Detection of Risky Riding Patterns of Motorcyclists based on Deep Learning and Linear Regression

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ABSTRACT

Motorcycle accidents are the most fatal road accidents found in many regions especially in Asian countries. From the accident statistics, a major cause is due to riders' riding behaviors such as fast, drunk or reckless ridings which are generally defined as abnormal riding. Detection of such riding pattern is challenging and would be beneficial for preventing possible road accidents. This paper proposes a novel framework to detect abnormal riding in three risky cases: weaving, swerving and drifting from recorded video footages. The methodology comprises of two main steps. First we localized motorcycles in video frames using Convolution Neural Network with a model namely 'rfcn_resnet101_coco'. Second all detected centroids of motorcycles were fitted with two linear regression models i.e. Ordinary least square (OLS) and Random sample consensus (RANSAC) to find their linearity. The riding patterns whose regression scores are high tends to be normal ridings. From experiments, OLS and RANSAC showed a good performance to differentiate between normal and abnormal driving. The thresholds around 0.95 for OLS score or R squared and 0.94 for RANSAC score are sufficient for this classification. In addition, RANSAC provided an advantage over OLS when there exist noises e.g. nearby parking motorcycles.

Keywords: Abnormal riding, Motorcycle accident, motorcycle detection, deep learning, linear regression

INTRODUCTION

With an increasing number of uses of motorcycles as a general means of transportation in emerging countries such as Thailand, there has been a significant growth of accidents and fatality rates. Nichamon & Pornpimol (2019) described that in Thailand, the road traffic death toll used to be the second highest in the world in 2015. In 2018, about 70 percentages of road traffic death came from motorcycle accident. The major factor of the accident is users' behavior, for example, riding without helmet, drunk riding, and telephone while riding. In addition, these risky behaviors can be described as abnormal driving which is a term describing reckless behavior of drivers. Abnormal driving normally can be divided into three types which

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are reckless driving, drowsy driving, and distracted driving. The abnormal driving has a huge impact on motorcyclist, for example, distracted driving is when the drivers are watching something alongside the road or playing mobile phone. All these behaviors will take the drivers attention from the road and the accident is likely to take place. Mostly this situation occurs between cars and motorcycles because motorcycles are hard to be noticed in a specific area for drivers' view. Some of motorcyclists also have distracted riding when they ride in group, they would miss being aware of other vehicles changing lane or getting close toward them.

Therefore, there are many researches on abnormal driving. They focused mainly on a status of drivers. For example, researchers used a camera to detect eyes of drivers who might be distracted while driving. Driving patterns are another way to differentiate normal drying from abnormal drying. NHTSA (1998) described patterns which can lead to accident such as weaving, swerving, and drifting. However, detecting drivers might be hard because of a tint windows or a helmet. As a result of this, in order to eliminate a concern of window or helmet, an idea of detecting a vehicle by using image processing could be one of a solution to the problem. Image processing has a process which can extract a centroid of the vehicles for each image from a video. Therefore, observing the coordinate from the video could recognize the abnormal riding patterns.

To understand the relationship between motorcycle accidents and riding patterns, we can install a camera in a specific area where accidents occur very often. The video from the camera is an important data to analyze riding patterns which could relate to serious accidents. By knowing this information, we can propose a measure like a riding regulation or prohibition to prevent the possible accidents.

LITERATURE REVIEW

From literature, many definitions of abnormal driving behavior have been proposed. Normally, abnormal driving behavior is related to drivers who are under an influence of alcohol or have a problem with mental or physical aspect. NHTSA (1998) defined the abnormal driving as a problem in maintaining proper lane position. Starting with vehicle weaving which is when a vehicle moves to one side of the lane and then moves to the other. This situation might occur when driving under an influence of alcohol. Another problem is a vehicle drifting where the vehicle moves straight line and side slipping to another lane. The problem may take place when there is heavy rainfall which causes a slippery road. Swerving is when a vehicle swerved off the lane. For instance, when drivers fall asleep at the wheel and then realize that the vehicle drifts out of the lane, the driver tries to get back to a proper lane.

There are many works which contributed solutions to detect abnormal driving by using sensors. Kwangsoo et al. (2018) proposed a system which will generate an alert on abnormal driving situation and warn the drivers of incoming danger. The situation of abnormal driving is separated into three situations which are distracted driving, drowsy driving, and reckless driving. Many researchers used hardware sensors to detect these danger situations and generate the alert. Jiadi, et al (2017) proposed a Driving behavior Detection and identification system (D3) to monitor an abnormal driving behavior by using smartphone sensors. The author used a smartphone to collect a coarse-grained result to differentiate a normal driving from an abnormal driving and use fine-grained monitor to detect an abnormal driving and identify types of abnormal driving e.g. weaving, swerving, side slipping and fast U-turn. D3 provided an average accuracy of 95.36 percentages. Jie, et al. (2020) applied a deep learning approach to detect abnormal driving. The researcher established a novel deep learning based model for detecting abnormal driving. The data of drivers' behaviors were gathered by using an instrumented vehicle. An auto-encoded model was applied to learn feature of abnormal driving and the researchers were able to achieve 98.33 percentages of the abnormal detection accuracy. Xinrong, et al (2018) focused on abnormal driving behavior for bus, the researchers aimed to improve bus drivers' safety and road safety. They classified abnormal driving behavior into five types which are lane changing, sudden break, quick turn, fast U-turn, and longtime parking. In the early process, the researcher collected bus driving data by using accelerometer and orientation sensor of smartphone. Bayesian classifier was applied to identify various types of abnormal driving behavior and it provided accuracy at 98.40 percentages. Sometime social drinking is unavoidable; it is about companionship. However, drinking too much alcohol can harm people mental and affect an ability to drive properly. There are researches that aimed to detect drunk driver behavior. Hasanin & Hassan (2019) focused on drunk driving behaviors and developed a Hidden Markov Model (HMM) from their previous work. Data of drivers' behavior were collect through Controller Area Network (CAN) that linked to on board unit (OBU). They expanded their work by applying Recurrent Neural Networks and were able to reach above 90 percentages of accuracy. Sandeep et al (2017) applied Raspberry Pi3 and several sensors such as heart beat sensor, GPS devices, alarm device to detect drunk driver. Facial recognition was used to know whether the drivers are drunk or not. Saif, et al (2013) combined intelligent component of transportation system called Vehicular Ad-hoc Networks (VANETs) with sensor to perform high effectiveness of detecting abnormal driving. They used context-aware system in VANETs to capture information of driver's behavior and environment. Moreover, different kinds of sensors were used to gather contextual information. Finally, they proposed an algorithm to receive the information as an input and generate a system that can detect abnormal driving and warn other vehicle to prevent an accident from occurring. Jang & Ahn (2020) proposed the idea to prevent road accident from drowsiness by applying machine learning and a CO_2 sensor chip. The author used machine learning to predict drowsiness by observing face recognition and eye-blink and the sensor to detect additional drowsiness.

The subject of detecting abnormal driving is widely proposed by many researchers with several methods. Normally, most methods used sensors as a main core to collect the data from the drivers. Detection techniques required many sensors in order to achieve the goal. If one of them is damaged, there will be a problem during detecting process. Moreover, previous abnormal driving detection methods mainly focus on four-wheel vehicle such as cars or buses which are not applicable to motorcycles. Thus our work aims to detect abnormal riding behavior for motorcycles relying only to the video from a camera. It means that the cost of resources will be minimized and no sensor is required.

This paper is organized as follows. The next section gives a methodology of experiments including data preparation, selection of motorcycle model, and detecting abnormal patterns. Then experimental results are given. Finally, discussion and conclusion are drawn in the last section.

METHODOLOGY

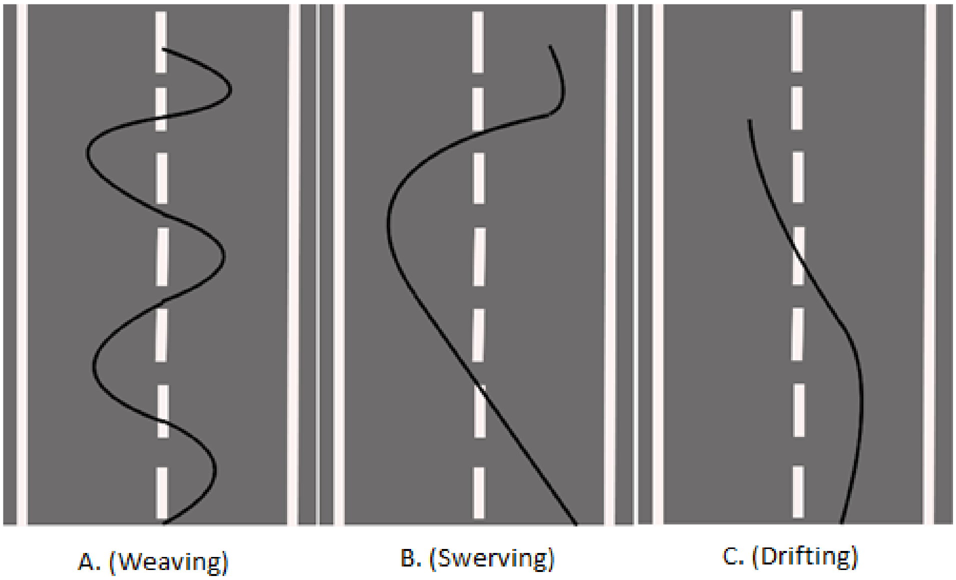


Figure 1. Abnormal riding pattern (weaving, swerving, and drifting)

In this section, we present an experimental investigation of identifying abnormal riding pattern by using motorcycle detection model and linear model. The proposed methodology is consisted of three parts, which are data preparation, selection of motorcycle detection model, and detecting abnormal pattern. We classify specific types of abnormal riding patterns including weaving, swerving, and drifting as shown in Figure 1. The first process is to collect videos of both normal riding pattern and abnormal riding pattern. Finding a specific type of abnormal riding on the road is quite difficult because of congestion and other vehicles might interfere in the scene. Hence, we created scenes which abnormal riding pattern will properly occur. We recorded 3 short videos for each pattern. According to Vattiya, et al. (2020), the optimized resolution of the videos is 480x270 pixels which provided the most efficiency, so we resized all videos to this scale. The next process is to feed the videos to motorcycle detection model to acquire X and Y coordinate of motorcycles from each video's frame. ‘Rfcn_resnet101_coco’ is a chosen model to detect motorcycle because it provided the best efficiency in term of time consuming and accuracy. When we feed the videos to the detection model, the model will detect motorcycles and create a bounding box frame by frame. For each frame, we acquire a centroid of motorcycles by computing X coordinate (left corner of bounding box plus right corner of bounding box and divided by two) and computing Y coordinate (top of bounding box plus bottom of bounding box and divided by two). The next process is to use a centroid as an input in Ordinary least square algorithm and RANSAC algorithm. Finally, we observe the result from both algorithms and differentiate normal riding from abnormal riding. An overall scheme of our proposed methodology is shown in Figure 2.

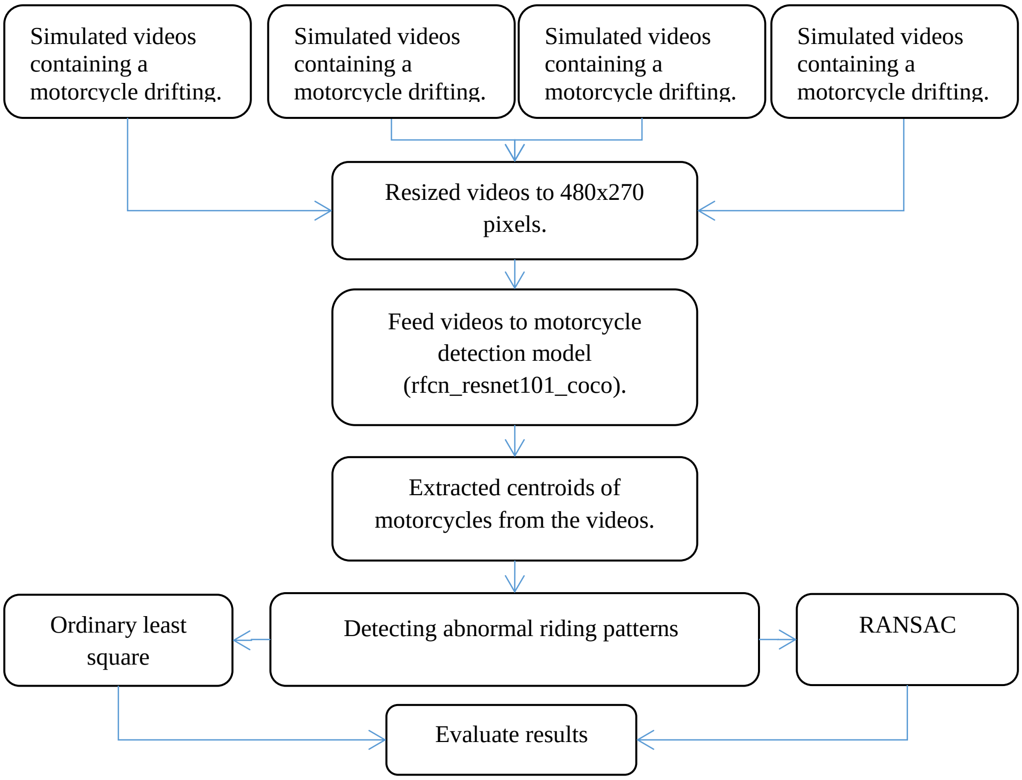
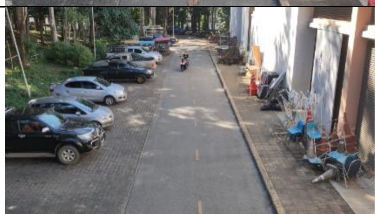
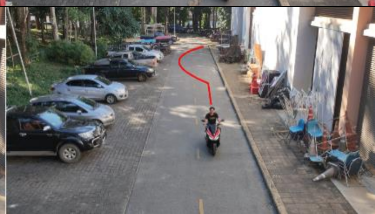
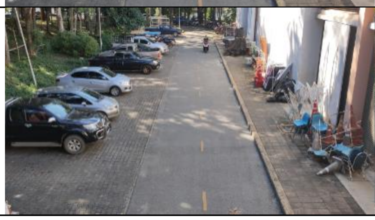


Figure 2. Methodology

3.1 Data preparation

Due to the absence of motorcycle riding datasets which cover our target riding patterns, we decided to simulate the riding situations and use a camera to record the motorcycles. Seven riding patterns were set as shown in Table 1 and we asked the riders to ride according to these patterns. Each pattern was repeated for three times so that totally we have 21 video clips.

Table 1: Sample images from the collected videos

No	Riding patterns	Sample images from videos	
1	Straight		
2	Weaving (Small curve)		
3	Weaving (Big curve)		
4	Swerving (Small curve)		
5	Swerving (Big curve)		
6	Drifting (Small curve)		

No	Riding patterns	Sample images from videos
7	Drifting (Big curve)	

3.2 Selection of motorcycle detection model

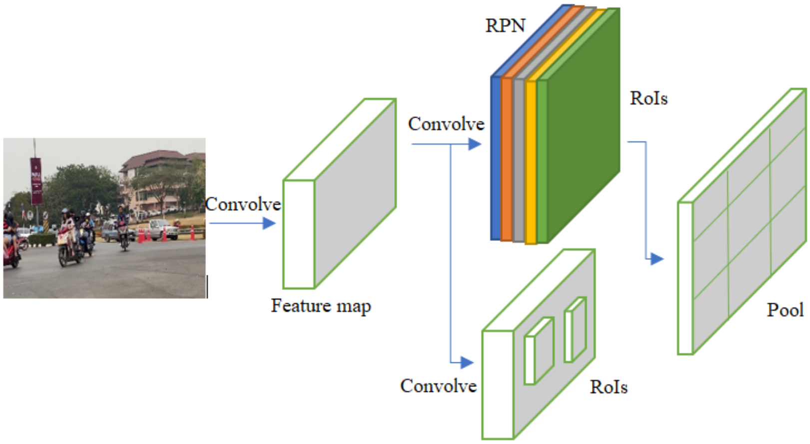


Figure 3. R-FCN's structure

We applied a work (Vattiya, Surapong & Worasak, 2020) which is a survey of machine learning model of motorcycle detection. Twenty different models were chosen to evaluate accuracy and time. 'rfcn_resnet101_coco' is a model that provided the highest efficiency with a size of 480x270 pixel. Region-based Fully Convolutional Networks, or R-FCNs has similar architecture to RCNN which has three independent neural networks (feature network, region proposal network, and detection network). R-FCNs still have RPN (region proposal network) but it removed ROI pooling which will decrease number of parameters. Therefore, it has less time consuming than R-CNN because of using position-sensitive score maps. The architecture of R-FCNS is shown in Figure 3. Therefore, we resized all videos to 480x270 pixels and then employ rfcn_resnet101_coco to generate X and Y coordinates of motorcycles.

3.2 Detection of abnormal riding

After acquiring centroids of the motorcycle, we aimed to differentiate normal riding from abnormal riding. At the first stage, normal riding will be defined, when the motorcyclist rides on straight. Thus, R-Squared (1) could be a suitable method to identify normal riding pattern by using ordinary least square (2) because straight line will normally provide high value of R-Squared. R-squared is statistic measure for a regression model which specify the proportion of variance for a dependent variable that is explained by an independent variable. To put it another way, R-squared demonstrates the goodness of fit of the data for regression model. 0% of R-squared means the model cannot be explained by a variability of the data. On the other hand, 100% means the model explains all variability of the data. Riding weaving, drifting, or swerving will have great impact on low value of R-squared, then we could be able to distinguish normal pattern from abnormal pattern by observing R-squared which R-squared is computed using (1).

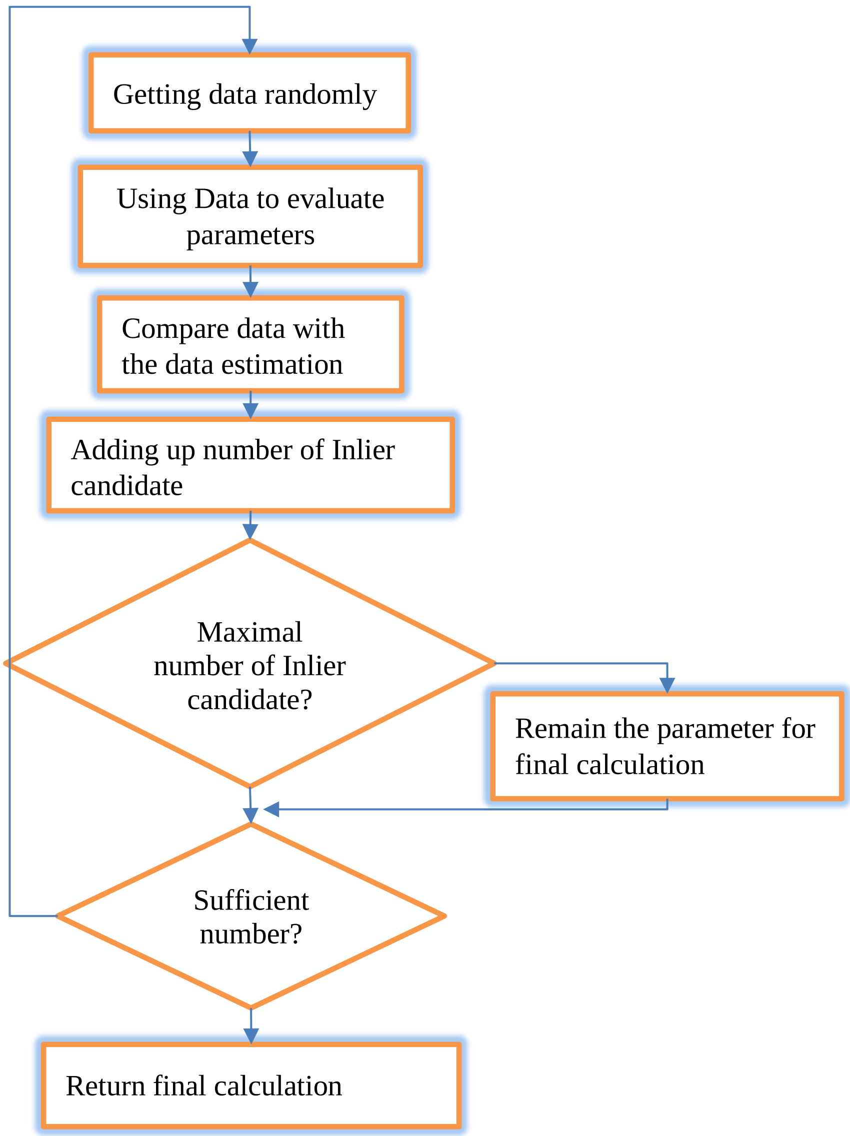


Figure 4. Flowchart of RANSAC

$$R^2 = 1 - \frac{Unexplained\,Variation}{Total\,Variation} \tag{1}$$

Where Unexplained Variation is error component of regression equation and Total variation means the sum of explained and unexplained variation.

An equation of Ordinary least squares is

$$Y_i = B_0 + B_1\, X_i + \; \varepsilon_i \tag{2}$$

Whera Y is independent variable, $B_0 + B_1\, X_i$ is linear component and ε_i is random error component.

Pedregosa et al. (2011) provides RANSAC, which is linear, model that being used in this paper to observe a result providing by another linear model apart from OLS. The flowchart of RANSAC is shown in Figure 4.

4. EXPERIMENTAL RESULTS

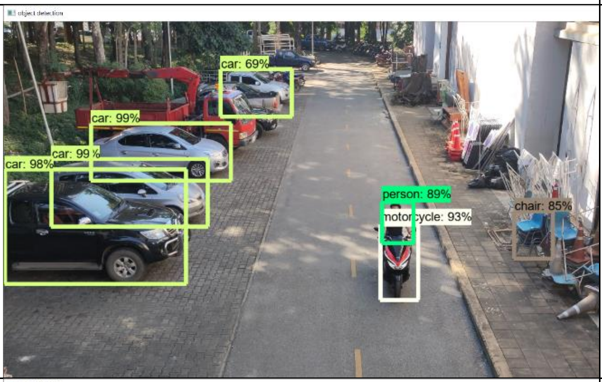
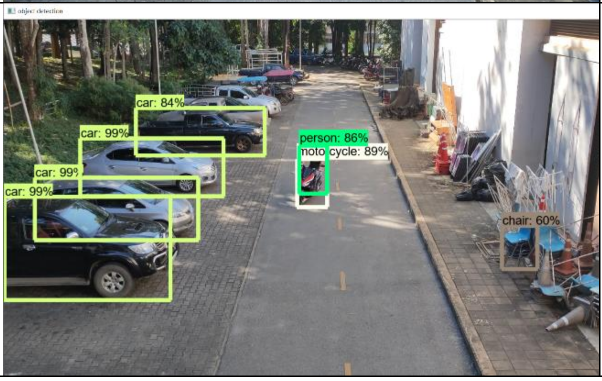
The experiments were conducted on a desktop PC with Intel® Core™ i7-8750H CPU @ 2.20GHz, 16 GB RAM and SSD storage and the software platform is Python, TensorFlow, and Scikit-learn on Windows 10.

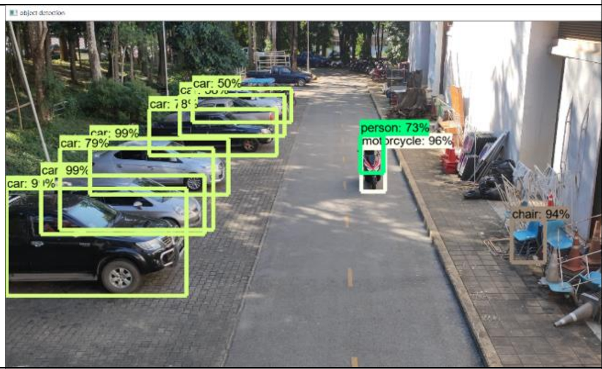
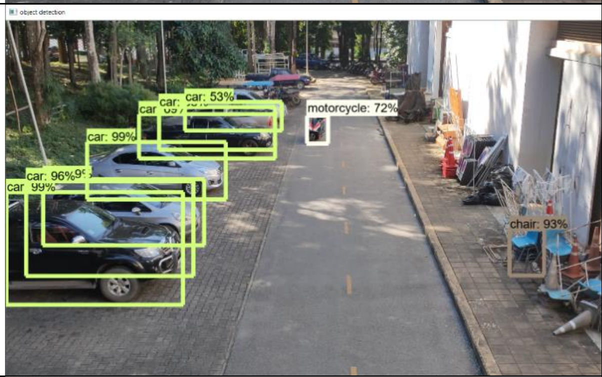
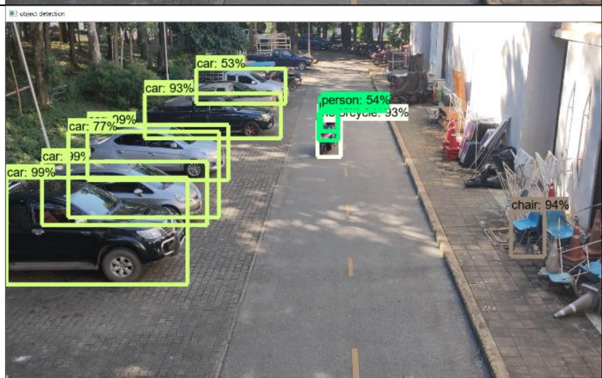
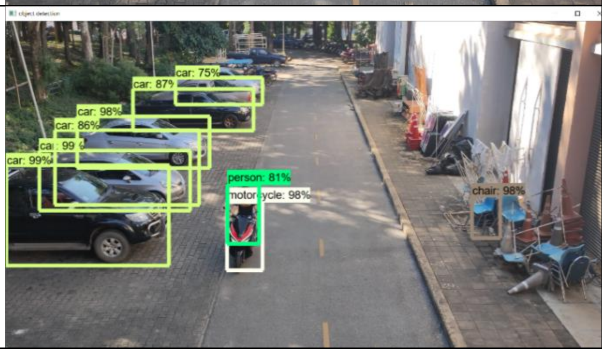
4.1 Motorcycle detection

The first part of the results is the motorcycle detection. We used a Convolutional Neural Network model namely ‘rfcn_resnet101_coco’. From Vattiya, et al. (2020), this model provides the best motorcycle detection efficiency in terms of accuracy per detection speed. The example of detection results and the corresponding detection accuracy are illustrated in Table 2.

The accuracy from Table 2 is calculated from a ratio between a number of video frame where the motorcycle detected and the ground truth. It is observed that the average detection accuracy is around 61.31%. This value seems to be mediocre but in fact it trades off with the detection speed. The reason why the model provided the quite low accuracy because among twenty different detection model, ‘rfcn_resnet101_coco’ gave out the highest efficiency. Plus, there were 3 perspective of camera including front view, top view, and back view. The detection model performed best for the top view but we simulated the video as a top view because it is similar to CCTV’s view. Additionally, because the video frame rate is 30 frames per second, this detection accuracy of 61.31% yields around 18 frames per second which are sufficient for a riding pattern detection in the next step.

Table 2. Motorcycle detection result

No	Riding patterns	Detection result	Accuracy
1	Straight		62.5%
2	Weaving (Small curve)		59.2%
3	Weaving (Big curve)		61.1%

No	Riding patterns	Detection result	Accuracy
4	Swerving (Small curve)		61.66%
5	Swerving (Big curve)		62.13%
6	Drifting (Small curve)		60.21%
7	Drifting (Big curve)		62.34%

4.2 Abnormal Riding Pattern Detection

18 videos of abnormal riding and 3 videos of normal riding were experimented on ordinary least square model. The three R-Squared results are given out by normal riding which are 0.9956, 0.9938, and 0.4015 as shown in Table 3. In contrast, weaving with big curve yielded low R-Squared for all three videos. Moreover, the results of R-Squared which are below 0.95 can be classified as abnormal riding patterns. According to Figure 6, when noises or outliners are found, we can see that RANSAC performs better than OLS.

Table 3: R-Squared and RANSAC score

Patterns	R-Squared	RANSAC score
Straight	0.9936	0.9936
Straight	0.9956	0.9956
Straight	0.4015	-1.1884
Weaving(Small curve)	0.3258	0.0878
Weaving(Small curve)	0.8881	0.8572
Weaving(Small curve)	0.6790	0.8537
Weaving(Big curve)	0.0121	-0.7239
Weaving(Big curve)	0.0085	-0.7524
Weaving(Big curve)	0.1158	-0.8548
Swerving(Small curve)	0.9361	0.9352
Swerving(Small curve)	0.9275	0.9256
Swerving(Small curve)	0.7047	0.6050
Swerving(Big curve)	0.5850	0.5101
Swerving(Big curve)	0.6793	0.6542
Swerving(Big curve)	0.8225	0.8004
Drifting(Small curve)	0.7889	0.7087
Drifting(Small curve)	0.7438	0.7124
Drifting(Small curve)	0.7505	0.7689
Drifting(Big curve)	0.9474	0.9124
Drifting(Big curve)	0.9231	0.9268
Drifting(Big curve)	0.9425	0.9336

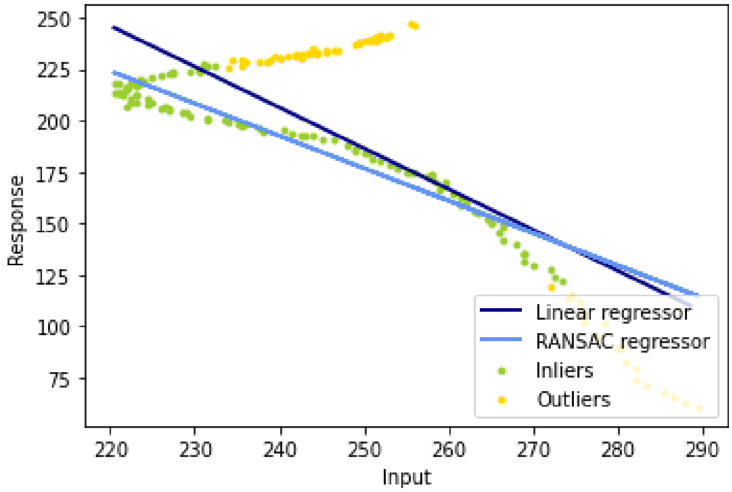


Figure 5. Swerving (Big curve)

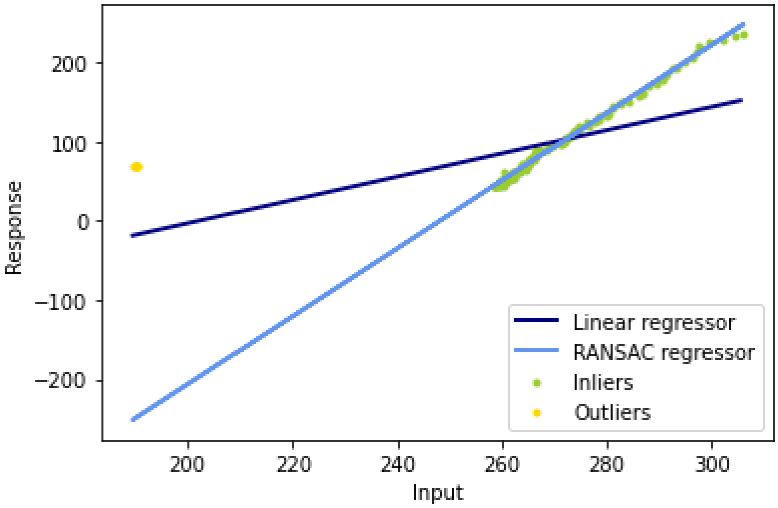


Figure 6. Straight

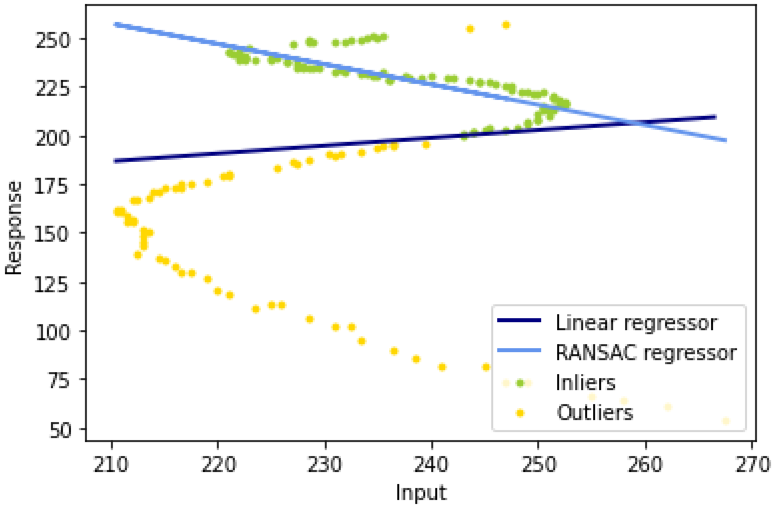


Figure 7. Weaving (Big curve)

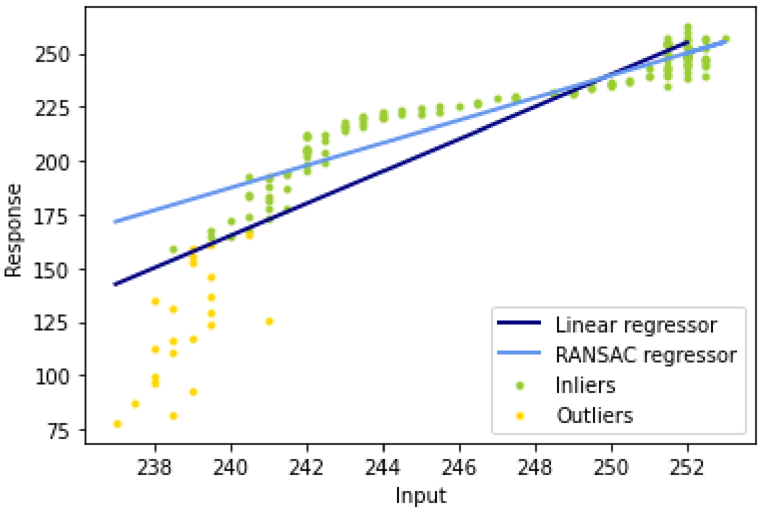


Figure 8. Drifting (Small curve)

DISCUSSION

The results of OLS and RANSAC are quite similar for some riding cases such as straight, swerving (small curve), swerving (big curve), drifting (small curve), and drifting (big curve). According to Table 3, the R-square results of normal riding are 0.9956, 0.9938, and 0.4015 respectively. It is noticeable that why normal riding provided such a very low R-squared of 0.4015, the main problem is noises of unwanted motorcycles. While filming the simulated video, there were some motorcycles parking in the scene and the detection model could also detect them. As a result, the efficiency from OLS was low. To solve the problem, RANSAC was applied to eliminate noises and make the data more fit with the model as shown in

Figure 6. However, there is still a limitation of these two models. The model could not fit well with some riding cases such as weaving. The problem is shown in Figure 7. When the model could be fit, for OLS the result is very low as it should not be so low. For RANSAC, the result is unclear and unexplainable, for example, the result was negative for weaving (big curve) as shown in Table 3. More regression models should be explored for a future work.

CONCLUSIONS

This research focuses on a detection of abnormal riding behaviors of motorcyclists which could lead to road accidents. A normal riding and three risky riding patterns from video footages are chosen and simulated: weaving, swerving and drifting. The detection pipeline consists of 1) motorcycle detection using Convolutional Neural Network and 2) data fitting via linear regression models. Two fitting models were selected which are Ordinary least square (OLS) and Random sample consensus (RANSAC). The results revealed that the normal riding provide a very high regression scores and both linear regression models are efficient to separate the normal riding from the abnormal ones. It is also noticed that RANSAC has a higher robustness than OLS when noises or outliers are found. Nevertheless, there still exist some limitations in this work. First, all video clips are simulated in a single environment. More real traffic videos should be collected and tested. Second, the two chosen linear regression could not fit well with some riding cases especially for weaving. Other regression models must be explored. Finally, though the proposed method seems to be effective to separate normal and abnormal ridings, they should be tested further to see whether they are efficient to classify correctly each case of abnormal riding.

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