A CNN-Based Crack Analysis Model for Metal Specimens

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Abstract. In the field of engineering, the combination of deep learning and traditional simulation has become a research hotspot. In healthy structure monitoring problems, strain sensors are spaced and spatially arranged to collect strains. However, methods such as strain gauges can only capture single-point strains, and in many cases these more discrete strain information is insufficient to determine the damage of the target. In this paper, we combine the strain field with deep learning methods to propose a novel damage detection method based on strain image inversion to perform crack information of workpieces. The method defines the type and location of cracks on the specimen as labels, a large number of simulated strain images as datasets, and uses CNN networks to train the model. The results show that the obtained crack inversion model for metal specimens can achieve 93.99% accuracy.

Keywords: Convolutional Neural Network, strain field, Image Recognition.

1. Introduction

Currently, non-destructive testing is one of the more common methods for detecting cracks [1]. Common NDT methods include ultrasonic technology [2], eddy current testing [3] and Lamb testing. Although NDT has a high degree of accuracy, NDT techniques require specialized inspectors and expensive inspection equipment. In addition, many times these methods are confined to laboratory conditions and have limited practicality. On the other hand, traditional inspection methods require regular maintenance by personnel, making it difficult to meet the requirements of real-time and in-situ inspection. Therefore, in-situ identification of crack growth and monitoring of damage evolution is an imminent technology in the next step.

We mainly use a crack growth monitoring method based on strain information [4]. The main principle of this method is that when cracks appear in the structure, the strain of the damaged area in the structure will change sharply due to the crack expansion and initiation, so that the strain information of the structure can be measured to realize the identification of the crack growth inside the structure. The current resistance strain gauge technology has been quite mature, and the adhesive process on the structure is complete and standardized. The strain gauge has the advantages of small size, light weight and convenient use, and can also collect ideal experimental data for analysis. Direct strain measurement can be used to monitor fatigue crack activity and has the potential to provide effective fatigue crack detection. If the crack occurs below or near the sensor, a sudden change in strain in a local area can be detected. Therefore, both traditional foil strain gauges and optical fiber sensors have been applied to crack detection. However, these sensors are often small and have a limited measurement range [5], so a large number of traditional strain sensors are required to monitor large structural surfaces, which greatly increases the cost and reduces the practicality. Therefore, despite the simplicity of the concept, the continuous monitoring of fatigue cracks on the surface of large structures using strain sensing elements remains a major challenge.

In this paper, the discrete strain field on the surface of a metal specimen is captured in the simulation, which is interpolated and processed to be reduced to a strain image on the surface of the specimen, and then the deep learning method is introduced into the automatic crack recognition, and the recognition model is trained with a large number of strain images containing crack information.

2. Simulation Methodology

2.1. Simulation Model

Deep learning is a data-driven algorithm. The data source of this paper is the extraction of uniaxial tensile simulation data of dog bone specimen by ABAQUS. In the simulation, the tensile stress-strain test of dog bone specimen, which is common in mechanical experiments, is taken as an example, and the strain cloud map of prefabricated cracks in different positions in the test stage of metal materials is taken as the data set of this neural network project.

Dog bone specimen was established. Young's modulus is 200 GPa and Poisson's ratio is 0.3 set in the material properties. Using concentrated force coupling, apply to the entire right end area, as shown in Fig. 1.

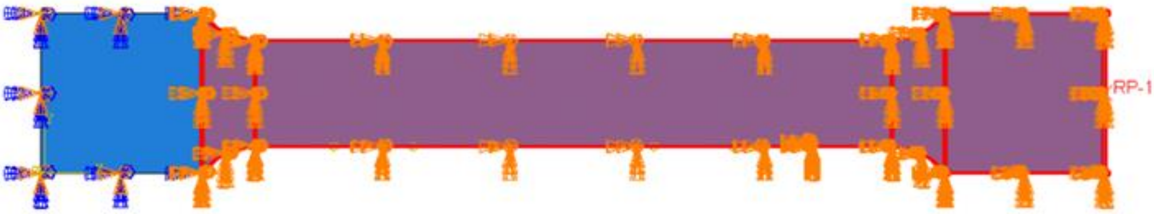


Figure 1. Load Settings

In the simulation, 4 damage forms and 7 transverse positions were set as crack information. Moreover, 11 kinds of loads are applied to stretch the specimen to make the crack propagation. Strain measuring points were selected on the surface of the specimen at a certain interval, and E11 strain changes of all measuring point cells over time were extracted and recorded for subsequent processing. There were 660 strain measuring points on the surface of the specimen, as shown in Fig. 2.

According to the uniaxial tensile standard of the dog bone specimen, the crack propagation simulation experiment under different stresses of the simulated workpiece was carried out. Under the action of the XFEM module, the prefabricated cracks could be well expanded according to the real situation. After grid division, each grid element had a specific number, and the strain value of the unit near the crack would be significantly larger, and the corresponding unit was extracted according to the preset discrete element set. The strain value of the element as it changes with step.

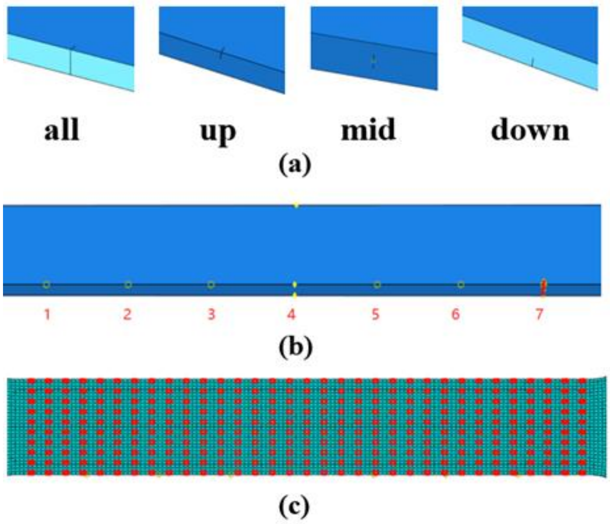
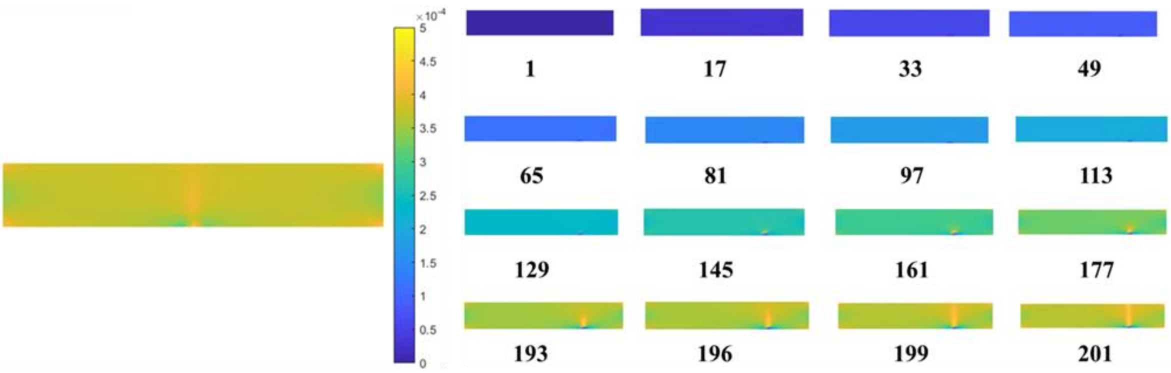


Figure 2. (a) Four forms of damage (b) Crack transverse position; (c) Surface strain measurement points

2.2. Strain image processing

We used a Python program to retrieve the course analysis step of each specimen in the simulation, and recorded the strain values in each analysis step of the discrete set of strain monitoring points in chronological order. The MATLAB program was used to reduce the strain maps by interpolation according to the spatial location of the cells, and the colors (strain values) in the maps were normalized according to the same standard, and the colors reached a certain degree to be regarded as the existence of cracks.

The change process of the overall strain map under the same working condition is shown in the figure below. A large number of strain maps under different working conditions constitute the data set of this project, totaling 30453 maps. Fig. 3 Strain maps over time for a single condition. The reduced cloud map is shown in Figure 3.



(a) (b)

Figure 3. (a) Interpolated reduced strain images (b) Strain images as a function of analysis step

3. Deep Learning Model

3.1. Model Training

A 2D convolutional neural network was chosen for the deep learning method used to train the test and generate the strain damage inversion model. Deep learning is a data-driven algorithm [6]. Data types such as structured data (databases), time-series signals (vibrations that fluctuate over time), and image data [7]. Images represent spatial information, each pixel on the image appears at the same time and has only spatial attributes without temporal attributes. Two-dimensional convolutional neural network is the most widely used technology in image processing. Further is the data-based method, through the measurement of strain or guided wave signals and other methods to obtain data containing damage information to train the neural network [8,9], so that the model obtained for any state of the skin containing damage can be recognized and inverted out of the type of damage and location information, and even as long as the similar conditions can be input by the relevant data to determine the damage situation. In summary, combining damage-related information with deep learning methods has become a cutting-edge and effective damage inversion method [10].

Table 1. ResNet Network Architecture

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		[3×3, 64 3×3, 64] ×2	[3×3, 64 3×3, 64] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3
conv3_x	28×28	[3×3, 128 3×3, 128] ×2	[3×3, 128 3×3, 128] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×8
conv4_x	14×14	[3×3, 256 3×3, 256] ×2	[3×3, 256 3×3, 256] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×23	[1×1, 256 3×3, 256 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512 3×3, 512] ×2	[3×3, 512 3×3, 512] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

The deep learning method used in this paper is two-dimensional convolutional neural network ResNet [11], which uses 34-layer residual network, which has a good performance for image classification tasks [12]. Firstly, the cloud images in the sample set were preprocessed, including dividing 80% of the cloud images as the training set,20% of the cloud images as the test set, cutting the excess parts, standardizing the resolution, and dividing two types of labels. The important parameters are set as follows: batch size =128 batch training sample size 128, arch =34 residual 34 layers, lr =1e-3 learning rate 0.001, Epoch =100 Maximum number of iterations 100. The ResNet network structure is shown in Table 1:

3.2. Test Results

The accuracy of the crack information in the test set of strain maps inverted by the model is the technical index to verify the superiority of the model, and the strain information crack defect inversion model trained by 25 iterations finally achieves an accuracy rate of 93.99%. The loss function and accuracy of the model are shown in Figure 4:

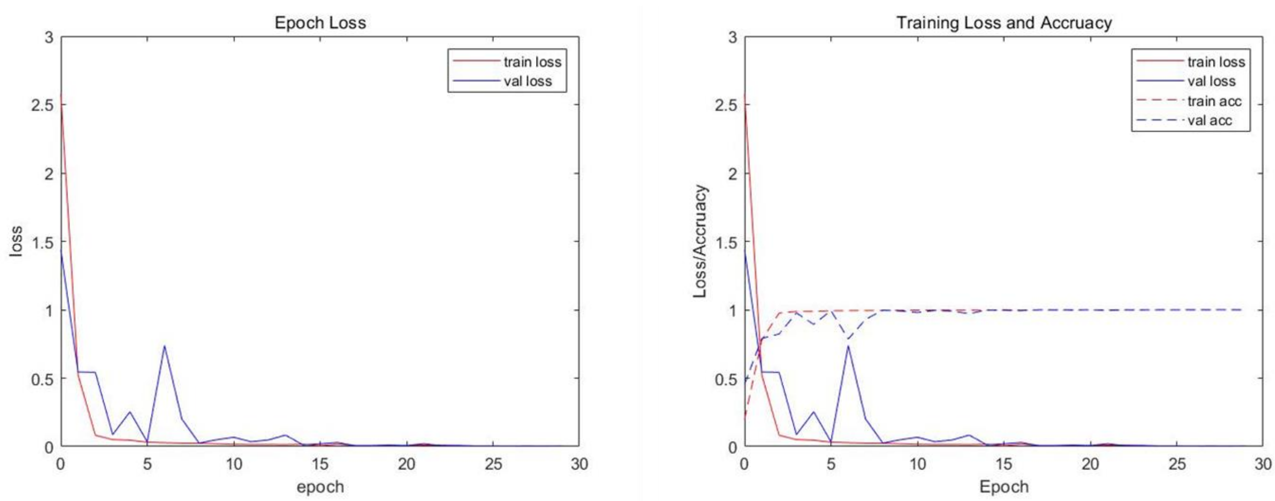


Figure 4. Loss function and accuracy of the model

In order to facilitate the presentation of the test results, we wrote the UI interface for the validation session. Simply by selecting the strain field image in the dataset where the inversion of crack information is performed, the crack information contained in this image, including the crack type and transverse location, can be quickly recognized. As shown in Figure 5:

Figure 5. Crack identification results

4. Summary

This article proposes a CNN-based crack recognition method that extracts discrete strain values from the surface of a simulation model as raw data. After processing, a large number of strain field images are put into the training set to obtain a crack inversion model for metal specimens. The method only needs to collect the discrete strains on the surface of the test specimen, and can accurately invert the crack information of the specimen itself updated over time. Similarly, the method can be extended to other strain collection methods and damage forms, and NDT combined with deep learning is bound to find more long-term applications.

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