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Wavefield character in high rise building under earthquake shake and CNN based damage detection

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Abstract. Vibration of buildings can be regarded as the wave propagation in the vertical direction. Stiffness deterioration of structures due to damages could be altered by the changes in velocity and attenuation of the traveling waves. Previous studies have proposed methods to construct a new wavefield from the original wavefield of the building, in which the propagation path of the waves can be more easily recognized. In this study, firstly, we construct the wavefield with the virtual source at the top of the building (deconvolved wave), which consist of one acausal up-going wave and one causal down-going wave. Then, the changes of deconvolved waves over time at the base and inter floors are visualized. Finally, the CNN is constructed to automatically recognize the change of the visualized wavefield. To generate training data of the CNN model, multivariate nonlinear vibration simulation, reconstruction of the wavefield and visualization of the wavefield based on the vibration data was performed. To validate the trained CNN, the data of a shake table test on a 1/3 scaled 18-story steel frame building is used. As the damage progresses, the changes in the wavefield are recognized.

Introduction

Evaluating the changes of dynamic properties (eg., natural frequencies) of structures under the ground motion can indicate potential damages or deterioration of structural components. However, natural frequencies are easily to be wandering by environmental factors, such as temperature [1]. Seismic response of buildings can be regarded as wave propagation in the vertical direction. During the past decades, wave propagation has been widely used to measure the vibration response of a structure [2]. In addition, after an earthquake happens, it is essential to quickly evaluate the building damages and behaviors after earthquakes to avoid further financial loss and the secondary destruction of buildings, achieving the purpose of Structural Health Monitoring (SHM). With the development of technology in image classification, the Convolutional Neural Networks (CNNs) based methods have been verified as one of the most accurate methods to classify images.

To fast evaluate the behavior of buildings, a wave-propagation and CNNs-based method were proposed in this study. At first, a Multiple-Degree-of-Freedom (MDOF) Model was established by referencing the specimen of the 18-story steel frame building for the shake table test, and it is used to generate the CNN training dataset. Then wavefield figures from acceleration deconvolved waves of the simulations were used as the feature input for the CNN model, which is divided into two classifications, linear and non-linear. The trained CNN model can automatically recognize the classification of wavefield figures (linear or non-linear). Finally, the performance of the trained CNN model was verified by the shake table test data.

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Shake-table tests of steel structures

The shake-table test of a 1/3-scaled 18-story moment-frame steel building structure was performed at E-defense on December 9-11, 2013 [3], as shown in Figure 1. The responses are not only used to identify the reliability of the MDOF model but also used to generate data in the later section to test the performance of the trained CNN model. The seismic excitations were applied only in the longitudinal direction. The magnitude of input motion is evaluated in pseudo response velocity, which is adjusted following the value of pSv (pseudo response velocity) from 40 to 340 cm/s (with a damping ratio of 5%). The schedule of loading to the specimen is listed in Table 1. The maximum value of the pSv of the original seismic motion is 110 cm/s, which is named Case110. In Table 1, the numbers after the 'Case' present the maximum values of the pSv.

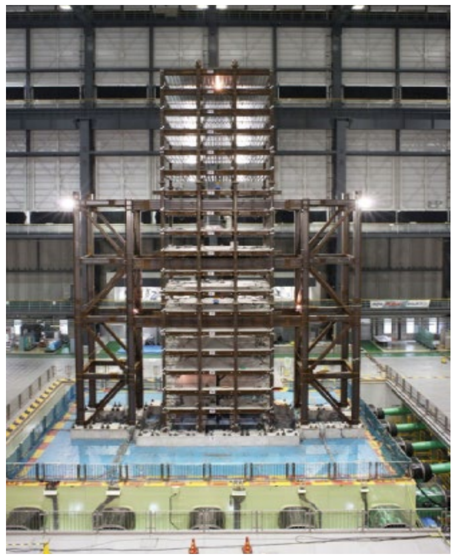


Figure 1. *The specimen of shake-table test. [3]*

Table 1. *The loading schedule and status.*

Case	States
40	No damages (elastic)
110	Plasticizing of the beam ends (2F to 7F) and columns (1F)
180	Yielding of beam ends (2F to 14F) and cracks of beam ends (2F to 5F)
220	Break of beam ends (2F)
300	Break of beam ends (2F to 5F)
340	Buckling of the columns base (1F)

Simulation and evaluation of MDOF model

Multiple-Degree-of-Freedom system

Multiple-Degree-of-Freedom (MDOF) systems can model the behaviors of a shear building. In this paper, the establishment of the multi-degree-of-freedom equivalent model is based on the shake table test 18-story steel frame building in Section 2, which is used to generate the CNN training dataset.

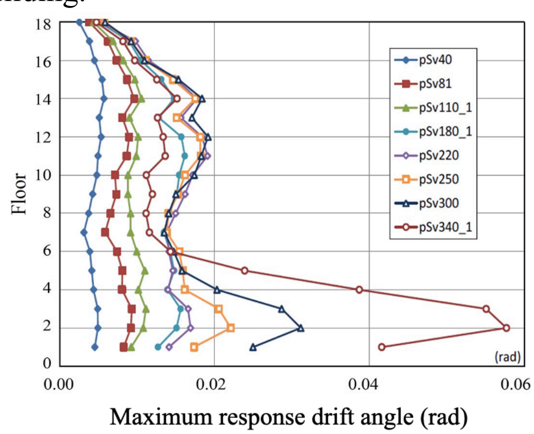
Table 2 shows the detailed parameters of the 18-floor steel frame building. The weight of each floor of the building is ununiform and the stiffness is different. The height of the first story is 1.75 m, and the story height of other stories is 1.35 m. Besides, the restoring force characteristic of each floor is Tri-linear, the first turning point is 0.005 rad and the second turning point is 0.01 rad, respectively.

Table 2. *The detailed parameters of the shake table test 18-story steel frame building*

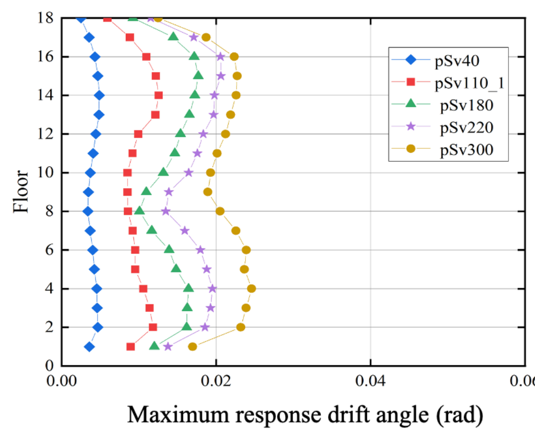
Floor	Height of floor (cm)	Mass (kN)	Initial stiffness K_1 (kN/cm)	Yield displacement (cm)	Second stiffness ratio K_2/K_1	Third stiffness ratio K_3/K_2
18	135	202	363	0.75	0.5	0.3
17	135	206	491	0.89	0.5	0.3
16	135	206	562	1.00	0.5	0.3
15	135	206	619	1.08	0.5	0.3
14	135	206	660	1.13	0.5	0.3
13	135	206	712	1.23	0.5	0.3
12	135	206	788	1.23	0.5	0.3
11	135	208	824	1.30	0.5	0.3
10	135	208	840	1.32	0.5	0.3
9	135	208	876	1.30	0.5	0.3
8	135	208	938	1.30	0.5	0.3
7	135	208	963	1.34	0.5	0.3
6	135	208	990	1.34	0.5	0.3
5	135	208	1028	1.34	0.5	0.3
4	135	208	1028	1.28	0.5	0.3
3	135	208	1073	1.22	0.5	0.3
2	135	208	1092	1.18	0.5	0.3
1	170	208	1155	1.18	0.5	0.3

Evaluation of MDOF

To evaluate the reliability of the equivalent MDOF models, the shake-table test data of Case40, Case110, Case 180, Case 220, and Case300 were selected as the input motions. The distribution of the maximum response drift angle and maximum response acceleration of measured and simulated data in the direction of building height are shown in Figures 2 and 3, respectively. Considering the expression of the measured data obtained from the recorded report [4], these figures use ‘pSv’ instead of ‘Case’. It can be seen that the simulation values of the MDOF model are in good agreement with the true values of acceleration and story drift angle for all floors of the building.

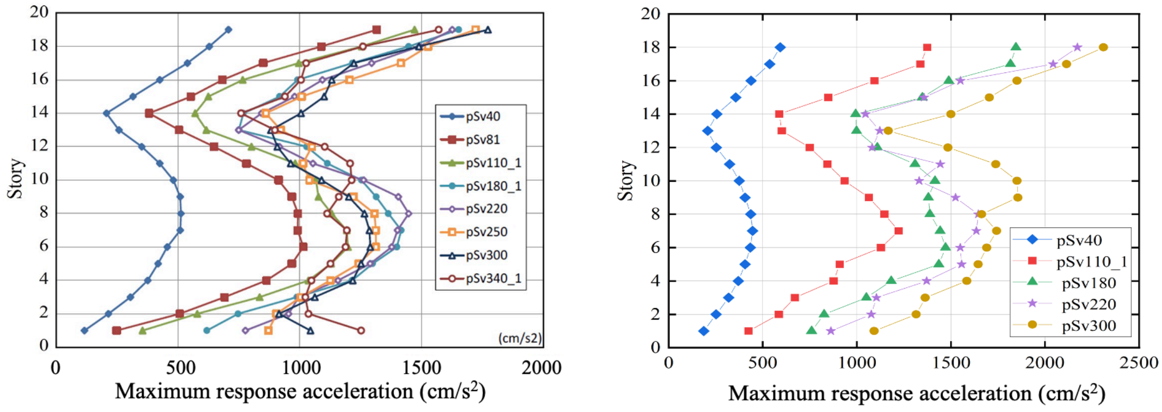


(a)



(b)

Figure 2. *The maximum response drift angle of (a) Measured data [4] and (b) Simulated data.*



(a) (b)

Figure 3. *The maximum response acceleration of (a) Measured data [4] and (b) Simulated data.*

Training and verification of CNN model

Reconstruction of wave filed

From the changes of wave propagation within the stories, such as the travel time, the local properties of the traveled stories can be examined [5, 6]. However, it is difficult to read the wave travel time from the waveforms directly. Because the propagation velocity of shear wave in the vertical direction depends on the shear stiffness of the stories, it is possible to evaluate the damages of inter stories. Therefore, in this study, we pay attention to the propagation of shear waves, which generates horizontal vibrations at the floors.

In order to construct a new wave field, from which it is easier to read the shear-wave propagation, in the study, the deconvolved waves of inter stories with respect to the response of the top are used. In the new wave field, the virtual source (impulse) is at the top of the building. As examples, the travel time and deconvolved waves calculated from the responses in Case40 (linear case) and Case300 (non-linear case) are shown in Figure 4. By comparing Figure 4 (c) and (d), we can find that because of the occurrence of damage, the trace of impulse becomes blurry and even disappeared for non-linear cases, while the impulse in the linear case is obvious. This feature will be regarded as the recognition feature for using the CNN model to identify linear and nonlinear cases automatically.

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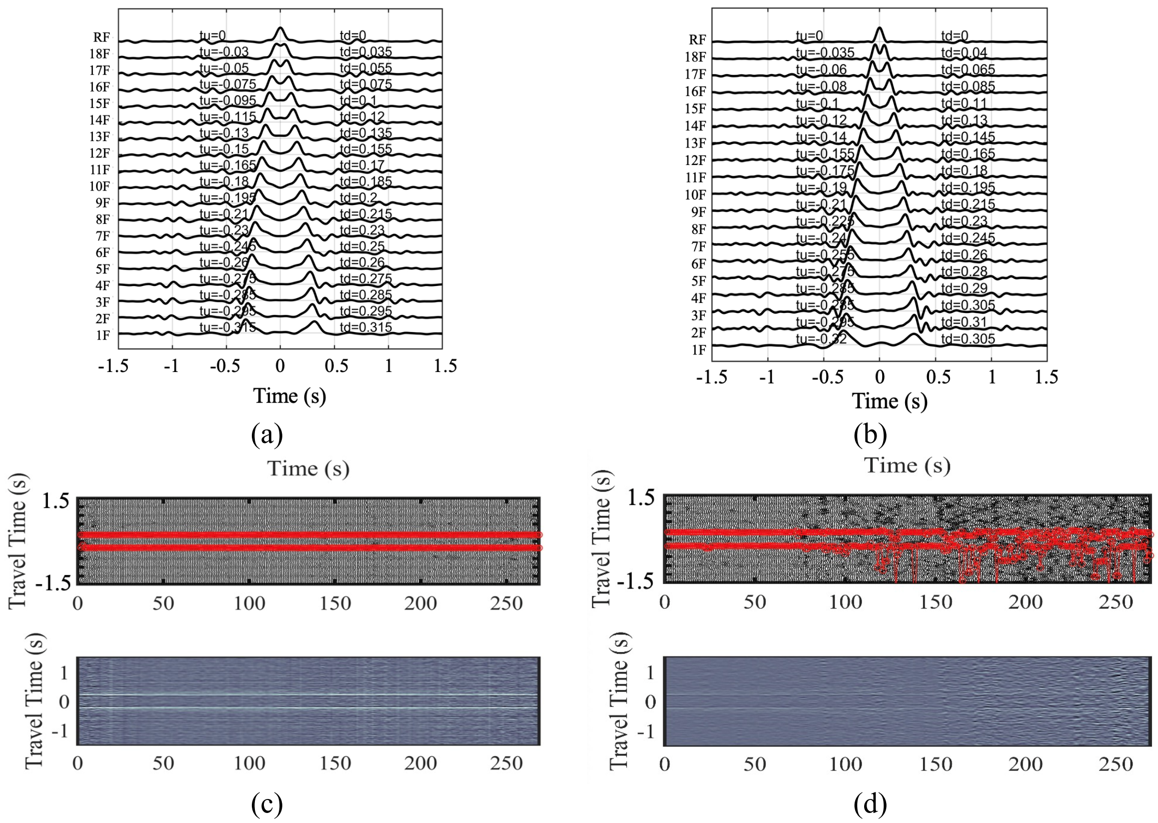

Figure 4. *(a) Deconvolved waves in Case40 (linear case) and (b) in Case300 (non-linear case) with the virtual source at the top of buildings; Visualization of varying of deconvolved waves within the duration of vibration at the first floor for the (c) Case40 and (d) Case300. The lower figures are the 3D expression of the upper figures, which are input to the CNN for feature recognization.*

Establishing the ground motion dataset for CNN model training

The architecture of the CNN model used is shown in Figure 5. As illustrated in this figure, AlexNet [7] network is used as CNN architecture in this study, which consists of 8 layers of a convolutional neural network, including five convolutional layers and three fully connected layers. The input figures were resized to 224 × 224 pixels, but the actual size is 227 × 227. The training data were classified into two classifications, “linear” and “non-linear,” with “linear” set to 0 and “non-linear” set to 1, and the learning rate was set to 0.01.

Although the number of real data for the training CNN models is limited, it can be overcome by numerical simulation. At present, there are several open-access ground motion databases such as the K-NET database [8] of Japan that can be used for training the CNN models. For this study, almost 80 ground motion records are selected from the K-NET database, as shown in Table 3. The reliability of MDOF models is evaluated at different performance levels, ranging from elastic to highly inelastic behavior.

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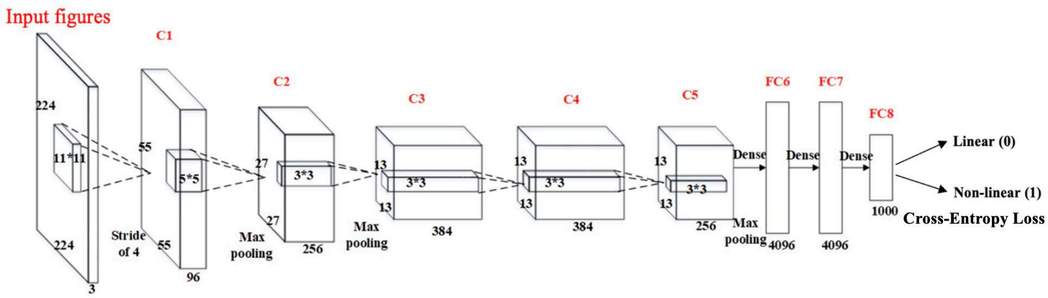


Figure 5. *Convolutional neural network architecture based on AlexNet [7].*

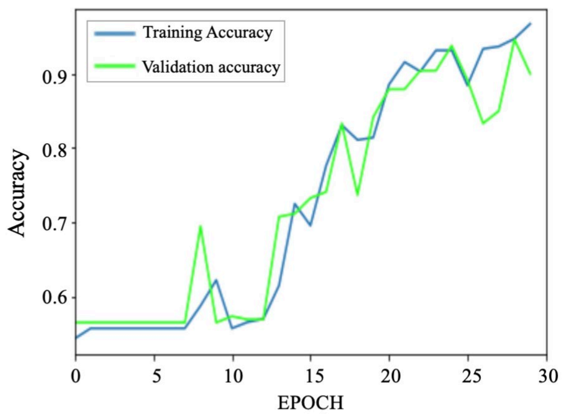
Table 3. *The earthquake input motions for generating CNN training dataset*

Year/Month /Date	Earthquake name	Magnit-ude	Site code	PGA (cm/s^2)	Direction used	Site code	PGA (cm/s^2)	Direction used
2016/4/14	Kumamoto	7.3	KMM001	49.3	EW	KMM018	50.1	EW
			KMM002	160.8	EW	KMM019	56.3	EW
			KMM003	79.5	EW	KMM022	36.2	EW
			KMM004	207.1	EW	FKO004	43.6	EW
			KMM005	195.5	NS	FKO005	55.5	EW
			KMM006	381.4	EW	FKO011	41.8	EW
			KMM007	205.9	EW	FKO013	70.9	EW
			KMM008	149.9	NS	FKO015	92.0	EW
			KMM009	304.2	EW	FKO016	80.6	EW
			KMM010	263.5	NS	FKO004	42.5	EW
			KMM011	546.9	EW	KGS001	52.4	EW
			KMM012	380.9	NS	KGS001	48.3	EW
			KMM013	145.3	NS	KGS003	90.0	EW
			KMM014	62.8	NS	KGS006	75.5	EW
			KMM015	58.8	EW	MYZ001	53.2	EW
			KMM016	48.7	NS	MYZ002	50.1	EW
			KMM017	39.3	EW	MYZ003	56.3	EW
2022/3/16	Fukushima	7.4	FKS001	727.5	EW	FKS001	565.6	NS
			FKS002	750.5	EW	FKS002	572.9	NS
			FKS003	294.7	EW	FKS003	277.1	NS
			FKS004	608.9	EW	FKS004	519.9	NS
			FKS005	514.6	EW	FKS005	607.8	NS
			FKS006	530.4	EW	FKS006	530.9	NS
			FKS007	456.1	EW	FKS007	512.9	NS
			FKS008	517.6	EW	FKS008	658.9	NS
			FKS009	309.5	EW	FKS009	375.7	NS
			FKS010	426.8	EW	FKS010	525.9	NS

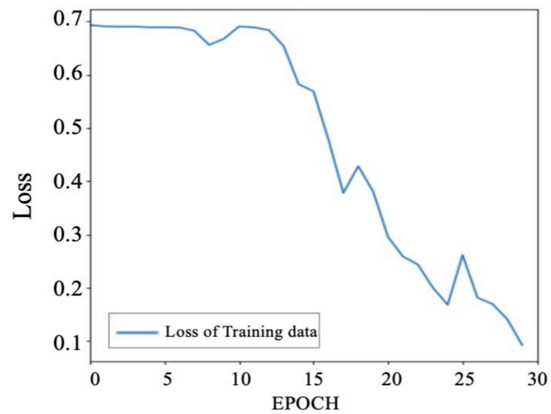
Training and verification CNN model

The ground motions obtained from the K-NET database are designated as the training (including validation) datasets using the simulation of the MDOF model. The CNN was trained and validated using a total number of 2000 images of deconvolved waves at 1F to 18F of the MDOF model, in which 1000 images are linear cases and 1000 images are non-linear cases. Besides, 1800 figures were used for training, and the remaining 200 images were used to verify the trained CNN. For testing the trained CNN model, 60 figures of deconvolved waves of 1F~18F using the shake-table test data were selected.

The results of training and test data are shown in Figure 6, including the changes of accuracy value and mean loss value with the increase of the epoch. As can be seen in these figures, 94.7% accuracy is achieved for CNN training data for the recognition of linear or non-linear cases and 94.6% accuracy is achieved for CNN test data. For the mean loss value, the training data and test data both show decreasing trends with the increase of epoch. In short, the trained CNN model achieves good performance.



(a)



(b)

Figure 6. *The accuracy and loss results of training and validation data.*

Conclusions

In this study, a CNN-based approach for recognizing the linear and non-linear behavior of buildings using visualized deconvolved waves is proposed. To generate training data, a multiple-degree-of-freedom model of the 18-story specimen of the shake-table test is established to simulate the seismic response. Numerical simulations can overcome the limited amount of actual data for training CNN models. Furthermore, we calculated the deconvolved waves from the numerical simulation seismic response, which are visualized and fed to train a convolutional neural network (CNN) to classify “linear” or “non-linear.” The trained CNN model is used to recognize figures of linear and non-linear cases of structures, and the accuracy of proposed method is satisfactory (94.7% and 94.6%). The findings of this study can be used to monitor the health situations of the structures in the future.

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