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Eye Gaze Detection Using Hough Circle Transform

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Abstract

Driver distraction is one of the main causes of road accidents in Malaysia. There are three types of driver distraction discussed in this paper including visual distraction, manual distraction and cognitive distraction. Each of them is all described different context of distractions. Statistics shows that about 3 death per 10 000 registered vehicles reported by Malaysian Institute of Road Safety Research (MIROS) in 2016. Mercedes Benz, Volvo, Mazda and Lexus have introduced their driver assistant system for their certain models of their cars to monitor the condition of the drivers. The assistant system is a part of main system known as advanced driver assistance systems (ADAS) are systems developed to enhance vehicle systems for safety and better driving. Demand for ADAS is caused by desire to build safer vehicles and roads in order to reduce the number of road accidents and by legislation. However, there are several challenges to design, implement, deploy, and operate ADAS. The system is expected to gather accurate input, be fast in processing data, accurately predict context, and react in real time. Suitable approach is needed to fulfil the system expectation. There are four types of detection including by using physiological sensors, driver performance, computer vision, and hybrid system. So, this paper describes the eye distraction detection using computer vision approach. Our approach aims to determine whether the driver is distracted or not. We proposed two different modules for feature extraction focusing on eye gaze detection and percentage of eye closure (PERCLOS). Both output then will be integrated and combined using SVM classifier.

Keywords: driver distraction; Harr like-features; visual analysis; eye gaze.

INTRODUCTION

Distraction is a situation that prevents individual from concentrating while doing an activity or the state of being bored or annoyed. This situation is also related to a state when the visual concentration of a human interrupted by an event which can affect the current activity. This situation commonly related to some activities which require full concentration such as driving, walking, studying, and reading. Driver distraction is one of the factors contributing to road accidents in Malaysia. The most recent provisional data provided by Malaysian Institute of Road Safety Research (MIROS) reported 6706 cases of road deaths in 2015, in conjunction with Royal Malaysian Police (RMP). Table 1.1 shows the road safety and traffic data from 1990 until 2014 provided by MIROS [1]. In this table, number of fatalities increased year by year from 1990 to 2013 and slightly decreased in 2014. However, the death rate is still high, about 2.7 deaths per 10 000 registered vehicles in 2014 even though the number decreased by 0.2 death per 10 000 registered vehicles from the previous year, as a result of rapid growth in number of registered vehicles.

Table 1: Road safety and traffic data

	1990	2000	2010	2013	2014
Fatalities	4048	6035	6872	6915	6674
Death per 10 000 registered vehicles		5.7	3.4	2.9	**2.7**
Registered vehicles (thousands)		10 599	20 189	23 706	**25 101**

A cross-sectional study is conducted in 2013 by [2] at urban areas of West Malaysia, assessing drivers' conditions in terms of fatigue, sleep quality and risk of Obstructive Sleep Apnea (OSA). The study revealed that out of 130 drivers, 17.7% were found fatigued, 34.7% had poor sleep quality and 14.6% were at high risk of OSA. The study also reveals that medication intake and neck circumference were the most significant factors contributing to fatigue. OSA has also been identified as one of the cause contributing to road accidents.

Therefore, this research focuses on the type of eye distractions which can cause drivers' distractions, hence leads to road accidents. Our approach aims at determining whether the driver is distracted or not and in case the driver is, the system should be able to recognize and warn the driver. Based on the computer vision approach, we propose two different modules for feature extraction focusing on eye gaze estimation and PERCLOS. We propose to combine the output information from each module using SVM classifier

LITERATURE REVIEW

Driver distraction is driving in the meantime engaged in other activities. Driver distraction can lead to serious injuries and fatalities. This will threatens safe driving. Technology that can detect and mitigate distraction is needed to play a central role in maintaining safety by providing drivers with feedback and alerts [3]. Either eye measures or driver performance measures, numerous solutions to detect distraction have been developed. For example, Saab's Driver Attention Warning System AttenD, Volvo's Driver Alert Control, Delphi's SAVE-IT system, Mercedes- Benz's Attention Assist, and Lexus' Driver Monitoring System which are mention in [4] are actually developed to detect distraction based on visual behaviour and driving performance. It is almost the same to Ford Driver Alert, Lane Keeping Warning and Lincoln Driving Alert. In order to develop the driving assistant system, it is important to distinguish the type of driver distraction, method of distraction detection and how to classify the type of distraction.

Type of Driver Distraction

There are three types of driver distraction which are visual distraction, manual distraction and cognitive distraction [5][4][6][7]. Manual distraction indicates a state of the driver takes his hand off the wheel [5][4][6][7]. Visual distraction is the distraction indicates a state when the driver's attention is diverted from the direction [5][4][6] or eyes- off [7] from vehicle travel, such as when not looking forward. Cognitive distraction indicates a state of diminished attention with regards to the driving environment[5] or not fully focused on driving [7] for example conversation with other vehicle occupants and distracting thoughts. Kutila in [8] performed experiments to simulate cognitive distraction by providing tasks (cognitive loads) unrelated to driving to drivers who were driving actual vehicles. The national Traffic Safety Administration (NHTSA) classifies distraction into cognitive distraction, visual distraction, auditory distraction and biochemical distraction from the viewpoint of the driver's functionality[9]. Takatsu Hirayama in [10] focused on cognitive distractions in his study. Cognitive distraction can be considered an internal state of the driver. He also inferred that other distractions are external factors that disturb the activity and can be observe more easily.

Klauer defined driver distraction as being caused by four tasks; driver engagement in secondary task, drowsiness, driving-related inattention to the forward roadway and non-specific eye glance away from the forward roadway. He define the categories of the distractions mentioned in Table 2 [11]. Yuan Liao in [12] has stated that driver distraction competes attention of driver potentially cause awareness of the driver to decrease until to some extend the driving may prone to cause severe car accidents. Cognitive secondary tasks distraction may happen during driving and would competes for cognitive resources with main tasks including talking through a hand-free hand phone, reading auditory e-mails and being lost in thought. Proper distraction like simple conversation can mitigate driving boredom and fatigue. However, driving safety will be threatened when cognitive workload is too high or driving environment changes dramatically[12]

Method of Detection

Regarding on previous works, several methods for detecting distraction have been proposed. The methods fall into the following five categories based on the types of measures such as subjective report measures, driver biological measures, driving performance measures, driver physical measures, and hybrid measures [10]. Every researcher has their own way to measure distraction. Craye in [7] classify the method into 4 main approaches; Physiological sensors, driver performance, computer vision and hybrid system:

Table 2: Categories of the distractions

Tasks	Definitions
Secondary task distraction	Driver behaviour that diverts the driver's attention away from the driving task. This may include talking/listening to hand-held device, eating, talking to a passenger, etc.
Driving-related inattention to the forward roadway	Driver behaviour that is directly related to the driving task but diverts driver's attention away from the forward field of view. This includes reductionists observing drivers checking the speedometer, checking blind spots, observing adjacent traffic prior to or during a lane change, looking for a parking spot, and checking mirrors.
Drowsiness	Driver behaviour that includes eye closures, minimal body/eye movement, repeated yawning, and/or other behaviours based upon those defined by Wierwille and Ellsworth (1994).

Non-specific eye glance away from the forward roadway	Driver behaviour that includes moments when the driver glances, usually momentarily, away from the roadway, but at no discernable object, person, or unknown location. Eye glance reduction and analysis of these events was done for crashes, near-crashes, incidents, and 5,000 of the baseline events

1) Physiological sensors

This approach detect physiological features including brain activity, heart rate variability and skin conductance[13]. In precisely, electrocardiograph (ECG), electroencephalograph (EEG) and electrooculography (EOG) has been found valid, objective and accurate measure of driver inattention. In [13], Li Shiwu used two indicators to identify fatigue level of the driver. Firstly, he used the frequency of brainwave in EEG with different bands to indicate the condition of the driver. Table 2.2 shows the driver conditions presented by different frequency.

Table 3: Driver condition presented by different frequency

Frequency	Rhythm	Driver condition
0-4Hz	Delta, δ	In transition to drowsiness and sleep
4-8Hz	Theta, θ	In variety psychological states including low level of alertness and hypnagogic imagery
8-13Hz	Alpha, α	In relax state
13-20Hz	Beta, β	In alert state

Then, he used ECG to portrait the driver distraction by measuring R-R interval (RRI) of ECG waveform. The RRI indicates the duration of a heartbeat and the standard deviation of RRI can reflect the variability of heart rate. However, this approaches not suitable to be used inside a car for commercial application. They can be used as ground truth for studies but do not represent a practical solution for driver inattention monitoring [7].

2) Driver performance

In this approach, external information and indicators of driver performance are used to deduce the level of inattention[7]. This includes steering movement, drastic speed changes and pedal activities. However, this approach also affected by external factors such as driving environment, driver experiences, road condition and car condition.

3) Computer vision

The third approach currently used by many researchers. This approach relies on visual driver features. Camera is placed in front of the driver and analyzing his face expression and movements makes a lot of sense. It is considered as an efficient way for assessing driver inattention[7]. In [6], percentage of eye closure is used to detect distraction by processing the eye region in the face tracking. The system uses the horizontal projection in the top half-segment of the facial image to extract symptom of distraction and fatigue. Percentage of eye closure and eyelid distance changes are used for fatigue detection and eye closure rate is used for distraction detection.

Another method is using driver gaze and peripheral vehicle behaviour in [10]. Hirayama study the timing of gaze reaction to the overtaking event of other car by host driver. When peripheral vehicle (called the overtaking vehicle) overtakes the host vehicle driven by the driver, a visual change that occurs in front view of the host driver will attract driver's attention. Figure 1 shows the overtaking event.

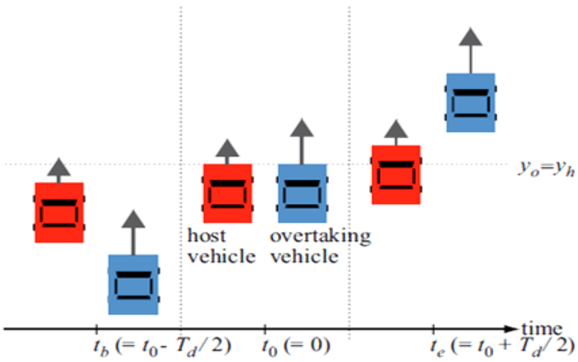


Figure 1: Overtaking event

The event has a base-point, *t0* (= 0), a beginning time *tb* (= *t0* − *Td*/2), and an ending time *te* (= *t0* +*Td*/2). *t0* is the time when the position *yo* of the overtaking vehicle in the direction of forward movement becomes equal to the position *yh* of the host vehicle. Td is the duration of the overtaking event, which is a configuration parameter of the analysis.

Hirayama in [10] define the gaze timing *tg* as the time when the driver gazes toward the overtaking vehicle. A temporal relationship characterizing the gaze reaction to the overtaking vehicle is the time difference between the gaze timing *tg* and the base-point time *t0* of the event. Figure 2 shows the timing structure of the driver's eye gaze towards the overtaking vehicle.

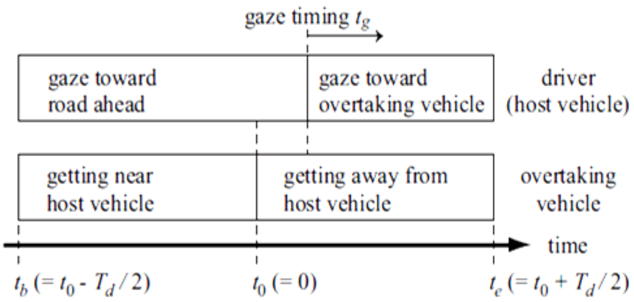


Figure 2: Timing of the driver's gaze towards the overtaking vehicle

4) Hybrid system

Lastly, some of the approaches use a combination of 3 above mentioned techniques. For example, Masahiro in [5] used movement of gaze, heart R-wave in Electrocardiograph (ECG) and head orientation angle to measures distraction shows in Figure 3. Due to the fact that eye and head movement acts synchronise, Masahiro came out the items by measuring the angle of head movement and RRI in ECG (Refer Figure 3) to use for detection of distraction in Table 4.

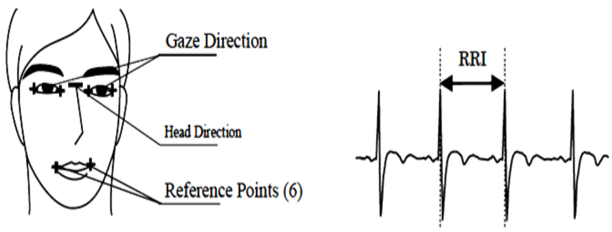


Figure 3: Coordinate system and the ECG waveform

Table 4: Items for head movement and eye glance

Amount of movement of eye position and head position	Right gaze angle : pitch	Standard deviation of combined gaze angle of right eye
	Right gaze angle : yaw	
	Left gaze angle : pitch	Standard deviation of combined gaze angle of left eye
	Left gaze angle : yaw	
	Head orientation angle : pitch	Standard deviation of combined head orientation angle
	Head orientation angle : yaw	
Tracking Quality index	Right eye's gaze tracking quality, average value	
	Left eye's gaze tracking quality, average value	
	Head position tracking quality, average value	

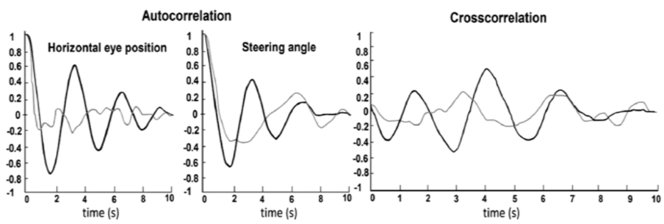


Figure 4: Auto- and cross-correlation functions change with distraction

Meanwhile Yekhshatyan used the different approach in detecting distraction in [4] where the correlation between eye and steering movement used to detect distraction. This approach focused on eye glance behaviour and steering angle. Two parameters define the relationship between the two variables are the magnitude of cross-correlogram peak (CC) and relative timing (TL) shown in Figure 4.

The grey lines represent the non-distracted condition and the black lines represent the distracted condition. The vertical axis is the correlation coefficient (CC) and the horizontal axis is the time lag. However, the relationship between visual behaviour and driver performance measures is not well established since the data collected limited with certain condition such as driving in suburban straight road with certain task as distraction.

As mentioned in section II (*A*), previous researchers have been classified type of driver distraction into three which are:

- Manual distraction
- Visual distraction
- Cognitive distraction

Each type of distraction indicates different level of distraction according to drivers' behaviour. Then, in section II (*B*), four significant approaches have been identified to detect drivers' distractions which are:

- Physiological sensors
- Driver performance
- Computer vision
- Hybrid system

Craye in [7] highlighted the physiological sensors approach suitable to be used as a ground truth for studies, and do not represent a realistic solution for inattention monitoring. Besides, driver performance approach is also correlated with driver inattention monitoring. However, they are affected by external factors such as road type, weather conditions and driver experience.

Then, computer vision and hybrid system are the most popular and efficient approach to assess driver inattention. The suitable approach is needed to be implemented in portable device and reduce the computational time of the system. Hence, the computer vision is the most suitable and practical approach to develop this system.

Therefore, the combination of two methods in computer vision approach is used to detect eye distraction. Both methods rely solely based on visual driver features which are eye activities or movements. The eye gaze detection and percentage of eye closure (PERCLOS) will be used to detect eye distraction.

PROPOSED METHODOLOGY

Throughout the system, there is the flowchart of the whole system. There are four main modules: Face detection, Eye detection, Feature extraction and Classification. Figure 5 shows the flowchart of the whole system.

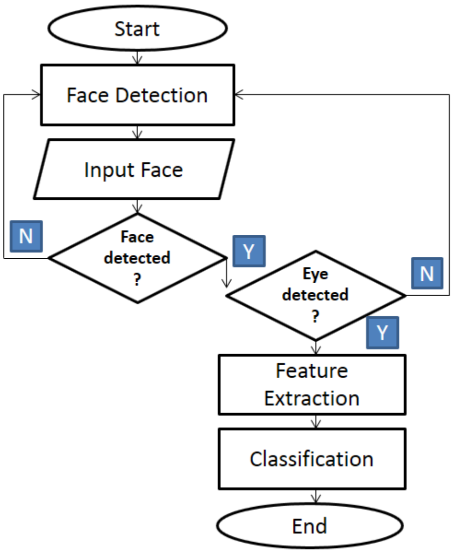


Figure 5: System flowchart

A) Face detection

The existing method introduced by Viola and Jones [14] is used for face and eye detection. A rectangular Haar-like feature can be defined as the difference of the sum of the pixels of area inside the rectangle, which can be at any position and scale within the original image. Each Haar-like feature consists of two or three jointed black and white rectangles. The natural set of fundamental functions which encode the differences in average intensities in different regions. Figure 6 shows the example of rectangle features of Haar wavelets.

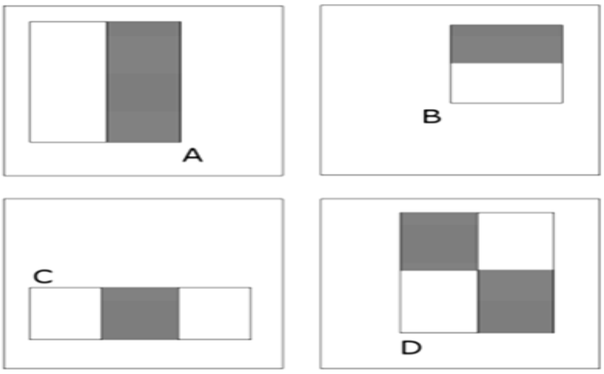


Figure 6: Four different basic types of rectangle feature used to train cascade of classifier comprehensively. Two-rectangle features are shown in A and B. C shows a three-rectangle feature and D a four-rectangle feature.

The value of Haar-like features is demonstrated in equation (1).

$$f(x) = Sum_{black\ rectangle} - Sum_{white\ rectangle} \quad (1)$$

The sum of pixels in the white box is substracted from the sum of pixels in the black areas.

The image acquisition for face detection module is based on the low-cost action camera . The camera was placed in front and adjusted to obtain relevant and clear image of face. The segment of the face is isolated by a square patch with Horizontal projection, HP in image *I* is computed by equation (2).

$$HP\ (j) = \sum_{i=1}^{M}(i,j) \quad (2)$$

Length of *HP* is equal to height, *h* of *l*. Top Half-segment (*h/2*) of facial image, *I* will be used.

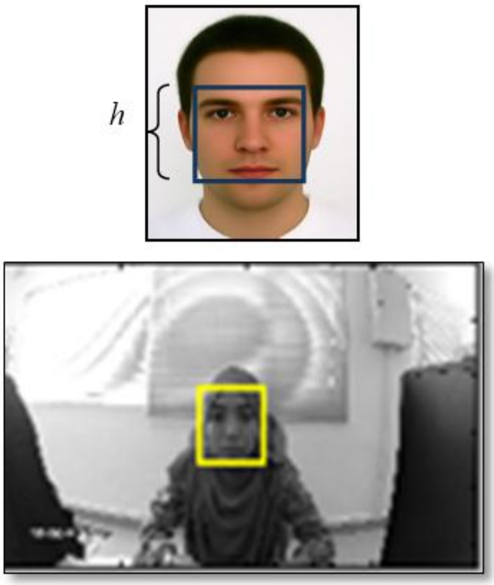


Figure 7: Face detection

B) Eye detection

An efficient eye detection or eye tracking is needed for eye gaze detection. Iris detection relies on finding the eye corners positions. Top Half-segment (*h/2*) of facial image, *I* will be used. We use the iris detection method to isolate the area by creating a square patch of 2/h of the facial image.

The Hough Circle (HC) method is one of the effective algorithm to find circles in images [15]. The foundationa idea of Hough Circle transform is similar to Hough Transform. In Hough Transform,every point in regular 2D space is transformed to a sine-like periodic curve in Hough space as shown in equation (3). A point in (*x*,*y*) is represented by a vector starting from origin with the length *R* and angle, θ.

$$R = x \sin\theta + y \sin\theta \qquad (3)$$

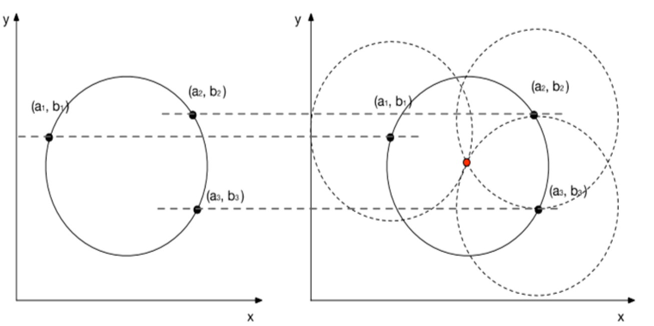


Figure 8: Illustration of Hough Circle Transform

Figure 8 shown the illustration of Hough Circle Transform (HCT). Referring to the Figure 8, three points on a circle with radius R is mark by black dots. By conducting the HCT, each dot on the circles creates a circle in Hough space by finding the intersection of these circles[15]. Hence, the center of the circle in original image can be located (mark as *C*). Practically, the radius R of the circle is unknown. Same goes to the movement of the iris. The center of iris will be located through the intersection. Then, the distance from left and right edge (eye corner positions) from center of iris are obtained and used to estimate the eye gaze.

C) Feature extraction

When iris is detected, a feature set (distance of eye corner position to center of iris) based on eye gaze detection is generated. From eye detection, we extract the iris localization eye, corner positions and gaze detection. All extracted features will be used to classify the distracted and non-distracted eye behaviour.

D) Classification

Through eye corner comparison and Support Vector Machine classifier, produce the result of gaze detection.

RESULT

To verify the validity of the experiment of these algorithms, simple experiment was conducted. Throughout the experiment, same pre-processing and post-processing procedure are applied on the images taken by camera. Figure 9 shows every single step of the process.

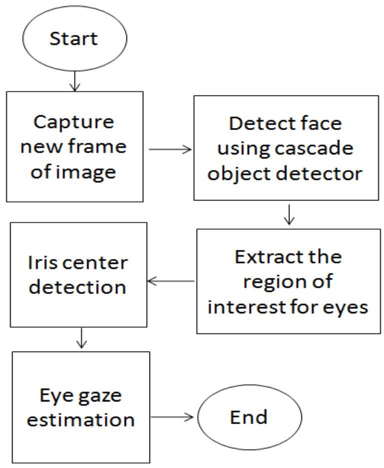
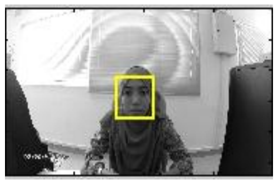


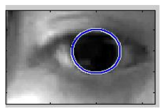
Figure 9: Flowchart of every single step of the process

The outcome is shown in Figure 10. In Figure 10, subfigures 10(a) shows the face is detected in the original image. The original image then sent to the algorithm.



(a) Face detection in original image

(b) ROI of face



(c) The result of eye detection

Figure 10: Result of each single step

Figure 10(b), the face is detected using cascade object detector introduced by Viola and Jones as mention in section III (A). In order to minimize processing speed, each of the face is scaled to the same fixed size regardless of its original size. Then, in Figure 10(c), once the face is detected, the region of eyes can be obtained since the location of eyes and face are fixed. Lastly, using HCT, the eye center can be located and eye gaze can be detected using eye corner position.

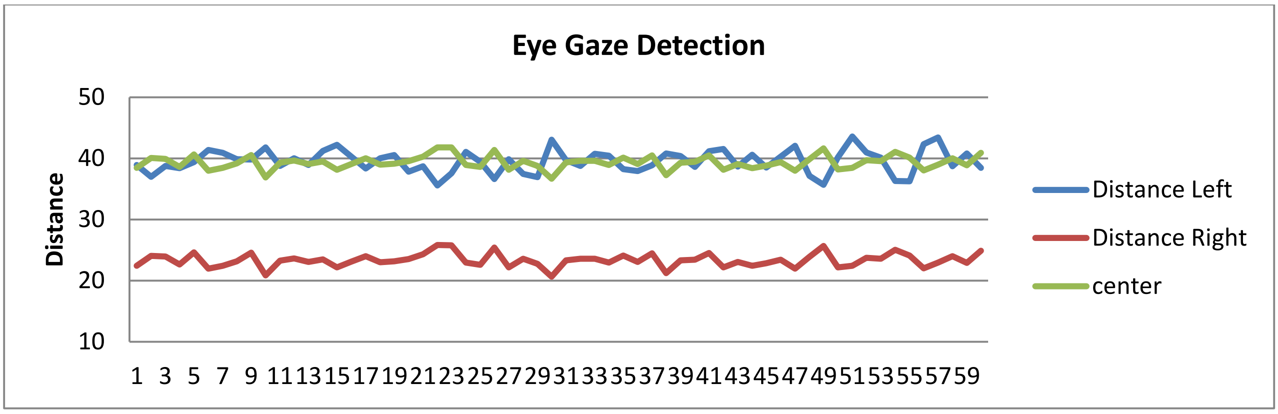


Figure 11: Eye gaze detection

Figure 11 shows the eye gaze detection obtained through an experiment. Distance left and right is the distance of left and right from iris center detection. The result of detection is shown in Table 5.

Table 5: Total eye gaze detection

Eye gaze	Total Detection
Right	32
Left	0
Straight	28

CONCLUSION

We have presented an approach of eye gaze detection using Hough Circle transform. The approach was used to construct face detection at first place and the eye gaze detection. Based on the data collected, the system was able to differentiate the eye gaze.

For future work directions, we believe that eye gaze detection will be able detect driver distraction in term of time taken. The comparison of time taken of normal gaze and abnormal gaze can be used to classify distraction. For example, time taken for a driver to look at handphone is longer than to look at side mirror. Then, the next modules we have designed could allow distraction detection using PERCLOS, nodding and yawning frequencies for example. Lastly, we also plan to combine the modules and compare the results of detection in term of time consumption and accuracy.

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