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LATERAL CONTROL WITH NEURAL NETWORK HEAD ROLL PREDICTION MODEL FOR MOTION SICKNESS INCIDENCE MINIMISATION IN AUTONOMOUS VEHICLE

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Abstract

Generally, the passengers of an autonomous vehicle suffer substantial motion sickness (MS) compared to the driver. This particularly occurs during cornering as the passengers are inclined to tilt their heads in the direction of lateral acceleration whereas the driver tends to tilt their head in the opposite direction. Therefore, it is crucial for the passengers to reduce the head roll angle towards the direction of lateral acceleration to decrease the susceptibility to MS. This study proposed a lateral control approach based on the head roll angle which was estimated by head roll prediction models to reduce the severity of MS in an autonomous vehicle. The prediction models were developed via the Artificial Neural Network (ANN) technique. A Proportional-Integral (PI) controller was implemented to produce a corrective wheel angle based on the predicted head roll angle responses of the driver and passenger. The corrective angle caused a decrease in the lateral acceleration. The decrement in lateral acceleration then reduced the passenger's head roll angle towards the direction of lateral acceleration. The findings indicated that the suggested control approach was capable to decrease the MS Incidence (MSI) index by 5.97% over a single lap and 14.48% over 10 laps.

Keywords: Artificial neural network, Autonomous vehicle, Head roll angle, Lateral control, Motion sickness.

1. Introduction

An autonomous vehicle is a component of progressive growth that has gained significant interest in automotive technology. This technology is promising for transportation systems in terms of ensuring transformative security, mobility, and environmental impact [1]. According to the Society of Automotive Engineers (SAE), there are six levels of automated driving systems varying from level 0 to level 5 [2]. Levels 0 to 2 entail the driver overseeing the automation system. On the other hand, levels 3 to 5 do not require the driver to attend to the vehicle control or even monitor the traffic condition. In this study, the autonomous vehicle is assumed to be operated at autonomy level 3 or higher, where the driver can be considered as a passenger.

Despite drawing a lot of attention, there is a drawback that leads to significantly negative impact on the passenger's comfort and public acceptance, which is motion sickness (MS). MS is a painful disorder which commonly occurs when travelling in a moving vehicle. MS is expected to be more prevalent among autonomous vehicle users than conventional vehicle users [3]. The symptoms of MS are dizziness, headache, nausea, and vomiting [4]. The well-known cause of MS is the sensory conflict between visual and vestibular systems [5]. Moreover, the aetiology of MS also includes loss of control of one's actions and lowered capacity to predict the course of movement. Normally, passengers are more susceptible to MS than drivers. Studies revealed that the different head tilt directions of driver and passenger towards the direction of lateral acceleration when driving round a curve causes varying severity of MS [6-8]. During cornering, passengers tend to tilt their heads in the same direction as the lateral acceleration whilst the drivers tilt their head in the opposite direction. Thus, this suggests that the passengers can minimise their susceptibility to MS if they decrease their head tilting angle in the direction of lateral acceleration.

The development of measures to reduce and avoid the severity of MS is expected to become an important topic of automotive research to ensure the public acceptance of autonomous vehicles [9]. Yusof et al. [10] presented a haptic feedback device that provides data pertaining to the direction of the vehicle so that passenger will be aware of the situation. Wiederkehr et al. [11] indicated that the increase of lateral acceleration will lead to more severe MS. This means that the severity of MS can be minimised if the lateral acceleration is reduced. Furthermore, Elbanhawi et al. [12] reported that the MS can be overcome by a smooth lateral control strategy. Based on the finding concerning the correlation between head tilting movement in the direction of lateral acceleration and MS, a posture control device is developed to reduce the severity of MS sustained by the passenger by prompting the passenger to move their head in the opposite direction to the lateral acceleration [13, 14]. The study revealed a positive outcome of the control device as it tended to reduce the impact of MS.

Based on the above discussion, the general idea to overcome the severity of MS in an autonomous vehicle is to reduce the passenger's head roll angle towards the direction of lateral acceleration when driving around a curve. This can be achieved by lowering the lateral acceleration when cornering. Numerous control design studies had been undertaken to control vehicle lateral motion, for example, using the active steering system which used information from the yaw rate and Direct Yaw Control (DYC) which used information from the yaw rate and body slip [15-17]. There are also studies that adopted human factor element in the active steering system design. Human mechanical impedance properties of the arms [18], steering behaviour [19] and visual anticipation [20] are the examples of human factor proven to be successful in assisting the steering system. However, the interaction of the human factors with vehicle in terms of MS is unclear.

In order to investigate the capability of human factor elements in assisting the MS mitigation control design for vehicle, it is necessary to apply a human factor variable that has correlation with vehicle and MS. Therefore, based on the correlation between the head roll angle and lateral acceleration, the main contribution of this study is proposing the head roll angle as the new controlled variable in the lateral control strategy to generate a corrective wheel angle to diminish lateral acceleration in an autonomous vehicle. A Proportional Integral (PI) controller was utilised for the corrective wheel angle generation. PI was selected because it has a simple configuration and less computation. The corrective wheel angle enabled the minimisation of the lateral acceleration. The minimisation causes the reduction of the passenger's head tilt movement in the direction of lateral acceleration, ultimately leading to the mitigation of the MS.

The next concern in this study was the indefinite values or the head roll angles of the driver and passenger towards and against the direction of lateral acceleration during cornering. Thus, head roll prediction models are applied with the aim to predict both driver's and passenger's head roll responses without the necessity to directly measure them through any type of device or sensor. Since the relationship of human Behavior and motion are complex and vague, prediction modelling method using NN is considered as the most suitable method to be adopted compared to the mathematical modelling. Previously, head roll prediction models were developed based on the correlation between the lateral acceleration and the head roll angle during cornering. The modelling process were carried out using experimental data. Modelling methods such as System Identification (SI), Artificial Neural Network (ANN), Radial Basis Function Network (RBFN) and Time Delay Neural Network (TDNN) were successful in developing the prediction model [21-25]. In this study, the ANN modelling method was adopted to develop the head roll prediction models. The advantage of ANN over a statistical modelling method like SI is that prior knowledge or assumption is not required during the modelling process. Moreover, ANN has a less complex configuration than TDNN and RBFN.

2. Vehicle Model and its Path Tracking Control System

2.1. Vehicle dynamic model

Figure 1 shows a 7-degree-of-freedom (DOF) nonlinear model applied in the current study as the vehicle plant for the suggested control approach. Table 1 summarises the model's parameters. Determination of parameters was based on the vehicle that was utilised in the experiment.

The equations of the longitudinal, lateral, and yaw motions are detailed as shown below [26]:

$$m(\dot{v_x} - v_y\gamma) = (F_{xFL} + F_{xFR})cos\delta - (F_{yFL} + F_{yFR})sin\delta + F_{xRL} + F_{xRR} \quad (1)$$

$$m(\dot{v_y} + v_x\gamma) = (F_{yFL} + F_{yFR})cos\delta + (F_{xFL} + F_{xFR})sin\delta + F_{yRL} + F_{yRR} \ldots \quad (2)$$

$$I_z\dot{\gamma} = l_f\left((F_{yFL} + F_{yFR})cos\delta + (F_{xFL} + F_{xFR})sin\delta\right) - l_r\left(F_{yRL} + F_{yRR}\right) +$$

$$+\frac{T}{2}((-F_{xFL}+F_{xFR})cos\delta+(F_{yFL}-F_{yFR})sin\delta-F_{xRL}+F_{xRR})) \quad (3)$$

where F_{xi} and F_{yi} $(i = FR, FL, RR, RL)$ denote the longitudinal and lateral forces of each wheel and γ indicates the yaw rate. The vehicle model was also included with the nonlinear wheel model for which the equations can be found in [27].

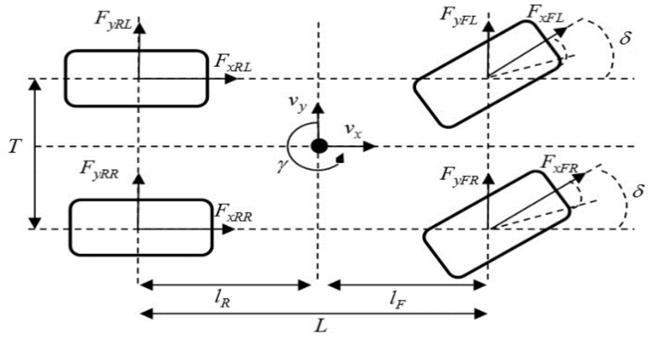


Fig. 1. Nonlinear vehicle model.

Table 1. Parameters of the nonlinear vehicle model.

Symbol	Definition	Value	Unit
v_y, v_x	Lateral and longitudinal velocities	30	km/h
T	Track width	1.53	m
l_F	Front wheel distance to the COG	1.26	m
l_R	Rear wheel distance to the COG	1.9	m
m	Vehicle mass	2023	kg
I_z	Yaw inertia	6286	$\mathrm{kg.m^2}$

2.2. Path tracking control system

The purpose of implementing a path tracking control system was to provide a wheel angle input to the vehicle based on a pre-defined trajectory. Here, a Stanley controller was selected to fulfil this purpose. The reason of the selection was because of the simplicity and ability of the controller to ensure good performance [28, 29]. Additionally, the Stanley controller had the benefit of not necessitating any selection of look-ahead distance. The Stanley steering control law is expressed as follows [30]:

$$\delta_s(t) = \emptyset + tan^{-1}\left(\frac{ke(t)}{v(t)}\right) \quad (4)$$

where, δ_s denotes the wheel angle and $\emptyset$ denotes the heading error between the pre-defined trajectory and the vehicle direction, calculated from the difference of yaw angle of the vehicle and trajectory, v is the velocity, k is the gain parameter, and e is the lateral error.

3. The Proposed Inner-loop Lateral Control Strategy

3.1. Proposed control structure

Figure 2 illustrates the structure of the proposed control system strategy that includes the outer loop and inner loop lateral control systems. The objective of the outer loop is to control the vehicle's tracking performance to move proportionally to the pre-defined path. The main contribution of this study is proposing the head roll angle as the new controlled variable in the inner loop lateral control system to generate a corrective wheel angle. The goal of totalling the inner loop is to reduce the passenger's head roll angle, θ_{H_P} during slalom driving. Previous investigations and findings demonstrated the correlation between the passenger's head roll angle with lateral acceleration [8-10]. The passenger's head roll angle response is in the same direction with the lateral acceleration. This implies that if the lateral acceleration is decreased, the head roll angle will also be lowered. Hence, to decrease the lateral acceleration, a corrective wheel angle is added to the vehicle system.

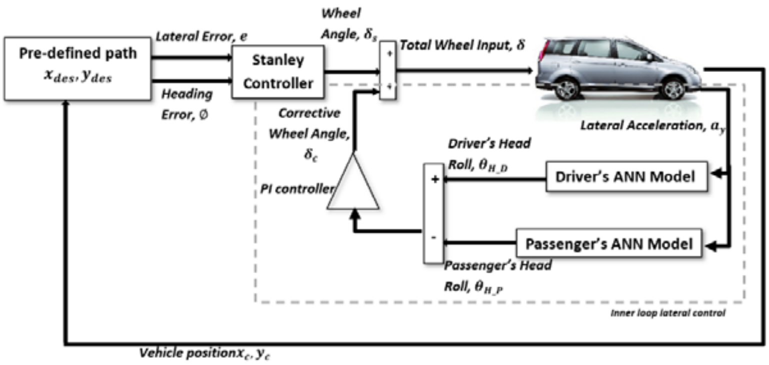


Fig. 2. Structure of the proposed control system.

The head roll prediction model utilised in this study was based on the previous study [23]. Figure 3 illustrates the configuration of the ANN head roll prediction model. The driver and passenger modelling processes were conducted separately. The input is the lateral acceleration, a_y while the output of the model is either driver's estimated head roll angle, θ_{H_D} or the passenger's estimated head roll angle, θ_{H_P}. The number of hidden neurons was selected based on the well-known Kolmogorov Theorem [31]. Using this theory, the appropriate number of hidden neurons was calculated based on the $2n$+1 formula, where n is equal to the number of inputs. Thus, for this study, the chosen number is 3.

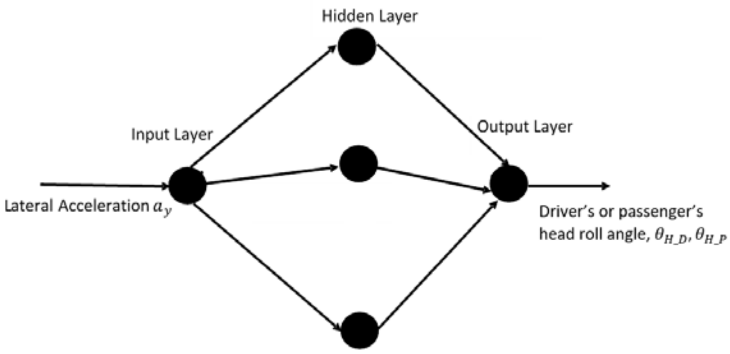


Fig. 3. Structure of the ANN head roll prediction model.

An experiment was conducted to obtain the data of lateral acceleration and the head roll responses of the drivers and passengers for the modelling process [23]. The experiment outlined by Wada et al. [32], was a slalom driving test through six cones. The cones were placed at the gaps of 20 m wide on a 150 m-long straight normal road. The drivers were asked to carry out a slalom driving course from the first cone to the last cone at a constant velocity of 30 km/h. The nominal frequency of lateral acceleration during the test was 0.21 Hz a frequency that aggravates MS.

It is essential to determine the generalisation ability of the trained network. It represents the capability of the developed ANN models in handling unseen data. Unseen data is a set of unused data during the modelling process. The generalisation is examined through comparison between the estimated output data generated by the developed model and the unseen data. The results presented in the previous study indicated that the estimated and unseen data responses had pattern similarities [23]. The outcome of the generalisation test suggests that the developed models succeeded in predicting the head roll responses.

Based on Fig. 2, the concept that lies behind the additional corrective wheel angle arises from the fact that drivers experience less MS than passengers because they tilt their head against the direction of lateral acceleration. Utilising this in the control structure, the estimated driver's head roll angle was treated as the reference, and the estimated passenger's head roll angle was considered as the actual response. Then, the difference between the reference and the actual responses was calculated to determine the error of head roll angle.

For the next step, a Proportional Integral (PI) controller was applied to reduce the lateral acceleration and head roll responses. It was used to generate the corrective wheel angle, which was later introduced into the vehicle system. As mentioned previously, in this study, the vehicle was assumed to be moving autonomously without assistance from the driver. Thus, for the analysis of results, only the response of the passenger's head roll angle was considered.

3.2. Simulation setup

The effectiveness of the control structure was investigated by running the simulation in Matlab/Simulink software. The vehicle was set to run at a constant speed of 30 km/h. The pre-defined trajectory as shown in Fig. 4 was a slalom driving path taken from the experiment in the previous study [23]. The curves along the path were labelled as curve 1 to curve 6 for the ease of understanding the simulation results.

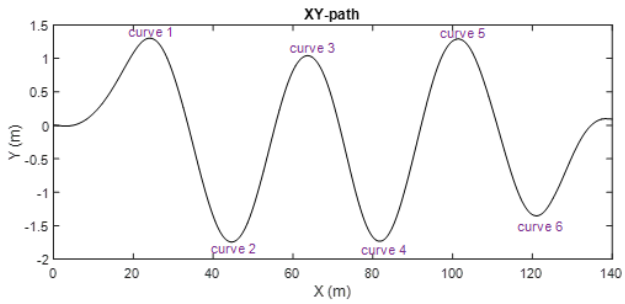


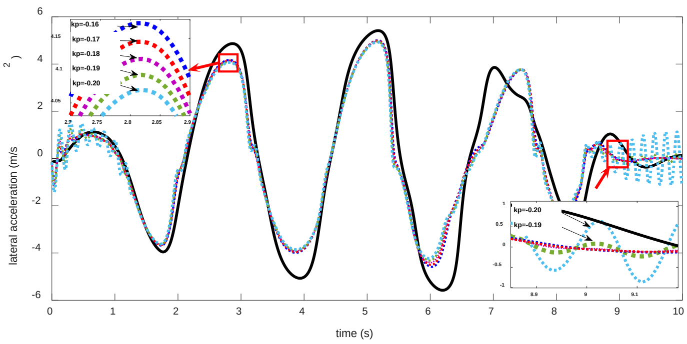
Fig. 4. Pre-defined trajectory.

There are three tuning parameters in the structure. To begin with, it was crucial to adjust gain k in the Stanley controller to obtain accurate path tracking behaviour according to the desired path. The control law expressed as Eq. (4) was saturated about δ_{max} as demonstrated in Eq. (5) [33]. In this study, the δ_{max} was fixed to be

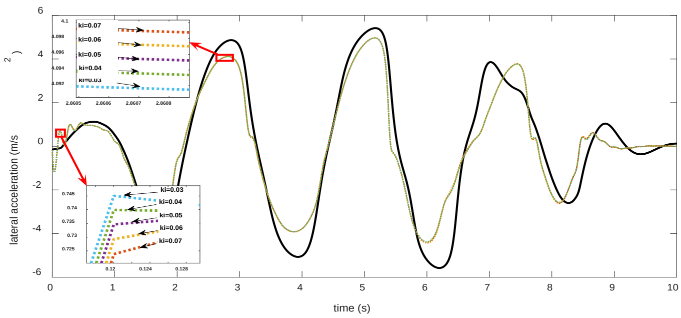
20o. At this juncture, gain k was tuned according to the saturation limit in Eq. (5), by a heuristic technique, till it was able to attain the lowest tracking error.

$$\delta(t)=\begin{cases}\delta_{max} & if\ \emptyset+tan^{-1}\left(\frac{ke(t)}{v(t)}\right)\geq\delta_{max}\\ \emptyset+tan^{-1}\left(\frac{ke(t)}{v(t)}\right) & if\ \left|\emptyset+tan^{-1}\left(\frac{ke(t)}{v(t)}\right)\right|<\delta_{max}\\ -\delta_{max} & if\ \emptyset+tan^{-1}\left(\frac{ke(t)}{v(t)}\right)\leq\delta_{max}\end{cases}\qquad(5)$$

The second and third tuning parameters are k_P and k_i in the PI controller. These gains were tuned until the lateral acceleration achieved the lowest point without negatively affecting the vehicle’s tracking performance and the system stability. The tuning procedure of the PI controller underwent a sensitivity analysis to choose the utmost appropriate gains for the system. The analysis started with low value gain until the maximum value gain before the lateral acceleration starts to form oscillation. Fig. 5 demonstrates the lateral acceleration response when the tuning parameters were varied between -0.16 and -0.2 for kp and between 0.03 and 0.07 for ki. Based on Fig. 5(a), when k_P was augmented, the lateral acceleration decreased. Nonetheless, once the gain was fixed at -0.19, the response started to oscillate. In contrast, according to Fig. 5(b), when k_i was reduced, the lateral acceleration decreased. Nonetheless, when the reduction in the value of k_i was smaller than 0.05, a larger oscillating response was formed. Thus, the maximum k_P and k_i values were set to -0.18 and 0.05, respectively. These values were chosen as the appropriate gain for the system. Table 2 summarises the parameters of the tuning gain, which were selected based on the evaluation performed.



(a) Sensitivity analysis of k_p.



(b) Sensitivity analysis of k_i

Fig. 5. Sensitivity analysis of k_p and k_i gains towards the lateral acceleration response.

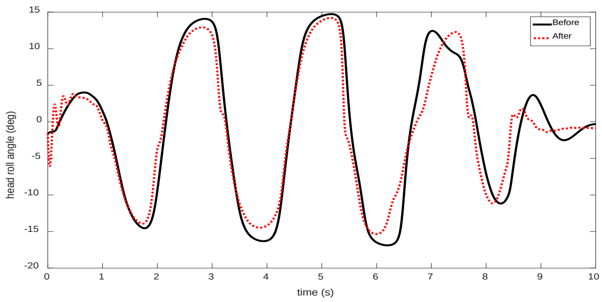
Table 2. Stanley and PI controllers gain parameter.

Gain	k	k_P	k_i
Value	3.8	-0.18	0.05

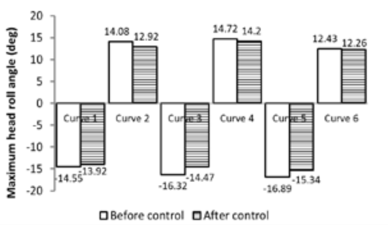
4. Results and Discussion

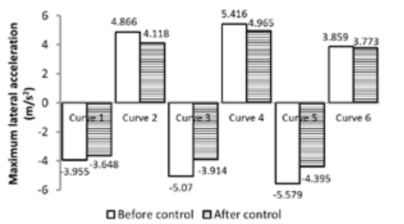
4.1. Simulation results

Figure 6(a) shows the passenger's head roll angle responses before and after the implementation of the recommended inner-loop control system. Meanwhile, Fig. 6(b) displays the findings of the maximum passenger's head roll angles of all curves. The purpose of observing the maximum head roll angle value was to determine the extent of decrease once the vehicle had attained peak cornering speed. The results show that the maximum passenger's head roll angle response had declined in every curve. On the other hand, based on the lateral acceleration responses in Fig. 5, the maximum value of the lateral acceleration response at the peak of every curve was recorded and presented in Fig. 6(c). Figs. 6(a), 6(b) and 6(c) indicate that the proposed control strategy had successfully achieved the objective of reducing the lateral acceleration and the passenger's head roll angle during cornering.



(a) Passenger's head roll angle response.





(b) Numerical results of the maximum passenger's head roll angle.

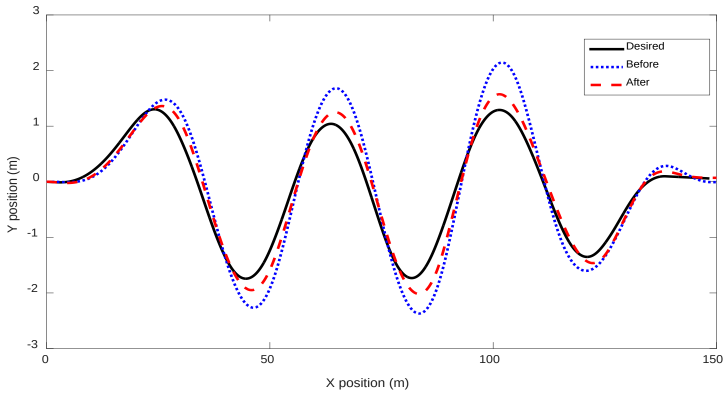
(c) Numerical results of the maximum lateral acceleration.

Fig. 6. Results of passenger's head roll angle and lateral acceleration.

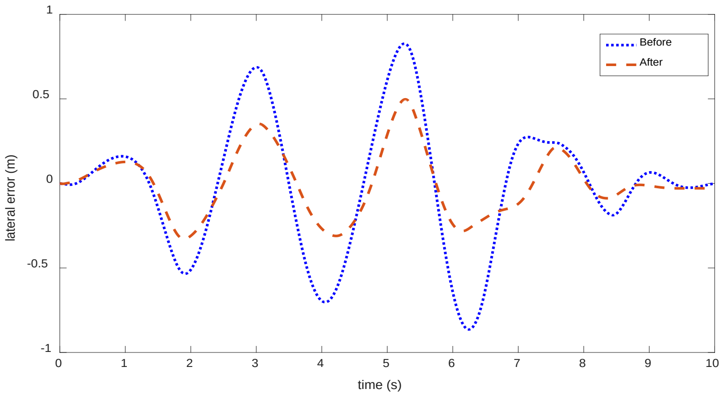
The influence of the inner loop lateral control system on the vehicle's trajectory tracking performance was also assessed. Figure. 7(a) illustrates the tracking results in XY global position, whereas Fig. 7(b) shows the lateral error. The findings revealed that the Stanley controller produced overshooting during sharp cornering. This was due to the no-look ahead selection in the Stanley technique as per the application of lateral offset from the front axle of the vehicle to the trajectory [34, 35]. Despite its disadvantages during sharp cornering, the inclusion of the inner loop lateral control enhanced the trajectory tracking performance. Based on Fig. 7(b), the lateral error was reduced prior to application of the recommended control approach. The numerical analysis of the lateral error is tabulated in Table 3. The analysis shows that the lateral error was reduced by 37.46%.

Table 3. Lateral error (RMSE).

	Before control (RMSE)	After control (RMSE)	Reduction (%)
Value	0.3054	0.1910	37.46



(a)Tracking performance in X-Y global position.



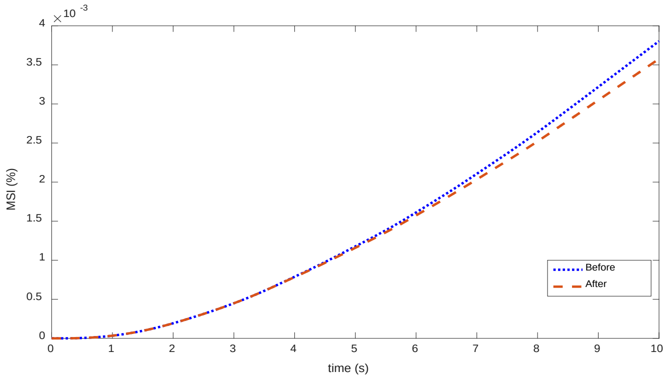
(b) Lateral error.

Fig. 7. Trajectory tracking performance.

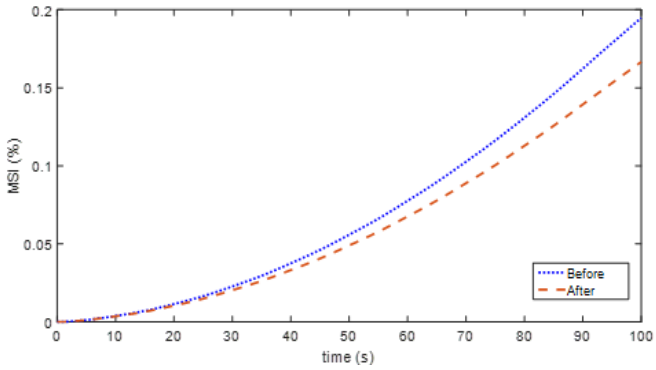
4.2 Analysis of motion sickness incidence

Lastly, the severity of MS experienced by the passenger is the key parameter measured in this study. The MS value is calculated through a 6 degree-of-freedom (DOF)-Subjective Vertical Conflict (SVC) model that was obtained from previous studies [32]. The model was able to quantify motion sickness incidence (MSI), which is an index of the severity of MS. The model was utilised to measure the MSI by using the lateral acceleration and head roll responses as the inputs.

Figure 8 displays the findings of the MSI, before and after the implementation of the proposed control system. Meanwhile, the numerical results of the MSI are tabulated in Table 4. The pre-defined trajectory illustrated in Fig. 4 was referred to as one lap. To investigate the MSI value when the time was increased, the simulation was continued for 10 laps. Based on Fig. 8(a), the MSI declined by 5.97% throughout the simulation of a single lap. The MSI had a small percentage value due to the short simulation time which was only 10 seconds. In the meantime, based on Fig. 8(b), the MSI of the 10-lap simulation was declined by 14.48%. According to Fig. 8, the gap between the responses before and after the implementation of the control system expanded following the extension of time. Hence, this finding was in agreement with the previous studies by Wada et al. [7], where the gap of driver's and passenger's MSI continue growing when the simulation time continue increasing. The findings indicated that the recommended control approach was useful in lowering the severity of the passenger's MSI when driving around a curve. It is expected to achieve greater enhancement percentage when the time elapsed.



(a) 1 lap



(b) 10 laps

Fig. 8. MSI index.

Table 4. Analysis of MSI Index.

Conditions	MSI (%)		Reduction (%)
	Before	After	
1 lap	0.003804	0.003577	5.970
10 laps	0.194800	0.166600	14.48

5. Conclusions and Future Work

The severity of MS endured by the passenger can be mitigated by lowering the lateral acceleration during cornering. The decline in the lateral acceleration will cause minimisation of the passenger's head roll angle. Subsequently, the minimised head roll angle will lower the MSI of the passenger. Therefore, this study recommends a lateral control strategy with the head roll angle as the controlled variable to generate a corrective wheel angle to reduce the lateral acceleration. PI controller was used as the corrective wheel angle generator and ANN was used as the head roll prediction modeling method. The findings from the simulation indicated that the proposed control strategy had succeeded in decreasing the lateral acceleration and the passenger's head roll angle for the duration of driving around a curve. In addition, the current study applied a 6 DOF-SVC model to measure the MSI of the passengers. Simulation results show that the MSI of the passenger was decreased by 5.97% in a single lap and 14.48% over 10 laps. The findings of this study indicated that the proposed control strategy was succeeded in achieving its objective to mitigate the passenger's MSI. In light of this breakthrough, for future work, it is necessary to validate the proposed control strategy using a real autonomous vehicle to investigate its effectiveness in real time.

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Nomenclatures

a_y	Lateral acceleration
e	Lateral error
F_{xi}	Longitudinal force
F_{yi}	Lateral force
I_z	Yaw inertia
k	Stanley controller gain parameter
k_i	PI controller gain parameter
k_P	PI controller gain parameter
l_F	Front wheel distance to the COG
l_R	Rear wheel distance to the COG
m	Vehicle mass
n	Number of inputs of neural network
T	Track width
v_x	Longitudinal velocity
v_y	Lateral velocity

Greek Symbols

γ	Yaw rate
δ	Wheel angle
δ_{max}	Maximum limit of wheel angle
δ_s	Wheel angle output from Stanley controller
θ_{H_D}	Driver's head roll angle

θ_{H_P}	Passenger's head roll angle
$\emptyset$	Heading error
Abbreviations	
ANN	Artificial Neural Network
DOF	Degree-of-freedom
DYC	Direct Yaw Control
MS	Motion sickness
MSI	World Health Organization
PI	Proportional Integral
RBFN	Radial Basis Function Network
SAE	Society of Automotive Engineers
SI	System Identification
SVC	Subjective vertical conflict
TDNN	Time Delay Neural Network

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