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PREDICTION OF DRIVER'S OSCILLATORY COMFORT USING AN ARTIFICIAL NEURAL NETWORK IN CONDITIONS OF HORIZONTAL VIBRATIONS

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While driving, forces from the road are transmitted to the vehicle in the form of vibrations, impacting the driver and passengers and potentially causing discomfort. Defining comfort has proven challenging and has evolved over the course of research. Referring to the Cambridge dictionary [1], comfort can be described as a pleasant and satisfying feeling when an individual is mentally and physically free from pain and suffering. The assessment of oscillatory comfort in the human body can be approached through two methods: subjective and objective. Subjective assessment involves experiments where participants provide subjective ratings based on a series of statements, measured against a predefined scale. Objective comfort assessment relies on standardized methods, such as the ISO 2631 standards and the British standard BS 6841.

The human body is exposed to excitation along one axis in the fore-and-aft and vertical directions. Uniaxial vibrations in the vertical and fore-and-aft axis induce significant movements in the sagittal plane (vertically, fore-and-aft, and laterally) of the upper body, indicating a strong coupling effect [2], [3]. Whole body vibration holds particular significance in the frequency range from 1 Hz to 80 Hz, aligning with the main resonance points of specific organs and body parts (e.g., head, eyes, stomach, and spine) [4].

In order to ascertain the scope of the biodynamic response of the human body to vibration, ISO-5982 (1981) and ISO CD 5982 (1993) have introduced seat-to-head transmissibility (STHT) magnitude, driving-point mechanical impedance, apparent mass, and phase characteristics [5]. This is achieved by averaging data sets provided by various investigators [6], [7], [8]. The STHT function is influenced by several factors, including body weight, seat back angle, subject gender, as well as the type, magnitude, and frequency of vibration [9], [10].

Over the past decade, researchers have increasingly embraced the opportunities afforded by advancements in technology, particularly artificial neural networks (ANNs). ANNs have found widespread application in diverse fields [11], [12], thanks to their ability to model complex nonlinear systems by learning from input and output signals. The interconnected artificial neurons in ANN layers give them an edge over systems using traditional algorithmic methods. ANNs can learn from examples, showcasing adaptability as a key property [13].

While numerous studies have explored the effects of vibrations on the human body, the focus has predominantly been on vertical vibrations. Understanding the STHT function values during fore-and-aft vibrations remains incomplete. Fore-and-aft vibrations can induce significant head movements, potentially leading to collisions with the surrounding environment. Identifying factors influencing such motions is crucial for prevention. This research builds upon prior studies, extending the exploration of the impact of horizontal fore-and-aft vibrations on the human body under various seating conditions and stimuli values, introducing a novel approach with ANN.

To induce vibrations of varying amplitudes and frequencies, an electro-hydraulic pulsator, HP-2007, was employed. This pulsator includes a car seat on which subjects were exposed to vibrations. Capable of generating independent vibrations in two directions, this device was utilized in the experiment. A plastic helmet equipped with a three-axis accelerometer system, utilizing the AC102-1A accelerometer, was secured on the subjects' heads. The data acquisition system utilized in the experiment was the 01dB-Metravib NetdB PRO-132.

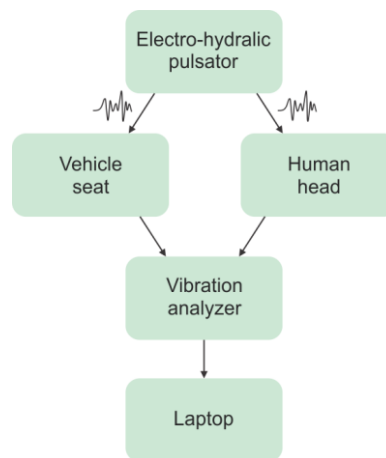
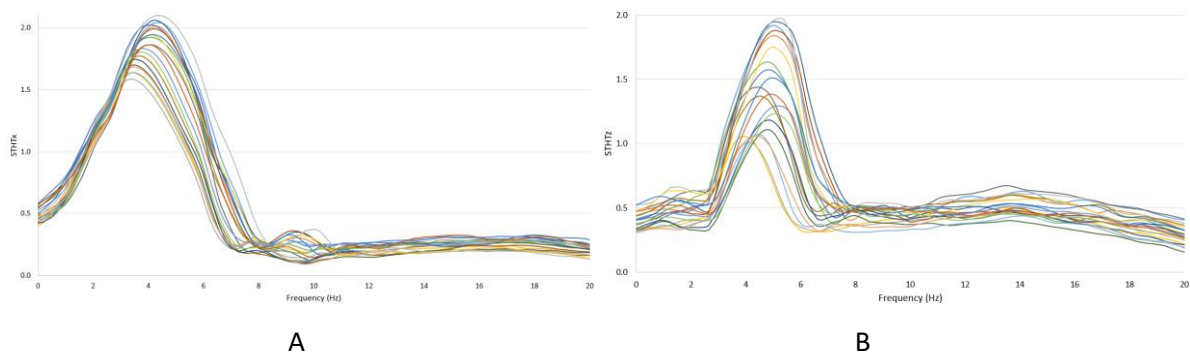


Figure 1 – A laboratory setup of the experiment

In the evaluation of fore-and-aft seat vibrations, twenty subjects were exposed to two different vibration magnitudes:  $0.8 \text{ m/s}^2 \text{ r.m.s.}$ , and  $1.1 \text{ m/s}^2 \text{ r.m.s.}$  The excitation frequency spanned from 0.5 Hz to 30 Hz, a crucial range for assessing oscillatory driving comfort. Seating angles varied at  $100^\circ$  and  $110^\circ$  degrees of inclination with respect to the z-axis. The Figure 2 reveals the nonlinearity of the seat-driver system. Changing the excitation amplitude alters the shape of the STHT, reflecting a shift in the resonant frequency value. Increasing the excitation amplitude leads to an increase in STHT amplitude and a decrease in the resonant frequency, indicating that the seat-driver system is nonlinear and possesses the capability to dampen excitations.



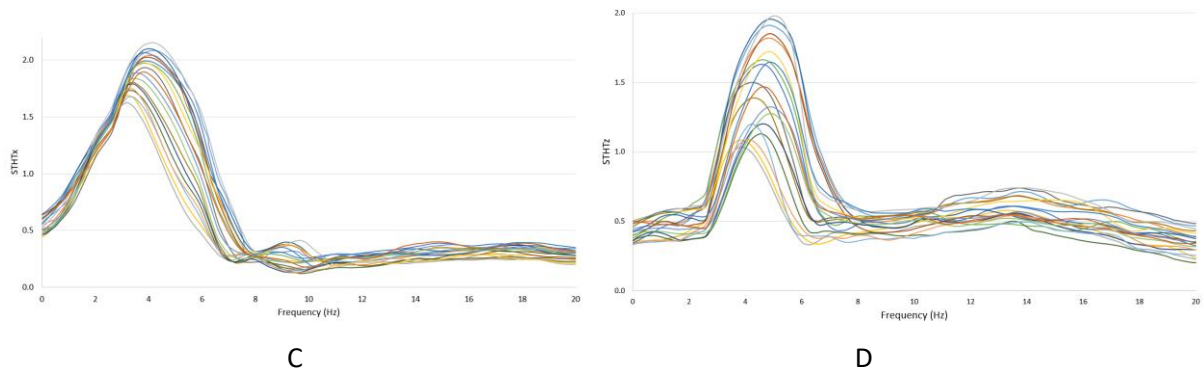


Figure 2 – Measured STHT values. A - Inter-subject variability in fore-and-aft STHT measured at  $0.8 \text{ m/s}^2$  r.m.s with  $100^\circ$  degree backrest angle; B - Inter-subject variability in vertical STHT measured at  $0.8 \text{ m/s}^2$  r.m.s with  $100^\circ$  degree backrest angle; C - Inter-subject variability in fore-and-aft STHT measured at  $1.1 \text{ m/s}^2$  r.m.s with  $100^\circ$  degree backrest angle; D - Inter-subject variability in vertical STHT measured at  $1.1 \text{ m/s}^2$  r.m.s with  $100^\circ$  degree backrest angle

Second part of this paper were dedicated to predict the seat-to-head transmissibility magnitude using Recurrent Neural Networks (LSTM). To assess the robustness of the models, the dataset was divided into training, validation, and test sets. Eighteen randomly selected subjects were allocated to the training set, one for validation, and one for testing. Each subject's individual data (height, weight, seating height, years, and BMI) were coupled with the two analyzed amplitudes and two seating angles. The initial hidden layer of the LSTM comprised 30 neurons, with one neuron in the output layer designed for predicting STHT for the chosen subject. The input shape involved a single time step with 10 features. The Mean Absolute Error was employed as the loss function, and the efficient Adam version of stochastic gradient descent was utilized. The model underwent training for 50 epochs, employing a batch size of 20. Time-series forecasts on test set, in this case it was the frequency response function seat-to-head, for each frequency and angle separately, were shown in Figure 3.

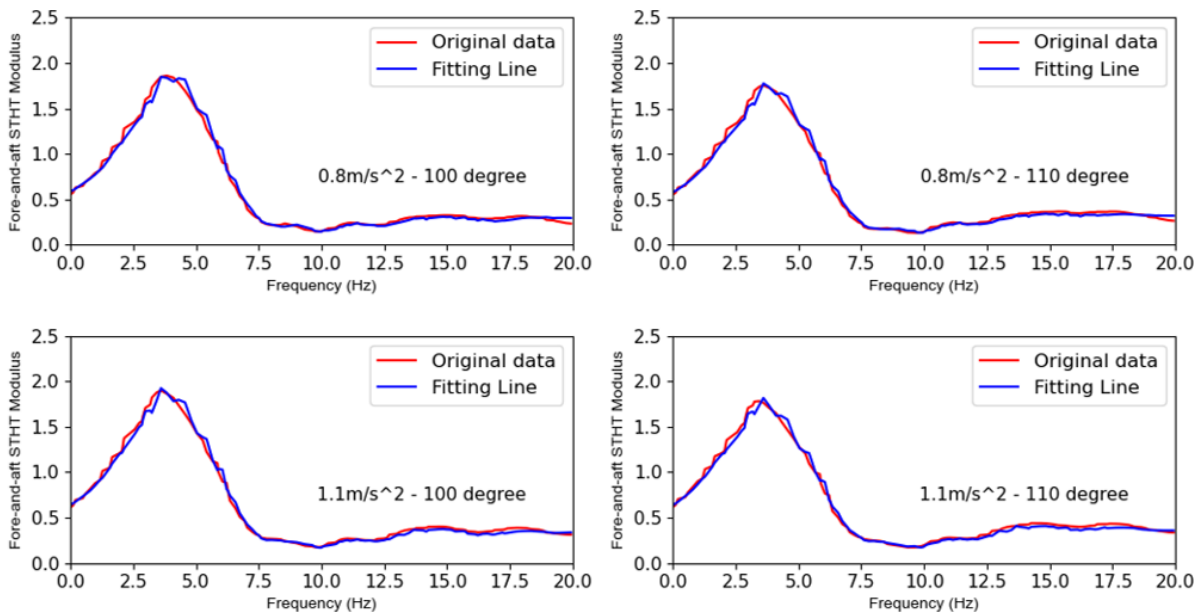


Figure 3 – Original and predicted values for one user, for each combination of frequency and angle

The Root Mean Square Error for the LSTM model across the nine combinations was 0.07, indicating high accuracy of the trained model. This underscores the effectiveness of applying machine

learning, specifically recurrent neural networks, to time series data, providing an efficient and accurate approach for data analysis, forecasting, and prediction.

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