Bridge structural damage identification based on parallel CNN-GRU

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Abstract: Structural damage identification has been the focus of engineering fields, while the existing damage identification methods heavily depend on extracted “hand-crafted” features. Recently, due to the powerful feature learning capability of deep learning, it has been widely used in structural damage identification. However, those methods only consider the local dependence or temporal relation of data. Thus, in this paper, a structural damage identification method by combining the convolutional neural network (CNN) and gated recurrent unit (GRU) is proposed. The CNN model is used to extract the local dependence of data, and the GRU model is used to extract the temporal feature of data. These two extracted feature matrices are spliced horizontally to a fused eigenvector. The eigenvector is input to the final softmax classifier layer to identify the structural damage state. Experiments on a scale model of the three-span continuous rigid frame bridge shown that the CNN-GRU model performs significantly better than CNN, LSTM, and GRU models for structural damage identification.

1. Introduction
With the rapid development of technologies including signal processing and data transmission, structural health monitoring (SHM) systems have been widely used in high-rise buildings, large-span steel structures, bridges, and other important structures. At present, a large number of service structures have been installed with SHM systems to achieve long-term monitoring of the structure. However, the existing SHM systems faced with the problems: 1) the massive data is difficult to deal with; 2) the measured data is not complete enough; and 3) there is no benchmark data and quantitative standard. These problems seriously restrict the practicability of SHM systems [1].

Structural damage identification is an important part of SHM systems. For structural damage identification, a key step is to extract data features quickly and effectively. The traditional characteristic parameters acquired from structural vibration including frequency [2] and mode shapes [3] are not sensitive to structural damage. Furthermore, some information will be lost in the process of Fourier transform. The modal parameters based on the dynamic characteristics of the structure, such as curvature mode [4], modal assurance criterion [5], have good results in the experimental stage. But in the practical application, it is difficult to measure the complete model of the structure limited by the number of sensors. Besides, wavelet transform [6], wavelet packet transform [7], and so on, are used to capture
mutation from wavelet signal. Shallow neural networks are then integrated to achieve structural damage identification. However, some features extracted by shallow neural networks are sensitive to damage, these features are single-layer feature without hierarchical structures. Moreover, the training parameters will increase geometrically along with the increase of monitoring data. Therefore, the actual application scenarios of these technologies are limited.

In recent years, the deep learning algorithms including convolutional neural network (CNN) have gradually become the research focus in SHM. These algorithms can learn characteristics from data independently, and discover hidden law between numerous data [8]. Lin et al. [9] realized the identification of different damage degrees and locations of a simply supported beam by CNN thus proving the CNN has a strong feature extraction ability and damage identification competence. Yu et al. [10] used deep convolution neural network (D-CNN) to identify the damage to the building structure. Taking acceleration response data under various damage conditions as input on which a five-story framed structure to carry out the experiments, proving D-CNN has higher identification accuracy and robustness. Zhao et al. [11] proposed a feature extraction of collected time series data by gate recurrent unit (GRU) to identify different machine conditions. However, in the above research of damage identification methods based on deep neural networks, the damage sensitive features have not been extracted from temporal sequence and the local dependence characteristics of the data, as a result, the joint model for monitoring data still needs to be constructed.

Based on the previous studies, this paper chooses CNN and GRU model to construct a joint neural network. In our model, damage sensitive features are simultaneously extracted from temporal sequence and local dependence of monitoring data. The CNN model automatically extracts the local association information among multiple sensors. The GRU model discovers the complex long-term trend of multivariate temporal sequence, afterward maps the two feature matrices which subjected to matrix stitching into rows. Then, the feature matrix which belongs to output layer of the softmax classifier is applied to structural damage state identification. Through the moving load test on the scale model of a continuous rigid frame bridge, it takes the vibration acceleration data under various damage conditions as input to verify the model can effectively identify the damage under the condition of weak excitation and shows a high identification accuracy.

2. Structure of the model

2.1. Convolution Neural Network

CNN is a deep feed-forward neural network structure proposed by Lecun, it consists of input layer, convolution layer, pooling layer, full connection layer, and output layer. The convolution layer is used to extract the features of input monitoring data, while the pooling layer is used to screen the features thus further reduce data dimension. After the alternate operation of the convolution layer and the pooling layer, abstract representation is formed in the full connection layer, and the final classification result is output by the top-layer classifier of the network. Compared with the traditional machine learning methods, CNN reduces the complexity of the model as its weight sharing and local connection characteristics, hence solving the problem that the network cannot learn when the data is too large.

2.2. Gated Recurrent Unit

GRU is an improved long-term and short-term neural networks (LSTM) model, its network structure shown in figure 1. Compared with the LSTM model, the GRU network structure is simpler and has better training speed and calculation efficiency. In the GRU model, there is a memory state unit and two gate control mechanisms: reset gate \( r \) and update gate \( z \) [12]. The reset gate is responsible for discarding useless information of the last neuron and controlling the degree of neglecting the previous state information. The update gate determines the degree of previous time enters current time status. By selectively deleting or adding information, to a certain extent, it will solve the “gradient explosion” of Recurrent Neural Network (RNN), thereby, it will achieve effective feature extraction of time series data.
2.3. Structural Damage Identification Model Based on Parallel CNN-GRU

When moving load passes through damage position, structural response signal detected by the sensor will suddenly change at this moment. The neural network can identify damage by capturing signal singularity. In the field of SHM, the temporal sequence data under moving load excitation has a long-term complex regularity. CNN convolutes input data into an abstract representation with features while preserving the topology of original data. GRU is good at discovering the long-term complexity of temporal sequence data, it’s suitable for processing it. Therefore, in this paper, the CNN-GRU parallel model is introduced into the field of SHM to overcome the shortcomings of CNN’s attention to temporal characteristics of monitoring data, as well as GRU’s attention to local characteristics of data, it will improve the effect of damage identification and classification. In this paper, the structure of CNN-GRU parallel model is shown in figure 2, composed of four parts. The first part is input layer, the second is CNN and GRU parallel layer, the third is feature fusion layer and the fourth is output layer.

Figure 1. GRU network structure.

Figure 2. Architecture of the CNN-GRU parallel model.
In the input layer, acceleration data of structural vibration response is inputted into neural network which in the form of a sliding window. Numerous acceleration sensors constitute an N-dimensional vector. In the moving window, the length is $M$, and the sliding step is $S$. The collected temporal sequence data is split into $M \times N$ size characteristic graphs, as shown in figure 3.

![Figure 3. Schematic diagram of moving window.](image)

The second part composed of CNN and GRU networks. The paper regards acceleration data collected by multiple sensors as one-dimensional data with multi-channel, so this paper uses one-dimensional CNN to extract the acceleration signal characteristics. The size of the input convolution layer is $M \times N$, the first convolution layer has $L$ convolution kernels, and the size of convolution kernels is $K \times N$. The calculation process of convolution is shown in equation (1).

$$X_i = f \left( x_{i+k} \otimes \omega + b \right)$$

In the equation (1), $X_i$ is the vector which consisted of layer $i$ and layer $i+k-1$, the convolution kernel is represented by $\omega$, $b$ is the offset, and $\otimes$ is used for convolution operation. $f$ is the non-linear activation function by using the ReLU function. After the convolution layer, the characteristic matrix $X = [c_1, c_2, \ldots, c_{M \times N}]$ is obtained. Then input it into the pooling layer to get the maximum value of local eigenvector $C$. In this work, the size of the pooling layer is 2, max-pooling is used to maximize the eigenvector, and the $J$ vector after the pooling layer is received, as shown in equation (2):

$$J = \max (c_1, c_2, \ldots, c_{M \times N}) = \max \{ X \}$$

After multi-layer convolution and pooling alternation operations, the multi-dimensional input transforms into one-dimensional by adding the Flatten layer, the feature vector $R = [J_1, J_2, \ldots, J_L]$ extracted by convolution is obtained. The lower branch GRU network is used to extract the temporal sequence data of monitoring data, its time step is $M$. The specific update method is as follows:

$$z_t = \text{sigmoid}(w_z \cdot [h_{t-1}, x_t])$$
$$r_t = \text{sigmoid}(w_r \cdot [h_{t-1}, x_t])$$
$$h_t = \tan h(w_h \cdot [r_t \cdot h_{t-1}, x_t])$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t$$
Which $z_i$ represents update gate, $r_i$ represents reset gate, $x_i$ represents the status for the current time, $h_{t-1}$ represents output state of hidden layer at $t−1$ time, $h_t$ represents candidate hidden state and $h_t$ represents hidden state at current time; $w_x$, $w_r$ and $w$ refer to weight matrix of update gate, reset gate and candidate hidden state respectively, $*$ represents product of each corresponding element. The output vector $H=[h_t,h_2,...,h_n]$ is obtained from temporal characteristic extracted by the GRU layer, where $n$ is the number of hidden layers in the GRU layer.

The third part is the feature fusion layer. CNN layer captures the local association features of data, GRU layer extracts fore-and-aft dependency of data, integrate feature vectors through the Merge layer, as shown in equation (4):

$$V = V_{CNN} \oplus V_{GRU}$$

Which $\oplus$ represents the concatenate operation in the Merge layer. After this procedure feature vector $S=[R,H]$ is obtained, so as to input the full connection layer. Finally, hidden feature space is mapped to the sample label space through full connection layer. In the full connection layer, structural damage model is classified by softmax logistic regression. The function of softmax is shown in equation (5):

$$z_i = \sum_j l_j W_{pj}, \quad \text{softmax } z(\cdot) = \frac{e^z}{\sum_{j=1}^{n} e^{z_j}}$$

Which $z_i$ represents the output of softmax, $l_j$ is the activation function, $W_{pj}$ is the weight matrix. In the final step, the model is trained, while it is often limited by an under mount of sample data, so it is prone to over fitting. Therefore, this paper adds a Dropout mechanism to network model for preventing occurrence, through a certain probability, the weight of input eigenvector is randomly removed from the part, Dropout ignores a specific proportion of $R$ hidden layer nodes in each training batch, it could be expressed as $R_p = \text{Dropout}(R)$, where $R$ is the proportion number of ignored hidden layer nodes.

3. TCRF Bridge Experiment

To effectively evaluate the CNN-GRU parallel model, a scaled model of the Three-span Continuous Rigid Frame (TCRF) Bridge is taken as an experimental object. Based on the common idea of SHM, the damage identification based on vibration is transformed into multivariate temporal sequence classification. The acceleration response data under moving load is taken as input to judge current state. The CNN, LSTM, and GRU models are commonly utilized in deep learning as comparative tests to verify the performance of the parallel model.

3.1. Experimental Dataset

The physical and a scale model of the three-span continuous rigid frame bridge are shown in figure 4. The spans of the real bridge are 98m+180m+98m, with a total length of 377.3m. The bridge adopts a single-cell box girder structure, top plate width of box girder is 12.5m and its bottom plate width is 6.5m. The main beam material is C50 concrete. While in the laboratory, as it subjects to limitations of size and other conditions, thereby main beam, bridge pier, and abutment are constructed at a scaling ratio of 20:1. Selected elastic modulus and acceleration of the scale model are consistent with original bridge, geometric similarity coefficient is $1/20$, additionally, and other physical similarity coefficients are obtained by dimensional analysis. The spans of the scale model bridge are 4.9m+9m+4.9m, with a total length of 18.8m. APL-70 grouting material is used in the scale model, then infiltrate 20% river sand into it according to mass ratio thus ensure the material strength is close to original C50 concrete.

By applying concentrated force in the mid-span, cracks are produced in the bottom plate to simulate the stiffness degradation of the bridge structure. To monitor the changes of the structural state degradation, 18 piezoelectric acceleration sensors are arranged on the scale model, including 12 at the beam bottom and 6 on the web. The selected acceleration sensor has a maximum measurable acceleration of $\pm$ 5g and sensitivity up to 1000 mv/g to collect instantaneous acceleration signals. The
arrangement of acceleration sensors is shown in figure 5. The acceleration vibration signals of core points within bridge structure are monitored by manually pulling the trolley to simulate moving load of the vehicle.

Figure 4. The real bridge and a scale model of rigid frame bridge.

The model car passes through the model bridge at a uniform speed

Figure 5. Location of sensors point.

In this experiment, each working state is mainly defined according to the mid-span damage degree. Firstly a finite element model established in Midas has calculated the theoretical value of loading concentration force is 2.5KN. Considering the finite element model is not equipped with rebar so the theoretical calculation value would be lower than expected. Actually when the load is 2.8KN, bottom plate presents a transverse crack. By using concrete crack width observation, working states of different damage degrees are obtained from the scale model. Each working condition passes the model trolley with 0.30kg masses. More specifically working condition settings are shown in table 1.

Table 1. Structural damage state description.

| Working States | Damage Degree Description |
|----------------|---------------------------|
| DC 1           | No structural damage in mid-span |
| DC 2           | A transverse crack 1\# appears on bottom plate after applying a force of 2.889 KN, which length is 14.3 cm and width is 0.10 mm. |
| DC 3           | Two transverse cracks appeared in bottom plate, of which 1\# crack width develops to 0.12mm and 2\# crack width grows to (0.03-0.04)mm by the force of 6.097 KN. |
| DC 4           | The width of two transverse cracks on bottom plate have increased, of which width of 1\# crack is (0.12-0.13)mm, and width of 2\# crack develops into (0.06-0.07)mm after exerting a force of 8.519 KN. |

3.2. Data Pre-processing
In the experiment, LMS software is mainly applied to acquire acceleration signals of each measuring point, the acquisition frequency is 8192 HZ. To enhance training speed of the neural network, it is necessary to normalize data. In this paper, it employs z-score normalization, the equation is $x' = (x - \mu) / \delta$, where $\mu$ is the data average value, and $\delta$ is the data standard deviation. After the pre-processing, it is hard to directly input the oversized data into the neural network, the data needs to be
divided by moving window method. Considering the sample balance, this paper selects $M$ to be 20, sliding window step size is 20, so that the move data window can just traverse entire data without missing. The dimension of each sample feature map is 20×18 (18 is the number of sensors).

4. Analysis of Results
Speaking of the experimental environment, it employs a laptop with 16G memory, GeForce GTX1060 GPU, and Intel i7-8750H CPU as a test platform. In the python3.6.8 development environment and Tensorflow1.14.0 version of keras2.24 deep learning framework for testing. The data is divided into training, test, and validation set (60%; 20%; 20%).

4.1. Parameter Setting of Neural Network
Genetic algorithm is used to optimize parameters, the accuracy of each model test set is taken as the target function. The classification results are calculated by the softmax classifier. According to the results of multi experiments, model parameters are shown in figure 6.

Figure 6. Model parameter setting.

Figure 7. Confusion matrix of each model.
4.2. Comparative Experiment Settings
In the experiment, CNN, LSTM, and GRU models are selected for comparative analysis. The input size of each model is 20×18. All the deep learning models are trained with Adam optimizer with which learning rate is 0.001 and batch size is 128. The number of epochs is 100. CNN model includes a 2-layer CNN where the number of kernels is 32 and 64 respectively. The size of convolution kernels is 5. LSTM and GRU models include 2 hidden layers, with 64 hidden state.

4.3. Results of TCRF Bridge Dataset
To intuitively present the identification ability of damage state, the confusion matrix of CNN, LSTM, GRU, and CNN-GRU are drawn in terms of the final results as shown in figure 7 below. The results show classification effect on DC 1 and DC 2 are better than DC 3 and DC 4. The reason is data characteristics of DC 1 and DC 2 are quite different, which belong to the judgment of damage from scratch, change of characteristics are relatively obvious, so the damage identification effect is distinguished. However, DC 3 and DC 4 are defined by gradual deepening of damage degree. Their data characteristics are relatively similar and changes are correspondingly infirm, so the accuracy of state identification is lower. At the same time, it can be seen the CNN-GRU model proposed in this paper strengthens the effect of damage identification obviously in DC 3 and DC 4, final accuracy as shown in table 2. It has some advantages in accuracy, precision, recall, and F1-score. Compared with LSTM and GRU network, model referred in this paper has obvious improvement.

Table 2. Results of each model on the test set.

| Model     | Accuracy | Precision | Recall  | F1-score |
|-----------|----------|-----------|---------|----------|
| CNN       | 0.9344   | 0.9343    | 0.9344  | 0.9340   |
| LSTM      | 0.9103   | 0.9127    | 0.9103  | 0.9066   |
| GRU       | 0.9141   | 0.9172    | 0.9141  | 0.9102   |
| CNN-GRU   | 0.9415   | 0.9411    | 0.9415  | 0.9410   |

5. Conclusion
To settle the problem of current damage identification cannot extract structural features with quick-speed and effectiveness, this paper proposes a parallel CNN-GRU structure damage identification method, it obtains data features simultaneously from two aspects: local data dependence characteristics and monitoring data temporal feature. In the experiment of the TCRF bridge dataset, the proposed model finally gets 94.15% identification accuracy. Considering the experiment is relatively simple, so much more complex structural damage condition will be further set up to verify the method.

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