

Intelligent Receiver for Optical Camera Communication

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Abstract—Optical camera communication (OCC) is considered as a potential option for wireless communication due to the recent surge adoption of LED technology. Massive adoption of LED technology creates a problem in OCC due to the interference caused by other LEDs that do not transmit data. Hence, in this research work, we propose an intelligent receiver for the OCC system which can differentiate LED, whether the LED is transmitting data or not. We differentiate the LED by using an AI-based object detection algorithm and we compare the performance of four object detection algorithms, such as Faster RCNN, MobileNet SSD, YOLO V4, and YOLO V4 Tiny, to detect the data transmitting LEDs or non-data-transmitting LEDs. Experimental results show that the four algorithms can achieve above 0.95 mAP when detecting and classifying the LEDs. Thus, the object detection algorithm can be implemented in the OCC system and can be used to improve the OCC performance and robustness.

Index Terms—optical camera communication, object detection, intelligent receiver.

I. INTRODUCTION

The wireless communication system has a lot of advantages compared to the wired communication system. The wireless communication system is easier to deploy due to the absence of wire. By using wireless communication, the data communication is conducted wirelessly as long as the receiver is still in the coverage area of the transmitter. Wireless communication nowadays is utilized in various application fields such as mobile networks, Internet of Things (IoT), and satellite communication systems. Radiofrequency (RF) technology is one of the popular wireless communication technology. Currently, the RF technology is at the center of attraction although the exponential growth of users causes the traffic to become congested [1] and the interference due to too many RF devices in a region is forcing them to search for complementary spectrum [2][3]. However, due to the nature of RF technology which uses radio to transmit the data, increasing the data rate using RF technology can be done by increasing the frequency band. However, that technique of increasing the frequency band has a negative effect on human health [4].

Optical wireless communication (OWC) is a potential alternative to existing RF technology communication systems [5]. Basically, OWC is divided into three techniques: light fidelity (Li-Fi), visible light communication (VLC), and optical

camera communication (OCC) [6]. All three techniques have similarities which using LEDs as the transmitter because of many benefits of LED such as high energy efficiency and low power consumption. Meanwhile, for the receiver, the VLC and Li-Fi are using photodiodes to receive the signal transmitted from the LED transmitter that propagates through the optical channel [7]. For OCC, it uses an image sensor as the receiver which the image sensor can be divided into two types, global shutter camera and rolling shutter camera. Compared with other OWC techniques, OCC presents superiority such as low cost, high reliability, and high resistance against interference [1].

In OCC, the camera received the optical signal with non-interference communication because the camera's image sensor has the capability to do spatial separation [8]. The image received by the camera is processed frame-wise which limits the OCC system data rate. To solve that issue, we can use a high-speed camera to increase the number of frames processed at a time [9]. However, using a high-speed camera will need a high-performance computer because it also needs a fast frame processing time. Another disadvantage is the price of the high-speed camera is expensive. Hence, MIMO techniques are proposed to increase the data rate of OCC systems [10]. Recently, several researchers also propose hybrid modulation techniques based on intensity, spatial, color, frequency, and phase to increase the data rate in the OCC system [11].

Due to the increasing number of LEDs adopted in daily life, those LEDs cause interference with the OCC systems. The OCC systems cannot focus only on the LED that actually transmitting the data because the other LED that is located near with the transmitting LED also blinking but doesn't transmit any data. In this paper, we designed a system that enables the OCC system to locate the location of LED that transmits modulated data. We use an object detection algorithm to detect the location of transmitting LED and non-transmitting LED. Then, we also compare the performance of four object detection algorithm to detect the LEDs.

II. METHODOLOGY

A. Experiment Scenario

For conducting the experiment, we build an OCC system that consists of a transmitter and receiver. For the transmit-

ter part, we use one LED to transmit the modulated data. The modulation technique used is FSOOK modulation that modulates the data at a frequency between 2-4kHz. Then, we also use another LED that only turned on without transmitting any data. Those LEDs are separated 8cm horizontally and both are controlled by an Arduino microcontroller board. The receiver, which is a camera with a frame rate of 60 fps, is located in front of the LEDs and establishes a line of sight (LOS) connection. For this experiment, we variate the distance between the LED transmitter and receiver with a distance of 10cm, 20cm, and 30cm. Then, we use four types of object detection algorithms: Faster RCNN [12], MobileNet SSD [13][14], YOLO V4 [15], and YOLO V4 Tiny. From those four object detection algorithms, we will compare their performance in detecting and classifying the LEDs from a distance of 10cm, 20cm, and 30cm. Also, we will calculate the data rate of the OCC system from various distances of 10cm, 20cm, and 30cm. Figure 1 shows the OCC architecture used in this experiment.

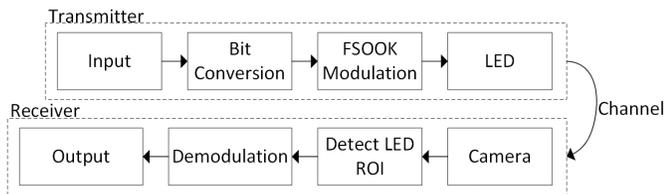


Fig. 1. OCC Architecture.

B. Dataset

To develop the AI object detection, we need an image dataset to train the AI algorithm for detecting the LEDs. We create the dataset by doing the scenario as described in the previous section. The difference is we don't detect the ROI and demodulate the data, we only record the LEDs from a distance of 10cm, 20cm, and 30cm. At each distance, we record a video for 60 seconds long. Because our camera operates at 60fps, hence, for 60 seconds, we will get 3600 individual frames. According to the scenario, we will get three videos and total images of 10,800 images. From those images, that contain the transmitting LED and non-transmitting LED, we manually label each image by applying a bounding box to each LED location and the class of that object. The labeling is done by using `labelImg` software.

From 10,800 images in the dataset, we divide it into three parts, first, 70% of the data will be used for the training process. Then, the other 20% is used for the testing process and the last 10% will be used for validation. After dividing the data, we also apply preprocessing to the data such as resizing the images, rotating, and mirroring the images randomly.

III. DEVELOPMENT OF THE OBJECT DETECTION AI MODELS

After creating the database, we have data that can be used for the AI model to learn. In this paper, we decide to use four

types of AI models: Faster RCNN, MobileNet SSD, YOLO V4, and YOLO V4 Tiny. We choose those AI models because those models are notorious for their detection performance in detection accuracy and detection speed.

To develop the AI models, we use two different environments. For YOLO V4 and YOLO V4 Tiny, we use darknet to train the models using our dataset. For the training process in the darknet, we use hyperparameters such as a learning rate of 0.001, a momentum of 0.9, and a decay rate of 0.0005. Both AI models is using input images with a size of 416x416 pixels, and each image has 3 channels. Then, we train the models for 2000 epochs while calculating the training mAP every 100 epoch. After the training process is finished, we test our model using the validation dataset and calculate the mAP. Figure 2 shows the training loss for YOLO V4 Tiny and YOLO V4. The loss is already very small which indicates that the models have already learned the image dataset. Also, the mAP, which shown in Figure 3, shows that the model is able to learn well about the target.

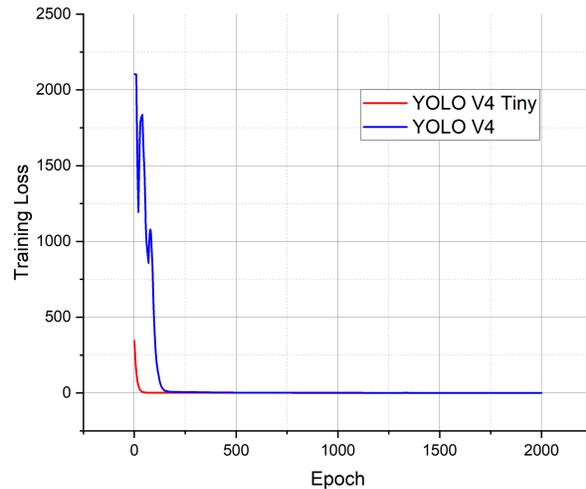


Fig. 2. Training Loss for YOLO V4 and YOLO V4 Tiny

Then, for the Faster RCNN and MobileNet SSD, we use Tensorflow development environment. The training method is similar to the darknet. Here, we use hyperparameters such as a learning rate of 0.01 and momentum of 0.9. For this part, we use an image size of 640x640 pixels as input. Then, we train the models for 10,000 epochs. After the training is finished, we calculate the mAP of the model by testing it using the validation dataset. The training result is shown in Figure 4 and Figure 5 which shows the training loss for 10,000 epochs and mAP during training process of Faster RCNN and MobileNet SSD.

After the training process is finished, we will use the weight of the model for the testing process. We conduct the testing process by implementing it in the OCC system so that we can measure the data rate and mAP of each model. Different from the training process, we conduct the testing process using embedded computer NVIDIA Jetson Xavier NX. The

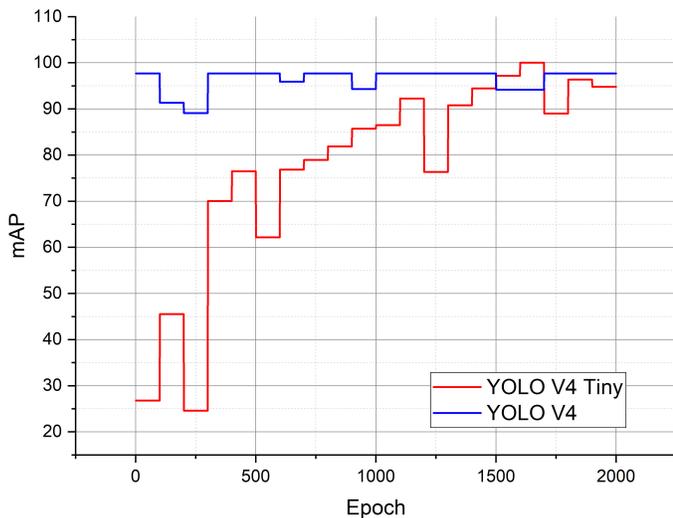


Fig. 3. mAP during training for YOLO V4 and YOLO V4 Tiny

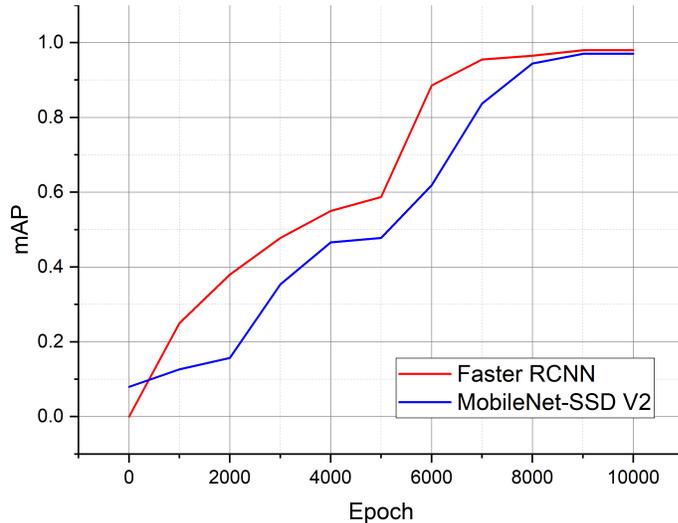


Fig. 5. mAP during training for Faster RCNN and MobileNet SSD

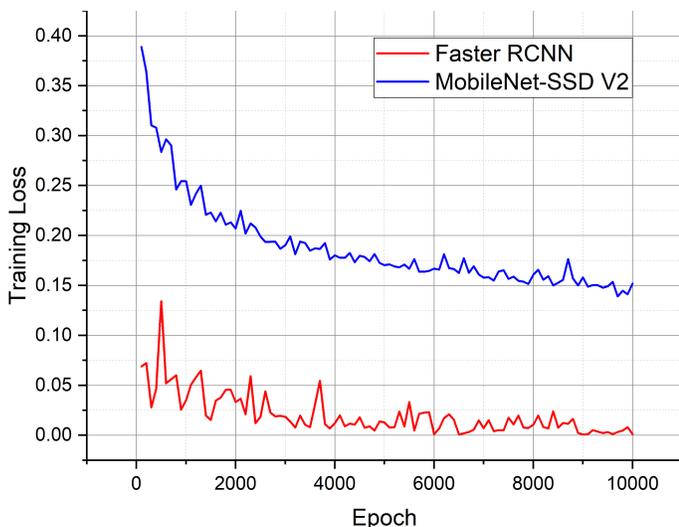


Fig. 4. Training Loss for Faster RCNN and MobileNet SSD

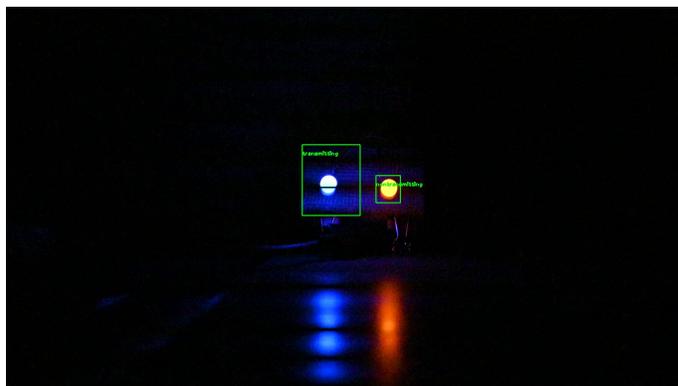


Fig. 6. AI model result predicted location of transmitting LED and non-transmitting LED.

embedded computer will be installed by the AI models and OCC receiver software to detect the transmitting LED and non-transmitting LED.

IV. EXPERIMENT RESULT

The experiment is done by implementing an AI object detection model in the receiver part to intelligently differentiate the transmitting LED and non-transmitting LED. The camera continuously captures the image of the LED at 60fps and the receiver system will process that frame. The AI model is utilized to detect the location of the actual transmitting LED and LED that is only turned on. Then, the AI model will output the predicted location of the LEDs and give a bounding box and label to each detected LED. Figure 6 shows the predicted location of transmitting LED and non-transmitting LED. After that, the receiver system will only focus on transmitting LED ROI to demodulate the data and restore the data.

From the experiment, we also obtain the mAP of the four developed AI models. The mAP value is shown in Figure 7. From that figure, we can see that all four AI models achieve high mAP values which are above 0.95. This indicates that all AI models can classify the transmitting LED and non-transmitting LED successfully. Also, the location prediction of each AI model is good due to the high mAP value. This means that all four AI models can be utilized in the OCC receiver system to solve issues of interference from other LEDs. However, this is depending on the hardware of the receiver. In this experiment, we use NVIDIA Jetson Xavier NX as the receiver computer. When running four AI models, we observe that each algorithm produces a different frame processing time. This is due to the complexity of each AI model. When using YOLO V4, we only get an average of 2.9 fps, then for the YOLO V4 Tiny, we get an average of 12.7 fps. After that, for MobileNet SSD, we get an average of 3 fps and 0.2 fps for Faster RCNN. Hence, although all AI models produce high mAP, when used in the receiver system, the frame processing time for each AI model is different which

affects the OCC performance. If the frame processing time is very slow, it cannot capture all information transmitted by the LED. Therefore, the fast frame processing time is a necessity to capture all transmitted information.

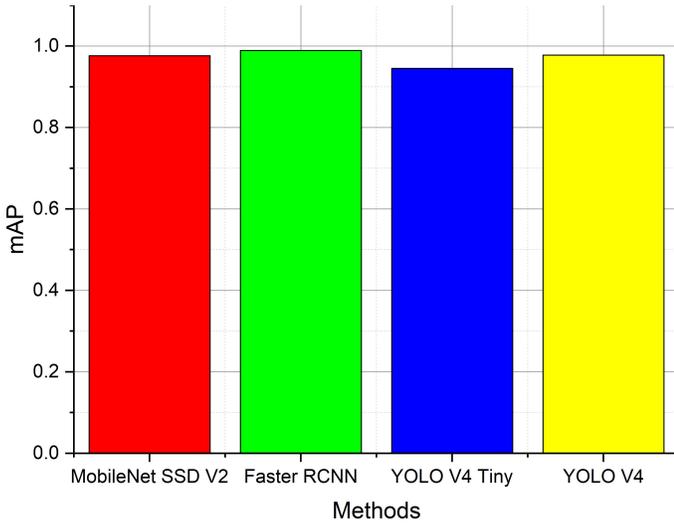


Fig. 7. mAP value of each AI models in testing process.

Besides that, in the experiment, we also calculate the data rate of the OCC systems from a distance of 10cm, 20cm, and 30cm. The result is displayed in Figure 8. We can see that the data rate is decreasing while the distance between receiver and transmitter is longer. This is caused by the emitted power of the LED is weakening when the distance is longer which causes the camera only to see fewer stripes in the long distance. Meanwhile, in a short distance, the LED power is still strong, and the camera can capture many stripes.

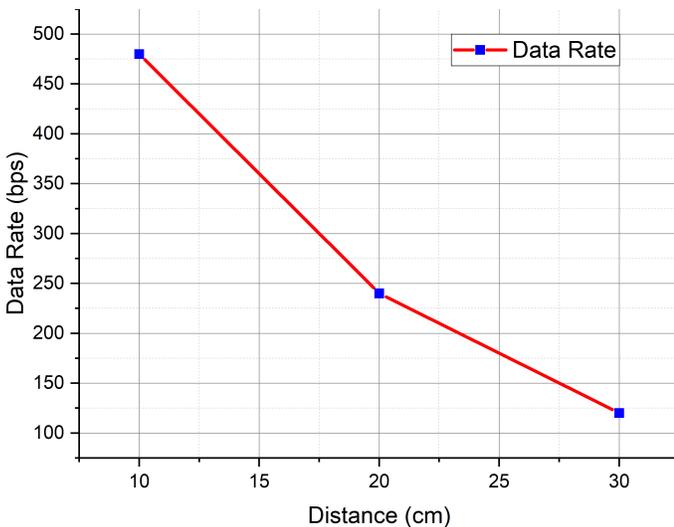


Fig. 8. Data rate from various distance.

V. CONCLUSION

In this paper, we have implemented an OCC system that uses an AI object detection algorithm to differentiate trans-

mitting LED and non-transmitting LED. We successfully developed the AI algorithm to predict LED location and classify the LEDs. From the experiment result, we can see that four AI models can achieve excellent performance with high mAP. However, for implementation of OCC in embedded computers, high mAP is not enough, the AI model also should have a low computational cost to produce a fast frame processing time. Hence, the YOLO V4 Tiny is the best AI model compared to the other because it can produce a high mAP while having a low computational cost that enables the receiver system to achieve 12.9 fps. Then, the distance between transmitter and receiver is also necessary to the OCC performance. As such, the issue of interference from other LEDs in OCC can be solved by using an AI object detection algorithm to detect and classify the LED. It enables the OCC system to know the actual transmitting LED location and only focus on that location which will increase the system robustness and stability.

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