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Research Paper

Damage detection in structural health monitoring using combination of deep neural networks

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ABSTRACT

Structural Health Monitoring is a process of continuous evaluation of infrastructure status. In order to be able to detect the damage status, data collected from sensors have to be processed to identify the difference between the damaged and the undamaged states. In recent years, convolution neural network has been applied to detect the structural damage and with positive results. This paper proposes a new method of damage detection using combination of deep neural networks. The method uses a convolution neural network to extract deep features in time series and Long Short Term Memory network to find a statistically significant correlation of each lagged features in time series data. These two types of features are combined to increase discrimination ability compared to deep features only. Finally, the fully connected layer will be used to classify the time series into normal and damaged states. The accuracy of damaged detection was tested on a benchmark dataset from Los Alamos National Laboratory and the result shows that hybrid features provided a highly accurate damage identification.

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1 Introduction

Damage detection in structures plays an important role in the field of Structural Health Monitoring (SHM). In fact, there are a lot of factors affecting the quality of structures such as overload and environment, making them not stable and arising de-formation and damage. To monitor the levels of damage, multiple sensors are attached to the locations of the structure to measure the vibration response. However, good damage sensitive features are difficult to be extracted [1]. Traditionally, mode shapes and natural frequency are two of the most commonly used features in damage detection

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problem. Mode shape is sensitive to damage location because it contains the local information of the structure, but it is less sensitive to the effect of temperature [2]. Besides, natural frequency is not very effective in dealing with multiple damages, especially when the change in the structure is small [1, 3]. Moreover, the unwanted noise collected from accelerometers during measurement can affect the accuracy and reliability of the analyzed results [4].

With the increase in the amount of data collected and the development of high performance hardware, researchers have proposed different approaches for Machine Learning-based SHM [5-7]. In these methods, input data from initial and damaged scenarios are fed to the machine for training. In the next step, unknown scenarios features can be predicted and categorized to be healthy or damaged. Damage can then be identified with high accuracy using Support Vector Machine (SVM) combined with radial basis and wavelet kernel function [8]. The acceleration time series data are fitted with the Autoregressive model and these model coefficients can be used as damaged sensitive features [9]. In [10], vibration frequency data from large wireless sensors is trained by an artificial neural network to detect the damage. Several optimization algorithms have been proposed to detect and localization the damage in the structure. In [11], an optimization algorithm is used to estimate the location of a crack by minimizing the differences between measured and estimated frequencies. Genetic algorithm as well as Cuckoo search algorithm have been employed to detect the damage in the beam like and truss structures fast and efficient [12-14]. Recently, several algorithms have been combined with ANN to reduce the collected data for training and computation time for damage quantification in composite structures [15, 16]. Although machine learning obtained accurate results in damage detection, they still need to evaluate the valuable features and being sensitive to noise.

To overcome this limitation, convolution neural network, which automatically extracts sensitive features, has been proposed for structural health monitoring [17, 18]. In damaged detection, the vibration data is converted into images to take the advantage of Convolution Neural Network (CNN) in image processing. CNN can automatically extract and select optimal features for damaged classification [17]. In [19], the 1D convolution neural network was applied to the raw acceleration data to detect the damage status in the structure. However, 1D CNN can only learn the internal features of time series and ignore the correlation of time series observations. To capture the relationship of each lagged features in time series data more effectively, autocorrelation has been used with CNN to increase the discrimination between damaged and undamaged states [20].

In this paper, we propose a novel method that combined CNN with Long Short Term Memory (LSTM) network for damage detection. This combination takes advantage of extracting deep features in CNN and learning long-term dependency features from LSTM. This paper is organized as follows: in section 2, we present the method to detect the damage. Then in the next section, the data in test-bed structure will be used to illustrate the performance of the method [21]. Finally, we make a conclusion in section 4.

2 Methodology

2.1 Time series classification using Convolution Neural Network

The Convolution Neural Network (CNN) is a deep learning model that first was proposed by Le Cun [22] and is used mainly for image processing or classification. A CNN comprises of convolution and pooling layers, then these layers are connected to one or more fully-connected layers. From convolution and pooling layers, feature maps are extracted, which are two dimensional matrices of CNN neurons.

A key advantage of CNN is that they are able to learn relevant features from data and weight sharing. It can help to reduce computation complexity and to save memory compared to traditional neural network. As CNN's input data has traditionally been two-dimensional, a modified model of CNN, called 1D CNN, can be developed to accept input data as one-dimensional time series, while keeping the existing advantages of CNN in image processing. Recent studies show that 1D CNN has certain advantages using time series as input in certain applications. Using 1D CNN, the forward propagation & backward propagation computation only implements array operations instead of matrix operations, which helps reduce computation complexity. Also, 1D CNN with shallow architecture can learn the task in time series problems. These architectures are much easier in training and implementing for damage detection [20]. The architecture of the 1D CNN for damaged detection is shown in Figure. 1.

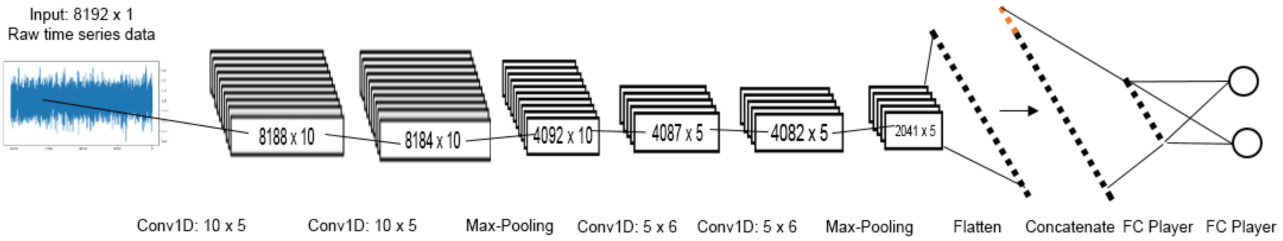

Fig. 1 – Framework of the designed convolution neural network

The architecture in this paper includes two main parts: the convolution layers that concurrently implement both 1D convolution and pooling operations to extract features. Followed by fully connected layers operating as multi-layer perceptron that implements classification tasks.

In each layer, the forward propagation is calculated as below

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} conv\left(\mathrm{w}_{ik}^{l-1}, \mathrm{s}_i^{l-1}\right) \tag{1}$$

where x_k^l is the input, b_k^l is the bias of the k^{th} neural at layer l, s_i^{l-1} is the output of i^{th} neural at layer $l-1$, w_{ik}^{l-1} is the kernel from i^{th} neural at layer $l-1$ to k^{th} neural at layer l. The operation $conv$ performs the convolution by multiply the overlapping values of the kernel and time series at each position of the kernel, and add up the results. The activation function $f(.)$ can be used with the input x_k^l to produce the intermediate output $y_k^l = f(x_k^l)$.

To train the 1D CNN, the back propagation algorithm will be used to compute the gradient of the loss function $E(y)$ with respect to the weights of the network. The derivative of the error with respect to each weight is calculated by:

$$\frac{\partial E}{\partial \mathrm{w}_{i,k}^l} = \Delta \mathrm{w}_{i,k}^l \tag{2}$$

By using the chain rule, we can compute the gradient one layer at a time, iterating backwards from the last layer,and update the weight as below:

$$\mathrm{w}_{i,k}^{l*} = \mathrm{w}_{i,k}^l + \eta \mathrm{w}_{i,k}^l \tag{3}$$

where $\mathrm{w}_{i,k}^{l*}$ is weights of the next iteration and η is the learning rate. The detail of the algorithm are described in [19].

2.2 Long Short Term Memory Network

Long Short Term Memory network is an extension of recurrent neural network with more node inside including two input and output to keep track of the long and short term memory. The architecture of LSTM is shown in Figure 2 [23].

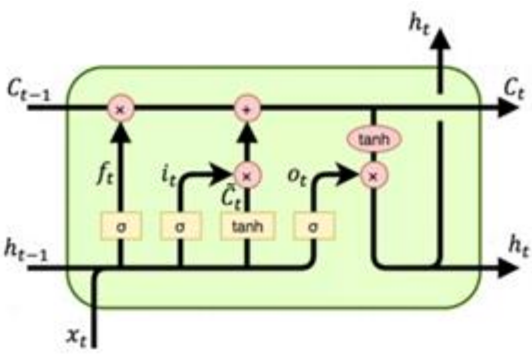

Fig. 2 - A t**th* **state of LSTM model

Here x_t is tth state input of the model, c_{t-1}, h_{t-1} is output of previous layer, c_t, h_t is output of current layer.

$$c_t = f_t \times c_{t-1} + i_t \times \tilde{c}_t \quad (4)$$

Where $f_t = \sigma\left(U_f \times x_t + W_f \times h_{t-1} + b_f\right)$ is the forgotten gate and $i_t = \sigma\left(U_i \times x_t + W_i \times h_{t-1} + b_i\right)$ is an input gate, which decides what information from previous cell state and update the new cell state. $\tilde{c}_t$ here is new candidate values that could be added to the state. $h_t = o_t \times \tanh(c_t)$ is output gate which is filtered cell state, the tanh and sigmoid function lead the desired output.

2.3 Proposed method

The proposed method includes two main steps, as shown in Figure 3. The method takes the raw time series signals as an input to the framework. As explained above, in the case of the vibration time series data, CNN cannot capture the temporal relations from beginning to the end of the time series. In this method, the features are extracted by CNN and followed by LSTM for classification. The framework of the method is shown in Figure 3.

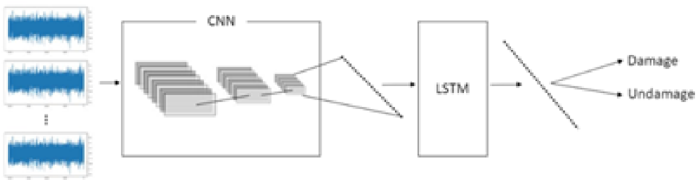

Fig. 3 - Combination of CNN and LSTM architecture

In our method, the time series were fed to the convolution neural network to automatically extract the features. We constructed the CNN by adjusting all the two-dimensional layers to one-dimensional layers for training and testing. The network settings are shown in Table 1. Here, the kernel moves in one direction from the beginning of a time series towards the end to perform convolution. The elements of the kernel get multiplied by the corresponding elements of the time series that they cover at a given point. Then the results of the multiplication are added together and a nonlinear activation function is applied to the value. These features are go through the LSTM as sequences and will be classified as damaged and undamaged state.

3 Experimental Results

3.1 Data set

Data used in this paper is from Los Alamos National Laboratory (LANL) [21], which is a three-story building structure and is used as a damaged detection test-bed structure. The structure includes several aluminum columns and plates connected using bolted joints to form 3 floors, and slides on rails that allow movement in the horizontal direction forming a four degree of freedom system, as shown in Figure 4 (left). The damage was simulated using the center column on the top floor connected to the bumper, which is adjusted to variation. The position of the bumper can be adjusted to vary the extent of impacting that occurs at each excitation level. This source of damage is intended to simulate the fatigue crack that can open and close under the loading condition or loose connection that can rattle under dynamic loading. There are 5 sensors installed at each floor to capture the dynamic response during the excitation. The state conditions can be divided into two states, undamaged states (state 1 to 9) and damaged states (state 10 to 17). For each state, 10 times testing were performed in order to measure the variability in the data. The damage is simulated by change mass and stiffness of the columns. The detail of the structure and data collected is described in [21]

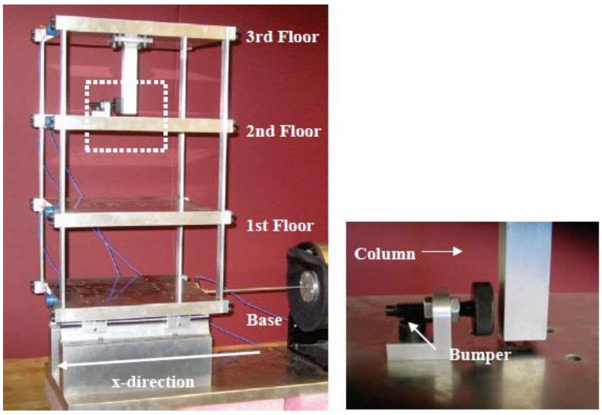

Fig. 4–The base excited three-story test bed structure [15]

3.2 Results

Data are divided into training and testing set randomly, which is 70% for training and 30% for testing. During training phase, the features and labels are provided for all the time series in the training set. Afterwards, the model has built to capture the relationship between features and class labels. Here, in our method, the features are extracted from deep neural network automatically and LSTM is used as classification. Here the CNN configuration includes three layers, which receive time series with 8192 time points, the number of nodes are 512, 256 and 128 for layer one, two, three, respectively. Figure 5 shows the training and testing performance of the combined network.

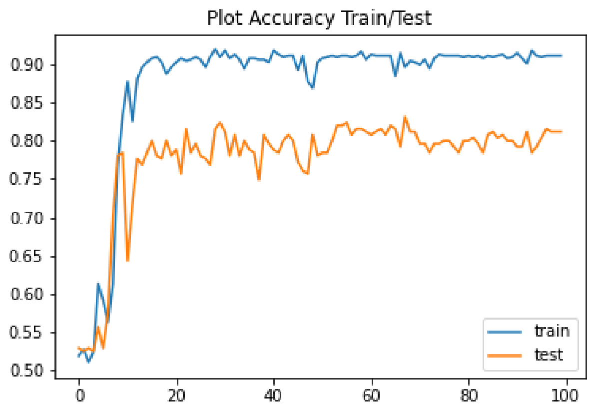

Fig. 5 - Training and testing accuracy

As described in Figure5, the model in training phase with 20 epochs was optimal. Here the graph is not smooth due to the data is not large enough.

Prediction accuracy is evaluated on the testing set. We evaluate the accuracy of the methods using the ground truth notion of positive and negative detection. The confusion matrix for three methods CNN, CNN with handcrafted features and CNN with LSTM is shown in Table 1. The accuracy of the method will be calculated as the percentage of correctly classified samples compared with the total number of samples.

$$Accuracy = \frac{(TP2 + TN)}{(\mathrm{TP+TN+FP+FN})} \tag{5}$$

where TP is true positive, TN is a true negative, FP is a false positive, FN is false negative. We also evaluate the results using F-measure[24], which takes both false positive and false negative into account and useful when the data are unbalanced.

$$F - measure = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \tag{6}$$

where Recall = TP/(TP + FN) and Precision = TP/(TP + FP)

Table 1. Confusion matrix for CNN-LSTM (upper- left), CNN feature (upper-right), and CNN with a handcrafted method (bottom)

CNN with handcrafted	Predicted		CNN	Predicted		CNN with LSTM	Predicted	
Actual	109 (TP)	20 (FP)	Actual	122 (TP)	7 (FP)	Actual	124 (TP)	5 (FP)
	16 (FN)	110 (TN)		44 (FN)	82 (TN)		27 (FN)	99 (TN)

The 30% of testing data including 129 samples of undamaged and 126 samples of damaged state. Based on the matrix of CNN with a handcrafted feature (top left), we can see that 109 data sample of undamaged and 110 data sample damaged were correctly detected, as well as 16 data sample of undamaged and 20 data of damaged were misclassified. It means 16 data sample of undamaged state were classified as damaged and 20 data sample of damaged state were classified as undamaged state. It leads tothe accuracy of the method is 85% and f-measure is 86%, as calculated by equation (5) and (6). Similarity, the accuracy and f-measure of CNN method (top right) is 80% (122 data samples of undamaged were correctly classified and 7 data samples were incorrectly classified)and 79% (82 data samples of damaged were correctly classified and 44 data samples were incorrectly classified), respectively [20]. In the CNN with a handcrafted feature, the undamaged state is low accuracy than CNN method, while the damaged state is more accuracy than CNN method. In the method of combination of CNN and LSTM, 124 data sample of undamaged and 99 data sample of damaged were correctly classified, lead to accuracy is 96.12%, outperform than CNN and CNN with handcrafted feature methods, while the classification result of a data sample of damaged state is less accuracy than CNN with handcraft feature, which is 78.57% (99 data samples of damaged were correctly detected and 27 data samples were incorrectly detected). Figure 6 shows the accuracy comparison of among three methods, which is the CNN with LSTM has got highest accuracy compare two other methods in the classification of undamaged case (left). But in the damaged case (right), the accuracy of CNN with handcrafted is better than other methods.This suggests the CNN method cannot learn the temporal relation from previous to present of the time series.Here the accuracy of CNN with LSTM less than CNN with handcrafted feature in data sample of damaged due to the features are not balance in a damaged state, which the source of damage is located near sensors 4 and 5, while data in sensors 1 to 3 is similar to undamaged state. The results also show thatCNN with LSTM method can ignore some information from previous to present of the time series.

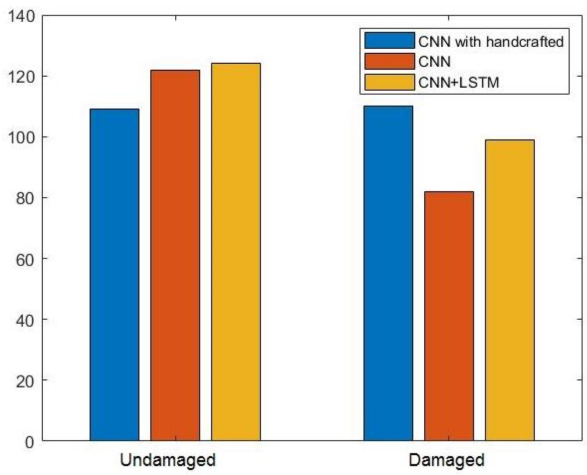

Fig. 6 – Accuracy comparison among three methods

4 Conclusion

In this paper, we proposed the new damaged detection method using a convolution neural network with Long Short Term Memory network. The LSTM received the deep features extracted from CNN to learn the temporal relation and implement the classification. Our results indicated that our proposed method out performs CNN method in damaged detection by employing the relationship of each lagged features in time series data. The combination of CNN and other feature selection methods overcomes the disadvantage of missing the temporal features extraction of CNN. For future work, we will investigate how to apply multi CNN-LSTM to damage detection using imaged vibration data, which employ the ability to learn the spatial-temporal features.

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REFERENCES

[1]- Y. Lin, Z. Nie, Structural Damage Detection with Automatic Feature-Extraction through Deep Learning. Comput. Aided. Civil Infrastruct. Eng. 32(12) (2017) 1025-1046. doi:10.1111/mice.12313

[2]- C.R. Farrar, G.H. James Iii, System identification from ambient vibration measurements on a bridge. J. Sound. Vib. 205(1) (1997) 1–18.doi:10.1006/jsvi.1997.0977

[3]- O.S. Salawu, Detection of structural damage through changes in frequency: a review. Eng. Struct. 19(9) (1997) 718–23. doi:10.1016/S0141-0296(96)00149-6

[4]- A.P. Adewuyi, Z. Wu, N.H.M.K. Serker, Assessment of vibration-based damage identification methods using displacement and distributed strain measurements. Struct. Health. Monit. 8(6) (2009) 443–61. doi:10.1177/1475921709340964

[5]- F.R. Piazzaroli Finottia, C.A. Abrahão, B.F. Souza, An SHM approach using machine learning and statistical indicators extracted from raw dynamic measurements. Lat. Am. J. Solids. Struct. 16(2) (2019). doi:10.1590/1679-78254942

[6]- G. Gui, H. Pan, Z. Lin, Y. Li, Z. Yuan, Data-driven support vector machine with optimization techniques for structural health monitoring and damage detection. KSCE J. Civil. Eng. 21(2) (2016) 523–534. doi:10.1007/s12205-017-1518-5

[7]- M. Noori, Y. Cao, Z. Hou, S. Sharma, Application of support vector machine for reliability assessment and structural health monitoring. Inter. J. Eng. Under. Uncertainty: Hazards. Assess. Mitigation. 2(3-4) (2010) 89-98.

[8]- R. Ghiasi, P. Torkzadeh, M. Noori, A machine-learning approach for structural damage detection using least square support vector machine based on a new combinational kernel function. Struct. Health. Monit. 15(3) (2016) 302-316. doi:10.1177/1475921716639587

[9]- S.D. Silva, J.A.S. Paixão, Extrapolation of Autoregressive Models for Structural Health Monitoring. In: Proceedings of the 7th International Symposium on Solid Mechanics, São Carlos, 2019.

[10]- X. Xie, J. Guo, H. Zhang, T. Jiang, R. Bie, Y. Sun, Neural-network based structural health monitoring with wireless sensor networks. In: Proceedings of the 9th International Conference on Natural Computation (ICNC), Shenyang, 2013, pp. 163-167.

[11]- S. Khatir, K. Dekemele, M. Loccufier, T. Khatir, M. Abdel Wahab, Crack identification method in beam-like structures using changes in experimentally measured frequencies and Particle Swarm Optimization. Comptes. Rendus. Mécanique, 346(2) (2018) 110-120.doi:org/10.1016/j.crme.2017.11.008

[12]- R. Zenzen, I. Belaidi, S. Khatir, M. Abdel Wahab, A damage identification technique for beam-like and truss structures based on FRF and Bat Algorithm. Comptes Rendus Mécanique. 346(12) (2018) 1253-1266 doi:10.1016/j.crme.2018.09.003

[13]- S. Khatir, M. Abdel Wahab, Fast simulations for solving fracture mechanics inverse problems using POD-RBF XIGA and Jaya algorithm. Eng. Fract. Mech. 205 (2019) 285-300. doi:10.1016/j.engfracmech.2018.09.032

[14]- H. Tran-Ngoc, S. Khatir, T. Le-Xuan, G. De Roeck, T. Bui-Tien, M. Abdel Wahab, A novel machine-learning

based on the global search techniques using vectorized data for damage detection in structures. Int. J. Eng. Sci. 157 (2020) 103376. doi:10.1016/j.ijengsci.2020.103376

[15]- R. Zenzen, S. Khatir, I. Belaidi, C.L. Thanh, M. Abdel Wahab, A modified transmissibility indicator and Artificial Neural Network for damage identification and quantification in laminated composite structures. Compos. Struct. 248 (2020) 112497. doi:10.1016/j.compstruct.2020.112497

[16]- S. Khatir, S. Tiachacht, C.L. Thanh, T.Q. Bui, M. Abdel Wahab, Damage assessment in composite laminates using ANN-PSO-IGA and Cornwell indicator. Compos. Struct. 230 (2019) 111509. doi:10.1016/j.compstruct.2019.111509

[17]- I. Tabian, H. Fu, Z.S. Khodaei, A Convolutional Neural Network for Impact Detection and Characterization of Complex Composite Structures. Sens. 19(22) (2019)1-25. doi:10.3390/s19224933

[18]- Z. Tang, Z. Chen, Y. Bao, H. Li, Convolutional neural network-based data anomaly detection method using multiple information for structural health monitoring. Struct. Control. Health. Monit. 26(1) (2019). doi:10.1002/stc.2296

[19]- S. Malek, F. Melgani, Y. Bazi, One-dimensional convolutional neural networks for spectroscopic signal regression. J. Chemom. 32 (2018) 1-17. doi:10.1002/cem.2977

[20]- B.N. Dung, B.T. Thanh, N.T. Hieu, M. Abdel Wahab, R.D. Guido, Damaged Detection in Structural Health Monitoring using Handcrafted Features and Convolution Neural Network. In: Proceedings of 1st International Conference on Structural Damage Modelling and Assessment, Belgium, 2020.

[21]- E. Figueiredo, G. Park, J. Figueiras, C. Farrar, K. Worden, Structural Health Monitoring Algorithm Comparisons using Standard Data Sets. Los Alamos National Laboratory LA-14393, 2009. doi:10.2172/961604

[22]- Y. Le Cun, B.E. Boser, J.S. Denker, D. Henderson, R.E. Howard,W.E. Hubbard, L.D. Jackel, Handwritten digit recognition with a back-propagation network. In: Advances in Neural Information Processing Systems; MIT Press: Cambridge, 1990, pp. 396–404.

[23]- C. Olah, Understanding LSTM Networks, 2015. http://colah.github.io/posts/2015-08-Understanding-LSTMs/

[24]- A. Tharwat, Classification assessment methods In: Applied Computing and Informatics (2018).