Impact Monitoring of Large and Complex Structures Based on Transfer Learning

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ABSTRACT

Aircraft structure impact monitoring is important to the safe operation of aircraft. However, aircraft structures are often structurally complex, increasing the uncertainty of the signal during transmission. Traditional impact monitoring methods need to obtain sufficient structural change signals through dense sensor arrays to obtain good monitoring results. But too many sensors can increase the cost of operating an aircraft. Therefore, this paper adopts sparse sensor array arrangement, proposes a two-step impact monitoring strategy from region to point location, and adopts deep learning and traditional methods to monitor impact events. Firstly, the test structure is divided into several regions of a certain size, and a model capable of accurate regional location is trained by convolutional neural network. In this process, in view of the large size of the aircraft structure and the difficulty in obtaining training data, the transfer learning strategy of model fine-tuning is adopted to transfer the trained feature knowledge of the source domain model to the target domain model, reducing the cost required for data acquisition and training model. Then in the second step, on the basis of accurate regional positioning, weighted centroid method is used to estimate the impact location.

1. Introduction

Impact is a common accident form in the process of aircraft service, which will damage the integrity of aircraft structure and threaten the safe operation of aircraft. Therefore, it is necessary to monitor the impact event. At present, the daily inspection of aircraft mainly relies on manual visual inspection, but for such a large structure as aircraft, this is a costly work, which takes a lot of labor and time [1]. Therefore, automatic monitoring and reporting the impact location can greatly improve the efficiency of the work. To solve these problems, the structural health monitoring technology (SHM) can be used to achieve continuous monitoring of aircraft impacts through a large intelligent sensor network system permanently integrated inside or on the surface of the aircraft structure, combined with advanced and efficient intelligent monitoring algorithms [2-4].

There are two main approaches to impact monitoring: the model-based approach and the neural network approach. The model - based method is mainly to build a model of the mathematical relationship between "stress wave velocity - arrival time – sensor spacing". However, it is difficult to establish an accurate mathematical model because the structure is usually complicated and the material parameters are difficult to obtain in the actual application process. The method based on neural network usually depends on the input and output to adjust the connection weight and connection mode of each internal neuron. The advantage is that the process of model establishment is relatively simple, while the disadvantage is that a large amount of training data is required for training, and the training of the model usually takes a long time. On the other hand, the aircraft structure may be damaged in the process of data collection, it is not suitable for large-scale data collection. Therefore, data source has become one of the main obstacles limiting the application of neural network method in structural health monitoring.

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In order to reduce the operational costs brought by the data acquisition system to the aircraft load, and the practical problems that training data samples are not easy to obtain. In this paper, sparse sensor array is adopted and the impact monitoring strategy is adopted from region to point. Firstly, according to the requirements, the structure to be tested is divided into a number of small regions that need to be accurately located and used as the source domain to collect data. The powerful classification function of convolutional neural network is used to convert the regional positioning into a classification problem. Then, based on the precise region positioning, weighted centroid algorithm is used to predict the impact location. Finally, to solve the problem of insufficient data sources of the training model, the transfer learning method of model fine-tuning is adopted to transfer the trained knowledge of the source domain model to the target domain model, it can reduce the data samples and training time required by the training target domain model to reduce the training cost [5-7].

2. Impact monitoring principle

There are many kinds of sensors that can be used to monitor impact, but piezoelectric sensors become one of the most common sensors in passive structure health monitoring due to their low cost and convenient layout. When an impact occurs, the piezoelectric can use the inverse piezoelectric effect to convert stress waves into electrical signals that are easier to monitor. A typical passive impact monitoring system mainly consists of three parts: monitored structure, data acquisition system, impact positioning and evaluation system.

3. Convolutional Neural Network

Convolutional neural network (CNN) is a feedforward network mainly composed of convolutional layer, pooling layer and fully connected layer. It is good at classification tasks. The structure of convolutional neural network is briefly introduced below [8, 9].

(1) Convolutional layer

The convolutional operation layer is the core of the whole convolutional neural network, which can extract the features of the input data and realize the characteristics of local connection and weight sharing of the neural network. Compared with the traditional fully connected neural network, the number of parameters of the convolutional neural network is greatly reduced.

(2) Pooling layer

The function of pooling layer is to compress and reduce the dimension of data, which can not only reduce the number of parameters required in the training model process, but also reduce the overfitting phenomenon in the training process.

(3) Activation Function

In this paper, the most commonly used Relu function in convolutional neural networks is selected as the activation function. The main function of Rel activation function is to perform threshold operation on each input value. For input values greater than or equal to 0, linear function padding is used. Relu function can greatly accelerate the convergence rate of stochastic gradient descent by virtue of its linear unsaturated property.

(4) Fully connected layer

In order to complete the final classification task, softmax function is selected to present the classification result in the form of probability.

4. Transfer learning

To obtain a neural network model with good performance, three factors are usually required: (1) large quantity and excellent quality data set, (2) a reasonably designed network model architecture, and (3) sufficient training time. However, in the real background of structural health monitoring, the data is not easy to obtain and the process of data acquisition is usually time-consuming and laborious, which greatly limits the practical application of neural network in impact monitoring. Therefore, in order to solve the problem of high data source and training cost, and expand the application ability of neural network, transfer learning has become one of the research directions of machine learning [10-12].

Because different layers of convolutional neural networks will extract different features, the shallow convolutional network layer usually extracts some general features such as contour and color, while the deep convolutional network layer can extract specific damage features. This paper adopts the transfer learning method of model fine-tuning. Firstly, a model with good performance is obtained by training source domain data. Then the shallow convolutional network layer is frozen and fixed, and the deep convolutional layer is retrained. By feeding the trained features of the source domain model into the target domain model, a new model can not be trained from scratch, thus saving a lot of computing resources and computing time.

5. Weighted centroid algorithm

In order to assess whether the impact has caused damage to the structure, it is necessary to predict the location of the impact. Due to the sparse sensor array adopted in this paper, there are only a few or even no sensors in some positioning areas, which restricts some traditional methods based on "arrival time - wave velocity". Therefore, the weighted centroid algorithm is adopted in this paper to make more accurate point positioning prediction for the location of impact [13]. The schematic diagram of weighted centroid algorithm is shown in Figure 1.

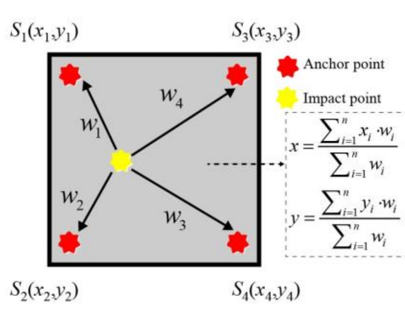


Figure 1. Schematic diagram of weighted centroid location method

The weighted centroid location algorithm is shown in Equation (1). When a new impact event occurs, the similarity between the new impact signal collected by the sensor and the standard point signal obtained in the data acquisition process is calculated as the weight of the weighted centroid algorithm.

$$\begin{aligned} x &= \frac{\sum_{i=1}^{n} x_i \cdot w_i}{\sum_{i=1}^{n} w_i} \\ y &= \frac{\sum_{i=1}^{n} y_i \cdot w_i}{\sum_{i=1}^{n} w_i} \end{aligned} \tag{1}$$

Where, x_i and y_i are the coordinates of each standard point, and w_i is the weight assigned to each standard point. When the distance between the new impact point and the standard point is closer, the signal will be less affected by the structure, the greater the similarity between the signals and the greater the corresponding weight, and vice versa.

6. Experimental setup

The test piece is shown in the figure below. Its length, width and height are 3750mm*2000mm*2mm, and it is made of aluminum alloy. The back of the measured component is evenly divided into different small areas by a large number of reinforced structures. The central position of each small area is arranged with a PZT sensor. The sensor spacing in the vertical and horizontal directions is 500mm and 240mm, respectively. Although the overall structure is similar, each area contains different types and amounts of reinforcement structures such as rivets. In this paper, one of the regions is selected as the source domain and three different target domains A, B and C. As shown in Figure 6 (c), the size of each small area is 500mm*240mm. In order to obtain an ideal detection effect, each small area is evenly divided into 16 parts.

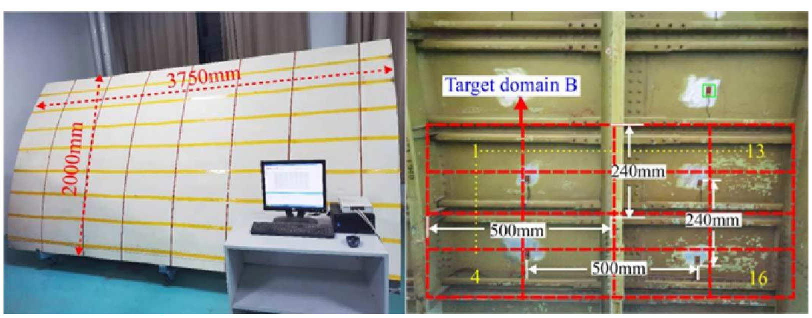
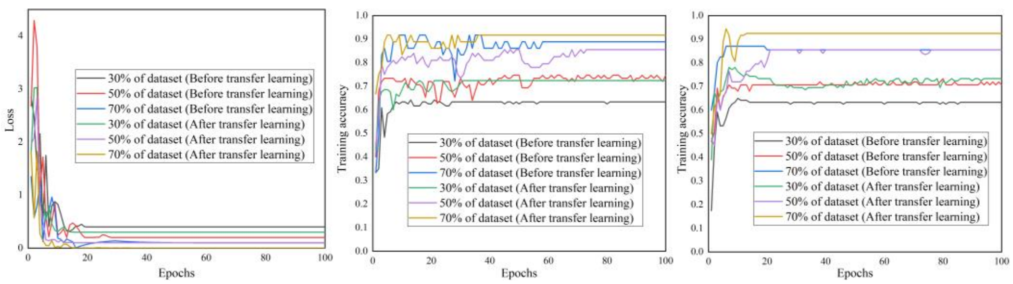


Figure 2 Schematic diagram of the structure under test

7. Accuracy and transferability

This paper uses the data collected in source domain to train a model. Since the structure of each target domain is similar to that of the source domain, the source domain data set and the target domain data set have similar initial features. By fine-tuning the trained model, the repeated process of initial feature extraction and model training can be avoided to achieve the purpose of migration. This can not only reduce the cost of model training, but also improve the accuracy of prediction. As shown in Figure 6 (a-c), is the accuracy rate of the model before and after migration when different amounts of data are used.



(a) (b) (c)

Figure 3 The training accuracy curves of the three target models: (a) target model A (b) target model B (c) target model C

It can be seen from the figure:

(1) Increasing the amount of data used to train the model is an effective way to improve the accuracy of the model. Both before and after transfer learning, the accuracy of the model is improved with the increase of data volume.

(2) After transfer learning, the target model can obtain part of the feature knowledge from the source model, which can reduce the time and data amount required for training the model.

(3) Compared with the model before transfer learning, the model after transfer learning can converge in a shorter time.

(4) The initial verification accuracy of the model after transfer learning is better than that of the model without transfer learning.

8. Impact location result

In order to evaluate the location effect of the weighted centroid algorithm more accurately, some test points are selected at equal intervals on the aircraft structure. As shown in Figure 4, the distribution of these points on various reinforcement structures, such as rivets and reinforcement structures, includes all possible impact scenarios.

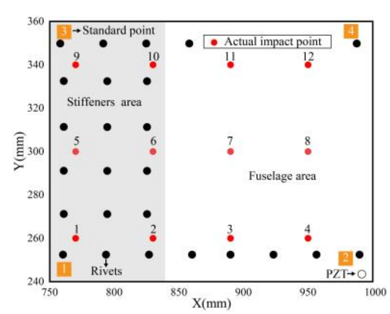


Figure 4 Distribution of test points in structure

In this paper, the relative error defined by Equation (2) is used to evaluate the positioning effect.

$$Error_x = \frac{\left|x_{actual} - x_{predict}\right|}{dis_x}$$
$$Error_y = \frac{\left|y_{actual} - y_{predict}\right|}{dis_y} \tag{2}$$

Where, x_{actual} and y_{actual} represent the horizontal and vertical coordinates of the real impact point respectively, while $x_{predict}$ and $y_{predict}$ represent the horizontal and vertical coordinates of the predicted impact point respectively. dis_x and dis_y represent the horizontal and vertical spacing between sensors, respectively. Table I shows the positioning effects of the 12 impact points mentioned above.

Table I. Impact location effect

Number	Actual	Predict	$Error_x$	$Error_y$	Number	Actual	Predict	$Error_x$	$Error_y$
1	(2,2)	(3.5,3.3)	3.0	5.4	7	(14,6)	(16.3,4.8)	4.6	5.0
2	(8,2)	(10.1,3.3)	4.2	5.4	8	(20,6)	(22.7,4.4)	5.4	6.7
3	(14,2)	(17.8,3.2)	7.6	5.0	9	(2,10)	(2.9,11.8)	1.8	7.5
4	(20,2)	(16.8,4.6)	6.4	4.6	10	(8,10)	(6.7,11.8)	2.6	7.5
5	(2,6)	(4.6,4.5)	5.2	6.3	11	(14,10)	(16.1,11.5)	4.2	6.3
6	(8,6)	(10.2,7.4)	4.4	5.8	12	(20,10)	(22.8,11.8)	5.6	7.5
Average	\	\	\	\	\	\	\	4.6	6.1

9. Conclusion

The main work of this paper is as follows:

(1) The sparse sensor array can reduce the extra weight load brought by the monitoring equipment to the aircraft

(2) CNN can be used to complete accurate regional positioning. Based on this regional positioning, centroid algorithm can be used to complete the prediction of impact location.

(3) The transfer learning idea of model fine-tuning is adopted, which can reduce the unnecessary process of initial feature extraction and model training, and reduce the cost of data acquisition and model training.

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