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ORIGINAL ARTICLE

Comparison of Transfer Function Models to Represent the Correlation Between Vehicle Lateral Acceleration and Head Tilting Angle in Motion Sickness

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ABSTRACT – Motion Sickness (MS) is described as an unpleasant feeling caused by a forceful movement; hence vehicle movement impacts the severity of MS. While negotiating a curve, drivers and passenger tilt their heads differently, affecting their motion sickness incidence (MSI), which is the severity of MS. MS is a negative feeling, that affects occupant's comfort, and to further understand the correlation between occupants' behavior and vehicle movement in MS and then represent it using mathematical models, it was proven that MSI could be predicted through mathematical models. However, there is an indefinite value between values between occupant's behavior and vehicle movement. Based on that it is vital to express it the correlation mathematically. An experiment adopted from a prior study was utilized to get the data and develope the mathematical models with different proportions to represent the correlation between vehicle movement and occupant behavior in motion sickness in transfer function equations using system identification (SI), by utilising black-box feature to use the experimental data as input and output to allow SI to predict the transfer function models. The aim of this study is to investigate MS factors in relation to the vehicle movement and occupant's behavior, to develop multiple transfer function models, to analyze and compare them. The results were obtained in the three different transfer function orders, second, third and fourth order functions for each proportion used for both the driver and passenger, the driver models' results were in between 64.68%-67.87%, and the passenger results were in between 63.75%-67.93%, after the comparison the highest fits for each order were obtained. The highest fits amongst driver models were 67.87% (4th Order), 66.78% (3rd Order) and 65.17% (2nd Order) and 67.93% (4th Order), 66.3% (3rd Order) and 64.82% (2nd Order) amongst the passenger models. Those fits were then validated via Simulink with unseen data that was not used in identification process, and lastly the models Root Mean Square Error (RMSE) was obtained for all of them to determine their efficiency.

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INTRODUCTION

Motion sickness (MS) or also known as kinetosis, was first defined by the Greek physician Hippocrates who wrote "Sailing on the sea proves that motion disorders the body". Irwin used the phrase "motion sickness" in 1881 to characterize a condition brought on by frequent oscillatory movements of the body. It involves a sense of uneasiness or discomfort that appears while traveling in vehicles, as well as using an elevator, amusement ride, swing, or, less frequently, a horse [1]-[3]. However, real motion is not necessary for the disease to appear; the sense of motion can also cause motion sickness [4]. Thus, even when the affected individuals are not actually moving, they can nevertheless suffer MS while watching a vast moving field or riding a virtual reality ride in an amusement park [5].

MS can be caused by travelling by air, land, or sea [6]-[9], and it can also be caused by vestibular stimulation [10]. MS is a disorder in which the visual perception of movement differs from the vestibular system's sense of direction. When exposed to intensive motion stimuli, nearly everyone experiences motion sickness [11]. The main symptoms and signs of MS are nausea and vomiting [12] as well as sweating, stomach awareness, facial pallor, and drowsiness (often referred to as "cold sweating" and "sopite syndrome" respectively), warm sensation in the body, dizziness, and usually losing appetite, and headache [13],[14].

There are many hypotheses about the causes of MS. The first theory states that the sensory conflict between visual and vestibular system inputs is the most general theory. The second theory states that when the brain gets confused due to a discrepancy between the integrated pattern of sensory input under actual motion or in a simulated environment and the expected internal model, the brain becomes confused. The last theory is that people are overstimulated. This theory is about how the occupant is affected by the repetitive acceleration stimulus from vehicle action. However, the most widely accepted theory for MS is the sensory conflict hypothesis [13]. The theory of Subjective Vertical (SV) conflict (which is the ability to perceive verticality) states that all MS-inducing situations classify by a state in which the sensed SV through visual, idiotropic, and gravity inputs varies from the anticipated vertical. This theory effectively predicts MS in many vehicles [15].

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Many factors affect MS. Firstly, the conflict between the vestibular, somatosensory, and visual input is its leading cause. If one of these inputs was absent or inconsistent, the possibility of getting MS increased [16]. Secondly, the eye's movement induces optokinetic nystagmus (OKN), which stimulates the vagus nerve resulting in MS [17]. Lastly, MS is often preceded by SV conflict, also known as vection [18]. Another theory suggests that MS affects people who have lower control over their bodies, including their ability to stand and move around [19]. Unusual or uneven vehicle movement is one of the factors that contributes to an unstable posture [20]. According to this theory, limiting swaying and maintaining a firm posture when traveling will help prevent MS. According to research by Dong and Stoffregen [20], people who move consistently throughout time are less likely to get MS than people who move differently.

While negotiating a curve, drivers' innate make them tilt their heads toward the centre of the curve; meanwhile, passengers do the opposite and tilt their heads to the centrifugal [21][22][23], which makes drivers less vulnerable to getting MS than passengers because of their controllability viewpoint [21]. Additionally, the effects of head-tilt strategies are possible to interpret in such situations. There are many interpretations, such as the occupant's body posture also affects motion sickness [23]; an increment in MS occurs when the body axis aligns in the same direction as the acceleration. As well as obtaining visual information of the road shape, the head tilt correlates with the road shape obtained visually [24]. Moreover, another interpretation is the reduction of MS severity which can happen when the driver tilts their head towards the centripetal direction, which correlates with lateral acceleration while negotiating a curve [25]. Since MS is a negative feeling that affects drivers' and passengers' comfort during driving [26], it is important to understand the correlation and represent it mathematically; due to the issue that vehicle movement and occupants have an indefinite value between them. With that, the reasons that make MS more severe can be reduced and lead to the occupants to be more comfortable. And since vehicle movement and occupant's behavior have indefinite value, they must be identified mathematically.

The index of MS severity MSI [27] is typically predicted using mathematical fits through experimental data [28]-[30]; based on that, SI will predict the fits using the black-box method. SI is a MATLAB toolbox that allows the user to choose an adequately precise model structure to fit its unknown parameters to map the existing I/O data properly [31]. Additionally, it can estimate the behavior of the system's output towards an unknown input. SI has a wide range of usage apart from the industrial scope; it is also used in the economy, biology, and biomedical research as it has reliable design techniques. Black-box is a data-driven method of modeling that does not require knowledge of the mechanics of the Black-Box interactions [32][33][34]; hence the models will be created using black-box because there is no physical insight on the model.

METHODOLOGY

Experiment

This section demonstrates the adopted experiment [35] conducted to obtain the data used in the identification process on MATLAB. This experiment's vehicle was a multi-purpose Vehicle (MPV) Proton Exora, it weighs around 1400–1486 kg (3086.5–3276.1 lb), and it was equipped with sensors to measure and store the data. The locations of the sensors, which are shown in Figure 1, were on the participant's caps and the center of gravity (COG) of the vehicle. The vehicle's boot was equipped with a monitor to acquire all the data. This experiment was chosen due to its ability to generate MS at low frequency; the frequency in this experiment was 0.21 Hz since drivers were required to slalom drive along the road with a fixed speed of 30 km/h and that frequency provokes MS [26]. The speed was maintained via the trial-and-error method, by repeating the experiment multiple times to all the drivers to familiarize themselves with the acceleration and deceleration of the vehicle to maintain it.

Figure 1. Equipment used along with their respective locations

The experiment was 150 m long along with six cones distributed along the way with a 20 m distance difference between them, as illustrated in Figure 2, and they are assumed to be disturbances. Drivers were asked to slalom drive on this track avoiding the cones with a constant velocity of 30 km/h. In this experiment, there were three iterations, which means every driver had been a participant, and every participant had been a driver three times in total. Hence, the overall number of data sets obtained was 30 sets for each participant and driver [35].

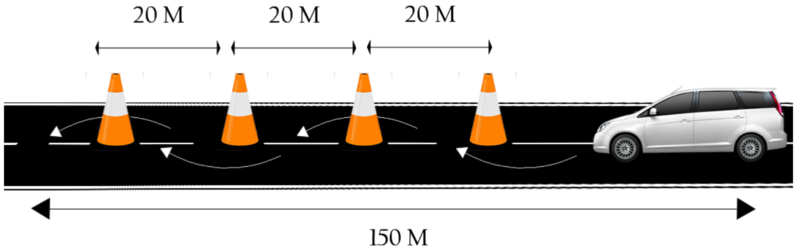


Figure 2. The experiment track

In this experiment, a total of 10 people participated, their good health and safety were confirmed along with having a valid driving license before commencing the experiment, and those who were not healthy were not able to participate. In the experiment, safety measurements were done, including fastening seatbelts and wearing helmets. In addition, the different driving style was considered normal. Passengers were asked to act naturally and not avoid tilting their heads towards the centripetal direction in purpose; meanwhile, drivers had to tilt their heads towards the centripetal direction, as illustrated in Figure 3, which represents the general head movement during travelling. Any actions that could result in an error or affect the measurements were prohibited, such as chatting and using mobile phones [35].

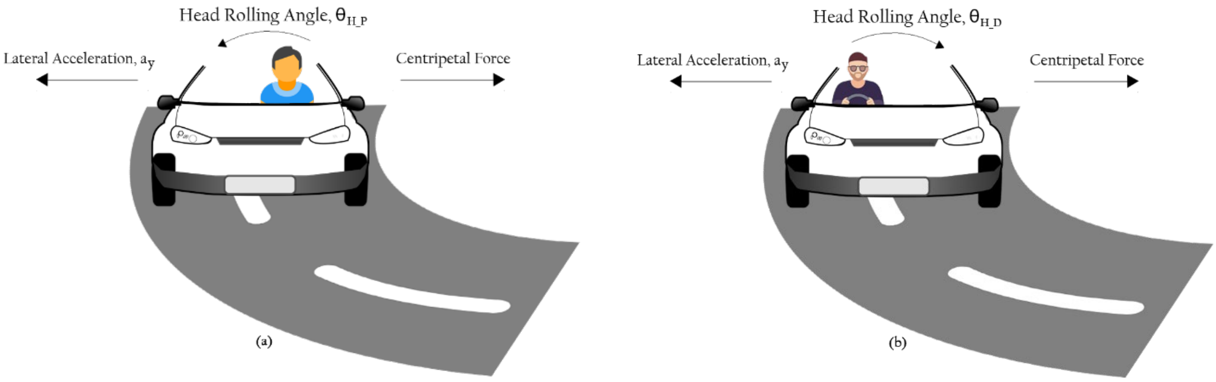


Figure 3. General head movement for passengers (a) and drivers (b) while navigating a curve

Modeling

This section is about the methodology and flow chart shown in Figure 4 to create the mathematical model using SI black-box toolbox on MATLAB, including the flow chart of creating the model, the experimental data used, and the method to process the model for best fit to validate the data. There are four steps to creating a model via SI. In this study, the input will be lateral acceleration, and the output is the occupant's head movement. After obtaining the data needed to create the model, the next step is selecting a model structure from the SI toolbox's graphical user interface (GUI). GUI is the control panel to which the data can be imported, select the type of structure/model, and pre-process and process data. In this research, the model is a transfer function model. The third step is to process the data to find the best fit for the model generated, then evaluate the model and validate the data. In this study, the transfer function model will represent the relationship between the output and input signals, including all values in an algebraic equation rather than complex equations [36].

Selecting Model Structure

The data imported from the experiment was driver and passenger lateral acceleration and head rolling head angle. The lateral acceleration was used as input, while hear rolling angle was used as output. The imported data will develop two models as Transfer Function Models which are illustrated in Figure 5 and Figure 6. The first model will represent the passenger head rolling angle correlation with the lateral acceleration. The second model will represent the driver head rolling angle correlation with the lateral acceleration.

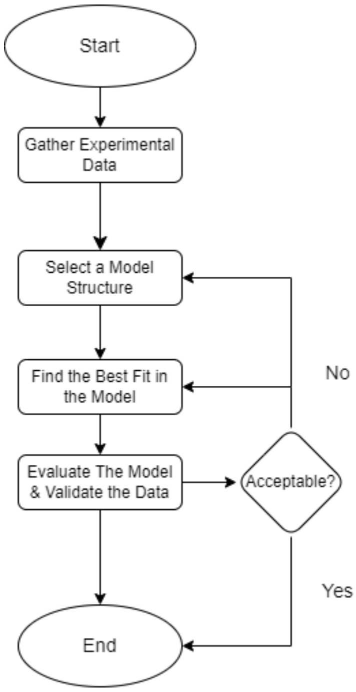


Figure 4. Model creation flow chart

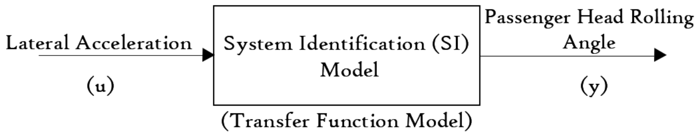


Figure 5. Model of the correlation between lateral acceleration and passenger head rolling angle

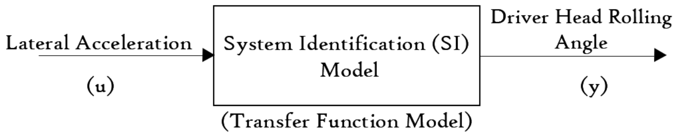


Figure 6. Model of the correlation between lateral acceleration and driver head rolling angle

FIND THE BEST FIT FOR THE MODEL STRUCTURE

In this step, SI will process the data to produce an estimated fit for the model depending on the order of the transfer function, which is the number of zeros (n), and poles (p). Usually, the higher the number of zeros and poles, the better the fit and the more complex the model; this is because it makes the system more stable and, thus improves performance as well. To achieve this, SI will use black-box modelling, which is a data-driven method to create models based on input/output data only, without having any physical insight of the model as shown in Figure 7.

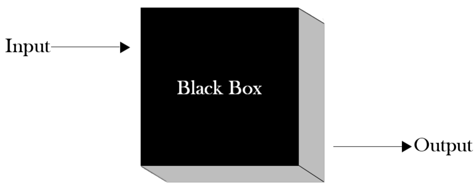


Figure 7. The concept of black-box modeling

The first step in processing the data and getting the best fit for the model is to import the data obtained from the experiment and add the validation data, which determines if the model is suitable for other applications. The data in the working data slot is the data that is processed and then used to estimate the model, as illustrated in Figure 8.

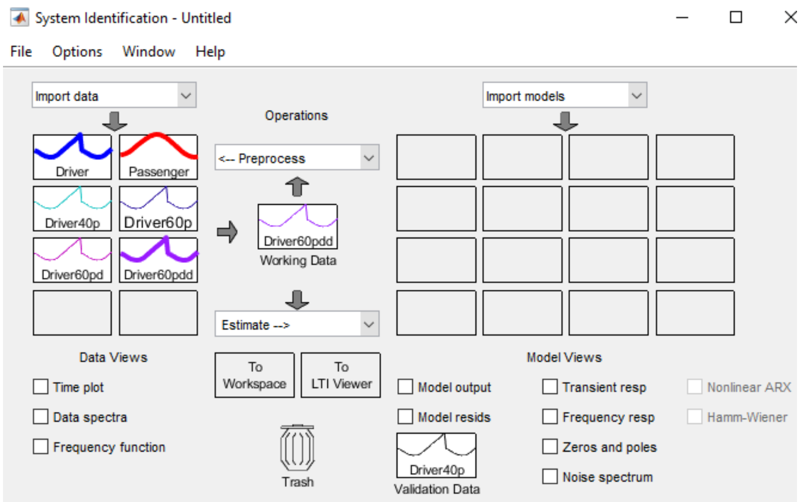


Figure 8. Graphical user interface (GUI) of the SI after importing the data

Next up is pre-processing the data means performing certain or special restrictions on the data that has been imported into the working data to achieve a particular output. Shows the list of pre-processes that can be performed before processing it and estimating the model. Pre-processes usually improve the performance and accuracy of the model estimated since arbitrary differences in the I/O signals cannot be captured by linear models. Since the input data has many columns, removing trends and means will treat each column separately and allow the user to focus on analyzing the data fluctuations; however, this depends on the objectives and the application of the estimation.

After performing the desired prepossess on the data, the next step will be to use the newly processed data to estimate the model. The estimation can be done through the drop-down list on the GUI. The models that can be estimated are transfer function models, state-space models, polynomial models, and non-linear models such as ARX and Hammerstein-Wiener. After choosing the desired model to estimate, in this case, the transfer function model, the user selects the order of the Transfer Function to evaluate it by specifying the poles (p) and zeroes (n) from the Graphical User Interface (GUI) in Figure 9. The user can also set a delay time for the input and the output.

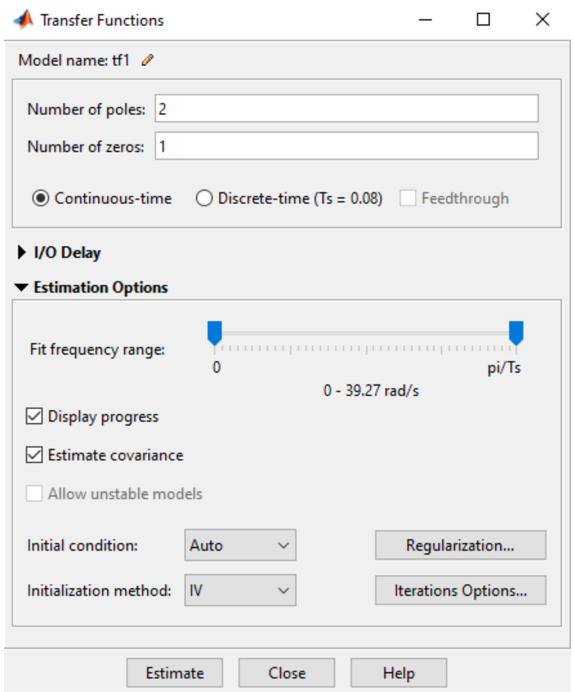


Figure 9. The GUI for estimating transfer functions in SI

After specifying the order of the transfer function, the model will be estimated and produce a fit for the model. The estimated model appears on the right-hand side of the GUI, as shown in Figure 10. The output can then be viewed by checking the model output box underneath the model views space, along with all the other models estimated to compare and choose the best fit that satisfies the user's needs**.** The user can also decide which data to appear in the output by clicking on it from the Models View space as in Figure 11.

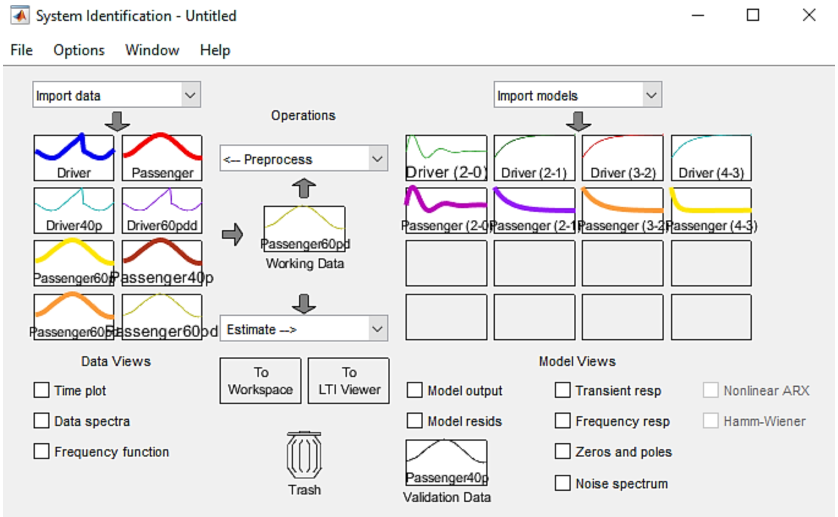


Figure 10. Estimated models in the graphical user interface (GUI)

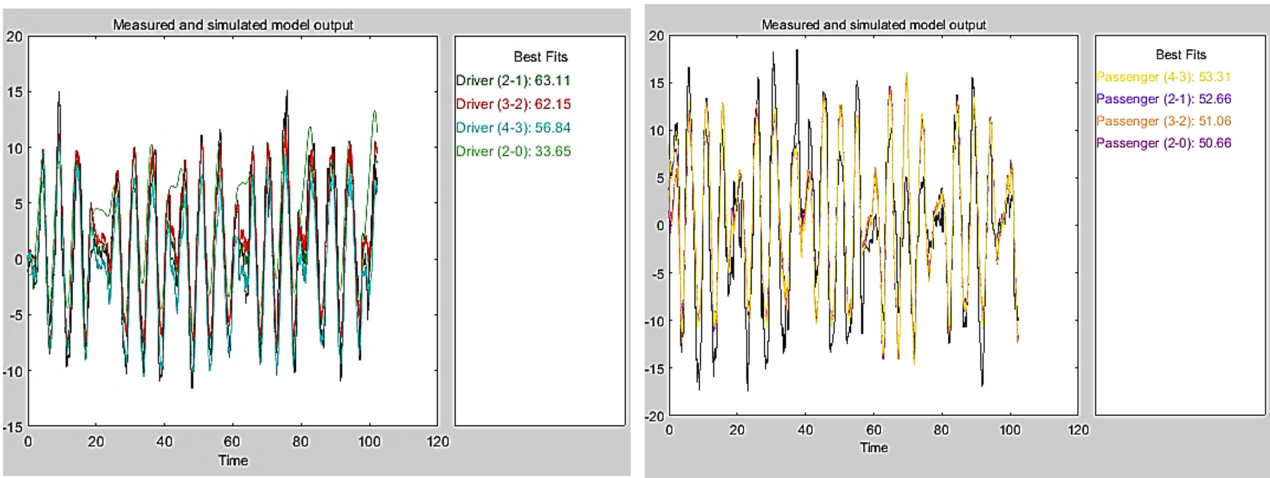


Figure 11. The output and fit of the estimated model

Evaluate the Model and Validate the Data

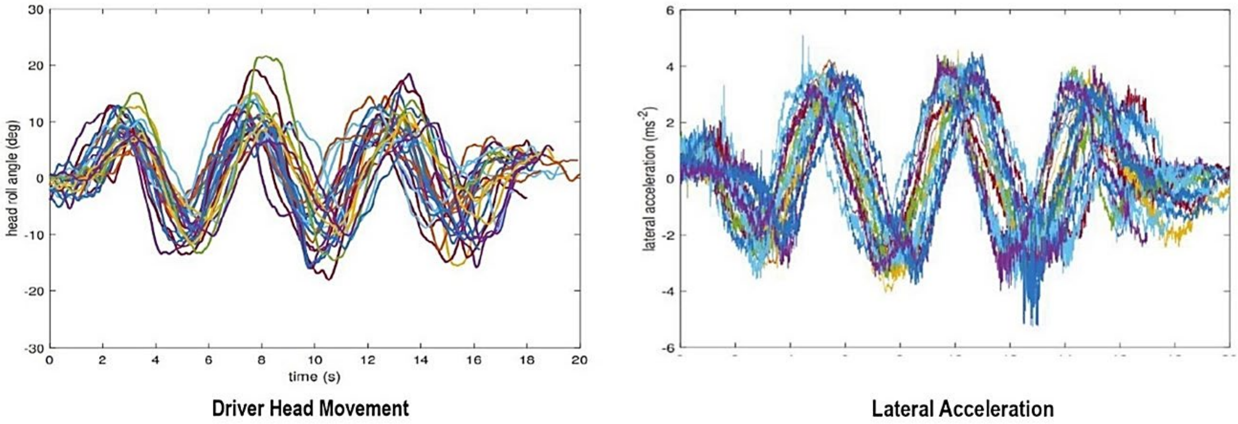
Finally, the data validation is the method to evaluate the model efficiency for general applications; for instance, when the model output is plotted, the input used for the modelling is the input signal from the validation data. There are many ways of data validation: Comparing the estimated model output to the measured output, analyzing the model response, or plotting the poles and zeroes of the linear parametric model. The model fit is how accurate the output provided by the model is to the actual output entered. A good fit should be around 60% or above to be acceptable, according to Saruchi et al. [26].

RESULTS AND DISCUSSION

To conclude the procedures, the result of understanding the correlation is illustrated in Figure 12 and Figure 13, which show that driver head movement goes against lateral acceleration, and passenger head movement matches lateral acceleration. That proves that drivers tilt their heads opposite the lateral acceleration. In contrast, passengers do the opposite and tend to tilt their heads towards the lateral acceleration direction, which causes MIS to be more intense. As for the results in Table 1, various proportions were used (80-20%, 70%-30%, and 60%-40%). The data is used for the estimation and validation, respectively, to identify the fits shown in the table below. Most of the proportion has the third-order transfer function as the best fit; other orders kept fluctuating according to the order.

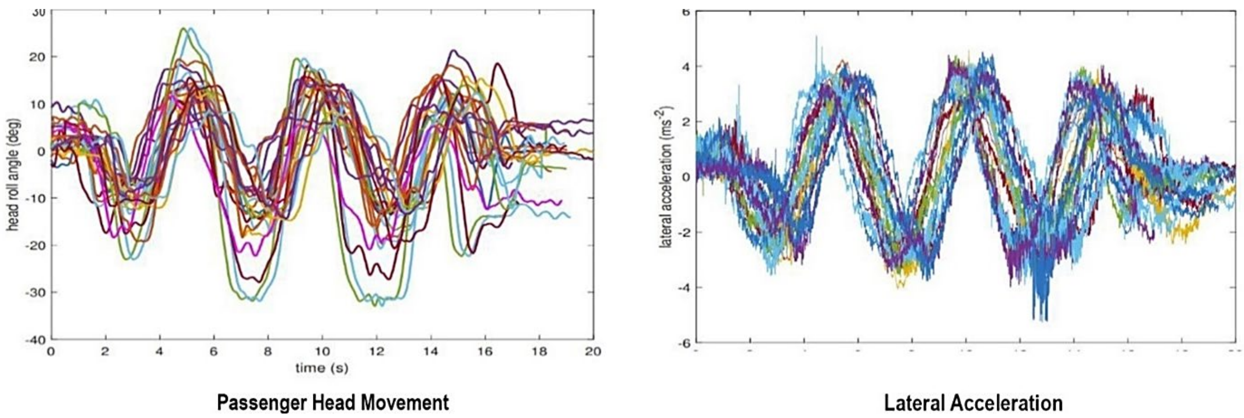
Table 1. Driver and passenger modelling results

Subject	Proportion/Transfer function order	2nd	3rd	4th
Driver	80%-20%	66.18%	67.51%	67.87%
	70%-30%	66.56%	66.78%	65.67%
	60%-40%	65.17%	65.05%	64.68%
Passenger	80%-20%	66.76%	66.7%	67.93%
	70%-30%	66.3%	66.11%	64.07%
	60%-40%	64.82%	64.8%	63.75%



(a) (b)

Figure 12. (a) Head movement of driver contrasting with (b) lateral acceleration



(a) (b)

Figure 13. (a) Head movement of passenger contrasting with (b) lateral acceleration

Based on the comparison results illustrated in Table 1, the modeling process was a success. The results obtained are acceptable as they match and slightly surpass previous study results obtained by Saruchi et al. [26]. The models then undergo the validation process, where the output response from these models is verified with unseen data taken from the same experiment. From the above results, the Transfer Functions should be as follows in Table 2.

Table 2. Driver and passenger best fits transfer functions

Subject	Proportion/Transfer Function Order	Best Fit Transfer Function
Driver	Model 1- 80%-20%	$\frac{-47.03s^3 - 98.54s^2 - 109.1s + 34.09}{s^4 + 15.22s^3 + 47.54s^2 + 37.3s + 10.93}$
	Model 2 - 70%-30%	$\frac{-423.3s^2 - 238.9s + 91.09}{s^3 + 170.2s^2 + 93.09s + 27.33}$
	Model 3 - 60%-40%	$\frac{-68.19s + 7.042}{s^2 + 21.7s + 2.061}$
Passenger	Model 1 - 80%-20%	$\frac{18.12s^3 + 274.8s^2 - 6.513s + 0.2759}{s^4 + 10.01s^3 + 71.76s^2 + 4.795s + 1.505}$
	Model 2 - 70%-30%	$\frac{26.58s + 0.6236}{s^2 + 6.557s + 1.722}$
	Model 3 - 60%-40%	$\frac{27.35s + 0.5556}{s^2 + 6.607s + 1.602}$

Data Validation

Simulink was used to validate the data, as shown in Figure 13. The block "From Workspace" was used to import the data to Simulink. The imported data was the input to the predicted transfer function model; to validate it with the unseen data. Then, the block "To Workspace" was used to import the data back to the workspace to calculate the RMSE for each transfer function model in Table 2.

Based on Figure 14(a) to 14(f) illustrated, the graphs showcase how close the graph obtained from the model created by the transfer function predicted through System Identification to the validation graph. After that, RMSE can be calculated in MATLAB using the formula $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)}{N}}$

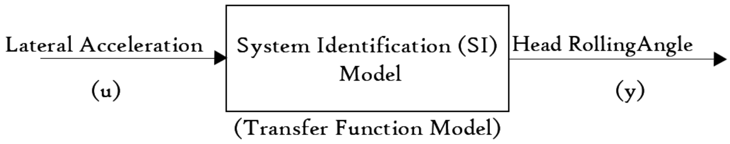
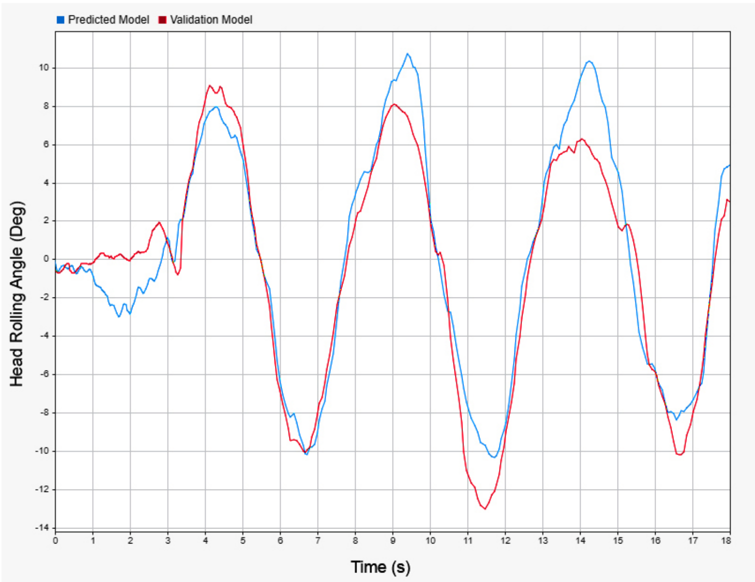
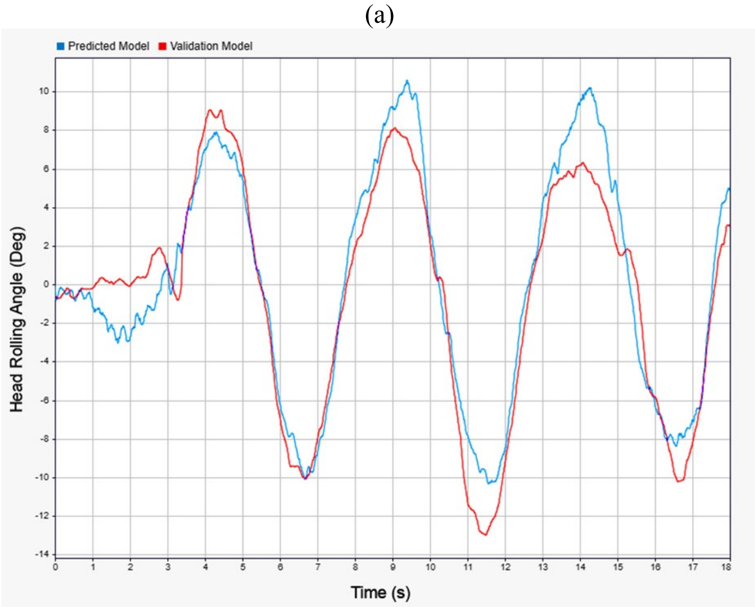


Figure 13. Simulink simulation model to validate the data



(a)



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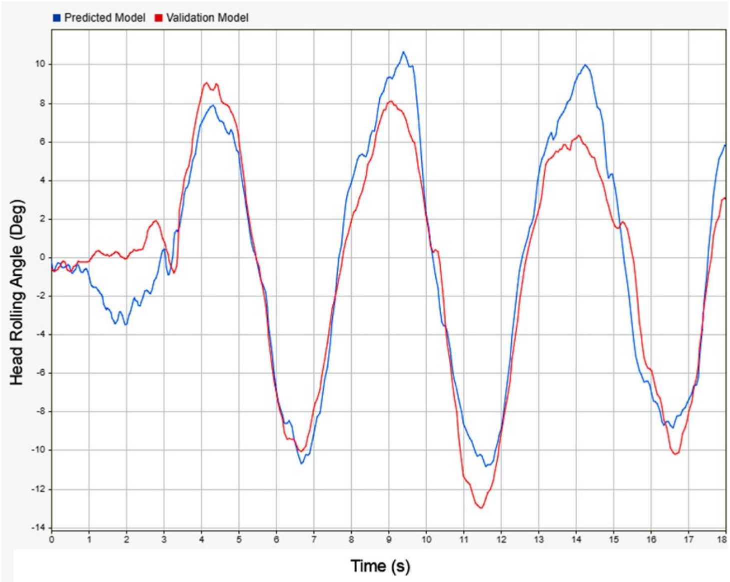
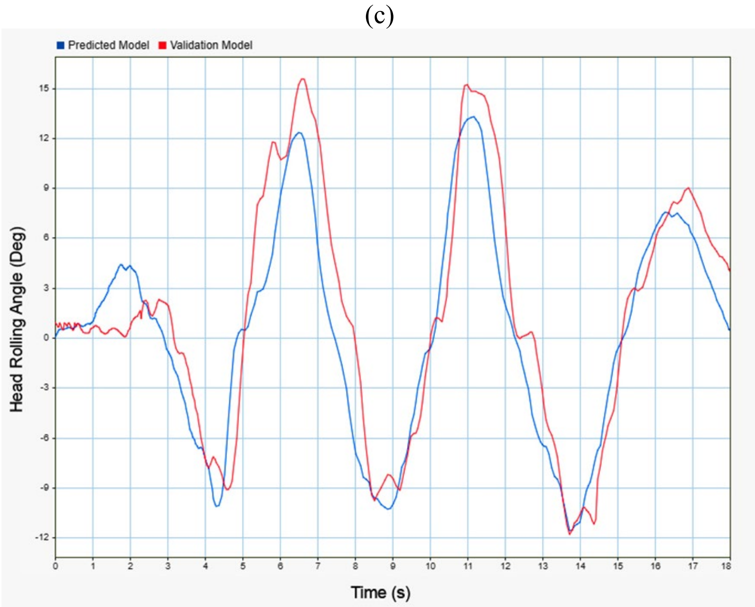
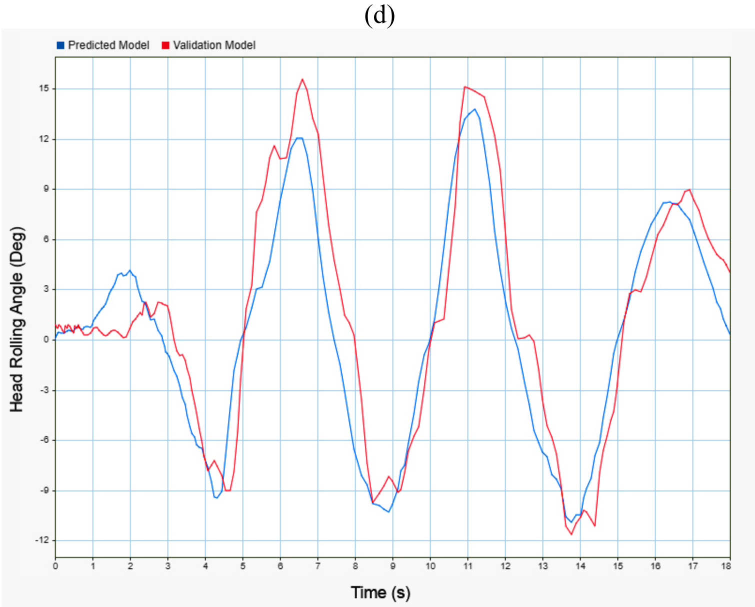

Predicted Model
Validation Model
Head Rolling Angle (Deg)
Time (s)

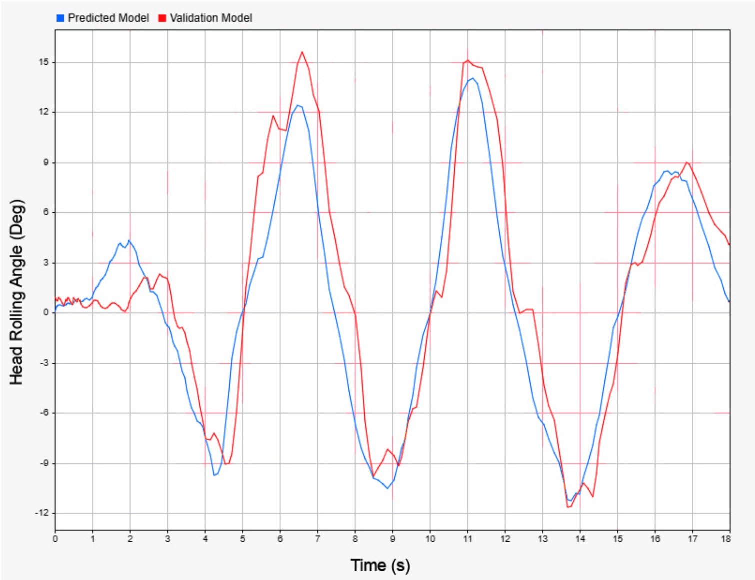
(c)


Predicted Model
Validation Model
Head Rolling Angle (Deg)
Time (s)

(d)


Predicted Model
Validation Model
Head Rolling Angle (Deg)
Time (s)

(e)



(f)

Figure 14. Validation graphs for (a) driver model 1, (b) driver model 2, (c) driver model 3, (d) passenger model 1, (e) passenger model 2, and (f) passenger model 3

Based on the RMSE values obtained and shown in Table 3, the fits are good; however, there are slight differences in the RMSE values due to the difference in equations order or fit percentage. However, all values are low and approximately close in value, indicating that these models are good fits. However, these models are acceptable as they match and surpass previous obtained by Saruchi et al. [19]. Higher accuracy models will further improve the quality of the research. The study achieved the objectives of comparing different mathematical models to represent the correlation between Motion Sickness, find the best fits, and then analyze the models.

Table 3. RMSE values

Subject	Model number	Root mean square error
Driver	1 (80% - 20%)	1.7351
	2 (70% - 30%)	1.7652
	3 (60% - 40%)	1.8325
Passenger	1 (80% - 20%)	2.7349
	2 (70% - 30%)	2.5909
	3 (60% - 40%)	2.5419

CONCLUSIONS

This study illustrated different mathematical models representing the correlation between the vehicle's movement and occupant's behavior in terms of head movement and the car's lateral acceleration with different proportions to obtain the best fit. Based on this comparison between the models, it can further help in designing a more accurate vehicle control system to decrease MS.

The correlation has proven that MIS is more intense when tilting the head towards the centrifugal direction, and the opposite occurs when the head is tilted towards the centripetal direction. As for the models fits obtained here, the highest fit percentages for the driver are 67.87% (4th order) with 1.7351 RMSE, 66.78% (3rd Order) with 1.7652 RMSE, and 65.17% (2nd order) with 1.8325 RMSE. The highest fit percentages for the passenger being 67.93% (4th order) with 2.7349 RMSE, 66.3 (2nd order) with 2.5909 RMSE, and 64.82% (2nd order) with 2.5419 RMSE along with their corresponding transfer function equation that were mentioned in Table 2, they are acceptable; however, they can be improved to better fit, enhancing the study's overall performance. The models results surpassed a previous study.

It is noticeable that the fits percentage affects the model's accuracy. More comprehensive experiments with more data samples and different proportions can significantly improve this study area since SI is a trial-and-error method [34]. Additionally, trying out other modeling strategies such as non-linear Hammerstein-Wiener or NARX and compare them to find the best. Then utilize that by improving it furthermore because these methods use more complex algorithms that can contribute to achieving better results overall.

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