Lane Change Behaviour Recognition Using Neural Network

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ABSTRACT

Lane change behaviour recognition is one of the significant elements in advanced vehicle active system for the purpose of collision avoidance and traffic flow stability to ensure a safer driving experience. The system recognizes either the driver in situations of normal or evasive lane change maneuver which respond and assist the driver negligence. This paper proposes a lane change behaviour recognition using Artificial Neural Network (ANN) model by classifying the behaviour either evasive or normal lane change. An ANN model was adopted in order to combine several vehicle state information to generate the lane change behaviour classification. The vehicle state parameters such as vehicle speed, yaw rate, time taken for one complete steer cycle and steering angle were used as the inputs to develop in the ANN model. The state parameters were acquired from a real-time experiment conducted by several selected normal drivers. The result shows that the proposed ANN model has successfully recognized 94% and 92.8% of the lane change samples in training and test data set respectively. Hence, the proposed ANN model has a promising potential to handle system nonlinearity.

Keywords: *Lane Change, Artificial Neural Network (ANN) Model, Normal, Evasive.*

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Introduction

Lane change can be defined as a driving manoeuvre that moves a vehicle from one lane to another where both have the same direction of travel [1]. Generally, in the lane change process, there are two different elements of lane change behaviour which is a normal or evasive lane change [2]. According to [2], a normal lane change is the condition in which the driver changes lane to enhance driving conditions, for example, overtaking slow vehicles, passing substantial/heavy vehicles, and maintaining a strategic distance near an on-ramp. While the evasive lane change occurs when the driver makes an unpredicted lane change to avoid an obstacle. This cause the operations of the driver such as steering, braking, or accelerating reaching the limits of the vehicle's potential [3]. Normal lane change may be performed if the driver is not satisfied with the condition of the traffic flow as they unable to maintain the desired speed in the current lane. In general, there are several factors that will cause the normal lane change to occur such as the lower speed in the current lane, queuing, and sudden deceleration because of the lead vehicle [4]. While evasive lane change is necessary when a gap in between obstacle in front with the subject vehicles in the current lane is very close.

Although there are quite a number of publications [5]– on the lane-changing model have been published, however, it is noticed that there is a lack of discussion on the classification for lane change behaviour. Previous works focused more on the prediction of the lane change using a multi-parameter that was identified from the driving behaviour based on eye and head movement and drivers' visual search [5] and vehicle motions [6]. McCall *et al* [7] has studied on the driver intent inference system which deduced that the driver head motion and the vehicle parameter collection system as key for lane change predictions. Meanwhile, M. Itoh *et al* [8] has proposed a method based on drivers' eye glance behaviour analysis to detect the drivers' attention during change lanes. In order to detect the drivers' lane changing intentions, some researchers proposed both of the eyes and head movements [9]. However, application of an assistance system in identifying drivers' lane-changing intentions has its own weakness. The lane change steer action might not be executed even though the system has detected the driver's intention to change lanes. For instance, if there is a fast approaching vehicle from the rear side of the target lane, most drivers might change their mind and decided to stay in the current lane [5]. The identification technologies or the device cannot accurately predict the drivers' lane-changing intentions. Hence, the 'faceLAB' system was proposed to detect the intentions of the driver to perform lane change which is functioning as an eye tracking system [5]. This system not only can detect the eye movement and head position, but also the eyelid aperture and pupil size. However, because of the driving seat is on the left side, this system has a low wide range of lateral measurement as it is installed in front of the car. Thus, it is difficult to detect the driver's fixation points on the far right [5].

Most recent study has focused on adopting several capable methods such as Fuzzy logic, Support Vector Machine, Random Neural Network, Sparse Bayesian Learning and Artificial Neural Network for the driver lane change behaviour recognition [6]. According to [2], the complex system nature (i.e. lane change) and the lack of large-scale data analysis are the main challenges in lane changing study. Due to that, the Artificial Neural Network (ANN) model is selected to deal with this issue. An ANN model can represent the effect of surrounding vehicles on lane changing study [2]. Therefore, this method is able to deal with the noisy data and resemble any level of complicated in a nonlinear system [10]. Moreover, the specification of the inherent relationship between the system variables such as exponential, polynomial, linear, and etc. is unnecessary via ANN model. Whereas, in a statistical model (i.e. regression model), input-output variables relationship specification is a prerequisite for model estimation [2]. Therefore, this paper aims to adopt an Artificial Neural Network to classify the lane change behaviour because of aforementioned advantages. In this study, the parameters involved are the vehicle state parameters such as yaw rate, vehicle speed, steering angle, and time taken for one complete steer cycle of lane change are used as the input component for the network model. A pattern recognition using two layer feed-forward networks with a sigmoid transfer function in the hidden layer, and the output layer are adopted. The collected data for the network will be selected by using the application of the Neural Pattern Recognition and trained using gradient back-propagation.

The rest of the paper is organized as follows. In the next section, design procedure which includes the associates hardware setup and strategy adopted to develop the proposed ANN model are described. Performance analysis of the proposed recognition method with a tangible results performance are presented in the third section. Finally, the drawn conclusion and future direction of this work are described in last section.

Methodology

Configuration of Research Platform

Figure 1 show the work flow for configuration of research platform. Test vehicle which is i-Drive fitted with auxiliary external sensor modules and modified steering system component is used for data acquisition purposes. The data acquisition platform developed in the test vehicle included the following sensors such as the potentiometer, motor (electronic power), inertia sensor, rotating encoder and also embedded computer to process and monitor the data. The potentiometer is used to check the brake position, motor (electronic power) is used for automatic steering movement, and rotating encoder is used for checking steering angle while Inertia Measurement Unit and Vision Monitoring Unit are required in data acquisition.

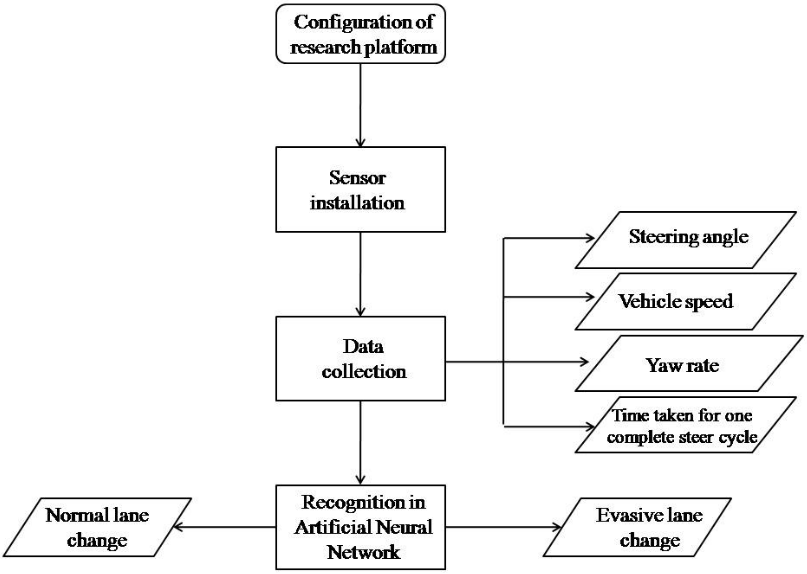

Figure 1: Work Flow Chart.

Experimental Setup and Data Collection

For data acquisition, the information about lane change behavioural characteristics such as steering angle, vehicle speed, yaw rate, and time taken for one complete steer cycle of the lane change were required. Next, 48 samples were collected consists of 26 and 22 data samples for evasive and normal lane change respectively. The experiment was conducted by four selected subjects (i.e. drivers) that have clear visual and healthy physical status. The demographic profiles of the drivers are tabulated in Table 1.

Table 1: The demographic profiles of the subjects

Driver	Age (Years Old)	Gender	Driving experience (year)
1	26	Male	7
2	28	Male	8
3	33	Female	13
4	33	Female	10

Each of the drivers must perform 10 times of normal and evasive lane change. The drivers were requested to drive the i-Drive at an average constant speed (i.e. 50-60km/h) and when the i-Drive vehicles achieve cone B, drivers should observe the right side of the street to see the distracter hand's signal until the distracter pull down his/her hand (i-Drive vehicle as of now achieved cone A). As of now, drivers need to look into straight and perform the steering maneuver to avoid the obstacle. The move practices were measured from cone B until drivers completed the trajectory. The configuration of the experiment as shown in Figure 2 and the detail can be found in [11].

To ensure the safety of the driver during the experiments, some safety precautions were taken which is the soft static obstacle (i.e. box) was utilized to replace the real and hard obstacle in this experiment. The function of the soft static obstacle is to prevent any injured if any unexpected collision occurs.

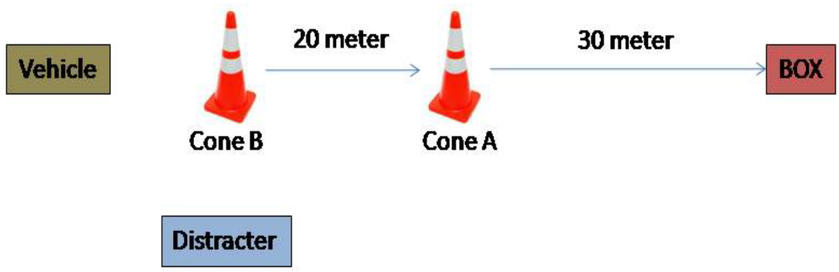

Figure 2: The configuration of the experiment.

Normal lane change

The experiment for normal lane change maneuver was conducted by maneuvering the vehicle with a slight turn of steering angle to the targeted lane. During the maneuver, it is assumed that the driver has the awareness of incoming vehicle on the rear side of the targeted lane and at the same time, securing a safe gap between vehicles at the front side of the current lane to avoid the potential collision. This experiment was conducted on the two-lane road traveling in one direction with a width of 3.5 meters for each lane. The average speed of the vehicle was 50-60km/h.

Evasive lane change

Data acquisition in evasive lane change is related to deceleration of the preceding vehicle at higher speed and the behaviour of driver's steering maneuver during avoiding obstacles [11]. Aforementioned, a two-lane road was selected to conduct the experiment. The obstacle was placed in the middle left of the lane and the test vehicle travelled towards the obstacle with an average speed of 50-60km/h. The configuration of the evasive lane change experiments as shown in Figure 3.

Figure 3: The configuration of the evasive lane change experiment.

Neural Network Classification

Applications of Artificial Neural Networks (ANN) has been started in 1943 created by Warren Mc Cullech and Watter Pitch as a method in machine learning [12]. It is a solution for complex tasks consist of nonlinear data and arrays, which are hard to be handled by a common rule-based programming. It comprises of four main components that are neurons, inputs, outputs, and weight [13]. Neuron activates the network through comparison method between results with a threshold value, ɵ, from the computation of weighted sum in the input signals. In this paper, the information of the input signals was processed in the form of sigmoid function. The sigmoid function is an activation function in ANN which converts the input signal to the mathematical value and returns the value mostly in the range between 0 and 1 [14].

$$y_{sigmoid} = \frac{1}{1+e^{-x}} \tag{1}$$

The architecture of the proposed ANN model consists of 3 layers. The input layer of the designed model consists of four input vectors which are having a connection with the hidden layer (10 number of neurons), sigmoid function as activation function and structure of the output layer in the frame. The network architecture of the proposed model is as shown in Figure 4.

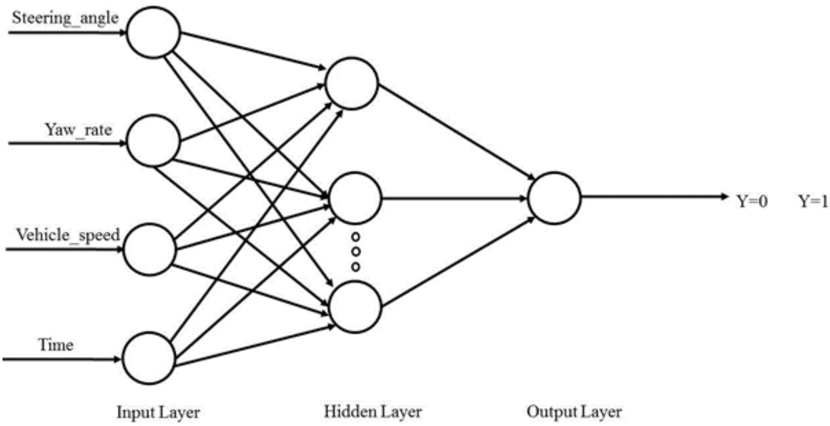

Figure 4: Artificial Neural Network architecture

The function of weight component in ANN is to store the information of input signal in the lasting period [13]. This model operates through a learning process which frequently updates these weights from the training set [13]. In this work, as the inputs and desired outputs were introduced to the network, the weight will be adjusted automatically to produce the desired outputs. Next, a total of 20 test data were collected and the network was analyse based on the targeted input for training, validation, and testing. The confusion matrix was adopted to analyse the accuracy of the network outputs and the Receiver Operating Curve (ROC) was plotted to evaluate the performance of the network.

Result and Discussion

Experimental Results

Based on the driving record carried out by the selected normal driver, the lane change data was extracted as shown in Figure 5 and Figure 6. In this work, 14 driving data with 7 from each of evasive and normal respectively, were selected for pattern recognition of lane change behaviour. Next, 70% of the selected data was used in classification training while another 30% was used in classification tests. The output value of this model is between 0 and 1. 0 is normal lane change and 1 is shown that the lane change manoeuvre is in evasive.

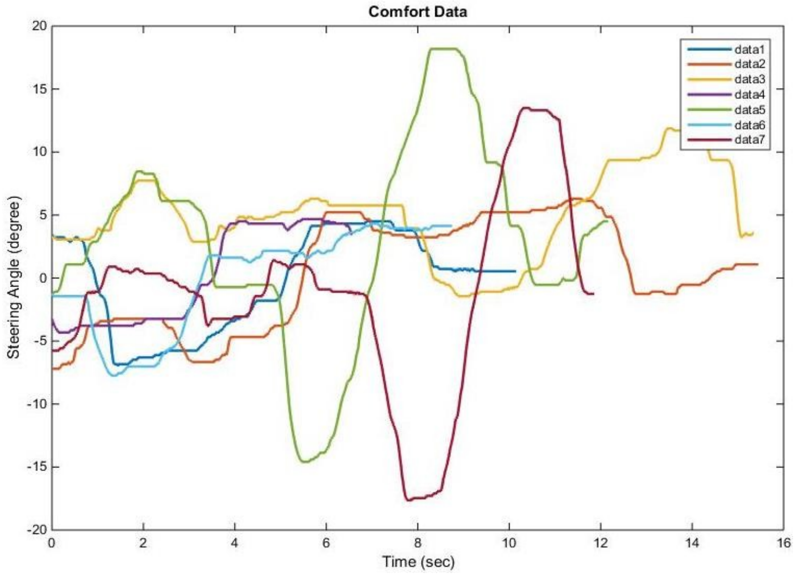

Figure 5: Driver’s steering manoeuvre against time for normal data.

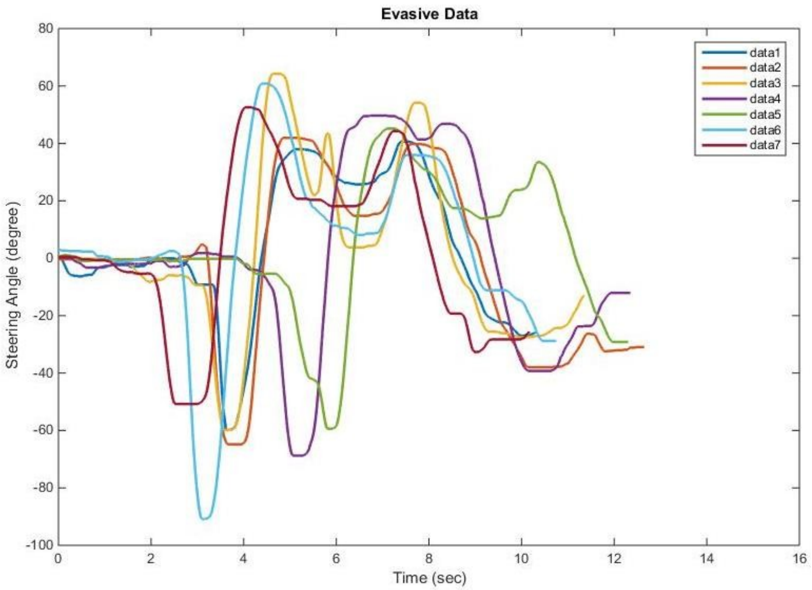

Figure 6: Driver’s steering manoeuvre against time for evasive data.

Figure 5 and 6 shows the plots extraction of driving record signal for lane change behaviour with driver's steering manoeuvre against time for the normal and evasive lane change. The signal denotes the samples of data corresponding to the performance of steering manoeuvres during the experiment. The steering angle for evasive data is higher compared to only within $\pm 20^0$ in normal data as shown in Figure 5 and 6 respectively. Time taken for evasive lane change data was also longer because the vehicle speed was reduced during obstacle avoidance. Data during evasive lane change can be divided into three phases. First phase is straight line and almost approaching obstacle, second phase is avoidance process which is lane change is activates as steering angle is increases over the time. The changes of the steering angle is noticeable. The last phase is the recovery phase as the test vehicle is back to original lane. In this work, the chosen parameters for input data were the steering angle, time taken for one complete steer cycle of a lane change, yaw rate, and vehicle speed as shown in Figure 7 and Figure 8.

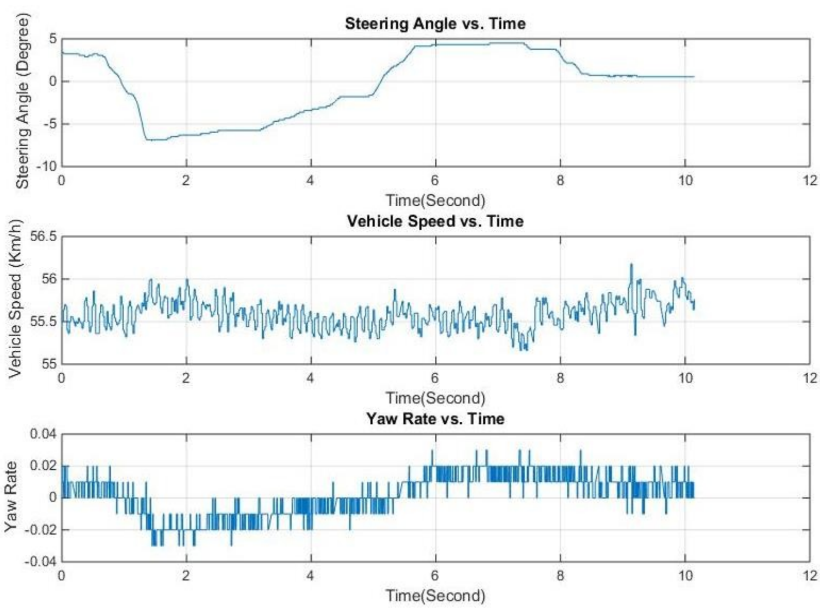

Figure 7: A normal lane change manoeuvre parameters.

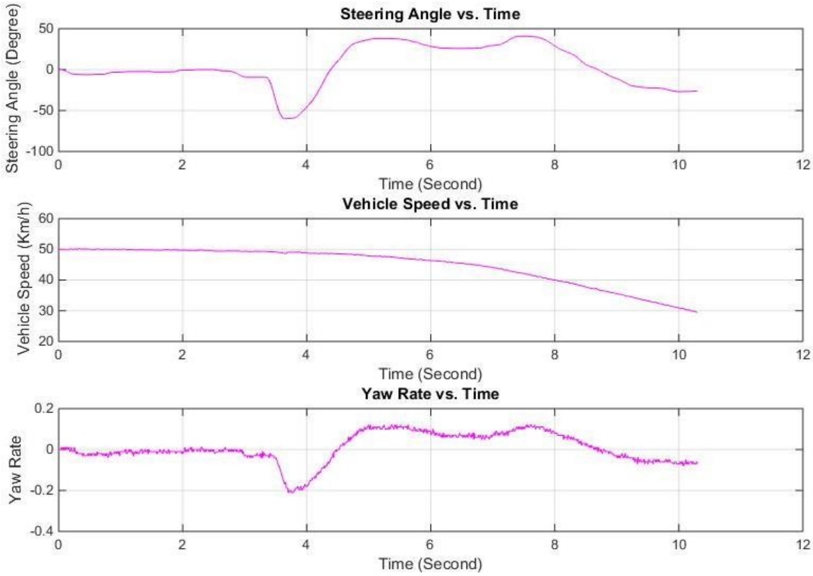

Figure 8: An evasive lane change parameters

Lane Change Classification Result

The Artificial Neural Network simplifies the behaviour of a lane change into two states which is normal and evasive from driving data after 277 times iteration training with Mean Square Error is 0.084534 as shown in Figure 9. The network used in this work is a standard feed-forward and adopted from the scaled conjugate gradient back-propagation.

The performance of the network was evaluated using a Receiver Operating Characteristic (ROC) curve analysis. It is the most preferred method in diagnostic of making a decision [15]. It is a plot of the true positive rate (TPR) against the false positive rate (FPR) that represent the classification performances of the network in a binary system when threshold values are varied. Generally, the acceptable value for FPR in engineering application is about 5% and it is used as a threshold value to distinguish the behaviour of lane change samples data [5]. In this work, the points show closer in the upper left corner which is almost reaching 100% true positive rate and 0% in false positive rate as depicted in Figure 10. Due to a large Area Under Curve (AUC) which is close to 1, the trained network has demonstrated a promising classifier performance.

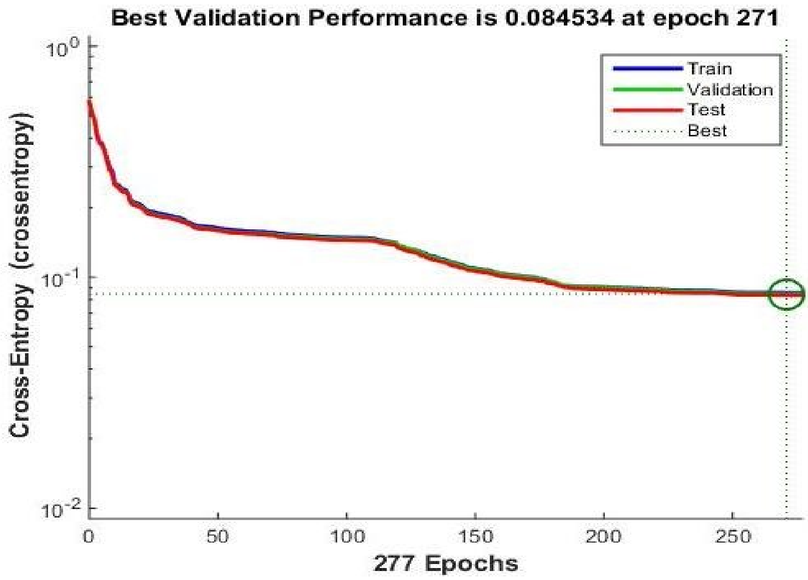

Figure 9: Mean square error curve of the network

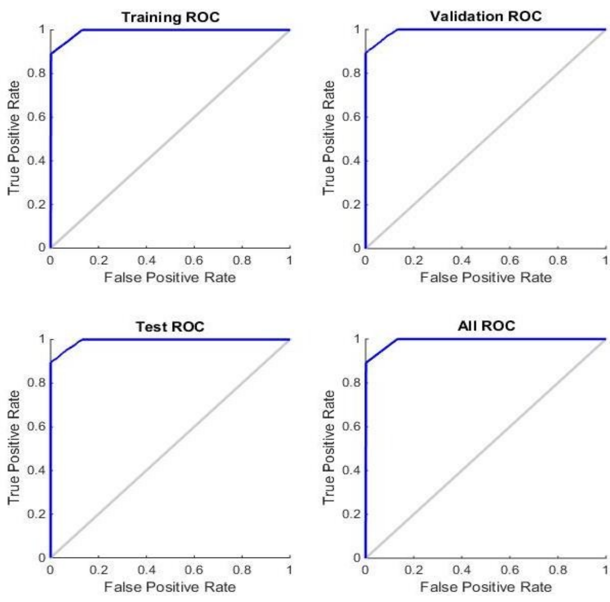

Figure 10: Receiver operating curve

Moreover, to further analyse the classification performance of the proposed network model, the confusion matrices were tabulated. Considering a trained data, the network model has effectively recognized the lane change behaviours (i.e. the classification of normal and evasive lane change) with the accuracy of 94% as shown in Figure 11. It is desirable to achieve a decent classification accuracy performance in training mode. This is in order to produce a good classification performance for an untrained data (i.e. test data) set.

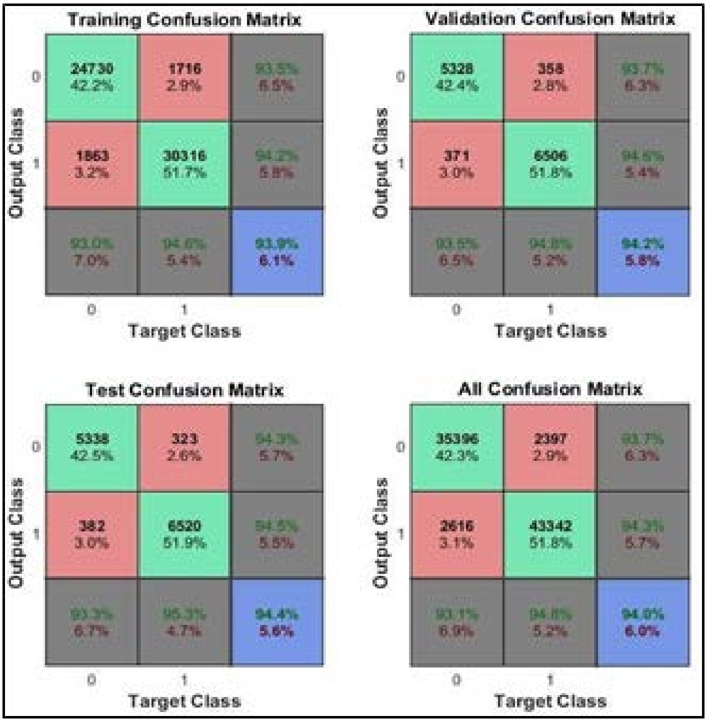

Figure 11: Confusion matrix (Trained data)

Therefore, to verify the performance of the developed model, a new dataset was collected. After training process, another sample of data was used for classification test purpose. About 139 lane change manoeuvre data were selected. Based on the confusion matrix, classification accuracy performance of the untrained data (i.e. test data) has produced a promising result with an accuracy of 92.8% as shown in Figure 12. The recognition (i.e. classification) result for trained data and untrained (i.e. test) data are shown in Table 2.

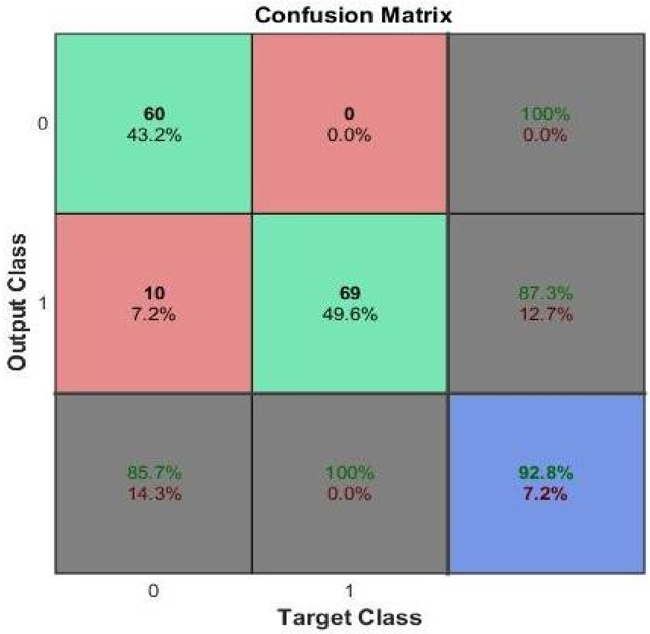

Figure 12: Confusion matrix (untrained data)

Table 2: The recognition result in trained and untrained data

Data	Iterations	Epoch	Driving experience (year)	Confusion Matrix (%)
Trained	277	271	0.085	94
Untrained (i.e. Test)	-	-	-	92.8

For comparison purposes, the two ANN model with different training algorithm was performed. In this study, an ANN model using the Levenberg-Marquardt algorithm was also develop to compare with the ANN model using the scaled conjugate gradient backpropagation that has been discuss in the previous study. Therefore, the same dataset collected in the experiment conducted before that is briefly discussed in the previous section was used in this model.

The Mean Square Error (MSE) of this model shows the high number of error compare with the previous study which is 0.20144 as shown in Figure 13.

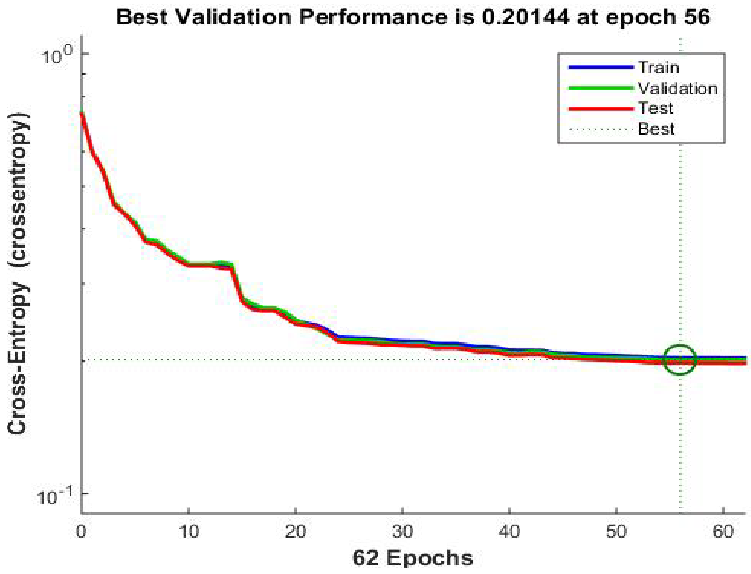

Figure 13: Mean square error curve of the network

Table 3 show the Mean Square Error value from the scaled conjugate gradient backpropagation and Levenberg-Marquardt algorithm model obtained from Figure 9 and Figure 13. From this table, the different of the MSE value of both model is calculated which is 0.116906. (MSE plot already provided). Figure 14 is a detail plot of the MSE value for both model in form of bar chart. In addition, the Receiver Operating Curve of the model as showed in Figure 15 show the points of the network which is only reaching 90% true positive rate.

Table 3: Mean square error (MSE) value

	Scaled conjugate gradient backpropagation	**Levenberg-Marquardt algorithm**
Mean Square Error (MSE) value	0.084534	0.20144

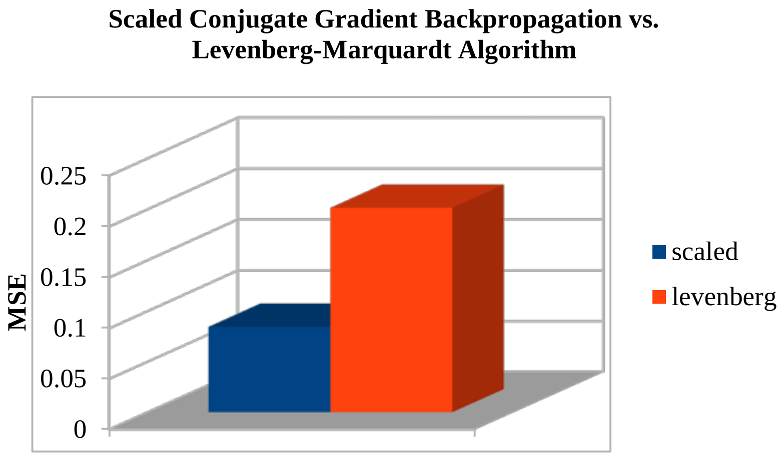

Figure 14: Bar chart of Mean square error plot Scaled conjugate gradient backpropagation vs. Levenberg-Marquardt algorithm

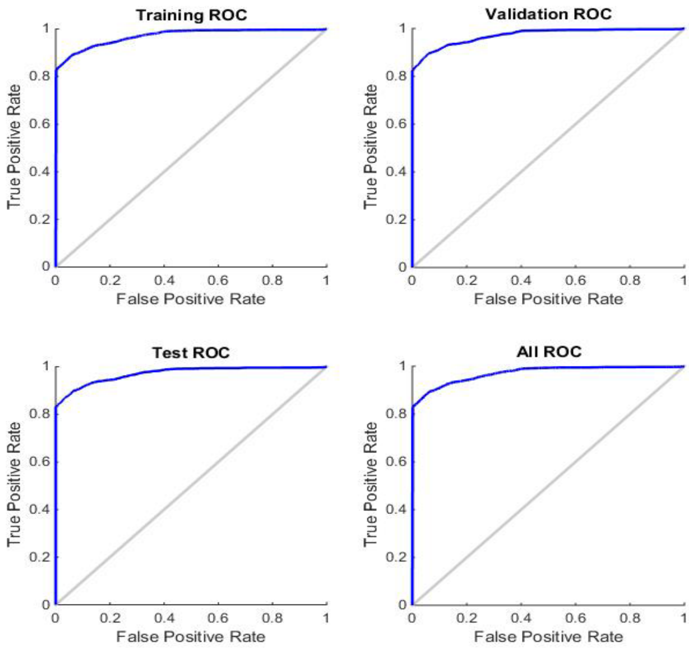

Figure 15: Receiver operating curve

Based on the confusion matrix, classification accuracy performance of the trained data is only 91.3% compare with the previous study which is 94% as depicted in Figure 16. Meanwhile, Figure 17 shows the classification accuracy performance of the untrained data (i.e. test data) which is similar to the previous study.

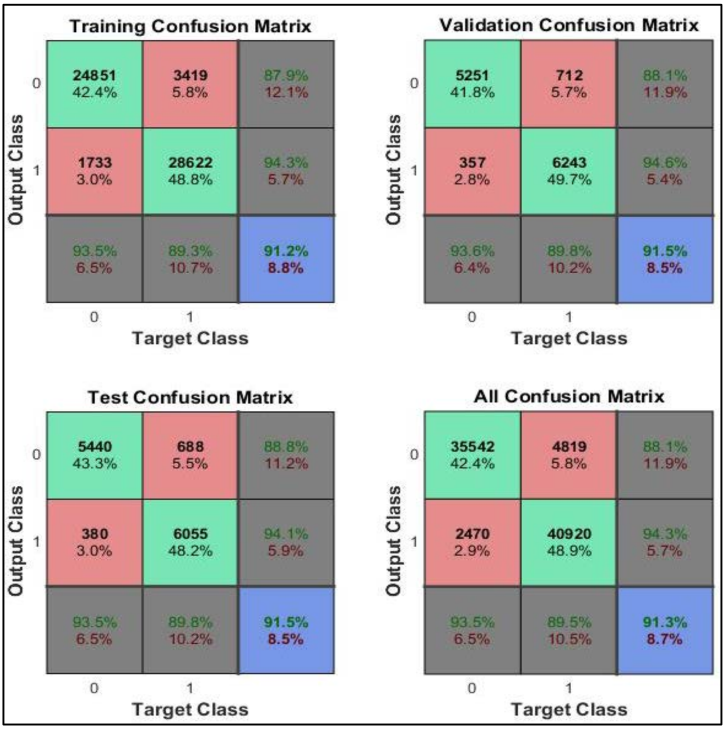

Figure 16: Confusion matrix (trained data)

Figure 18 show the detail plot of the accuracy of artificial neural network using Scaled conjugate gradient back propagation and Levenberg-Marquardt algorithm in form of bar chart.

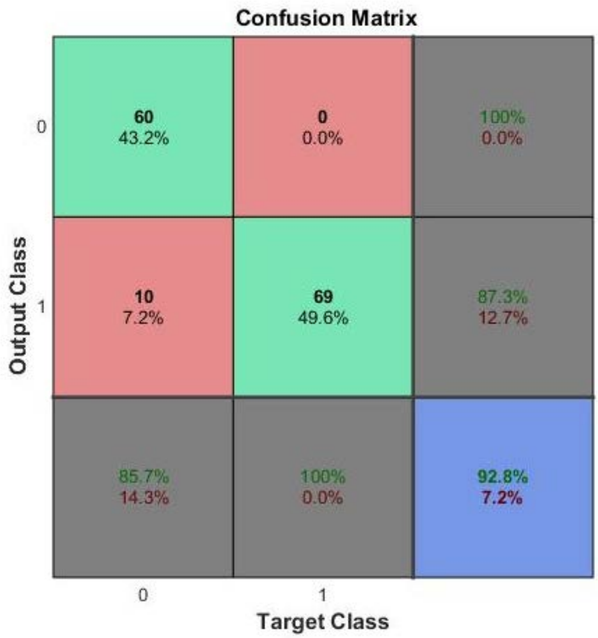

Figure 17: Confusion matrix (untrained data)

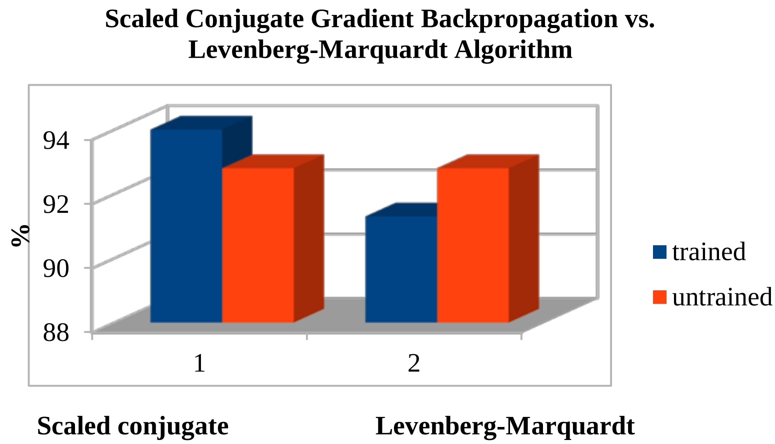

Figure 18: Bar chart plot of accuracy of the ANN of Scaled conjugate gradient backpropagation vs. Levenberg-Marquardt algorithm

As the accuracy performance of the ANN model with scaled conjugate gradient backpropagation in the previous study is much higher than the accuracy performance of the ANN model with the Levenberg-Marquardt algorithm and have the low value of the MSE value, it is clearly show that the previous model is more general. Hence, that in the ANN model with scaled conjugate gradient backpropagation is more general than the ANN model with the Levenberg-Marquardt algorithm.

The limitations faced during the study which is challenging in data acquisition during the experiment was conducted as existing many cars at test platform, the subjects cannot drive at high speed because of the safety and the location for the experiment is in the small range.

Conclusions

In this paper, a lane change behavioural recognition model developed using ANN model is presented. Input signals data for the model were obtained from experiments conducted by the selected normal drivers, performing two types of lane change manoeuvres that are normal and evasive. The output value of the model was either 0 or 1 to represent the normal or evasive lane change manoeuvre respectively. The lane change behaviour recognition results had shown a decent performance which is relative percentage of classification accuracy between trained and untrained (i.e. unknown environment) data was approximately 100%. This demonstrates that the proposed ANN model is applicable and has a promising potential to handle system nonlinearity. Next, the future direction of the work will focus on accuracy improvement of the network performances by considering other additional potential inputs such as the behaviour of driver's visual.

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