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Damage Detection Based on Wavelet Transform and Convolution Neural Networks

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ABSTRACT: The performance of conventional damage detection systems depends mainly on the physical and geometrical damage characteristics and the choice of damage classifier. Some works directly use Convolutional Neural Networks (CNN) for damage pattern recognition analysis of experimentally measured vibration signals. This work proposes a method that combines wavelet transform and CNN for Structural Health Monitoring (SHM). Firstly, we obtain numerically simulated structures with sensors arranged on them to collect data and perform the cut-off; then, we perform the wavelet transform to the acceleration signals of different simulated damage patterns and use them to train the CNN; finally, the trained CNN can predict the structural damage patterns. A four-level benchmark building introduced by the IASC-ASCE Structural Health Monitoring Working Group is used to validate this damage identification method. The numerical results show that the proposed method can effectively solve the problem of quantifying structural damage.

1. INTRODUCTIONS

Structural Health Monitoring (SHM) is essential to assess the condition and safety of engineering structures during their life cycle. One of the core tasks in establishing a practical and efficient SHM system is to improve its structural damage identification capability. In the early stages, structural damage is mild and usually does not affect the regular use of the structure; however, if it is not detected and effectively repaired in time, the damage will gradually increase and eventually lead to severe damage. Therefore, it is crucial to identify and quantify the structural damage promptly. Damage identification methods based on vibration information have been widely studied for decades (Das and Saha (2018)). However, due to complex and variable operating and environmental conditions, as well as various engineering structural forms and damage types, there are significant challenges in practice.

In recent years, deep learning algorithms have also been increasingly used in vibration-based structural damage recognition studies due to the dramatic increase in computational power and a significant reduction in sensor fabrication costs (Zhao et al. (2019)). Due to its excellent feature extraction capability, the application of CNN has gone beyond the traditional field of computer image recognition to become a versatile feature extraction tool (Xu et al. (2020), Abdeljaber et al. (2018)). Cofre-Martel et al. (2019) proposed a new deep CNN-based method for localization and quantification of structural damage. It operates on images generated by the transmission function of a structure and uses the image processing capability of CNN that automatically extracts and selects features relevant to the structural degradation process. Abdeljaber et al. (2017) proposed a structural damage detection system using a one-dimensional CNN with an inherently adaptive design that fuses feature extraction and classification blocks into a single, compact learning body. Yu et al. (2019) proposed a deep CNN-based identification and localization of damage to building structures equipped with intelligent control devices. All these works successfully implemented damage pattern recognition analysis of vibration signals using CNN.

To overcome the limitation of small data size collected during the shake-table test that hindered the use of artificial neural networks and recurrent neural networks. Khodabandehlou et al. (2019) introduced a novel vibration-based SHM approach that uses two-dimensional deep CNN. The CNN extracts the features from acceleration response histories and reduces the dimension of response history to make damage state classification possible with limited number of acceleration measurements. Mantawy and Mantawy (2022) explored the use of time-series acceleration or displacement data collected from a shake-table experiment of a two-span bridge utilizing pretensioned rocking columns to predict the damage state of each bridge bent, where the major identified damage was the fracture of the longitudinal bars. The time-series data were encoded into images using three methods: Gramian angular summation field, Gramianan gular difference field, and Markov transition field. Then, the encoded images were used as an input for CNN models. However, these data conversion methods cannot achieve high accuracy and few computation at the same time when facing large volume of data.

This work presents a method to accurately assess structural health by combining wavelet transforms and CNN. With its multi-resolution signal analysis capability, the wavelet transform can simultaneously analyze signals in both time and frequency domains. It is particularly suitable for handling non-stationary signals, and is widely used in research in various disciplines. A four-level benchmark building introduced by the IASC-ASCE Structural Health Monitoring Working Group was used to validate this damage identification method (Johnson et al. (2004)). Firstly, we simulate different levels of structural damage on a finite element model of the structure and collect acceleration signals at fixed points of the structure. Then, we slice the collected acceleration signals under different simulated damage patterns, perform wavelet transform calculations, and feed them to the CNN for training; finally, the trained CNN can accurately predict the structural damage patterns. The numerical results show that the proposed method effectively solves the problem of structural damage recognition.

Section 2 outlines the proposed structural damage estimation method, including wavelet transform theory and CNN. Section 3 describes the benchmark structure of IASC-ASCE, the adopted CNN network structure and the hyperparameters used for training, and the training and test sets of the CNN. Conclusions are given in Section 4.

2. DESCRIPTION OF THE PROPOSED METHOD

2.1. *Wavelet Transform*

Analyzing signals in the time domain is a common and effective way of modern signal processing. Fourier transform is a powerful tool, and it can reflect the overall spectral characteristics of the signal well. However, the Fourier transform can only obtain information about the frequency components of the signal to be processed, but not time information of each frequency component, which results in two signals with very different time domains may have the same spectrum. For non-smooth signals such as structural fault vibration signals, the signal frequency changes with time, and the instantaneous frequency and amplitude information at each moment are also important, which will increase the success rate of damage identification. The wavelet transform is very effective in denoising non-stationary signals, extracting characteristic parameters of signals, and numerical analysis (Wang et al. (2010)). A wavelet is a particular type of waveform with finite length and zero means. It is called a "wavelet" because the function that can be used as the basic wavelet has two characteristics: first, it has the property of fast decay, i.e., it has a tight branching or near tight branching in the time domain; second, it has the form of oscillation with alternating positive and negative amplitudes, i.e., the DC component is zero. The wavelet has very concentrated energy in the time domain, which is finite and concentrated near a certain point.

Mathematically, when the function $\psi(t)$ satisfies the following two conditions:

- function $\psi(t)$ can be square integrable, i.e.

$$\psi(t) \in L^2(R), \tag{1}$$

- $\hat{\psi}(\omega)$ is the Fourier transform of the function $\psi(t)$, i.e.

$$\int_{-\infty}^{+\infty} |\hat{\psi}(\omega)|^2 |\omega|^{-1} d\omega < +\infty, \tag{2}$$

then $\psi(t)$ can be called a Mother Wavelet. Once a mother wavelet is obtained, it can be translated and scaled to obtain:

$$\psi_{\mathrm{a,b}}(\mathrm{t}) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (a > 0, b \in R), \tag{3}$$

$\psi_{\mathrm{a,b}}(\mathrm{t})$ is called the wavelet basis function, where a represents the scale factor, b means the scale translation factor. Also, if a and b are continuous, then $\psi_{\mathrm{a,b}}(\mathrm{t})$ is called the continuous wavelet basis function.

Let $\psi(t)$ be a mother wavelet, and $\psi_{\mathrm{a,b}}(\mathrm{t})$ be a continuous wavelet basis function obtained by stretching and translating, then for any function $x(t)$, its wavelet transform is:

$$WT_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \bar{\psi}\left(\frac{t-b}{a}\right) dt, \tag{4}$$

where $WT_x(a,b)$ is called Continuous Wavelet Transform (CWT) of $x(t)$, where: $\bar{\psi}(t)$ is the conjugate operation of $\bar{\psi}$. As Equation 4 shows, the function after the wavelet transform is two-dimensional; that is, when we perform the wavelet transform of the original one-dimensional signal into a two-dimensional signal, realizing the analysis of the signal in the time-frequency domain. Essentially, the wavelet transform is a superposition of projections on $\psi_{\mathrm{a,b}}(\mathrm{t})$ with different translation and scaling factors for any function $x(t)$ in $L^2(R)$ space. The Fourier transform can only project $x(t)$ onto the frequency domain. Moreover, the wavelet transform maps a one-dimensional time-domain signal onto a two-dimensional "time-frequency" domain, so the wavelet transform has a multi-resolution feature. By adjusting the scaling factor and translation factor, wavelet transform with different time-frequency widths can be obtained, which can be matched with the original signal at any time to complete the time-frequency localized two-dimensional analysis of the signal, as shown in Figure 1. From

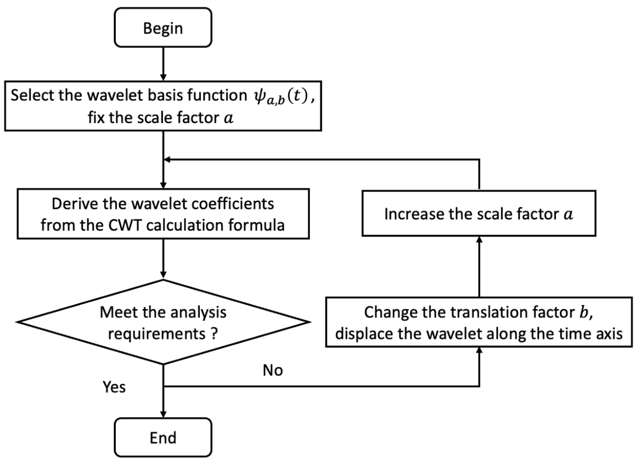

Figure 1: Basic flow of wavelet transform.

the definition of the continuous wavelet transform, it is clear that the information of continuous wavelet transform of a signal $x(t)$ is redundant when the stretching factor a and translation factor b continuously vary. From the perspective of computational convenience and saving computational effort, we want to minimize the redundancy of wavelet transform coefficients without losing the original signal $x(t)$ information. In practice, the factors a and b of the continuous wavelet transform are usually discretized.

To demonstrate the effect of wavelet transform on non-stationary signals, we defined three sinusoidal signals with 1000 Hz sampling frequency, a sampling time of 1000 s, and center frequencies of 10 Hz, 20 Hz, and 30 Hz. Then we added random normally distributed noise with amplitudes between 0 and 1 to simulate the non-stationary state. We perform the wavelet transform of the simulated non-stationary sinusoidal signal, as shown in Figure 2, where the horizontal coordinate represents the main components of the frequency, and the vertical coordinate represents the change of frequency with time. Label 1 represents a sine signal with a defined center frequency of 10 Hz, label 2 denotes a sine signal with a defined center frequency of 20 Hz, and label 3 means a sine signal with a defined center frequency of 30 Hz. As seen in Figure 2, even though we have added noise to the sinusoidal signal after the wavelet transforms, we can still see very clearly the main components of the frequencies and how they change with time.

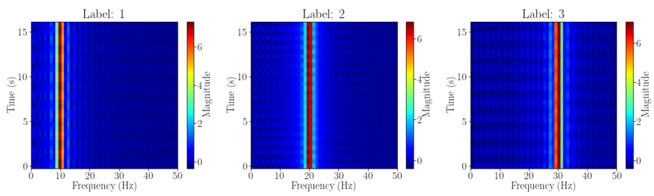

Figure 2: Wavelet transform of simulated non-stationary sinusoidal signal (Label 1: 10 Hz, Label 2: 20 Hz, Label 3: 30 Hz).

2.2. *CNN Training*

The CNN model originated from biological neuro-vision research, it has been widely used in object detection in images, videos, and the classification of images (Li 2021). Each CNN mainly includes the input layer, the convolutional layer, the pooling layer, the fully connected layer, and the output layer modules. The CNN extracts the signal feature information in the convolution process. Its basic principle is as follows:

$$Z(i,j) = \sum_m \sum_n I(i+m, j+n) K(m,n), \tag{5}$$

$$y = g(ZW + b), \tag{6}$$

$$g(x) = \max(x, 0), \tag{7}$$

$$Z_{\text{sub}} = \text{subsampling}(y), \tag{8}$$

Equation 5 is the convolution process, where one convolution layer can include multiple convolution kernels for extracting different features (e.g., edge, texture, color) of the image, where I is the input parameter, K is the convolution kernel, (m,n) is the size of the convolution kernel, and (i,j) is the convolution position. Equation 6 is the calculation of the convolution result y after inputting the convolution result Z into the activation function $g(x)$, where W is the weight matrix, and b is the bias. Equation 7 is the expression of the activation function. Equation 8 represents the process of downsampling the signal in the pooling layer of the model, where Z_{sub} is the output result of the pooling layer, and $subsampling()$ is the expression of the activation function.

In this study, a CNN with four convolutional layers (kernel size = 3), four max pooling layers (kernel size = 2), one fully connected layer (number of neurons = 9), and a softmax layer as the output layer is adopted, see Table 1 for details.

Table 1: Hyper-parameters used in the proposed CNN.

Hyperparameter	Value
Number of convolutional layers	4
Number of MaxPooling layers	4
Activation function	SoftMax
Loss function	Negative Log Likelihood Loss
Learning rate	0.001
Maximum number of epochs	1000

3. RESULTS AND DISCUSSIONS

3.1. *Benchmark Description*

The IASC-ASCE benchmark was constructed at the Seismic Research Laboratory at the University of British Columbia, and the benchmark problem was described by Johnson et al. (2004). Figure 3 shows the geometry of this benchmark structure, which is a four-store, quarter-scale (grade 300W) steel frame with a footprint of 2.5 m × 2.5 m and a

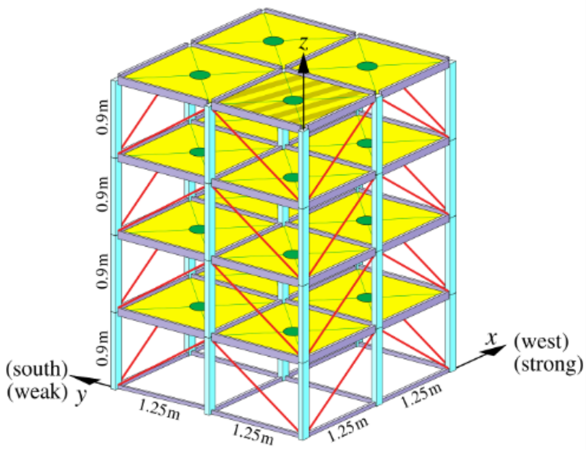

Figure 3: Model of the benchmark structure, the floor beams are marked with violet bars, the columns are noted by blue bars, and the braces are represented by red bars.

Table 2: Damage Patterns of benchmark structure for CNN Training and Testing.

Patterns	Configuration
0	Undamaged
1	Removed braces on 1st floor in one bay on southeast corner
2	Removed braces on 1st and 4th floors in one bay on southeast corner
3	Removed braces on all floors in one bay on southeast corner
4	All east side braces removed
5	Removed braces on all floors on east face, and 2nd floor braces on north face
6	All braces removed on all faces
7	Configuration 7 + loosened bolts on floors 1 and 2 at both ends of beam on east face, north side
8	Configuration 7 + loosened bolts on all floors at both ends of beam on east face, north side

frame height of 3.6 m. The sections are specifically designed for this scale model: the columns are indicated in blue, their section type is B100 × 9; the floor beams are shown in purple, their type is S75 × 11; the support system is marked in red and consists of two 12.7 mm diameter threaded steel rods placed diagonally. The damage introduced in the benchmark was obtained by removing diagonal bracing at specific locations or loosening bolts at several connection locations.

Caicedo et al. (2004) introduced two benchmark FEM models, the simple numerical model 12-DOF and the complex numerical model 120-DOF, for the numerical simulation of the structure's dynamic behavior. Specifically, every single layer of the 12-DOF shear frame is described by three DOFs. The 120-DOF model introduces both out-of-plane motion and rotation of the floor slab on top of the 12-DOF, which is more in line with the real world. As Johnson et al. (2004) reported, the numerical model simulates the presence of 16 single-axis accelerometers, two in each of the X and Y directions for each floor. The proposed method is applied to a 120-DOF Benchmark FEM model.

3.2. CNN Training & Testing dataset

To test the performance of the proposed method, we use nine damage patterns to train and test the CNN, as shown in Table 2. For each damage pattern, the number of channels of the sampled signal is 16, the sampling frequency is 1000 Hz, and the sampling time is 400 s (i.e. 40,000 data points). We divide the data for each channel into "Frames", by defining the "Frame" length as $128*128$. For each data "Frame", we perform the Wavelet Transform. When the structural damage varies, the "images" of the corresponding vibration signal also changes. Therefore, for one channel of data (400 s), we can get $40,000/(128*128)/2 \approx 48$ "images"; for each damage pattern i, we have 16 channels so that we can get $16*48 = 768$ "images"; for all damage patterns, we can get $9*16*48 = 6912$ "images". We divide 70% of the processed data into a training set and 30% into a test set. That is, the training set $6912*0.7 \approx 4838$ is used to train our CNN and the testing set $6912*0.3 \approx 2074$ is used to test the performance of our CNN.

Confusion matrix of the trained CNN prediction failure mode results is shown in Figure 4. We can find that the prediction accuracy is 100% for damage pattern 0, 1, 3, 4, 5; the prediction accuracy is 99% for damage pattern 7 and 98% for damage pattern 2; damage patterns 6 and 8 are easily confused with each other for CNN, the accuracy of damage recognition is not as high compared to other damage patterns. In summary, the final training time is 36 s and the overall accuracy is 97%.

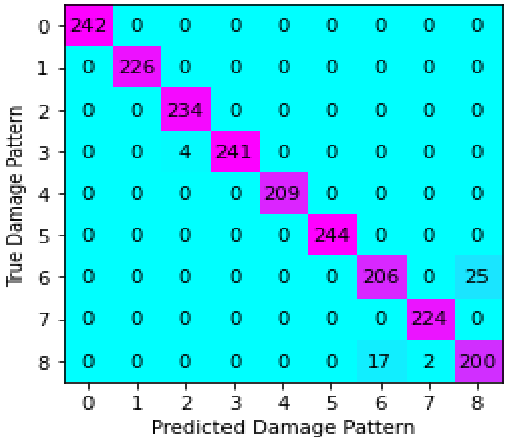

Figure 4: Confusion matrix of the trained CNN prediction failure mode results.

4. CONCLUSIONS

To maximize the beneficial effects of structural reliability on the occurrence of catastrophic events and to reduce structural repair and maintenance costs, there is an urgent need to predict structural damage with a high degree of accuracy. This paper proposes a new damage detection method that includes wavelet transform and CNN to address this goal. The method outputs the learned damage features and predicts unknown damage, while the wavelet transforms further enhance the processability of the data. The performance and feasibility of the proposed technique in real-time SHM and structural damage detection processes are illustrated by validating the IASC-ASCE structure. The results show that the proposed CNN can automatically learn to extract the best features without manually extracting or adjusting parameters. Also, due to the simple structure and low computational cost of CNN, its mobile and low-cost hardware implementation is feasible and can be easily applied to other engineering structures (e.g., civil, mechanical, or aerospace) for real-time structural health monitoring. We believe that an interesting future research is to use useful information provided by different types of sensors (e.g. temperature, humidity, displacement, etc.) together with dynamic monitoring data from acceleration signals as input to the damage detection method. Further extending the effectiveness of the method to different service conditions without the risk of masking the presence of damage.

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