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Title: Deep Convolutional Neural Network for Condition Identification of Connections in Steel Structures

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ABSTRACT

The deep learning technologies have transformed many research areas with accuracy levels that the traditional methods are not comparable with. Recently, they have received increasing attention in the structural health monitoring (SHM) domain. In this paper, we aim to develop a new deep learning algorithm for structural condition monitoring and to evaluate its performance in a challenging case, bolt loosening damage in a frame structure. First, the design of a one-Dimensional Convolutional Neural Network (1D-CNN) is introduced. Second, a series of impact hammer tests are conducted on a steel frame in the laboratory under ten scenarios, with bolts loosened at different locations and quantities. For each scenario, ten repeated tests are performed to provide enough training data for the algorithm. Third, the algorithm is trained with different quantities of training data (from one to seven test data for each scenario), and then is tested with the rest test data. The results show that the proposed 1D-CNN with three convolutional layers provide reliable identification results (over 95% accuracy) with sufficient training data sets. It has the potential to transform the SHM practice.

INTRODUCTION

Bolted connections are widely used in steel structures, such as bridges and buildings. Recently, they become a popular choice for the off-site construction, e.g. public buildings, schools, and social buildings. The conditions of the connections are important for the overall structural performance of the steel frames [1]. However, it is not easy to assess their conditions once built, because they are normally not accessible or "hidden". To identify structural conditions, vibration-based structural health monitoring (SHM) methods are most mature, compared with other non-destructive evaluation methods [2]. However, the interpretation of vibration-based monitoring data remains a major challenge in many practical scenarios.

The vibration data interpretation methods can be generally classified into either physics-

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based or data-driven. The former has been studied predominantly in the last 20-30 years. Despite their popularity, physics-based methods face two main challenges: first, it is often difficult to find a feature that is sensitive to structural conditions while insensitive to the noise and uncertainties from different sources, such as materials, geometry, environment, and model. Second, such methods suffer from relatively low computational efficiency due to their reliance on refined simulation models. To address these challenges, efforts have switched into data-driven approaches in recent years, which transform the structural condition identification problem into pattern recognition. Using such methods, the features can be generated automatically through machine learning algorithms and thus the computational costs can be significantly reduced. Further, since the features can be created and optimised based on the sensitivity, they may achieve better structural condition identification results than traditional methods. The main challenge for the existing data-driven condition identification methods is that they often lack the complexity embedded in numerous and diverse scenarios in real structures, considering different possible conditions, environmental factors, and loading histories.

Recently developed deep learning methods [3] has enabled the modelling of complexity by using multiple learning layers. Since they were introduced, they have attracted significant scientific interest from different domains, and achieved revolutionary results [3, 4], e.g. image understanding, language processing, and the game of Go. In the SHM domain, the application of deep learning algorithms has gained increasing yet still limited research attention [5–8]. The existing studies can be categorized into two groups. The first group is a direct adaptation from computer vision application, i.e. detecting different structural conditions based on image analysis [5, 8]. The second group is to construct a machine learning algorithm based on a training set of vibration data under different scenarios [6, 7]. These methods are mainly adapted from the algorithms in image and video recognition domains, i.e. auto-encoder method and convolutional neural networks (CNN), which classify the input data by computing the features of these data and comparing them with those of existing data.

The network architecture of the deep learning algorithm controls its performance of structural condition identification. Generally speaking, with deeper and wider convolution layers, the network will provide more accurate training results, however, it may lead to over-fitting problems. Therefore, how to optimise the network architecture is a challenge in this field. Further, the quality and quantity of the available training data sets significantly affect the identification results. The question on how many training data are needed for the reliable training of a deep learning algorithm needs to be answered.

To address above issues, in this study, we develop a novel deep learning algorithm for structural condition identification, and perform a challenging case study to determine the optimal number of training samples. A series of impact hammer tests on a steel frame with different levels of bolt connection damage, as small as just one bolt loosening, are performed in the laboratory. The collected time-domain acceleration data from the middle point of the beam are directly used to train the developed algorithm. The results on the performance of the algorithm are presented, with different numbers of convolutional layers and different quantities of training samples. The paper will conclude with conclusions and future recommendations.

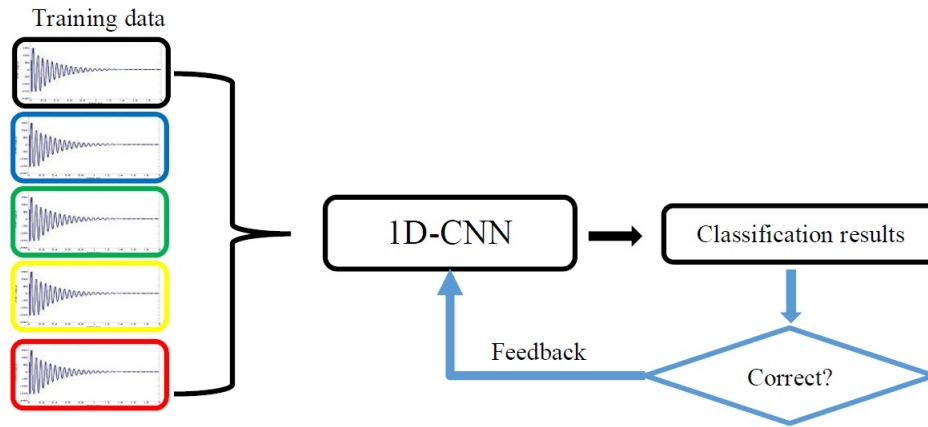


Figure 1. Structural condition identification framework

METHODOLOGY

From the machine learning perspective [9, 10], SHM is based on a hypothesis that the monitoring data embody various patterns under different structural conditions. Therefore, with sufficient training data sets (monitoring data $X(x_1, \dots, x_n)$ and their associated structural conditions $Y(y_1, \dots, y_n)$), the distances between a particular monitoring data set x_i and the existing vectors in X can be calculated. The label of x_i will be assigned to the one with the least distance.

In this paper, time domain vibration data from a single accelerometer under different scenarios are used directly as the training data. The reason is that this kind of data contain all the vibration information, including non-linear and transient effects which are often missed by the frequency domain data. Further, the process is more straightforward, because there is no need for domain transformation. The flowchart of the structural condition identification framework is shown in Figure 1.

Since the vibration monitoring data are intrinsically time-series, i.e. one-dimensional (1D), we constructed a 1D-CNN by adapting an existing two-dimensional (2D) CNN model. Considering better performance and efficient training and testing, we constructed the 1D-CNN based on the idea of the popular Alex-Net [11], which achieved revolutionary results in computer vision. Specifically, we adjusted all the 2D layers to 1D modified the parameters and convolutional layers based on empirical results, and selected the Adam method [12] for optimisation. The architecture of the proposed 1D-CNN algorithm and its initial parameter settings are detailed in [13]. The network contains two main parts: feature extraction and classification. The feature extraction part consists of three 1D convolutions layers with kernel size 7, 5 and 3, each followed by a rectified linear unit (ReLU) activation [14], and max pooling with kernel size 3 and stride of 2. The program is written in PyTorch (<https://pytorch.org>).

With deeper and wider convolution layers, it is expected that the accuracy of training will increase, but whether the test accuracy will increase will depend on whether the network has the over-fitting problem. Therefore, we modify the classification part from three (original) to five or more convolutional layers to address the challenging case in this study. This helps to optimise the network architecture for this case.

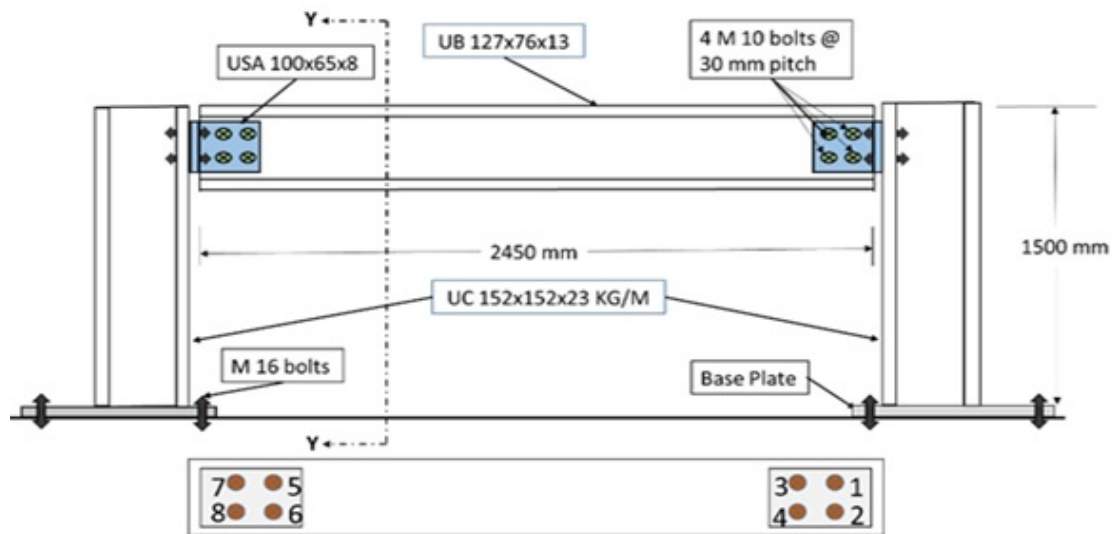


Figure 2. The laboratory test set-up

LABORATORY CASE STUDY

A single bay single storey steel frame is considered in this study. The experimental test set-up, including the geometric details of the frame and bolted connection details with specified bolt numbers, is shown in Figure 2. The beam is connected to the columns with the help of gusset angles and pre-tensioned bolts. A total of eight bolts with 10 mm diameter are used with a pretension torque of 55 Nm. The pretension torque is applied using a torque wrench. The columns are welded to the base plates which are then bolted to the strong floor using 16 mm bolts. All the bolts used in this study are high tensile bolts of grade 8.8.

The modal test was carried out using an instrumented impulse hammer, and six accelerometers. The maximum impulse capacity of the instrumented hammer is 35584 N, with a sensitivity of 0.023 mV/N. The instrumented hammer and the accelerometers were manufactured and supplied by Meggitt. The accelerometers are rated at 100 mV/g with an acceleration measurement range of 50 g. They (the impact hammer and accelerometers) were connected to a National Instruments sound and vibration module, PXIe-4492, within the National Instruments compact data acquisition module, cDAQ-9174.

The impact point was selected close to but not at the exact quarter point of the beam, to avoid the vibration node locations. The locations of the accelerometers were estimated using the algorithm of damage measurability (reference). In this study, only the data from Accelerometer 4, which is located at the middle point of the beam, are used as training data. Since this location is a vibration node, the vibration responses from all the even number modes will be ignored. This increases the difficulty of structural condition identification significantly. However, in many practical scenarios, the middle point may still be used. So this study aims to test the developed algorithm in this extremely challenging condition.

In this study, the damage scenarios are designed to serve as challenging cases. As listed in Table I, ten damage scenarios plus the intact scenario are considered. For each

damage scenario, ten repeated tests were performed, and the modal parameters were identified from the average of these ten repeated tests. For scenarios 1-3, we examine the conditions with only one bolt loosened at different location. For scenarios 4-6, we consider the conditions with two bolts loosened with different combinations. For scenarios 7 and 8, we address two bolts loosened on both sides of the beam. For scenario 9, we examine the condition with three bolts loosened. Therefore, the first nine scenarios address the conditions that only a part of bolted connections are loosened. Indeed, most existing studies deal with the identification of the whole connection loosened, which is represented as scenario 10 in this work.

The identified natural frequency results is shown in Table I. Based on the results, it can be seen that the changes of natural frequencies between the intact structure and damaged structure up to scenario 9 are very small, and this is the same as those of mode shapes (not presented here). Particularly, only damage scenario 10 shows approximately 5 percent change. For the rest damage scenarios, the maximum frequency changes for all three modes are around 1 percent, except that for the second mode for scenario 9 being around 3 percent. These small changes can be easily smeared by noise and/or other uncertainty factors. Therefore it is very challenging to identify these conditions using the traditional modal parameter based methods.

RESULTS AND DISCUSSIONS

In this work, we first examine the effects of the number of convolutional layers on the structural condition identification results. Our previous work [13] on the condition identification of the whole connection demonstrated that at least three or four repeated test data are needed for training data. Since this case addresses the condition identification of a single bolt, which is more challenging, five repeated test data are used as

TABLE I. DAMAGE SCENARIOS AND THEIR ASSOCIATED MODAL PARAMETERS

| Description | Damage scenario | Bolts loosened | Natural frequencies (Hz) | | |
|--|-----------------|----------------|--------------------------|--------|--------|
| | | | 1st | 2nd | 3rd |
| Intact | 0 | All tight | 82.43 | 258.80 | 563.20 |
| One bolt loosened at one end at different locations | 1 | 1 | 83.34 | 254.3 | 563.3 |
| | 2 | 3 | 83.34 | 254.70 | 564.60 |
| | 3 | 2 | 82.92 | 254.70 | 563.30 |
| Two bolts loosened at one end at different locations | 4 | 1 and 2 | 81.63 | 251.70 | 560.70 |
| | 5 | 1 and 3 | 82.92 | 254.70 | 562.5 |
| | 6 | 1 and 4 | 83.34 | 254.30 | 563.70 |
| Two bolts loosened at both ends at different locations | 7 | 1, 2, 5 and 6 | 81.63 | 251.70 | 560.70 |
| | 8 | 1, 3, 5, and 7 | 82.92 | 255.20 | 561.60 |
| Three bolts loosened at one end | 9 | 1, 2, and 3 | 81.21 | 250.90 | 559.00 |
| Four bolts loosened at one end | 10 | 1, 2, 3 and 4 | 78.64 | 245.30 | 550.10 |

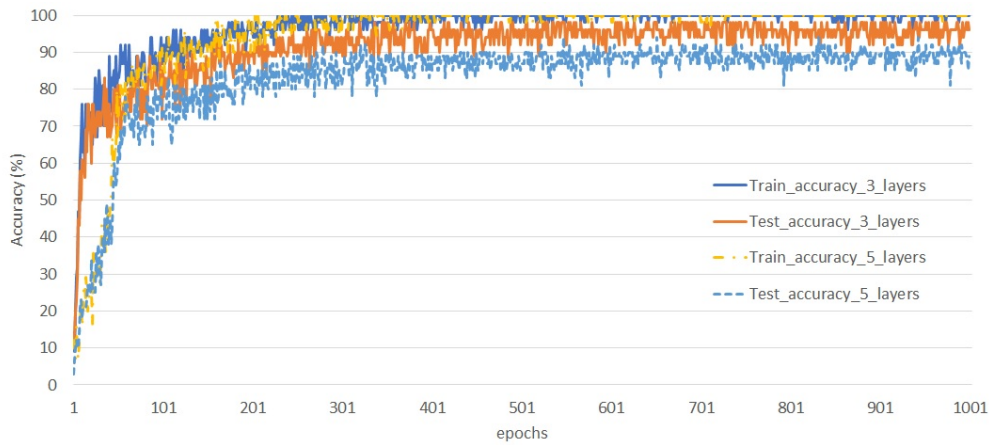


Figure 3. The comparative study on different numbers of convolutional layers

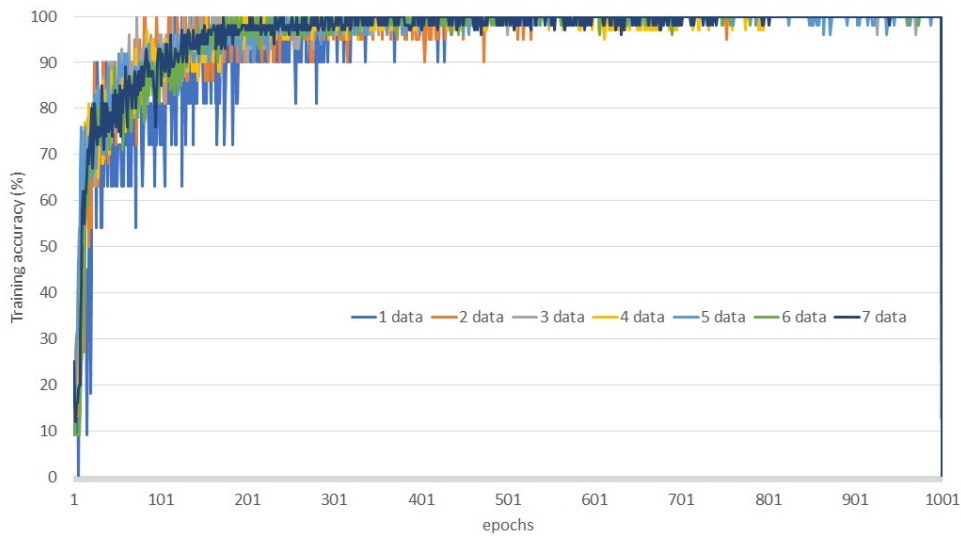


Figure 4. The train accuracy using 1-7 sets of repeated test data

training data, and the rest five are used for testing. We used 1000 epochs for training.

The training and testing accuracy results are shown in Figure 3. As can be seen, the training accuracy results using both three convolutional layers and five layers can achieve 100%. However, the test accuracy results differ to a large degree. Specifically, the accuracy using three layers is 96%, while that using five layers is only 89%. These mean that with more layers, the test accuracy does not increase as expected. Further, the network using three layers converges much quicker than that using five layers. Based on these, we can conclude that the network with five convolutional layers has the over-fitting problem, and therefore the one with three layers is more suitable for this case.

Secondly, we examine how many training data can deliver reliable networks for structural identification for this case. We trained the developed 1D-CNN algorithm with three convolutional layers for seven times, with 1-7 experimental data sets as training data and the rest as testing data. Figure 4 shows the evolution of training accuracy results. It can be seen that the training speeds using different numbers of data sets are almost identical. In contrast, the testing accuracy using different numbers of data sets

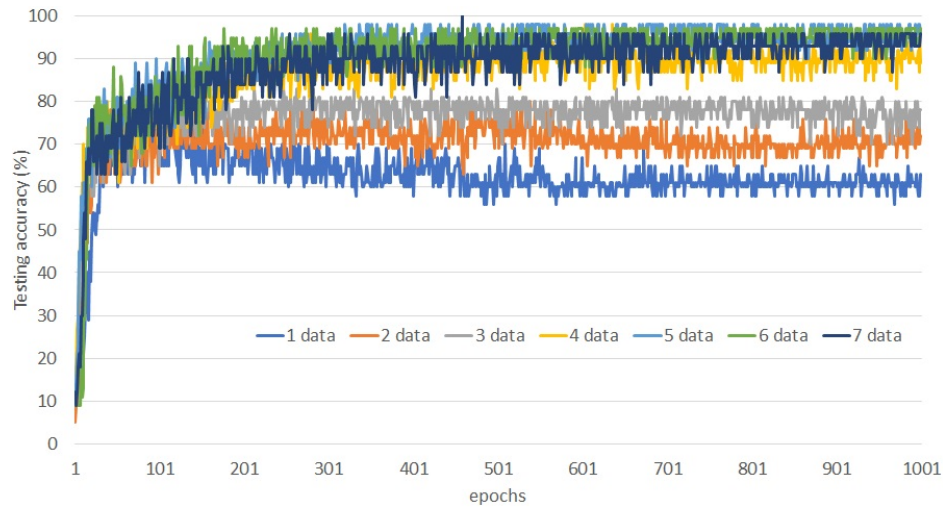


Figure 5. The testing accuracy using 1-7 sets of repeated test data

are quite different, as shown in Figure 5. Specifically, based on the trained network, the best testing accuracy results using 1-7 data sets are 63, 72, 78, 89, 96, 97, 96, respectively. Further, the testing accuracy results using 1-3 data sets decline over the epochs. This means that to train a suitable network, at least four repeated test data are needed. To achieve better testing results, five repeated test data are needed for training. With more training data, the testing accuracy does not improve. This is reasonable, because the location of accelerometer 4 is at the middle point of the beam, which is a vibration node. Using sensor data at other locations than the vibration nodes will lead to better testing results. This will be reported in our future papers.

CONCLUDING REMARKS

This paper developed a novel 1D-CNN framework for structural condition identification, and evaluated it with a challenging case on bolt loosened damage identification. A steel frame with eight bolts was constructed in the laboratory. Ten damage scenarios were designed to test the performance of the algorithm under very subtle structural condition changes. Ten repeated impact hammer tests were performed for each scenario. The training and testing results demonstrate:

1) The proposed 1D-CNN framework is very effective in structural condition identification, achieving over 95% accuracy under challenging conditions, e.g. the sensor at a vibration node.

2) By increasing the number of convolutional layers, the performance of the algorithm may not improve, because of the over-fitting problem. It demonstrated that three convolutional layers are the optimal setting in this case.

3) With fewer training data, the structural condition identification performance inevitably degrades. For the case being studied, four repeated test data are the minimum requirement for reliable structural condition identification. And five repeated test data will be ideal.

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