Biodynamic Modelling of Hand for Glove Transmissibility Prediction using Artificial Neural Networks

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Abstract. Prediction of glove transmissibility to the hand plays an important role in order to improve its vibration reduction capability. This study presents a non-parametric biodynamic modelling of the hand based on artificial neural networks (ANNs) model for predicting the apparent mass in order to estimate the transmissibility of a glove to the hand. An experimental investigation was carried out to obtain the input-output vibration data using five subjects. Then, an ANNs model was used to map between the input and the output with its weight and bias parameters optimized using chaos-enhanced stochastic fractal search (CFS) algorithm. The results indicate that the developed ANNs hand model capable to predict the apparent mass of the human hand with an average accuracy of 97.67%.

1. Introduction
Hand-transmitted vibration (HTV) deal with mechanical vibration entering the body at the fingers or the palm of the hands which produced by powered tools or processes. Prolonged exposure to HTV can lead to the vascular, neurological and osteoarticular disorder of the upper limbs [1]. Thus, the development of anti-vibration gloves plays important roles in order to attenuate vibration transmitted to the hand. If the transmissibility of the glove to the hand can be predicted, improvement of a glove capability to reduce vibration transmitted to the hand can be performed [2]. Previously, many attempts by researchers around the world to model the hand system and to study its biodynamic response to HTV using multiple approaches i.e. lumped parameter, distributed-parameter, mechanical impedance and etc. However, these modelling approaches have limitation due to entangled with highly non-linear effects and many parameters to be considered [3, 4].

Artificial Neural Networks (ANNs) is an established supervised modelling approach in machine leaning research area. Many ANNs-based biodynamic models have been previously developed. Gohari et al. [5] develop ANNs-based biodynamic model to simulate transmitted vibration to head for seated human body. An indoor vertical vibration experiments using five males was conducted. The developed ANNs-based biodynamic model possess high accuracy in comparison to other lumped models. An ANNs-based model was developed by Kumar et al. [3] to measure biodynamic response seat to head transmissibility (STHT) for seated human subjects exposed to random whole-body vibration (WBV). The constructed model capable to predict STHT with high accuracy when compared with experimental findings. Taghavifar and Rakheja [4] employed ANNs to predict seated body apparent mass under different levels of vibration excitations with two different sitting postures were considered. The model has the ability to predict the seated body response within the range of trained data. In this paper, the development of biodynamic hand model using an ANNs-based non-parametric system identification approach for predicting apparent mass is proposed.
2. Experimental Setup

An experimental investigation was conducted to collect vibration response data of human hand. Figure 1 shows the direction of the dynamic force and acceleration for the calculation of the apparent mass of the hand to vibration based on ISO 5349-1; 2001. The participated human subject's height and weight was tabulated in Table 1. Five healthy male subjects were selected for the experimental test. The participants placed the palm of their hand on the circular wooden adapter without any support on the arm as in Figure 2. They pushed the circular wooden support plate downward while maintaining a force of 10 N. A 10-s period of random vertical vibration was generated using MATLAB with the HVLab toolbox (version 1.0). More details regarding the experimental setup and procedures can be found in [6].

![Figure 1. The direction of the input output data based on ISO 5349-1;2001.](image1)

![Figure 2. Experimental setup.](image2)

| No. of subject | 1   | 2   | 3   | 4   | 5   |
|----------------|-----|-----|-----|-----|-----|
| Height (cm)    | 172 | 161 | 168 | 181 | 163 |
| Weight (kg)    | 68  | 56  | 72  | 77  | 65  |
| BMI            | 22.99 | 21.6 | 25.51 | 23.50 | 24.46 |

Table 1. Height and weight value of human subject.

Figure 3 illustrated the input output data for the modelling of biodynamic response of the hand for Subject 5.
3. ANNs based Modelling and Validation

System identification is a well-established area in automatic control for constructing models to be used for simulation, prediction and control design for dynamical systems [7]. In this study, an ANNs-based non-parametric model is developed using experimental input-output data.

3.1. Modelling Phase

In system identification, there are two main processes involved; model structure selection and estimation of model parameters. A nonlinear auto-regressive model with exogenous input (NARX) structure was employed in this study due to its lowest complexity and without noise term incorporated. However, this model structure possesses capability to adapt with the nonlinearity [8]. The NARX model can be defined as in Eq. 1.

\[
y(t) = f(y(t-1), y(t-2),...,y(t-n_y),u(t-1),u(t-2),...,u(t-n_u))
\]

where, the next value of the output signal, \( y(t) \) is regressed on previous values of the output \( y(t-n_y) \) and input \( u(t-n_u) \) signals. The function \( f() \) can be approximated using feedforward neural networks (FNNs). Figure 4 shows the implementation of FNNs-based NARX model to estimate output force response of the hand. A 4-10-1 of FNNs architecture was employed with model order, \( n_y = n_u = 2 \) and number of hidden neurons of 10. The details regarding the FNNs matrix encoding strategy used in the study can be referred in [9].

Figure 3. Sample of recorded data for Subject 5 for training and validation phases.

![Figure 3](image)

![Figure 4](image)

Figure 4. ANNs architecture.
A total of 61 weight and bias parameters of the FNNs were optimized using a metaheuristic algorithm named chaos-enhanced stochastic fractal search (SFS) [10] within the searching range of [-5, 5]. The Sine chaotic map was embedded in Diffusion and First Updating Processes in order to improve the searching capability of SFS algorithm [11]. Sigmoid activation function was employed in both hidden and output layers. The input-output dataset was divided into two sets as shown in Figure 3. The first 2/3 of dataset was used to train the FNNs model and the balance unseen 1/3 of dataset was used to validate the model. The mean squared error (MSE) between the actual and estimated output was used as objective function. The population size and maximum iteration were set to 30 and 150, respectively. The maximum diffusion number (MDN) of 3 and first Gaussian walk was selected.

3.2. Validation Phase
In this study, several validation tests were used to ensure the adequacy of developed FNNs model which are one-step-ahead (OSA) prediction, mean square error and correlation tests. Model validation was done in both time and frequency domains by mapping and comparing between the actual and predicted outputs. Correlation tests are a statistical test that indicates the degree of relationship between two variables [12]. An adequate model can be indicated by the unbiased prediction error with all linear and nonlinear combination of past inputs and outputs and lay within 95% confidence limits. Finally, apparent mass (AM) prediction accuracy is computed for each human subject. Apparent mass can be calculated using Eq. 2 as follows;

$$AM(f) = \frac{F_{io}(f)}{A_{ii}(f)}$$

(2)

where, $F_{io}$ is the output dynamic force and $A_{ii}$ is the power spectral density of the input acceleration.

4. Results and Discussion
The computational calculation was performed using MATLAB 2014a environment on a PC with Intel Xeon 3.4 GHz, 8Gb RAM, a window 7 operating system. Figure 5 shows the convergence curve of the chaos-enhanced SFS (CFS) algorithm in training FNNs model of the biodynamic hand. A value of MSE = 0.0075 has been achieved in modelling phase. Table 2 tabulates the MSE between experimental and predicted force output by the FNNs model in modelling and validation phases while Figure 6 highlights the developed model performance. The FNNs model able to predict the force output with small MSE values for each subject. The average of MSE equal to 0.0089 was found in validation phase.

Figure 5. Convergence curve for training FNNs model using CFS algorithm.
Table 2. Mean squared of error (MSE) of between actual and predicted force outputs.

| Subject No. |   |   |   |   |   | Average |
|-------------|---|---|---|---|---|---------|
| Modelling   | 0.0055 | 0.0090 | 0.0136 | 0.0056 | 0.0034 | 0.0075  |
| Validation  | 0.0059 | 0.0113 | 0.0170 | 0.0048 | 0.0055 | 0.0089  |

Figure 6. Performance of CFS-FNNs model to predict the force output response.

The mapping between experimental and CFS-FNNs predicted force output for each subject were plotted in Figure 7. It is clearly can be seen that the generalized CFS-FNNs model possesses excellent capability to predict the force output response of the hand for every participant.
Next, the CFS-FNNs model was validated using correlation tests in order to evaluate its adequacy. Based on Figure 8, three out of five subjects successfully passed the auto-correlation and cross correlation tests.

**Figure 7.** The comparison between actual and CFS-FNNs model predicted force outputs.

**Figure 8.** Correlation tests for CFS-FNNs model for each human subject.
However, the CFS-FNNs model incapable to generate unbiased prediction error for Subjects 2 and 3 as correlation values lay outside the 95% confidence limits for cross correlation tests. Then, the estimated apparent mass values were computed using MATLAB HVLab toolbox based on force output response from CFS-FNNs model prediction and compared with experimental results. Figure 9 shows the performance of CFS-FNNs model to predict apparent mass of the hand for each subject within the interested frequency range of [5, 200] Hz. The CFS-FNNs model shows superiority performance to predict the biodynamic hand response with high accuracy as highlighted in Table 3. The average of prediction accuracy equal to 97.67% was achieved by the constructed CFS-FNNs model to predict the apparent mass of the hand for five human subjects.

![Graphs showing apparent mass prediction for Subjects 1 to 5.](image)

**Figure 9.** Apparent mass prediction by CFS-FNNs model.

| Subject | 1    | 2    | 3    | 4    | 5    | Average |
|---------|------|------|------|------|------|---------|
| Prediction Accuracy (%) | 98.08 | 98.22 | 97.42 | 96.81 | 97.82 | **97.67** |

**Table 3.** Overall performance of CFS-FNNs model to predict apparent mass.
5. Conclusion
An ANNs-based nonparametric model identification approach is proposed to model the biodynamic response of the hand exposed to HTV. The generated CFS-FNNs model were evaluated with various validation tests. It is found that the model has performed well in approximating the hand response for five human subjects in this study. Future works intended to develop generalized model of the human hand using the proposed approach for glove transmissibility prediction. Moreover, the developed hand model can also be used in designing active controller to attenuate unwanted HTV from the human hand system.

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