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Radial basis function neural network for head roll prediction modelling in a motion sickness study

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ABSTRACT

Motion Sickness (MS) is the result of uneasy feelings that occurs when travelling. In MS mitigation studies, it is necessary to investigate and measure the occupant's Motion Sickness Incidence (MSI) for analysis purposes. One way to mathematically calculate the MSI is by using a 6-DOF Subjective Vertical Conflict (SVC) model. This model utilises the information of the vehicle lateral acceleration and the occupant's head roll angle to determine the MSI. The data of the lateral acceleration can be obtained by using a sensor. However, it is impractical to use a sensor to acquire the occupant's head roll response. Therefore, this study presents the occupant's head roll prediction model by using the Radial Basis Function Neural Network (RBFNN) method to estimate the actual head roll responses. The prediction model is modelled based on the correlation between lateral acceleration and head roll angle during curve driving. Experiments have been conducted to collect real naturalistic data for modelling purposes. The results show that the predicted responses from the model are similar with the real responses from the experiment. In future, it is expected that the prediction model will be useful in measuring the occupant's MSI level by providing the estimated head roll responses.

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1. INTRODUCTION

The main text format consists of a flat left-right columns on A4 paper (quarto). The margin text from Motion Sickness (MS) arises from uneasy feelings such as a headache, drowsiness and vomiting that can be experienced by the occupants while driving or riding in a moving vehicle [1-5]. Automotive researchers have devised many ideas to reduce and prevent MS for the improvement of the occupant's comfort level. In order to analyse the effectiveness of the MS mitigation strategies, it is important to calculate the MS to determine the sickness level of the occupants. Numerous researchers have used questionnaire methods to scale the MS level of the vehicle's occupants. One of the earliest types of questionnaire was the Pensacola Motion Sickness Questionnaire (MSQ) [6]. The final outcome of this questionnaire was expected to be vomiting. Other than that, there was also the Simulator Sickness Questionnaire (SSQ) which basically was intended to scale the simulator sickness, but has been also been used in cyber and virtual reality sickness studies [7-12]. However, the main disadvantage of the questionnaire is that the data collection cannot be administered during the actual running of the motion stimulus because it may distracts the occupants. In addition, the length of the questionnaire also contributes to the possibility of the respondents not being able to answer the questions during the experiment. Other than by questionnaire, another method to quantify MS is by calculating the Motion Sickness Dose Value (MSDV) [13-15]. The measurement can be performed over short and long periods in separate equations. Electroencephalography (EEG) technology is another MS measuring tool. Data taken from the occupant's brain is used for measurement [16-18]. Wada et al. proposed a revised version of the 6 Degree-of-Freedom (DOF) Subjective Vertical Conflict (SVC) model to calculate the Motion Sickness Incidence (MSI) [19]. The MSI is defined as the percentage of people who vomit [20], [21]. The advantage of this mathematical model is that it does not require any kind of sensors or tools so it will not affect the overall operational cost. This model is also convenient because the MSI can be calculated online during the experiment or offline using the recorded experimental data.

In this study, the 6-DOF SVC model is assumed as the best MS measuring method compared to the others due to its advantages. The calculation is made based on the information from the vehicle lateral acceleration and the occupant's head roll angle. The response of the lateral acceleration and the occupant's head roll angle can be obtained by installing sensors in the vehicle and by attaching sensors on the occupant's head. However, this would normally not be practical and could be considered as improper to attach sensors on the occupant's head during driving. It is much easier and reduces the operational cost if the occupant's head roll angle can be predicted instead of measuring it directly. Therefore, this study proposes the use of the Radial Basis Function Neural Network (RBFNN) method for occupant's head roll prediction modelling in the MS study.

One way to predict the head roll movement is by referring to the correlation of the vehicle lateral acceleration and the occupant's head roll angle during cornering [19, 22]. Based on previous studies, it has been proven that when driving round a curve, the passenger's head roll angle is synchronised with the lateral acceleration direction. On the other hand, under the same scenario the driver's head roll angle is against the lateral acceleration direction [22, 23]. Figure 1 shows the general head movement behaviour of the occupants with respect to the lateral acceleration. The main idea of the modelling is to generate predicted head roll responses from the information of the vehicle lateral acceleration.

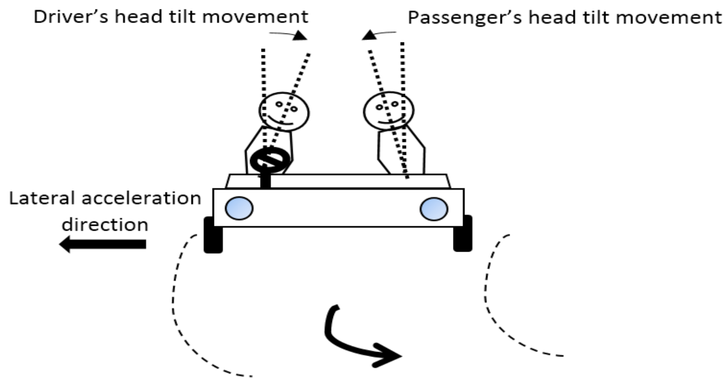


Figure 1. General head movement of the occupants with respect to the lateral acceleration during cornering

Previous research has identified the correlation between the vehicle lateral acceleration and the occupant's head roll angle and this has been modelled by using Linear Transfer Function, Hammerstein-Wiener and Artificial Neural Network (ANN) methods [24-26]. Alternatively, this current study focuses on modelling the correlation to generate a head roll prediction model via RBFNN. The RBFNN is a feedforward ANN which consists of three layers and uses a Radial Basis Function (RBF) as its activation function. The selection of RBFNN is due to its advantages which include the ability to forecast any continuous function with the prospective accuracy, local generalisation ability and rapid convergence speed [27].

2. RESEARCH METHOD

2.1. Experimental Setup

A slalom driving course has been designed based on the previous works conducted by Wada et al. to collect real naturalistic data of the lateral acceleration, the passenger's head roll angle and the driver's head roll angle during cornering [23]. Figure 2 illustrates the track with six cones. The gap between each cone is 20 metres. The nominal frequency of the lateral acceleration for this customized test track is 0.21 Hz, which is a frequency that provokes MS. Ten participants regardless of age, sex and skills participated in this experiment. Each participant took part as both a driver and a passenger. The drivers were instructed to drive in a slalom driving style through the cones at a constant velocity of 30 km/h. Meanwhile, the passengers were asked to tilt their heads naturally during the slalom test. One motion sensor was placed on a flat space in the vehicle to record the lateral acceleration data. Meanwhile, another two motion sensors were attached to the caps of both the passenger and the driver to acquire the head roll angle data. Figure 3 shows an overview of the placement of the motion sensors.

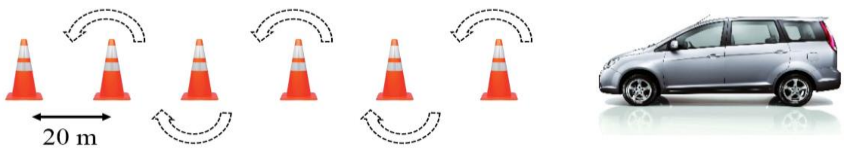
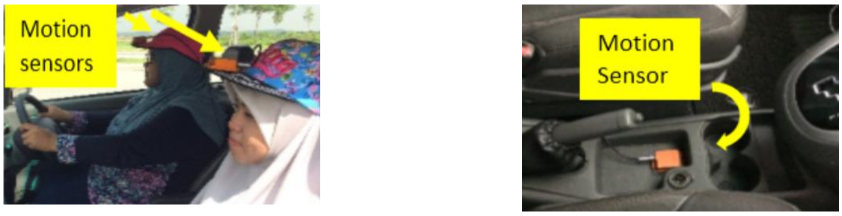


Figure 2. Slalom driving course



(a) Head roll angle sensor (b) Lateral acceleration sensor

Figure 3. Overview of the placement of the motion sensors

2.2. Modelling via RBFNN

Figure 4 shows the structure of the RBFNN that was used in this study. It should be noted that the models for the passenger and the driver were developed separately. It consists of an input layer with a single input vector, a nonlinear hidden layer with Gaussian RBF and a linear output layer. The input, x for the model was the lateral acceleration. The output, y was the predicted head roll angle of the passenger or the driver. Based on the experimental results, two RBFNN models were built in which one was a predictor of the passenger's head roll angle and the other was a predictor of the driver's head roll angle.

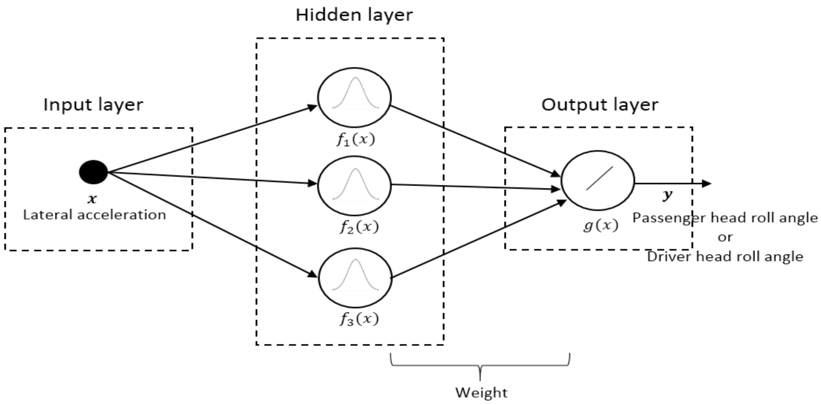


Figure 4. The structure of the RBFNN

The number of hidden neurons was selected based on the well-known Kolmogorov Theorem. 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 of hidden neurons was 3. The equation of the Gaussian function in the hidden layer can be expressed as [28-30],

$$f(x) = exp\left(\frac{-\|x-c_j\|^2}{\sigma^2}\right) \quad (1)$$

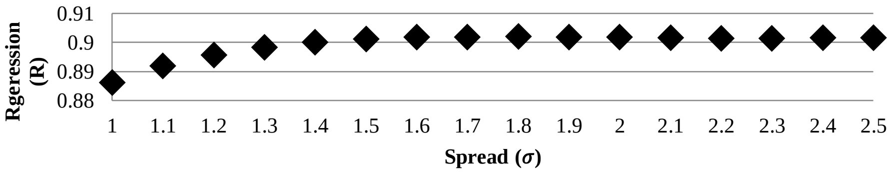
where, c is the centre point and σ is the RBF spread that is determined empirically. As the spread value in the Gaussian function may affect the accuracy of the model construction, this study implemented the trial and error method to seek the most suitable spread value. The spread was varied from a small value until the value where the output results were saturated. The procedure of adding the spread value, training and testing was repeated until satisfying results were obtained. Considering the Gaussian function in Equation (1), the output of the network can be expressed as,

$$g(x) = \sum_{j=1}^{N} w_j \; exp\left(\frac{-\|x-c_j\|^2}{\sigma^2}\right) \quad (2)$$

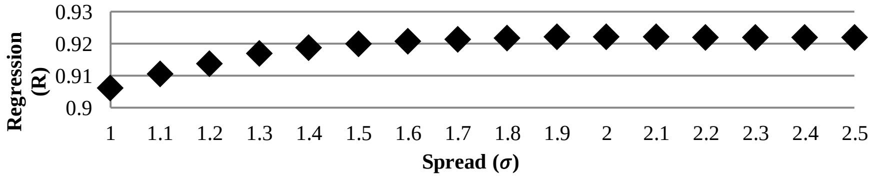
where, w is the weight. Details of the equations for passenger and driver models can be referred to in the Appendix.

3. RESULTS AND ANALYSIS

The performance of the model was determined by the regression value, training error and the testing error. Figure 5 shows the regression results of the model. As the spread value increased, the regression also increased and finally became saturated. The saturated regression results were assumed to be an indicator to determine that the spread value was already ample. The regression result which was above 0.9, further strengthened the notion that the vehicle's lateral acceleration was correlated with the head roll angle of the passenger and the driver during slalom driving. The training error during the modelling training phase is presented in Figure 6. As the spread value increased, the error decreased and started to saturate.

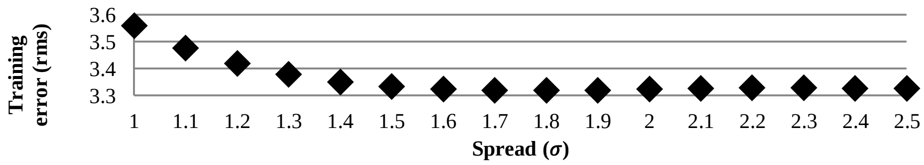


(a) Passenger model

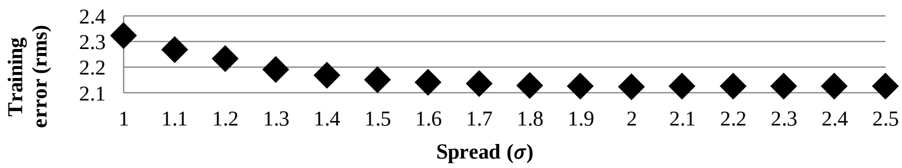


(b) Driver model

Figure 5. Regression results



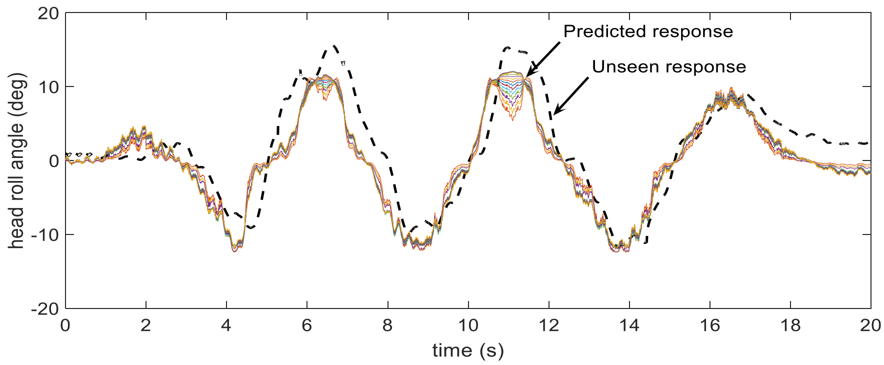
(a) Passenger model



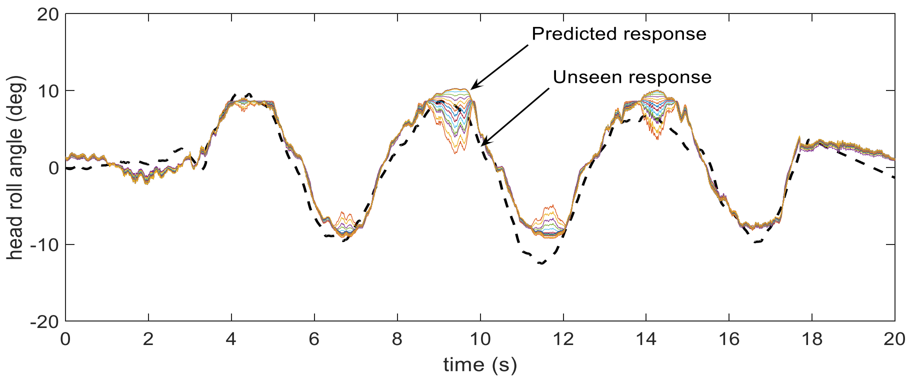
(b) Driver model

Figure 6. Training error results

Lastly, the model was validated in the testing phase. Data from the passenger's and the driver's experimental data collection were taken respectively before the network training process and both were recognised as unseen data. The unseen data was compared with the predicted data arising from the RBFNN model to analyse the generalisation ability of the model. Figure 7 show the comparison results for the unseen and the predicted responses for both the passenger and the driver models. The comparison results show that the predicted responses were reasonably similar in pattern with the unseen data. For the sake of analysis, the Root-Mean-Square (RMS) value of the comparison error has been calculated and presented in Figure 8.



(a) Passenger model
(b)



(b) Driver model

Figure 7. Comparison results between predicted and unseen responses

4. CONCLUSION

In MS studies, it is important to quantify the MS level of the occupants for detailed analysis and deep investigation. There are various methods available to measure MS such as through questionnaires, devices and mathematical models. In this study, a mathematical model namely 6-DOF SVC was assumed to be the best tool to measure MS due to its advantages. Head roll angle is one of the important elements to measure MSI using this model. In order to avoid the necessity of using sensors, it is compulsory to utilise a predictor to estimate the occupant's head roll responses. Thus, this study proposed the implementation of RBFNN as a modelling method to develop head roll prediction model for the occupants. Results from regression, training and testing show that the RBFNN model succeeded in predicting the responses of the occupant's head roll angle. For the future, it is expected that the RBFNN head roll prediction model can be applied in the MS mitigation field. In addition, to further investigate the generalisation ability of the developed models, they should be tested under different experiment scenarios such as different number of cones, different speeds and different distance between the cones.

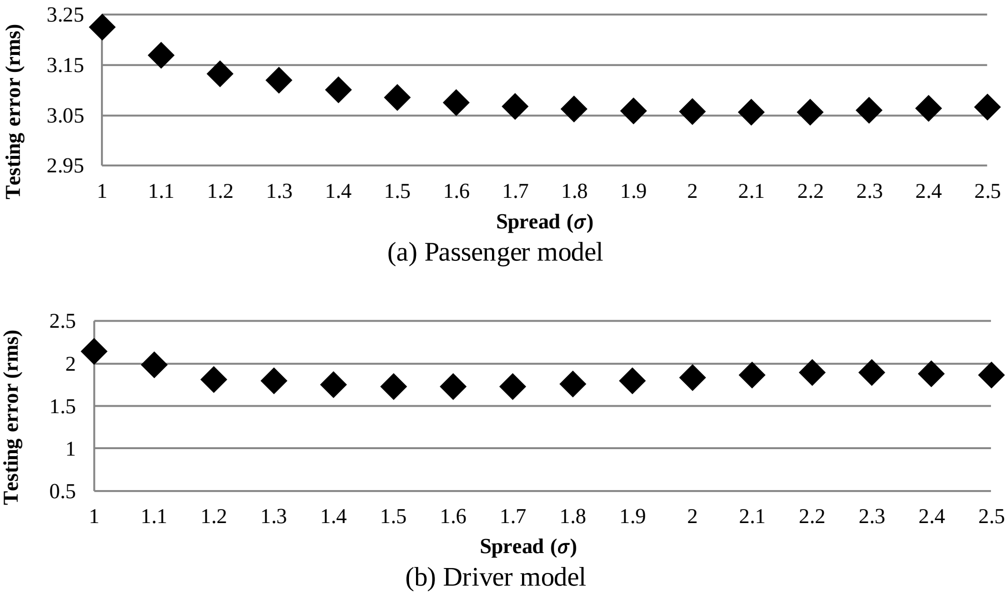


Figure 8. Testing error results

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APPENDIX

1. Based on Equation (2), the value of the centre point c, spread σ, weight w, and biases in the hidden layer and the output layer b_1, b_2 for the passenger's model are as follows:

$$c = \begin{bmatrix} -3.9402 \\ 3.7988 \\ -3.6039 \end{bmatrix}, \sigma = \begin{bmatrix} 2.1 \\ 2.1 \\ 2.1 \end{bmatrix} \quad , w = \begin{bmatrix} 14.5623 \\ 11.6248 \\ -26.7979 \end{bmatrix}, b_1 = \begin{bmatrix} 0.3965 \\ 0.3965 \\ 0.3965 \end{bmatrix}, b_2 = [0.3340]$$

2. Based on Equation (2), the value of the centre point c, spread σ, weight w, and biases in the hidden layer and the output layer b_1, b_2 for the driver's model are as follows:

$$c = \begin{bmatrix} -2.5560 \\ 3.6721 \\ -0.6546 \end{bmatrix}, \sigma = \begin{bmatrix} 1.6 \\ 1.6 \\ 1.6 \end{bmatrix} \quad , w = \begin{bmatrix} 8.6564 \\ -8.5897 \\ 0.8409 \end{bmatrix}, b_1 = \begin{bmatrix} 0.5203 \\ 0.5203 \\ 0.5203 \end{bmatrix}, b_2 = [-0.2521]$$

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