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Advances in Artificial Intelligence for Structural Health Monitoring

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Abstract: With the continuous advancement of infrastructure development, ensuring the health and safety of existing structures has become increasingly critical. Structural Health Monitoring (SHM) plays a vital role in assessing the integrity and longevity of buildings, bridges, and other infrastructures. However, traditional monitoring methods often face challenges related to efficiency, accuracy, and cost-effectiveness. The rapid development of Artificial Intelligence (AI) has opened new opportunities for SHM, offering intelligent, automated, and highly precise monitoring solutions. By integrating AI with SHM, it is possible to enhance detection accuracy, improve predictive maintenance, and significantly reduce operational costs. This paper aims to provide a comprehensive summary of AI technologies that have been successfully applied in the field of SHM. By reviewing current advancements, we seek to contribute to the ongoing development of intelligent monitoring systems and offer new perspectives on the future integration of AI in SHM.

Keywords: Artificial Intelligence, Structural Health Monitoring, Challenge, Applications

1. Introduction

With the continuous advancement of infrastructure construction such as roads and bridges, it greatly facilitates people's lives and promotes economic development [1]. However, due to natural or man-made factors, the performance of these structures inevitably deteriorates over time, leading to potential structural damage. If undetected and unrepaired, these damages may result in serious accidents, highlighting the critical need for effective structural health monitoring (SHM) [2].

Traditional SHM methods are often time-consuming, low efficiency, and high cost. The emergence of artificial intelligence (AI) technologies has provided new momentum for SHM, offering promising solutions to these challenges. Recent research has demonstrated that AI-based SHM approaches have been successfully applied in practice and achieved notable results.

This paper summarizes the progress in integrating artificial intelligence with structural health monitoring, aiming to advance the development of the combination of intelligent SHM systems and provide new ideas for future direction.

2. Artificial intelligence improves traditional SHM

The fundamental principle underpinning damage detection algorithms is that the structural characteristic parameters are functions of the physical properties of a structural system, consisting of mass, damping, and stiffness. Consequently, alterations in these physical properties invariably result in modifications to the structural characteristics parameters. It is hypothesized that damage has the capacity to modify structural stiffness and mass, thereby affecting the structural responses measured from an array of sensors interconnected within a SHM system [3]. However, traditional means of SHM face challenges in terms of economics and accuracy. Economically, these systems often require the deployment of numerous wired sensors, involving complex installations and expensive equipment that demand substantial initial investment, particularly for large-scale structures. In addition, specialized personnel are needed for installation, commissioning, and regular maintenance to ensure data accuracy. Finally, the large amount of data collected requires significant resources for storage, management, and analysis, further increasing costs [4]. In terms of accuracy, environmental factors such as temperature and humidity produce more noisy data, which affects the accuracy of the data. Additionally, the traditional data analysis methods struggle to handle the large volume and complexity of the data, often resulting in significant errors. Furthermore, traditional methods often fail to realize real-time monitoring, and may fail to detect structural damage in a timely manner [5].

The introduction of AI can be a more effective solution to the problems of traditional methods mentioned above. To address the economics aspect, the application of AI can reduce the time it takes for this monitoring system to detect structural damage. In structural health monitoring, both machine learning and covariance methods consider environmental impacts. The cointegration approach detected the damage within 10 hours and 15 minutes, while the machine learning method detected it within 20 hours and 30 minutes, both without false alarms, which is faster than traditional methods. AI methods are able to quickly and accurately detect structural damages at no additional cost, thus improving the economics of monitoring [6]. ML technology, especially Convolutional Neural Network (CNN), can automatically process and analyze a large amount of monitoring data to achieve efficient identification of damages such as concrete cracks and steel corrosion, thus reducing reliance on manual inspection and lowering operational costs. In addition, ML methods can optimize the data preprocessing process, improve the accuracy and efficiency of data analysis, and further enhance the economic benefits of SHM systems. Through these technical means, ML demonstrates significant cost-saving and efficiency-enhancing advantages in bridge SHM [7]. The potential of deep learning (DL) techniques to reduce reliance on expensive sensors in structural health monitoring (SHM). DL methods are able to process and analyze data from low-cost sensors or non-contact data sources (e.g., images and videos) to enable efficient identification of structural damage, thereby reducing the reliance on traditional high-cost sensors. In addition, DL technology can be integrated with devices such as Unmanned Aerial Vehicles (UAVs) to capture image data from hard-to-reach areas, further improving the economics and efficiency of monitoring. Through these technological means, DL demonstrates significant cost-saving and efficiency-enhancing advantages in SHM [8].

AI is just as effective at solving accuracy problems. A residual convolutional neural network (ResNet)-based method for denoising vibration signals can improve the accuracy of structural health monitoring (SHM). The method makes the model better at handling various kinds and levels of noise by using techniques like dropout, jump connection, and sub-pixel rearrangement. In the measured acceleration data of Guangzhou New TV Tower, after applying the method, the weakly excited modes and near modes that were originally masked by noise are clearly identified, which significantly improves the accuracy of modal identification. In addition, the model also shows good denoising effect when dealing with pink noise data not included in the training data, demonstrating its wide adaptability under complex environmental conditions. By automatically extracting high-level features in vibration signals, the ResNet model can keep essential vibration details and help tell apart real physical modes from fake ones, which makes the SHM system more reliable and accurate in real-world use [9]. When the Temporal Fusion Transformer (TFT) deep learning model is applied to the long-term dynamic monitoring of the Guinigi Tower in Lucca, Italy, the model is trained to incorporate the experimental frequency data of the tower and other environmental parameters, and is able to predict vibration characteristics (e.g., root-mean-square (RMS) values of intrinsic frequency and velocity time series), to and detect anomalous or unexpected events by comparing the deviation of the actual frequency from the predicted frequency. The method successfully identifies the effects of the February 6, 2022, Viareggio earthquake as well as structural damage induced by three simulated damage scenarios, demonstrating its ability to reduce analytical errors and improve monitoring accuracy under complex environmental conditions. By fusing multi-source time-series data, the TFT model effectively reduces the interference of changing environmental and operational conditions on the monitoring results and enhances the reliability of the SHM system in historic buildings [10]. An outlier detection method incorporating artificial intelligence techniques can improve the accuracy of structural health monitoring (SHM) under changing environmental and operational conditions. The method utilizes machine learning algorithms to model the behavior of a structure under normal conditions and identifies potential structural damage by analyzing the residuals between new observations and a reference model. Experimental results show that this AI-driven outlier detection method can effectively differentiate signal changes due to changes in environmental and operational conditions from actual structural damage, reduce the false alarm rate, and improve the reliability and accuracy of the SHM system under complex environmental conditions [11].

In summary, the application of AI in structural health monitoring can reduce the impact of environmental factors on the accuracy of measurement data and ensure the reliability of the monitoring system even in complex outdoor environments. Meanwhile, AI is also more advantageous than traditional methods when dealing with large amounts of complex data, which can significantly reduce errors and improve efficiency. In addition, the application of AI can also improve economics by increasing efficiency, reducing monitoring time, and decreasing reliance on expensive data collectors.

3. Emergence of deep learning for SHM

In the field of SHM, deep learning models are increasingly used, especially in damage detection, condition assessment, and fault diagnosis. Deep learning techniques help researchers extract meaningful features from large amounts of complex sensor data and perform accurate prediction and analysis through their powerful data processing and pattern recognition capabilities. Common deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Autoencoder, Deep Neural Networks (DNN), Generative Adversarial Networks (GAN), and Reinforcement Learning (RL), each contribute to the field of SHM in different ways.

Convolutional Neural Networks (CNNs) are primarily used to process image and signal data, and are particularly suited to dynamic response data acquired through sensors. These data are usually recorded by vibration, strain, infrared thermography, etc. After converting them into image format, CNNs are able to recognize signs of structural damage by automatically extracting features from the image or signal through their multilayer convolutional structure. The advantage of CNNs is that they can perform feature extraction efficiently without the need for manually designing complex feature selection algorithms. Therefore, CNNs not only excel in image processing but also show great potential in vibration signals, strain data, and other time-frequency domain converted signals, especially for damage detection in complex environments [12].

Recurrent Neural Networks (RNN) and their variants (e.g., LSTM and GRU) are, on the other hand, suitable for the analysis of time series data. In Structural Health Monitoring (SHM), sensor data are often changing signals collected over time, and RNNs can handle these time-series data while remembering information from previous moments to understand the relationships in the signals. LSTM (Long Short-Term Memory Network) and GRU (Gated Recurrent Unit) are advanced types of RNNs that can more effectively handle long sequences of data without losing important

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information or facing issues with gradients, making them very effective in SHM for tasks like analyzing vibrations, detecting damage, and predicting faults. For example, with LSTM modeling, researchers are able to capture potential damage features from the dynamic response of a structure and thus detect structural problems at an early stage [13].

Autoencoder is an unsupervised learning model widely used for feature learning and anomaly detection in SHM. An auto-encoder learns the underlying structure of the data by compressing the input data into a low-dimensional representation (encoding) and then decoding the reduction to the original data. In SHM, self-encoders are commonly used in damage detection tasks. Under normal conditions, the model is able to reconstruct the undamaged structural data well, while the reconstruction error increases when damage occurs to the structure. By monitoring these reconstruction errors, the damage of the structure can be determined. This makes the self-encoder an important tool in SHM, which is especially suitable for scenarios without labeled data and has significant advantages [14].

Deep Neural Networks (DNN) are a class of multilayer feed-forward neural networks that are used in SHM for damage classification, regression analysis, and structural health state assessment. DNNs learn nonlinear relationships in data through multiple hidden layers, and can be used to predict the type of damage to a structure or to assess its state of health from the input sensor data. For example, by using DNN models, researchers can classify different types of damage to a structure, such as cracks, corrosion, and fatigue damage. In addition, DNN is widely used to predict structural response in different environments and help assess the impact of external factors on structural health. Compared with traditional physical models, DNNs have stronger learning capabilities and can automatically extract effective features from complex sensor data for more accurate damage diagnosis [15].

Generative Adversarial Network (GAN) is a model that generates new data by training two adversarial networks (generator and discriminator). The main application of GAN in SHM is in data enhancement. Since damage data, in particular, is usually scarce in structural health monitoring, GAN can increase the generalization ability of the model by generating virtual damage data and expanding the training set. This is important in some specific applications, especially when there is not enough actual damage data. By generating different types of damage data, GAN can help train more robust deep learning models to further improve the accuracy and reliability of damage detection [16].

Reinforcement learning (RL), on the other hand, can be used to develop adaptive monitoring strategies and optimize the decision-making process. In SHM, reinforcement learning can help to automatically adjust the sensor arrangement and select the appropriate monitoring scheme, thereby improving the efficiency of damage detection. For example, through reinforcement learning, the system is able to continuously optimize the monitoring strategy based on the feedback of sensor data in order to perform the most effective damage detection under various environmental conditions. Reinforcement learning can also be used in fault diagnosis and decision support systems to help automate the identification of potential faults in structures and give appropriate maintenance recommendations [17].

4. Challenge in real-world applications

The application of AI in SHM faces multiple challenges, especially in handling complex and massive data, model interpretability, real-time, and data scarcity.

First, SHM systems need to collect a large amount of heterogeneous data from a variety of sensors, including different types of data, such as vibration, temperature, strain, and images. Processing these diverse data and extracting meaningful features from them is a significant challenge for AI models, especially when the types and formats of the data vary widely [18].

Second, many AI technologies, especially deep learning models, are often viewed as black boxes, their internal mechanisms are not easily explained or understood. This lack of transparency is

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particularly acute in the field of structural health monitoring, where engineers and decision-makers need to be confident enough in the results to take necessary repair or preventive measures. Therefore, how to improve the interpretability and transparency of AI models to make them more responsive to the needs of engineering applications is an urgent issue [19].

In addition, the application of AI in SHM faces real-time issues. In many cases, especially in health monitoring of large structures such as bridges, sensor data need to be processed and analyzed in real time. This requires AI systems to be able to run on devices with low power consumption and limited computing resources in order to give timely feedback in the field. However, monitoring and processing large amounts of data in real time is still a huge challenge, especially in edge computing environments, and how to ensure immediate analysis of data and accurate decision-making is one of the difficulties in AI applications [20].

Finally, insufficient data and labeling difficulties remain common challenges in AI applications. In many structural health monitoring projects, the scarcity of damage events leads to a lack of labeled data, while the effective training of AI models typically relies on large volumes of annotated datasets. Therefore, how to effectively solve the data insufficiency and realize unsupervised learning or a small amount of supervised learning becomes a key factor to improve the application of AI in SHM [21].

Overall, although AI technology shows significant potential in structural health monitoring, further technological advances and practical validation are needed to overcome the above challenges in practical applications. Solving these problems will provide a solid foundation for the popularization and application of AI in SHM and promote the realization of intelligent and efficient structural health monitoring systems.

5. Conclusion

At present, accidents caused by structural damage occur frequently at home and abroad, resulting in a large number of economic losses and casualties, so the technology of structural health monitoring has been widely used. However, there are some shortcomings in its economy and accuracy, and the rapid development of artificial intelligence in recent years has provided the possibility of improving the technology of structural health monitoring. The combination of these two technologies not only reduces the cost of structural health monitoring, but also improves the anti-interference ability of the monitoring system and the accuracy of monitoring. Among them, deep learning is the most widely used, in which various models have different applicable scenarios. When dealing with large-scale and complex data, deep learning can extract valuable information from massive sensor data, eliminate noise data, and greatly improve the efficiency and accuracy of monitoring.

However, there are several challenges in the application of AI in structural health monitoring. First, the processing of massive heterogeneous data poses significant difficulties. This issue can be addressed through data fusion techniques, which integrate multiple data types from different sensors into a unified representation. Methods such as sensor network integration, dimensionality reduction using autoencoders and feature extraction via convolutional neural networks (CNNs) can effectively optimize the data processing flow. Second, the lack of interpretability in AI models, often referred to as the "black box" problem, limits their practical application. To address this, the development of interpretable deep learning models is essential. By designing interpretable neural networks or integration methods, the output of the model can be interpreted by rational rules and feature associations. Third, the scarcity of labeled data remains a critical bottleneck. This challenge can be mitigated by employing data augmentation techniques, such as Generative Adversarial Networks (GANs), to synthetically generate damage scenarios and expand training datasets. In addition, unsupervised learning or semi-supervised learning methods can be used to reduce the dependence on a large amount of labeled data, especially through self-supervised learning and migration learning to improve the generalization ability of the model. In case of insufficient data, active learning techniques

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can be used to intelligently select the most representative data for labeling, thus improving the performance of the model. Future research should focus on addressing these key challenges to enable the large-scale, practical deployment of AI technologies in structural health monitoring.

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