



Faculty of Engineering

DEVELOPMENT OF DRIVER DROWSINESS DETECTION ALGORITHM

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Final Year Project Report

Masters

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DEVELOPMENT OF DRIVER DROWSINESS DETECTION ALGORITHM

YVONNE PHUA YEE WUN

A dissertation submitted in partial fulfilment
of the requirement for the degree of
Bachelor of Engineering with Honours
Electrical and Electronics Engineering

Faculty of Engineering
Universiti Malaysia Sarawak

2022

To my beloved God, lecturers, family, and friends.

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ABSTRACT

This project proposes two different non-intrusive approaches to detect driver drowsiness to ensure the safety of the drivers and road users. Psychophysiological-based measurement is not feasible in practice as it causes driving distraction and inconvenience for the drivers by wearing special equipment on the body. Some studies that use computer vision techniques only focus on the eyes to detect drowsiness, which leads to limitations for drivers with smaller eyes and with sunglasses. To contribute to the existing works of driver drowsiness detection systems, this project aims to develop a more useful drowsiness detection algorithm with low complexity and high performance using Python 3.10.1 software. The first proposed method uses facial landmarks to identify blinks and yawns based on suitable thresholds set for the drivers. The second approach applies deep learning methods with three different convolution neural network models, which are modified LeNet-5, MobileNet-V2, and DenseNet-201 to detect drowsiness. Two public video datasets are used to test the proposed algorithms, namely Yawning Detection Dataset (YawDD) and Driver Drowsiness Dataset (D3S). The deep learning approaches perform better than the technique that calculates the eye and mouth aspect ratios to detect drowsiness. The modified LeNet-5 achieved the highest accuracy of 92.22% among the four proposed algorithms. It sets a great benchmark for future work on driver drowsiness detection. This research has provided meaningful solutions to prevent drowsy driving accidents.

ABSTRAK

Projek ini mencadangkan dua pendekatan yang tidak mengganggu pemandu untuk mengesan rasa mengantuk bagi memastikan keselamatan pemandu dan pengguna jalan raya. Pengesanan berasaskan psikofisiologi tidak dapat dilaksanakan secara praktikal kerana ia menyebabkan gangguan dan ketidakselesaan bagi pemandu dengan memakai peralatan khas di badan. Sesetengah kajian yang menggunakan teknik penglihatan komputer hanya tertumpu pada mata untuk mengesan rasa mengantuk. Cara ini membawa kepada pengedaran untuk pemandu yang mempunyai mata yang lebih kecil dan berkaca mata hitam. Untuk menyumbang kepada kerja semasa sistem pengesanan mengantuk pemandu, projek ini bertujuan untuk mengembangkan algoritma pengesanan mengantuk yang lebih berguna dengan kerumitan rendah dan prestasi tinggi dengan menggunakan perisian *Python 3.10.1*. Kaedah pertama yang dicadangkan menggunakan mercu tanda muka untuk mengesan kelip dan menguap berdasarkan ambang yang sesuai untuk pemandu. Kaedah kedua menggunakan teknik pembelajaran mendalam dengan tiga model rangkaian saraf konvolusi yang berbeza, iaitu *LeNet-5*, *MobileNet-V2* dan *DenseNet-201* untuk mengesan rasa mengantuk. Dua dataset video umum digunakan untuk menilai algoritma, iaitu *Yawning Detection Dataset (YawDD)* dan *Driver Drowsiness Dataset (D3S)*. Pendekatan pembelajaran mendalam berprestasi lebih baik daripada teknik yang mengira nisbah aspek mata dan mulut untuk mengesan rasa mengantuk. *LeNet-5* yang diubah suai mencapai ketepatan tertinggi, iaitu 92.22% antara keempat-empat algoritma yang dicadangkan. Ia menetapkan penanda aras yang hebat untuk kerja masa depan pada pengesanan mengantuk pemandu. Penyelidikan ini telah memberikan penyelesaian yang bermakna untuk mengelakkan kemalangan jalan raya.

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LIST OF ABBREVIATIONS

| | |
|-----|-----------------------------------|
| AI | - Artificial Intelligence |
| ANN | - Artificial Neural Network |
| ANS | - Autonomous Nervous System |
| ASM | - Active Shape Model |
| BN | - Bayesian Network |
| CHT | - Circular Hough Transform |
| CNN | - Convolution Neural Network |
| CPT | - Conditional Probability Table |
| CPU | - Central Processing Unit |
| DAG | - Directed Acyclic Graph |
| EAR | - Eye Aspect Ratio |
| ECG | - Electrocardiogram |
| EEG | - Electroencephalogram |
| EMG | - Electromyogram |
| EOG | - Electrooculography |
| ERT | - Ensemble of Regression Trees |
| FFT | - Fast Fourier Transform |
| FN | - False Negative |
| FP | - False Positive |
| FYP | - Final Year Project |
| GPS | - Global Positioning System |
| GPU | - Graphics Processing Unit |
| GUI | - Graphical User Interface |
| HOG | - Histogram of Oriented Gradients |

| | |
|---------|--|
| HRV | - Heart Rate Variability |
| IDE | - Integrated Development Environment |
| IFFT | - Inverse Fast Fourier Transform |
| K-NN | - K-Nearest Neighbor |
| MAR | - Mouth Aspect Ratio |
| MMOD | - Max-Margin Object Detection |
| MTCNN | - Multi-Task Cascaded Convolutional Neural Network |
| NSF | - National Sleep Foundation |
| OSI | - Open-Source Initiative |
| PCA | - Principal Component Analysis |
| PERCLOS | - PERcentage of eyelid CLOSure |
| POM | - Percentage Of Mouth closure |
| ReLU | - Rectified Linear Unit |
| RGB | - Red, Green, Blue |
| RNN | - Recurrent Neural Network |
| ROI | - Region of Interest |
| SDLC | - Software Development Life Cycle |
| SGD | - Stochastic Gradient Descent |
| SOCSO | - Social Security Organisation |
| SVM | - Support Vector Machine |
| TN | - True Negative |
| TP | - True Positive |
| UML | - Unified Modelling Language |

CHAPTER 1

INTRODUCTION

1.1 Background

With an ever-increasing number of vehicles, road accidents have become one of the primary causes of mortalities and injuries in the world. During the Covid-19 pandemic in year 2020, Malaysia recorded 4,006 deaths involving car drivers and motorcycle riders [1]. Aside from fatalities and injuries, road accidents also cause economic loss to a country. The drivers are the most important factor determining road safety. According to statistics from the Social Security Organisation (SOCSO), road accidents involving e-hailing drivers increased due to the expansion of ride-hailing services during the pandemic. Most of the accidents occurred because of drowsiness or fatigue [1].

Driving drowsiness refers to the objective deterioration of driving skills caused by the imbalance of physiological activity after a long period of continuous driving [2]. Thus, people who work night shifts and drive for long distances like e-hailing drivers are more susceptible to drowsiness. A driver with reduced alertness level exhibits different characteristics on his or her body, behaviour, and driving style. Visual characteristics of a drowsy driver include smaller eye openings, slow eyelid movement, longer blink duration, yawning, and frequent nodding. Figure 1.1 illustrates the example of two car drivers who are in drowsiness condition [3].



Figure 1.1: Drivers in drowsiness condition [3]

Exhaustion, lack of sleep, mental stress, and alcohol intake are the main causes of drowsiness [4]. Drowsiness has serious effects on a driver's attention and reaction time on the road, which causes danger to the drivers and road users. Therefore, consistent monitoring and early detection of drowsiness are very crucial to ensure the safety of the drivers and road users.

To create a drowsiness detection system, the drivers' characteristics need to be extracted to determine the drowsiness level. With the advancement of information technology, many image-based driver alertness recognition systems have been developed using computer vision approaches. Computer vision is the technology based on artificial intelligence (AI) to help computers to see and deduce the content of digital images, videos, and other visual inputs. Eyes are the most significant parameter source to detect drowsiness as drowsiness has a strong effect on the eyes [4]-[5]. They are the most prominent and constant facial features compared to the other features on the face. Furthermore, yawning is another common feature for drowsiness detection. When the driver is tired, they continue to yawn to ensure that adequate oxygen is available for the brain's absorption before going into drowsy state.

Although there are significant contributions made by a lot of researchers, the existing driver drowsiness detection methods and algorithms still can be improved in terms of accuracy and efficiency. A more sustainable approach with high accessibility and affordability needs to be studied and implemented to further improve road safety. This project aims to analyse the different drowsiness detection methods used in the previous research, and hence develop a non-intrusive and more effective algorithm to detect driver drowsiness to help in minimising the number of traffic accidents.

1.2 Problem statements

The development of methods and technologies to detect driver drowsiness is a big challenge in the field of accident-avoidance systems. One of the current driver drowsiness detection methods is the vehicle-based measurements. Various vehicle parameters like steering wheel angle, lane tracking, lateral acceleration, and velocity are used to detect drowsiness [4]-[6]. Although the parameters are easily acquired, these measures are sensitive to conditions on the road and surrounding traffic. Other than that, vehicle-based measurement is also limited by several factors such as the vehicle type, geometric aspects, and driver experience [5]-[6]. Driving behaviour is different from one driver to another, so it is difficult to construct a correct driving model to analyse the driver's behaviour to detect drowsiness.

Also, psychophysiological-based measurements involve extensive computation and expensive equipment to monitor a driver's condition on the road [3], [5], [7]. Electrooculography (EOG), electroencephalogram (EEG), electromyogram (EMG), and electrocardiogram (ECG) are the common psychophysiological-based techniques to detect driver drowsiness [5]-[7]. For instance, EEG is used to detect brain waves, using a series of electrodes attached to the scalp. Small voltages from the brain are detected by the electrodes, which provide information about the condition of the driver. Although psychophysiological-based approaches are the most accurate method of detecting drowsiness, the drivers need to wear special equipment on the body. It is impractical as the wirings annoy the drivers and cause inconvenience when driving.

Even though several researchers have used computer vision techniques to construct image-based driver alertness recognition systems, significant issues remain. Some of the studies only focus on the eyes to detect drowsiness, which is insufficient in terms of accuracy. Drowsiness detection based on eyes only leads to limitations for drivers with small eyes and drivers who wear sunglasses. Hence, different computer vision techniques are analysed to determine which techniques are better in detecting drowsiness more accurately. A new drowsiness detection algorithm that is applicable and more effective is then developed.

1.3 Objectives

With the problems in the current driver drowsiness detection methods, this project is done with the following objectives:

1. To analyse different existing methods and algorithms used by researchers to detect driver drowsiness.
2. To develop an effective and non-intrusive driver drowsiness detection algorithm.
3. To validate the proposed driver drowsiness detection algorithm.

1.4 Project significance

Drowsy driving is a common and important public health issue that requires increased attention, education, and legislative measures to preserve lives and prevent disability caused by drowsy driving accidents. During the Covid-19 pandemic, road accidents involving e-hailing drivers, which include the delivery of parcels and food items have increased. Drivers are easily getting into crashed if do not detect any sign of drowsiness before they fall asleep on the road. Therefore, studying an effective and accurate method to identify the dangerous circumstance for a driver in the vehicle is significant.

In this project, computer vision techniques are used for the development of driver drowsiness detection algorithms to help in preventing road safety issues. The use of intrusive methods is prevented to avoid driving distraction. One of the benefits of using computer vision techniques is that facial characteristics are non-invasive visual data. It does not require a high cost to develop a computational algorithm for drowsiness detection. Computer vision techniques also require less processing time compared to psychophysiological methods by processing the raw input images or videos of drivers [8]. In other words, a sleepy driver can be detected quickly using computer vision techniques, which is effective in preventing traffic accidents.

1.5 Project scope

In this project, two different non-intrusive methods are proposed to detect driver drowsiness, which are drowsiness detection based on facial landmarks and drowsiness detection using deep learning. The proposed algorithms combine both eyes and mouth as the detection parameters to improve the accuracy. Firstly, image processing algorithm is used to process the drivers' images for face detection as well as extraction of the eyes and mouth features.

For the first drowsiness detection method, the eyes and mouth aspect ratios are calculated and compared with a fixed threshold value of eyes and mouth for drowsiness detection. The eyes and mouth threshold values are chosen by the heuristic search. For the second method, the modified LeNet-5, pre-trained MobileNet-V2, and pre-trained DenseNet-201 convolution neural network models are utilised to determine driver drowsiness by analysing the whole region of the detected face. The development of the algorithms is done using Python 3.10.1 software. The algorithms are tested on the online-available datasets that contain videos of drivers in cars to validate the results. The performance of the two proposed techniques is also compared with the existing works.

1.6 Relevancy of project

Since driver drowsiness contributes to road accidents, detecting a driver's attention or drowsiness is a very good approach to avoid car accidents. Besides vehicle driving, drowsiness is also the main cause of accidents in situations such as crane operations and mine-blasting.

This project is a hot issue that is still being refined and improved through studies, and it can be used in a variety of areas, such as driver activity tracking and detecting students' attention levels during lectures. Furthermore, the project is also relevant to the field of study for electrical and electronic engineering students as it requires the knowledge in electronic field, which involves image processing and deep learning used in computer vision.

1.7 Report organisation

There are five main chapters in this project report, which are introduction, literature review, methodology, results and discussion, and conclusions. The descriptions of the five chapters are as follows:

Chapter 1: Introduction

This chapter provides the introduction of the project. It includes the research background, problem statements, objectives, project significance, as well as the scope and relevancy of the project. The problem statements describe the limitations of the current methods to detect drowsiness. The objectives explain the goals to be achieved in this work.

Chapter 2: Literature review

The related studies with different techniques used for driver drowsiness detection are explained in Chapter 2. Literature review is done by studying journals, conference papers, and thesis.

Chapter 3: Methodology

This chapter presents the methodology used to conduct the research project. The flowchart of the overall project and Gantt chart for FYP1 and FYP2 are provided.

Chapter 4: Results and discussion

The experimental results or outcomes of the project are provided in Chapter 4. The results are validated by testing the proposed algorithms using publicly available datasets.

Chapter 5: Conclusions

The conclusions which include the contributions and achievements done in this project are explained in Chapter 5. The limitations and future improvements are also discussed.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter discusses the literature review on driver drowsiness detection. The symptoms of a drowsy driver and the overview of driver drowsiness detection systems are first explained. The previous and recent studies related to driver drowsiness detection methods are analysed. The different publicly available datasets, detection parameters, and algorithms used by the researchers are compared. The findings are discussed to select the suitable methods, parameters, and datasets for the development of a new driver drowsiness detection algorithm as an effective measure to minimise road fatalities.

2.2 Symptoms of a driver with drowsiness

According to National Sleep Foundation (NSF), a non-profit charitable organization, there are three different kinds of drowsiness levels as shown in Table 2.1 [9]. A normal driver with no signs of drowsiness is characterised as the one who opens their eyes without yawning. On the other hand, a driver who yawns and blinks frequently is less drowsy. Closed eyelids for more than 1.5 seconds is a symptom of severe drowsiness.

Table 2.1 Level of drowsiness [9]

| Symptoms | Output |
|----------------------------------|-------------------|
| Eyes open and no yawning | No drowsiness |
| Frequent blinking and yawning | Less drowsiness |
| Eyes closed for over 1.5 seconds | Severe drowsiness |

Besides visual characteristics such as smaller eye openings and yawning, a drowsy driver also demonstrates a low velocity of steering wheel movement and poor steering-wheel control [10]. Studies also show that a drowsy driver exhibits an irregular pattern of vehicle tracking on the road. When the level of drowsiness increases, the driver's capability to perceive the surrounding environment, judge the road condition, and control the vehicle will deteriorate.

2.3 Overview of driver drowsiness detection systems

The number of automobiles equipped with Android Auto or Apple Car has increased significantly in recent years. These components are now built-in to many new cars on the market and widely available in lower-cost vehicles as well. With Android Auto and Apple Car, drowsiness detection systems are developed in many Android and iOS platforms. For instance, Audi, Mercedes, and Volvo had offered the drowsiness detection system to analyse a vehicle's motions, including the steering wheel angle, time driven, lane deviation, and road situation. A sound and the appearance of a coffee cup icon are used to alert the drivers when drowsiness is detected. Recently, Samsung has also teamed up with Eyesight on a driver monitoring system to read facial features and patterns to track a driver's concentration [11].

Moreover, a simple camera setup can be utilised using embedded devices or mobile phones paired with the automobile dashboards for driver drowsiness detection. The camera and built-in sensors like accelerometer, gyroscope, microphone, and global positioning system (GPS) help to monitor a driver's behaviour on the road [12]. The examples of Android mobile apps for notifying drowsy drivers are WakeApp and DriveAlert [7]. Figure 2.1 demonstrates the setup of the mobile phone in a car to monitor the state of a driver.



Figure 2.1: Setup of mobile phone in a car for drowsiness detection [13]