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A Damage Recognition Method of Composite Structures Using Artificial Defections

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Abstract

The deep learning model can help to improve the reliability of guided-wave-based damage monitoring of composite structures, but it requires a large number of damage samples. Based on many simulated damage samples and a small number of real damage ones, a domain adaptive damage identification model is designed to realize the transfer from simulated damage identification to real damage identification. Firstly, simulated damage data are collected by pasting mass blocks, and a convolution time series hybrid neural network is designed to identify simulated damage with high accuracy; Then, a domain adaptive module is added to the model to approximate the distribution law of the simulated damage and the real damage data in the feature space, so as to achieve accurate identification without marking the real damage. The experimental results show that the detection accuracy of this method is 85.7%, which is better than the traditional deep learning model.

Keywords: Domain adaptive method, Guided-wave, Structural health monitoring, Composite structure, Transfer learning

1. Introduction

In recent years, carbon fiber reinforced plastics (CFRP) has been widely used in aircraft main load-bearing components because of its high specific strength/specific stiffness, designable performance and easy overall molding [1]. However, CFRP is sensitive to the impact of foreign objects. The impact of runway debris, maintenance tools and support vehicles may cause damage that is basically invisible on the surface and large-area delamination inside, sometimes reducing the structural compressive strength by more than 40% [2], bringing hidden dangers to flight safety. At present, in order to ensure the use safety of composite structures, it is necessary to set the design allowable value lower than the residual strength value of the structure with barely visible damage (BVID), but it is not conducive to give full play to the weight reduction advantages of CFRP structures.

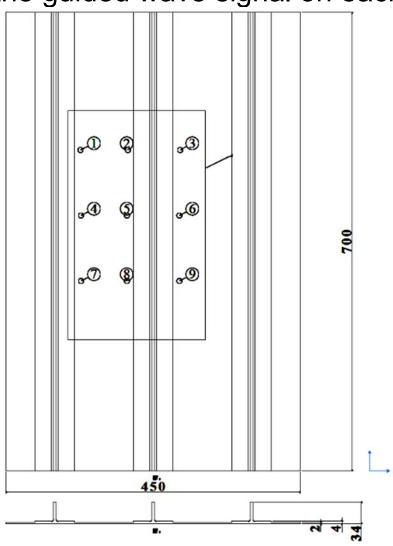
Structural health monitoring (SHM) technology, which can monitor the structural state in real time, provides a potential solution to the above problems [3]. Guided wave is one of the promising approaches in SHM. Taking advantages of sensor network, it can monitor over a wide area of thin-walled structures such as stiffened panel of airplanes. This enables the guided wave a low-cost monitoring way compared with other point-based monitoring ones such as Comparative Vacuum Membrane (CVM) or Smart Coating. This is especially helpful in full-scale fatigue test [4-6]. However, its performance in the field of aeronautical engineering has been unsatisfactory. This is because guided waves are very sensitive to structural configuration, damage form, service environment and other factors. The accuracy and reliability of damage diagnosis largely depend on experts' level and experts' prior knowledge of monitoring objects [7].

Researchers used deep learning to carry out guided wave based structural damage identification [8-10], location and quantitative research [11-13]. Shen[14] et al. used the deep learning technology to carry out the research on the debonding identification of stiffened panels. After wavelet transform preprocessing of the guided wave signal obtained from finite element simulation, it was input into the convolutional neural network (CNN) in the form of gray image for identification, and its accuracy was close to 99%. Cui[15] et al. applied the deep learning technology to damage imaging of key areas of reinforced composite test plates, and their designed one-dimensional CNN algorithm shows good damage diagnosis ability in skin, longitudinal beam flange and longitudinal beam cap areas. Khan[16] et al. proposed a deep learning framework for delamination damage evaluation of composite laminates based on structural vibration. The prediction accuracy of simulated damage location and size reached 94.5%. Zhang[17] and others have developed a deep learning framework that can transfer knowledge between damage location and damage quantification by using the transfer learning technology, and the effect is significantly better than the direct training of the two types of tasks.

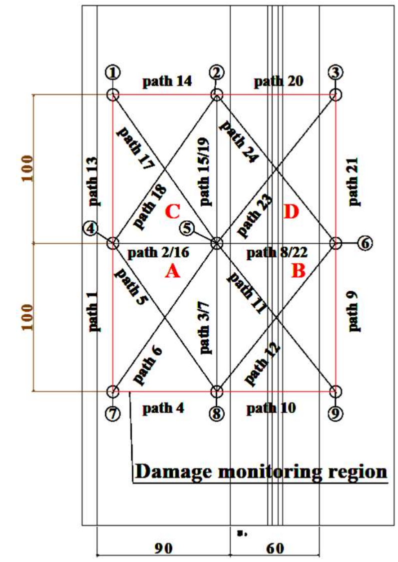
The results show that the deep learning method can effectively deal with the uncertainty caused by the change of material, structure, environment and other factors, and reduce the dependence on expert experience and prior knowledge. However, there are two obstacles encountered in the application of guided wave using deep learning models. One is the method development, which is quite expensive to collect large amount of damage samples for verification, even in element tests. Artificial damages have to be introduced during the method developing process. The other obstacle is that guided wave performs variably in simple element test and full-scale test. This is mainly due to different boundary conditions and uncertain damage location and size in large complex structure. It is impractical to perform a great number of real tests on full-scale structures to modify and calibrate the method obtained on the level of element test. Therefore, a set of transferring methods is essential, which are bridging the artificial-authentic damage gap and element-full-scale test gap, respectively, and enable the damage identification in an effective way. This paper endeavors to find the solution for the first gap.

1.1 Specimen and Experiments

The stiffened panel is made of CCF300/BA9916 carbon fiber reinforced composite, which is schematically illustrated in Figure 1(a). The skin layup sequence is $[90/-45/0/45]_{2S}$, and the stiffener's is $[90/-45/0/45/0/-45/90]_{S}$ for each side. It is 700mm long and 450mm wide, including three long trusses, of which the internal space is 150mm. Nine piezoelectric sensors are arranged in the central area of the stiffened plate to form a network with 24 monitoring paths, covering the skin and truss. The monitored area is divided into four sub-areas A, B, C and D, as shown in Figure 1(b). In this paper, the damage is identified according to the difference between the monitoring signal and the baseline signal. The sample is a 24*4000 matrix, in which 24 represents 24 paths and 4000 represents the number of sampling points of the guided wave signal on each path.



(a) The schematic illustration of specimen and sensor network.



(b) The sensor network and monitoring path.

Figure 1 - Structural form of the test piece (unit: mm).

The structural damage is simulated by pasting mass blocks on the stiffened panel, and a large number of guided wave monitoring data are collected as the source domain (Figure 2(a)).

Afterwards, the authentic damage is induced by weight dropping on the stiffened panel, and monitoring data are collected as the target domain (Figure 2(b)).

(a) Adhesion of mass block as simulated damage. (b) Real damage induced by drop weight test.

Figure 2 - Schematic diagram of simulation and impact test.

2. The Deep Learning Model of Damage Identification

A deep learning model of damage identification (hereinafter referred to as the model) is designed. It mainly includes two parts: feature extraction and target classification.

2.1 Feature Extraction

Because the guided wave monitoring signal has strong temporal characteristics, the long short term memory (LSTM)[18] network for processing temporal text is used as the main structure of the feature extraction network. The feature extraction of guided wave signal is divided into three steps: signal splitting, signal coding and temporal feature extraction. Signal splitting is to split the guided wave signal containing 4000 sampling points into 10 signal units with 400 sampling points; Signal coding is to write each signal unit into a semantic signal that is conducive to timing analysis according to certain rules; Temporal feature extraction uses LSTM to mine temporal correlation features among 10 signal units.

A 3-layer convolutional neural network is used to encode the signal units, and a hybrid neural network model is formed with LSTM, which is more conducive to the extraction of deep damage features. The structure of the coding network is shown in Figure 3, where LX and LY in the convolution layer parameters (LX, LY, LZ) represent the size of convolution cores, and LZ represents the number of convolution cores; The pooled layer parameters (CX, CY) represent the pooled window size.

After coding, each signal unit is converted into a 120 dimensional vector, and the vectors of 10 signal units enter the LSTM network in turn according to the time sequence of guided wave signal sampling to extract the timing characteristics. The structure of the LSTM network is shown in Figure 3, where XT represents the 120 dimensional vector of the tth signal unit in a guided wave signal, HT is the time sequence feature vector extracted from the tth signal unit of the model, C (T) is the model state after the LSTM model has processed the tth signal unit, the dotted line represents the time change of the LSTM model, and the model output and model state at time t are re-entered as historical values at the next time.

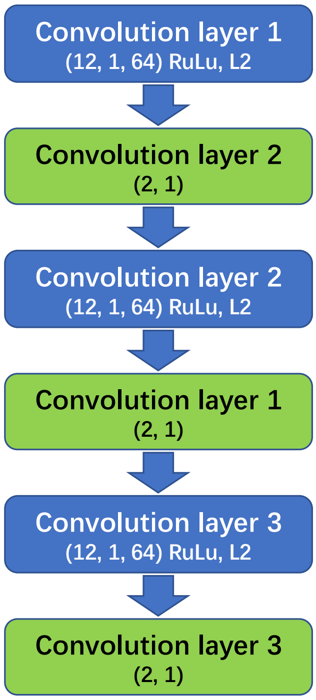


Figure 3 - Architecture of the coding network.

2.2 Target Classification

The eigenvectors of 24 guided wave paths are spliced to form a 24*28 dimensional vector, which is mapped to a 128 dimensional feature space through a single-layer fully connected neural network. If the data of the source domain and the target domain conform to the same distribution law in the 128 dimensional space, the in-depth learning model optimized with the accurate classification of the source domain data as the goal will be able to apply to the unlabeled target domain data at the same time. To achieve this goal, a domain adaptive module is designed in the classification network.

The input data of the domain adaptive module includes a large number of source domain data that have marked (simulated) damage and a small number of target domain data that have not marked (real) damage. Its function is to improve the distribution similarity of the two types of data in the feature space. In this paper, the maximum mean variance (MMD) is used to measure the similarity of data feature distribution between the source domain and the target domain. It can measure the distance between the two distributions in Reproducing Kernel Hilbert Space (RKHS). The specific expression is [19]:

$$\mathrm{MMD}(\boldsymbol{X}_{\mathrm{s}},\boldsymbol{X}_{\mathrm{T}})=\left\|\frac{1}{n_{\mathrm{s}}}\sum_{\boldsymbol{x}_{\mathrm{s}}\in\boldsymbol{X}_{\mathrm{s}}}\phi(\boldsymbol{x}_{\mathrm{s}})-\frac{1}{n_{\mathrm{T}}}\sum_{\boldsymbol{x}_t\in\boldsymbol{X}_{\mathrm{T}}}\phi(\boldsymbol{x}_t)\right\| \tag{1}$$

Where: X_s and X_T respectively represent the eigenvectors of source domain and target domain data, n_{s} and n_{T} represents the number of samples in the source domain and the target domain respectively; $\phi(.)$ represents a mapping function used to map primitive variables to RKHS. The essence of MMD is to find the mean distance between two types of data in RKHS.

The addition of domain adaptive module mainly changes the loss function of the model, and increases the MMD loss on the basis of the original classification loss. By minimizing MMD, the difference of data distribution between source domain and target domain is reduced; At the same time, the classification loss of the source domain data is minimized, so that the target domain data can accurately predict the damage after passing through the classification network. The loss function of the model can be specifically expressed as:

$$L = L_c(\boldsymbol{X}_L, \boldsymbol{y}) + \lambda \mathrm{MMD}^2(\boldsymbol{X}_s, \boldsymbol{X}_T) \tag{2}$$

Where: L_c refers to classification loss; X_L、 y represents the true value and predicted value of X_s respectively; λ Represents the weight parameter of two types of losses, which is a hyperparameter. The model optimizes MMD and classification error synchronously in the training process, and finally achieves the high accuracy classification of two types of data with the same distribution and source domain data.

3. Results and analysis

As shown in Table 1, of the 103 damaged samples, 10 were predicted as no damage and 2 location prediction errors, and the damage detection probability was 88.3%; Among the 109 samples predicted to be damaged, 14 were no damage and 2 were location errors, and the false alarm rate was 14.6%. In addition, in order to study the influence of domain adaptive technology on the accuracy of damage identification, the deep learning model trained based on source domain (simulated damage) data is used to detect the target domain (impact damage) data directly. The confusion matrix is shown in Table 2. The recognition accuracy, recall rate, damage detection probability and false alarm rate of the model are 76.9%, 83%, 78.6% and 30.2% respectively. In contrast, the isotropic indexes of the domain adaptive model have increased by 8.8%, 4.9%, 9.7% and 15.6% respectively, indicating that the domain adaptive technology can automatically modify the model parameters according to the real-time collected data in the state of unmarked data, so as to improve the damage identification accuracy of the newly collected data.

Table 1 - Confusion matrix for shock damage identification based on domain adaptive module.

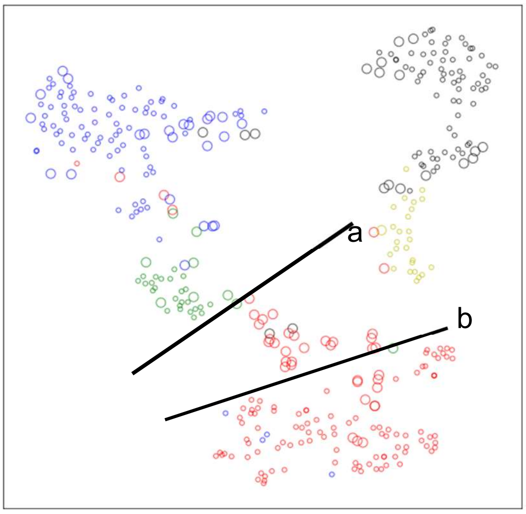
		Prediction				
	Damage location	0	A	B	C	D
Ground truth	0	64	8	0	0	4
	A	2	44	0	2	0
	B	4	0	14	0	0
	C	4	2	0	0	0
	D	0	0	0	32	3

Table 2 - Confusion matrix for shock damage identification without domain adaptive module.

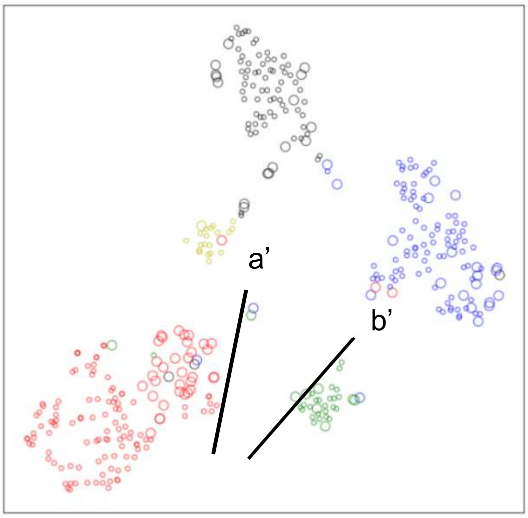
		Prediction				
	Damage location	0	A	B	C	D
Ground truth	0	58	4	6	2	8
	A	0	36	4	4	2
	B	2	0	16	0	0
	C	4	2	0	28	4
	D	0	0	0	0	3

In order to further illustrate the influence of domain adaptive module on the feature distribution and classification accuracy of real damage, firstly, the MMD value of real damage and simulated damage in 128 dimensional feature space before and after adding domain adaptive module is calculated, and its values are 4.12 and 0.89 respectively, indicating that domain adaptive module reduces the difference of feature distribution between the two types of data; Then, the principal component analysis method is used to reduce the 128 dimensional feature vector to 2 dimensions and display it, as shown in Figure 4. Figure 4(a) and (b) respectively show the characteristic distribution of simulated and real damage data before and after adding the domain adaptive module. The small circle and large circle represent the source domain and target domain data respectively, and red, blue, green, black and yellow represent that the sample is free of damage and the damage is located in areas A, B, C and D respectively. It can be seen from Figure 4 that before and after the domain adaptive module is added, the five types of data simulating damage can be well separated and the boundary is obvious;

Before adding the domain adaptive model block, the data of the five categories of real damage are distributed near the corresponding category of simulated damage, but on the outside of the simulated damage data cluster, and there is data superposition among various categories; After adding the domain adaptive module, the data of simulated damage and real damage are obviously more concentrated, and they are set into the same cluster. Then the category boundary of simulated damage can also be applied to real damage. For example, for red (no damage) and green (damage is located in area B) data, before the application of domain adaptive technology, the classification line of the two may be located at any position between lines a and b, so as to completely separate the red small circle and the green small circle (i.e. simulated damage). However, if the classification line is directly used to classify the red large circle and the green large circle (i.e. real damage), Then multiple red circles will be classified as green; After adding the domain adaptive module, the classification line obtained through the small circle classification optimization is located between the lines a’ and b’, while there are only two large green circles and no large red circles between a’ and b’. Therefore, the number of classification errors will be significantly reduced, which shows that the prediction accuracy of the model for real damage is significantly improved in the case of no label. This conclusion can be confirmed by the data comparison between Table 1 and Table 2. In Table 2, 6 undamaged samples were wrongly judged as damage in area B, while in Table 1, no undamaged samples were wrongly judged as damage in area B.



(a) No domain adaptive module



(b) With domain adaptive module

Figure 4 - The distribution of data features.

4. Conclusion

A domain adaptive guided wave damage diagnosis method based on deep learning is proposed. A large number of guided wave monitoring data similar to the real damage are generated by physical simulation damage, and the deep learning damage identification model is designed and trained;

Then the model is transferred to a small number of unlabeled impact damage monitoring data by domain adaptive technology, so that the identification accuracy of real damage is similar to that of simulated damage.

Using this method, the simulated damage data can be directly collected on the structure to be tested without disturbing the performance of the structure itself. The physical simulated damage and domain adaptive technology can better solve the problem that it is impossible to collect the damage signal of the monitoring object and formulate the damage judgment in advance in engineering practice.

An important factor for the domain adaptive deep learning model to perform well in guided wave damage diagnosis is that the data distribution laws of physical simulated damage and real damage are similar, and then the model parameters are adjusted through the domain adaptive module to make the simulated damage and real damage conform to the same classification rules. In complex application scenarios such as full aircraft fatigue test, the coupling of multiple interference factors and the analysis of signal mechanism are difficult. The domain adaptive deep learning model provides a new idea for damage monitoring. The further work is to introduce more representative real damages at various locations for model training, so that the accuracy could be improved, and the application of domain adaptive technology in engineering practice is the follow-up research direction of this paper.

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6. Copyright Statement

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