Chapter 7
Real-Time Structural Health Assessment of a Tension Rod Assembly Using Machine Learning

Ahmad Rababah, Osama Abdeljaber, Aniston Cumbie, Lauren Harpenau, and Onur Avci

Abstract This paper introduces a vibration-based damage detection method for monitoring the condition of structural members at a local level. The technique employs a piezoelectric patch as an actuator to excite the monitored member and another patch as a sensor to measure the resulting vibration response. The measured signal is processed by a one-dimensional convolutional neural network (1D CNN), which classifies the input signal segment as either undamaged or damaged. By calculating the classification output over multiple signal segments, an index representing the estimated structural health is determined, quantifying the deviation from the undamaged member's response. In this study, the method was experimentally evaluated on a tension rod assembly, where damage was simulated by reducing the tension applied to the rod. This application aims to demonstrate the method's potential for real-world structures, such as suspension bridge cables and prestressed concrete elements. The results indicated that the health values obtained using the proposed method closely matched the actual damage severity applied to the assembly.

Keywords Real-time anomaly detection · Structural health assessment · Piezoelectric patch · Structural Health Monitoring (SHM) · Structural Damage Detection (SDD)

Introduction

Structural health refers to a structure's ability to maintain its initial "undamaged" condition. Structural Health Monitoring (SHM) and Structural Damage Detection (SDD) focus on identifying deviations from this baseline. One of the methods used in SHM is vibration-based damage detection (VBDD), which involves applying a controlled excitation force to a structure and capturing the resulting responses with sensors. The collected data is then processed by certain algorithms, which analyze, classify, and evaluate the structural health.

Ahmad Rababah
Graduate Student, Department of Civil and Environmental Engineering, Engineering Sciences Building, 1306 Evansdale Drive, West Virginia University, Morgantown, WV, 26506, USA
(Corresponding author)
e-mail: ayr00002@mix.wvu.edu

Osama Abdeljaber
Associate Senior Lecturer, Department of Building Technology, Linnaeus University, 351 95 Växjö, Sweden
e-mail: osama.abdeljaber@lnu.se

Aniston Cumbie
Graduate Student, Department of Civil and Environmental Engineering, University of Illinois Urbana-Champaign, Newmark Civil Engineering Laboratory, 205 N. Matthews Avenue, Urbana, IL, 61801
e-mail: aniston2@illinois.edu

Lauren Harpenau
Undergraduate Student, Department of Civil and Environmental Engineering, Iowa State University, 813 Bissell Road, Ames, IA, 50011
e-mail: llh1@iastate.edu

Onur Avci
Assistant Professor, Department of Civil and Environmental Engineering, Engineering Sciences Building, 1306 Evansdale Drive, West Virginia University, Morgantown, WV, 26506, USA
e-mail: onur.avci@mail.wvu.edu

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Piezoelectric patch transducers offer a unique solution for SHM of structural members due to their ability to convert mechanical energy to electrical and vice versa based on the piezoelectric material principle [1]. When mechanical stress or strain is applied to them, an electrical field response is produced. Conversely, they undergo mechanical energy when exposed to an electric field. This phenomenon allows for the use of such transducers for both actuating (i.e., applying artificial excitations on the monitored structural member) or sensing (i.e., measuring the response due to the applied excitation) [2].

Utilizing piezoelectric patch transducers in SHM has increased considerably in recent decades. These transducers have been deployed across various structural types to detect damage, including cracks, loose bolts in connections, corrosion, debonding, and fatigue, among other forms of degradation. Markovic et al. (2015) employed piezoelectric patches in active monitoring systems for reinforced concrete structures to detect damage, such as notch and hole located at the middle of the beam, using wave propagation methods [3]. Sun et al. (2015) proposed a method for identifying midspan debonding in reinforced concrete beams strengthened with fiber-reinforced polymer (FRP) strips using piezoelectric patches attached to the FRP strips, enabling high-frequency structural excitations [4]. Fan et al. (2016) Investigated damage detection in a laboratory-constructed truss. They utilized piezoelectric patches to detect damage simulated by removing specific bolts. This method enabled the observation of the impact on the impedance-measured signals [5]. Pavelko et al. (2014) examined the full-scale tail beam of a Mi-8 helicopter to evaluate the condition of its bolt joints. By comparing the frequency domain impedance responses of undamaged and damaged structures, they successfully detected damage. One of the connecting frames of the tail beam was equipped with piezoelectric patches attached to the surface near the bolts. The study focused on investigating bolt loosening using Electrical Impedance Monitoring (EMI) technology [6]. Meyers et al. (2013) employed the VBDD method on an aluminum plate to identify simulated damage, which was introduced by progressively drilling deeper holes through the center of the plate. The plate was excited using a PZT actuator, and wave propagation was monitored by a piezoelectric transducer positioned on the opposite side. The detected wave patterns were then compared to a predefined baseline to assess the extent of the damage [7].

The integration of machine learning (ML) and artificial intelligence (AI) has significantly improved SHM and SDD. These technologies have revolutionized structural monitoring practices by providing powerful tools for the analysis of large datasets collected from pre-installed sensors, enabling continuous, automated, real-time monitoring and early detection of potential damages before they escalate into critical failures. AI algorithms enhance SHM systems by extracting relevant features from datasets and classifying structural conditions based on these features [8].

Several researchers have demonstrated the effectiveness of ML in creating highly reliable and accurate SDD systems. Khan et al. (2020) introduced a method that utilizes a one-dimensional convolutional neural network (1D CNN) to detect cracks by analyzing EMI signatures from piezoelectric patches. The study involved testing fiber-reinforced concrete specimens under compression loading, and the method achieved a mean accuracy of 95.24% in damage detection [9]. Xu et al. (2019) employed the EMI method alongside Back Propagation Neural Networks (BPNNs) to identify bolt looseness in bolted spherical joints (BSJs). Different torque levels were applied to the sleeve to represent varying degrees of joint looseness. As the torque increased, the looseness of the joint also increased proportionally. The root-mean-square deviation (RMSD) of the conductance signatures from the piezoelectric patches served as the primary metric for monitoring and evaluating the extent of joint looseness [10]. Teng et al. (2019) developed a parametric vibration-based model using a CNN to identify damage features in steel frame structures. They employed the finite element method (FEM) to analyze free vibrations and calculate the first-order modal strain energy (MSE) for various damage scenarios, which were used as training data for the CNN. Data were collected using ten accelerometers to capture vibrations from a hammer impact. The damage was simulated by a 50% reduction in the rod's cross-sectional area [11].

This paper introduces a novel approach for detecting damage in structural components by utilizing piezoelectric patches for both sensing and actuation. The sensor patch captures signals that are then analyzed using a one-dimensional convolutional neural network (1D CNN). The 1D CNN's output is used to compute an index that quantifies the severity of the damage. Unlike previous methods, such as the one by Khan et al. (2020), which were only validated numerically on finite element models, this approach has been experimentally validated using a tension rod assembly with varying tension levels. The aim of this work is to demonstrate the method's ability to detect tension loss in suspension bridge cables and prestressed concrete elements.

Methodology

The proposed method relies on a 1D CNN trained to classify the response measured by the sensor patch into two classes: healthy or damaged. The following subsections describe the architecture of the 1D CNN, the test structure used to train and evaluate the model, the training procedure, and the process of estimating damage severity based on the classification output of the 1D CNN.

CNN Architecture

Convolutional Neural Networks (CNNs) have been pivotal in image classification and segmentation tasks, particularly because of their ability to efficiently extract features from images. Unlike traditional computer vision and machine learning techniques, which depend on manually engineered low-level features, CNNs use their large number of parameters to automatically learn complex mid- to high-level image representations from pixel tensors [12]. 1D CNNs are a variant of CNNs specifically designed to deal with 1D data (i.e., signals) rather than images. This is achieved by using 1D convolution filters instead of 2D filters in conventional 2D CNNs. These models consist of three components: convolution layers, subsampling (or pooling) layers, and fully connected layers. Convolution layers extract features from small regions of the input data. Each convolution layer is followed by a subsampling (or pooling) layer that reduces the dimensionality of the feature maps and lowers the number of parameters while keeping essential information. Finally, the fully connected layers or multilayer perceptron (MLP) aggregate these extracted features to compute class scores, which represent the model's predictions, serving as the output for tasks such as classification or object recognition.

In this work, the implemented 1D CNN architecture consists of two convolution layers, each with 64 filters, a kernel size of 80, and rectified linear unit (ReLU) activation. After each convolution layer, a max pooling layer with a pool size of 2 is applied to downsample the input. The output is then flattened and processed by two fully connected dense layers with ten neurons each, also using ReLU activation. Finally, softmax activation is applied in the output layer to generate the binary classification results (damaged or undamaged), as illustrated in Figure 1.

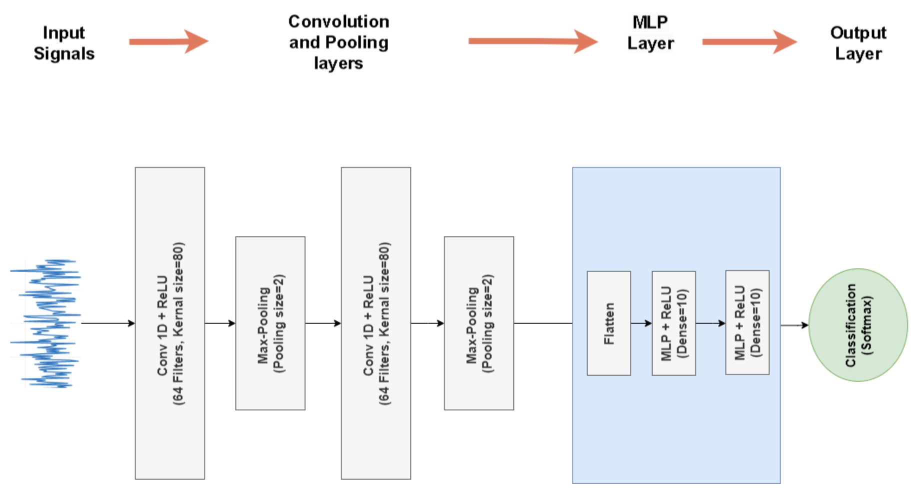

Fig. 1 Architecture of the 1D CNN.

Test Structure

A small-scale setup, illustrated in Figure 2, has been developed for training and testing the 1D CNN. This setup consists of a hollow steel section (540mm x 50.8mm x 38mm) with a tension rod extended through its center. Wing nuts were affixed on either side of the rod and can be adjusted to increase or decrease the tensile stress on the rod. Additionally, two PZTs (P-876.A15, 61 mm $\times$ 35 mm $\times$ 0.8 mm) were attached to the setup, serving as both actuator and sensor. These PZTs were mounted onto the steel section using wooden pieces and steel clamps. Attention was given to ensuring that the clamps were neither overly tightened, which could affect the PZTs' functioning, nor too loose, which could lose their stability and signal transmission. A data acquisition device (NI USB-6212) was used to drive the actuator patch and acquire the response from the sensor patch. A piezo amplifier (E-835.00) was used to amplify the low-voltage signal generated by the data acquisition device.

Training Procedure

The 1D CNN model was trained to distinguish between two conditions: healthy (undamaged) and damaged states. The training process involved the following steps:

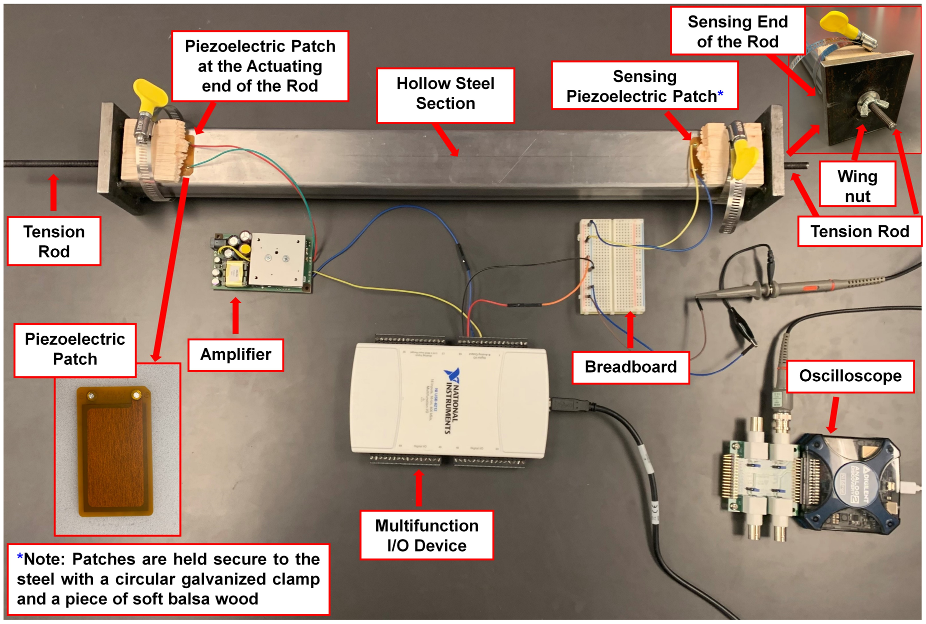

Fig. 2 Labeled diagram of the setup used in testing.

1. The wing nuts were fully tightened to represent the completely undamaged structural state. The actuator patch was then subjected to random white noise excitation, and the vibration response was recorded by the sensor patch for 60 seconds at a sampling frequency of 250 kHz.
2. The same procedure was repeated with the wing nuts completely loosened to simulate a fully damaged state.
3. The 60-second signals from both healthy and damaged states were divided into 256-sample segments, resulting in 58,594 segments for each condition.
4. Each segment was normalized between 0 and 1.
5. The segments were labeled, randomly shuffled, and split into 95% for training and 5% for validation.
6. The training was conducted using TensorFlow 2.10 [13], with Adam optimizer, a learning rate of 0.001, and a batch size of 64. The loss function used was binary cross-entropy between the model's predictions and the true labels. The classification error was evaluated on the validation set at the end of each epoch. The training was terminated when the error did not decrease for 8 consecutive epochs.

Structural Health Estimation

The training procedure described in Section 2.3 resulted in a binary 1D CNN that classifies an input 256-sample segment into two classes: completely healthy or completely damaged. However, it is possible to use the 1D CNN to quantify damage severities between these two extremes by calculating a damage severity index representing the estimated structural health (H%) according to the following steps:

1. Excite the structure with a white noise excitation for a short period of time (e.g., 2 seconds) at the same sampling frequency (250 kHz) and measure the response by the sensor patch.
2. Divide the measured signal into n segments, each having 256 samples.
3. Process each segment using 1D CNN to obtain its binary class (undamaged or damaged).
4. H% is calculated according to the following expression:

$$H(\%) = \frac{Number\ of\ segments\ classified\ as\ undamaged}{n} \times 100 \quad (1)$$

The methodology is depicted in Figure 3 below.

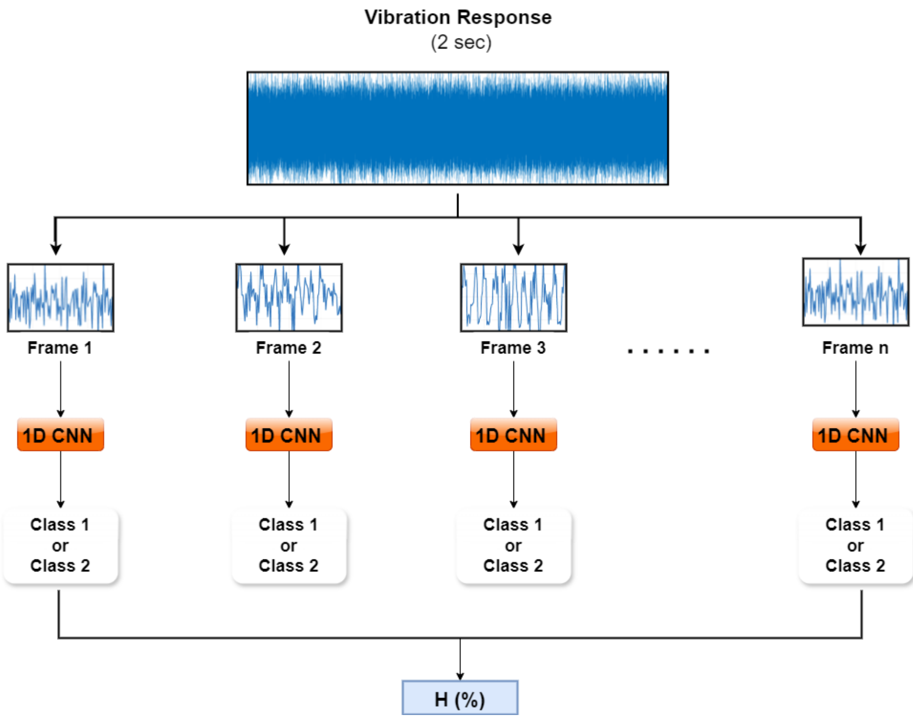

Fig. 3 Methodology for calculating the structural health (H%) using a 1D CNN classification model.

Results and discussions

After training the network as detailed in Section 2.2, it was employed to monitor changes in the health percentage (H%) resulting from variations in rod tension. During testing, the beam was continuously excited using white noise, and H% was recalculated every 2 seconds as outlined in Section 2.3. The wing nut was adjusted by tightening and loosening it to different extents to simulate various damage levels. Figure 4 illustrates the H% calculated during multiple cycles of tightening and loosening. Initially, the wing nut was fully tightened, and the estimated health was nearly 100%, indicating a completely healthy structure. As the wing nut was gradually loosened, the H% dropped below 40%, indicating an increased likelihood of structural damage. Repeating this process multiple times caused the H% levels to fluctuate between high and low values, depending on the current tension level. This demonstrates the model's accuracy and capability to reflect the real-time condition of the setup.

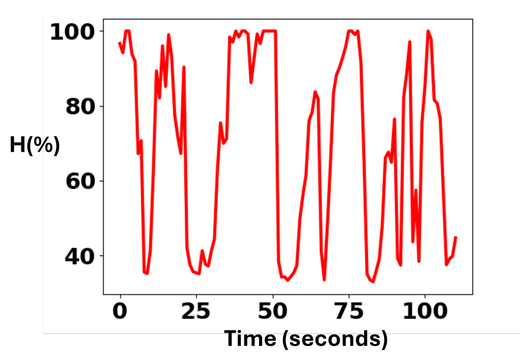

Fig. 4 Real-time structural health percentage, H(%), calculated using the 1D CNN.

During the testing process, several challenges were identified that impacted monitoring accuracy. One critical issue was the method of attaching the piezoelectric patches using steel clamps and wooden pieces, which notably affected the system's performance and outcomes. As shown in Figure 5a, if the clamps were tightened excessively, both the actuators and the sensor could not function optimally for excitation and data collection, leading to an underestimation of the damage. Conversely, if the clamps were too loose, the patches failed to maintain proper contact with the surface, resulting in inaccurate measurements and unreliable results. In this scenario, the excitation from the actuator would not be fully transferred to the setup, causing issues with measuring the initial healthy condition. As illustrated in Figure 5b, the fully healthy state does not accurately represent the connector health as 100%.

Additionally, disturbances from external sources, such as vibrations from movement and contact with the setup or vibrations from the desk, adversely affected the health estimation. While these disturbances were managed in a controlled laboratory environment, scaling the model for application in various conditions requires addressing this issue.

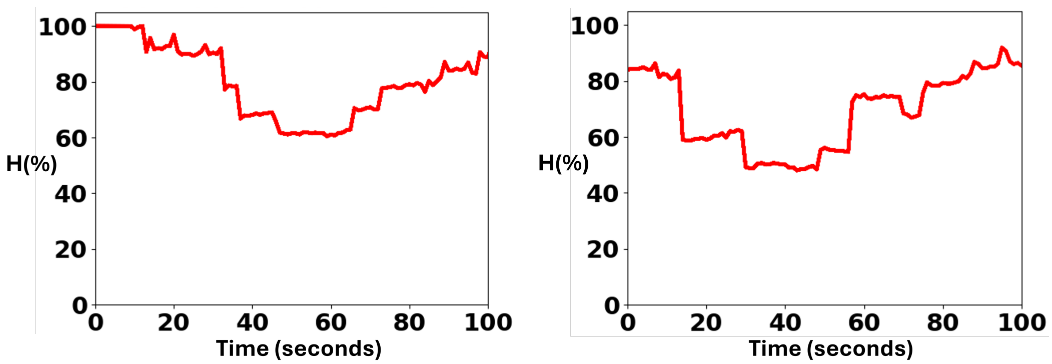

Fig. 5 Impact of clamp tightness on structural health accuracy: (a) Over-tightened clamps, (b) Under-tightened clamps.

Conclusions

This study proposed a vibration-based damage detection technique for monitoring the health of a tension rod assembly. The method utilized piezoelectric patch transducers for both sensing and actuating. A 1D CNN was trained to estimate the current tension level applied to the rod. The experimental verification showed that the proposed method successfully calculated a damage index H% that reflects the actual structural health of the monitored member. In future studies, the method can be extended and applied to detect damage in the strands of the prestressed concrete beams.

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