ARTIFICIAL INTELLIGENCE-ENABLED STRUCTURAL HEALTH MONITORING

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Extended Abstract

In this data explosion epoch, artificial intelligence (AI)-enabled structural health monitoring (SHM) using the state-of-the-art machine learning (ML) and deep learning (DL) technologies has become of great interest in civil engineering. Based on data type, it can be further classified into two major directions, namely *vision-based* [6] and *vibration-based* [1] SHM.

In vision-based SHM, two critical issues need to be addressed: (1) the lack of uniform automated damage detection principles based on domain knowledge, and (2) the lack of benchmark datasets with well-labeled large amounts of data. Therefore, we developed the automated and hierarchical framework called PEER Hub Image-Net (PHI-Net or simply φ-Net) [7]. The framework consists of eight basic benchmark detection tasks based on current domain knowledge and past reconnaissance experience. These tasks are: (1) scene level, (2) damage state, (3) concrete cover spalling condition (material loss), (4) material type, (5) collapse mode, (6) component type, (7) damage level, and (8) damage type. According to the φ-Net framework, a large number of structural images was collected, preprocessed, and labeled to form the φ-Net dataset, an open-source online large-scale multi attribute image dataset, which currently contains 36,413 images with multiple labels. However, compared to the general computer vision benchmark dataset, ImageNet containing 15 million labeled images, the size of φ-Net is still not large enough. Therefore, transfer learning (TL) was adopted to better utilize the features from source domain of general ImageNet to the target structural image datasets [5, 6, 17]. Besides, generative adversarial networks (GANs) for structural image data augmentation [4] and also Balanced Semi-Supervised GAN (BSS-GAN) [10] have been developed to address the lack of labeled data and imbalanced class issues.

Through φ-Net benchmarking experiments, promising results were achieved and reported, which provide the reference for future DL applications. The well-trained models in these experiments are named Structural ImageNet Models (SIMs) and they serve as benchmarks for future development of classification algorithms. Moreover, the direct application of these SIMs was further performed, namely image-based post-disaster assessment of the 1999 Chi-Chi earthquake, Taiwan, which revealed the high potential and contribution of the φ-Net in vision-based SHM [7]. From a structural engineering point of view, a recent important development pertains to a systematic and human-in-the-loop deep learning model interpretation & diagnoses framework, namely Structural Image Guided Map Analysis Box (SIGMA-Box), which gives better understanding of how deep convolutional neural network (DCNN) models work in vision-based SHM [8]. Moreover, adopting the SIGMA-Box increases the level

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of confidence of engineers in these DCNN models to further improve their performance, and effectively apply them to practical structural engineering problems.

Attention has been given to the applications of DL in practical bridge health monitoring (BHM) projects. In such AI-enabled BHM, crack identification and width measurement are two of the important metrics for evaluating the functionality of bridges. However, some problems still exist in extending previously developed ML/DL methods to practical applications, such as data annotation difficulty, limited model generalization ability, and inaccuracy of the DL identification of the actual crack width measurement. An application-oriented multi stage crack recognition framework is recently proposed and called Convolutional Active Learning Identification-Segmentation-Measurement (CAL-ISM) [18]. It includes four kernel steps: (1) pre-training of the benchmark classification model, (2) re-training of the semi-supervised active learning model, (3) pixel-level crack segmentation, and (4) crack width measurement. The performance of the CAL-ISM framework is validated from two practical applications: (i) test bridge column specimen, and (ii) field BHM project. The obtained results from these applications demonstrated the effectiveness of CAL-ISM for BHM applications, which is recommended for more future BHM deployments.

In the direction of vibration-based SHM, vibration data especially acceleration plays the major role [2, 3, 12]. Since the turn of this century, time series (TS) modeling of vibration signals using a family of auto-regressive (AR) models was found to be effective in damage detection and has been used to capture damage features in structures [2, 3, 9] . However, there are some drawbacks limiting the use of AR series modeling in practice. The most notable is the requirement of stationary input, which is difficult to achieve in real SHM applications, where TS data (i.e., vibration signals) collected from sensors after earthquakes are usually non-stationary. Thus, elaborate data pre-processing (e.g., segmenting, de-trending, and de-nosing) and stationarity checks are inevitable before modeling. However, these methods lack a systematic pipeline and may not guarantee stationarity. Thus, we developed a systematic two-stage framework, namely Auto-Regressive Integrated Moving-Average Machine Learning (ARIMA-ML), to combine TS modeling techniques and ML approaches for detecting structural damage [9]. The first stage focuses on the TS modeling, and the second stage performs the recognition tasks. Specifically, ARIMA-ML consists of four main modules: (1) pre-processing, (2) model parameter determination, (3) feature extraction, and (4) classification. The performance of the framework was validated using data from full-scale shaking table tests of a three-story steel frame making use of the average segment accuracy and confusion matrix. The validation experimental results demonstrated the robustness and accurate performance of the ARIMA-ML in all tasks. In addition, the feature importance (*FI*) score was analyzed to examine the most important features for damage detection and pattern recognition, illustrating the need for higher order coefficients and validating the superiority of the proposed framework.

Even though the number of AI-enabled SHM studies and applications is rising in the past five years, very few of them bridge the gap between ML/DL results and the final decision making procedure. In one of our ongoing project for developing the "Bridge Rapid Assessment Center for Extreme Events (BRACE2)", we developed a post-earthquake damage and functionality assessment framework and implemented it on Route 580/238 Separation in Hayward and demonstrated it with four other bridges. The developed framework uses the data to provide a real-time estimate of the bridge damage that can be used to inform decisions concerning whether to close the bridge to traffic and where to expect damage. At the core of the framework is a Decision-Making Platform (DMP) that utilizes data streamed in real-time from accelerometers along with limit states (LS) from component models as key features, e.g., [14], to extract using ML, response from a global bridge model subjected to the recorded ground motion signals, and ML/DL rapid recognition results. This facilitates the decision-making about the damage condition, location & severity, refer to [15, 16] for an earlier development of this DMP as a framework for Human-Machine Collaboration (H-MC). The H-MC framework combines ML tool using *novelty detection* and human (domain) expertise using structure-specific analytical model for damage assessment of instrumented structures with only data from undamaged cases. It was successfully used to detect undamaged and damaged 15 real instrumented buildings in California [13]. Moreover, such DMP can be expanded to be in terms of a full probabilistic formulation of the multi attribute utility theory (MAUT) for holistic designs/decisions. This was conducted in [11] where uncertainties were modeled by random variables defined through a performance-based engineering (PBE) approach to take into account not only safety issues in the face of extreme events such as major earthquakes, but also environmental responsibility and energy consumption.

In summary, the developed advances and obtained promising results in AI-enabled SHM studies shed light on the high potential of these state-of-the-art methodologies in more practical structural engineering applications. In future pursuits, improved monitoring, learning, maintenance, and ultimately effective decision-making regarding the conditions, replacement or retrofit of the built environment can be reliably achieved.

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