and outdoor environment. It has proved to be able to move smoothly in real-time owner tracking and obstacle avoidance. The recorded video is available at this link.

The tracking feature is examined in many cases including different distances, different rotations, different background or even when a part of the logo is hidden. The training phase gains 92% accuracy in logo detection. Failure cases are found in low-light environment. The detection speed is around 15-18fps, which allows the Raspberry Pi to transfer data to ARM with the sample rate 100ms.

Results of fuzzy controller for owner following are shown in Fig.2. In Fig.2(a), the suitcase starts to move when it is far from the tag, it moves straight forward as the tag is not too far to the left or right of the suitcase. Fig.2(b) indicates the situation when the owner is far to the left, the right motor moves faster to turn left.



(a)



(b)

Fig. 2. Results of fuzzy controller when the owner is a little far and around the middle (a), when the owner is far and to the left (b).

The suitcase model uses only low-cost devices.

B. *Conclusion*

The approach in this paper has provided a practical application by combining machine learning and fuzzy controller theory. Things become easier for engineers to make real robots in industry with basic principles and low-cost electrical components.

IV. References

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