Review of Development on Convolution Neural Network Based Structural Health Monitoring on Bridges

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Abstract. Structural Health Monitoring (SHM) has been a rising interest in civil, mechanical and aerospace research. Bridge health monitoring system is able to issue early warning on damages as well as appraising the durability and reliability on bridges. Bridges are exposed to several damages such as wind, overloading and earthquakes, to ensure its structural integrity and avoid costly repairs on late stage deterioration, utilizing Machine Learning (ML) algorithms in SHM on complex structures becomes more essential to bridge SHM systems in order to assess structural damage. With the increasing number of studies on integrating convolutional neural network (CNN) in SHM on the bridge. This paper aims to provide a review on the development of CNN based SHM on bridges with a case study.

1. Introduction
With the increasing number of newly built bridges across the world. Increasing the safety and reliability of bridge structures is the priority. Not only does it reduce the number of casualties, but it is also influential to the normal operation of the society as an important public infrastructure for people to get across. The application of Structural Health Monitoring (SHM) plays a vital role in extracting sensitive features and detecting possible damage on bridges in advance as well as evaluating the conditions on global(vibration-based) and local of the structure. Newly built bridges covered with comprehensive sensors include Confederation Bridge in Canada [1], Tsing Ma Bridge in Hong Kong [2], Akashi-Kaikyo Bridge in Japan [3] and Pont de Normandie bridge in France. Bridges are subjected to different types of structural damage. This includes metal fatigue in girders, structural coating degradation, metal corrosion. With the help of computer vision and machine learning, we can save a lot of manpower and gain more insights into the as-built structure. However, current SHM systems required laborious data pre-processing to remove noise from the accumulation of a massive amount of heterogeneous data acquired by sensors due to instances such as sensor faults, environmental inputs. To effectively and efficiently detect, locate and quantify the structural damage, Convolutional Neural Network (CNN) was also developed to detect data anomaly. [4] The goal of the application of CNN in the bridge SHM system is to achieve: (i) autonomous monitoring free of human intervention and feature selection (ii) defects and anomaly detection (iii) early stage warning and post disaster reconnaissance (iv) low cost and accurate system.

2. Development of SHM and neural network
The development of SHM can be traced back to the 1960s, visual inspection on structures was widely used at that time by inspectors to localize and determine the degree of deterioration on the structure. Although it is effective on simple structures, however, for complex and large-scale structures, the method becomes impracticable and infeasible as it is time consuming even for experienced inspectors to locate and determine the degree and types of defects. Moreover, the method also relied heavily on the subjective experience and knowledge of the inspectors. By the 1980s, modal testing techniques were developed and used in civil, mechanical and aerospace engineering. Dynamic characteristics alter when there is damage in the structure. Methods such as modal curvature, modal flexibility and modal strain are used to identify damage in the structure. However, modal properties can be subjected to various factors. In the 1990s, the researches evolved into the integration of machine learning, application of back propagation (BP) neural network was being used by Kudva to detect damage on a structure [5]. Recently, several researches have been delved deeper into this field of study, the application of CNN is proposed and developed for bridge health monitoring systems.

2.1. Literature review
With a deeper understanding of convolutional neural networks, many researches have been carried out to detect damages to structures. Teng et al. [6] used CNN to detect structural damage with modal strain and it was found that CNN has excellent accuracy in detecting damages and outperformed back BP neural network. In addition, Chen et al. [7] also used CNN to successfully identified damages in cable hangers of a tied-arched bridge through numerical simulation. Furthermore, Kong and Li [8] propose a contactless and economical method to identify fatigue cracks based on examining the surface motion of the structure. Apart from the damage localization, recent researches also emphasize increasing the efficiency of the algorithm on pre-process datasets and avoiding over processing. [9] On top of that, several researches have been focusing on the use of unmanned aerial vehicles (UAV) to detect damage in inaccessible areas. [10]

2.2. Convolutional neural network algorithm
As machine learning algorithms can perform SHM tasks on knowledge-based systems, fuzzy logic algorithms. Convolutional neural network algorithm is a well-known deep learning neural network architecture that has been attained breakthroughs in recent years. [11] It was inspired by the visual cortex of the human brain. The idea of sparse-connectivity and parameter-sharing characteristics makes it very effective in extracting salient features which in turn becomes commonly used in deep learning to perform image classification and data mining. [12] After successfully prepared and labelled the acquired data, a typical CNN-based SHM assessment usually contains 4 stages: (i) choose the specific CNN architecture (ii) Model training and validation (iii) Hyperparameter optimization (iv) Testing and classification. As shown in Figure 1, the algorithm contains several layers of convolutions, deconvolutions, and pooling, activation, fully connected layers depend on its usage. Compare to other neural networks such as backpropagation (BP), CNN requires less network parameters but still has a stronger feature learning ability due to its convolution layer. The operation of convolution is defined as:

\[ x_j^l = f \left( \sum_{i=M} x_i^{l-1} \times k_{ij}^l + b_j^l \right) \]  

Whereas the × is the convolutional operation; \( M \) being the combination of input feature map; \( k \) is the convolution kernel of the \( i \)-th input feature map and \( j \)-th output feature map; \( x_j^l \) is the \( l \)-th network output; \( f \) is activation function and \( b_j^l \) is bias neuron. [13] The application of CNN can be generalized into two types based on its application, image processing based on computer vision and data processing based on data collected by SHM sensors deployed over the structures.
2.3. Application of CNN in data pre-processing
An SHM system is made up of several sensors over the bridge such as acceleration, strain, wind speed. With bridges covered by sensors and generates a huge amount of data each year, data pre-processing is essential to eliminate abnormal data. The use of CNN for data pre-processing can be applied throughout the phases of construction. [14] During the stage of construction control (CC), the real time data provides feedback on the progress. Next, in the routine monitoring (RM) stage, a large flux of data will be generated by sensors. These datasets present a real time evaluation of the structural health of bridges. Last, on the stage of damage detection (DD), data stored in the sensors can provide insights on the damage upon its occurrences or even in advance. Recent studies also focus on Region-based Convolutional Neural Network (R-CNN) [15] and Fast Region-based Convolutional Neural Network (Faster R-CNN) [16] framework to provide faster detection and localization from various structural damages. Although enormous efforts have been put into both software and hardware development on the wireless sensors of the SHM system, data or signal loss persists during the transmission. Taking the advantage of CNN’s non-linear learning features, it can be used to recover some of the lost data by compressive sampling techniques [17] and Bayesian multi-task learning [18]. In contrast to data loss, the issue of data overfitting is another area where CNN can be adopted. To resolve data overfitting, data augmentation is used to balance the training set during image pre-processing. To improve overall accuracy on the predicted data, the dropout technique is sometimes used which includes randomly neglecting some calculation unit in the neural network.

2.4. Application of CNN in vision based SHM
Identifying and evaluating fatigue cracks is vital, although visual inspection has been used for SHM for a long time. Due to the limitation of accessibility, for instance, confined and hazardous areas under bridges remain challenging for the inspector to assess the damage. CNN is known for its robustness in field computer vision and its algorithm is effective in perform feature extraction from input data. Therefore, vision based Yang et al. [19] used CNN on 400 manually labeled images and fine-tuned the parameters to estimate the existence of cracks on asphalt pavement in several road sections on Da Nang city. Liang [20] used images collected on RC bridges around the world to determine the system-level failure classification and local damage-level damage localization. Apart from detecting damages, the use of CNN based SHM system on bridges can also be integrated with intelligent transport systems (ITS). Hou et al [21] proposed a framework that synchronized cameras, bridge monitoring system and weigh-in-motion (WIM) station. CNN detector was used to reidentify trucks and link corresponding vehicle weights to the bridge responses automatically. To better utilize our computer vision sensors and the algorithms, the application of UAVs and global positioning systems (GPS) [22] were also introduced to SHM systems, meaning that more comprehensive analysis can be done on the structure especially in areas that are unsafe and isolated environment. The aim is to learn damage sensitive features from images and developing autonomous UAVs navigation with quasi-real time detection. Despite some barriers that hinder this technology from the application such as legal restrictions, researches on developing computer vision-based non-contact sensing techniques have been very popular recently and have made significant progress.
3. Case study
In a case study of a long-span cable-stayed bridge, raw acceleration data were collected from the monitoring system of 38 channels throughout the year. [23] The raw datasets were plotted in sections of time and frequency domain respectively using Fast Fourier Transformation (FFT) and overlay one image on the other to obtain Time-Frequency(T-F) image. The T-F image is then being grouped into different anomaly patterns such as normal, minor, missing, outlier and train classifier under supervised learning. According to the data, the best results were obtained by a balanced set with an accuracy of 93.5±0.5% at a training ratio of 0.03. Although the result shows an imbalanced training set obtained the highest overall accuracy of 94.2±0.1% at the same training ratio. However, the effect of imbalance datasets presents a high misclassification rate on the class of Outlier (95%) and Drift (85%).

![Figure 2. Testing result of different groups](image)

A comparative study was also conducted to analyze the performance of the CNN-based anomaly detection method in comparison with deep neural networks (DNN)-based anomaly detection. The results are shown in Figure 3. The comparative studies displayed the exceptional performance of the CNN-based framework in data anomaly classification. It also showed that the CNN-based framework is efficient in intimating human vision and making the decision with high accuracy for data pre-processing. This makes a sound validation of the application of machine learning in maintaining and managing bridges.

![Figure 3 Test results of CNN and DNN on different groups](image)

4. Conclusion
Progressing from wired sensors to wireless sensors, short term SHM to long term comprehensive SHM system, there is an increasing number of breakthroughs in the area of SHM, sensing technology and machine learning algorithms. In particular, with more powerful CNN approaches and more computing power than we used to, we can train the neural network to have higher accuracy. However, there are a
lot of factors constraining us from achieving state-of-the-art SHM systems. For instance, as the neural network gets deeper and deeper, more dataset and computation power are required. We should continue to delve into the unsupervised learning of CNN. Overall, the use of CNN is an effective, accurate and economical method in implementing SHM on bridges. This study explores the development of researches in the field of CNN based application in the SHM system on bridges. Numerous methods and techniques were discussed in this study that aim to provide more insights for researchers to strive towards a better system in the future.

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