Application of neural network in prediction of frequency response of drivers during driving

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Abstract— **Vehicle comfort in oscillatory conditions is a multifaceted phenomenon affected by various factors including road conditions, driving speed, and driving mode, among others. Vibrations experienced during driving, irrespective of their intensity or waveform, significantly impact driving comfort. The Seat-to-Head Frequency Response Function (STHT) represents a complex connection between head movements and vibrations transmitted through the seat and headrest interface. In this study, an artificial neural network model was created to replicate the STHT function based on experimental data collected from twenty healthy male participants.**

Keywords— artificial neural network, seat-to-head frequency response function, whole body vibration

I. Introduction

The driver's comfort in the vehicle plays a crucial role in creating a safer and more pleasant driving experience. Modern research is focused on improving this aspect of driving, and one of the key factors is reducing vibrations that affect the driver's body. Exposure to vertical vibrations over an extended period leads to the occurrence of lower back pain [1], [2]. The exact cause of lower back pain is not well understood, but it is clear that resolving this issue requires a better understanding of spinal movement in vehicles subjected to vertical stimuli. Frequency domain analysis is an effective method for assessing the discomfort of the human body exposed to vibrational loads. It also allows researchers to gain valuable insights into human body behavior that may not be easily discerned in the time domain.

Author [3] investigated the nonlinear response behavior of the human body to vertical sinusoidal vibrations in the frequency range of 7 Hz - 75 Hz and vibration intensities of 0.2 m/s^2 - 4.0 m/s^2 r.m.s. The vertical head movement of 12 healthy males was monitored. The author concluded that vibration intensity significantly impacts the seat to head transfer function (STHT) in the frequency domain, with a more pronounced effect at lower frequencies. Furthermore, the analysis results showed that the nonlinear response is more pronounced at lower frequencies rather than higher ones. In a subsequent study [4], the author demonstrated negligible changes in intensity and phase of the STHT frequency response function for various vertical vibration values in the range of 0.4 m/s^2 - 2.8 m/s^2 r.m.s. Research [5] has shown that primary and secondary resonance frequencies decrease with increasing vibration intensity.

The application of artificial intelligence in assessing the oscillatory comfort of drivers exposed to vibrations brings significant advantages for improving vehicle design and enhancing the driver's experience. By using AI, large amounts of data obtained from sensors and vibration measurements during driving can be effectively analyzed. The implementation of Artificial Neural Networks (ANNs) in predicting vehicle comfort/discomfort began in the early 21st century. In a study [6], authors investigated vertical vehicle vibrations using the theory of random processes, and they also utilized the Radial Basis Function (RBF) ANN to predict vehicle acceleration amplitudes under various road conditions. The Gaussian process-based ANN served as the foundation for analyzing the parameters of vertical vibrations. Different vehicle body resonance frequencies and damping ratios under varying road conditions were used to analyze vehicle acceleration amplitudes. The results indicated that higher damping factors resulted in increased acceleration values at higher vehicle speeds. Furthermore, it was demonstrated that the ANN predictor results accurately aligned with the desired outcomes. This enables a deep understanding of the oscillatory comfort of the driver and the identification of patterns that can cause discomfort or fatigue [7], [8].

The authors [9] used ANN to predict the H-point Machine function in a seated position exposed to different levels of vibration. The frequency range was from 0.5 Hz to 20 Hz. Fifty-one adult men and women participated in the study, assuming two seating positions: with and without a backrest. The smallest mean squared error and the highest coefficient of determination were obtained using a multi-layer ANN with backpropagation and different structures. The first experiment was conducted with and without a backrest for male subjects, while the second was for female subjects. Comparisons showed that the ANN model could predict the H-point Machine response for the entire range of body masses, stimulus levels, and backrest conditions considered in 14 target data sets. The ANN model satisfactorily predicted resonance and corresponding values, with results suggesting a mean squared error of 2.13 kg and 1.83 kg for male and female subjects, respectively, and an R2 value exceeding 0.98 for participants. The authors confirmed that the ANN architecture has the ability to predict the seated body response within the range of trained input data.

A group of authors [10] assessed comfort when longitudinal low-frequency vibrations occurred in the vehicle during transmission shift operations. To evaluate the comfort method, the authors developed a model based on ANN. During various transmission shift operations, basic signals were collected using experimental instruments, and subjective assessments were provided by professionals. These signals were weighted, filtered, and transformed into three objective assessment indices. The neural network was based on the backpropagation algorithm. With 11 nodes in the hidden layer, the result was relatively stable within a certain range, avoiding uncertainty in subjective assessment. The error between the fitting results and subjective assessment was within 10%, indicating that this developed neural network model meets the accuracy requirements of the assessment.

In the study [11], a new method for assessing the comfort of passenger vehicles based on detailed vibration signal content was developed using deep learning. To generate an initial dataset, data were collected from four passenger vehicles traveling at different speeds on various road categories. Two neural networks, a feed-forward network and a gated neural network, were used to generate two fundamental models. An augmentation method was applied to artificially increase the amount of data by generating new data points from existing data. The results showed that the proposed data augmentation method effectively expanded the dataset, enabling the application of deep learning for assessing driving comfort. The gated recurrent unit with a fast Fourier transform layer yielded the best performance in predicting comfort levels for new vibration scenarios. To further improve prediction accuracy and understand the rules for applying deep learning in assessing driving comfort, hyperparameters of the superior architecture were fine-tuned through a parameter study. Subsequently, the prediction loss was reduced by 76.9%.

The research [12], [13] served as the starting point for this paper. In contrast to these studies, this research includes an analysis of two seatback angles. Based on the obtained results for three vibration intensities and vertical vibration direction, STHT functions for all experimental measurements were calculated in the frequency domain. Using these functions, ANN models were developed for predicting STHT functions and assessing the oscillatory comfort of the observed seating position in accordance with the ISO 2631 standard.

II. Methods

Twenty male participants took part in the experiment, and their task was to drive a car on the Kragujevac-Batočina highway. The average values for healthy male subjects were: 30.8 years of age, 183.6 cm height, 90.2 cm seating height, 93.4 kg weight, and 27.7 BMI. The vehicle studied in this paper is a Renault Megane 1.5dci. Subjects were exposed to random whole-body vibrations while driving. Two measurement points with accelerometers were placed on the seat and on the head. Simultaneously, 6 acceleration signals were recorded (in the x, y, and z axes for each measurement point). Movements in the lateral directions were negligible, and for this reason, the STHT responses in the lateral direction were not analyzed. The signals are collected through a six-axis acceleration sensor WitMotion WT61C-TTL, as shown in Fig. 1, and the specific parameters are in Tab. 1.

Fig. 1. Six-axis acceleration sensor (up); Schematic of the in-vehicle experiment setup (down)

TABLE I. SENSOR SPECIFIC PARAMETERS

Parameters	Value
input voltage	3.3-5V
range	0-16g, +-2000°/s
accuracy	6.1e-5g,7.6e-3°/s
sampling frequency	200Hz
output frequency	0.1-200Hz

The signal collected by the sensor contains a specific high-frequency component, which includes high-frequency vibrations generated during vehicle driving and noise interference present during sensor measurements. To more precisely assess the influence of low-frequency vibrations on vehicle comfort, three acceleration signals are filtered to preserve the low-frequency vibrations. In order to mirror how the human body perceives various vibration frequencies, different weighting factors are applied to the vibration amplitudes at varying frequencies. The specific weighting factors for different directions and frequencies are drawn from the weighting factors list in ISO 2631 standard.

The STHT values represent a sequence of successive data points occurring over a specific time period. This enables the application of algorithms for forecasting time series data. Time series forecasting involves analyzing time series data through statistical methods and modeling to make predictions and inform strategic decision-making. Recurrent neural networks have gained noticeable popularity due to their excellent performance in this task. Given that the best results in forecasting STHT values have been achieved using recurrent neural networks, this research utilizes this type of network, which employs LSTM (Long Short-Term Memory) cells.

The LSTM network (Fig. 2) was introduced by Hochreiter and Schmidhuber in 1997 as a solution to address the vanishing and exploding gradient problems. The model resembles a typical recurrent neural network but replaces the perceptron with what's known as an LSTM cell within the recurrent neural network layer. The LSTM cell can be thought of as a "subnetwork" that repeats itself. Each of these subnetworks has its own control system, consisting of an input gate, a forget gate, and an output gate. These gates collectively regulate the flow of information into and out of the so-called internal cell state [14].

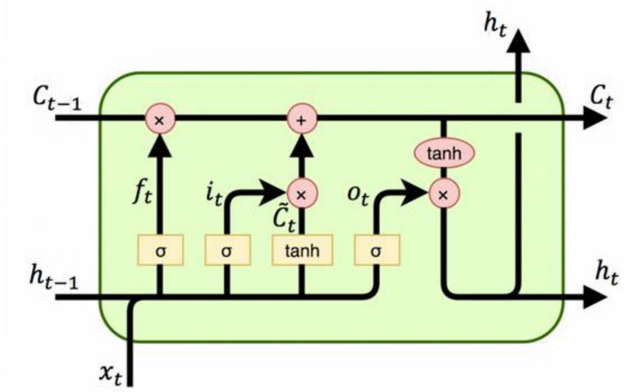

Fig. 2. The basic LSTM architecture

In the process of computing the next element, two values are passed instead of one, namely C_t - the cell state vector, and h_t - the output vector. LSTM has three gates: i_t (input gate activation vector) - which scales the influence of the newly calculated cell $\tilde{C}_t$ input activation vector, f_t (gate activation vector), which determines whether the previous h_{t-1} should forget part of the information, and o_t gate, which determines which information will be passed to the next layer as the variable h_t.

$$f_t = \sigma(W_f\,[h_{t-1};\, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i\,[h_{t-1};\, x_t] + b_f) \tag{2}$$

$$o_t = \sigma(W_o[h_{t-1};\, x_t] + b_o) \tag{3}$$

$$\tilde{C}_t = tanh(W_c\,[h_{t-1};\, x_t] + b_c) \tag{4}$$

$$C_t = i_t \cdot \tilde{C}_t + f_t \cdot C_{t-1} \tag{5}$$

$$h_t = o_t \cdot tanh\,(C_t) \tag{6}$$

For the purpose of building and training the entire dataset, the high-level programming language Python was used. Python has a wide range of standard modules developed, enabling efficient work in various domains. Most of these modules are portable across different platforms, allowing complete programs to often work on different machines and under different operating systems without modification. The training data for the neural network consisted of data obtained from experimental measurements of 20 participants who were in the car during real driving conditions. Each participant was characterized by BMI, height, weight, seated height, gender, and age.

The first step was preparing the experimental dataset for LSTM. This involved framing the dataset as a supervised learning problem and normalizing the input variables (Fig. 3).

```
# LSTM Data Preparation *************************************

# convert series to supervised learning
def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
    n_vars = 1 if type(data) is list else data.shape[1]
    df = DataFrame(data)
    cols, names = list(), list()

    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0, -1):
        cols.append(df.shift(i))
        names += [('var%d(t-%d)' % (j + 1, i)) for j in range(n_vars)]

    # forecast sequence (t, t+1, ... t+n)
    for i in range(0, n_out):
        cols.append(df.shift(-i))
        if i == 0:
            names += [('var%d(t)' % (j + 1)) for j in range(n_vars)]
        else:
            names += [('var%d(t+%d)' % (j + 1, i)) for j in range(n_vars)]

    # put it all together
    agg = concat(cols, axis=1)
    agg.columns = names
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=True)
    return agg
```

Fig. 3. Transforming time series into a supervised learning problem

The supervised learning problem is framed by predicting the function of the STHT frequency response at time t given the STHT measurement data and its data at the previous time step. After this transformation step, six input variables (input sequence) and one output variable (STHT value at a specific time), are represented as:

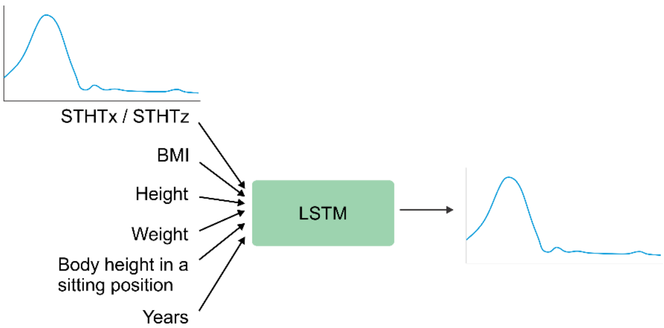

Fig. 4. A scheme of a LSTM recurrent neural network

To test the model's robustness, the dataset has been divided into training, validation, and test sets, where eighteen randomly selected participants are used for training, one for validation, and one for the testing phase. This data partitioning for training follows recommendations for working with large databases [15].

III. Results

The initial part of the results section displays the outcomes regarding the STHT functions of 20 subjects who experienced random vibrations during driving. The subsequent segment of this section illustrates the findings derived from employing artificial neural networks for forecasting STHT magnitudes.

A. Experimental results

In Fig. 5, the STHTx modulus is depicted, highlighting the variations in STHT magnitude responses among different subjects. Notably, a common trend emerges where the peak module of STHT in the fore-and-aft axis falls within the frequency range of 1.8 to 3.8 Hz for all subjects. This frequency range is commonly associated with the primary resonant frequency of the seated body [16], [17].

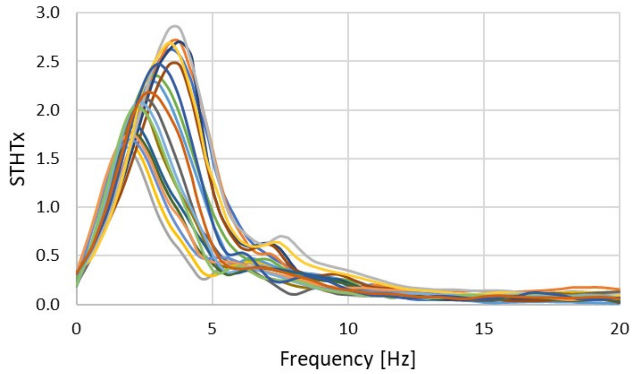

Fig. 5. Inter-subject variability in fore-and-aft STHT

It can be noticed that in the vertical direction, the appearance of the second maximum occurs in the frequency range 8 Hz - 10 Hz (Fig. 6).

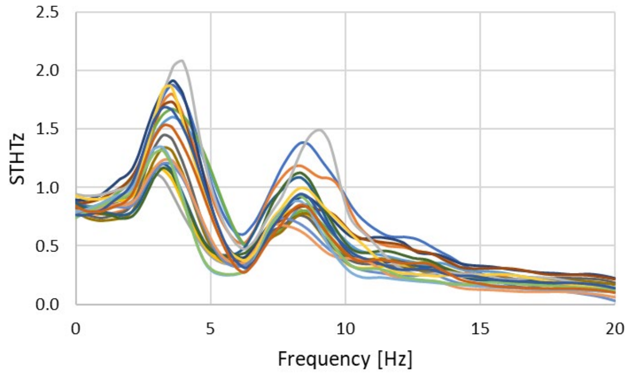

Fig. 6. Inter-subject variability in vertical STHT

B. Neural network results

The second part of the results is devoted to the application of neural networks. The LSTM was defined with 30 neurons in the first hidden layer and one neuron in the output layer for predicting STHT for the selected participant. Mean Squared Error was used as the loss function during network training, and the efficient Adam optimization algorithm was employed to minimize the loss function, representing an extended version of stochastic gradient descent. The model was trained for 50 epochs, with a batch size of 20. Finally, the history of the loss function during the training and validation phases was saved. The training, validation, and testing coefficient was 91%. The original and predicted values of STHT for one subject are shown on fig. 7 and 8.

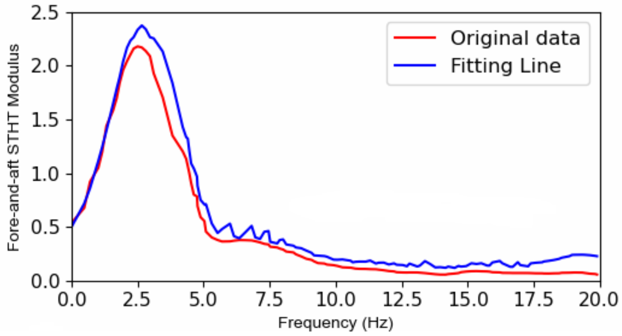

Fig. 7. Original and predicted STHTx values for one subject

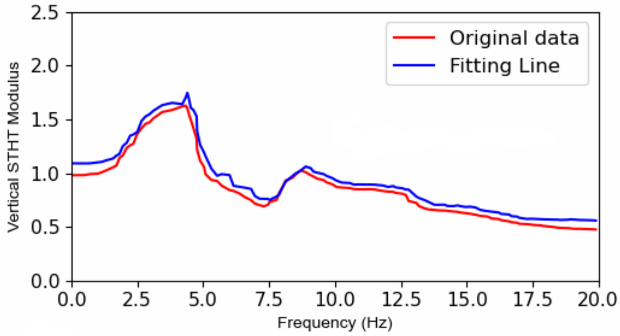

Fig. 8. Original and predicted STHTz values for one subject

The Root Mean Square Error (RMSE) for this LSTM model was 0.052, which shows high accuracy of the trained model. Figure 9 show loss curves during training and validation phases.

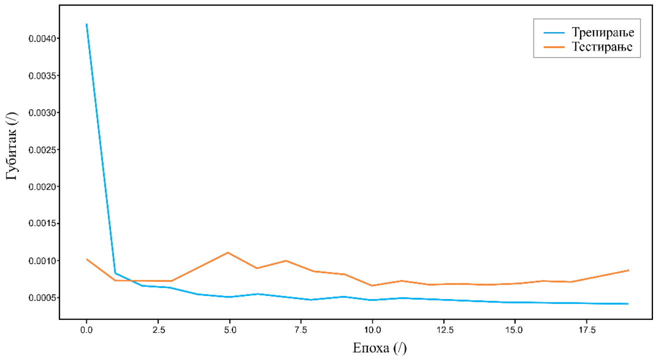

Fig. 9. Loss curves during training and validation phases

IV. Discussion and Conclusion

This paper demonstrates the application of artificial intelligence methods to predict the frequency response function based on measured experimental results. The model used was based on recurrent neural networks utilizing the LSTM cell. Training data for the neural network were obtained from experimental data collected from 20 participants. Each participant was characterized by BMI, height, weight, seated height, gender, and age. The mean square error of the predicted STHT response by the LSTM model was 0.052, indicating high accuracy of the trained model.

The complexity of the model, which takes into account various anthropometric characteristics of the participants as well as different vibration amplitudes due to driving, is not a problem but rather emphasizes the model's ability to predict the STHT response in the frequency domain.

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