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Driver Distraction Detection Using Machine Learning Algorithms – An Experimental Approach

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Abstract: Driver distraction is the leading cause of accidents that contributes to 25% of all road crashes. In order to reduce the risks posed by distraction, warning must be given to the driver once distraction is detected. According to the literature, no rankings of relevant features have been presented. In this study, the most relevant features in detecting driver distraction are identified in a closed testing environment. The relevant features are found to be the mean values of speed and lane deviation, maximum values of eye gaze in y direction, and head movement in x direction. After the relevant features have been identified, pre-processed data with relevant features are fed into decision tree classifiers to discriminate the data into normal and distracted driving. The results show that detection accuracy of 78.4% using decision tree can be achieved. By eliminating unhelpful features, the time required to process data is reduced by around 40% to make the proposed technique suitable for real-time application.

Keywords: Driver Distraction, Feature Extraction, Machine Learning, Decision Tree

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1 Introduction

The automotive technology has been developed in an unprecedented rate, which is represented by the fast developing of the technology in electrical, connected and automated vehicles. For automated vehicles, there are six levels of automation. From level 0 to level 2, the drivers are overseeing the vehicle operations. For level 3 (SAE International, 2013), drivers should be prepared to take over the vehicle whenever promoted. In the foreseeable future, most of the vehicles need to have certain level of human intervention during driving. Drivers' states are important to the safety of vehicles when drivers take control of the vehicle. Due to the importance of drivers' state information, vehicles must be equipped with driver monitoring system, which can detect drivers' state.

1.1 Necessity of Driver Distraction Detection

Driver distraction is one of the drivers' states and the leading cause of traffic accidents. NHTSA data shows that 25% of total crashes are caused by driver distraction. The 100-car driving study in natural conditions estimates that 25% to 50% of total crashes are related to driver distraction. (Harbluk and Noy, 2002) With the quick adoption of in-vehicle infotainment system in modern vehicles, driver distraction becomes more common and thus a more serious problem. The driver monitoring system aims at detecting the current drivers' state and reducing the risks of driver distraction. Progress has been made in driver distraction detection field.

1.2 Literature Review

The literature in the driver distraction detection field can be divided into three parts including the driver behaviour in normal driving state, the implementation of experiments to investigate the driver behaviour and the machine learning algorithms to discriminate driver behaviour.

Top-down and bottom-up factors of driving can be used to analyse the driver behaviour during cornering. The bottom-up factors refer to the surrounding environments near the driving scenarios. According to Sodhi (2002), the top-down factors refer to the drivers’ knowledge and driving skills

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There are two kinds of model that could predict driver gaze points during cornering. The first model is that drivers are focusing on the tangent point of the curve (Lappi and Lehtonen, 2012). The second model is about the future path or the far zone of the driving condition. According to the results obtained in corners, the drivers would fix at a certain point that lies at the future path. Driver would decide the steering angle by fixing at the future points. If the visual flow of driver is analysed, it will lie at the future path set by the driver and directions of visual flow would always be straight. Itkonen *et al.* suggests that the tangent point, the occlusion point, the waypoints (future path) is where driver should be looking at during cornering (Itkonen, Pekkanen and Lappi, 2015). The tangent point could be used as a control parameter in determining the visual gaze position of the driver.

There are two types of experimental methods to investigate the driver behaviour, the first method is to conduct the experiment in the real-world driving environment, the second method is to conduct the experiment in the simulated-driving environment. Drivers need to control the vehicle while doing secondary tasks. The secondary tasks include the interaction with in-vehicle infotainment system and mathematical calculations. Li *et al.* (Li, Jain and Busso, 2013) used several secondary tasks in their experiment, which includes the interaction with the GPS, the interaction with the cell phone and talking to the passenger, Similar secondary tasks had been conducted in the experiments of Du *et al.* (Du *et al.*, 2018) Liu *et al.* (Liu *et al.*, 2015) and Ou *et al.* (Ou *et al.*, 2019).The driving simulator is a safe environment to study the behaviour of distracted drivers and could reduce the potential risks caused by distracted drivers.

To detect driver distraction, a wide range of signals are collected in driving experiments for further analysis. The signals are fed into the detection algorithms. The input signals could be divided into three categories: the eye gaze and head related signals (Li *et al.*, 2015), the driving performance measures and driver physiological signals. Kutila *et al.* (Pohl, Birk and Westervall, 2007) estimated the coarse gaze directions and the eye-off-the road glances to driver distraction. Pohl *et al.* (Reyes and Lee, 2008) used the eye-off-the-road and lane deviation to estimate the driver distraction. The change in driver's state will be reflected on the change of driving performance measures. Driving performance measures include the speed, degrees of opening in acceleration pedal, the braking pedal input, the engine turning speed (rpm), the steering angle can be used to detect driver distraction (Khan, Khusro and Alam, 2019).

Decision tree, support vector machine, k-nearest neighbours and logistic regression are all used to detect driver distraction. Decision tree is a simple and efficient algorithm that has been successfully used to detect driver distraction. Support vector machine is the most widely used algorithm with different kinds of kernels to perform best in detecting driver distraction. The k-nearest neighbours (KNN) and logistic regression are two efficient methods to classify the input data. They are non-parametric machine learning algorithms and require less computational resources. The literature (Deshmukh and Dehzangi, 2019) have successfully applied KNN and logistic regression methods to classify the collected data.

1.3 Objectives of This Study

The gap in the literature can be identified as redundant and irrelevant input features, limited selection of algorithms and unreliable or unrealistic testing environments. The eye-gaze related features, driving performance measures are combined to detect driver distraction, however, the large amount of input features contain redundant or irrelevant features. The selection of algorithms is based on prior knowledge, thus the selection of algorithms is limited. The conventional testing environments are in driving simulators and public roads, the driving simulators create unrealistic environment compared to public roads, while on public roads there are too many uncontrollable variables in the experiment.

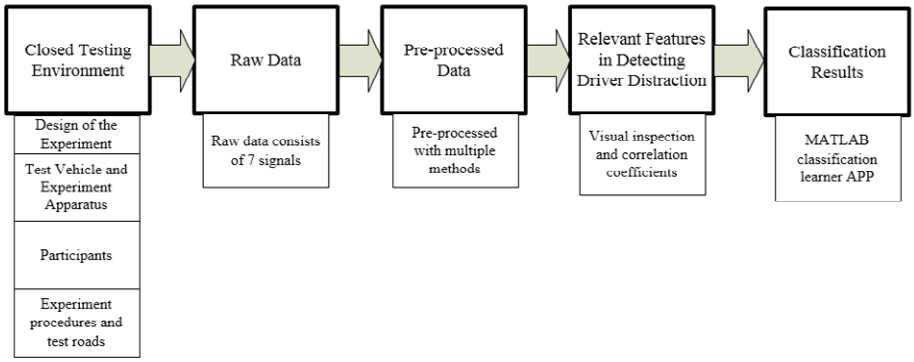
To address the gap in the driver distraction detection research, three objectives will be achieved in this paper. Firstly, reliable normal driving and distracted driving data based on an experiment in a closed testing environment will be collected. Secondly, the most relevant features in detecting driver distraction based on the experimental data will be identified. Finally, driver distraction efficiency will be improved by feeding the most relevant features into a wide range of classification algorithms.

2.Experimental Design and Data Analysis

Experimental techniques, time windows, matrix re-organisation, visual inspection, correlation coefficients and machine learning algorithms are applied together to collect, process and classify the data to detect driver distraction.

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Figure 1 The Schematic Diagram of Collecting, Processing and Classifying Data



A newly established experiment in the closed testing environment is conducted to investigate the driver behaviour in normal driving and distracted driving situations. The raw data consisting of eye gaze and head-related signals, speed, steering angle and GPS data. After the pre-processing of raw signals, visual inspection and relevancy analysis are implemented to extract the relevant features in detecting driver distraction. The algorithms provided by the MATLAB classification learner APP are utilised to classify the pre-processed data. The best algorithm is selected based on highest overall detection accuracies and shortest computation time.

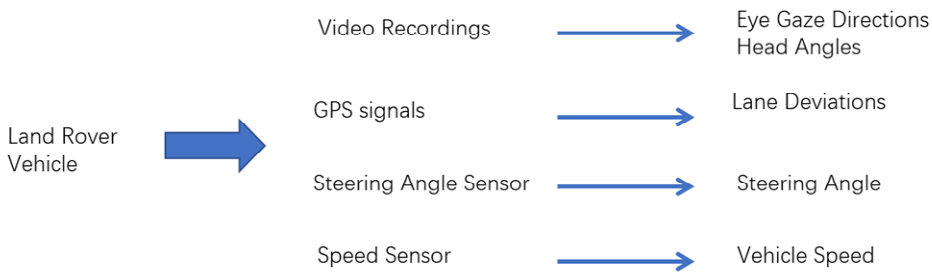
The experiment consists of the design and implementation of the experiment. The design aspect of the experiment includes the installation of apparatus and recruitment of participants. The implementation of the experiment consists of the experiment procedures and routes.

Figure 2 Driving Experiment Car and Measuring Apparatus: (a) test vehicle, (b) camera installed to monitor driver behaviour, (c) data logger device, and (d) measurement signals

(a) (b) (c)



(d)



A Land Rover Discovery 2017 test vehicle is installed with GPS, steering angle sensor, speed sensor, CAN-bus system and a central recording computer. *A dSPACE system is used to integrate the speed, steering angle and GPS channels. The steering angle sensor is placed on the steering column. The GPS system is used to determine vehicle's position and lane deviation.* A Logitech C520 web camera is installed on the windscreen in front of the driver, as shown in Figure 2. In order to make the camera functional, an additional computer placed in the passenger seat is used to record the videos by the Logitech camera. To synchronise between the time series in camera and the time series in vehicle's CAN-Bus system, a LED light is installed beside the B-pillar on driver's side. The LED light is linked to the computer and is set to blink following a certain pattern. The camera could capture the LED's blinks and get to 'know' the time series in the vehicle recording system. By setting the blink patterns, the time series in the two different recording system can be synchronised. To make the data logging process easier, a data logger that could log all the data in one place is suggested to be used

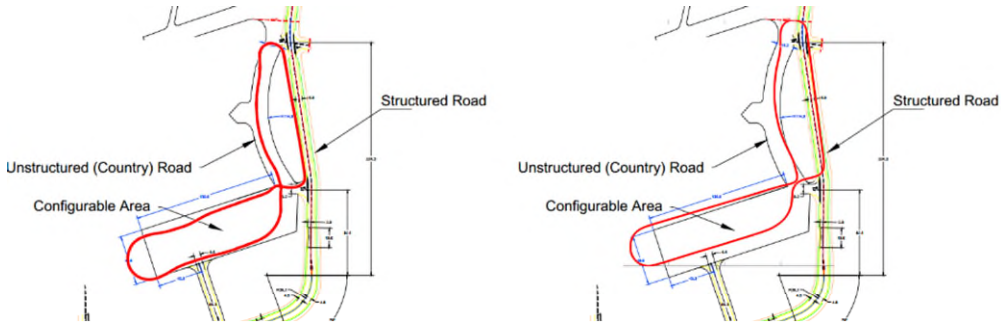
There have been 11 participants participated in the experiment, with 10 male drivers and 1 female driver. All participants are recruited from Cranfield University who have hold valid UK/EU driving licenses and have experiences driving in the UK. The drivers are in the age range of 18 to 40. It should be noted that the data set could be expanded in future studies by covering a wider range of age and also considering more female drivers. A brief introduction was made before the experiment started and the basic operations of the vehicle were also introduced.

There are in total 10 laps recorded for each participant. The first two laps are familiarisation laps, which guide the drivers through the route they will be driving. The second two laps are the start of the experiment and recording

the driver facial movements and driving response measures. The third two laps are cognitive distraction (talking) where the drivers will be talking to the passenger. The following two laps are driving while doing math questions, which is considered as cognitive distracted. Another kind of secondary tasks is texting, which is considered as manual distraction, completed between lap 9 and 10.

The secondary tasks in this experiment include talking to passenger, answering math questions and texting messages. The cognitive distraction tasks are questions asked by the experimenter in terms of questions in everyday life and double-digit calculations. The manual distraction task is texting. In order to analyse the impact of secondary tasks on driver behaviour, relevant measurements have been recorded. Parameters extracted from different signals could be used to analyse the impact of secondary tasks performed by participants.

Figure 3 The Two Routes in the Experiments (Left and Right)



The MUEAVI testing ground (Cranfield University, 2019), known as the multiuser environment for autonomous vehicle innovation, will be the primary testing environment for the experiment. Having been closely located in the Cranfield University, the MUEAVI testing ground provides the perfect environment for testing the driver behaviour due to its closed and flexible driving environment. The traffic, traffic signal and lane choice can be easily controlled in this testing ground, reducing the uncontrolled variables of the experiment. Additionally, the road layout of the MUEAVI allows for flexibly configuration of the experiment route. Two different routes are designed in the experiment to reduce predictability of the test scenarios by the participants. There will be two lane changes, a roundabout negotiation and curved driving during the testing, mainly for the purpose of analysing the driver behaviour in a controlled environment.

Figure 3 demonstrates the vehicle driving routes during the experiments. At first drivers would drive on the curved road in the 'unstructured' area. Before entering the configurable area, drivers negotiate a roundabout, which indicates the direction, which either signals straight or left. When the traffic signal indicates left, the driver would turn left, which is shown in the left figure. The test route is shown in the left part of Figure 3. When the traffic signal indicates right, the driver would go straight, as indicated in the right figure. In the configurable area, drivers would do a double lane change. In the next stage, drivers leave the configurable area and enter the structured road. Vehicle returns to starting point after turning left in the end of the structured road.

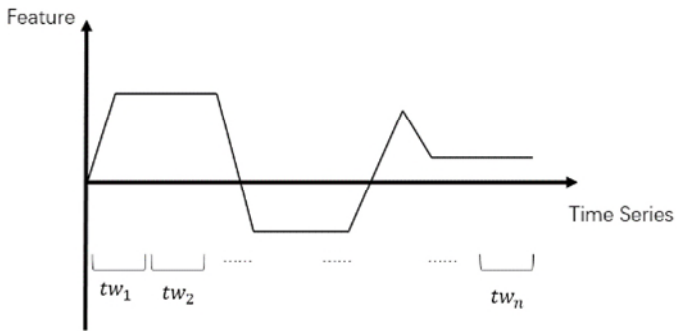
3. Pre-processing of Collected Data

The pre-processing of raw data includes the feature extraction, matrix reconstruction and relevancy analysis. In the feature extraction stage, time windows are applied, the feature within each time window is extracted. In the matrix construction stage, the features are assembled together, and data are labelled according to the type of distraction (no distraction included). Since relevancy analysis is an important aspect of this paper, it will be discussed individually.

The feature extraction is based on time window. Time windows whose lengths are 0.1, 0.2, 0.5, 1, 2, 5 and 10 seconds are applied to extract mean, maximum, minimum and standard deviation values of 7 signals within each time window. The 7 signals are eye gaze in x and y direction, head movement in x and y direction, speed, steering angle and lane deviation.

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Figure 4 The Time Windows in Pre-processing Stage



The new mean, maximum, minimum and standard deviation values of time windows are fitted together to construct new matrix, which is shown below:

$$\begin{bmatrix} Feature\,1 & Feature\,2 & \cdots & Feature\,n & Label \\ TW_{11} & TW_{21} & \cdots & TW_{n1} & 0 \\ TW_{12} & TW_{22} & \cdots & TW_{n2} & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ TW_{1x} & TW_{2x} & \cdots & TW_{nx} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ TW_{1m} & TW_{2m} & \cdots & TW_{nm} & 1 \end{bmatrix}$$

The matrix above demonstrates an example of input matrix. The input matrix is constructed using values extracted from signals by time windows. The matrix is labelled after the values of input features are determined and put into positions. The features in the input matrix is selected by the most relevant features in detecting driver distraction.

21 input matrices are obtained after feature extraction and matrix construction. There are eight different lengths of time windows and three different types of distraction. For each type of distraction and each length of time windows, there is a separate input matrix generated using the input matrix construction method. Relevant features are selected.

4. Identification of Relevant Features for Driver Distraction Detection

Relevant features are being identified by visual inspection and correlation coefficients. Identification and application of most relevant features are

important in improving driver distraction detection efficiency. The results obtained from visual inspection are validated by results from correlation coefficients.

4.1 The Motivation of Feature Rankings

Feeding the most relevant features into algorithms will improve the detection efficiency. Conventionally all available features are fed into detection algorithms to improve the detection accuracy. However, the input features may contain redundant and irrelevant features, which will slow the detection process down. Since timely warning should be given to drivers, efficiency of driver distraction must be improved.

4.2 The Methods used in the Relevancy Analysis

Visual inspection and correlation coefficients are used to identify the relevant features in detecting driver distraction. Visual inspection identified the relevant features with largest differences between normal driving and distracted driving. Relevant features are identified with largest average correlation coefficients.

Visual inspection is suitable for spotting the differences between objects. By plotting the features versus time of normal driving and distracted driving, the differences of features can be spotted and identified. Relevant features are identified when large differences are spotted. Irrelevant features have small differences between normal driving and distraction driving features.

Figure 5 The Comparisons between Features in Normal Driving and Distracted Driving Sections

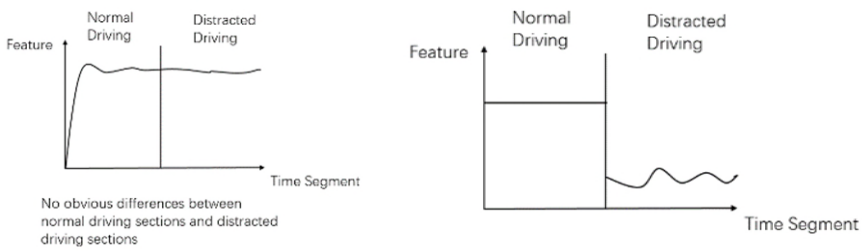


Figure 5 demonstrates two situations in the comparisons between normal driving and distracted driving. From the left figure, it can be seen that there are no obvious differences between normal driving sections and distracted

driving sections. Since the difference between the two sections is minor, the feature is considered to be irrelevant in detecting driver distraction. The right figure demonstrates another situation that distinct features are spotted between normal driving and distracted driving sections. This feature is considered to be relevant in detecting driver distraction This feature is determined as a relevant feature for detecting driver distraction when the difference between the normal driving and the distracted driving sections is significant.

Correlation coefficients are used to assess the relevancy between variables. It can also be used to identify the relevant features in detecting driver distraction since they have higher correlation coefficient. Pearson correlation coefficient is the conventional way of estimating correlations between variables. Since one of the variables is binary (the distraction level), point-biserial correlation instead of Pearson's correlation is used. The equation to calculate the correlation is:

$$r_{pb} = \frac{M_1 - M_0}{S_n}\sqrt{\frac{n_0 n_1}{n}} \quad \textbf{(1)}$$

where r_{pb} is the correlation coefficients, Sn is the standard deviation of x, M_1 is the mean value of group that binary value equals to 1, the M_0 is the mean value of group that binary value equals to 0, n_1 is the number of points in group that binary value equals to 1, n_0 is the number of points in group that binary value equals to 0.

The point-biserial correlation is suitable for calculating the relationship between a continuous variable and a binary variable. Therefore, point-biserial variable is used to estimate the relevancy between the features and distraction.

4.3 The Results of Relevancy Analysis

After the experiment, there are 7 signals extracted from CAN-Bus and video recordings including eye gaze in x and y direction, head movement in x and y direction, steering angle, speed and lane deviation. For each signal, there are 4 statistical features associated to it. In total, there are 28 features. Each feature is identified as either relevant or irrelevant in detecting driver distraction. There are 7 subplots corresponding to 7 features in figures that are used to identify the relevant features. In each subplot, the four sections represent four drivers' states, which are normal, cognitive distraction (talking), cognitive distraction (math) and manual distraction. After features

have been examined by visual inspections, the total number of relevant/irrelevant features are counted and then the most relevant features can be determined. In addition, correlation coefficients are used to validate the results obtained by visual inspection. Visual inspection and correlation coefficient methods are both applied to identify the most relevant features in detecting driver distraction.

Figure 6 The Comparisons of Mean Values between Normal Driving and Different Types of Distracted Driving for a Specific Driver

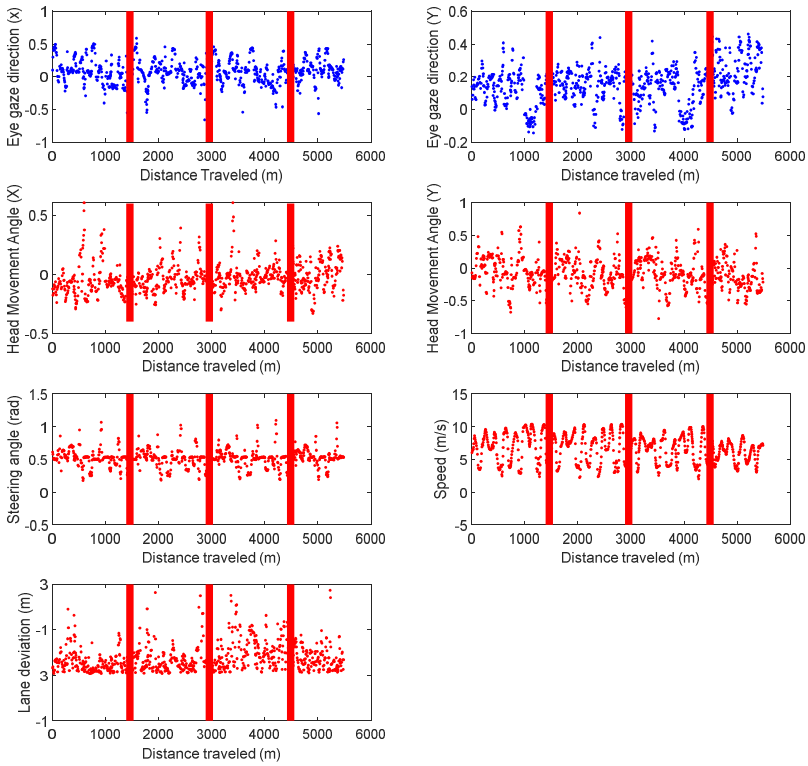


Figure 6 demonstrates the mean values of seven different features of normal driving and distracted driving. Three vertical lines separate four sections; from left to right: normal driving, cognitive (talking) distracted driving, cognitive (math) distracted driving and texting distracted driving sections respectively. The eye gaze in x direction is relevant in detecting driver distraction, the eye gaze distribution in x direction appears to be denser

when the driver is cognitive distracted and texting. The eye gaze in y direction is also relevant in detecting distraction, suggesting that the driver is looking more upwards during distraction. The head movement in x direction is relevant in detecting driver distraction. The results from it indicate that the driver spent more time keeping the head still when cognitively distracted and looking upwards and downwards when texting. The steering is not related in distraction detection since they have similar patterns of steering across different types of distraction. The speed is relevant in distraction detection since speed is reduced when the driver is distracted. Finally, the lane deviation is related to cognitive distraction since there are more deviations from normal position when the driver is cognitively distracted.

Table 1 The Results from Visual Inspection, Correlation Coefficients and Identified Relevant Features

Results identified by visual inspection	Results identified by correlation coefficients	Common relevant features
Mean values of speed and lane deviation	Mean values of head in x direction, speed and lane deviation	Mean values of speed and lane deviation
Maximum values of eye in x direction, head in y direction, speed and lane deviation	Maximum values of eye gaze in y direction, head in x direction, speed and lane deviation	Maximum values of eye gaze in y direction, head in x direction, speed and lane deviation.
Minimum values of head in y direction	Minimum values of speed and lane deviation	

The identified features are mean values of speed and lane deviation, maximum values of eye gaze in y direction, head in x direction, speed and lane deviation.

5. Driver Distraction Detection using Decision Tree Method

The pre-processed data are fed into MATLAB classification learner APP to detect driver distraction. The most suitable classifier is selected, the results are analysed.

5.1 The Selection of Algorithms and Main Idea of Decision Tree

The algorithms that are used in this study, are selected from the MATLAB classification toolbox. There are 25 classifiers built in the APP. While many of them are not suitable for detecting distraction, it becomes a priority to select the appropriate algorithms to detect driver distraction.

The ideal algorithm has fast detection speeds without compromising the detection accuracy. The most suitable algorithm among the 25 algorithms built in the app can be found by feeding all features into the APP and examine the detection accuracies and computation times for each algorithm. This is a trial and error process. 25 algorithms built in the APP are tested. The classifiers with the best overall performances are selected.

Table 2 The Detection Accuracy and Computation Time for 5 Types of Algorithms

Algorithm Name	Detection Accuracy (%)	Computation Time (s)
Decision Tree	83.5	2.5857
Logistic regression	71	2.8099
Support Vector Machine (Fine Gaussian)	83.9	10.102
Ensemble Decision Tree (Bagged)	89.2	7.8554
Ensemble KNN (Ensemble, subset)	85.7	31.148

From the figure above it can be seen that decision tree is the best algorithm that achieves a balance between accuracy and time. For example, the result from logistic regression method has similar computation time, but the detection accuracy has reduced. The result from support vector machine and ensemble methods show that algorithm detection accuracy has been improved, the computation times have also increased. In conclusion, decision tree is the optimum algorithm used to detect driver distraction.

The decision tree is a supervised classification/regression method. It can be used to discriminate the data into several different classes. The name of the decision tree is given for its tree like structures. It can be regarded as clusters of if-then rules. It can be also regarded as the distribution of probabilities of features pace. The decision tree is constructed based on the assumption of

smallest loss function. The main concepts of decision tree come from the ID 3 and C4.5 algorithms by Quinlan and CART algorithms by Breiman.

5.2 Classification Results by Decision Tree Method

The collected data is pre-processed with 0.1-second, 0.2-second, 0.5-second, 1-second, 2-second, 5-second and 10-second time window. After the data are extracted based on the time windows, the labels are added into the input matrix.

The size of the time window, the number of input features and the algorithms used will influence the detection results. The time window applied in this analysis are 0.1-second, 0.2-second, 0.5-second, 1-second, 2-second, 5-second and 10-second time window. The number of input features are 28 and 6 and the classification algorithm used to classify the collected data is decision tree. The detection results are listed in Table 3, Table 4, Table 5, each table for one kind of distraction.

Table 3 The Detection Accuracies for Manual Distraction

Time Window (s)	Accuracy (%)	Computation Time (s)	Number of features used
0.1	76.2	3.7632	28
0.1	73.5	0.6872	6
0.2	74.9	2.1119	28
0.2	71.6	0.85501	6
0.5	83.4	1.1548	28
0.5	78.4	0.6872	6
1	72.1	0.83452	28
1	69.7	0.56181	6
2	69.0	0.61491	28
2	68.3	0.48463	6
5	67.1	0.46611	28
5	66.8	0.49611	6

10	65.9	0.43124	28
10	57.0	0.44041	6

Table 3 shows the detection accuracies when the driver is manually distracted. When 0.1-second, 0.2-second and 0.5-second of time windows are applied, the detection accuracies are 76.2%, 74.9%, and 83.4% respectively when the number of input measures are 28. When the 1-second, 2-second, 5-second and 10-second time windows are applied, the detection accuracies are 72.1%, 69%, 67.1% and 65.9% respectively. For 0.1, 0.2, 0.5, 1, 2, 5 and 10-second time windows, the detection accuracies are 73.5%, 71.6%, 78.4%, 69.7%, 68.3%, 66.8% and 57% respectively when the number of input features are 6.

Table 4 The Detection Accuracies for Cognitive Distraction (Math Questions)

Time Window (s)	Accuracy (%)	Computation Time (s)	Number of features used
0.1	69.5	3.3465	28
0.1	68.1	3.6614	6
0.2	69.3	2.5117	28
0.2	66.3	0.86116	6
0.5	76.8	1.2442	28
0.5	73.8	0.6667	6
1	62.5	0.85749	28
1	63.7	0.58767	6
2	61.3	0.65802	28
2	62.5	0.53461	6
5	59.5	0.48528	28
5	56.8	0.47801	6
10	58.9	0.49678	28
10	58.3	0.45234	6

Author

Table 4 shows the detection accuracies when the driver is cognitive distracted (math questions). When no time window is applied in the pre-processing stage, the highest detection accuracy of manual distraction is 89.1% with all available input features. When 0.1-second, 0.2-second, 0.5-second, 1-second, 2-second, 5-second and 10-second time windows are applied, the detection accuracies are 69.5%, 69.3%, 76.8%, 62.5%, 61.3%, 59.5% and 58.9% respectively when the number of input measures are 28. The detection accuracies are 68.1%, 66.3%, 73.8%, 63.7%, 62.5%, 56.8%, 58.3% for 0.1, 0.2, 0.5, 1, 2, 5 and 10-second time windows respectively when the number of input features is 6.

Table 5 The Detection Accuracies for Cognitive Distraction (Talking)

Time Window (s)	Accuracy (%)	Computation Time (s)	Number of features used
0.1	65.2	3.3464	28
0.1	60.8	1.169	6
0.2	63.7	3.6882	28
0.2	61.3	0.96749	6
0.5	61.2	2.6433	28
0.5	58.3	0.74888	6
1	60.7	2.1822	28
1	56.3	0.68996	6
2	55.4	0.70455	28
2	55.2	0.51879	6
5	55.4	0.53592	28
5	52.7	0.4872	6
10	58.6	1.5212	28
10	53.9	0.54317	6

Table 5 shows the detection accuracies for cognitive distraction induced by talking. When 0.1-second, 0.2-second, 0.5-second, 1-second, 2-second, 5-second and 10-second time windows are applied, the detection accuracies are 65.2%, 63.7%, 61.2%, 60.7%, 55.4%, 55.4%, 58.6% respectively when

the number of input measures are 28. The detection accuracies are 60.8%, 61.3%, 58.3%, 56.3%, 55.2%, 52.7%, 53.9% for 0.1, 0.2, 0.5, 1, 2, 5, 10-second time windows respectively.

5.3 Results Analysis

The detection results using decision tree can be further analysed by plotting the accuracy and computation time versus lengths of time windows.

Figure 7 Detection Accuracy and Time for Manual Distraction

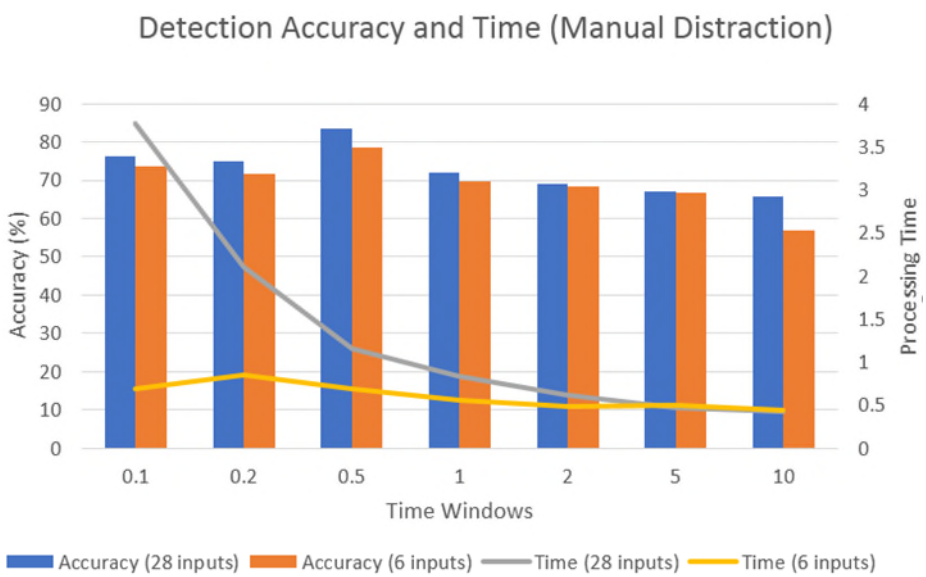


Figure 7 demonstrates the detection accuracy and computation time for manual distraction using decision tree method. The time windows, shown in x axis, ranges from 0 (no time window) to 10 seconds. The processing time, shown in yellow and grey lines for 28 and 6 inputs, have reduced with the increase of time window sizes. The detection accuracies, shown in blue and yellow bars, have reduced with the increase of time windows. The only exception is the detection accuracy of 0.5-second time window, which increases compared to detection accuracy of 0.2 and 1-second time window. With reduced processing time compared to 0.2-second time window, the detection of driver distraction achieves higher accuracy using 0.5-time window. Comparing the detection accuracy and processing time of 28 and 6 inputs, it can be seen that processing time reduces significantly when 0.1-

second time window is applied when the number of input feature is 6. In other cases, the processing time generally decreases for increasing time windows.

Figure 8 Detection Accuracy and Computation Time for Cognitive distraction Induced by Doing Math Questions

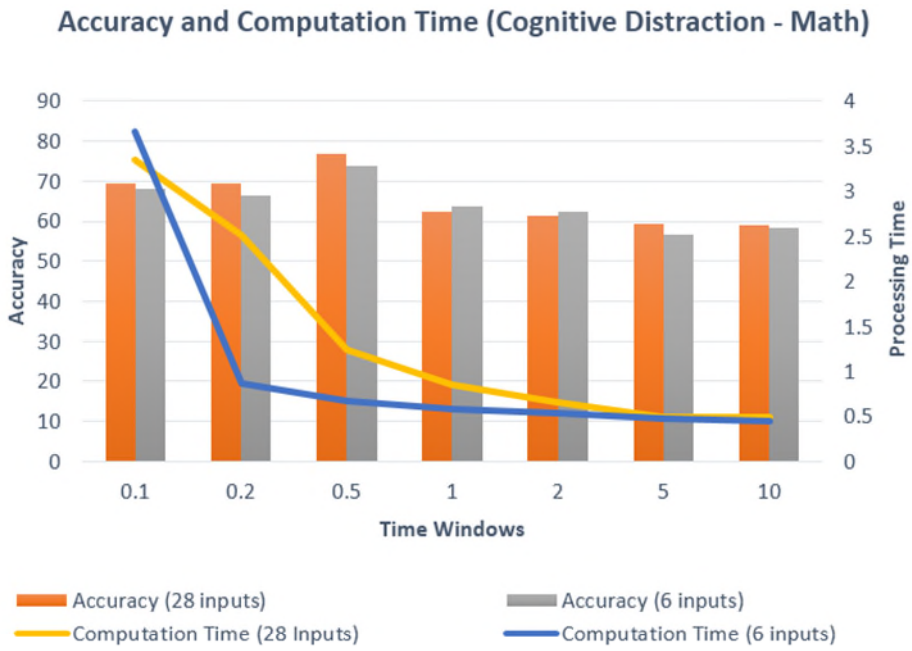


Figure 8 demonstrates the detection accuracy and processing time of cognitive distraction induced by doing math questions. The red and grey bars are showing the detection accuracies. The blue and yellow lines are showing the computation time. The x-axis is the time windows, which ranges from 0.1-second to 10-second time window. The results show that detection accuracy generally decreases with the increase of time windows. The only exceptional case is the increased detection accuracy when 0.5-second time window is applied. For the computation time, it generally decreases with the increasing time windows, except the sharp increase of processing time when 0.1-second is applied.

Figure 9 Detection Accuracy and Processing Time for Distraction Induced by Talking

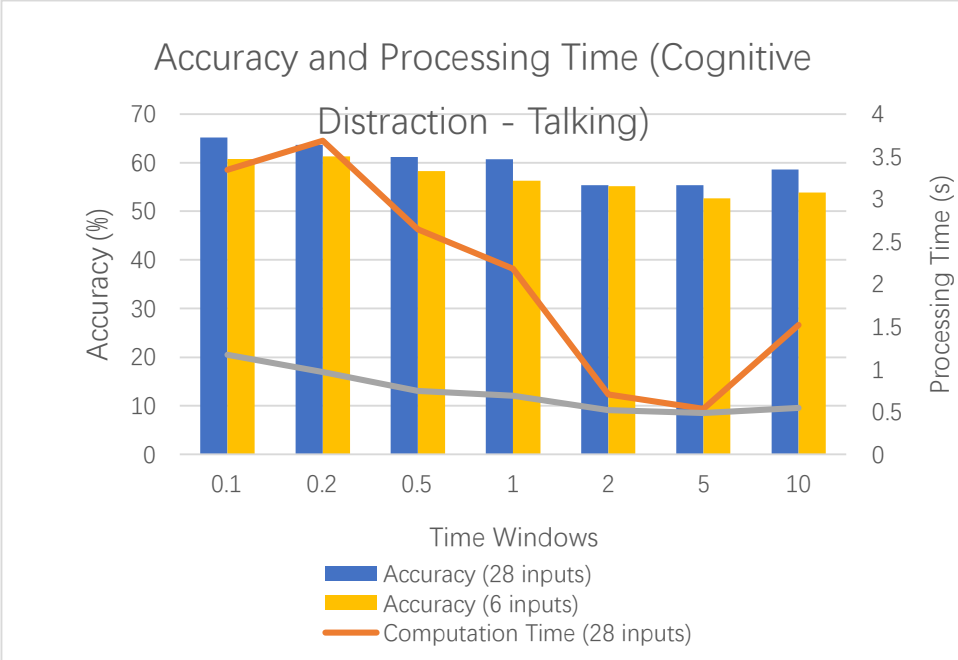


Figure 9 demonstrates the accuracy and processing time for distraction induced by talking. The blue and yellow bar demonstrates the detection accuracy when the number of input features are 28 and 6. The grey and orange line shows the processing time with 28 and 6 input features. The detection accuracies generally decrease with the increasing time window sizes. However, the processing time with 28 input features increase at first when the time window size increases from 0.1 to 0.2 seconds, whose values are exceptionally high. The processing time with 6 input features decreases with the increasing time window sizes.

6. Conclusions

An experimental approach was used to identify the most relevant features in detecting driver distraction and verify the usefulness of them according to the detection results. It cam out that the relevant features are mean values of speed and lane deviation, maximum values of eye gaze in y direction, and head movement in x direction. High detection accuracies can be achieved using these features and suitable machine learning algorithms.

The highest detection accuracies are 78.4%, 73.8% and 61.3% for distraction induced by texting, answering math questions and talking to

passenger respectively. Six input features were used in combination with the decision tree as the detection algorithm. The identified features were mean values of speed and lane deviation, maximum values of eye gaze in y direction, head in x direction, speed and lane deviation.

The study of relevant features can be applied to improve detection efficiencies. As presented in Table 3, the detection accuracy using 0.5-second time window is reduced by 5%, when the number of input features is reduced by 22. The 5% reduction is acceptable for the reason that the processing time is reduced by 0.4676 seconds or 40%. The result demonstrates that by inputting the relevant features, the number of input features needed in classification algorithms could be reduced while the detection accuracies are generally not compromised. In addition, it was concluded that 0.5-second time window is the most suitable choice to process the data when the driver is distracted manually cognitively by doing mathematical calculations. On the other hand, 0.2-second time window was concluded to be suitable to process the data when the driver is cognitively distracted by talking. As shown in Table 3, after applying the 0.5-second time window, the detection accuracy is reduced by 5% while the time required to process the data is reduced by 40% to 0.6872 seconds. When the 0.2-second time window is applied to the data of cognitive distraction induced by talking, the detection accuracy is reduced by 2.4% while the time required to process the data is reduced from 3.69 to 0.69 seconds.

Finally, the best combination of the relevant input features and the detection algorithms to achieve the highest detection accuracy were studied by trying various configurations. As a result, the most relevant features were fed into the most suitable detection algorithms to achieve maximum detection accuracy of 78.4%. This level of accuracy can be potentially improved even more if more computational time is allowed. However, considering the detection time and number of input features needed, a detection system with an accuracy of 78.4% is capable of giving timely warning to the driver in real-time. To further increase the detection accuracy, a larger training dataset with more experimental data will be useful. In addition, alternative methods such as deep neural networks could potentially increase the detection accuracy.

Compared to the standards such as ISO 26022 and ISO 16673:2007, which use the driving simulator as their primary test environment, the method proposed in this paper utilises a real word driving environment. An updated version of those standards can be potentially developed based on a closed-testing environment.

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References

Cranfield University (2019) *Multi User Environment for Autonomous Vehicle Innovation (MUEAVI)*. Available at: https://www.cranfield.ac.uk/facilities/mueavi (Accessed: 25 January 2020).

Deshmukh, S. V and Dehzangi, O. (2019) *Characterization and Identification of Driver Distraction During Naturalistic Driving : An Analysis of ECG Dynamics*. Springer International Publishing. doi: 10.1007/978-3-030-02819-0.

Du, Y. *et al.* (2018) 'Multimodal Polynomial Fusion for Detecting Driver Distraction', *arXiv preprint*.

Hansen, J. H. L. *et al.* (2017) 'Driver Modeling for Detection and Assessment of Driver Distraction: Examples from the UTDrive Test Bed', *IEEE Signal Processing Magazine*, 34(4), pp. 130–142. doi: 10.1109/MSP.2017.2699039.

Harbluk, J. L. and Noy, Y. I. (2002) 'The Impact of Cognitive Distraction on Driver Visual Behaviour and Vehicle Control', *Forum American Bar Association*, 13889(03/08), p. 19. Available at: http://www.elmar-inc.com/Papers/Driving/DriverCellPhone.pdf.

Itkonen, T., Pekkanen, J. and Lappi, O. (2015) 'Driver gaze behavior is different in normal curve driving and when looking at the tangent point', *PLoS ONE*, 10(8), pp. 1–19. doi: 10.1371/journal.pone.0135505.

Khan, I., Khusro, S. and Alam, I. (2019) 'Smartphone Distractions and its Effect on Driving Performance using Vehicular Lifelog Dataset', *2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*. IEEE, (July), pp. 1–6.

Lappi, O. and Lehtonen, E. (2012) 'Tangent Point Orientation and Anticipated Trajectory Curvature - A Field Study on the Visual Control of High Speed Steering', *CogSci 2012*, pp. 1846–1851.

Li, N. *et al.* (2015) 'Predicting Perceived Visual and Cognitive Distractions of Drivers With Multimodal Features', *IEEE Transactions on Intelligent Transportation Systems*. IEEE, 16(1), pp. 51–65. doi: 10.1109/TITS.2014.2324414.

Li, N., Jain, J. J. and Busso, C. (2013) ‘Modeling of driver behavior in real world scenarios using multiple noninvasive sensors’, *IEEE Transactions on Multimedia*. IEEE, 15(5), pp. 1213–1225. doi: 10.1109/TMM.2013.2241416.

Liu, T. *et al.* (2015) ‘Driver Distraction Detection Using Semi-Supervised Machine Learning’, *IEEE Transactions on Intelligent Transportation Systems*, 17(4), pp. 1108–1120. doi: 10.1109/TITS.2015.2496157.

Ou, C. *et al.* (2019) *Design of an End-to-End Dual Mode Driver Distraction Detection System*. Springer International Publishing. doi: 10.1007/978-3-030-27272-2.

Pohl, J., Birk, W. and Westervall, L. (2007) ‘A driver-distraction-based lane-keeping assistance system’, *Journal of Systems and Control Engineering*, 221, pp. 541–552. doi: 10.1243/09596518JSCE218.

Reyes, M. L. and Lee, J. D. (2008) ‘Effects of cognitive load presence and duration on driver eye movements and event detection performance’, *Transportation Research Part F: Traffic Psychology and Behaviour*. Elsevier Ltd, 11(6), pp. 391–402. doi: 10.1016/j.trf.2008.03.004.

SAE International (2013) ‘Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles’, *SAE International*, p. 30.

Sodhi, M. *et al.* (2002) ‘On-road driver eye movement tracking using head-mounted devices’, *Proceedings of the symposium on Eye tracking research & applications - ETRA ’02*, p. 61. doi: 10.1145/507072.507086.

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