International Journal of Offshore and Polar Engineering (ISSN 1053-5381)

Vol. 31, No. 2, June 2021, pp. 220–229; https://doi.org/10.17736/ijope.2021.ty11

http://www.isope.org/publications

Investigations on Plate Crack Damage Detection Using Convolutional Neural Networks

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This paper presents a prediction model to detect the location and level of cracks in plates using a method based on the convolutional neural network (CNN), which can automatically learn damage characteristics without prior knowledge. A simply supported plate with cracks is established in Abaqus/CAE. Node accelerations at representative locations are adopted as the CNN input parameters. Effects of the initial learning rate, kernel size, and pool size on CNN performance are discussed so as to select the appropriate combination of hyperparameters to train the CNN. The results show that, when predicting the location and level of single- and multi-crack damage on noise-free and noisy data sets, the proposed method is more accurate than the multi-layer perceptron method and multi-layer perceptron by wavelet packet transformation. In addition, the proposed method produces a reasonable prediction of crack lengths.

INTRODUCTION

Bridges, ships, and aircraft are important modes of transportation, playing a significant role in world development. However, under the action of alternating loads (Yang and Wang, 2018), manufacturing errors in their structures will cause cracks that reduce their structural safety. When a crack propagates to a certain extent, the structure will undergo brittle fracture, which will be accompanied by a catastrophic accident. To avoid potential safety hazards caused by structural damage, machine learning (ML), a data-driven damage-detection approach, has been studied by many scholars.

ML has been successfully applied to many fields, such as pattern recognition, statistical learning, data mining, computer vision, speech recognition, natural language processing, and image recognition. Hence, artificial neural networks (ANNs) for damage detection have attracted the attention of many researchers. This technique has impressive learning ability and is capable of associative memorizing, reasoning, synthesizing, and dealing with strong nonlinear problems. Its excellent parallel processing capability, tolerance, and robustness have also been demonstrated (Jiang et al., 2011). Diao et al. (2006) presented a three-step damage-detection method for offshore platforms using ANN and mode parameters obtained from a finite element (FE) model that were used to calculate the training samples. Samanta et al. (2003) found that an ANN classifier had better damage-detection performance than a support vector machine (SVM) classifier when a genetic algorithm was used to optimize the parameters of the classifiers. Mehrjoo et al. (2008) proposed a multi-layer perceptron (MLP) neural network-based damage-detection method that overcame data incompleteness for truss bridge damage detection and obtained good precision in damage location and severity assessment. Palomino et al. (2014) used a probabilistic neural network and fuzzy cluster analysis to identify and locate cracks. Gordan et al. (2018) suggested applying a data-mining framework, ANN, and imperial competitive algorithm hybrid algorithm to detect single-point damage of an I beam (experimental model). The inputs of this algorithm were the natural frequency and corresponding mode shape, and the method outperformed traditional ANN methods. Gomes et al. (2019) used a genetic algorithm (GA) and ANN to identify and predict delamination locations of laminated composite plates. This methodology can identify damage localization in structures and quantify damage severity. Morfidis and Kostinakis (2018) used a multi-layer feed-forward perceptron (MFP) ANN to predict the seismic damage of reinforced concrete buildings, examining several networks with different configuration parameters to obtain the optimum ANNs. Although NNs have achieved some success in damage detection, their performance depends heavily on input characteristics that are easily affected by noise (Djemana et al., 2017; Lin et al., 2017).

CNNs have been proposed to detect structural damage; this is a kind of deep learning method based on ANNs and composed of multiple nonlinear processing layers for feature learning of data. CNNs require no data preprocessing, can accurately detect and classify damage, and, with increasing computer capacity and data volume, have been widely used in damage detection (Modarres et al., 2018; Zhao et al., 2019). Unlike previous approaches, CNNs do not require human experts to determine features (Atha and Jahanshahi, 2018).

Cha et al. (2017) proposed a CNN-based method to detect concrete cracks. A dropout layer was used to solve the overfitting problem, and a sliding window technique was used to scan images larger than 256 × 256 pixels (the size of the image used for CNN training). The model was unaffected by image quality, camera specifications, and working distance. Cha et al. (2018) proposed a faster region-based CNN (R-CNN) structural visual inspection method to detect concrete cracks, medium- and high-level steel corrosion, bolt corrosion, and steel delamination. Liu et al. (2017) presented a dislocated time series CNN (DTS-CNN) damage diagnosis framework based on vibration signal characteristics. The method retained the advantages of the CNN and solved the problem of its inapplicability to periodic mechanical signals. Khodabandehlou et al. (2019) investigated the performance of 2-D CNN at reinforced concrete highway bridge damage detection. This method extracted features from the vibration response and reduced the dimensionality of the data without knowing the excitation or its characteristics. Zeng et al. (2016) used the CNN to identify and classify damage to a gearbox by converting vibration signals to time frequency images through an s-transform and

Received May 13, 2020; revised manuscript received by the editors July 24, 2020. The original version was submitted directly to the Journal.
KEY WORDS: Damage detection, convolutional neural network, plate crack, noise.