Applicability of modern correlation tools for ride comfort evaluation and estimation

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Abstract The automotive world is currently shifting focus towards electric vehicles (EVs) and the market of connected, autonomous vehicles (CAVs) is steadily growing. Vehicle ride comfort is an attribute which for years now have been a factor which has a significant influence on vehicle development programmes. Due to the complexity of ride comfort, achieving a good correlation between measured data and perceived comfort is a challenging task. Creating well-handling vehicles with pleasant ride characteristics is becoming not enough, as nowadays customers expect bespoke, tailored solutions such as active suspension systems instead of more traditional, passive solutions. The presented study aims to analyse the usability of modern correlation tools, such as artificial neural networks for objective and subjective data correlation, evaluation and explore the possibility of prediction of subjective responses based on the measured data. Data for the study was gathered on the HORIBA MIRA proving ground and public roads. Measured parameters consisted of the vehicle accelerations, anthropometric data of the experiment participants and subjective evaluations of perceived vibration magnitudes. Subjective responses were gathered using a group of 22 participants. The obtained dataset was divided into training and validation sets in the ratio of 80/20. Collected data was used in a correlation study using artificial neural networks (ANNs). The created model achieved a high correlation level of R=0.91. Presented study proves that correct use of advanced correlation techniques utilising artificial neural networks can create comfort models allowing for subjective comfort response estimation. Such an approach could significantly reduce the time required for the vehicle development process and would allow for more comfortable, bespoke vehicles in the future.

Keywords: Ride comfort, neural networks, whole-body vibration

1. Introduction

Vehicle ride comfort is an important characteristic, which is evaluated and tuned during the vehicle development process. Optimal vehicle comfort is achieved by balancing the shape and structure of the chassis and suspension characteristics[1]. With developments in technology, delivering higher comfort without compromising other valuable vehicle parameters such as handling, or stability has gotten easier as the suspension solutions used in the automotive industry became more sophisticated. Nowadays, the increased popularity of vehicles equipped with active and adaptive suspensions operated pneumatically or hydraulically can be observed[2]–[4]. Increased attention is being given towards autonomous vehicles (AVs)[5], which means that methods of evaluating ride comfort should be re-evaluated as the industry is slowly moving from a driver-centric model to more passenger-centric approach. Guidelines for ride comfort assessment can be found in ISO 2631:1997[6]. These guidelines are widely used and have been adopted by various manufacturers. Proper design of a vehicle suspension must balance two components, which are vehicle ride and handling. A significant amount of time during vehicle development is given to achieve the right balance between these two parameters. Therefore, it would be beneficial to automate that process. Ride comfort evaluation of any vehicle consists of two types of measurements[7]. The first one is the measurement of acceleration values that are transmitted from the road to the body of the driver or the passengers, which is referred to as objective data. The second type is the subjective measurement, which is obtained through questionnaires. Correlation between those two datasets is completed using statistical analysis. Studies have shown that a satisfying level of correlation can be achieved[8]. However, it requires many participants. It is common that during development stages of new vehicles discrepancies between objective and subjective data emerge [9]. Therefore, it would be beneficial to support the decision-making process based on previously gathered data [10]. Such an approach could be completed with existing tools such as artificial neural networks[11]. Authors of this paper explore the possibility of using modern correlation techniques involving artificial neural networks for correlation of objective and subjective data.

2. Methodology

The study presented in this paper has been divided into several stages. These were: data collection, analysis, preparation of the data for neural network training where the data were divided into training and validation sets, training of the data classifier using neural networks and validation of the trained classifier using validation dataset. Data collection was conducted with the cooperation of HORIBA MIRA from Nuneaton, UK. The researchers consulted vehicle dynamics team to utilise road sections which are used for vehicle ride comfort evaluation (fig. 1). To gather objective and subjective ride comfort data, a B segment vehicle was chosen. To minimise the influence of environmental parameters during testing, a professional driver was driving the car, and the data was collected from subjects seated in the passenger seat.

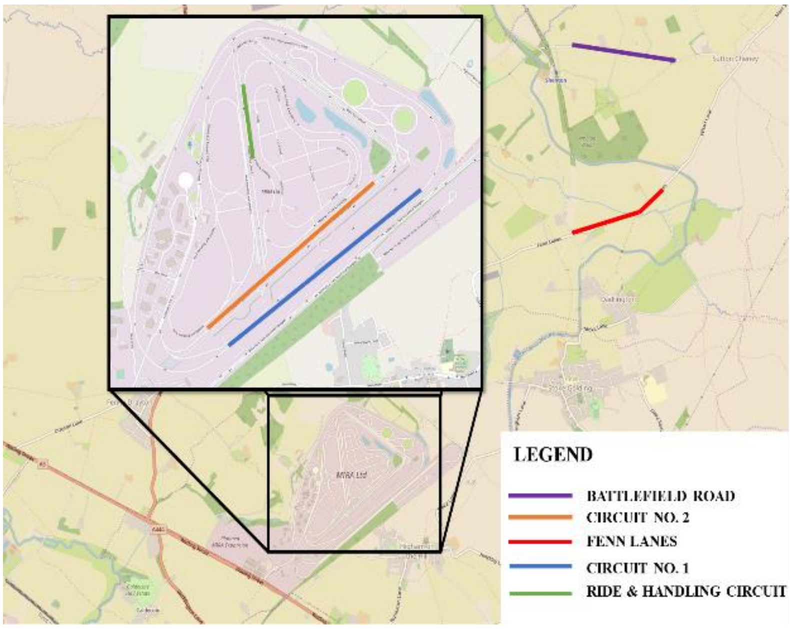

Fig. 1. Location of data collection road section.

Before data collection commenced, the vehicle was equipped with accelerometers. Total of 7 accelerometers was used. Four accelerometers attached to the bottoms of the suspension struts to measure the direct inputs from the road surface – the influence of the tire damping was neglected. To ensure minimal variance in collected data due to tire damping, the tire air pressure was controlled throughout the data collection phase. One accelerometer was placed on the seat rail beneath, and two accelerometer pads were placed on the seat – seat pad and seatback. Before data collection, calibration of the logging equipment was completed. The equipment used in the trials consisted of Bruel&Kjaer accelerometers connected to LMS SCADAS data logging equipment connected to a PC. Data was logged at a sampling rate of 1024Hz. Fig. 2 presents the power spectral density of the road sections used in the experiment.

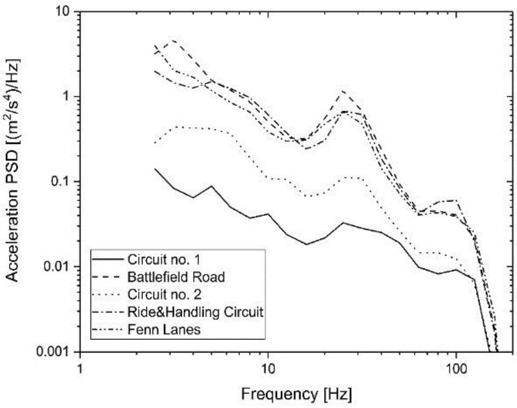

Fig. 2. Measured power spectral density of acceleration on test road sections.

Collected accelerometer measurements were analysed using MATLAB software. The data analysis procedure was based on the guidelines which can be found in the whole-body vibration standard and in the literature. Data were filtered using 6^{th} order bandpass Butterworth filter from 0.8Hz to 150Hz and weighted using weighting functions found in the ISO2631:1997[12]. Weighted acceleration and vibration dose values were calculated using the equations (1) and (2).

$$a_w(t_0) = \left\{\frac{1}{\tau}\int_{t_0-\tau}^{t_0}[a_w(t)]^2 dt\right\}^2 \quad (1)$$

$$VDV = \left\{\int_0^T [a_w(t)]^4 dt\right\}^{\frac{1}{4}} \quad (2)$$

Besides the objective measurements, a subjective evaluation was conducted. Study participants were asked to rate several ride comfort metrics using SAE J1060 scale (fig. 3)[13]. The subjects were presented with vibration stimuli from the smoothest road section – chosen according to the data recorded and shown on the PSD graph above (fig. 2), to the harshest. The industry divides overall ride feel into several thresholds which are linked with respective vibration frequencies. Vibration occurring within 1-6Hz is referred to as primary ride[14], 6-20Hz as secondary ride. Any abrupt motions of the vehicle due to encountering potholes or bumps are referred to, like a jerk. The subjects used provided scales to assess the level of comfort of these conditions as well as overall perceived comfort during the ride.

1	2	3	4	5	6	7	8	9	10
UNACCEPTABLE				BORDER LINE	ACCEPTABLE				
CONDITION NOTED BY									
ALL OBSERVERS		MOST OBSERVERS		SOME OBSERVERS	CRITICAL OBSERVERS		TRAINED OBSERVERS		NOBODY
Intolerable	Severe	Very Poor	Poor	Marginal	Barely Acceptable	Fair	Good	Very Good	Optimal
1	2	3	4	5	6	7	8	9	10

Fig. 3. Subjective comfort scale, according to J1060 standard.

Twenty-two participants (N=22) took part in the experiment. Apart from objective acceleration data, anthropometric measurements of the test subjects were recorded as the literature suggests that there are biodynamic differences between differently sized subjects occurring while experiencing ride conditions [15]–[17]. Averaged subject data is presented in table 1.

Table 1. Mean data of all 22 subjects participating in the study.

	Standing height	Sitting height	Sitting shoul-der height	Buttock popliteal length	Knee height	Shoulder breath	Hip Breadth	Age	Weight
Abbrev.	SH	SiH	SiSH	BPL	KH	SB	HB	-	-
Mean	179,7	105,9	77,2	51,1	53,3	45,7	36,4	35,8	80,6
SD	8,3	5,5	5,8	6,5	4,7	3,4	5,4	12,9	13,7

3. Ride comfort evaluation results

Some of the results obtained from the collected data are presented below. Figure 4 shows the on the left, the weighted acceleration values measured on each of the sections of road for the 22 participants. It is visible that the data shows a high level of consistency. To the right of the box, plots mean values of measured, weighted accelerations are presented. Fenn Lanes and Battlefield Road show the similar result of 0.75 and 0.77 m/s^2 respectively. Ride and handling circuit measured at $0.66 m/s^2$ mean weighted acceleration between all subjects, and the lowest scores were Circuit 2 and Circuit 1.

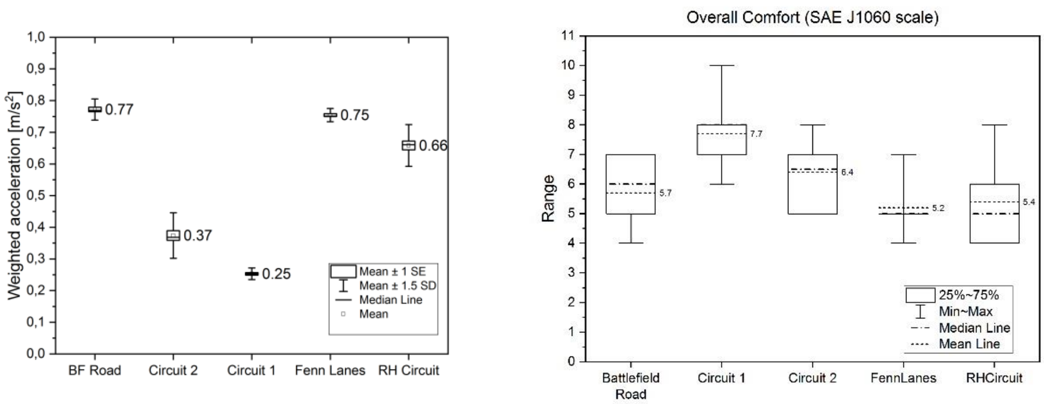

Fig. 4. Measured weighted acceleration and overall comfort scores between road sections.

In figure 4 on the right results of the subjective assessment are presented. The best mean score achieved on Circuit no. 1 (7.7), followed by Circuit no. 2 (6.4), Battlefield Road (5.7), Ride&Handling (5.4) and Fenn Lanes (5.2) respectively.

Table 2 shows current whole-body vibration standards guidelines regarding likely reaction to the vibration of absolute acceleration magnitude. Measured weighted acceleration values can be compared according to that table, to estimate likely subjective reaction. To increase fidelity and decrease the time required to conduct the subjective evaluation, we would like to propose an approach based on artificial neural networks, which is presented in the next subsection of this paper.

Table. 2 Likely reactions when exposed to vibration as per ISO2631:1997.

Weighted acceleration magnitude a_w [m/s^2]	**Likely reaction when exposed to vibration**
<0.315	not uncomfortable
0.315 – 0.630	a little uncomfortable
0.50 – 1.00	fairly uncomfortable
0.80 – 1.60	uncomfortable
1.25 – 2.50	very uncomfortable
>2.00	extremely uncomfortable

4. Deployment of neural network

Collected and analysed ride comfort data was used to create a ride comfort classifier based on artificial neural networks. The neural networks have been developed as a generalisation of mathematical models of biological nervous systems [18]. Essential elements of a neural network are artificial neurons which are also referred to as nodes. The connections between the neurons are represented by weights that modulate the input signals. Graphical representation of an artificial neuron is presented in fig 5.

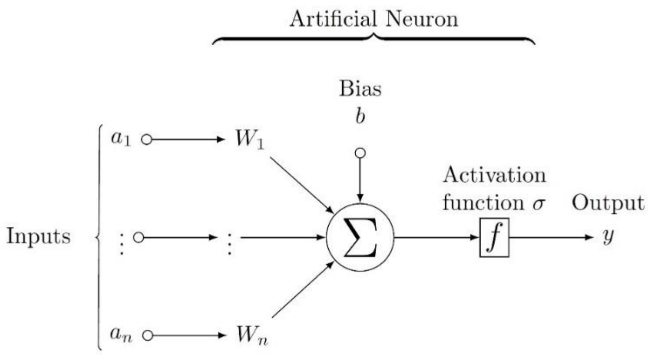

Fig. 5. Graphical representation of an artificial neuron.

The working principle of a neural network can be expressed mathematically as (3):

$$a^{(1)} = \sigma\left(\begin{bmatrix} W_{0,0} & \cdots & W_{0,n} \\ W_{1,0} & \cdots & W_{1,n} \\ \vdots & \ddots & \vdots \\ W_{k,0} & \cdots & W_{k,n} \end{bmatrix}\begin{bmatrix} a_0^{(0)} \\ a_1^{(0)} \\ \vdots \\ a_n^{(0)} \end{bmatrix} + \begin{bmatrix} b_0^{(0)} \\ b_0^{(0)} \\ \vdots \\ b_n^{(0)} \end{bmatrix}\right) \tag{3}$$

This can be shortened and expressed as (4):

$$a^{(1)} = \sigma(Wa^{(0)} + b) \tag{4}$$

Where σ – is the logistic activation function, W represents the weights of the neural network and b the biases.

The firing of the neuron is dependent on the state of the activation function. There can be different activation functions used in a neural network. The simplest activation function is the logistic activation function $\sigma(x)$ (5) which has been used in this case study.

$$\sigma(x) = \frac{L}{1+e^{-k(x-x_0)}} \tag{5}$$

For purposes of this study a multi-layer perceptron (MLP) network was used. MLP is a class of feedforward artificial neural network.

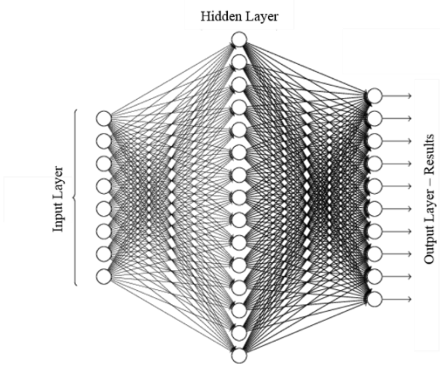

Fig. 6. Graphical representation of a multi-layer perceptron.

Such networks consist of at least three layers of nodes: an input layer, a hidden layer and an output layer (fig. 6) are using tabular data for inputs and outputs which correlates well with the type of dataset that was obtained from the ride comfort studies[19]. This type of network utilises supervised learning technique, called backpropagation for training. In training desired results are fed into the network and weights, and biases of nodes in the hidden layer are optimised in such a way so that the error between estimated result and the actual result is minimal. The calculated error is then backpropagated through the network and is used to modify the weights and biases to achieve optimum. Due to its multiple layers of nodes and non-linear activation function, an example of which has been presented in (5), this type of network is distinguished from a linear perceptron, and it can distinguish data that is not linearly separable.

The data from the data collection phase was analysed and prepared to be used in the neural network training process. As 22 separate datasets of results were obtained, the data was divided into two sets. One set of 16 used for neural network training and the other set of 6 used for validation of the trained classifier. Each set consisted of 19 measured parameters over five sections of road.

The inputs in equation (6), (7) and outputs in equation (8) have been prepared to be used in the neural network training process. A higher number of inputs, than the described minimum in the ISO2631:1997, was used in the input matrix. This data also included the anthropometric measurements of the test participants.

$$I_i = [SH \quad SiH \quad SiSH \quad BPL \quad KH \quad SB \quad HB \quad Weight \quad BMI \quad A_{wx} \quad A_{wy} \quad A_{wz} \cdots \tag{6}$$
$$\cdots MTVV_x \quad MTVV_y \quad MTVV_z \quad VDV_x \quad VDV_y \quad VDV_z]^T$$
$$inputs = [I_1 I_2 I_3 I_4 \cdots I_{80}] \tag{7}$$
$$outputs = [SCV_1 SCV_2 SCV_3 SCV_4 \cdots SCV_{16}] \tag{8}$$

The output (8) consisted of the subjective evaluation results (SCV = Subjective Comfort Value) of test participants collected on each of the road sections.

5. Results of the ride comfort classifier

The neural network was trained on the acquired dataset. As the outcome of the training, due to the nature of the neural networks, may differ between training runs, parametric analysis was conducted. Several parameters of the network, such as performance function or the backpropagation algorithm, were tested. As a result, the researchers concluded that for solving this particular problem the best performing network utilises Levenberg-Marquardt backpropagation algorithm, which combines characteristics of Gauss-Newton method and stochastic gradient descent, for calculating the weights and biases. The parametric study showed that using mean squared error function for calculating the errors will be optimal. The performance of the trained classifier is presented in fig. 7. The trained network has achieved R=0.91.

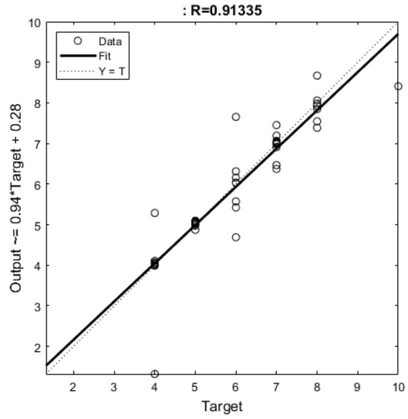

Fig. 7. Linear regression result of the trained correlation model.

To validate the classifier, the validation dataset was used, which consisted of data collected from 6 participants. Trained classifier was presented with measured objective data and anthropometric details of the participants. Calculation of estimated subjective responses was conducted. The error between estimated results and subjective responses given by the test participants are presented in fig. 8.

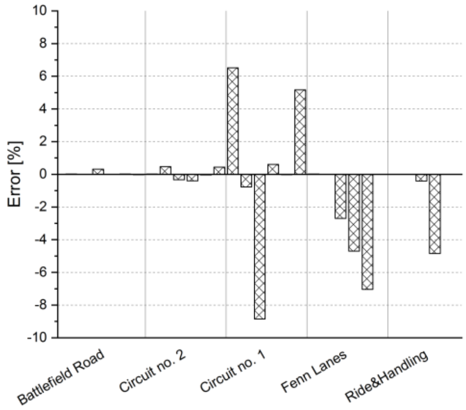

Fig. 8. Measured prediction error when applying the trained neural network model.

Fig. 8 is divided into five sections representing roads the test was conducted on. The percentage of error is visible on the vertical axis of the graph. The trained network performed very well when estimating the results on Battlefield Road section and Circuit no. 2. Calculated subjective responses are less accurate for Circuit no. 1, Fenn Lanes and Ride&Handling Circuits; however, they are still within 10% error from the actual response.

6. Conclusions

The technique presented in this paper shows the applicability of modern correlation techniques, such as artificial neural networks for ride comfort estimation. The presented study shows that implementation of artificial intelligence and neural networks into established procedures could speed up the development process of vehicles. The trained neural network achieved a high level of accuracy, R=0.91. Already automotive manufacturers are gathering vast quantities of data, which could potentially be used to increase the level of comfort of their customers and save money otherwise spent in development stages. The researchers recognise that the presented study can be treated only as a proof of concept. It would require larger dataset and further validation in a variety of environments to ensure the validity of estimated results produced by such an approach. We also recognise that the field bridging ride comfort with computer science is still relatively unexplored and requires further investigation.

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