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Using Deep Learning Techniques for Sandwich Panels with Truss Core Damage Detection

Yabo Wang^{1,2}, Lingling Lu^{1,2*} and Hongwei Song^{1,2}

¹Key Laboratory for Mechanics in Fluid Solid Coupling Systems, Institute of Mechanics, Chinese Academy of Sciences, Beijing, China

²School of Engineering Science, University of Chinese Academy of Sciences, Beijing, China

*Corresponding author's e-mail: lulingling@imech.ac.cn

Abstract. In the previous study, the accuracy of damage detection for the sandwich structures with truss core (SPTC) was affected by the selected damage index, Other than this, human subjective judgment could also not directly determine the degree and the location of damage for SPTC. In this paper, the deep learning method is applied to identify the damage for SPTC, and the dataset of the training deep learning model is obtained based on the dynamic method. This paper adopts to the Caffe, which is a deep learning open source framework, object detection model Faster R-CNN is utilized to study the lattice sandwich plate. The damage data set, the optimal hyperparameters for training the deep learning model, and the optimal ratios of the test set and training set for damage dataset are also studied. It is difficult to detect the damage of SPTC applying to the deep learning algorithms, so the good results cannot be gotten. In this paper, the method of Faster R-CNN has used extracts the deep features of the defective target by ZF that is a kind of Convolutional Neural Network (CNN), the method effectively solves the problem that the traditional algorithm cannot effectively detect the damage. As to the damage of SPTC that the traditional algorithms could also identify, the deep learning algorithm is excelled, the experimental mean average precision(mAP) can be raised to 90%. At the same time, the deep learning method can effectively identify locations and size of the damage in SPTC, the method is proven that the accuracy is higher and the speed is faster for damage detection. In the future, a real-time damage monitoring system is possible, and the theory is worth exploring further.

Abstract: deep learning, sandwich panels with truss core, damage dection

1. Introduction

In recent decades, because of structural health monitoring (SHM) helping to reduce operating costs and maintenance costs of aerospace equipment, such as aircraft, spacecraft. The technology for SHM has been continuously developed and gradually occupied to an important position in the aerospace field and engineering field. But other than that, the technology for SHM is also widely used in other application, including smart materials, sensors, damage diagnosis and prediction, signal processing etc. Metal lattice sandwich structure has various topological open cores; this structure has high specific strength, high specific stiffness and impact energy absorption. The open structure filled with heat insulation material can also be applied to in the thermal protection structure, which is a typical structure [1-4].

The combination of the sandwich and the panel can greatly improve the rigidity of the structure and the lighter quality, owing to those various advantages, this structure can be applied to many fields, whereas if there is some damage, similar to have cracks, off-grid etc. The damage, which happens to the panel and core when applied in a harsh environment, will reduce the strength of the whole structure



seriously, and even lead to the destruction of the entire structure[5]. Sandwich structure has potential application value; many experts and scholars have studied the manufacturing process of lattice structures. Vyacheslav N. Burlayenko et al[6] studied the influence of the debonding size, debonding location and debonding types on the modal parameters of damaged sandwich plates with various boundary conditions. Vladimir S. Sokolinsky et al[7] investigated The dynamical equations for free vibration response of sandwich beams with a locally damaged soft core.

Numerous methods applied to damage detection have been proposed for a composite structure, for example, the methods based on lamb wave, X-ray, guided-wave and vibration-based methods etc. In recent years, deep learning technology has developed rapidly and it is widely used in many fields, such as image detection technology[8], natural language processing technology⁹, speech recognition, automatic driving, etc. These technologies are achieved based on convolution neural network, GooleNet[10], ALEXNet[11] and Resnet[12], which have been developed in recent years, have achieved good results in image detection and classification. Similarly, the application of CNN in engineering is also an attempt, for example, CNN has been used to detect damage and cracks, some achievements have been made. Based on method of the visualization. However, the method based on CNN of detecting crack is still in the infancy, and the research has just begun. Therefore, by combining deep learning technology with the method of damage identification for SPTCs, it is possible to identify damage features (locations, styles and extent) accurately.

2. Deep learning techniques for SPTC damage detection

In SPTC damage detection, the sensitivity of different degree damage is sometimes different seriously, a method of identifying the damage based on deep learning is proposed. Therefore, the method related to deep learning and computer vision is reviewed in this chapter, and the application of detecting damage based on deep learning is also introduced.

2.1 The theory of training process

In this article, the deep learning method of object detection is used to identify the damage of SPTC. The type of prefabricated damage is as follows: half cell missing (HCM), single cell missing (OCM), two cells missing (TCM) and four cells missing (FCM). The different damage samples are used to create a dataset, the features of the different damage can be learned and extracted from the dataset by the method of deep learning, the location and extent of the damage can be identified accurately. In order to solve this problem, Faster R-CNN is utilized to learn the characteristics of different types damage, Faster-RCNN network structure is shown in Figure 1.

2.2 Training mode

In the training process of the Faster R-CNN, firstly, the weights of the network layers are randomly initialized based on Gaussian distribution, and then the weights of the other network layers are initialized through the pre-training model. In all network layers, the process of the training is mainly divided into four steps, and it can ensure that the weights can be shared between the RPN and the Fast R-CNN extracting features. The first part is to train the RPN, and the weight of the RPN network are initialized through the pre-trained network model, the second step is to generate a separate Fast R-CNN detector through the high quality and clear feature maps, which are generated by the RPN. In the third step, when pre-trained model is used to initialize the weights in the process of training Fast R-CNN. The shared weights are shared between RPN and Fast R-CNN and the RPN is only fine-tuned, in the final step, Fast R-CNN is trained and the shared weights are shared. The RPN and Fast R-CNN shared the same convolutional layers. Those networks are initialized using ZF network. The learning rate of 0.001 is set for 60k mini-batches, and the learning rate of is set to 0.0001 for the next 20k mini-batches on the SPTC damage dataset. A momentum of 0.9 is used and a weight decay is set to 0.0005. The deep learning model is trained on Caffe.

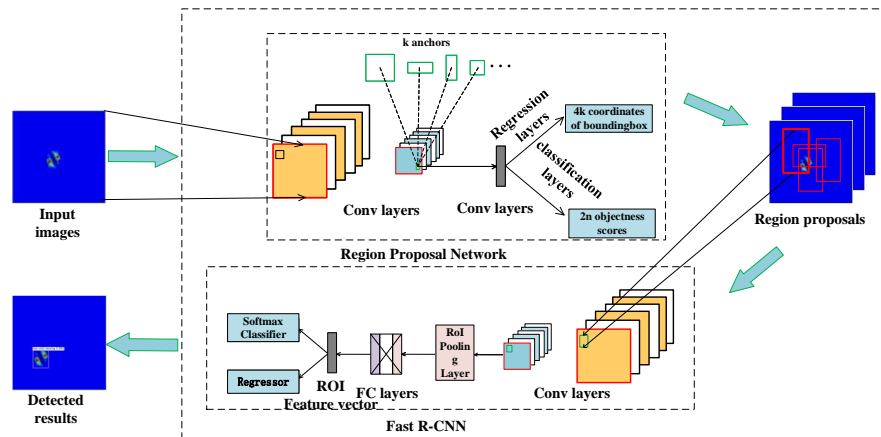


Figure 1. Faster R-CNN architecture

2.3 The process of RPN training

Before training the RPN, the labels of each category (HCM, OCM, TCM, FCM) is assigned to each anchor, in the network of Faster R-CNN, in the Faster R-CNN, the multiple tasks loss of RPN is used. The loss function is as follows:

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i L_{reg}(t_i, t_i^*) \quad (1)$$

Where, i is the number of anchors, p_i is the probability of anchor i being object, and p_i^* is the probability of the real anchor i being object, If the anchor i is a positive object, the value of p_i^* is 1, otherwise, if the value of p_i^* is 0, it is negative, t_i is a term of vector which represents the coordinate values of the predicted box, similarly, t_i^* is also a term of vector which represents the coordinate values of the ground-true box, the classification loss is log loss over two classes(object or not object) [8].

3. The Process of training and results

This paper mainly investigates the deep learning method of identifying cells missing of the SPTC accurately. When locating the same type damage, the deep learning method is used to solve the problem of sensitivity of different damage indexes. In the training process of deep learning modal, the key steps are as followings: (1) three different damage identification quantities to generate datasets for deep learning model training, (2) screening, classifying, cleaning the generated dataset. In order to make the training model general, the data enhancement method is used to preprocess the dataset for training; (3) For the damage of the SPTC, unless the optimal ratio of the test set and the training set in the generated data set is found, the trained model is the best in the data set under this ratio, (4) Faster R-CNN directly is applied to the generated dataset, the model is not optimal. It is necessary to adjust the network structure for classifying and detection classification. (5) Modifying different hyperparameters, retraining the network structure, and finding the best set of hyperparameters. Therefore, based on the proposed method the trained deep learning modal can accurately identify the damage in SPTC, and the effects on the accuracy of the model are also investigated.

3.1 Generated dataset

The schematic diagram of SPTC model is shown in Figure 2, Figure 2 shows that there are 15 units along the X and Y directions. In reality, SPTC is made by brazing technology, numerous types of

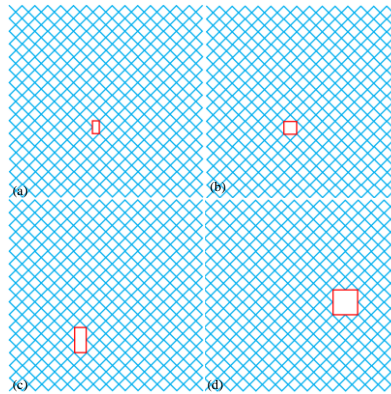


Figure 2. Four types of damaged models. (a) half cell missing. (b) one cell missing. (c) two cells missing. (d) four cells missing

in XML files, which consist of the real feature information of each sample image, are used to train the model.

Table 1. Number of samples for each type of damage

| The types of damage | Numbers | Numbers | Numbers |
|---------------------|---------|---------|---------|
| HCM | 557 | 511 | 450 |
| OCM | 396 | 414 | 449 |
| TCM | 287 | 269 | 224 |
| FCM | 387 | 370 | 391 |

damage happened to the SPTC, such as de-soldering, cell missing, panel damage, etc. In this article, we mainly study cell missing damage of SPTC. four types of damage in the array are studied: half one missing, one cell missing, two cells missing, four cells missing. The damage type is as shown in the Figure 3.

3.2 Samples enhancement and annotation

Four types of damage in this paper are as shown in the Figure 3, The number of datasets obtained by using the three types of damage markers are shown in Table 1. After the sample images being

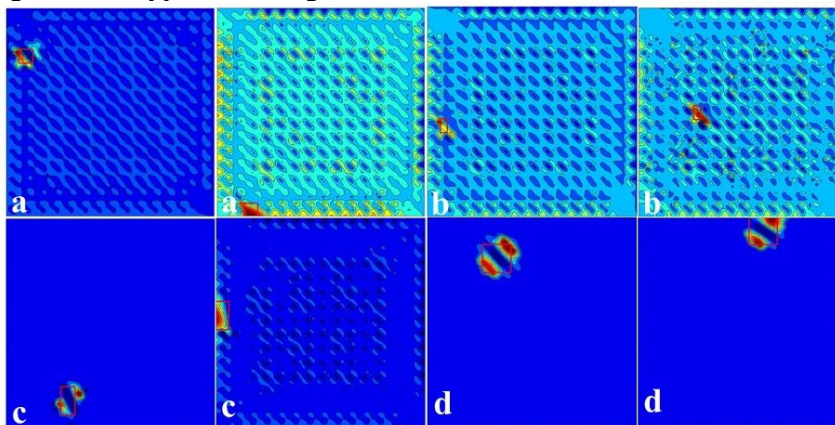


Figure 3. Samples of damage images. (a) Half cell missing. (b) One cell missing. (c) Two cells missing. (d) Four cells missing.

enhanced, each real damage feature needs to be annotated. Labellmg, which is the open source marking tool, is used to annotate the location of the damage and the class labels of the damage. Those the location of the damage and the class labels of the damage are stored.

3.3 Experimental setup

The models used in the experiments were all trained in Caffe, which is operated hardware environment is on an Ubuntu 16.04 system with an Intel Core i7-7700HQ CPU, 2×NVIDIA GeForce GTX 1080ti

GPU and 32G RAM. Implementation details and the results of each experiment are explained in the following sections.

3.4 The results of detection on model of optimal hyperparameter

In the previous sections, the training results of ZF on different datasets, which consist of the different ratio of training set and testing set, are discussed, the optimal dataset compositions for SPTC dataset is determined as 8:2. Different models are trained on the same dataset, the result in table 2 is shown that the complex of the network model has a less effect on the final results.

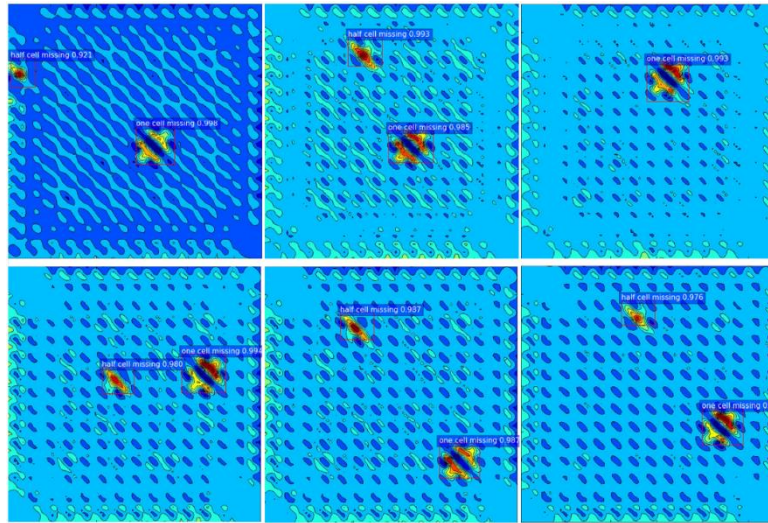


Figure 4. Detection results for Faster R-CNN of Optimal Parameters

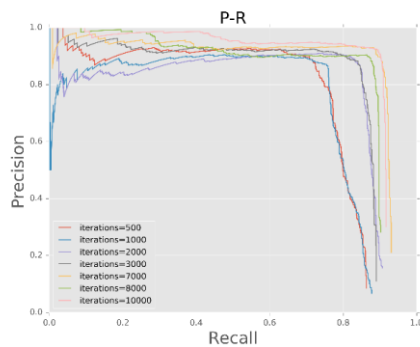


Figure 5. P-R curve for different iterations

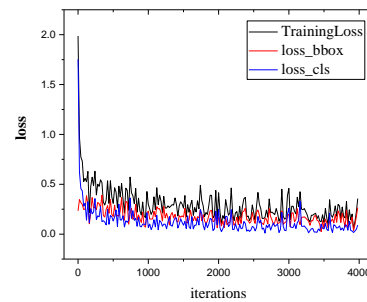


Figure 6. Loss curve for different iterations

In addition to this, the iterations is also discussed in the previous chapters, by comparing with the training results for different iterations, when the iteration is in the range of 500 from 1000, the different iterations has a great influence on the accuracy. Increasing iterations can improve

Table 2. The performance evaluation of the different models.

| Model | Architecture | Dataset | HCM | OCM | TCM | FCM | Time (min) |
|---------|--------------|---------|------|------|------|------|------------|
| FZR | ZF+RPN | A | 0.56 | 0.79 | 0.89 | 0.80 | 182 |
| FV1024R | VGG-1024+RPN | A | 0.53 | 0.79 | 0.87 | 0.88 | 679 |
| FVR | VGG-16+RPN | A | 0.54 | 0.79 | 0.87 | 0.89 | 679 |

the accuracy greatly, but when the iteration is 4000, the accuracy rate is with a little improvement, considering the training time, the optimal iterations for SPTC dataset are determined as 4000. A part of detection results can be seen from Figure 4 shows that the results of the damage detection for SPTC, and the accuracy is up to 90%. For the damage identification, Figure 5 and Figure 6 show that the

accuracy is high and the false positive rate is relatively low, the loss has not changed much as the iterations increasing.

4. Conclusion and Future works

In this paper, deep learning is applied to the damage detection of SPTC. For four types of damage (HCM, OCM, TCM, FCM) in SPTC, the detection results are more accurate, but in actual processing and manufacturing the types of damage are diverse, the non-bound and cell missing occupy a large proportion. Since the deep learning is applied to the damage detection of the lattice sandwich plate, it is only in the initial stage, as the result, in this article, the damage identification of cell missing is the focus of this paper is for SPTC. For the detection of cell missing (HCM, OCM, TCM, FCM), the accuracy of the modal is high. However, there is still a lot of tasks to do to apply deep learning techniques for the damage identification of SPTC. Firstly, as for the trained datasets, further expansion is required and various damage types should be added to enrich the datasets, the trained model can identify more types of the damage. Secondly, identifying the damage in SPTC based on the image, a one-step data processing and annotate damage feature are needed in the whole process, if the deep learning is directly trained on such dataset, the error will happen to the detection results, therefore, if the deep learning is trained in origin data, which has not been processed, the accuracy of the modal may be higher.

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