A Study on Analysis of Impact Sound Waveform by Answer-in-Weights Neural Network

Hajime Kanada*, Takehiko Ogawa*, Kiyomi Mori* and Masaru Sakata*

We have investigated the method to measure the elastic moduli of composite materials by impact sound. For estimating the degree of fatigue of the materials, it is important to detect long-term components as well as periodic components from the impact sound waveform. In this report, we propose to use answer-in-weights neural networks for measuring the damping ratio of actual sound waveform.

**Key Words:** composite material, impact sound, sound analysis, damping ratio, neural network

1. Introduction

The method to measure the elastic moduli of composite material by impact sound was proposed1). To determine the elastic moduli from the impact sound, it is necessary to measure the natural frequencies of the vibration from the obtained time-series waveform. Generally, the power spectrum is used for measuring them. It is often difficult to measure the natural frequencies of the waveform with low S/N ratio because of much noise or damping, in case of the composite material under high temperature and so on. To solve this problem, we proposed to introduce the time-frequency analysis based on short-time Fourier transform (STFT)2),3). And we discussed the information of the impact sound obtained by time-frequency analysis using this technique. However, for estimating the degree of fatigue of the material, it is important to detect long-term components as well as periodic components from the impact sound waveform.

On the other hand, we have investigated a neural network of answer-in-weights structure4),5). The neural network consists of two parts of the network that requires a solution to appear in the weights and expresses the fluctuation of time-series data, by multiplying each output. In this report, we propose to use the answer-in-weights network for measuring the damping ratio of impact sound waveform. To show the effectiveness of the method, we describe computer simulation on an example of the actual impact sound of composite material SiC-C/C.

2. Impact Sound Analysis

The setup of the measurement system is shown in Fig. 1. A beam of rectangular cross section was suspended in an infrared image furnace by thin ceramic threads or thin metallic wires so that it can vibrate without significant constraint. A steel ball was dropped onto the specimen using a guide tube. The ringing noise radiated from the impacted specimen was measured by a microphone which was set outside of the furnace as shown in the figure. The specimen generates a peculiar vibration by the impact. Then, the impact sound occurs corresponding to the vibration, which depends on the elastic moduli of the material.

The vibration of the specimen by the impulse impact of a metallic ball consists of flexural and torsional vibration, mainly.

The elastic moduli of the material is estimated by the natural frequencies of the vibration. Then, the envelope of the damped vibration is given by

\[ f(t) = A + B \exp(-\xi \omega t) \]

where \( A \) is the offset value, \( B \) is the amplitude of the vibration, \( \xi \) is the damping ratio, \( \omega_n \) is the natural frequency and \( t_0 \) is actual time.

3. Answer-in-Weights Neural Network

A neural network based on the answer-in-weights scheme was proposed for time series prediction6),9). This network takes into account the idea of two parts; long-term fluctuation and periodic fluctuation, by combining two sub-networks with a multiplication unit. The answer-in-weights network is shown in Fig. 2. And the concepts are schematically shown in Fig. 3. In this network structure, it is possible to predict by the extrapolation that is difficult for conventional multi-layer neural networks. Each sub-network has the function inputs, and the specific coefficient weights to yield the waveform of the time series data at the output. The period of the basis function of the periodic fluctuation was determined from a priori given period of the time series data. Ogawa and Kosugi6) expressed the long-term fluctuation using a step-like function whose step-length was determined from the period. The step-like functions are discontinuous. Therefore, we use a...
set of continuous functions to identify the long-term fluctuation.

The network is used in two phases; identification phase and prediction phase. In the identification phase, we provide the function inputs to the input layer, compare the output with the given vibration data and update the coefficient weights. The network can identify the long-term fluctuation and the periodic fluctuation at the same time. We show the procedure of weight update. First, we consider the total output error \( E(t) \) as

\[
E(t) = (Y(t) - Y'(t))^2, \quad (2)
\]

where \( Y(t) \) and \( Y'(t) \) denote the network output and tutorial output, respectively, and \( t \) denotes the time on the simulation. Total output \( Y(t) \) and sub-network outputs \( Y_i(t) \) and \( Y_j(t) \) are given by

\[
Y(t) = \sum_{i=1}^{M} w_i x_i(t), \quad Y_i(t) = \sum_{j=1}^{N} w_{ij} x_{ij}(t), \quad (3)
\]

where \((w_1, \ldots, w_M), (w_{11}, \ldots, w_{MN})\) are the answer-in-weights of the sub-networks and \((x_1(t), \ldots, x_M(t)), (x_{11}(t), \ldots, x_{MN}(t))\) are the function inputs. Therefore, we obtain the weight update law as

\[
\text{new} \quad w_i = \text{old} \quad w_i - \alpha \frac{\partial E(t)}{\partial w_i}, \quad (5)
\]

where \( \alpha \) is the learning constant.

In the prediction phase, we use the weight values obtained in the identification phase and provide the function inputs to the input layer.

4. Simulation and Experiment

To show the effectiveness of the neural network, we perform simulation on actual vibration data occurred by the impact sound of composite material SiC-C/C. The damped data used in the simulation are shown in Fig. 4. We use the data of period A in the figure. The number of the data is 115 \((t=1\sim115)\), where the period of the adjacent sampled data is 10 ms. The proposed network identifies the damped vibration waveform in the form of the answer-in-weights values after the adjustment. The parameters of the neural network are

Long-term functions: \( M=6 \)

\[
(1, e^{-at}, e^{-2at}, e^{-4at}, e^{-8at}, e^{-16at}),
\]

Periodic functions: \( N=26 \)

\[
(\sin at, \cos at, \sin 2at, \cos 2at, \sin 13 at, \cos 13 at),
\]

Learning constant: \( \varepsilon = 0.001 \),

Learning times: 1000

where \( a = 1/115 \) and \( \omega = 2\pi/T = 2\pi/7 \) [rad]. The values of the constant \( a \) and the period \( T \) were determined from the given data.

In Fig. 5, we show the simulation result in the form of the actual data and the reproduced data generated by the estimated answer-in-weights values. The long-term component and the periodic component of the reproduced data are shown in Fig. 6. And we show the weight values obtained as the identification result in Table 1. The mean value of the absolute errors of the reproduced data was 1.19. Applying the values \( y_1(1)=17.378, y_2(51)=4.5755, \)}
$y_2(101) = 2.1674$ of the long-term component to the equation (11), we can derive the equation $y_2(t)$ of the long-term component in Fig. 6 as

$$y_2(t) = 1.61 + 16.30 \exp(-0.0373\sqrt{t}) \quad (6)$$

Then, in Fig. 6, the reproduced data $y(t)$ can be obtained from $y(t) = y_1(t) y_2(t) / d_M$, where $y_1(t)$ denotes the periodic component and $d_M = 13.425$ is the maximum value of the given data. Furthermore, applying $\omega t = \omega a \tau \quad [\text{rad}]$ and $f(t_a) = y_2(t) \cdot 0.1 \quad [\text{V}]$ to the equation (6), we get the envelope $f(t_a)$ of the damped vibration as

$$f(t_a) = 0.161 + 1.630 \exp(-0.0373\omega a \tau) \quad [\text{V}] \quad (7)$$

where the damping ratio is $\xi = 0.0373$ with frequency $\omega_a \quad [\text{rad/\mu s}]$ and actual time $t_a \quad [\mu s]$.

From these results, we can see that the network classified the long-term and the periodic components involved in the given data. These components are obtained as the outputs of the long-term and periodic estimation parts, respectively.

5. Conclusion

In this report, we proposed to use the neural network for detecting the envelope of damped vibration waveform. To show the effectiveness of the method, we performed the simulation on the vibration data occurred by the impact sound of the composite material. As the result, we confirmed the effectiveness of using the answer-in-weights network for measuring the damping ratio of the impact sound waveform.

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References