

FAULTS DETECTION VIA MOBILE SAFETY INSPECTION SYSTEM

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ABSTRACT

Fire accidents due to damaged wiring cables have claimed many buildings and lives. Refrigerant leakage might cause fire and it is poisonous if inhaled in large amount. Regular inspection and maintenance works are compulsory to have early detection to prevent such tragedies. However, the inspection works are tedious and incurring ineffective costs. In this paper, we present a robot CABtec with artificial intelligence capability to conduct close range inspection and detection missions in wiring systems of buildings. This robot will continuously navigate the entire area for damaged cables and gas leakages. If any fault is detected, CABtec can conduct thorough inspection using multi-sensing feature. Users can then utilise the front robot arm to have a closer inspection on the suspected faults. Should any damages to be found, technicians will have to carry out maintenance job using the GPS location sent by the robot as a guide.

1.0 INTRODUCTION

Electrical wirings for fire alarm systems, heating, air conditioning systems, interior and external lightings are crucial to be in place for large retail facilities such as shopping malls, office premises and etc. The installation of these systems is usually located at the top of the building and covered with ceilings and exterior decoration to ensure the pleasant appearance of the building. However, maintenance work of the electrical systems is often complex, requiring the intervention of certified mechanical & electrical (M&E) technician. These cables are vulnerable to accidental or rodent damage which may cause electrical fires to happen [1]. Furthermore, in the event of refrigerant leakage or power failure, the causes and leakage location are difficult to detect immediately [2]. Many news reporting on the fire casualties. Based on statistics by the Malaysian Fire and Rescue Department (BOMBA), 5,300 cases of fire in buildings were caused by damaged cables from 2015-2017 [3]. In 2017, a fire broke out in a convenient store at Mid-Valley Megamall, Kuala Lumpur due to the damaged wiring connected to the chiller motor led to overheating. Another incident took place at the Quadricentennial Pavilion of the University of Santo Tomas (UST) in Manila with similar cause. Even though there were no casualties reported, but this is a strong indication to the management of such large retail premises that the electrical systems and wiring require consistent and frequent inspection to prevent the mishaps.

When maintenance work is to be carried out at large premises, technicians examine the feasibility of the task at hand and offer alternative approaches in accordance with the client's requirements. Technician is usually equipped with infrared camera and crawl in to the tight space to inspect the electrical or air conditioning systems [4]. There is always potential risk to the technician as refrigerant leakage from air conditioners could poses fatal death with excessive inhalation [5]. Damaged wiring in electrical systems might be caused by old and worn-out cables, weather or rodent. Damaged wires are one of the most common causes of fire breakouts in dilapidated buildings or old malls[6]. Detection of these damaged cables is a job that is too tedious and risky to carry out. Our team developed CABtec, a

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real-time mobile safety inspection system with AI capability. CABtect is able to execute safety inspection mission to identify the faulty wiring cables located at the top ceilings of the building.

CABtect initiates the safety inspection mission to identify the faulty wiring cables located at the top ceilings of the building. Our CABtect is capable to navigate along the pathway with detection of wiring cables. It is trained with thousand cable images to predict the model using deep learning pre-trained model [7][8]. With this artificial intelligence feature, it automatically detects cables with images captured by raspberry pi video camera. When cable is detected, CABtect will navigate following the cable for focus inspection. The thermal sensor continuously scans the cable for abnormal temperature (50°C-250°C). Should an abnormal temperature be detected in the cable, the system automatically halts the robot, the robot's current GPS location will be sent to the technician. Then, the technician is given option to either automatic or manual control. For manual control, the inspection is further conducted with the expandable front arm which is equipped with a FPV video camera and photo sensor. The top extendable arm can extend upward to reach a higher position to have clearer view with using Adafruit AMG 8833 thermal sensor and the raspberry pi video camera. If the fault is confirmed, technician will take over for maintenance service. In addition, a gas sensor is fitted on the front part of the robot chassis. If gas leakages are detected, the robot automatically alerts user and sends its current GPS location to the technician.

2.0 CONSTRUCTION OF MOBILE SAFETY INSPECTION SYSTEM

2.1 Navigation Of The Robot

Initially, CABtec as illustrated in Figure 1 is set to be in autonomous mode, which it takes wall as the guidance to navigate it. The algorithm that has been followed by CABtec is Left Hand Rule, which the robot will move near the left wall and used it as guidance. Thus, IR sensor has been placed on the left-hand side of the robot and the front. Whenever there is a junction, the robot priorities to turn left. Else, if turning left is not an option, it will turn right. Besides, the key feature that had been added to CABtec is image processing using deep learning. As the main purpose of the robot is to search for any burned or broken wirings and gas leakage, thus deep learning is used to identify the wire for focus area searching to avoid moving to unnecessary track.

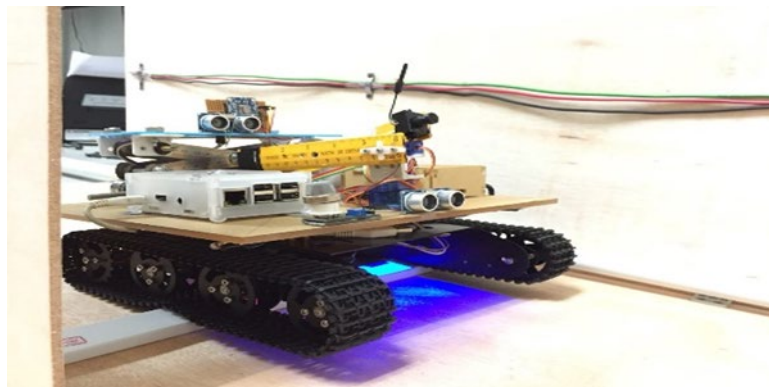


Figure 1. CABtec

Thermal and gas sensors are used to detect faulty of the wire and gas leakage, as any of the sensor detect danger, users are able to select manual mode to monitor. The sensors are MQ2 gas sensor and AMG8853 Thermal Sensor. MQ2 sensor can detect gasses such as LPG, smoke, alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations ranging from 200 to 10000ppm. Figure 2 shows CABtec gas detection when a flammable gas butane is tested as a gas input. After the gas detection, CABtec will locate its location and send location information to the user via NEO 6M GPS module.

Figure 3 shows CABtec GPS sensor output for 3 different locations in UPNM. During manual mode, users are able to gain control of the whole robot including robot arm and expandable part to obtain the information of the faulty area. The live feed video will be sent to the computer so that the users are able to detect the location of the robot. When gas or high temperature detected, users are able to observe the current situation. There are two sets of raspberry pi in the operation. The Raspberry Pi 1 is used as the mainboard which control the movement of all the robot including the motors and sensors. Raspberry pi 2

is used to conduct deep learning of wire detection and then send the information to Raspberry 1 to ensure that robot is going in the correct track. Raspberry Pi 2 also connected to the camera to allow users to inspect damage and faulty area. Figure 4 shows CABtec flowchart in safety inspection system.

```

Sensor Value:100
Sensor Value:100
Sensor Value:200
Sensor Value:400 Gas detected
Sensor Value:400 Gas detected
Sensor Value:400 Gas detected
    
```

Figure 2. Gas detection via MQ2

Satellite Count:	Satellite Count:	Satellite Count:
8	8	7
Latitude:	Latitude:	Latitude:
3.052088	3.052372	3.051964
Longitude:	Longitude:	Longitude:
101.726905	101.727096	101.727310
Speed MPH:	Speed MPH:	Speed MPH:
0.08	0.07	0.92
Altitude feet:	Altitude feet:	Altitude feet:
146.65	397.31	330.38

Figure 3. GPS sensor output

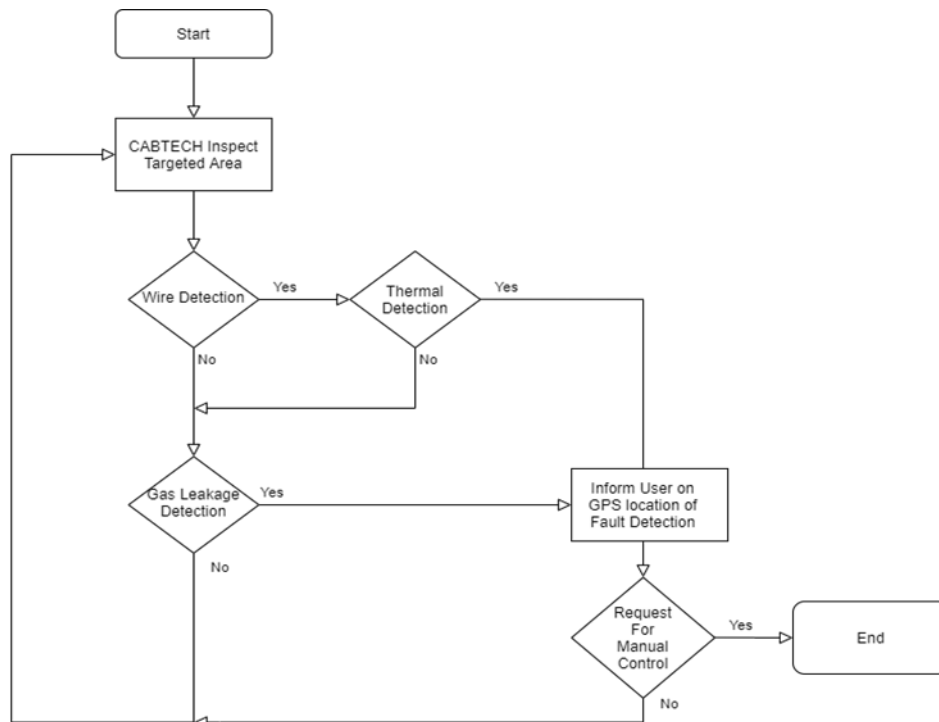


Figure 4. CABtec system integration

2.2 Thermal Sensor Module

Panasonic AMG8833 IR thermal sensor is a heat vision sensor from Adafruit collection. A simple connection between AMG8833 with any microcontroller can return an array of 64 individual infrared temperature reading over I2C data transfer in 8 x 8 grid. The sensor has dimension of 25.8mm x 25.5mm x 6.0mm with weight of 2.9g. Due to its compactness and portability, it is used in to detect heat. It is used to measure temperature ranging from 0°C to 80°C with an accuracy of +- 2.5°C. The sensor is capable to detect up to 7 meters distance with maximum frame rate 10Hz. In Figure4, the thermal camera was tested to measure the temperature of a hand palm. Meanwhile, Figure 5 and Figure 6 shows the temperature readings of the thermal sensor to detect a burnt cable.

[35.2	35.4	35.3	35.1	35.2	35.5	35.4	35.3
	35.3	35.3	35.5	35.5	35.1	35.4	35.2	35.1
	35.4	35.2	35.1	35.4	35.5	35.3	35.5	35.4
	35.2	35.2	35.3	35.4	35.4	35.1	35.3	35.1
	35.2	35.4	35.1	35.1	35.2	35.2	35.5	35.3
	35.2	35.2	35.5	35.2	35.3	35.1	35.3	35.1
	35.5	35.3	35.2	35.2	35.1	35.2	35.4	35.1
	35.2	35.3	35.2	35.1	35.1	35.4	35.1	35.1]

Figure 5. Thermal detection of hand palm

[78.7	78.6	78.7	78.9	78.7	78.9	78.8	78.6
	78.7	78.7	78.8	78.6	78.9	78.8	78.6	78.8
	78.9	78.9	78.7	78.7	78.9	78.9	78.8	78.9
	78.8	78.6	78.6	78.7	78.7	78.7	78.6	78.6
	78.8	78.6	78.9	78.7	78.6	78.6	78.6	78.8
	78.6	78.9	78.7	78.6	78.8	78.8	78.6	78.7
	78.8	78.9	78.7	78.8	78.7	78.9	78.7	78.7
	78.7	78.7	78.6	78.8	78.7	78.9	78.8	78.9]

Figure 6. Thermal detection of high temperature wire

2.3 Top and Front Extendable Arms

The design of the top extendable arm is based on the scissor lifting technique. The extendable unit is constructed using stainless steel due to its high corrosion resistivity, high strength and sturdiness. The initial height of the scissor lifting arm is 5.2 cm and the whole unit is 9 cm, the scissor arm can reach a height of 25.6cm at full extension and the maximum height of the whole unit is 29.4 cm. As the whole unit weighs about 250 g, a force of 0.2108N is sufficient to lift the scissor arm. Thermal camera, ultrasonic sensor and a raspberry pi camera are installed on the extendable arm. The main function of the scissor extendable arm is to ensure that users can have a clear view of conditions behind walls higher than itself.



Figure 7. Top extendable part of CABtect

The arm as shown in Figure 7 is connected to the sensor and motor. So, the arm will receive command from raspberry pi. The raspberry pi receives signals from the ultrasonic sensor. Commands calling for the scissor to extend will be sent if an obstacle higher than the arm is encountered. The mechanism to lift the arm is a DC motor is connecting at one of the bottom legs to move the scissor lifting arm and another bottom leg will directly fix on the body of robot.

$$\frac{\sin 90^\circ}{a} = \frac{\sin \theta}{h} \quad (1)$$

Since $a = 6.5$ cm (constant), minimum $\theta = 10^\circ$, maximum $\theta = 80^\circ$, hence, when θ increases, the length of h will also increase. From the theory of equilibrium of forces,

$$F = (W + \frac{W_a}{2}) / (\tan \theta) \quad (2)$$

where

- F = the amount of force required
- W = weight of the payload and the load platform, 100g
- W_a = the weight of the scissor arm, 150g
- θ = the angle that the scissor makes with the horizontal

The front extendable arm is made by wooden stick. It is combined 3 wooden sticks as shown in Figure 8.

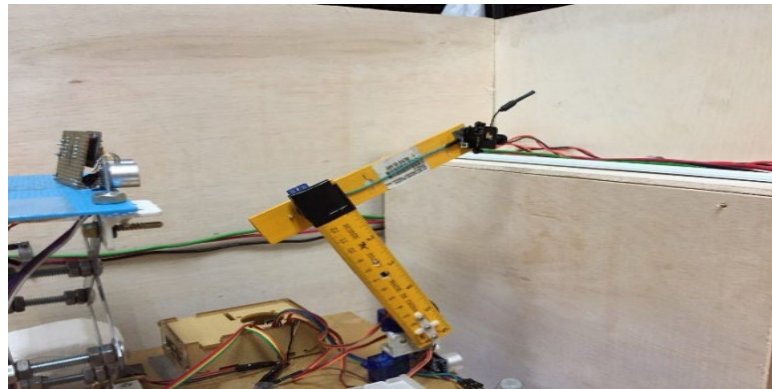


Figure 8. Front extendable arm

3.0 RESULTS AND DISCUSSION

Artificial Intelligence (AI) in the CABtect is built step by step with a pre-trained Convolutional Neural Network (CNN) called Alexnet. Alexnet allows users to detect significant numbers of objects that have been implemented into the database of Alexnet. Alexnet consists of 8 layers of CNN with 5 layers of feature extraction and 3 layers of feature classification (fc). The structure of the network and the number and dimension of filters in each layer are shown in Figure 9. The feature extraction is the process of transforming raw data into numerical features that can be process into a computer which preserving the original form of the data set. After feature extraction is completed, the data set then are categories into several categories based on its similarities in data set. This feature is called classification.

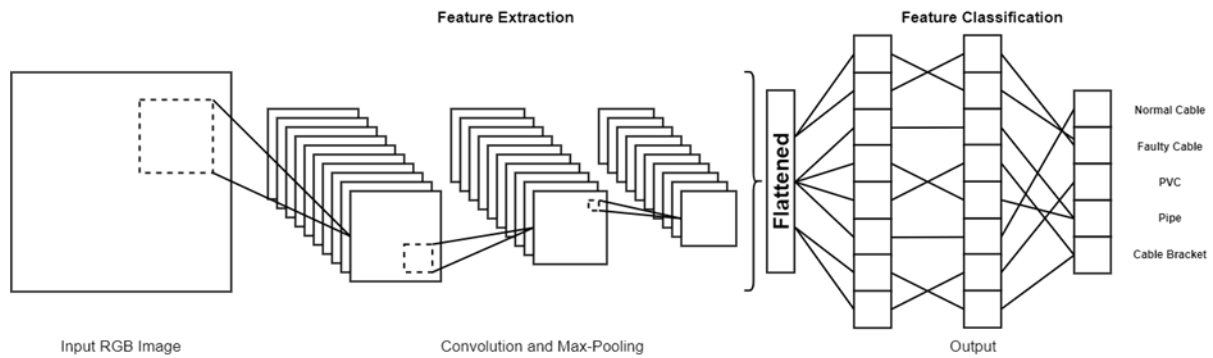


Figure 9. The Structure of Alexnet [7]

In this project, it is necessary to re-train the CNN with our own data for wire detection. This process is known as transfer learning. First, thousands of photos of cables need to be taken. These photos will be taken at different angles, under different lux level (illumination level), different backgrounds and different positions. This step is crucial to train the CABtect to be capable of detected cables under different lighting conditions, sizes, different backgrounds and at different positions. MATLAB is a suitable tool to be used to train the CNN with our own data. The 23rd layer of Alexnet needs to be resized to only 5 categories of images. These 2 categories of images are put into a file and divided into 2 subfolders. These images are cables and PVC pipes. These images will then be read into MATLAB using imageDatastore function. Re-training process can now be carried out on Alexnet. After training is complete, the program will be tested on images captured by laptop webcam.

- A) Loading a pre-trained CNN (Alexnet)


```
alex = alexnet;
layers = alex.Layers
Modifying the CNN to process 2 categories
layers (23) = fullyConnectedLayer(2);
layers (25) = classificationLayer
```
- B) Setting up own training data for CNN


```
allImages = imageDatastore('myImages','IncludeSubFolders', true,'LabelSource','foldernames');
[trainingImages, testImages] = splitEachLabel(allImages,0.8,'randomize');
```
- C) Re-training the network with own data


```
opts = trainingOptions('sgdm','InitialLearnRate',0.001,'MaxEpochs',20,'MiniBatchSize',64);
myNet = trainNetwork(trainingImages,layers,opts);
```
- D) Measuring the accuracy of the program


```
predictedLabels = classify(myNet, testImages);
accuracy = mean(predictedLabels == testImages.Labels);
```

In section A, a pre-trained CNN will be loaded into MATLAB program. In this project Alexnet will be used. Alexnet contains millions of images available for object detection. In this project we need to re-train Alexnet with our own images. In section B, the 23rd layer of Alexnet is modified to process only 2 categories of images. These images are placed in a folder with two separated sub folders. In section C, all images saved in the same folder will be set and prepare for re-training purpose. The function image Datastore MATLAB understands the structure and will load all the images with their own labels for users. As in section D, the process of re-training the CNN (Alexnet) with our own data begins. After training the CNN, a few images will be used to test for the accuracy of the program.

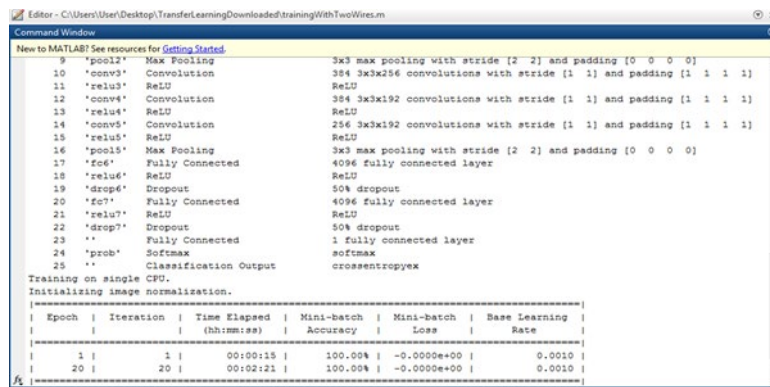


Figure 10. CNN training with new data in MATLAB

Figure 11 shows that MATLAB is training the CNN with our own data. In this case there are only 2 categories as this is a test for the program. The actual MATLAB program for CABtec’s AI system will have at least 5 categories of objects to be taught to the CNN.

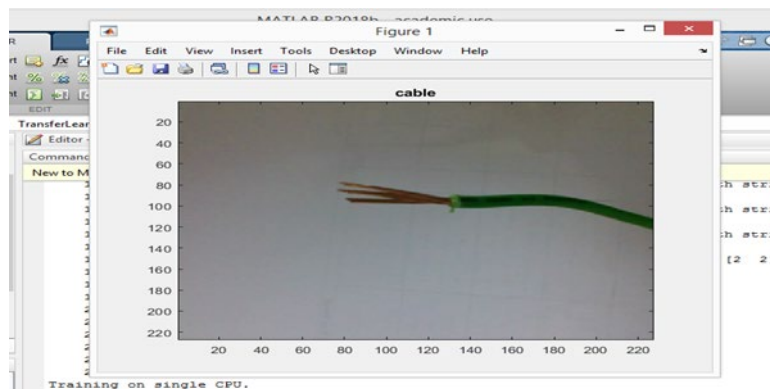


Figure 11. MATLAB detects cable with live streaming video through webcam

```

Editor - C:\Users\User\Desktop\TransferLearningDownloaded\trainingWithTwoWires.m
trainingWithTwoWires.m x raspberrypiMatlab.m x alexnet.m x FullyConnectedImageStrategy.m

16 - myNet = trainNetwork(trainingImages, layers, opts);
17
18 %% Measure network accuracy
19 - predictedLabels = classify(myNet, testImages);
20 - accuracy = mean(predictedLabels == testImages.Labels);
21
22 %%Trying
23 - mypi = raspi('192.168.137.51', 'pi', 'raspberrypi');
24 - mycamera = cameraboard(mypi, 'Resolution', '320 x 240');
    
```

Figure 12. Connecting raspberry pi microcontroller and camera to MATLAB

Figure 11 shows that MATLAB can detect cable from complex background from live video streaming using a webcam. The codes used to connect a raspberry pi camera module to MATLAB is shown in Fig 12. The MATLAB function raspi requires three input arguments. The first argument will be the valid IP address of raspberry pi microcontroller. The second argument will be the username of the raspberry pi. Finally, the third input argument is the password of the raspberry pi. The function raspi simply tells MATLAB that there is a device called raspberry pi connected to it. The camera board function is the code that allows MATLAB to have access to live streaming videos, static images and video recording from raspberry pi camera module.

4.0 CONCLUSION

CABtec with artificial intelligence capability to conduct detection of faulty wirings. The safety inspection system can navigate the entire area to detect damaged cables and gas leakages. If any fault is detected, CABtec can conduct thorough inspection using multi-sensing features with flexible top and front robot arm to have a closer inspection on the suspected faults.

5.0 ACKNOWLEDGEMENT

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