Predicting Fractures in Reinforcing Steel Bars: A Low Cycle Fatigue CNN Approach

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Abstract

Resilience is enhanced by machine-learning-based structural health monitoring (ML-SHM). ML-SHM minimizes delays in recovery after events, offering continuous monitoring for improved resourcefulness. This paper discusses the use of convolution neural networks (CNNs) for SHM with time-series data from seismic events. Current ML approaches overlook the temporal nature of the data. The proposed ML-SHM approach involves converting time-series data into images using the Markov Transition Field (MTF), obtained from strain data collected during shake table tests, and utilizing these encoded images in training and testing CNN models. CNN models achieved impressive accuracy in training (100%) and testing (96.7%) using only 3 layers. By stacking eleven earthquake excitation representations through MTF images, particularly for low-cycle fatigue, this method shows promise in revolutionizing fracture estimation from strain data.

Keywords: Resilience; Structural Health Monitoring; Convolutional Neural Network; Machine Learning; Low-cycle fatigue

1 Introduction

Structural Health Monitoring (SHM) is vital for asset management, ensuring safety and functionality. Traditional methods are resource-intensive, relying on laborious sensor-based data collection. Advances in machine learning and computer vision offer efficient options for SHM, enhancing effectiveness and streamlining processes [1-6]. The use of convolutional neural networks (CNNs) to analyze visual data from cameras or sensors adds advantages to SHM toolkits. CNNs have shown great potential in detecting and characterizing structural damage, which could improve the efficiency and accuracy of SHM techniques [1,2,4,5].

Several researchers have advanced machine learning and deep learning techniques in civil engineering applications. Mantawy and Mantawy used acceleration and displacement time-series data to develop a convolutional neural network model for the structural health monitoring of the rocking bridge specimen by encoding the time series into images [3], in which the present paper is advancing this technique to utilize strain data for accumulated damage detection.

As evident in the abovementioned references, researchers can utilize machine learning and CNN techniques for vibration-based damage detection using acceleration and displacement time series data either by (1) extracting meaningful features from the time series data [2], (2) converting time series data (mainly acceleration) into 2D matrix, or (3) encoding time series data into images [3]. However, strain time-series data presents complex challenges for machine learning techniques due to the accumulation effects due to low-cycle fatigue, e.g., damage in reinforcing bar does not only depend on the current strain time series but also the history of strain experienced by the reinforcing bars throughout the life of the structures.

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