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Image-driven structural steel damage condition assessment method using deep learning algorithm

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ABSTRACT

This paper presents a deep learning based structural steel damage condition assessment method that uses images for post-hazard inspection of ultra-low cycle fatigue induced damage in structural steel fuse members. The deep learning model – Convolutional Neural Network (CNN) model, can be trained to represent the high dimensional features in huge amount of raw data which traditional mathematical models are unable to describe. A saliency-based visualization method is employed to visualize the feature-related pattern recognized by the deep learning model. To quantify the damage condition of the inspected structure fuse members, a micromechanical fracture index is defined as the damage index and used for labeling the images in the training data set. To provide large training dataset, cumulative plastic strain contour plot images generated through finite element (FE) simulation are adopted for the training data. Parametric studies were performed to validate and optimize the deep learning based damage condition assessment method. The method and findings are further examined using real experimental images collected from cyclic testing of a steel notched plate specimen. The results suggest that the proposed method provides a promising automation tool for rapid inspection of structural steel fuse member damage condition.

1. Introduction

New design trends for seismic resistant structures is to incorporate fuse members (sacrificial elements to dissipate energy) into structures so that damage can be confined to limited number of structural fuse members while other structural members would remain undamaged during design level earthquakes. Examples of structural fuses are buckling restrained braces, steel shear links and slit steel plate wall with buckling restrain cover plate (see, e.g., [29,30]. For example, Qu et al. [17] developed buckling-restrained brace (BRB) with replaceable steel angle fuses which offers ease of post-earthquake examination of fuse damage, convenient and prompt replacement of damaged fuses, and reuse of the buckling restraining elements. Such structure design concept is also appealing to structural health monitoring (SHM) since condition assessment or monitoring work can now be concentrated to a limited number of fuse members. For such smart fuse members instrumented with sensors, rapid inspection of fuse members for damages likely inflicted by strong earthquakes could be carried out in an efficient way, which would accelerate damage condition assessment and thus enhance structural resilience through quick and less subjective inspection practice. Currently, visual inspection is typical practice for post-hazard condition assessment of structural fuses (e.g., [32]). Intensive labor, high cost and variable results are typical of such manual operation. Furthermore, in buildings, structural members are often hidden behind fireproof coating and drywalls, and thus damage of these hidden steel fuse members are difficult to detect, often requiring removal of coverings and thus time consuming and costly. For efficient operation with instrument-assisted inspection, researchers have been looking into automated structural health monitoring technology such as computer vision based or acoustic emission based method [31].

To assess the damage condition of structural fuse members, image-based structural condition assessment shows a strong potential in addressing the rapid inspection need in practical applications: convenient data collection by snapping photos (e.g. using smart phones, wearable imaging devices or drones) and availability of well-designed algorithms for accurate image pattern recognition. Several research works have been reported in using images to assist with structural condition assessment [9,24,14,3,4]. For examples, [9] identified the maximum drift angle during an earthquake event by using strain patterns in steel slit plate walls to train an artificial neural network. Despite the promising potential of using image-based method for condition assessment, a robust algorithm to identify structural damage from collected data

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are difficult to define because the detection results are usually sensitive to such pre-defined damage features. To address this need of high-level features that might not be accurately described with current mathematical models, deep learning methods have been adopted which can learn such features from training data.

Popularized by Hinton and others in the last decade, deep learning methods have been reported recently to have achieved impressive success in image and speech recognition [11]. It is reported that deep learning-powered image recognition is now performing better than human vision on many tasks. AlphaGo is an example of the tremendous achievements by deep learning in recent years. Convolutional Neural Network (CNN) is one of the deep learning models which lays the foundation of the state-of-art performance for image classification and object detections in several data benchmarks [11,19,18]. Kumar et al. [12] developed prototype system that uses deep convoluted neural networks (CNNs) to classify multiple defects in sewer CCTV images including root intrusions, deposits, and cracks. The viability of this approach in the automated interpretation of sewer CCTV videos is demonstrated by average testing accuracy of 86.2% using trained CNN model based on 12,000 images collected from over 200 pipelines.

This study investigates applying deep learning method to image-based rapid inspection of structural steel fuse damage condition. Firstly, a procedure for incorporating a customary deep learning model into structural condition assessment is presented, in which a micromechanical fracture index is defined to label the damage condition of the structural steel fuse member. The proposed method is demonstrated in a case study of a replaceable shear link beam, which is designed as a structural fuse member for eccentrically braced frames. A CNN model was adopted for the image-based structural damage condition recognition in this case study. This case study validates and optimizes the method by using FE simulation-generated images as training data. The method is further verified by a second case study involving photo images taken during experimental testing of a dogbone steel plate specimen. The results from both case studies suggest that the proposed method can effectively identify damages in structural steel fuse members.

2. Deep learning model description

Deep convolutional neural network (CNN) is adopted here for image-based structural condition assessment because of its advancement and demonstrated success in computer vision field. However, a few issues discussed next distinguish the present study from the research works on image classification in the computer vision field. The first one is that the label of the structural condition images is assigned to reflect the quantitative damage condition of the structural elements; therefore, a damage index has to be established first to characterize the damage. Another issue is that generating the millions of training image data as observed in the ILSVRC or ImageNet is not practical in near future simply because of the limited availability of field reconnaissance data and experiment test data. Due to the limited amount of available training data, the training strategy needs to be adjusted to avoid the overfitting problem. Finally, no benchmark testing data is available for evaluating the performance of trained model. Thus, the testing data needs to be properly designed to fit the objective of damage condition assessment (e.g. considering the relation of damage condition to the loading history and different loading protocols).

Details of deep learning or the CNN methods can be found in references (e.g., the review article by LeCun et al. [13] or the book by [8]. A brief description that helps readers to gain necessary background knowledge on the specific algorithm of the deep learning model used in this study is presented next. Additionally, a salience map based visualization technique is also used to interpret results. The adopted CNN model is modified from the VGG-16 model pre-trained by Simonyan and Zisserman [19].

2.1. Architecture

The architecture of CNN is specialized for processing the 2D grid-like topology of input images and the CNN model usually includes multiple stacks of alternating convolution and max-pooling layers to function as feature extractors, followed by a small number of fully connected layers as classifier [8]. The architecture of the adopted CNN model is shown in Fig. 1. The input images are converted into numerical vectors with RGB values at size of 224 (pixels) $\times$ 224 (pixels) $\times$ 3 (color channels: red, green and blue). The vectors are then forwarded into multiple convolutional and pooling layers, outcoming with features followed by fully connected layers. Finally, a SoftMax layer is used to score the activations into a vector consisting C (possible classes) values with each ranging from 0 to 1 and all summating to 1. The prediction is made by choosing the class with the highest score.

2.2. Layers

Convolutional layer, max pooling layer and fully connected layer are frequently used in the adopted CNN model. The convolutional operation computes features based on a local field of the preceding layer as described in Eq. (1),

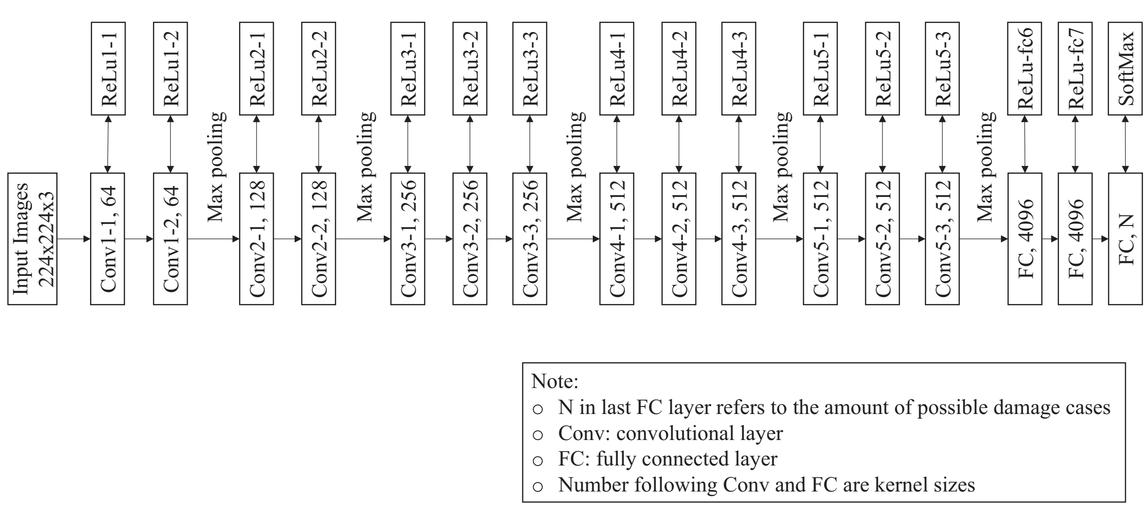

Fig. 1. Architecture of VGG-16 model.