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Velocity Analysis on Moving Objects Detection using Multi-Scale Histogram of Oriented Gradient

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ABSTRACT

An autonomous car is a one-of-a-kind specimen in today's technology. It is an automatic system in which most of the duties that humans undertake in the car can be done automatically with minimum human supervision for road safety features. Moving automobile detections, on the other hand, are prone to more mistakes and can result in undesirable situations such as minor car wrecks. Moving vehicle identification is now done using high-speed cameras or LiDAR, for example, whereas self-driving cars are produced with deep learning, which requires much larger datasets. As a result, there may be greater space for improvement in the moving vehicle detection model. This research intends to create another moving car recognition model that uses multi-scale feature-based detection to improve the model's accuracy while also determining the maximum speed at which the model can detect moving objects. The recommended methodology was to create a lab-scale model that can be used as a guide for video and image capture on the lab-scale model, as well as the speed of the toy vehicles captured from the Arduino Uno machine before testing the car recognition model. According to the data, Multi-Scale Histogram of Oriented Gradient can recognize more objects than Histogram of Oriented Gradient with higher object identification accuracies and precision.

1. Introduction

Artificial Intelligent is a hot topic in technology, especially machine learning. It can do complex things that humans unable to do, which is a benefit. Machine learning systems can give helpful tools for humans to utilise because they are easy to use and lessen the demand for personnel [1-5].

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Machine learning is employed practically everywhere, including self-driving cars, face recognition, solar radiation prediction, and object detection [6-13]. Machine learning gets solutions from data quickly and addressing complicated problems.

Self-driving cars such as Tesla have object detection mechanisms that were developed from Tesla's own neural net model, or specifically called Autopilot was designed to detect objects that may impact the car that otherwise resulted in car accidents and collisions and brakes accordingly while the other features were also there such as auto high beam and front and side collision warnings to keep the car has the most active standard safety features [14]. All these functions are automated. Object recognition in Tesla cars, if not all, may also have flaws [6]. Some circumstances were not working properly and still caused minor automobile wrecks. Most consumers were unaware of these processes' improvements.

In recent years, as the object detection studies has become more prevalent as technologies are embracing for autonomous devices without the need of human supervision [15, 16]. The idea of these studies is to develop an object detection model, in this case, on car for example. There can be two types of recognition on cars such as in stationary state or moving state.

Stationary state may be ideal for counting how many cars in the image, as the car are not subjected to movements. Similarly, some may use the recognition model while in the moving vehicle. These methods however had been done to develop car detection model, only with the presence state condition regardless of velocity analysis. For example, Bogdan Djukic and his team was detecting the vehicle using machine learning in 2017. While Jin Liu and his team had done research on vehicle detection using improved YOLO-3 algorithm [17].

For moving car recognition, the car detection results may be varied due to the conditions of the subject movements. Most cameras that were used for car recognition model are typically in high exposure, meaning that it has more lights that reaches into camera for object detectability. Wei Zhan et al done research on moving vehicle detection [18] and Yongbin Gao and his friends developed moving car detection and recognition model based on deep learning [19]. From all this research, most of the time vehicle detection on static state can be applied successfully in most applications while moving vehicles tend to have its lower accuracy on the results than static vehicles. Therefore, moving vehicles are selected as an input to establish an improved car recognition model while analysing the car velocity to what extent that vehicle can be detected from the model.

Like most things nowadays, velocity analysis in object detection is always improving [20, 21]. There are some researches carried out to analyse velocity on moving objects from a set of blurred images [22-24] while a few of these researches are using some types of recognition methods. Each researcher used various methodology that involves different object detection model to analyse velocity detection on moving object such as using grey level, oscilloscope, and image deblurring [25, 26]. From all the existing researches, the experiment results were various, and this was dependent on the images that was captured for a model that was analysed and subjected to more improvements that can be made from these experiments.

One of the feature detections explored in this project is Histogram of Oriented Gradient (HOG), which can detect pedestrians [27-29]. When an image was converted to HOG, it turned into an object's contour, offering an object detection model for safety features in an autonomous automobile more accuracy [29, 30]. Single scale feature detection may not yield more accuracy, especially when the car is travelling faster, as the model tends to identify more features in the image than the intended subject of interest. Multi-scale feature detection gives even higher accuracy than single scale from fewer image features. So, the model can effectively detect the intended object without false detections.

The paper is organized as follows. Section 2 presents the experiment setup for velocity analysis on moving objects. Section 3 compares the properties of HOG and Multi-Scale Histogram of Oriented Gradient (MSHOG). Section 4 discusses the results. Section 5 concludes this research.

2. Mathematical Formulation

2.1 Data Collection

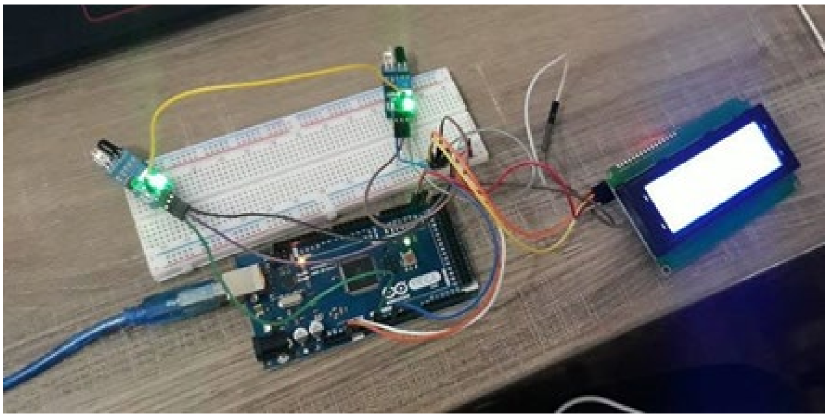
The approach for this study will be described in this chapter. First, the toy car's speed was measured using an Arduino Uno machine to determine the average speed for each angle and the speed for each testing image that was obtained as a screenshot from a video. Then, hundreds of photos were collected as a training dataset for object detection. One can be created from the data collected for testing purposes of the car identification model, and the accuracy and precision of the model can be assessed. Likewise, ascertain the highest speed the MSHOG model is capable of detecting.

There are 5 different toy automobiles that can be used to train an object detection model by simulating them as real cars. The majority of these come in a variety of shapes and toy vehicle colour tones. As shown on Figure 1 below shows an example of them.

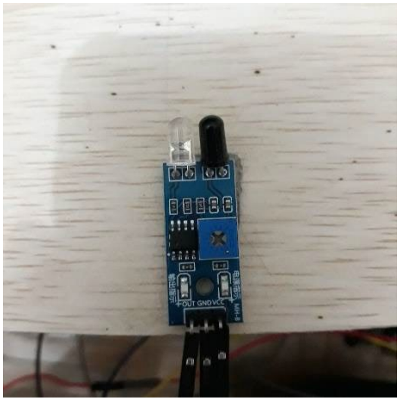
Fig. 1. Example of a toy car on the lab scale model

The Arduino Uno machine was designed to determine the toy car's speed after it went through two IR sensors. Left side IR sensors were 10 cm apart. The IR sensors are 7.5 cm from the plastic rail track, allowing them to detect a moving car swiftly and nearby. Milliseconds. In km/h. I2C LCD Display Unit 20x4 can display the toy car's speed and distance. The data was loaded into a Microsoft Excel spreadsheet, and speed readings were repeated ten times for each angle. Repeating the steps gives a different angle.

There are 5 different toy automobiles that can be used to train an object detection model by simulating them as real cars. The majority of these come in a variety of shapes and toy vehicle colour tones. As shown on Figure 2 below shows an example of them.



(a)



(b) (c) (d)

Fig. 2. (a) Arduino Uno Setup (b) I2C LCD Display Unit 20x4 (c) Arduino Uno (d) IR Sensors

2.2 Video and Image Capture

To compare single scale HOG to multi scale HOG, images must be taken from a lab-size model made from four 30 cm x 30 cm x 1.5 cm plywood pieces. The model supports the inclined plane and Arduino Uno. The smartphone camera was installed on the model's left or right side, depending on the image size chosen from a captured video. In this experiment, the photograph was taken 7.5cm from the model's left side to the plastic train track put on the inclined plane. As the plane's attitude changes, the camera arm must be moved. An old angle adjuster was used to make 5-degree adjustments to the inclined plane. Protractor measurements confirmed the revised inclined plane angle. The setup is as shown on Figure 3 below.

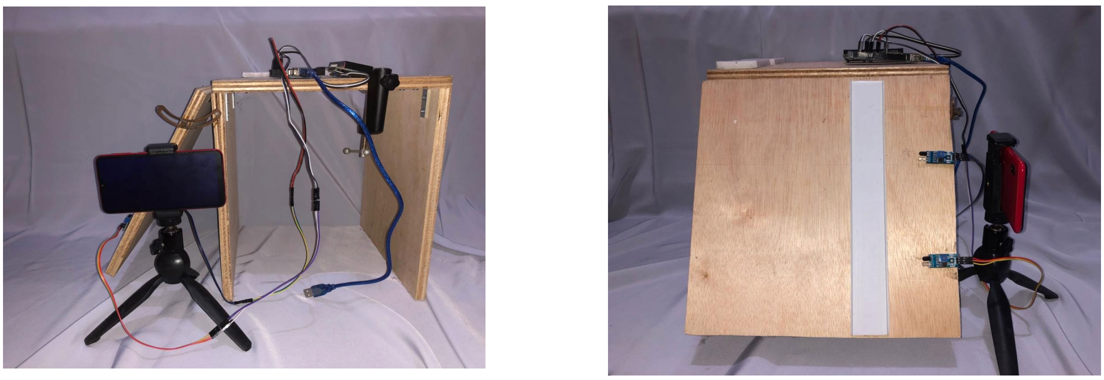


Fig. 3. The lab-scale model

For this experiment, photos must be taken in video mode because photo mode has a slow camera response time. Smartphone camera app utilized. The camera was set up to shoot continuously. This means the 1/60s shutter speed, ISO, white balance, and exposure remain constant, allowing the camera to adapt to the lighting and environment automatically. Camera settings vary. Depending on the camera shutter speed, a blurred image may represent an object's speed. The background should be white, such as A4 white paper or white cloth, to keep the image focused on one subject or with little image noise, because the image will be analysed in MATLAB using an object identification model of choice.

2.3 Classifier

Next, a classifier was chosen to determine the model's effectiveness. Linear SVM was utilized. A model for HOG and MSHOG characteristics was trained. This resulted in 2 object detection models, or 2 classifier features. All models were trained in MATLAB. Separately trained positive and negative images. Linear SVM is used to train the object detection model because it can be trained quickly. Linear SVM is employed because it has the simplest object interpretation, a graph with a hyperplane in the centre and two categorized items, positive and negative or 1 and 0.

2.4 Testing Image

The object detection model needs test images. Objects rolled down an inclined plane were recorded. Camera setup followed earlier instructions. To test the model's correctness, the programming code variables were altered for each set of orientations according to laptop folders. This was repeated till 85o. Later in the testing results, 1 and 0 can be represented to see if the model can detect the objects or false results, opposite categorized items than what the trained object detection model meant to. Steeper angles on an inclined level can induce faster car movement, blurring the image. This process determines if the blurrier image can still be detected by HOG and MSHOG.

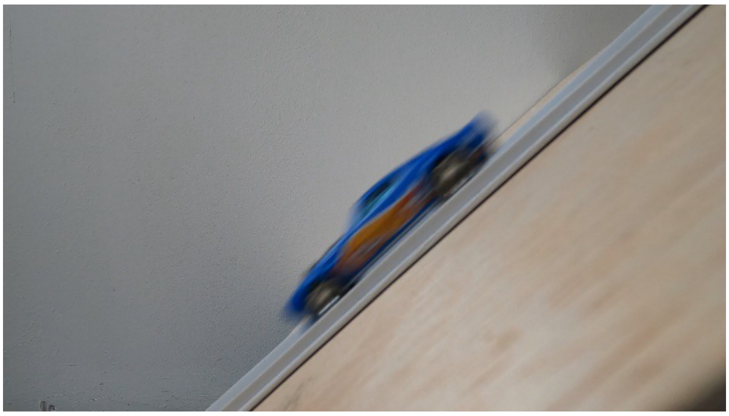


Fig. 4. Example of testing image

2.5 Evaluation

Confusion matrix was calculated from true positive (TP), true negative (TN), as well as false positive (FP), and false negative (FN) values to evaluate accuracy and precision. Equations below show the formula for accuracy and precision. Precision of the model is defined as proportion of the car detected correctly among those cars detected.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

3. Feature Comparison

Table 1 show the properties of both features used in this research. As shown in the table below, HOG feature is extracted from the image with resolution of 64 pixels * 128 pixels. Therefore, the vector length to represent the HOG feature ended up with 3780. Meanwhile, for MSHOG, the features will be extracted from 3 different size of images which are 64x128, 32x64 and 16x32. The vector length of MSHOG for each image is 1152. This has greatly reduced the vector length up to 70% compared to normal HOG.

Table 1
Comparison of HOG and MSHOG

Feature	HOG	MSHOG
Image size	64x128	64x128 32x64 16x32
Vector length	3780	1152

4. Result and Discussion

The toy car speed readings from Arduino Uno in the graph below are linear and constant from 5 degrees to 85 degrees. Except between 70 and 80 degrees, where the graph line shows a dramatic spike in speed reading, notably on automobile 5 (red). Due to the sloped plane of the lab scale model, things fell with practically free fall acceleration. The average speed of each toy car is affected by its shape, design, and weight. Heavier toys have more momentum. The heavier toy car will accelerate quicker on the sloped level due to downward pressures acting on it. As shown on Figure 5 below.

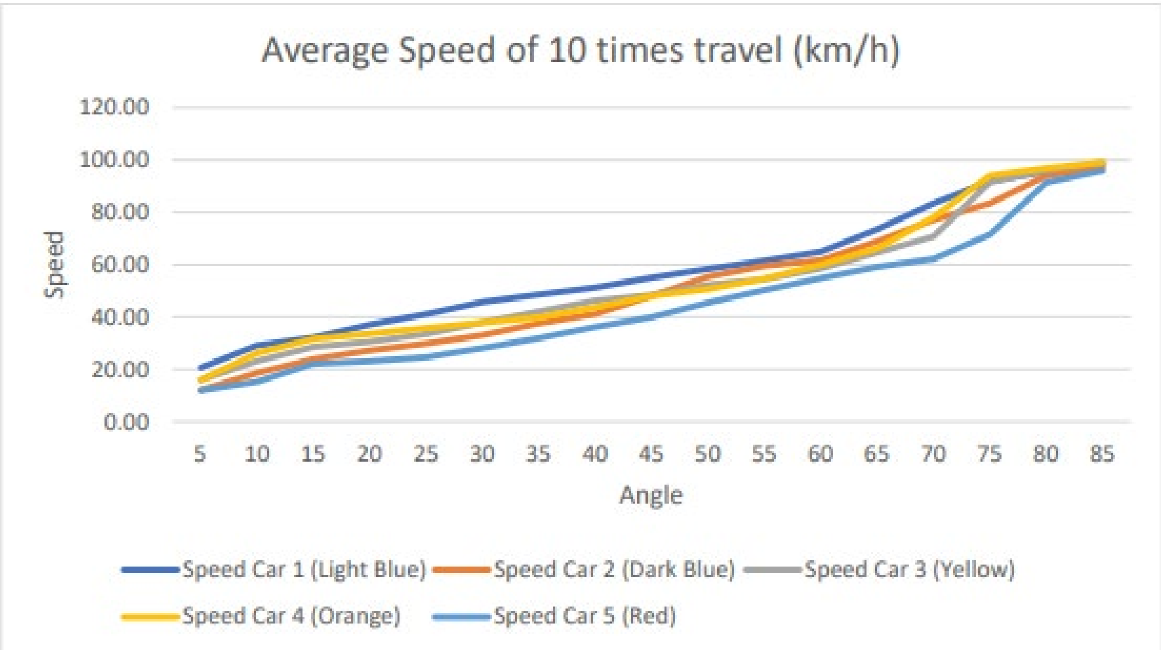


Fig. 5. Speed graph recorded from Arduino Uno

The graph in Figure 6 below comparing HOG and MSHOG object detection accuracy shows that MSHOG is more accurate. The HOG and MSHOG lines crossed at angles between 10 and 20, providing slightly opposite results. Most object detection models have a minor error on the results due to the training dataset, picture quality, background, and choice of items used to train and test the model. As shown on Figure 6 below.

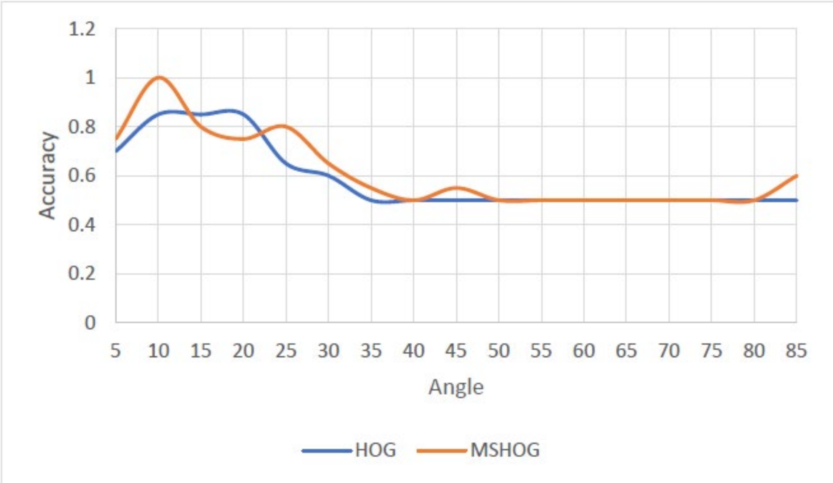


Fig. 6. Accuracy of HOG and MSHOG Object Detection Model

From the graph above, accuracy of HOG starts to decline at around angle 20 while the accuracy of MSHOG declined at angle 25. Accuracy of both models dropped is due to the model have high bias. When convert the angle into speed, HOG model can detect well until 20 km/h. Meanwhile, MSHOG model can detect the car until 30km/h. This mean MSHOG model is better than HOG model in terms of detecting object in blurring images.

The graph in Figure 7 above comparing the precision of HOG and MSHOG object detection models. It is evident from the graph depicting the object detection model's precision for the results of HOG and MSHOG that MSHOG has higher precision than HOG. However, even when the MSHOG line are always higher than HOG, it has a slight drop of values from angle 10 degree before backing up again at 25-degree angle though it continued to be lowered down its values at further angle onwards. On the HOG line on the other hand, the values are not dropped and steadily stagnant before dropped again at 20-degree angle onwards.

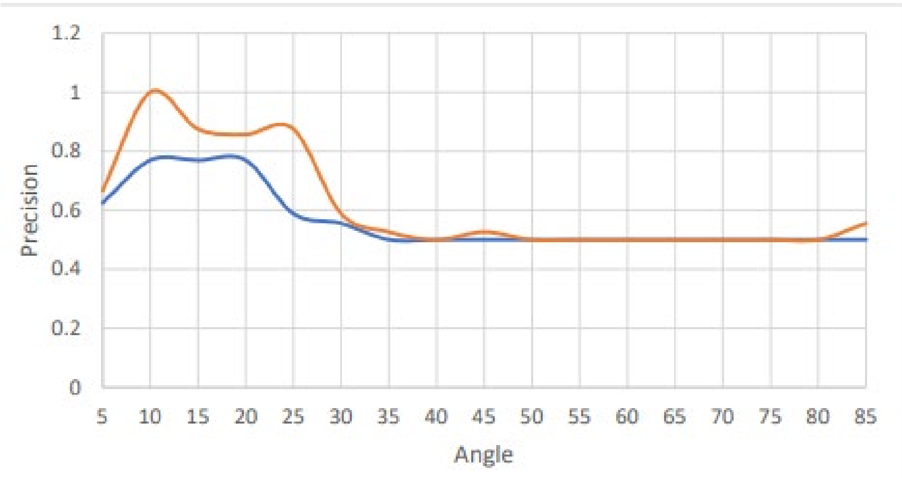


Fig. 7. Precision of HOG and MSHOG Object Detection Model

Based on the results, it can be said that MSHOG is still able to detect moving cars with higher accuracy and even at further angle than HOG regardless of some errors that was occurred in these graphs. Though the accuracy starts to fade out from MSHOG model on 40-degree angle. Meaning that the maximum speed the model can still detect at around 30 km/h.

5. Conclusions

Due to inadequacies in self-driving car moving object detection, it is improved in several period of times. Several approaches were taken to discover the most accurate and efficient moving object identification model, even at high speeds. This research uses multi-scale feature-based extraction instead of single scale in most feature-based detection models. A method to determine the MSHOG model's maximum speed and compare it to the HOG model was proposed. MSHOG's reading accuracy are higher than HOG, according to this research. Accuracy results are linear to angle and speed. Conclusion is that detectability relies on car speed and on the blurred images.

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