Machine Learning Based Quantitative Damage Monitoring of Composite Structure

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ABSTRACT

Composite materials have been widely used in many industries due to their excellent mechanical properties. It is difficult to analyze the integrity and durability of composite structures because of their own characteristics and the complexity of load and environments. Structural health monitoring (SHM) based on built-in sensor networks has been widely evaluated as a method to improve the safety and reliability of composite structures and reduce the operational cost. With the rapid development of machine learning, a large number of machine learning algorithms have been applied in many disciplines, and also are being applied in the field of SHM to avoid the limitations resulting from the need of physical models. In this paper, the damage monitoring technologies often used for composite structures are briefly outlined, and the applications of machine learning in damage monitoring of composite structures are concisely reviewed. Then, challenges and solutions for quantitative damage monitoring of composite structures based on machine learning are discussed, focusing on the complete acquisition of monitoring data, deep analysis of the correlation between sensor signal eigenvalues and composite structure states, and quantitative intelligent identification of composite delamination damage. Finally, the development trend of machine learning-based SHM for composite structures is discussed.

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1. Introduction

Advanced composite materials have been widely used in many large structures in the fields of aerospace, wind power generation, rail transit, high-tech ships, due to the advantages of high specific strength and stiffness, designable mechanical properties of materials, and convenient integral molding [1,2]. The use of composite materials has become an effective way to reduce the weight of significant structures, improve the efficiency and reduce the operating costs. Composite structures have to withstand not only the complex fatigue loads and unexpected impact loads, but also the harsh external environmental factors such as temperature and humidity. These factors, whether acting individually or simultaneously, can lead to the deterioration or even destruction of composite structures. The timely detection of damage in composite structures is of great significance to avoid sudden damage and structural failure [3,4].

It is difficult to analyze the integrity and durability of composite structures due to their own characteristics and the complexity of load and use environment. Although the existing conventional nondestructive testing (NDT) technology can play a certain role in the damage detection of composite structures, it can neither perform on-site real-time monitoring, nor detect the damage in hidden parts, and is also greatly affected by human factors. In addition, the existing NDT technology is not only expensive to detect large-scale composite structures, but also difficult to meet the requirements of various aspects in terms of detection speed and efficiency. How to effectively and intelligently monitor the composite structure states in real time, conduct online diagnosis, evaluate the structural reliability and integrity is a key technology that needs to be solved urgently.
Structural health monitoring (SHM) technology based on distributed sensor networks permanently integrated on the surface of or embedded inside composite structures is a revolutionary and innovative technology for determining the structural integrity of composite materials [5–12]. Through the built-in sensor network on the composite structure, the SHM technology obtains the information of the structure state and service environment in real time, so as to grasp the health status of structure in real time, and further predict the possible damage and failure, so that it can take timely action to ensure the safe use of the structure. SHM provides an important technical basis for establishing condition-based maintenance strategies based on the actual health and performance of structures to improve the safety and reduce the operation and maintenance costs. SHM can be generally divided into four levels: (1) determine whether the structure is damaged, (2) identify the location of damage, (3) assess the severity of damage, and (4) predict the remaining useful life of the structure. It can play an important role in the whole life cycle of composite structure, including design, manufacture, service and maintenance.

In the past two decades, many scholars carried out a lot of research work on the damage monitoring of composite structures, and proposed a variety of monitoring methods based on physical models [4–19]. However, most of them can only qualitatively monitor the structural damages under laboratory conditions. In the face of complex damage modes of composite structures and their service environments, most of these methods have limitations such as insufficient complete monitoring data, unclear sensing mechanism and unintelligent diagnosis algorithm, and difficulty to provide robustness quantitative damage monitoring results. With the advent of the era of big data, new technologies led by machine learning have been developed rapidly. A large number of machine learning algorithms have been applied in many disciplines. They are also being applied in the field of SHM [20,21]. The advantage of machine learning is not to require specific physical models, but is directly driven by massive data, mining its implicit internal laws from a large number of historical sample data, and using the laws to intelligently identify or predict new sample data. It has powerful clustering, regression and classification capabilities.

Accordingly, a method combining multi-functional sensor network with numerical simulation and generative adversarial network (GAN) is needed to fully obtain multi-source heterogeneous information characterizing the structural state of composite structures. By analyzing the feature information contained in the multi-field coupled sensing signals, the mapping relationship between the eigenvalues of the multi-source heterogeneous signals and the structural state parameters of the composite structures can be revealed. Finally, a variety of modern machine learning algorithms can be combined to build a deep migration diagnosis network for feature adaptive characterization and quantitative identification of damage in composite structures, which is an effective way for quantitatively monitoring the damage in composite structures.

This paper first briefly outlines the damage monitoring technologies often used for composite structures. Then, the application status of machine learning in composite damage monitoring are focused on review. Finally, the challenges and solutions for quantitative damage monitoring of composite structures based on machine learning are discussed, as well as the development trend of SHM based on machine learning.
2. Damage monitoring technology of composite structure

As a widely used load-bearing structure, the composite structures are subject to the comprehensive effects of different static/dynamic loads and environmental factors during service, and are prone to various complex damage modes, such as delamination, debonding, matrix cracking and fiber breakage, where the delamination is the most typical damage form of the carbon fiber reinforced resin matrix composite structures. Due to the inconsistent laying angles of the upper and lower layers of composite structure, there is a difference in stiffness, resulting in uncoordinated deformation, and interlayer stress difference. When this interlayer stress difference exceeds the shear strength between the layers, the delamination in composite structure will occur. The delamination will lead to a significant decrease in the compressive strength and bearing capacity of composite structures. However, the delamination of composite structures (especially the small damage caused by low-speed impact) is difficult to detect from the surface, which brings great risk to the safe service of composite structures. Therefore, it is of great significance to identify the size and location of early delamination and evaluate its impact on the structural integrity to ensure the safe and reliable operation of composite structures.

The functions of SHM can be summarized into three aspects: (1) Monitoring structural loads and environmental parameters, such as the flight speed of aircraft, aerodynamic pressure. (2) Sensing structural state parameters, such as strain/stress, temperature. (3) Monitoring structural damage, including delamination, debonding, etc. According to the different monitoring objects, choosing the right sensor is the primary task of SHM. The following briefly introduces the advanced sensing technology of SHM and the typical methods for damage monitoring of composite structures.

2.1 Advanced sensor technology

Many types of sensors can be used for SHM, including optical fibers, piezoelectric materials (such as piezoelectric lead zirconate titanate (PZT)), nanomaterials, air/vacuum galleries, eddy current foil sensors [22–26], besides traditional sensing systems. Table 1 lists the sensors commonly used for structural health monitoring in the field of aerospace.

For monitoring the structural state, optical fiber sensors have great advantages and can be used to monitor various state parameters such as temperature, strain, and aerodynamic pressure [26–29]. Piezoelectric sensors have been widely used in damage monitoring of composite structure due to its light weight and small size, as well as the capability for being used as either actuators or sensors [6,30,31].

Sensor networks integrated on the monitored composite structures are an important part of SHM. How to integrate the networks with composite structures is the first problem needs to be solved in SHM. The SMART Layer proposed by Stanford University provides a convenient and effective means for integrating sensor networks with the monitored structures [32–34]. Distributed sensor networks are embedded on thin, flexible film carriers. According to different requirements, the SMART Layer have different structural forms. In addition to the commonly used piezoelectric sensors, the SMART Layer can also integrate other types of sensors, such as strain, temperature and humidity sensors [35,36]. It can either be mounted on the surface of existing structures or embedded inside composite structures during fabrication, as shown in Figure 1.
Due to the large size of composite structures and many state performance parameters, a large-scale multifunctional sensor network is usually required to sense the structural state and monitor structural damage. The concept of multi-modal sensing capabilities with built-in sensor network was proposed [37], and an expandable lightweight polymer-based flexible sensor network that can carry multiple types of high-density sensor arrays was developed at Stanford University and Xiamen University [38–42]. Learning from the design process of microelectronic integrated circuits, the polyimide film is processed into a stretchable microwire network, and the excess base material other than the network wire is removed. By stretching in all directions, the network can be expanded from a microscopic size to the macro scale. If various types of sensors, excitation sources, electronic components or other functional materials are placed on the functional nodes, and the functional nodes are connected by micro-wires, a sensor network is formed, as shown in Figure 2 [6]. Similar to the above-mentioned SMART Layer, the expandable flexible multifunctional sensor network can be mounted to the surface of composite structure or embedded inside the composite structure to monitor the state during its life cycle.

2.2 Damage monitoring of composite structure

The damage monitoring of composite structure during service can be divided into two categories: one is to monitor the random damage in a large area, where the damage location is unknown (such as delamination caused by external impact). The other is to monitor the damage at a local high stress area, where the damage location is approximately known.

Since the ultrasonic guided wave can propagate a long distance in the structure, and is sensitive to the damage such as delamination, debonding, and cracks in the composite structure, the damage monitoring technology based on ultrasonic guided wave is currently the most effective technology for the active monitoring of composite structural damage in a large area [43]. It usually uses piezoelectric elements as actuators and sensors, and ultrasonic guided waves as damage information transmission medium to actively monitor the damage and its expansion of composite structures in real time. The basic principle of the damage monitoring technology based on ultrasonic guided wave is shown in Figure 3. The piezoelectric element used as actuator generates ultrasonic-guided wave in the structure, while the surrounding piezoelectric elements used as sensors pick up the guided waves propagated through the structure. When damage occurs, the arriving time $T_D$ of guided waves picked up by the sensors will delay, and the amplitude $W_D$ will decrease, comparing to the arriving time $T_B$ and amplitude $W_B$ of baseline signals without damage.

The damage diagnosis algorithm is the core of damage monitoring based on ultrasonic guided wave. A variety of damage monitoring algorithms have been developed, including phased array [44–46], delay and sum (DAS) [47,48], tomography [49,50], elliptical weighted distribution damage imaging [51–53], time reversal [54,55], and other methods. In phased array algorithm, several PZTs in the sensor network are used to form a dense sensor array. It is the same as the principle of a radar that the phase of excitation signal of each PZT can be adjusted independently so that Lamb wave propagation can be focused on the specific direction for the far field or on the specific location for the near field.
because of the sum of Lamb wave field excited by all PZTs. In the DAS algorithm, according to the damage scattering signal received by multiple pitch-catch paths, the damage is located according to the group velocity and the propagation time of guided wave. In the tomography algorithm, sensors are usually arranged around the monitored area and form a great number of transmitting-receiving paths. The monitoring principle is that the signal changes of guided wave varying with the damage are fusing to contour the damage. More details about these algorithms can be found in literature [6].

However, due to the material properties and structural complexity of composite structures (such as material anisotropy, variable thickness structures, structures with curvature, and reinforced structures, etc.), the propagation of guided waves in these structures is very complicated. It is difficult to obtain accurate wave speeds, and compensate the effect of environmental noise, most of methods are challenging in terms of reliability and effectiveness when applied to actual composite structures in real world.

Some key areas of composite structures, such as bolted joints, not only bear cyclic loads, but also have complex nonlinear coupling factors. The probability of damage occurring is relatively high at these key areas. Local damage diagnosis techniques must be developed for these structures [6]. Some local damage monitoring methods based on new sensor technologies have been proposed, including comparative vacuum monitoring (CVM) [56], intelligent coating monitoring (ICM) [57], flexible eddy current (FEC) sensors [58–60], PZT sensors [61–69], acoustic emission (AE) sensors [70–72] and other monitoring methods. The monitoring modes of these methods are shown in Table 1.

Local damage monitoring methods based on PZT sensors include electromechanical impedance method and ultrasonic guided wave-based monitoring. The generation and expansion of local damage in the composite structure will affect the electromechanical impedance response of the area around the damage, so the local damage of structure can be characterized by monitoring the impedance change of the piezoelectric sensor mounted on the structure. The ultrasonic guided wave method of piezoelectric sensors is also one of the most common methods for local damage monitoring of key areas.

Compared with the monitoring methods based on CVM, ICM, and flexible eddy current sensors, the ultrasonic guided wave monitoring method of piezoelectric sensors has two main advantages: (1) The piezoelectric sensors can be far away from the damaged area, it can monitor the damage on the propagation path of

| Monitoring principle                  | Sensor                                      | Monitoring object   | Monitoring mode |
|--------------------------------------|---------------------------------------------|---------------------|-----------------|
| Strain                               | Fiber optical sensor (e.g. FBG)             | Loads and impact    | Passive         |
| Wave propagation                     | Stress wave                                | Impact              | Passive         |
| Wave propagation                     | Acoustic emission                          | Global/local damage | Passive         |
| Ultrasonecs                          | Guided wave                                | Global/local damage | Active          |
| Electro-mechanical impedance         | Piezoelectric electromagnetic/sensor        | Local damage        | Active          |
| Electric resistance                  | Piezoelectric sensor                        | Local damage        | Active          |
| Intelligent coating monitoring       | Piezoelectric sensor/laser                  | Local damage        | Passive         |
| Comparative vacuum monitoring        | Nanomaterial                                | Local damage        | Passive         |
| Eddy current                         | Air/vacuum galleries                       | Local damage        | Passive         |
| Eddy current                         | Eddy current foil sensor                   | Local damage        | Active          |
Lamb wave. (2) It can monitor various damage forms inside and on the surface of the structure, including cracks, delamination, debonding, holes, etc. The quantification of damage is the difficulty of ultrasonic guided wave monitoring of piezoelectric sensors. Currently, the quantitative monitoring of damage expansion of complex composite structures usually needs to be realized by semi-empirical methods, which has great limitations in practical engineering applications.

Most of the damage monitoring methods based on ultrasonic guided waves need to collect the baseline data of the structure without damage, and compare the current sensor date with the baseline data to determine if the damage occurs. However,
environmental changes such as temperature, load, humidity, and radiation can also cause changes in sensor signals, which interfere with signal changes caused by actual damage, resulting in false alarms.

A variety of temperature compensation techniques have been developed to reduce the effect of temperature change, such as baseline signal stretch (BSS) [73], optimal baseline subtraction (OBS) [74], combination of BSS and OBS [75,76], and combination of adaptive filtering (AF) and optimal baseline selection [77]. In view of the limitations of monitoring method using baseline data, Baseline-free damage monitoring technologies have been proposed, especially the baseline-free time inversion method [55,78–81]. However, due to the complexity of the composite structures and the complex signal reconstruction, it is difficult to apply the damage monitoring algorithms without baseline in practical engineering. Therefore, it is urgent to explore structural health monitoring methods that can quantitatively identify the location, size, interface depth and other parameters of damage in composite structures.

Figure 2. Expandable multifunctional sensor network [6].

Figure 3. Principle of damage monitoring technology based on ultrasonic guided wave [4].
In addition, real-time monitoring of external impacts occurring on composite structures can be performed by passive SHM systems [82–86]. According to the position and energy of the external impact obtained from the passive SHM system, the damage caused by the external impact can be determined by combining the relevant theory of composite mechanics and numerical calculation.

3. Machine learning for damage monitoring of composite structure

Machine learning is divided into supervised learning, unsupervised learning and other machine learning according to whether labeled data is used [87]. The application of machine learning in SHM includes two main steps: (1) Combine advanced sensing technology and numerical simulation methods to obtain monitoring data that can characterize the state of structural damage. (2) Use machine-learning methods to mine the hidden properties of the monitoring data, and complete intelligent diagnosis of structural damage. The specific process of machine learning for damage monitoring of composite structures is shown in Figure 4. Both experiments and simulations are utilized to obtain monitoring data. After signal processing and analysis, the features of monitoring data are extracted and input to the machine learning algorithms. The machine learning algorithms further mine the hidden properties of the monitoring data and intelligently identify the damage in composite structure.

Currently, machine learning has many applications in structural health monitoring based on several sensing technologies, such as ultrasonic guided waves, strain, acoustic emission, structural vibration and electromechanical impedance, extracting features from frequency domain, time domain, time-frequency domain, impedance domain, and modal analysis domain [88–92]. This section summarizes the application of machine learning in damage monitoring of composite structures, including damage pattern recognition, damage location, and damage size quantitative monitoring.

3.1 Application of machine learning in damage monitoring based on ultrasonic guided waves

Ultrasonic guided wave monitoring based on piezoelectric sensors is one of the most common and effective methods for monitoring damage in composite structures. The monitoring principle is that when the ultrasonic guided wave signal passes through the damage in composite structure, various signal changes such as reflection, scattering, energy attenuation, and mode transition will occur [93]. By identifying these signal changes, the damage diagnosis can be realized, as shown in Figure 3. The application of machine learning in damage monitoring based on ultrasonic guided waves is mainly divided into two categories: one is the classification of health and damage status; the other is damage localization and quantification. Figure 5 summarizes the basic process for using machine learning to achieve the classification of health and damage status of composite structures or damage localization and quantification for ultrasonic guided wave monitoring. The steps can be summarized as: (1) The guided wave signals are obtained from experiments and/or numerical simulations. (2) The time-frequency domain features of the ultrasonic guided wave signals are extracted according to the signal processing method. (3) The features of signals are input into the machine learning
algorithms for training and testing to achieve the goal for monitoring damage in composite structures. The application of machine learning in ultrasonic guided wave damage monitoring is generally based on this basic paradigm, with differences in data analysis methods or machine learning algorithms.

In the classification of health and damage status of composite structures based on ultrasonic guided wave monitoring, some researchers used supervised learning methods, including artificial neural network (ANN) [94], Support Vector Machine (SVM) [95,96], Linear Discriminant Analysis (LDA) [97], Bayesian method [98], K-Nearest Neighbor (KNN) [99], etc. Some others tried to integrate a variety of different machine learning algorithms to achieve the goal of damage classification [100]. In addition, there are studies using unsupervised learning, such as Self-Organizing Map (SOM) [101,102], Gaussian Mixture Model (GMM) [103,104], Principal Component Analysis (PCA) [104].

In terms of damage localization and quantification, supervised learning is often focused, mainly including ANN [105-109] and Convolutional Neural Network (CNN) [110-117]. In view of the excellent performance of CNN in two-dimensional image feature extraction, ultrasonic guided wave signals are often converted into pictures by continuous wavelet transform or discrete wavelet transform. The pictures are then input to the CNN for training to establish a complex mapping relationship between the picture data and the damage location or degree of damage, and the localization and quantification of damages in composite structures will be finally determined [110-113]. There are also studies using one-dimensional CNN to directly train ultrasonic guided wave data for damage localization [114-117]. In addition, Bayesian Neural Network (BNN) [118], SVM [119,120], Random Forest (RF) [121], Bayesian method [122,123], Multiple Linear Regression (MLA) [124] were also used to identify the location, size and shape of delamination in composite structure. In order to improve the accuracy of damage localization and quantification, some studies have also combined Autoencoders (AE) and SVM [120] to greatly improve the robustness and portability of prediction networks, which is of great significance for future industrial applications. Figure 6 summarizes the typical applications of machine learning in damage monitoring based on ultrasonic guided waves in recent years.

### 3.2 Application of machine learning in damage monitoring based on acoustic emission

Acoustic emission (AE) is the transient elastic waves within a material, caused by the rapid release of localized stress energy. Detection and analysis of AE signals can supply valuable information regarding the origin and importance of a discontinuity in a material. It has many industrial applications, including assessing structural integrity, detecting delamination [125,126]. Figure 7 summarizes the basic process for using machine learning to achieve the SHM based on AE. The general idea is to use the acoustic-electrical conversion of piezoelectric sensors to collect the AE signals, and then use signal processing methods to extract the characteristics of AE signals such as rise time, energy, duration, amplitude,
peak frequency, absolute energy or ringing count [127]. Then, an appropriate machine learning algorithm is selected to train and test the selected features to achieve the goal of damage monitoring.

The application of machine learning in damage monitoring based on AE mainly focuses on the classification of health and damage status of composite structures, and most of the methods used in literatures are unsupervised learning, including K-means [128–131], PCA [132], GMM [133], SOM [134,135], C-means [136], etc. There are also some studies using supervised learning methods, such as KNN [137], ANN [138,139], SVM [140], Bayesian method [141], etc. Few studies have used semi-supervised learning methods (such as the density peak algorithm) to identify cracks in composite matrices [142]. In terms of damage localization and quantification, the existing methods are mainly using supervised learning. For example, using CNN to achieve the damage localization, determine the location of impact damage and quantify the extent of damage [143,144]. There is also a small number of studies based on Bayesian methods for the localization of damage [145,146] and prediction of remaining life [145]. Typical applications of machine learning in damage monitoring based on AE are shown in Figure 8. AE signal is generated only when damage occurs or propagates, and the signal is relatively weak and easily submerged in the environmental noise. Therefore, in practical applications, it is necessary to pay attention to the interference of environmental noise.
3.3 Application of machine learning in damage monitoring based on structural vibration

Structural vibration based SHM is a global damage identification technology. The changes of structural stiffness caused by the damage lead to the changes in the dynamic parameters of structure. By comparing the measured structural dynamic parameters with the reference parameters, the damages in composite structures can be detected [93,147]. Common vibration parameters include modal frequency, modal shape, damping ratio, frequency response function, modal guarantee criteria [148]. A variety of vibration-based SHM algorithms were developed for damage assessment of composite structures [149–151]. In addition, vibration-based SHM is widely used in fault diagnosis of rotating machinery [152], bridge health monitoring [153]. Figure 9 shows the process framework of machine learning in damage monitoring based on structural vibration.

The application of machine learning in damage monitoring based on structural vibration is mainly for damage localization and quantification. Most of the applications use supervised learning methods, mainly ANN. By inputting the structural modal frequency, mode shape, strain energy, etc. into the network for training and testing, damage localization and quantification can be achieved [154–158]. Besides ANN, radial basis neural network (RBNN) [159], Bayesian neural network (BNN) [160], wavelet neural network (WNN) [161], fuzzy neural network (FNN) [162], backpropagation neural network (BNN) [163], SVM [164] and Bayesian method [165] are also used to determine the location and size of damage. In
addition to supervised learning methods, there are a small number of unsupervised learning methods, such as K-means [166,167], PCA [168] used for damage localization and quantification. In the classification of structural health and damage, supervised learning algorithms are mainly used, such as CNN [169], deep belief network (DBN) [170], Bayesian methods [171,172], etc. There are also a few studies using PCA [173] and Gaussian process (GP) [174] to achieve the classification of delamination. Typical applications of machine learning in damage monitoring based on structural vibration are shown in Figure 10.

Because of the extremely complex service environments of composite structures in the fields of aerospace, rail transit, advanced ship technology, the changes in environmental factors such as the loads and temperatures will also lead to the changes in structural stiffness, damping and other characteristics. The changes in the vibration modes of structure caused by the environment factors are often aliased with them caused by the structural damage, resulting in the reliability of vibration based damage monitoring decreases [175].

The damages in composite structures need to be detected are usually small in aerospace, and the small damage has little impact on the overall dynamic characteristics of large composite structures, causing the low sensitivity that limits the application of structural vibration-based damage monitoring in composite structure of aerospace.

3.4 Application of machine learning in damage monitoring based on stress/strain measurement

The damage occurring in the structure will lead to the change of the bearing state of structure, causing the change of stress and strain distribution in the structure. By comparing the measurement of stress and strain with the reference values, it can be determined whether the structure is abnormal [176]. The process framework of machine learning in damage monitoring based on stress/strain measurement is shown in Figure 11. Firstly, the stress and/or strain of composite structure is obtained by means of experimental test or

![Figure 6. Typical applications of machine learning in damage monitoring based on ultrasonic guided waves.](image-url)
numerical simulation. Then the stress and/or strain is input into a suitable machine learning algorithm for training and testing, thereby the monitoring of structural damage is realized.

The applications of machine learning in damage monitoring based on stress-strain measurements mainly focus on the classification of structural health and damage, including supervised learning (such as back propagation neural network (BPNN) [177], SVM [178], etc.), unsupervised learning algorithms (such as PCA [179], SOM [179], autoregressive (AR) models [180], etc.). In terms of localization and quantification of structural damage, supervised learning algorithms are mainly used, such as ANN [181], BPNN [182], Bayesian method [183], etc. It should be pointed out that most of the damages in these studies were simulated by imposing blocks of weight on the composite structures, not actual damages. Typical applications of machine learning in damage monitoring based on stress/strain measurement are shown in Figure 12.

Figure 7. Process framework of machine learning in damage monitoring based on AE.

Figure 8. Typical applications of machine learning in damage monitoring based on AE.
In addition to the applications of machine learning in damage monitoring based on ultrasonic guided wave, AE, structural vibration, stress/strain, studies based on the combination of machine learning and some other detection methods, such as electromechanical impedance, have been also carried out to realize the damage localization and quantification in composite structures. The application of machine learning in damage monitoring based electromechanical impedance mainly focus on damage localization, and supervised learning methods are adopted, such as probabilistic neural network (PNN) [184,185] and fuzzy neural network (FNN) [186]. By inputting the characteristics of impedance signals obtained by experiments or numerical simulation into the network for training, the identification and localization of damage in composite structures can be realized. In the application of machine learning in damage monitoring based on X-ray, supervised learning algorithms (such as ANN and CNN) are used to achieve the goal of damage identification and quantification [187–189].

Besides the typical machine learning algorithms mentioned above, some other machine learning algorithms have also been used in SHM. For instance, a health monitoring system based on a long short-term memory (LSTM) network was proposed to estimate the remaining fatigue life of automotive suspension [190], and a hybrid deep learning algorithm featuring two algorithms-CNN and LSTM was developed to make use of physical features embedded in raw data [191].

**Figure 9.** Process framework of machine learning in damage monitoring based on vibration.
3.5 Application evaluation of machine learning algorithms in composite damage monitoring

It is clear that machine learning has been widely used in SHM based on ultrasonic guided waves, acoustic emission and structural vibration, as shown in Figures 6, 8, and 10. But researches on some other sensing technologies, such as stress/strain measurements, electromechanical impedance and X-ray, are relatively lacking. Among these applications, various machine learning algorithms are used for monitoring damage in composite structures. Table 2 summarizes the advantages and disadvantages of different machine-learning algorithms mentioned above.

There is no machine learning algorithm that has absolute advantages for damage identification and classification in the composite structure, but K-means is used more often because of the advantages of easy implementation, simple principle and strong interpretability. On the other hand, in terms of structural damage localization and quantification, CNN and ANN have significant advantages due to their good scalability and strong nonlinear generalization ability. With the further development of big data and advanced sensing technologies, massive and effective training data in a more convenient and efficient manner will be obtained for machine learning algorithms, which will significantly improve the accuracy of damage prediction. Therefore, machine learning has broad application prospects in damage monitoring of composite structures.

4. Challenges in damage monitoring of composite structures based on machine learning

As mentioned above, a lot of research work on the health monitoring of composite structures based on machine learning have been carried out. However, due to the diversity of damage modes of composite structures and the complexity of service environment, most of these methods have limitations including insufficient monitoring data,

Figure 10. Typical applications of machine learning in damage monitoring based on structural vibration.
inadequate sensing mechanism, unintelligent diagnostic algorithm. It is difficult for these methods to provide robust quantitative damage monitoring results in practical applications. This section discusses the major challenges and solutions for damage monitoring of composite structures based on machine learning.

4.1 Completed acquisition of SHM data of composite structures based on multifunctional sensor network

4.1.1 Establishment of multifunctional sensor network

Completed acquisition of structure state monitoring data is the basis for realizing SHM of composite structures. Due to the complex service environments and diverse damage modes of composite structures, it is difficult for a single sensing technology to obtain the information required to quantitatively characterize the damage of composite structure. Therefore, a multifunctional sensor network with multi-modal sensing capability is needed to achieve the data acquisition of SHM and ensure the quality of data.

Considering the characteristics of delamination initiation and expansion of carbon fiber reinforced laminates under impact loads and fatigue loads, a multifunctional sensor network with active and passive sensing capabilities is proposed, as shown in Figure 13. Taking the advantage of multifunctional sensing capabilities of piezoelectric sensor,
including AE, electromechanical impedance and ultrasonic guided wave monitoring functions, the sensor network can not only realize real-time passive monitoring of delamination initiation/expansion events, but also realize periodic active quantitative monitoring of delamination area. In addition to piezoelectric sensors, it is supplemented by a small amount of temperature and strain sensors to sense the service environment information of composite structure. The comprehensive acquisition of spatiotemporal information on the damage state of composite structures can be achieved by the sensor network combining dynamic and static measurements with active and passive sensing capabilities.

By designing a carrier film as the carrier layer of the multifunctional sensor network to form a multi-modal sensing layer, zero-interference integration of the sensor network with the monitored composite structure can be realized. Similar to the SMART Layer [36], the multi-modal sensing layer can be either mounted on the surface of composite structure or embedded inside the composite structure during the manufacturing process, as shown in Figure 1. Preliminary studies have shown that the embedding of a SMART Layer with a thickness of 0.075 to 0.1 mm inside a composite structure with a thickness of more than 5 mm has a negligible impact on the mechanical properties of composite structure, and its embedding does not affect the integrity of composite structure.

4.1.2 Generation of completed damage samples for composite structures
Due to the complex service environments and diverse damage modes of composite structures, it is difficult for multifunctional sensor networks to obtain completed damage data of composite structures cost-effectively. Incomplete damage samples will seriously restrict the generalization learning ability of machine learning deep diagnosis model, and affect the accuracy of damage detection.

Therefore, it is first necessary to build a high-fidelity numerical simulation model of composite structures to generate new samples that can fully represent the distribution of damage samples, including different damage modes and different delamination sizes. Then, a GAN suitable for time series monitoring signals is constructed, combining recurrent neural network and adversarial learning algorithm. The GAN is driven by the measured samples and the simulated samples as input, and generates other new damage samples after in-depth mining and characterization of the feature information of the samples. As shown in Figure 14, a completed sample data set for composite structure state can be constructed.

4.2 Analysis of the correlation between the eigenvalues of multi-field coupled sensing signals and the composite structure

4.2.1 Coupling mechanism of damage information and environmental interference in signals
When the composite structure is under non-stationary service environments such as different temperatures and loads, the sensing signals will be nonlinearly modulated by these environmental factors. In order to provide a basis for effectively extracting the damage information in the signals, it is necessary to analyze the characteristics of signals under different damage types, different damage areas, etc., through combining
Table 2. Advantages and disadvantages of machine learning algorithms used for monitoring damages in composite structures.

| Algorithm | Advantages | Disadvantages | Training time |
|-----------|------------|---------------|---------------|
| ANN       | Ability of learning and modeling the nonlinear and complex relationships | Difficult to understand and interpret | Long |
| CNN       | Quick and easy to get meaningful insights from data set | Difficult to understand and interpret | Long |
| SVM       | Effective in high-dimensional spaces | Sensitive to kernel function | Long |
| Bayesian  | Easy implementation, small training data required | No interdependency between the features | Average |
| LDA       | High ability to downscale | Overfitting the data | Quick |
| KNN       | Easy implementation | Easy to overfitting in high-dimensional space | Quick |
| BNN       | Good results even with small samples | Time-consuming | Long |
| AE        | Strong dimensionality reduction and nonlinear modeling capabilities | Difficult to understand and interpret | Long |
| RF        | Fast prediction/training | Noisy data prone to over-fitting | Quick |
| MLR       | Easy implementation, easy and convenient | Difficult to meet conditions of use | Average |
| RBNN      | Strong generalization ability | Time-consuming | Long |
| WNN       | Strong nonlinear mapping capability | Time-consuming | Long |
| FNN       | Strong multivariate processing capability | Time-consuming | Long |
| DBN       | Easy to expand | Difficult to understand and interpret | Long |
| BPNN      | Ability of learning and modeling the nonlinear and complex relationships | Time-consuming | Long |
| SOM       | Quick and easy to get meaningful insights from the data set | Time-consuming | Long |
| GMM       | The fastest algorithm among the hybrid models | Overfitting in high-dimensional space | Quick |
| PCA       | High ability to downscale | Low clarity of naming | Quick |
| K-means   | Easy implementation | Choosing the initial value manually | Average |
| C-means   | Easy implementation | Sensitive to initial values | Average |
| GP        | Versatile, can specify different kernel | Overfitting in high-dimensional space | Average |
| AR        | Easy implementation | Inaccurate prediction when autocorrelation coefficient less than 0.5 | Average |

numerical simulations with experiments. By further summarizing the characteristic distribution of sensing signals of composite structure with typical damages in the time domain, frequency domain, and time-frequency domain, the essential difference between multi-source interference and damage related components in the sensing signals is clarified, and a customized feature index selection criterion can be established.

However, the service environment temperature of composite structure varies widely (for example, the service temperature of composite structure of civil aircraft can be between −65°C~ +125°C). Environmental compensation (especially temperature compensation) is inevitable in the damage monitoring methods such as ultrasonic guided waves and electromechanical impedance based. Although a variety of temperature compensation methods for damage monitoring based on ultrasonic guided wave have been proposed [73–81], each compensation method has certain limitations in different application scenarios. By establishing the optimal matching of baselines and current signals, it is the most effective way to realize the compensation of sensing signals in a non-uniform temperature field. Figure 15 shows the effect of this optimal matching principle applied to temperature compensation for damage monitoring in a typical large composite structure in the non-uniform temperature field [36].
4.2.2 Targeted enhancement and extraction of damage features

How to effectively enhance and extract the damage features in the sensing signals is the core technology for quantitatively monitoring the damages in composite structures. Among the multi-field coupled sensing signals, the electromechanical impedance signals and ultrasonic guided wave signals of the piezoelectric sensors are the primary data for predicting the structural damages (position and size) of composite structures. Some preliminary explorations in the targeted enhancement and extraction of damage features of electromechanical impedance signals and ultrasonic guided wave signals have been carried out. A new method of DCMI (Directly Coupled Mechanical Impedance) was proposed for eigenvalue extraction of electromechanical impedance signals [68,69], as well as a new method with multi-damage index (DI) fusion for characterization of ultrasonic guided wave signals to effectively improve the sensitivity to damage [192].

According to the theoretical model of electromechanical admittance in the coupled state of circular piezoelectric sensor PZT, its electromechanical admittance can be expressed as [68,69]

\[
\mathcal{Y} = j \omega \cdot \mathcal{C} \cdot \left(1 - \kappa_p^2\right) + j \omega \cdot \mathcal{C} \cdot \kappa_p^2 \cdot \frac{2}{\phi} \cdot \frac{J_1(\bar{\phi})}{J_0(\bar{\phi})} \cdot \frac{Z_{P,SC}}{Z_{P,SC} + Z_{str}}
\]

(1)

where \(k_p\) denotes coupling coefficient, \(J_1(\phi)\) denotes 1-order Bessel function, \(J_0(\phi)\) denotes 0-order Bessel function, \(\phi\) denotes variable of Bessel function, \(Z_{P,SC}\) denotes electromechanical impedance of PZT under short-circuited condition, \(Z_{str}\) denotes mechanical impedance of host structure, \(\mathcal{C} = \varepsilon_{33}^T \pi a^2 / h\), \(\kappa_p^2 = 2d_{31}^2 / [s_{11}^E \cdot \varepsilon_{33}^T (1 - \nu)]\), \(\bar{\phi} = \bar{k} \cdot a\), \(c_p = 1/\sqrt{\rho s_{11}^T (1 - \nu^2)}\), \(s_{11}^E = s_{11}^F \cdot (1 - \eta \cdot j)\), \(\varepsilon_{33}^T = \varepsilon_{33}^T \cdot (1 - \delta \cdot j)\). \(s_{11}^E\) denotes dielectric constant of PZT, \(s_{11}^T\) denotes compliance coefficient, \(a\) denotes radius of circular PZT.
$h$ denotes thickness of circular PZT, $\nu$ denotes Poisson ratio, $\kappa$ denotes wavenumber, $c_p$ denotes phase velocity, $\rho$ denotes density, $\eta$ denotes mechanical loss factor, $\delta$ denotes dielectric loss factor.

According to the above formula, the electromechanical admittance is divided into two parts: component I and component II. Component I is only related to the material parameters of the circular PZT itself, and has nothing to do with the change of structural impedance. Component II is also related to the structural impedance, in addition to the material parameters of the PZT itself. When the damage in composite structure causes the change of structural impedance, it will directly affect component II, so this item has a high sensitivity to damage. The basic idea of DCMI is to derive an expression related only to $Zstr$, extract the term most sensitive to structural damages, and use this expression for signal processing. The research results are shown in Figure 16. After using the DCMI method to process the measured impedance or admittance signals, characteristic signals that are more sensitive to structural damages can be obtained.

Among many damage diagnosis algorithms based on guided Lamb waves, the elliptical weighted distribution imaging technology, extracting the features of scattered signals to eliminate the influence of errors of sensor placement, environmental noise, dispersion characteristics and complex structures, is getting more and more attention, where the DI is often used to characterize the damage features of the signals. According to the DI weighted value of each sensing path, the first order differential fusion algorithm was used to fuse the DI values of all paths [192]. Combining the probability weighted imaging algorithm and the fusion DI, relatively accurate damage imaging results were obtained, as shown in Figure 17.
4.2.3 Mapping relationship between the eigenvalues of signals and the state parameters of composite structures

The mapping relationship between the eigenvalues of multi-field coupled sensing signals and the state parameters in the damage evolution process of composite structures is the theoretical guarantee for building a multi-functional sensor network, and also an important basis for damage monitoring of composite structures. Combining the experimentally measured damage data with numerical simulation results, the mapping relationship between the eigenvalues of multi-field coupled sensing information and the structural states of typical composite structures (especially different damage states) can be obtained.

From the perspective of positive problems, their internal connection mechanism can be clarified by investigating the eigenvalues of multi-field coupled sensing signals corresponding to various damage states of composite structures in different service environments. Then, the mapping relationship between the eigenvalues of the multi-field coupled sensing signal and the damage states of composite structures is established from the perspective of the inverse problem. Combined with various parameters, such as the types of composite structures, service environments, and load conditions, through the evolution and dimensional combination of different physical parameters, the network mapping relationship of measurement parameters, characteristic parameters and damage modes of composite structures in different failure stages is established, which lays the foundation for the establishment of a knowledge map of composite structural damage diagnosis.

Figure 15. Temperature compensation for damage monitoring of composite structures.
4.3 Quantitative and intelligent identification of damage in composite structures based on deep fusion of multi-source heterogeneous data

4.3.1 Identification of damage in composite structures based on deep learning

As mentioned above, the current machine learning algorithms for health monitoring of composite structures are mostly based on a single type of sensor data and diagnostic model. Their learning capabilities are not enough, and the abilities to migrate and reuse are limited. Therefore, it is difficult to meet the needs for monitoring damages in large scale composite structures under actual environments. The key to identifying different damage modes in composite structures and quantitatively characterizing the damage is to integrate multi-source heterogeneous monitoring data, establish deep learning diagnostic models that can be migrated and reused, and build a deep diagnosis network for multi-feature adaptive characterization and quantitative identification of damage in the composite structures, through integrating multiple modern machine learning algorithms.

Figure 18 shows a schematic diagram of the construction of a deep multiple damage pattern recognizer. To realize the deep identification of different damage modes and quantitative intelligent identification of delamination in composite structure, a variety of modern machine learning algorithms are integrated, the multi-source heterogeneous monitoring data are fused, an integrated deep transfer learning diagnosis model and a deep transfer diagnosis network for multi-feature adaptive characterization and quantitative identification of delamination in composite structure are constructed.

Through the modular design and optimized combination of deep neural networks, the intelligent representation of damage information and a deep integrated diagnosis model are constructed. Utilizing the strongly compatible network learning units, the diagnosis accuracy is improved. Based on the deep network modular construction and adjustment criteria, a deep learning module library is formed. The model structure learning algorithm driven by evolutionary algorithm is used to realize adaptive optimization of network structure and dynamic adjustment of hyperparameters. Through the deep network lightweight technology based on structural pruning and compression, the mapping

![Figure 16. Conductance curve of a typical PZT mounted on the fuselage wall (a) the measured conductance signals, (b) the extracted real part curve of the DCMI signals.](image-url)
relationship between network information channels and model diagnostic behaviors is established, redundant information channels are identified, and structural pruning of the model is realized. In view of the problems of various monitoring data sources and formats, using classifier adaptive fusion and multi-fault mode deep identification technology, fusion technology of different deep learning models, the information mapping optimization of damages in composite structure can be established.

4.3.2 *Migration and reuse of composite damage diagnosis knowledge*

Although there are many SHM methods based on machine learning, it is difficult to find a method with high damage sensitivity, robustness, portability and strong anti-interference ability due to the various structural forms, significant differences in service environments, damage types, sensor networks and sensing signals. As shown in Figure 19, by establishing a cloud/local monitoring device collaboration based diagnostic knowledge migrated mechanism, the efficient training set of the individualized damage diagnosis model for composite structures can be rapidly deployed. According to the influence mechanism of factors, such as structural changes and differences in service conditions on the deep learning model, a subspace set of similar working conditions is constructed. Obtaining the common weight parameters of the model between similar structures and working conditions, the model initialization based on parameter sharing is established. By constructing a domain-adaptive migration learning model, developing a domain-adaptive migration network construction method, and adopting the techniques of selective reuse of model weights and domain-invariant feature map learning, the migration and reuse of damage diagnosis knowledge between work domains is realized.

![Figure 17. Detected damage based on DI fusion and probability weighted imaging algorithm.](image-url)
5. Outlook for future development trend

There are three main key issues in machine learning-based quantitative damage monitoring of composite structures, which are data quality assurance, algorithm selection and design, algorithm result analysis and evaluation. With the development of composite damage mechanics, intelligent sensing technology, advanced data processing, cloud computing and blockchain technology, the development trend of damage monitoring of composite structures based on machine learning is as follows:

(1) Efficient data storage and traceability management

The foundation of machine learning is data, and the quality of data directly affects the performance of machine learning algorithms. With more and more sensing technologies available for monitoring damages in composite structures, the types and sizes of monitoring data will grow significantly. Therefore, the efficient storage and scientific management of multi-source heterogeneous data directly affects the performance of machine learning algorithms. In addition, the variability and inconsistency of complex service environments of composite structures leads to the coupling of sensor data with the influence of changes in environmental factors. Three aspects need to be addressed: 1) multi-level association of multi-source heterogeneous data is required, including spatio-temporal associations, causal associations, and correlational associations. 2) Automated label processing is needed, especially for impact events that have a significant impact on the performance of composite structures. 3) Consistent processing of data acquisition time, especially structured time series signals with inconsistent sampling rates. In order to achieve the above goals, it is necessary to adopt cloud storage and blockchain technology to manage data traceability.

(2) Spatiotemporal feature extraction and multi-level fusion of multi-source heterogeneous monitoring data

![Diagram](image)  
*Figure 18. Intelligent representation of damage information and construction of deep integrated diagnosis models.*
Existing sensing technologies can be generally divided into two categories: passive and active sensing. Different techniques have different sensitivities, advantages and disadvantages for monitoring damages in composite structures. From the perspective of time, passive sensing data is generally a real-time continuous signal (such as acoustic emission signals, impact signals, strain signals). Active sensing data are generally periodic continuous signals (such as ultrasonic guided wave signals, electromechanical impedance signals). From the spatial perspective, even for the same data, different diagnostic algorithms may obtain different damage results at different locations. In order to reduce the uncertainty, it is needed to integrate the background information, knowledge and experience to maximize the utilization of process knowledge through the fusion of multi-source data. Therefore, it is necessary to develop advanced signal processing technology to analyze and extract the spatiotemporal features of multi-source sensor data. Through feature enhancement and optimization, appropriate machine learning algorithms are used to perform multi-level fusion at the data level, feature level and decision level, to improve the reliability of damage diagnosis for composite structures.

(3) Architecture design and parameter optimization of machine learning algorithms guided by physical models

There are still some challenges for the applications of machine learning in damage monitoring of composite structures (especially from damage quantitative monitoring, damage pattern identification to life prediction), such as the lack of interpretability of monitoring results, and the low diagnosis rate caused by imbalanced samples, and low model transferability. In order to solve these problems, the first need is to embed the failure mechanism and criterion of composite structures into the architecture design of machine learning algorithms, map and correlate the failure criteria of composite structures with the typical monitoring physical parameters, and build physical model-guided machine learning architectures to improve model interpretability. The second need is to

Figure 19. Damage diagnosis knowledge transfer and reuse mechanism for local monitoring device and cloud collaboration.
develop GAN based on failure criteria to solve the sample imbalance. The third need is to develop a normalization method for the input parameters of machine learning models to solve the problem of model transferability.

(4) Whole life cycle health management of composite structures based on digital twin

On the basis of existing machine learning models, the physical models, expert knowledge and experience are used to assist machine learning to build a knowledge base of SHM. The monitoring process is developing to the life cycle of structure design, manufacture, service and maintenance of composite structures to provide accurate and effective decision-taking information for intelligent operation and maintenance. Using high-fidelity macro-mechanical analysis of composite structures and digital twin technology, a digital/virtual body constructed from a physical model is embedded in a machine learning algorithm. Measured data and simulation data are continuously introduced into the virtual body, making the virtual body closer to the real structure to increase the intelligence, feature transferability, and result interpretability of SHM. At the same time, SHM is being combined with big data, artificial intelligence, 5G and other technical means to form a smart diagnosis network for composite structures.

6. Conclusions

Advanced composite materials have been widely used in many industries to reduce the weight of structures, improve efficiency and reduce operating costs because of the advantages of high specific strength and stiffness, designable mechanical properties, and easy integral molding. However, it is very difficult to analyze the integrity and durability of composite structures due to their own characteristics and the complexity of loads and use environments. SHM is a revolutionary and innovative technology for determining the structural integrity of composite structures. But in the face of complex damage modes of composite structures and their service environments, most of these SHM methods have limitations to accurately and quantitatively monitor the damages in composite structures. With the rapid development of machine learning and application in SHM, it provides a good opportunity for more accurate and robust damage monitoring of composite structures in complex service environments.

In this paper, some damage monitoring technologies often used for composite structures were briefly outlined. The research progress of machine learning based damage monitoring technologies of composite structures was concisely reviewed. Based on the challenges for the applications of machine learning in SHM, including insufficient monitoring data, inadequate sensing mechanism, unintelligent diagnostic algorithm, innovative technologies were proposed to solve the challenges from three aspects: (1) complete acquisition of the monitoring data of composite structure based on multifunctional sensor network, (2) deep analysis of the correlation between multi-field coupling sensor signal eigenvalues and composite structure state, (3) quantitative intelligent identification of composite delamination damage based on deep fusion of multi-source heterogeneous data. Finally, the development trend of machine learning based SHM for composite structures was discussed. It is clear that the combination of machine learning and
structural health monitoring technology provides an effective way to improve the accuracy and robustness of damage pattern recognition and quantitative damage monitoring of composite structures in complex service environments.

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**References**

[1] Du S. Composite materials and strategic emerging industries. Sci Technol Rev. 2013;31(7):3. in Chinese.
[2] Chang F, Markmiller J, Ihn J, et al. A Potential link from damage diagnostics to health prognostics of composites through built-in sensors. J Vibration Acoustics. 2007;129(6):718–729.
[3] Senthil K, Arockiarajan A, Palaninathan R, et al. Defects in composite structures: its effects and prediction methods-A comprehensive review. Compos Struct. 2013;106:139–149.
[4] Qing X, Liu Q, Zhang Y, et al. Life-cycle health monitoring technology for aircraft composite structures. J Xiamen Univ (Natural Science). 2021;60(3):614–629. in Chinese.
[5] Yuan S, Qiu L, Lei J, et al. Challenge in structural health monitoring of large aircraft development. Aeronaut Manuf Technol. 2009;52(22):62–67. in Chinese.
[6] Qing X, Li W, Wang Y, et al. Piezoelectric transducer-based structural health monitoring for aircraft applications. Sensors. 2019;19(3):545.
[7] Aliaabadi M, Khodaei Z. Structural health monitoring for advanced composite structures. London UK: World Scientific Publishing Europe Ltd; 2017.
[8] Qing X, Liu X, Zhu J, et al. In-situ monitoring of liquid composite molding process using piezoelectric sensor network. Struct Health Monit. 2020 September;147592172095808. DOI:10.1177/1475921720958082
[9] Wu Z, Qiu X, Gao D, et al. Impact location identification of stiffened composite plates based on FBG sensors embedded. Aeronaut Manuf Technol. 2016;15:92–102, 109. in Chinese.
[10] Liu X, Li Y, Zhu J, et al. Monitoring of resin flow front and degree of cure in vacuum-assisted resin infusion process using multifunctional piezoelectric sensor network. Polym Composites. 2020;42(1):113–125.
[11] Mei H, Giurigiutiu V. Guided wave excitation and propagation in damped composite plates. Struct Health Monit. 2018;18(3):690–714.
[12] Sekine H, Fujimoto S, Okabe T, et al. Structural health monitoring of cracked aircraft panels repaired with bonded patches using fiber bragg grating sensors. Appl Compos Mater. 2006;13(2):87–98.
[13] Hosseini S, Remmers J, Verhoosel C, et al. Propagation of delamination in composite materials with isogeometric continuum shell elements. Int J Numer Method Biomed Eng. 2015;102(3–4):159–179.
[14] Ren Y, Qiu L, Yuan F, et al. A diagnostic imaging approach for online characterization of multi-impact in aircraft composite structures based on a scanning spatial-wavenumber filter of guided wave. Mech Syst Signal Process. 2017;90:44–63.
[15] Donadon MV, Lauda DP. A damage model for the prediction of static and fatigue-driven delamination in composite laminates. J Compos Mater. 2014;49(16):1995–2007.
[16] Corbetta M, Saxena A, Giglio M, et al. An investigation of strain energy release rate models for real-time prognosis of fiber-reinforced laminates. Compos Struct. 2017;165:99–114.

[17] Katnam K, Silva L, Young T. Bonded repair of composite aircraft structures: a review of scientific challenges and opportunities. Prog Aerosp Sci. 2013;61:26–42.

[18] Elenczezhian M, Vadlamudi V, Riahan R, et al. Artificial intelligence in real-time diagnostics and prognostics of composite materials and its uncertainties—a review. Smart Mater Struct. 2021;30(8):083001.

[19] Mencattelli L, Pinho ST. Herringbone-bouligand CFRP structures: a new tailorable damage-tolerant solution for damage containment and reduced delaminations. Compos Sci Technol. 2020;190:108047.

[20] Malekloo A, Ozer E, Alhamaydeh M, et al. Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Struct Health Monit. August 2021. DOI:10.1177/14759217211036880.

[21] Ghrib M, Rébillat M, Vermot Des Roches G, et al. Automatic damage type classification and severity quantification using signal based and nonlinear model based damage sensitive features[J]. J Process Control. 2019;83:136–146.

[22] Davijani AAB, Hajikhani M, Ahmadi M. Acoustic Emission based on sentry function to monitor the initiation of delamination in composite materials. Mater Des. 2011;32(5):3059–3065.

[23] Roach D. Real time crack detection using mountable comparative vacuum monitoring sensors. Smart Struct Syst. 2009;5(4):317–328.

[24] Rakow A, Chang F. A structural health monitoring fastener for tracking fatigue crack growth in bolted metallic joints. Struct Health Monit. 2011;11(3):253–267.

[25] Saeedifar M, Zarouchas D. Damage characterization of laminated composites using acoustic emission: a review. Compos Part B Eng. 2020;195:108039.

[26] Tserpes K, Karachalios V, Giannopoulos I, et al. Strain and damage monitoring in CFRP fuselage panels using fiber Bragg grating sensors. part I: design, manufacturing and impact testing. Compos Struct. 2014;107:726–736.

[27] Grave J, Hâheim M, Echtermeyer A. Measuring changing strain fields in composites with distributed fiber-optic sensing using the optical backscatter reflectometer. Compos Part B Eng. 2015;74:138–146.

[28] Alvarez M, Carvajal C, Sierra P. In-flight and wireless damage detection in a UAV composite wing using fiber optic sensors and strain field pattern recognition. Mech Syst Signal Process. 2020;136:106526.

[29] Kwon H, Park Y, Kim J, et al. Embedded fiber Bragg grating sensor-based wing load monitoring system for composite aircraft. Struct Health Monit. 2019;18(4):1337–1351.

[30] Qing X, Beard S, Kumar A, et al. Advances in the development of built-in diagnostic system for filament wound composite structures. Compos Sci Technol. 2006;66(11–12):1694–1702.

[31] Wang Y, Qing X. Progress on study of structural health monitoring technology for composite joints. Acta Materiae Compositae Sinica. 2016;33(1):1–16. in Chinese.

[32] Qing X, Beard S, Kumar A, et al. Built-in sensor network for structural health monitoring of composite structure. J Intell Mater Syst Struct. 2006;18(1):39–49.

[33] Lin M, Qing X, Kumar A, et al. Smart layer and smart suitcase for structural health monitoring applications. In: Anna-Maria Rivas McGowan, editor. SPIE, Smart Structures and Materials 2001: Industrial and Commercial Applications of Smart Structures Technologies. Bellingham; 2001. p. 98–106.

[34] Qing X, Beard S, Amrita K, et al. Stanford multiactuator-receiver transduction (SMART) layer technology and its applications. New York: John Wiley and Sons, Ltd; 2009.

[35] Qing X, Chang FK. Method of manufacturing a structural health monitoring layer. US Patent 20060154398A1. 2006July13.

[36] Qing X, Beard S, Ikegami R, et al. Aerospace applications of SMART layer technology. New York: John Wiley and Sons, Ltd; 2009. p. 1881–1896.

[37] Qing X, Wang Y, Gao L, et al. Multifunctional structural state sensing system for composite structures. J Exper Mech. 2011;26(5):611–616. in Chinese.
Fan Z, Wang Y, Qiu X, et al. Design and manufacture technology of expandable multifunctional composite structure state sensing network. J Exper Mech. 2018;35(1):85–92. in Chinese.

Lanzara G, Salowitz N, Guo Z, et al. A spider-web-like highly expandable sensor network for multifunctional materials. Adv Mater. 2010;22(41):4643–4648.

Guo Z, Kim K, Lanzara G, et al. Bio-inspired smart skin based on expandable network. Structural health monitoring 2011: condition-based maintenance and intelligent structures lancaster. Destech Publications; 2013. p. 1717–1723.

Salowitz N, Guo Z, Kim S, et al. Microfabricated expandable sensor networks for intelligent sensing materials. IEEE Sens J. 2014;14(7):2138–2144.

Salowitz N, Guo Z, Li Y, et al. Bio-inspired stretchable network-based intelligent composites. J Compos Mater. 2012;47(1):97–105.

Mitra M, Gopalakrishnan S. Guided wave based structural health monitoring: a review. Smart Mater Struct. 2016;27;25(5):053001.

Giurgiutiu V, Bao J. Embedded-ultrasonics structural radar for in situ structural health monitoring of thin-wall structures. Struct Health Monit. 2004;3(2):121–140.

Ambroziński Ł, Stepinski T, Uhl T. Efficient tool for designing 2D phased arrays in lamb waves imaging of isotropic structures. J Intell Mater Syst Struct. 2014;26(17):2283–2294.

Qiu L, Liu B, Yuan S, et al. A scanning spatial-wavenumber filter and PZT 2-D cruciform array based on-line damage imaging method of composite structure. Sens Actuators A. 2016;248:62–72.

Michaels J, Michaels T. Guided wave signal processing and image fusion for in situ damage localization in plates. Wave Motion. 2007;44(6):482–492.

Qiu L, Liu M, Qing X, et al. A quantitative multidamage monitoring method for large-scale complex composite. Struct Health Monit. 2013;12(3):183–196.

Prasad S, Balasubramaniam K, Krishnamurthy C. Structural health monitoring of composite structures using Lamb wave tomography. Smart Mater Struct. 2004;13(5):N73–N79.

Chan E, Rose L, Wang C. An extended diffraction tomography method for quantifying structural damage using numerical Green’s functions. Ultrasonics. 2015;59:1–13.

Liu K, Ma S, Wu Z, et al. A novel probability-based diagnostic imaging with weight compensation for damage localization using guided waves. Struct Health Monit. 2016;15(2):162–173.

Wu Z, Liu K, Wang Y, et al. Validation and evaluation of damage identification using probability-based diagnostic imaging on a stiffened composite panel. J Intell Mater Syst Struct. 2014;26(16):2181–2195.

Qing X, Beard S, Shen S, et al. Development of a real-time active pipeline integrity detection system. Smart Mater Struct. 2009;18(11):115010 (10pp).

Cai J, Shi L, Yuan S, et al. High spatial resolution imaging for structural health monitoring based on virtual time reversal. Smart Mater Struct. 2011;20(5):055018 (11pp).

Wang C, Rose J, Chang F. A synthetic time-reversal imaging method for structural health monitoring. Smart Mater Struct. 2004;13(2):415–423.

Rulli R, Da S. Overview of CVM technology tests performed by embraer. In: Chang, F K. Proc. of the 8th International Workshop on Structural Health Monitoring. Lancaster: Destech Publications Ltd; 2011. p. 432–438.

Ran Y, He J, Dong B, et al. Assessment of reliability performance of fatigue crack detection by intelligent coating monitoring and piezoelectric sensors. 2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC); 2017. p. 482–487.

Liu Q, Sun H, Wang T, et al. On-site health monitoring of composite bolted joint using built-in distributed eddy current sensor network. Materials. 2019;12(17):2785.

Sun H, Wang T, Liu Q, et al. A two-dimensional eddy current array–based sensing film for estimating failure modes and tracking damage growth of bolted joints. Struct Health Monit. 2019;20(3):877–893.

Sun H, Wang T, Liu Q, et al. A novel eddy current array sensing film for quantitatively monitoring hole-edge crack growth in bolted joints. Smart Mater Struct. 2019;28(1):015018 (14pp).
[61] Ihn J, Chang F. Detection and monitoring of hidden fatigue crack growth using a built-in piezoelectric sensor/actuator network: iDiagnostics. Smart Mater Struct. 2004;13(3):609–620.
[62] Yan J, Jin H, Sun H, et al. Active monitoring of fatigue crack in the weld zone of bogie frames using ultrasonic guided waves. Sensors. 2019;19(15):3372.
[63] Jin H, Yan J, Li W, et al. Monitoring of fatigue crack propagation by damage index of ultrasonic guided waves calculated by various acoustic features. Appl Sci. 2019;9(20):4254.
[64] Djemana M, Hrairi M, Jeroudi A. Using Electromechanical impedance and extreme learning machine to detect and locate damage in structures. J Nondestr Eval. 2017;36(2):39.
[65] Gao D, Wu Z, Yang L, et al. Integrated impedance and Lamb wave-based structural health monitoring strategy for long-term cycle-loaded composite structure. Struct Health Monit. 2018;17:763–776.
[66] Fan X, Li J, Hao H. Impedance resonant frequency sensitivity based structural damage identification with sparse regularization: experimental studies. Smart Mater Struct. 2019;28(1):015003.
[67] Castro BA, Baptista FG, Ciampa F. Comparative analysis of signal processing techniques for impedance-based SHM applications in noisy environments. Mech Syst Signal Process. 2019;126:326–340.
[68] Zhu J, Wang Y, Qing X. Modified electromechanical impedance-based disbond monitoring for honeycomb sandwich composite structure. Compos Struct. 2019;217:175–185.
[69] Zhu J, Qing X, Liu X, et al. Electromechanical impedance-based damage localization with novel signatures extraction methodology and modified probability-weighted algorithm. Mech Syst Signal Process. 2021;146:107001.
[70] Huang J. Non-destructive evaluation (NDE) of composite: acoustic emission (AE). In: Karbhari V, editor. Non-destructive evaluation (NDE) of polymer matrix composite. London UK: Woodhead Publishing Ltd; 2013. p. 12–32.
[71] Fotouhi M, Najafabadi M. Acoustic emission-based study to characterize the initiation of delamination in composite materials. J Thermoplast Composite Mater. 2014;29(4):519–537.
[72] Saeedifar M, Najafabadi M, Zarouchas D, et al. Barely visible impact damage assessment in laminated composites using acoustic emission. Compos Part B Eng. 2018;152:180–192.
[73] Lu Y, Michaels J. A methodology for structural health monitoring with diffuse ultrasonic waves in the presence of temperature variations. Ultrasonics. 2005;43(9):717–731.
[74] Konstantinidis G, Drinkwater B, Wilcox P. The temperature stability of guided wave structural health monitoring systems. Smart Mater Struct. 2006;15(4):967–976.
[75] Croxford A, Moll J, Wilcox P, et al. Efficient temperature compensation strategies for guided wave structural health monitoring. Ultrasonics. 2010;50(4–5):517–528.
[76] Clarke T, Cawley P, Wilcox P, et al. Evaluation of the damage detection capability of a sparse-array guided-wave SHM system applied to a complex structure under varying thermal conditions. IEEE Trans Ultrason Ferroelectr Freq Control. 2009;56(12):2666–2678.
[77] Wang Y, Gao L, Yuan S, et al. An adaptive filter-based temperature compensation technique for structural health monitoring. J Intell Mater Syst. 2014;25(17):2187–2198.
[78] Sohn H, Park HW, Law KH, et al. Damage detection in composite plates by using an enhanced time reversal method. J Aerospace Eng. 2007;20(3):141–151.
[79] Poddar B, Kumar A, Mitra M, et al. Time reversibility of a Lamb wave for damage detection in a metallic plate. Smart Mater Struct. 2011;20(2):025001 (10pp).
[80] Bijuadus C, Mitra M, Mujumdar P. Time reversed Lamb wave for damage detection in a stiffened aluminum plate. Smart Mater Struct. 2013;22(10):105026 (8pp).
[81] Lim H, Sohn H, Yeum C, et al. Reference-free damage detection, localization, and quantification in composites. J Acoust Soc Am. 2013;133(6):3838–3845.
[82] Seydel R, Chang FK. Impact identification of stiffened composite panels: iSystem development. Smart Mater Struct. 2001;10:370.
[83] Chen C, Li Y, Yuan F. Impact source identification in finite isotropic plates using a time-reversal method: experimental study. Smart Mater Struct. 2012;21(10):105025.
[84] Banerjee S, Ricci F, Monaco E, et al. Autonomous impact damage monitoring in a stiffened composite panel. J Intell Mater Syst Struct. 2007;18(6):623–633.
[85] Fu H, Vong CM, Wong PK. Fast detection of impact location using kernel extreme learning machine. Neural Comput Appl. 2016;27:121–130.
[86] Calífano A, Chandarana N, Grassia L, et al. Damage detection in composites by artificial neural networks trained by using in situ distributed strains. Appl Compos Mater. 2020;27(5):657–671.
[87] Alzubi J, Nayyar A, Kumar A. Machine learning from theory to algorithms: an overview. Journal of Physics: Conference Series. 2018; Vol.1142, 012012.
[88] Yuan F, Zargar S, Chen Q, et al. Machine learning for structural health monitoring: challenges and opportunities. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems. 2020; SPIE Proceedings, Vol. 11379, 1137903.
[89] Bao Y, Tang Z, Li H, et al. Computer vision and deep learning–based data anomaly detection method for structural health monitoring. Struct Health Monit. 2019;18(2):401–421.
[90] Flah M, Nunez I, Chaabene W, et al. Machine learning algorithms in civil structural health monitoring: a systematic review. Arch Comput Methods Eng. 2021;28:2621–2643.
[91] Gutkin R, Green C, Vangrattanachai S, et al. On acoustic emission for failure investigation in CFRP: pattern recognition and peak frequency analyses. Mech Syst Signal Process. 2011;25(4):1393–1407.
[92] Carden E, Fanning P. Vibration based condition monitoring: a review. Struct Health Monit. 2016;3(4):355–377.
[93] Su Z, Ye L, Lu Y. Guided lamb waves for identification of damage in composite structures: a review. J Sound Vib. 2006;295(3–5):753–780.
[94] Mardanshahi A, Nasir V, Kazemirad S, et al. Detection and classification of matrix cracking in laminated composites using guided wave propagation and artificial neural networks. Compos Struct. 2020;246:112403.
[95] Das S, Chattopadhyay A, Srivastava A. Classifying induced damage in composite plates using one-class support vector machines. AIAA Stud J. 2010;48(4):705–718.
[96] Dib G, Karpenko O, Koricho E, et al. Ensembles of novelty detection classifiers for structural health monitoring using guided waves. Smart Mater Struct. 2018;27(1):015003 (13pp).
[97] Khan A, Kim HS. Classification and prediction of multidamages in smart composite laminates using discriminant analysis. Mech Adv Mater Struct. 2020; 29(2):1–11.
[98] Cantero-Chinchilla S, Malik MK, Chronopoulos D, et al. Bayesian damage localization and identification based on a transient wave propagation model for composite beam structures. Compos Struct. 2021;267:113849.
[99] Tibaduiza D, Vitola J, Anaya M, et al. A damage classification approach for structural health monitoring using machine learning. Complexity. 2018;2018:1–14.
[100] Yang Y, Zhou Y, Wang L. Integrated method of multiple machine-learning models for damage recognition of composite structures. J Data Acquisition Process. 2020;35(2):278–287. in Chinese.
[101] Tibaduiza DA, Torresarredondo MA, Mujica LE, et al. A study of two unsupervised data driven statistical methodologies for detecting and classifying damages in structural health monitoring. Mech Syst Signal Process. 2013;41(1–2):467–484.
[102] Yuan S, Wang L, Peng G. Neural network method based on a new damage signature for structural health monitoring. Thin Walled Struct. 2005;43(4):553–563.
[103] Larrosa C, Lonkar K, Chang FK. In situ damage classification for composite laminates using Gaussian discriminant analysis. Struct Health Monit. 2014;13(2):190–204.
[104] Wang Q, Ma S, Yue D. Identification of damage in composite structures using Gaussian mixture model-processed Lamb waves. Smart Mater Struct. 2018;27(4):045007 (11pp).
[105] Su Z, Ye L. Lamb wave-based quantitative identification of delamination in CF/EP composite structures using artificial neural algorithm. Compos Struct. 2004;66(1–4):627–637.
[106] Fenza A, Sorrentino A, Vitiello P. Application of artificial neural networks and probability ellipse methods for damage detection using lamb waves. Compos Struct. 2015;133:390–403.
[107] Su Z, Yang C, Pan N, et al. Assessment of delamination in composite beams using shear horizontal (SH) wave mode. Compos Sci Technol. 2007;67(2):244–251.
[108] Pan N, Su Z, Ye L, et al. A quantitative identification approach for delamination in laminated composite beams using digital damage fingerprints (DDFs). Compos Struct. 2006;75(1–4):559–570.

[109] Qian C, Ran Y, He J, et al. Application of artificial neural networks for quantitative damage detection in unidirectional composite structures based on Lamb waves. Adv Mech Eng. 2020;12(3):1–9.

[110] Su C, Jiang M, Lv S, et al. Improved damage localization and quantification of CFRP using Lamb waves and convolution neural network. IEEE Sens J. 2019;19(14):5784–5791.

[111] Wu J, Xu X, Liu C, et al. Lamb wave-based damage detection of composite structures using deep convolutional neural network and continuous wavelet transform. Compos Struct. 2021;276:114590.

[112] Azuara G, Ruiz M, Barrera E. Damage localization in composite plates using wavelet transform and 2-D convolutional neural networks. Sensors. 2021;21(17):5825.

[113] Tabian I, Fu H, Khodaei Z. A convolutional neural network for impact detection and characterization of complex composite structures. Sensors. 2019;19(22):4933.

[114] Rautela M, Gopalakrishnan S. Ultrasonic guided wave based structural damage detection and localization using model assisted convolutional and recurrent neural networks. Expert Syst Appl. 2021;167:114189.

[115] Zhang B, Hong X, Liu Y. Deep convolutional neural network probability imaging for plate structural health monitoring using guided waves. IEEE Trans Instrum Meas. 2021;70:1–10.

[116] Rautela M, Senthilnath J, Moll J, et al. Combined two-level damage identification strategy using ultrasonic guided waves and physical knowledge assisted machine learning. Ultrasonics. 2021;115:106451.

[117] Cui R, Azuara G, Francesco L, et al. Damage imaging in skin-stringer composite aircraft panel by ultrasonic guided waves using deep learning with convolutional neural network. Struct Health Monit. 2021;0(0):1–16. https://doi.org/10.1177/14759217217211023934

[118] Matteo C, Giuseppe M, Aimé L. Incremental Bayesian learning for in-service analysis of aeronautical composites. IET Sci Meas Technol. 2013;7(6):334–342.

[119] Liu X, Wang B, Ai F, et al. Damage identification of composite laminates based on SPSO-WK-TWSVM. J Vibro Eng. 2021;40(15):290–302. in Chinese.

[120] Lee H, Lim HJ, Skinner T, et al. Automated fatigue damage detection and classification technique for composite structures using Lamb waves and deep autoencoder. Mech Syst Signal Process. 2022;163:108148.

[121] Gao D. Ultrasonic guided wave structural health monitoring technology based on machine learning method. Fiber Compos. 2020;3:1–8. in Chinese.

[122] Huo H, He J, Guan X. A Bayesian fusion method for composite damage identification using Lamb wave. Struct Health Monit. 2020; 14:1–23.

[123] Peng T, Saxena A, Goebel K, et al. A novel Bayesian imaging method for probabilistic delamination detection of composite materials. Smart Mater Struct. 2013;22(12):125019.

[124] Liu H, Liu S, Liu Z, et al. Prognostics of damage growth in composite materials using machine learning techniques industrial technology (ICIT), 2017 IEEE International Conference on IEEE. 2017; Toronto, Canada; 2017;1042.

[125] He Y, Li M, Meng Z, et al. An overview of acoustic emission inspection and monitoring technology in the key components of renewable energy systems. Mech Syst Signal Process. 2021;148:107146.

[126] Khamedi R, Abdi S, Ghorbani A, et al. Damage characterization of carbon/epoxy composites using acoustic emission signals wavelet analysis. Compos Interfaces. 2019;27(1):111–124.

[127] Barré S, Benzegagh ML. On the use of acoustic emission to investigate damage mechanisms in glass-fibre-reinforced polypropylene. Compos Sci Technol. 1994;52(3):369–376.

[128] Pashmforoush F, Fotouhi M, Ahmadi M. Acoustic emission-based damage classification of glass/polyester composites using harmony search k-means algorithm. J Reinf Plast Compos. 2012;31(10):671–680.
[129] Mariem B, Abderrahim E, Jean-Luc R, et al. Investigation and identification of damage mechanisms of unidirectional carbon/flax hybrid composites using acoustic emission. Eng Fract Mech. 2019;216:106511.

[130] Farzad P, Ramin K, Mohamad F, et al. Damage classification of sandwich composites using acoustic emission technique and k-means genetic algorithm. J Nondestruct Eval. 2014;33(4):481–492.

[131] Al-Jumaili S, Holford K, Eaton M, et al. Classification of acoustic emission data from buckling test of carbon fibre panel using unsupervised clustering techniques. Struct Health Monit. 2014;14(3):241–251.

[132] Xu D, Liu PF, Li JG, et al. Damage mode identification of adhesive composite joints under hygrothermal environment using acoustic emission and machine learning. Compos Struct. 2019;211:351–363.

[133] Sobhani A, Saeedifar M, Najafabadi M, et al. The study of buckling and post-buckling behavior of laminated composites consisting multiple delaminations using acoustic emission. Thin Walled Struct. 2018;127:145–156.

[134] Saeedifar M, Najafabadi MA, Zarouchas D, et al. Clustering of interlaminar and intralaminar damages in laminated composites under indentation loading using Acoustic Emission. Compos Part B Eng. 2018;144:206–219.

[135] Oliveira RD, Marques AT. Health monitoring of FRP using acoustic emission and artificial neural networks. Comput Struct. 2008;86(3–5):367–373.

[136] Fotouhi M, Heidary H, Ahmadi M, et al. Characterization of composite materials damage under quasi-static three-point bending test using wavelet and fuzzy C-means clustering. J Compos Mater. 2012;46(15):1795–1808.

[137] Crivelli D, Guagliano M, Eaton M, et al. Localisation and identification of fatigue matrix cracking and delamination in a carbon fibre panel by acoustic emission. Compos Part B Eng. 2015;74:1–12.

[138] Ramasamy P, Sampathkumar S. Prediction of impact damage tolerance of drop impacted WGFRP composite by artificial neural network using acoustic emission parameters. Compos Part B Eng. 2014;60:457–462.

[139] Bhat C, Bhat MR, Murthy CRL. Acoustic emission characterization of failure modes in composites with ANN. Compos Struct. 2003;61(3):213–220.

[140] Xu J, Liu X, Han Q, et al. A particle swarm optimization-support vector machine hybrid system with acoustic emission on damage degree judgment of carbon fiber reinforced polymer cables. Struct Health Monit. 2020;20(4):1551–1562.

[141] Rabiei E, Drogue E, Modarres M. Damage monitoring and prognostics in composites via dynamic Bayesian networks. 2017 Annual Reliability and Maintainability Symposium (RAMS). Florida, United States; 2017. p. 978.

[142] Xu D, Liu P, Chen Z, et al. Achieving robust damage mode identification of adhesive composite joints for wind turbine blade using acoustic emission and machine learning. Compos Struct. 2020;236:111840.

[143] Sikdar S, Liu D, Kundu A. Acoustic emission data based deep learning approach for classification and detection of damage-sources in a composite panel. Compos Part B Eng. 2022;228:109450.

[144] Jung K, Chang S. Advanced deep learning model-based impact characterization method for composite laminates. Compos Sci Technol. 2021;207:108713.

[145] Loutas T, Eleftheroglou N, Zarouchas D. A data-driven probabilistic framework towards the in-situ prognostics of fatigue life of composites based on acoustic emission data. Compos Struct. 2017;161:522–529.

[146] Kundu A, Eaton MJ, Al-Jumali S, et al. Acoustic emission based damage localization in composites structures using Bayesian identification. 12th International Conference on Damage Assessment of Structures Kitakyushu, Japan; 2017. 842(1):012081.

[147] Shi B, Cao M, Wang Z, et al. A directional continuous wavelet transform of mode shape for line-type damage detection in plate-type structures. Mech Syst Signal Process. 2022;167:108510.
[148] Barroso LR, Rodriguez R. Damage detection utilizing the damage index method to a benchmark structure. J Eng Mech. 2004;130(2):142–151.

[149] Hassani S, Mousavi M, Gandomi AH. Structural health monitoring in composite structures: a comprehensive review. Sensors. 2021;22(1):153.

[150] Zou Y, Tong L, Steven G. Vibration-based model-dependent damage (delamination) identification and health monitoring for composite structures - a review. J Sound Vib. 2000;230(2):357–378.

[151] Montalvão D. A review of vibration-based structural health monitoring with special emphasis on composite materials. Shock Vib Dig. 2006;38(4):295.

[152] Jia F, Lei Y, Lin J, et al. Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mech Syst Signal Process. 2016;72-73:303–315.

[153] Sony S, Dunphiy K, Sadhu A, et al. A systematic review of convolutional neural network-based structural condition assessment techniques. Eng Struct. 2021;226:111347.

[154] Zhang Z, Pan J, Luo W, et al. Vibration-based delamination detection in curved composite plates. Compos Part A Appl Sci Manuf. 2019;119:261–274.

[155] Okafor C, Chandrashekhara K, Jiang Y. Delamination prediction in composite beams with built-in piezoelectric devices using modal analysis and neural network. Smart Mater Struct. 1996;5(3):338–347.

[156] Mojtahedi A, Hokmabady H, Kouhi M, et al. A novel ANN-RDT approach for damage detection of a composite panel employing contact and non-contact measuring data. Compos Struct. 2022;279:114794.

[157] Nasiri MR, Mahjoo MJ, Aghakasiri A. Damage detection in a composite plate using modal analysis and artificial intelligence. Appl Compos Mater. 2011;18(6):513–520.

[158] Khatir S, Tiachacht S, Thanh CL, et al. Damage assessment in composite laminates using ANN-PSO-IGA and Cornwell indicator. Compos Struct. 2019;230:111509.

[159] Li Z, Zheng S. Research on damage monitoring for composite structures based on HHGA—RBF neural network. J Astronaut. 2008;29(1):347–351. in Chinese.

[160] Frederick JA, Serrano D, Shafiq B, et al. Neural network based nondestructive evaluation of sandwich composites. Compos Part B Eng. 2008;39(1):217–225.

[161] Zheng S, Li Z, Wang H. Research on delamination monitoring for composite structures based on HHGA—WNN. Appl Soft Comput. 2009;9(3):918–923.

[162] Zheng S, Li Z, Wang H. A genetic fuzzy radial basis function neural network for structural health monitoring of composite laminated beams. Expert Syst Appl. 2011;38(9):11837–11842.

[163] He M, Wang Y, Ram R, et al. A comparison of machine learning algorithms for assessment of delamination in fiber-reinforced polymer composite beams. Struct Health Monit. 2020;20(4):1997–2012.

[164] Huang M, Pan J, Jiang J, et al. Assessment of multiple delaminations in fiber reinforced composites. Compos Sci Eng. 2021;5:21–30. in Chinese.

[165] Boscato G, Civera M, Zanotti Fragonara L. Recursive partitioning and Gaussian process regression for the detection and localization of damages in pultruded glass fiber reinforced polymer material. Struct Control Health Monit. 2021;28(10):e2805.

[166] Ihesiulor O, Shankar K, Zhang Z, et al. Delamination detection with error and noise polluted natural frequencies using computational intelligence concepts. Compos Part B Eng. 2014;56:906–925.

[167] Villalobos A, Ruiz R, Meruane V. Generalized Gaussian smoothing for baseline-free debonding assessment of sandwich panels. Struct Control Health Monit. 2021;28(6):e2727.

[168] Meruane V, Lasen M, Ortiz A. Modal strain energy-based debonding assessment of sandwich panels using a linear approximation with maximum entropy. Entropy. 2017;19(11):619.

[169] Meruane V, Aichele D, Ruiz R, et al. A deep learning framework for damage assessment of composite sandwich structures. Shock Vib. 2021;2021:1–12.

[170] Ding Z, Li J, Hao H. Structural damage identification by sparse deep belief network using uncertain and limited data. Struct Control Health Monit. 2020;27(5):1–20.
[171] Kahya V, Okur F, Karaca S, et al. Multiple damage detection in laminated composite beams using automated model update. Structures. 2021;34:1665–1683.
[172] Corbetta M, Sbarufatti C, Giglio M, et al. A Bayesian framework for fatigue life prediction of composite laminates under co-existing matrix cracks and delamination. Compos Struct. 2018;187:58–70.
[173] Huang B, Koh B, Kim H. PCA-based damage classification of delaminated smart composite structures using improved layerwise theory. Comput Struct. 2014;141:26–35.
[174] Liu Z, Ardabilian M, Zine A, et al. Crack damage identification of a thick composite sandwich structure based on Gaussian processes classification. Compos Struct. 2021;255:112825.
[175] Lopez I, Sarigul N. A review of uncertainty in flight vehicle structural damage monitoring, diagnosis and control: challenges and opportunities. Prog Aerosp Sci. 2010;46(7):247–273.
[176] Udd E. Fiber optic smart structures. Fiber optic sensors. Crit. Rev 1993;10266:246–270.
[177] Panopoulou A, Fransen S, Gomez V, et al. Experimental modal analysis and dynamic strain fiber bragg gratings for structural health monitoring of composite antenna sub-reflector. CEAS Space J. 2013;5(1–2):57–73.
[178] Loutas T, Panopoulou A, Roulias D, et al. Intelligent health monitoring of aerospace composite structures based on dynamic strain measurements. Expert Syst Appl. 2012;39 (9):8412–8422.
[179] Julián S, Miguel T, Cabanes G, et al. Structural health monitoring by means of strain field pattern recognition on the basis of PCA and automatic clustering techniques based on SOM. IFAC-PapersOnLine. 2015;48(28):987–992.
[180] Nardi D, Lampani L, Pasquali M, et al. Detection of low-velocity impact-induced delaminations in composite laminates using Auto-Regressive models. Compos Struct. 2016;151:108–113.
[181] Panopoulou A, Roulias D, Loutas T, et al. Health monitoring of aerospace structures using fibre bragg gratings combined with advanced signal processing and pattern recognition techniques. Strain. 2012;48(3):267–277.
[182] Latha B, Senthilkumar V. Application of artificial intelligence for the prediction of delamination in drilling GFRP composites. Int J Precis Technol. 2010;1(3/4):314–330.
[183] Yan G, Sun H, Büyüköztürk O. Impact load identification for composite structures using Bayesian regularization and unscented Kalman filter. Struct Control Health Monit. 2017;24 (5):e1910.
[184] Na S, Lee HK. Neural network approach for damaged area location prediction of a composite plate using electromechanical impedance technique. Compos Sci Technol. 2013;88:62–68.
[185] Selva P, Cherrier O, Budinger V, et al. Smart monitoring of aeronautical composites plates based on electromechanical impedance measurements and artificial neural networks. Eng Struct. 2013;56:794–804.
[186] Oliveira M, Araujo N, Inman D, et al. Kappa-PSO-FAN based method for damage identification on composite structural health monitoring. Expert Syst Appl. 2018;95:1–13.
[187] Stamopoulos A, Tserpes K, Dentsoras A. Quality assessment of porous CFRP specimens using X-ray computed tomography data and artificial neural networks. Compos Struct. 2018;192:327–335.
[188] Sammons D, Winfree W, Burke E, et al. Segmenting delaminations in carbon fiber reinforced polymer composite CT using convolutional neural networks. 6th Europ6th European-American Workshop on Reliability of NDEean-American Workshop on Reliability of NDE. 2016;1706;110014–110021.
[189] Li C, Nie X, Chang Z, et al. Infrared and ultrasonic intelligent damage recognition of composite materials based on deep learning. Appl Opt. 2021;60(28):8624–8632.
[190] Hu H, Luo H, Deng X. Health monitoring of automotive suspensions: a lstm network approach. Shock Vib. 2021;2021:6626024.
[191] Dang H, Tran-Ngoc H, Nguyen, et al. Data-Driven structural health monitoring using feature fusion and hybrid deep learning. IEEE Trans Autom Sci Eng. 2021;18(4):2087–2103.
[192] Jin H, Yan J, Liu X, et al. Quantitative defect inspection in the curved composite structure using the modified probabilistic tomography algorithm and fusion of damage index. Ultrasonics. 2021;113:106358.