Medical Simulation

Simulation

Simulation: Transactions of the Society for Modeling and Simulation International
2020, Vol. 96(2) 131–140

DOI: 10.1177/0037549719862864
journals.sagepub.com/home/sim
SAGE SCS

Modeling of occupant's head movement behavior in motion sickness study via time delay neural network

Sarah 'A Saruchi[1], Mohd HM Ariff[1], Hairi Zamzuri[1], Nurhaffizah Hassan[2] and Nurbaiti Wahid[2]

Abstract

Passengers are more susceptible to experiencing motion sickness (MS) than drivers. The difference in the severity of MS is due to their different head movement behavior during curve driving. When negotiating a curve, the passengers tilt their heads towards the lateral acceleration direction while the drivers tilt their heads against it. Thus, to reduce the passengers' level of MS, they need to reduce their head's tilting angle towards the lateral acceleration direction. Designing MS minimization strategies is easier if the correlation between the head movement and lateral acceleration is known mathematically. Therefore, this paper proposes the utilization of a time delay neural network (TDNN) to model the correlation of the occupant's head movement and lateral acceleration. An experiment was conducted to gather real-time data for the modeling process. The results show that TDNN manages to model the correlation by producing a similar output response to the actual response. Thus, it is expected that the correlation model could be used as an occupant's head movement predictor tool in future studies of MS.

Keywords

Motion sickness, time delay neural network, head roll, lateral acceleration, correlation model, head movement predictor

1. Introduction

Motion sickness (MS) is an unpleasant condition commonly faced by passengers who are traveling by car, train, air, and particularly by the sea.[1] MS has received considerable attention within the automotive research community because it negatively affects passengers' comfort. Generally, the wide range of signs and symptoms of MS include sweating, salivation, dizziness, nausea, vomiting, and other physical discomforts.[2,3] In a conventional car, passengers are more prone to MS compared to drivers. The most widely accepted theory of MS occurrence is the conflict of sensory inputs between the visual and vestibular inputs.[4] Contrary to the driver, a passenger has less ability to foresee the vehicle direction and thus loses of control over their movement.[5] Another well-known theory is that MS is preceded by postural instability.[6] Dong and Stoffregen found that those who were consistent in their movement over time are less likely to experience MS compared to those who exhibited changes in movement.[7] Another reason for passengers to be more at risk of getting MS is because of their restricted vision of the outside world as they are not required to have an out-of-the-window view to control the car.[8] Several studies have suggested that the reason behind the passengers' and drivers' different level of MS is because of the difference in their head tilting behavior towards lateral acceleration direction when the vehicle is negotiating a curve.[9,10] It has also been reported that there is a correlation between head movements and the vehicle's lateral acceleration.[11] Typically, during a curvature, passengers tend to tilt their heads according to the lateral acceleration direction while the drivers tend to tilt their heads against the lateral acceleration direction. Figure 1 illustrates the natural head tilt movements of a passenger and a driver in a situation when the vehicle turns into a corner.

The correlation between the head tilt movement and lateral acceleration direction clearly indicates that to reduce passenger susceptibility towards MS it is necessary

[1]Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Malaysia
[2]Faculty of Electrical Engineering, Universiti Teknologi Mara, Malaysia

Corresponding author:
Mohd HM Ariff, Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur, 54100, Malaysia.
Email: mohdhatta.kl@utm.my

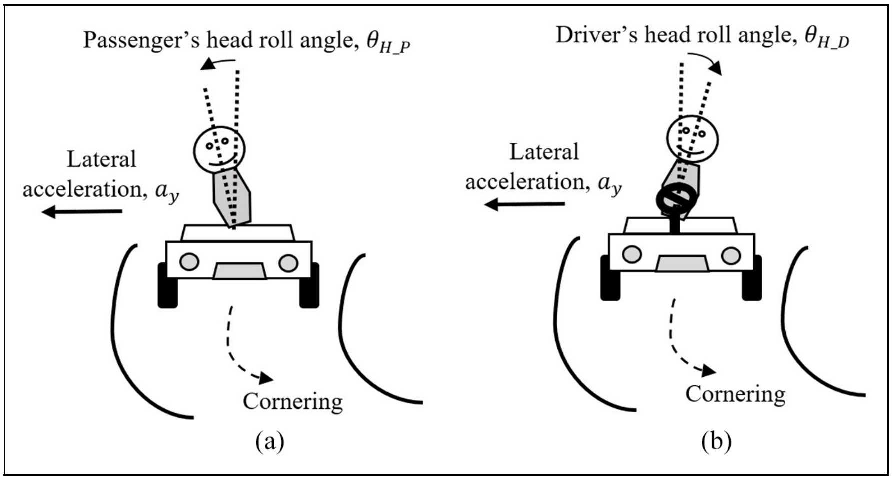

Figure 1. Passenger's and driver's typical head tilt movement during a curvature. (a) Passenger. (b) Driver.

to design strategies and approaches leading to passengers imitating and mimicking the driver's head tilting movement. In 2011 and 2012, the passenger posture control device was introduced, aiming to encourage passengers to change their natural head tilt direction into the opposite direction.[12,13] The results indicate that the device managed to reduce the passengers' level of MS. Another method to lessen the risk of MS among passengers is to minimize the passenger's head tilting angle towards the lateral acceleration direction. The minimization can be realized by reducing the vehicle lateral acceleration during curve driving. The method corroborates with the statement by Wiederkehr and Altpeter that MS will increase if the lateral acceleration is increased.[14] Meanwhile, Elbanhawi et al. suggest that a smooth lateral control strategy can be one of the MS solutions.[15] Wada et al. propose a speed control strategy where the vehicle decelerates when it reaches a corner.[11] The reduction of the speed will affect the reduction of the lateral acceleration indirectly. Through the proposed strategy, the minimization of MS was achieved.

From the discussion, the findings on the correlation are worth mentioning because of their importance. However, it would be more convenient if the correlation could be represented in a mathematical expression. Previously, the correlation between head movement and lateral acceleration in curve driving had been modeled by Saruchi et al. using the system identification (SI) method.[16,17] SI is a statistical method that can build a mathematical model based on the measured data. The author used the linear transfer function identification and Hammerstein–Wiener as the modeling tools. However, the efficiency achieved by the developed model is less than 70%. Therefore, alternatively, this study proposes to model the correlation between the head tilt movement and the vehicle lateral acceleration using the time delay neural network (TDNN) method. The popularity of artificial neural networks (ANNs) is because of their ability in handling noisy data and approximating the degrees of complexity in nonlinear systems.[18] An occupant's head movement is nonlinear in nature with no particular form. Thus, an ANN is an effective candidate to model such a nonlinear system. Moreover, compared to statistical models, an ANN does not require any simplifying assumptions or prior knowledge to solve problems. It is one of the optimal solutions through learning input and output data and has been commonly used in pattern recognition, data classification, speech processing, control systems, and weather forecasting.[19] In general, TDNN has a similar topology as ANN in that they both have input, hidden, and output layers.[20] TDNN application is appropriate in developing the correlation model because the interactions between head tilt movement and lateral acceleration are nonlinear in nature, have no specific form, and vary depending on time. For the sake of the modeling process, a scenario that triggers MS is set up under a real experimental environment and the naturalistic data from the experiment, namely the vehicle's lateral acceleration, passenger's head roll angle, and driver's head roll angle, were collected. The effectiveness of the TDNN model is compared to the ANN model, which is built under similar conditions. The influence of the number of time delays on the model's accuracy is investigated as well.

The remainder of this paper is structured as follows. The next section presents the procedures of the experiment. The third section describes the TDNN and ANN architecture to model the correlation based on the experimental data. Then, the results and discussions from the conducted experiment and the modeling process are presented in the fourth section. Finally, in the last section, concluding remarks are given and targeted areas for future work are described.

2. Experiment

An experiment that considers MS provocation was set up based on the research works of Wada et al.[21] The objective

Figure 2. The placement of equipment installed in a Proton Exora.

Table 1. List of equipment installed in the MPV.

Type	Function
Dewesoft	Data acquisition module
Monitor	Data monitoring
MTi-G sensor (Xsense Technologies)	Data measuring

is to investigate the correlation between the vehicle occupant's head tilt movements and vehicle lateral acceleration direction during cornering. To realize the objective, the experiment focuses on gathering data of the passenger's and the driver's head roll angle and the vehicle lateral acceleration in the slalom path.

2.1. Apparatus

In this experiment, a multi-purpose vehicle (MPV) is used for data acquisition. The MPV was equipped with several pieces of equipment and sensors, as depicted in Table 1.

Dewesoft, the device used as the data acquisition module, was placed in the vehicle's trunk. Meanwhile, the monitor was attached behind the passenger's front seat. There were three MTi-G motion sensors used in this experiment. Each of the sensors was used to measure the passenger's head roll angle and the vehicle lateral acceleration, respectively. The sensors used for the head roll measurement were attached to the cap worn by the participants. The lateral acceleration sensor was attached to the vehicle's center of gravity, which was located approximately at a flat space close to the hand brake. Figure 2 illustrates the equipment placement in the car.

2.2. Design

Six cones were arranged in a straight line of 150 m on a standard track. The gap between each cone was set at 20 m. The drivers were instructed to drive in a slalom driving style through the cones at a constant velocity of 30 km/h. The nominal frequency of lateral acceleration for this customized test track was 0.21 Hz, a frequency that triggers MS. Figure 3 illustrates the schematic of the test track used in this study.

A total of 10 healthy adults participated in this experiment. The participants participated as both the passenger and driver. The driving behavior was considered and treated as a normal driving behavior regardless of gender, age, and skill. Participants were asked to act naturally with the tilting movement and avoid any intentional action to move to the opposite with the typical head tilt movement.

2.3. Procedure

The driver and passenger were seated in a normal sitting position. For safety reasons, both participants were required to wear safety belts. During the experiment, they were constantly reminded not to be distracted by other activities such as chatting and interacting with mobile phones. Before the real test began, all participants had some practice runs to get accustomed to the slalom path. It is possible for the participants to subconsciously tilt their heads more or less because of their awareness of what kinds of behaviors are being measured. Thus, the trial sessions were important because they can somehow reduce that possibility. When the participants are used to the path, they would naturally tilt their heads. Extra practices were allowed upon request. Each participant experienced the role of a passenger and a driver three times per role.

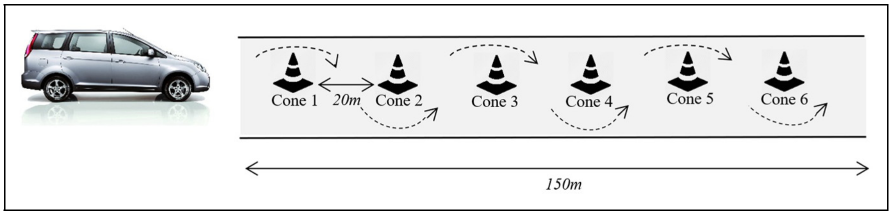

Figure 3. Schematic of the test track.

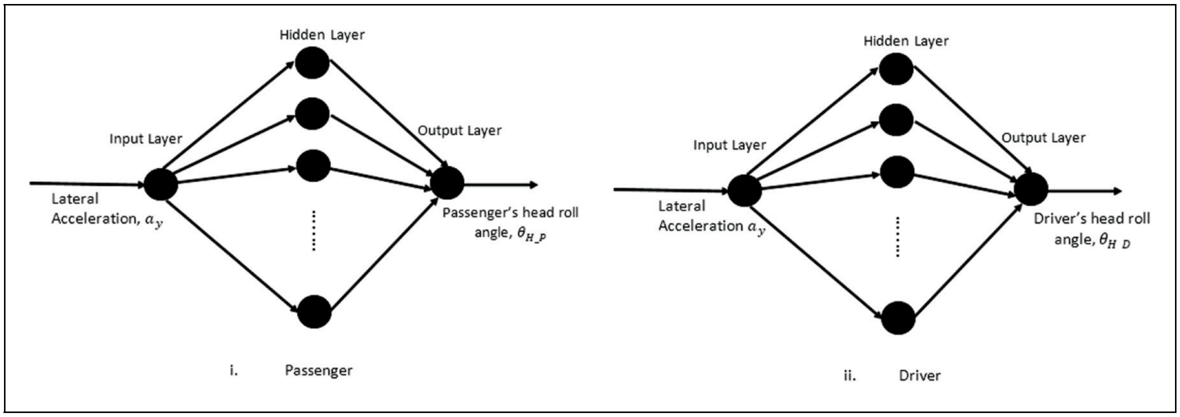

Figure 4. The overview of ANN and TDNN for passenger's and driver's models.

Therefore, with 10 participants, there are 30 results for passenger and 30 for driver. The data were then used in the TDNN modeling process, which is discussed in the following section.

3. Time delay neural network modeling

The main contribution of this work is the proposal of the TDNN method to model the correlation between the vehicle occupant's head tilt movement and vehicle lateral acceleration. TDNN is considered one of the effective candidates to model such a system where the relation between input and output is unknown or very complex. Modeling of TDNN can be done by going through a training phase where it learns to recognize patterns based on the given input and output data. TDNN is reported to be an effective feed-forward network architecture in modeling a wide and long range of temporal contexts.[22,23] It is a network that has a hidden time factor inside the signal with implicit representation.[24] Its modeling process includes extracting information from the present and past inputs.[25] The difference between TDNN and ANN topologies is the existence of tapped delay line memory at the input to the first layer of the static feed-forward network in TDNN.[26] Because of the delay, it is possible for the TDNN model to capture the dynamic behavior between consecutive elements of a sequence.[27] Moreover, the tapped delay line, which appears only at the input of the network, enables TDNN to train faster than other dynamic networks. The response of TDNN in time t is based on the previous inputs $x(t-1), x(t-2), \ldots, x(t-N)$, which makes it suitable for a time-series prediction. The mathematical equation for the TDNN output $y(t)$ at time (t) is as follows:

$$y(t) = f[x(t), x(t-1), x(t-2), \ldots, x(t-N)] \qquad (1)$$

where $x(t)$ is the input at time t and n is the maximum time delay. The value of time delay depends on the system's sampling time. In this study, the value of one time delay is equal to 0.01 s.

This study adopted the TDNN approach to generate the estimated output responses of the passenger's and the driver's tilt movements based on the input response of the vehicle lateral acceleration. Data for the head roll angle and lateral acceleration were directly measured from the motion sensors during the experiments and used to establish the correlation model. To sum up, the comparison between TDNN and ANN models with the same number of hidden neurons were carried out to analyze the proposed model's accuracy.[28] Figure 4 illustrates an overview of ANN and TDNN models structures which are implemented in this study. Basically, both feed-forward network models are organized in three interconnected layers, namely an input layer, a hidden layer, and an output layer.

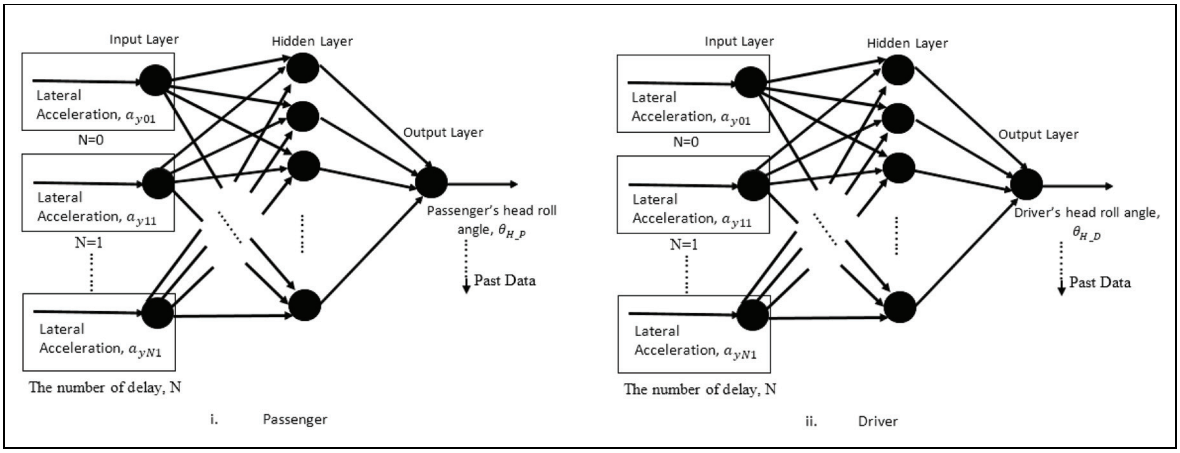

Figure 5. TDNN architecture.

The input layer consists of input data, the hidden layer consists of processing nodes called neurons, and the output layer consists of neurons whose output is considered the network output. The strength of the interconnection is known as weight. As shown by the figure, passenger and driver are modeled separately. The input and output data for the passenger's TDNN and ANN models are the passenger's head roll angle, θ_{H_P}, and vehicle lateral acceleration, a_y. The output data for driver's TDNN and ANN models are the driver's head roll angle, θ_{H_D}, and vehicle lateral acceleration, a_y. The respective data are divided into two parts. The first part is for the training process to create a nominal model with regards to the loaded data. The second part is the unlearned data, which is used for the evaluation of the developed model's efficiency and the analysis of its generalization ability. In the training process, data were divided into two sets: (1) 70% input samples for network training; and (2) 30% input samples for network validation.

Figure 5 describes the details of TDNN architecture. In the figure, x_i is the input data, t is the time, N is the number of delay, $w_{1,i,j}$ is the connecting weight between input and hidden layers, b_j is the bias of neuron at the hidden layer, $w_{2,j,k}$ is the connecting weight between hidden and output layers, c_k is the bias of neuron at the output layer, and y is the network output. The mathematical representation of the architecture is expressed as follows:

$$y = f\left(\sum_{j=1}^{M} w_{2,j,k} \cdot f\left(\sum_{d=0}^{N} w_{1,i,j}(t-d) + b_j\right) + c_k\right) \tag{2}$$

where d is the delay $(0 \leqslant d \leqslant N)$ and j is the number of neurons in the hidden layer $(1 \leqslant j \leqslant M)$.

For Equation (2), a set of optimum weights are needed to obtain the desired output. This study used the Levenberg–Marquardt back propagation (LMBP) algorithm as the network's training scheme. The Levenberg–Marquardt (LM) technique is a widely used tool to solve fitting problems.[29] Its advantage is that it requires less training time during a modeling process.[30] In the LM algorithm, the training process optimizes the weights through iterations based on the input–output time series.[28] The back propagation (BP) algorithm consisted of the forward and backward paths.[31] In the forward path, the feed-forward network was created, the weights were initialized, and the network was trained. Meanwhile, weights and biases were updated in the backward path.

In accordance with Figure 5, the TDNN configuration consisted of two activation functions. The sigmoid function was located in between the input layer and hidden layer, while the linear function was located in between the hidden layer and the output layer. The combination of these two functions is typical in the two layers of the BP neural network.[32] The sigmoid function maps the real numbers into the range of 0 until 1. The advantage of the sigmoid function is that it allows both the linear and non-linear decision boundaries, thus making computation easy to perform and computation time for the network's training can be minimized.[33] In addition, another usage of the linear activation function is to generate unbounded output values.

The accuracy of the model construction is affected by the number of neurons in the hidden layer. Various strategies have been introduced to find the best numbers. These are trial and error, rule of thumb, simple, two-phase, and sequential orthogonal approaches.[34] It has been indicated that it is impossible to accurately determine the parameters of the numbers of neurons and the delays by calculation since they depend on many factors.[35] Therefore, this study implemented the trial and error method to search for the most suitable neuron number. In order to obtain a fair comparison of TDNN and ANN models, it was necessary to set the same number of neurons for both models. The trial and error approach was tested during the ANN modeling process. It started by selecting the smallest number of hidden neurons from 1 to 20. Then, the ANN networks were trained. The developed models from the training process were compared with the unlearned data to investigate its generalization ability. The procedure of adding the neuron number, training, and comparing were repeated until the optimum number of neurons was obtained. The optimum number was chosen by selecting which model can produce the lowest comparison error with the unlearned response. The results of this method showed that the best number of neurons for passenger's ANN and driver's ANN models were 8 and 17. Thus, to train the proposed TDNN model, the number of neurons was selected based on the ANN model's optimal number. Details of the ANN training process can be referred to elsewhere.[36] As TDNN utilized the present and past time-series data in the learning process, it has the number of delays that showed to what extent the present and past data had been input into the model.[28] The influence of time delay on the model's accuracy was investigated. In this study, the parameter of time delay is set to be 0 until 10 with an interval of 1 and 10 until 100 with an interval of 10.

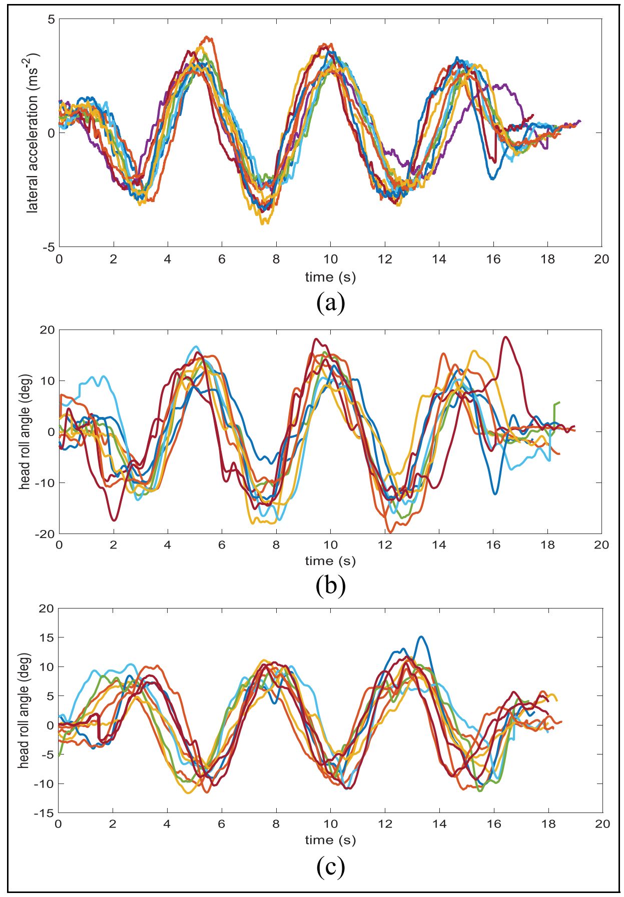

Figure 6. Experimental results based on 10 driving tests. (a) Lateral acceleration. (b) Passenger's head roll. (c) Driver's head roll.

4. Results and discussion

4.1. Experimental results

For this experiment, 30 data values consisting of lateral acceleration, the passenger's head roll angle, and the driver's head roll angle were measured and recorded. Figure 6 presents data from 10 driving tests.

The experimental results show that the directional pattern of passenger's head roll and lateral acceleration are synchronized. Meanwhile, the directions pattern of the driver's head roll and lateral acceleration are the opposite of each other. The results are in agreement with the typical vehicle passenger's head movement towards the lateral acceleration direction, which supports the previous study by Wada et al.[21] Next, in the following analysis, the focus is restricted to the correlation between the passengers' and drivers' head roll angle and the vehicle's lateral acceleration.

4.2. Modeling results with the influence of the number of delays

In this study, the TDNN model is built using MATLAB software. Two models representing the data of passenger and driver were derived. The analysis of their regression, root-mean-squared-error (RMSE), and generalization ability are carried out to investigate the performance of the TDNN model.

Figure 7 presents the regression results of ANN and TDNN modeling methods for both the passenger and driver models. Initially, the model is trained from time delay 1 until 10 with an interval of 1. However, as illustrated in Figure 7, the regression value fluctuated within a small range. Then, the time delay was extended to 100 with an interval of 10 in consideration of the effect of large time delay towards the model's accuracy. Based on the figures, the regression values from time delay also fluctuated within a small range. The result shows that the ANN's regression at time delay 0 is 0.901 for the passenger's model and 0.922 for the driver's model. The TDNN's minimum regression values for both models were 0.903 and 0.912, while their maximum regression values were 0.922 and 0.933. Based on the results, the TDNN's had 2.28% and 1.18%, a slightly higher regression value than ANN's. Table 2 provides a summary of the regression results for both models.

The analysis process continued by investigating the ANN model performance based on the validation error in terms of root-mean-square (RMS) values. Figure 8 shows

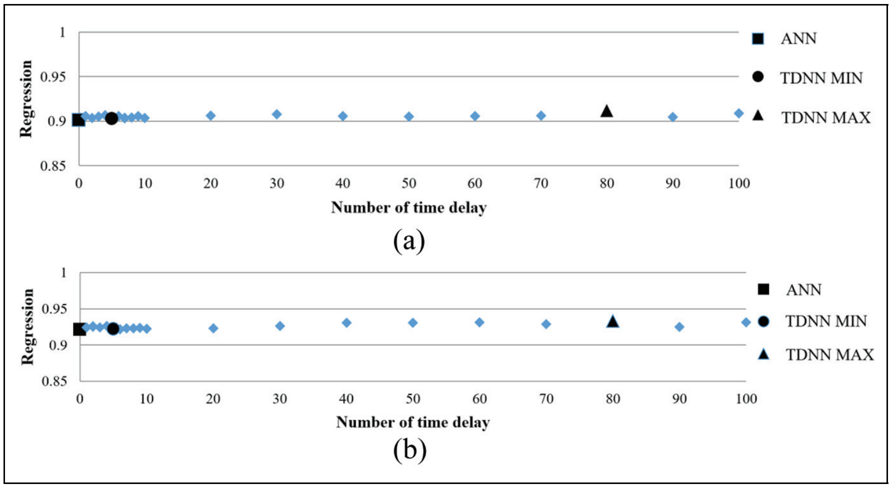

Figure 7. Regression results from time delay 0 until 100. (a) Passenger. (b) Driver.

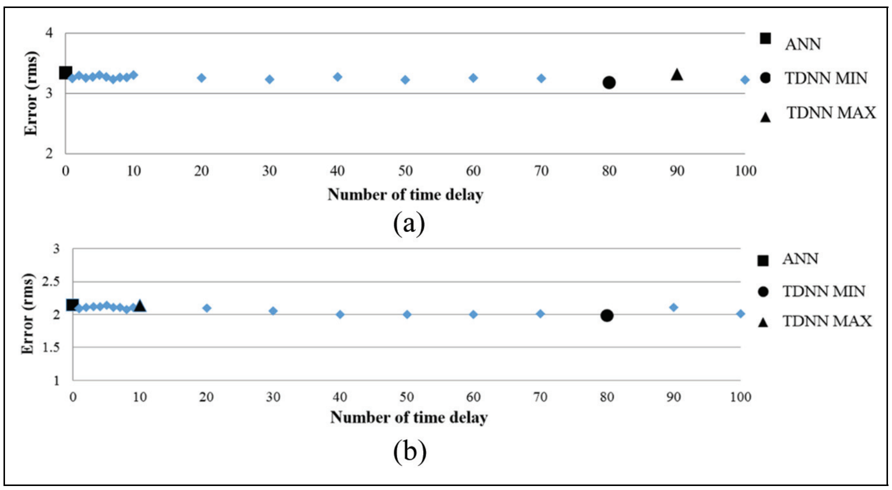

Figure 8. Validation error (RMSE) from time delay 0 until 100. (a) Passenger. (b) Driver.

Table 2. Summary of the regression results for ANN and TDNN models.

Model	ANN	TDNN		Improvement (%)
		Min	Max	
Passenger	0.901	0.903	0.922	2.28
Driver	0.922	0.912	0.933	1.18

Table 3. Summary of the validation error results for ANN and TDNN models.

Model	ANN (RMS)	TDNN (RMS)		Improvement (%)
		Min	Max	
Passenger	3.35	3.18	3.32	5.07
Driver	2.15	1.97	2.14	8.37

the validation error results for the passenger and driver models developed by ANN and TDNN modeling tools from time delay 0 until 100. The RMSE value of ANN is 3.35 for the passenger's model and 2.15 for the driver's model. Based on the previous regression results, it is expected that the RMSE results of TDNN were also fluctuated within a small error span, although the time delay increased to 100. The minimum and maximum RMSE values for passenger's model are 3.18 and 3.32, respectively, while the driver's model produced 1.97 and 2.14 of minimum and maximum RMSE values, respectively. The comparison between ANN's and TDNN's validation error results shows that TDNN generated 5.07% and 8.37% lower values than ANN. Table 3 presents a summary of the validation error for both models.

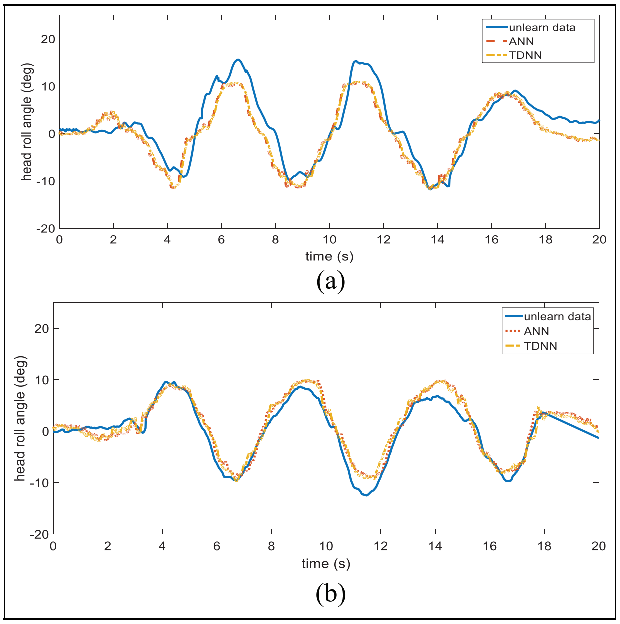

Figure 9. Comparison between estimated and unlearned responses. (a) Passenger. (b) Driver.

Table 4. Summary of the comparison error results for ANN and TDNN models.

Model	ANN (RMSE)	TDNN (RMSE)		Improvement (%)
		Min	Max	
Passenger	3.39	3.14	3.52	7.37
Driver	1.84	1.76	1.94	4.35

Some data from the passenger's and driver's experimental data were taken before the learning process, and both were recognized as unlearned data. The unlearned data was compared with the estimated output responses generated by the ANN and TDNN models, as shown in Figure 9. Additionally, the comparison error between the unlearned and estimated responses from time delay 0 to 100 was calculated and presented in Figure 10. Table 4 summarizes the comparison results for both the passenger's and driver's models based on ANN and TDNN. According to the table, the passenger's and driver's models developed by ANN produced comparison errors of 3.39 and 1.84. Meanwhile, the passenger's and driver's model utilized by TDNN produced lesser comparison errors, which were 3.14 and 1.76. Figure 10 illustrates the comparison between the output responses of ANN and TDNN models with the unlearned data. In addition, the estimated responses from TDNN model with the number of delays 9 (passenger) and 30 (driver) were used as they achieved the least error values. The figure also shows that both the ANN and TDNN models managed to produce output responses that imitated the pattern of unlearned data regardless of the number of delays. From the numerical results, TDNN produced lower comparison error than ANN for the passenger and driver models, which amounts to 7.37% versus 4.35%.

Based on the above results, it can be concluded that the proposed TDNN method has better modeling performance compared to the ANN method. Even though the parameter of time delay was increased from 1 to 100 during the TDNN modeling process, there was no significant difference in the model's accuracy. Since this study utilized only a single input parameter to predict the output, the system still captures the same information even though data from the same input was introduced to the network. As a result, the developed model produced similar output responses even though the parameter of the time delay was set to be 100 times larger.

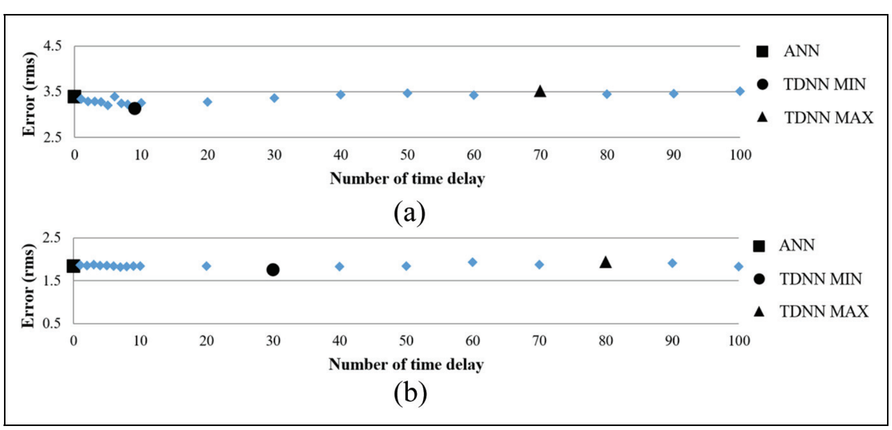

Figure 10. Comparison error of estimated and unlearned responses from time delay 0 to 100. (a) Passenger. (b) Driver.

5. Conclusion and future work

This study established a correlation model between the passenger's and driver's head tilt movements with vehicle lateral acceleration using the TDNN modeling method. The results show that the TDNN model is capable of producing similar output responses with real data taken from the experiment. TDNN achieved a higher regression value with a lower validation and comparison errors than ANN. The influence of the number of time delays on the efficiency of the models also shows that TDNN has better modeling performance than ANN.

The correlation model can be useful in predicting occupant' head movement while traveling in curved paths. It is expected that these models can be used as head movement predictor in the future MS studies. By predicting the head movement, researchers do not need to rely on for hardware sensors and other tools to measure the movement

Acknowledgements

The authors thank all Vehicle System Engineering Laboratory team members for their participation in this experiment.

Funding

This work was supported by a Universiti Teknologi Malaysia (UTM) trans-disciplinary grant (grant number 05G44).

ORCID iD

Sarah 'A Saruchi https://orcid.org/0000-0003-4516-890X

References

1. Diels C. Will autonomous vehicles make us sick? In: *Contemporary ergonomics and human factors*, Southampton, UK, 7–10 April 2014, pp.301–307. Abingdon, UK: Taylor & Francis.
2. Diels C and Bos JE. User interface considerations to prevent self-driving carsickness. In: *Adjunct proceedings of the 7th international conference on automotive user interfaces and interactive vehicular applications*, 1–3 September 2015, Nottingham, UK, pp.14–19.
3. Kennedy RS, Drexler J and Kennedy RC. Research in visually induced motion sickness. *Appl Ergon* 2010; 41: 494–503.
4. Cunningham M and Regan MA. Autonomous vehicle: human factors issues and future research. In: *Proceedings of the 2015 Australasian road safety conference*, Gold Coast, Australia, 14–16 October 2015, pp.1–11.
5. Yusof NM, Karjanto J, Kapoor S, et al. Experimental setup of motion sickness and situation awareness in automated vehicle riding experience. In: *9th International ACM conference on automotive user interfaces and interactive vehicular applications*, Oldenburg, Germany, 24–27 September 2017, pp.104–109.
6. Bos JE. Nuancing the relationship between motion sickness and postural stability. *Displays* 2011; 32: 189–193.
7. Dong X and Stoffregen TA. Postural activity and motion sickness among drivers and passengers in a console video game. *Proc Hum Factors Ergon Soc Annu Meeting* 2010; 54: 1340–1344.
8. Kuiper OX, Bos JE and Diels C. Looking forward: in-vehicle auxiliary display positioning affects carsickness. *Appl Ergon* 2018; 68: 169–175.
9. Wada T, Fujisawa S, Imaizumi K, et al. Effect of driver's head tilt strategy on motion sickness incidence. *IFAC Proc Vo* 2010; 43: 192–197.
10. Wada T, Konno H, Fujisawa S, et al. Can passengers' active head tilt decrease the severity of carsickness? Effect of head tilt on severity of motion sickness in a lateral acceleration environment. *Hum Factors* 2012; 54: 226–234.
11. Wada T, Fujisawa S and Doi S. Analysis of driver's head tilt using a mathematical model of motion sickness. *Int J Ind Ergon* 2016; 63: 89–97.
12. Konno H, Fujisawa S, Wada T, et al. Analysis of motion sensation of car drivers and its application to posture control device. In: *SICE annual conference*, Tokyo, Japan, 13–18 September 2011, pp.192–197. New York: IEEE.
13. Fujisawa S, Wada T, Konno H, et al. Analysis of head-tilt strategy of car drivers and its application to passenger's posture control device. *Trans Soc Instrum Control Eng* 2012; 48: 60–66.
14. Wiederkehr T and Altpeter F. Review of motion sickness evaluation methods and their application to simulation technology. *Simpack News* 2013: 12–15.
15. Elbanhawi M, Simic M and Jazar R. In the passenger seat: investigating ride comfort measures in autonomous cars. *IEEE Intel Transp Syst Mag* 2015; 7(3): 4–17.
16. Saruchi S'A, Zamzuri H, Hassan N, et al. Modeling of head movements towards lateral acceleration direction via system identification for motion sickness study. In: *2018 International Conference on information and communications technology, ICOIACT*, Yogyakajarta, Indonesia, 6–7 March 2018, pp.633–638. New York: IEEE.
17. Saruchi S'A, Zamzuri H, Ariff MHM, et al. Modelling of passenger's head tilt movement in motion sickness study using Hammerstein–Wiener system. In: *Proceedings of 7th international graduate conference of engineering, science and humanities*, Johor Bharu, Malaysia, 13–15 August 2018, pp.25–27.
18. Zheng J, Suzuki K and Fujita M. Car-following behavior with instantaneous driver-vehicle reaction delay: a neural-network-based methodology. *Transp Res C* 2013; 36: 339–351.
19. Abhishek K. Novel multi input parameter time delay neural network model for traffic flow prediction. In: *2016 online international conference on green engineering and technologies, IC-GET*, Coimbatore, India, 19 November 2016, pp.1–6. New York: IEEE.
20. Tyasnurita R, Ozcan E and John R. Learning heuristic selection using a time delay neural network for open vehicle routing. In: *2017 IEEE congress on evolutionary computation, CEC*, San Sebastian, Spain, 5–8 June 2017, pp.1474–1481. New York: IEEE.
21. Wada T, Kamiji N and Doi S. A mathematical model of motion sickness in 6DOF motion and its application to

vehicle passengers. In: *2nd International conference on digital human modeling*, Ann Arbor, MI, 11–13 June 2013, pp.1–6.
22. Peddinti V, Povey D and Khudanpur S. A time delay neural network architecture for efficient modeling of long temporal contexts. In: *16th Annual conference of the International Speech Communication Association, INTERSPEECH 2015*, Dresden, Germany, 6–10 September 2015, pp.3214–3218.
23. Peddinti V, Chen G, Povey D, et al. Reverberation robust acoustic modeling using i-vectors with time delay neural networks. In: *16th Annual conference of the International Speech Communication Association, INTERSPEECH 2015*, Dresden, Germany, 6–10 September 2015, pp.2440–2444.
24. Tsai C and Chang AY. Early warning system for DDoS attacking based on multilayer deployment of time delay neural network. In: *2010 Sixth international conference on intelligent information hiding and multimedia signal processing*, Darmstadt, Germany, 15–17 October 2010, pp.704–707. New York: IEEE.
25. Rawat M, Rawat K and Ghannouchi FM. Adaptive digital predistortion of wireless power amplifiers/transmitters using dynamic real-valued focused time-delay line neural networks. *IEEE Trans Microwave Theory Tech* 2010; 58: 95–104.
26. Belovski I, Sotirov S, Aleksandrov A, et al. Recognition of heat-conductive filling agents of a thermoelectric refrigeration system with focused time-delay neural network. In: *15th International conference on electrical machines, drives and power systems, ELMA*, Sofia, Bulgaria, 1–3 June 2017, pp.166–169. New York: IEEE.
27. Meng H, Bianchi-Berthouze N, Deng Y, et al. Time-delay neural network for continuous emotional dimension prediction from facial expression sequences. *IEEE Trans Cybern* 2016; 46: 916–929.
28. Hirose T, Gokan M, Kasuga N, et al. A study on modeling of driver's braking action to avoid rear-end collision with time delay neural network. *SAE Int J Passenger Cars Mech Syst* 2014; 7: 1016–1026.
29. Sutagundar M, Nirosha H and Sheeparamatti BG. Artificial neural network modeling of MEMS cantilever resonator using Levenberg–Marquardt algorithm. In: *2nd International conference on applied and theoretical computing and communication technology, iCATccT*, Bangalore, India, 21–23 July 2016, pp.808–811. New York: IEEE.
30. Hassan N, Zamzuri H, Wahid N, et al. Driver's steering behavior identification and modelling in near rear-end collision. *Telkomnika* 2017; 15: 861–868.
31. Alwakeel M. Face recognition based on Haar wavelet transform and principal component analysis via Levenberg–Marquardt back propagation neural network. *Eur J Sci Res* 2010; 42: 25–31.
32. Yang S, Ting TO, Man KL, et al. Investigation of neural networks for function approximation. *Procedia Comput Sci* 2013; 17: 586–594.
33. Karlik B. Performance analysis of various activation functions in generalized MLP architectures of neural networks. *Int J Artif Intell Expert Syst* 2011; 1: 111–122.
34. Panchal FS and Panchal M. Review on methods of selecting number of hidden nodes in artificial neural network. *Int J Comput Sci Mobile Comput* 2014; 3: 455–464.
35. Htike KK and Khalifa OO. Rainfall forecasting models using focused time-delay neural networks. In: *International conference on computer and communication engineering, ICCCE 2010*, Kuala Lumpur, Malaysia, 11–13 May 2010, pp.1–6. New York: IEEE.
36. Saruchi S'A, Ariff MHM, Zamzuri H, et al. Artificial neural network for modelling of the correlation between lateral acceleration and head movement in a motion sickness study. *IET Intell Transp Syst* 2018; 18: 340–346.

Author biographies

Sarah 'A Saruchi is currently a PhD student in Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia under the faculty of Malaysia-Japan International Institute of Technology.

Mohd HM Ariff is a senior lecturer in Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia.

Hairi Zamzuri is an Associate Professor in Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia.

Nurhaffizah Hassan is currently a PhD student in Universiti Teknologi Malaysia. She is also working as a lecturer in Faculty of Electrical Engineering in Universiti Teknologi Mara, Terengganu, Malaysia.

Nurbaiti Wahid is a senior lecturer in Faculty of Electrical Engineering, Universiti Teknologi Mara, Terengganu, Malaysia.