Application of Neural Network Entropy Algorithm and Convolution Neural Network for Structural Health Monitoring

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ABSTRACT

This study combines Neural Network Entropy (NNetEn) and Convolutional Neural Network (CNN) to develop a practical structural health monitoring system. In order to verify the feasibility of the system, the failure experiment of a seven-story steel frame has been carried out with a numerical model of the same structural characteristics as the steel frame. The state space method is used to simulate the sixteen failure modes on the steel frame, where the acceleration signals of each floor at the time of failure are analyzed by neural network entropy. An entropy database is established based on the model to train the neural network model. To avoid the misjudgment and automatic interpretation of human factors, this study uses the visualized heatmap to quantify the change of entropy value, and the convolutional neural network analysis is selected for image processing. By converting the entropy value into image data, not only the number of parameters in the model can be reduced, but its operation speed can be improved. During the training process, the neural network model extracts and learns the damage features in the entropy value. After the training is completed, the model can allocate the damage area of the structure by identifying the damage features of the input data. Finally, through the verification of 16 failure cases simulated on the seven-story steel frame of the National Center for Research on Earthquake Engineering (NCREE), the performance of the proposed SHM system is evaluated by both numerical simulation and experimental verification with confusion matrix. The SHM system proposed in this study combines the emerging entropy analysis method with a neural network. The test results of the final verification have an accuracy rate of 93.13%.

INTRODUCTION

Structural health monitoring [1-3] has been practiced for many years with the development of time and technology. Many studies have shown that collecting the vibration of the structure and analyzing it is a more efficient method for structural health monitoring. By analyzing the vibration response of structures, it is possible to detect structural damage that cannot be recognized by the naked eye. If this technique is successfully applied to structural health diagnosis, many shortcomings of non-destructive evaluation(NDE) [4] can be solved.

This study is based on NNetEn [5], and combines this entropy analysis method with CNN [5] to develop a practical structural health monitoring system. The state-space program (SSP) [6] method is used to establish a numerical model, simulate the signals of various failure modes of the target structure, analyze with the neural network entropy, establish an entropy database, and then use the entropy database to train the neural network model. The change of entropy value is then quantified through heatmap, and a CNN model suitable for image processing is established. By converting the entropy vai-

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lue into matrix data, it can not only reduce the amount of parameters in the model, but also improve its operation speed. The neural network model extracts and learns the damage features in the entropy value during the training process. After the training is completed, the model can locate the damage area of the structure after identifying the damage features of the input data. Finally, the experimental steel frame of the seven-story building verifies the various failure cases designed. The output values of the model are discussed case by case and the prediction results of numerical simulation and experimental verification are classified by confusion matrix.

METHODOLOGY

In order to use NNetEn and CNN to build a structural health monitoring system, the following will describe the entropy analysis method used in the research, the state space method used in numerical simulation and artificial intelligence model.

LogNNet Model

LogNNet uses the MNIST-10 digital handwritten digit data set as the research object. There are 70,000 handwritten digital pictures from 0 to 9 in this database, and the pixels are all 28x28. The database is divided into two parts, 60,000 handwritten pictures for training and 10,000 pictures for model testing. The gray-scale intensity of each picture is in the range of 0 to 255. Use T-pattern to convert a 2D image to a 1D array before feeding it into a neural network. The architecture of the LogNNet neural network model is shown in Figure 2. According to (1), the data processing is similar to the feedforward neural network.

$$S_h = f_h(Y \cdot W_1), S_{out} = f_{out}(S_h \cdot W_2) \tag{1}$$

Among them, W_1 and W_2 are weight matrices; S_h has an active element P and a bias element and a hidden layer with $S_h[0] = 1$; S_{out} is the output layer; f_h is the identity excitation function, normalized between -0.5 and 0.5.

$$x_{p+1} = 1 - r \cdot x_p^2 \tag{2}$$

x_p is a number between 0 and 1 and r is a positive parameter. By applying equation (2) to the weight matrix, equation (3) will be obtained

$$W_1[i][p+1] = 1 - r \cdot (W_1[i][p])^2 \tag{3}$$

The initial value of the first row of $W_1[i][1]$ in the above equation is set by equation (4)

$$W_1[i][1] = A \cdot sin\left(\frac{i}{784} \cdot \frac{\pi}{B}\right) \tag{4}$$

The LogNNet neural network architecture algorithm utilizes the concept of unimodal mapping to achieve high accuracy for digit classification in the MNIST-10 handwritten digitized image dataset. Due to the characteristics of this model algorithm, it uses less memory than many known neural network models, allowing LogNNet to be able to make artificial intelligence applications more popular on more performance-constrained devices. The advantages of LogNNet allow it to have an extended application, that is, neural network entropy.

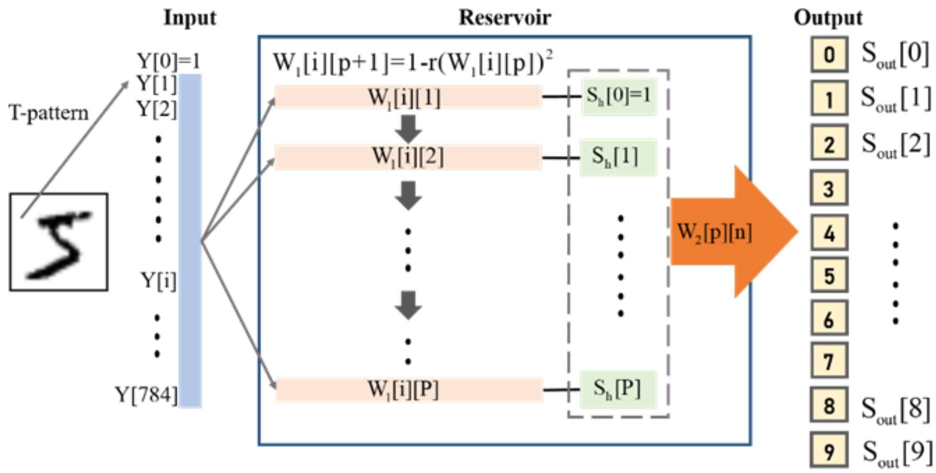


Figure 1. Example of figure.

NNetEn

The model structure of NNetEn is shown in Figure 2, in which the active element P is preset to 25. The purpose of this entropy analysis method is to avoid over-reliance on parameters such as m value and r value in the entropy analysis algorithm. NNetEn successfully avoids the above parameters, only the epoch needs to be adjusted. NNetEn is an entropy analysis method that analyzes signals through the LogNNet neural network model. It first fills the input signal into the weight matrix W_1 in the LogNNet storage layer, and then uses the classification accuracy of MNIST-10 handwritten image recognition as the entropy value. The classification accuracy ranges from 0% to 100%, so the resulting NNetEn will be in the range of 0 to 1, that is, the higher the entropy value, the higher the classification accuracy; the lower the entropy value, the lower the classification accuracy. The classification accuracy is regarded as the entropy value of the neural network entropy, which is represented by NNetEn, as shown in equation 5.

$$\mathrm{NNetEn} = \frac{Classification\ Accuracy}{100\%} \tag{5}$$

W_1 in the neural network entropy does not use the unimodal mapping recursive method used in LogNNet to fill the matrix, but needs to fill the pre-analyzed time series into the weight matrix. Because W_1 has 25 rows and 785 columns, the time series that needs to be filled has a total of 19,625 elements, but the length of the actual time series can be greater or less than 19,625 elements through a special matrix filling method.

Suppose there is a time series $x_n = (x_1, x_2, x_3, \dots, x_N)$ with N elements. If $\mathrm{N} \geq 19{,}625$, ignore the $\mathrm{N} - 19{,}625$ elements of the time series, and use the remaining 19,625 elements to fill the matrix column by column; if $\mathrm{N} < 19{,}625$, fill the matrix column by column and fill in the missing time series elements zero. A schematic diagram of this matrix filling method is shown in figure 3.

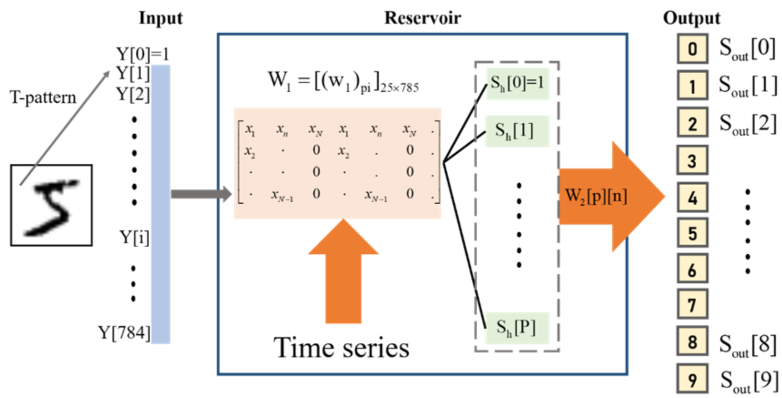


Figure 3. NNetEn architecture

NNetEn is the first method for entropy analysis based on artificial intelligence. By modifying the neural network architecture of LogNNet, the model can predict the MNIST-10 handwritten digit test set, and the accuracy of its prediction is used as the NNetEn value of the time series. This entropy analysis method combined with neural network not only improves the shortcomings of over-reliance on specific parameters in the past entropy analysis, but also greatly reduces the impact of the length and amplitude of the time series on the analysis results. Many advantages show that it is superior to many entropy analysis methods, so that the time series can be analyzed by the change of NNetEn value, and then the analysis target can be judged by the change of entropy value.

$$\begin{bmatrix} x_1 & x_n & x_N & x_1 & x_n & x_N & \cdot \\ x_2 & \cdot & 0 & x_2 & \cdot & 0 & \cdot \\ \cdot & \cdot & 0 & \cdot & \cdot & 0 & \cdot \\ \cdot & x_{N-1} & 0 & \cdot & x_{N-1} & 0 & \cdot \end{bmatrix}$$

Figure 4. Matrix filling method

EXPERIMENTAL VERIFICATION

After verification by numerical simulation, it is known that the neural network model of this study has a very high accuracy in predicting damaged floors through confusion matrix and multiple objective parameters. The trained convolutional neural network makes multiple sets of predictions for each damage mode, and integrates the results with a confusion matrix to explore the performance of the model and the possibility of practical application.

Experimental setup

The experimental structure is a seven-story experimental steel frame erected by the NCREE, as shown in Figure 5. The cross-section of this steel frame column is about 150mm×25mm, and the height is about 1.1 meters, the width is about 1.1 meters, and the length is about 1.5 meters. In order to simulate the real stress situation of the structure, a mass block of about 500 kg is placed on each floor, and the L-shaped steel with a diagonal brace of 65mm × 65mm × 6mm is connected to the opposite corner of the weak axis of each floor. In order to simplify the failure form, the basis for failure is whether the diagonal bracing is installed or not, as shown in Figure 6.

Figure 5. Experimental specimen

(a)healthy type (b) damaged type

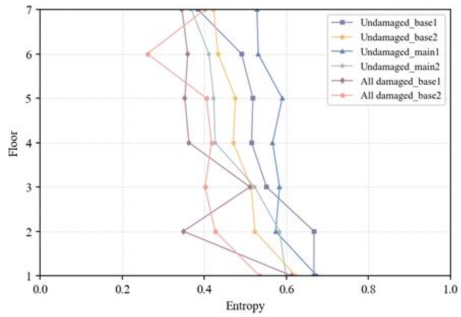
Figure 6. Damage simulation

The sensor used in the experiment to measure the micro-vibration signal is shown in Figure 7. The sensor is the Tokyo Vibration Measurement VSE-15D Speedometer. The sensor was used to perform several measurements on the experimental structure, each for five minutes, with a sampling frequency of 200Hz.

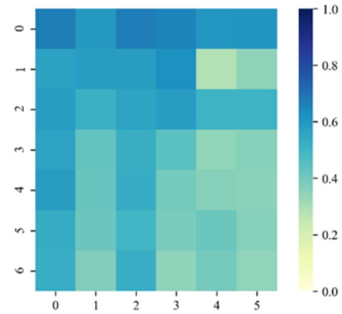
Figure 7. VSE-15D

Damaged detection

The time series measured in the experiment is analyzed as entropy. Figure 8(a) is a line chart of entropy, and Figure 8(b) is a heatmap after converting entropy into matrix form. Let the CNN model predict the entropy matrix data of multiple damage patterns and interpret the health status of each floor.



(a)line chart of entropy



(b) heatmap of entropy

Figure 8. Entropy presentation(experiment)

After the statistics are completed, the above four types of values are used to calculate the values of the four evaluation parameters of Accuracy, Precision, Recall and F1 score. The values and results of the confusion matrix are shown in TABLE I. From the confusion matrix, it can be known that the evaluation parameters obtained by applying the neural network model to the actual measured signals are Accuracy is 93.13%, Precision is 87.74%, Recall is 88.31% and F1 score is 88.02%.

The CNN model can give the corresponding prediction value to the input data after extracting the entropy value of the damaged floor, so as to achieve the effect of predicting the health status of each area of the structure. After comparing with simulated data, it is found that although the values are slightly lower than the analysis results of numerical simulation, the model has certain reference value after analyzing the above evaluation parameters from an objective point of view. Therefore, this study believes that this method of combining entropy analysis and convolutional neural network has the feasibility of its application in structural health diagnosis.

TABLE I. CONFUSION MATRIX (EXPERIMENT)

Case Number	Damage floor	TP	FP	TN	FN
1	None	0	0	45	4
2	1F	4	0	24	0
3	2F	3	1	23	1
4	3F	4	0	24	0
5	4F	2	2	23	1
6	5F	4	0	24	0
7	6F	6	1	41	1
8	7F	5	3	46	2
9	1F & 2F	8	0	18	2
10	3F & 4F	6	2	18	2
11	5F & 6F	8	0	18	2
12	1F & 2F & 3F	12	0	16	0
13	4F & 5F & 6F	10	2	16	0
14	1F & 2F & 3F & 4F	20	0	12	3
15	4F & 5F & 6F & 7F	20	4	18	0
16	All	24	4	0	0
Total		136	19	366	18
Accuracy		93.13%			
Presicion		87.74%			
Recall		88.31%			
F1 score		88.02%			

SUMMARY AND CONCLUSION

By applying the neural network entropy analysis method, it not only successfully solved the problem of over-reliance on parameters during the analysis process and the situation that the entropy value was occasionally undefined can be largely improved. The method uses the probability of handwriting recognition in the model as the entropy value of the time series, where NNetEn will be between 0 and 1. Instead of using the entropy value change as a polyline, the convolutional neural network is used to present the entropy value as a two-dimensional matrix. The entropy value is quantified, and the data type of the entropy analysis database is closer to the image than the vector. Therefore, the amount of parameters in the model can be effectively reduced through the convolutional neural network to achieve the purpose of reducing the amount of calculation and improving the accuracy.

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