Vibration Data Synthesis by using Finite Element Analysis and Artificial Neural Network

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Abstract. The research on vibration-based structural damage detection methods via supervised learning methods has achieved remarkable results in recent years. However, those methods have an obvious limitation, that the acceleration data collected from the target structure in its damaged states are indispensable for training machine learning models. Actually, it is very difficult, or even impossible, to acquire sufficient data from the damaged structure. This is also the reason why most of the publications only demonstrated the effectiveness of the vibration-based damage detection methods on numerical simulation datasets or real structures with simulated damage. Meanwhile, the vibration data generated by using finite element (FE) analysis are not suitable to be directly used as training data, because these data are unrealistic compared to the measurement data. To address this problem, we proposed a method to synthesize realistic vibration data. The method requests both the vibration data collected from the real structure and the simulated vibration data generated by FE analysis. Then an artificial neural network is trained to project the vibration data from the space of FE analysis to the space of real structure through supervised learning. To validate the proposed method, experiments were conducted on an I-shaped steel beam. The quality of synthetic vibration data by the proposed method is analyzed. The merits and the limitations of the proposed method are also discussed.

Keywords: vibration data synthesis, finite element analysis, neural network, space projection

1 Introduction

To address the safety problems caused by civil structures like bridges, buildings, tunnels, etc., various structural health monitoring (SHM) systems and structural damage detection (SDD) methods have been developed in recent decades. Typical SDD methods include but are not limited to image [1,2] and vibration [3,4]. Structural health states can be estimated by using these SDD methods to analyze the monitoring data acquired from civil structures. These SDD methods show different and complementary advantages, making them suitable for different engineering scenarios. For instance, visual-based SDD methods are intuitive and highly deterministic, while the information and estimation are only limited to the visible areas of structures. On the contrary, vibration-based SDD methods can estimate both the invisible global and local health state of structures. Such a characteristic makes vibration-based SDD a prevalent topic in the civil engineering field.

Traditional vibration-based SDD methods mainly focus on mining structural information from the frequency domain of vibration data, modal parameters of structures, and their variants. The performances of these methods are prone to be affected by environmental factors and measurement uncertainties [5]. In fact, it is impossible to decouple all the factors and uncertainties from vibration data, making it very challenging to detect small-scale or low level damage in actual engineering scenarios by using the traditional vibration-based SDD methods.

With the advent of the artificial intelligence (AI) wave in 2015 [6], researchers were soon attracted by machine learning (ML) methods, which had shown high potential to solve complex problems. Complicated correlations between observation data and results can be accurately modeled by training ML models in a data-driven manner, with no requirement of domain knowledge. Considering the features of SHM and SDD problems, such as massive monitoring data, intricate factors and correlations, ML is very suitable to be adopted in SHM and SDD methods. Vibration data that include damage information can be directly used for training ML models, then the correlation between vibration data and the damage information can be automatically modeled. The article [7] indicates the effectiveness of using supervised ML models for vibration-based SDD. Very high accuracies were achieved in detecting the structural changes in actual structures.

However, there is an obvious limitation when applying supervised learning methods for vibration-based SDD. Negative samples that represent the damage states of structures are indispensable for training. In other words, ML algorithms must learn real knowledge from the negatives samples before obtaining the ability of damage detection. Indeed, negative samples are very difficult to acquire. Many real structures are in an intact state with no damage, and artificial damage is generally not allowed to be induced. Meanwhile, because there are huge differences between structures, the vibration data of different structures normally cannot be used for training a universal SDD model. For similar reasons, simulated vibration data generated through finite element analysis (FEA) may have some differences from the measurement data due to idealized boundary conditions or other assumptions and cannot be used as training data directly in most cases. As a result, the problem of obtaining enough realistic negative samples must be solved for successfully training ML models that can detect actual structural damage.

To address the above problem, as our first attempt, we proposed a method to synthesize realistic vibration data in this article. The proposed method combines vibration experiment, FEA, and neural network (NN). The vibration experiment and FEA are for generating one-to-one matched vibration data. NN is used to project the vibration data from the simulation space to the measurement space. The effectiveness of the proposed method is discussed, and the quality of the synthetic data is also analyzed. The article is finalized with some conclusions, limitations, and future work.

2 Methodology

The proposed method for vibration data synthesis is illustrated in Fig. 1. Vibration experiment, FE simulation, and NN are incorporated in this method. Firstly, impulse loads are applied to the structure by using an instrumented electrical hammer. Both the impulse loads and the free damped vibrations of the structure are measured. A dataset of measurement data can be established by repeating the process. Secondly, a finite element (FE) model of the structure is created. The impulse loads recorded in the vibration experiment are input into the corresponding locations of the FE model respectively. The structural responses from the FE model are then computed through the time-history dynamic analyses data. Then a dataset of simulation data is built. As both the vibration tests and the FEA share identical input, the measurement data and the simulation data can be one-to-one matched. As a result, the two datasets are paired. Finally, a neural network is trained using the data pairs. The FE simulation dataset is used as input, and the measurement dataset is for the labels. The simulated vibration data can be projected to the measurement data space through the NN.

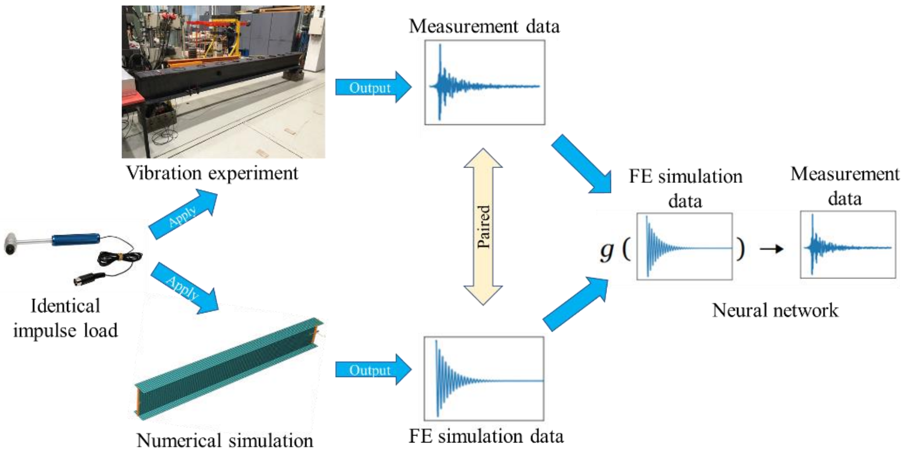

Fig. 1. Architecture of the proposed method for vibration data synthesis

Neural network is a classical data-driven modeling method. It can approximate correlations between two datasets through a training procedure, with no requirement of domain knowledge. The training process can be summarized into 3 steps. Firstly, training data are fed into the NN, and then corresponding predictions are obtained. Secondly, loss is calculated by comparing the predictions and the labels via a certain loss function, e.g., mean square error and cross entropy. Finally, the loss is minimized using gradient descant. When the loss of a neural network is relatively low, the training is accomplished.

3 Experiment

3.1 Vibration experiment

Fig. 2 shows the details of the vibration experiment. An I-shaped steel beam is simply supported at its two ends. The total length of the beam is 4.4 m, and the span length is 4 m. In total 9 accelerometers are evenly distributed on the upper flange, named from Ch. 0 to Ch. 8. The sampling frequency is 2000 Hz, and the measurement time for each test is 2 s. As a result, each measurement data is a matrix with a shape of 4000 data points × 10 channels. The first channel is the force of hammer impact, and the other 9 channels are the acceleration data. The experimental setup of the vibration test is shown in Fig. 3. The impact locations are in the middle of every two adjacent accelerometers. In total, the hammer impact loads are applied on 8 locations, termed from Loc. 0 to Loc. 7. The impact forces are generally in a range between 3 N and 11 N. An example of the hammer impact force is shown in Fig. 4. Each impact triggers a measurement of the free damped vibration of the beam. The numbers of hammerings in all locations are summarized in Table 1. Over 140 times of impact were applied in each location. In total, 1277 free damped vibration data are acquired. Fig. 5 shows an example of the measurement data (Ch. 5 of the 14th data impacted at Loc. 0).

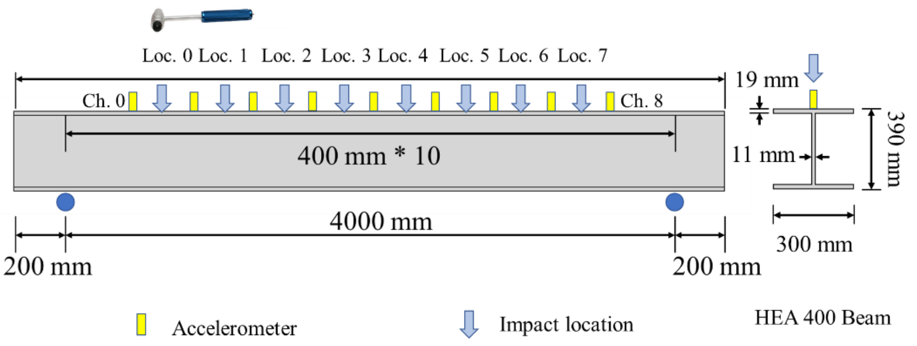

Fig. 2. Locations of sensors and hammer impacts

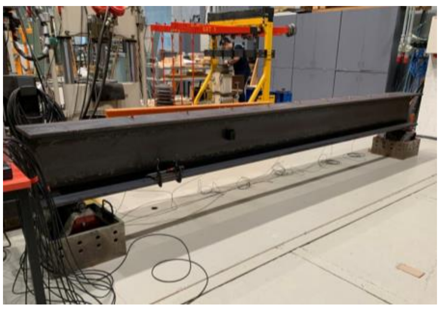

Fig. 3. Photo of the vibration experiment

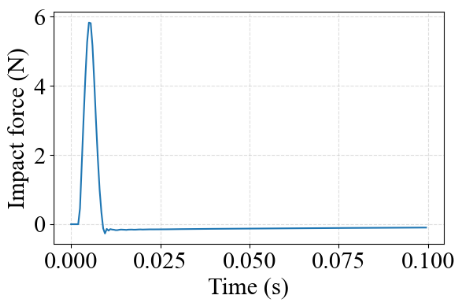

Fig. 4. Example of hammer impact load

Table 1. Data distribution

Impact location	Number of data	Impact location	Number of data
0	201	4	142
1	218	5	143
2	145	6	142
3	143	7	143
4	142	In total	1277

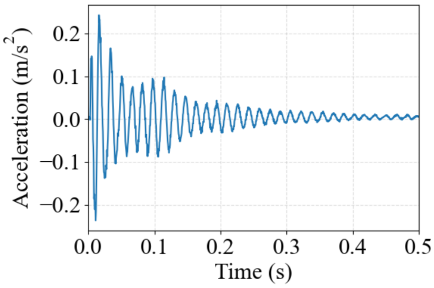

Fig. 5. Example of measurement data

3.2 Simulation using finite element analysis

To verify the proposed data synthesis method, a FE model of the steel beam is built. The 3-D beam element (B31) in Abaqus is utilized to simulate the beam's vibration under a certain impulse excitation. The basic parameters of the FE model can be found in Table 2. The beam is divided into 22 elements, as shown in Fig. 5, and the length of each element is 0.20 m. There are 23 nodes in total, and each node has 6 degrees of freedoms (DOFs). The beam is simply supported with span length of 4.0 m as shown in Fig. 2. The calculation of the beam's vibration is based on the Mode Displacement Superposition method. The first 30 modes are selected for analysis, and Rayleigh damping is utilized with α of 2×10-3 and β of 5×10-5.

Table 2. Basic parameters of the FE model

Length	Span length	Young's module	Poisson Ratio	Density
4.4 m	4.0 m	210 GPa	0.3	7850 kg/m^3

To compute the simulated vibration data, the impact loads recorded from the vibration experiment are applied to the corresponding locations of the FE model. As a result, 1277 simulation data are obtained to create the data pairs. Fig. 6 shows an example of the simulation data Ch. 5 of the 14th data with the excitation applied on Loc. 0. Compared to the measurement data in Fig. 4, the simulated vibration data are damped in an over ideal way.

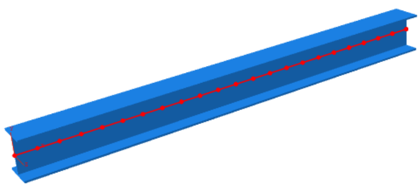

Fig. 5. Finite element model of the beam

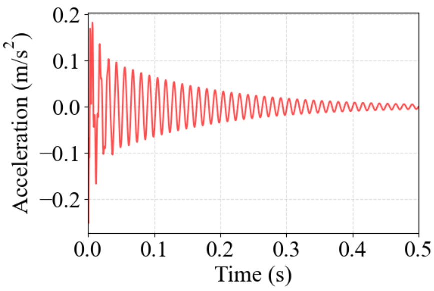

Fig. 6. Example of FE simulation data

3.3 Neural network modeling

The proposed NN is designed to transfer the vibration data from the simulation space to the measurement space. The structure of the NN is shown in Table 3. Five layers (including an input layer, a flatten layer, two dense layers, and a reshape layer) are stacked from the beginning to the end. The input shape and the output shape are identical to the simulation data (4000 points × 9 channels). Each of the two dense layers has over 64 million trainable parameters. In total, the NN has over 129 million trainable parameters. The training was performed on a computer with a Core i9 11900 CPU and an NVIDIA GeForce RTX 3090 GPU. As the structure of the network is very simple, the large number of parameters does not affect the efficiency of training. The neural network is trained with 1149 data and validated with 128 data. The ratio of training data and validation data is 9 to 1.

Table 3. Structure of the NN

Layer	Output shape	Number of Parameters
Input	4000×9	0
Flatten	36000	0
Dense 1	1800	64,801,800
Dense 2	36000	64,836,000
Reshape	4000×9	0
In total	-	129,637,800

4 Results

By performing the vibration experiment and the FE simulation, two matched vibration datasets are established. One is the measurement dataset, and the other is the FE simulation dataset. The natural frequencies of the 1st bending mode in the experiment and the FE simulation are 62.5 Hz and 80.5 Hz, respectively. We did not perform modal updating, because we intended to investigate whether the NN projection requests a high similarity between the FE simulation data and the measurement data. Fig. 7 compares the Ch. 4 of a paired FE simulation data and measurement data in the validation set. Clear differences in frequency and phase can be observed.

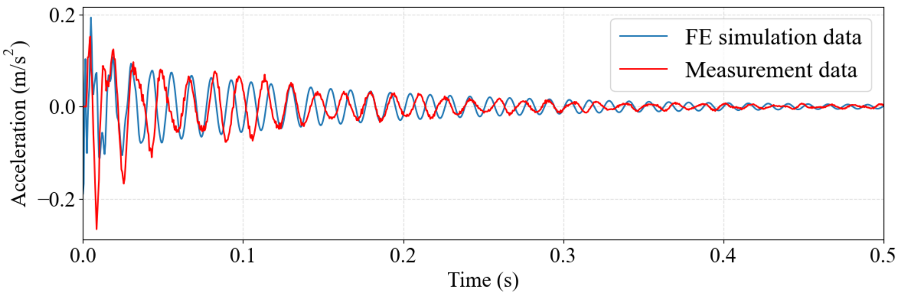

Fig. 7. Comparison between the FE simulation data and measurement data

The NN was trained for 300 epochs, and the loss reduced smoothly, as shown in Fig. 8. Very low training and validation loss were finally obtained, indicating the high performance of the NN.

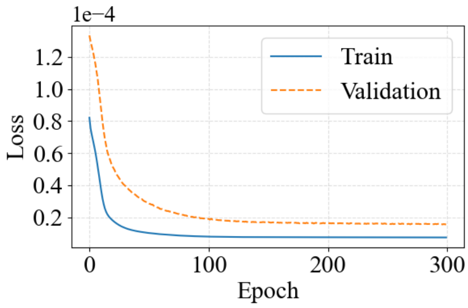

Fig. 8. Training history

By using the NN to transfer the vibration data from the FE simulation data space to the measurement data space, the synthetic vibration data are obtained. A synthetic data from the validation set is visualized in Fig. 10. All the 9 channels of the synthetic data are compared to the measurement data respectively. The amplitude, phase, and frequency of the synthetic data almost perfectly match the measurement data. The root mean square errors of the 9 channels are in a range between 0.0036 to 0.0063. Such a small error indicates the high quality of the synthetic vibration data.

5 Conclusions

In this paper, we proposed a method to synthesize realistic vibration data by combining vibration experiment, FE simulation, and NN. The method transfers simulated vibration data to measurement vibration data via NN projection. Such an achievement can be used to address the problem of insufficient training data. Through the presented experiment, the feasibility of the method is fully demonstrated. All the frequency, phase, and magnitude of the synthetic data can accurately match the measurement data, representing the high quality of the synthetic vibration data.

As this research is in its beginning phase, in this paper we only prove the concept by using the data acquired from an intact structure. Thus, whether the proposed method can accurately synthesize the vibration data that represents damaged structural cases is unknown. Further study will focus on this question and explore other scenarios to utilize the synthetic vibration data.

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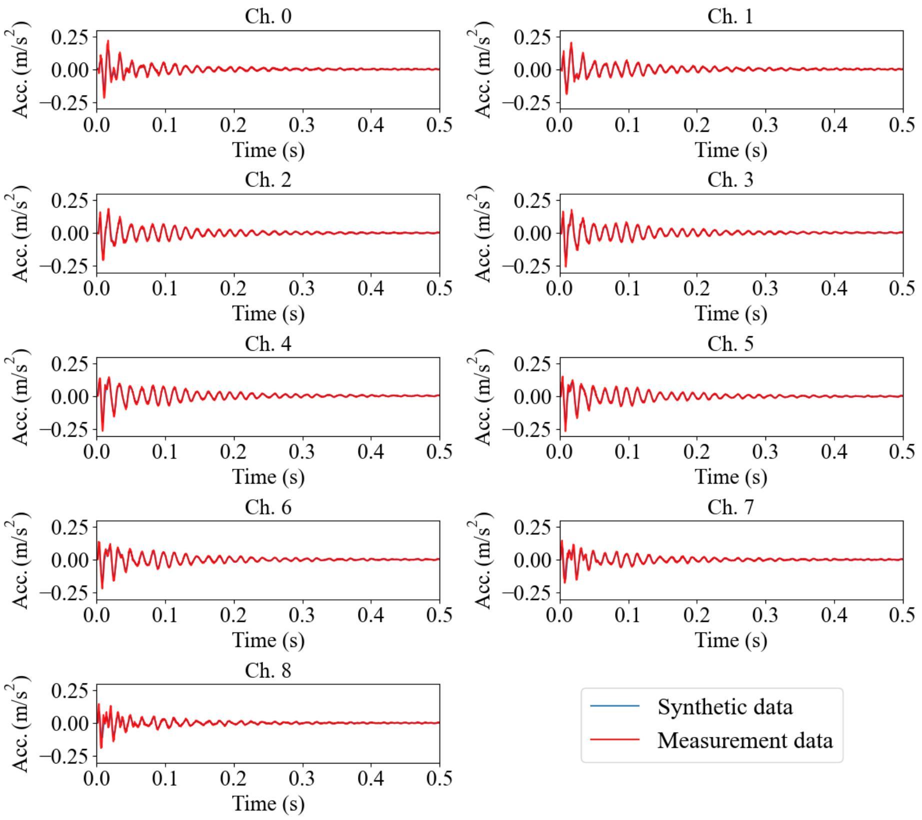

Fig. 10. Comparison between the synthetic and measurement data

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