Recognition of Nonlinear Hysteretic Behavior by Neural Network using Deep Learning

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Abstract. In Japan, large earthquakes have caused many damages to structures. Cracks in the reinforced concrete and plasticization of the steel bar and steel components resulted in increased damage. In the seismic design, the dynamic response analysis is carried out by using a mathematical model that appropriately evaluates the nonlinearity of the material and the components and the seismic performance is confirmed by performing a dynamic response analysis. However, when applying new materials and components, much time and much effort are required to select a mathematical model. In this study, we focused on the high pattern recognition capability of the neural network. We attempt to directly model using a neural network without replacing the complex nonlinear hysteretic behavior using the mathematical model. By improvement of learning data and introduction of deep learning, it was confirmed that the recognition ability for nonlinear hysteretic behavior of neural network was greatly improved, and its applicability as a numerical operation subroutine for time history response analysis was drastically improved.

1. Introduction

In the seismic performance evaluation of the highway bridges with nonlinear dynamic response analysis, some modeling is required to evaluate how they affect the seismic response when new materials and newly developed components are applied to the bridges. Usually, various static loading tests, dynamic loading tests, and in some cases, shaking table tests are conducted. It is possible to confirm the complex nonlinear load-displacement relationships, the energy absorption performance, and the damping characteristics from the results of these tests. Based on these characteristics, a mathematical model capable of expressing complex load-displacement relations is proposed and incorporated into the analysis program. The mathematical models obtained in this procedure can reasonably express the single nonlinear hysteretic behavior of the materials and members to be evaluated, but it is usually necessary to make a drastic correction when applying to the expression of the nonlinear hysteretic behavior of different materials and components. J. Ghaboussi et al. [1] conducted a pioneering study to apply neural networks to the recognition of the nonlinear stress-strain relationship of concrete. K. Yamamoto [2] also applied the neural network to the nonlinear hysteresis recognition of the Ramberg- Osgood model. J.D. Wei [3] applied the neural network to the construction of hysteresis, too. In this study, we focused on the high pattern recognition capability of the neural network. We attempt to model directly using a neural network without replacing the complex nonlinear hysteretic behavior using the mathematical model.
2. Construction of Neural Networks

2.1 Neuron Model.
Neuron model shown in Figure. 1 can simulate the information processing of brain nervous system industrially. This information processing organization is called a node in following. The characteristic of this node has multiple inputs and single output. One node receives the input signals from n nodes. These input values are x1, x2, … , xn. W shows strength of connection between each node, and is called the weight of connection. b is the bias input to restrain or accelerate the output of node. Input signals x1, x2, … , xn are amplified or reduced by the weight of connection, and are summed up as internal potential x. X is transformed to output value Y through fReLU (x) which is called activation function. ReLU shown in formula (1) was used as activation function in this study. And identity function was used only for output layer.

\[ f_{ReLU}(x) = \max(0, x) \]  

2.2 The Hierarchical Neural Network.
Hierarchical neural network was adopted in this study. Information is transmitted toward the output layer from the input layer in one-way direction on the network. Neural network transmits the signals from the input layer to the output layer by way of the hidden layers. When an error between these output signals and the data for learning occurred, the weights of connection are modified to reduce this error. This modification process is equivalent to learning of neural network. Modification proceeds to minimize the error toward the input layer from the output layer in learning algorithm. The hierarchical neural network used in this study is shown in Figure. 2. In this study, we set 11 nodes in the input layer with reference to the results of the previous study. The hidden layer was made into 6 layers and the number of nodes was set to 100. The output layer consists of 1 nodes and outputs the tangential stiffness at the present time.

2.3 Selection of Information in Input Layer.
The information that can evaluate complex hysteretic behavior like a Ramberg-Osgood model need to be selected adequately for the input layer of hierarchical neural network. It is to be desired that selected information can be taken easily from loading tests as the data for learning of the network. The information in input layer were selected as follows referring the past studies[4-8]. Hysteretic curve including non-linear behavior like a Ramberg-Osgood model depends upon magnitude of displacement and load. Hysteretic curve forms the most outer loop renewing maximum experienced point when loading direction changes. So, maximum displacement, maximum load, minimum displacement and minimum load were selected as an information in input layer. And when maximum displacement isn’t renewed, hysteretic curve goes toward for opposite maximum experienced point. Load and displacement at latest turning point are important as an information in input layer. Displacement and load were considered at maximum
Experienced point and the latest turning point individually. Increases of previous displacement, increases of previous load were added as information to consider the transformation of stiffness. Previous displacement and previous load were added to consider the continuity hysteretic curve. Above ten information and present displacement were defined as inputs for the input layer. The output layer has one node of present tangential stiffness.

\[X_{\text{max}}: \text{maximum experienced displacement}
\]
\[X_{\text{min}}: \text{minimum experienced displacement}
\]
\[P_{\text{min}}: \text{minimum experienced load}
\]
\[X_{o}: \text{the latest displacement at turning point}
\]
\[P_{o}: \text{the latest load at turning point}
\]
\[X_{n-1}: \text{previous displacement}
\]
\[P_{n-1}: \text{previous load}
\]
\[X_{n-1}-X_{n-2}: \text{increase of displacement}
\]
\[P_{n-1} - P_{n-2}: \text{increase of load}
\]
\[X_{n}: \text{present load}
\]
\[K_{n}: \text{present tangent stiffness}
\]

**Figure 2.** Hierarchical neural network

### 2.4 Recognition of Non-linear Hysteretic Behavior.

Forced displacement of increased and decreased sinusoidal wave was given to non-linear spring of Ramberg-Osgood model. The relationship between road and displacement was adopted as a data for learning of the neural network. Forced displacement was formed with continuously and gradually increased and decreased sinusoidal wave which the period is 0.25 second with an amplitude of 20%, 40%, 60%, 80%, 100% of the maximum one. Maximum amplitude was 5cm. Figure 3 shows time history of forced displacement. Using this data, the learning for neural network was conducted. The repetition of learning of neural network was one million times. Figure 4 shows the comparison of hysteretic curves that was estimated by the network after learning and the hysteretic curve of the data for learning in Ramberg-Osgood model. In previous studies, only learning data such as Figure 3 were prepared, but this time, the superimposed sinusoidal wave with small amplitude and high frequency sinusoidal wave was prepared. Figure 5 shows superimposed sinusoidal wave. The data for learning were prepared using this superimposed forced displacement. By using this forced displacement, the load displacement relationship, which is closer to the behavior in the actual earthquake, is reapplied, and the construction of high quality learning data is expected.
3. Dynamic Response Analysis using Neural Network

3.1 Input Earthquake Motion and Analytical Model.

The input earthquake motion used for the analysis is shown in Figure 6. The earthquake ground motion is a record of Kawayo point in the South Aso village, which was observed at the Kumamoto Earthquake in 2016. The main part of the ground motion was adjusted so that the response displacement was not higher than the maximum amplitude of the learning data of 5 cm. Figure 7 shows an analytical model used for dynamic response analysis using a neural network. The neural network, which was trained so that the tangential stiffness at any displacement can be output, was incorporated as a numerical arithmetic subroutine representing the springs of the analytical model of the single degree-of-freedom system.
3.2 Dynamic Response Analysis.

Figure 8 shows a comparison of the time history obtained by using a neural network learned with sinusoidal forced displacement and the time history of the response displacement obtained by using the mathematical model. Comparing the analytical results, the results obtained by using neural networks in the first half of the analysis time showed a relatively good agreement in the amplitude and phase with the results obtained by using the mathematical model. However, in the latter half of the analysis time, there are differences of the amplitude and phase due to the accumulation of the errors. Figure 9 shows a comparison of the time history obtained by using a neural network learned with superimposed forced displacement and the time history of the response displacement obtained by using the mathematical model. From these results, obtained time history by using a neural network learned with superimposed forced displacement was roughly agreed with the time history by using the mathematical model in the phase. On the other hand, it was recognized that the amplitude was slightly larger or smaller in the first half of the analysis time as a result.
4. Conclusion

Function approximation ability of the neural network was evaluated through comparison between estimated response using neural network model and calculated response using mathematical models. From obtained results, the followings became clear.

Hierarchical neural network with deep hidden layer for recognition of non-linear hysteretic behaviors was constructed. Information of selected units in input layer can be taken easily from loading tests.

An improvement proposal was made on how to provide the learning data. In addition to the sinusoidal wave used at the previous study, small amplitude sinusoidal wave with relatively short period was imposed for forced displacement. The load deformation relationship close to the actual dynamic behavior was realized.

The neural network, which has learned based on the improved learning data, reproduced the response equivalent to the response calculated using mathematical model in all duration time of the analysis.

Applicability of neural network as a subroutine to dynamic response analysis will be confirmed by dynamic loading test of new material and device in future.

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