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An internal crack detection method using machine learning algorithm

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ABSTRACT

Internal crack detection without destructive testing is very important for safety management of structures. In this study, we propose an internal crack detection method using machine learning of external deformation data. For machine learning, we perform finite element analysis of various types of cracks. The numerical results are preprocessed as image data. The Variational Autoencoder (VAE) is modified for learning the image data. We confirmed that the proposed method can detect the position and shape of internal cracks from arbitrary deformation data. From the results of this study, we expect to be able to detect internal cracks in various structures using 3D finite element models.

1. INTRODUCTION

Crack is one of the major causes of structural failure. Because the crack in the structure is directly connected with structural safety, the technology to detect and manage cracks is required. However, the crack inside the structure is difficult to detect with naked eyes. Therefore, non-destructive testing was conducted to analyze data caused by external stimuli. At present, ultrasound technology, radiation transmission technology and eddy current technology are used.

Research has also been conducted on using machine learning to analyze data for crack detection. Chady (1999) used the results of the eddy current responses obtained from experiments for neural network training. S.W. Liu (2002) uses vibration response data obtained from FEM for training in the neural network to detect the position and size of cracks. Because previous studies used limited data, there is a limit to the possibility of detection only if the location and shape of the crack are simple. However, since the actual cracks appear in general shape, the detection of arbitrary cracks is required.

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With the development of image recognition and generation technology using deep learning, various researches are being conducted using image generation modeling techniques such as Variational Autoencoder (VAE) by Kingma (2013) and Generative Adversarial Network (GAN) by Goodfellow (2014). Y Yu (2019) studied the use of generative modeling in the field of topology optimization where there is a problem of computational efficiency. Spurr (2018) presented a methodology for obtaining motion pose images from human hand photographs using multiple VAEs. In addition, using conditional GANs, a study was made to generate a sketch image as a colored image by Isola (2017). Among these generation modeling methods, VAE can be applied to express numerical analysis results defined by high-dimensional images (deformed shapes, cracked shapes, ……) with a limited number of variables. We can also use VAE to construct an artificial neural network that infers the shape of cracks inside structures from deformed images.

In this study, we are going to show the feasibility of detecting the various shape internal cracks when given the deformation of the structure. Therefore, we used the generation modeling technique to intuitively detect cracks in a general form from the deformation of the structure. We also use the finite element models to efficiently generate crack data for various cases for machine learning.

2. PROPOSED INTERNAL CRACK DETECTION METHOD

2.1 Generating the training dataset

FEM code is used to generate crack data for use in training of the generation model (Jeon HM 2014, Lee Y 2014, Lee Y 2015, Ko Y 2016, Ko Y 2017, Kim. S 2018, Jun H 2018, Lee C 2018, Kim. G 2018). For purposes of predicting internal cracks, we create random cracks within simple two-dimensional square structures. To obtain easy-to-learn deformed shapes, we generate force and boundary conditions on the structure as shown in Fig. 1(a). The bottom and left sides have displacement boundary conditions in the y- and x- directions, and uniformly distributed forces are given normal to the top and right sides. For the training of the generative model, the results of finite element analysis are preprocessed into images. The deformed shape obtained from numerical analysis is small as shown in Fig. 1(b). These images are difficult to characterize through training. Therefore, the deformation is normalized so that it can be used for training. As a result, we generated a total of 2000 pairs of crack images and deformation image datasets as shown in Fig. 1(c). To improve training speed and performance, the size of the data has been converted to 100×100 pixels.

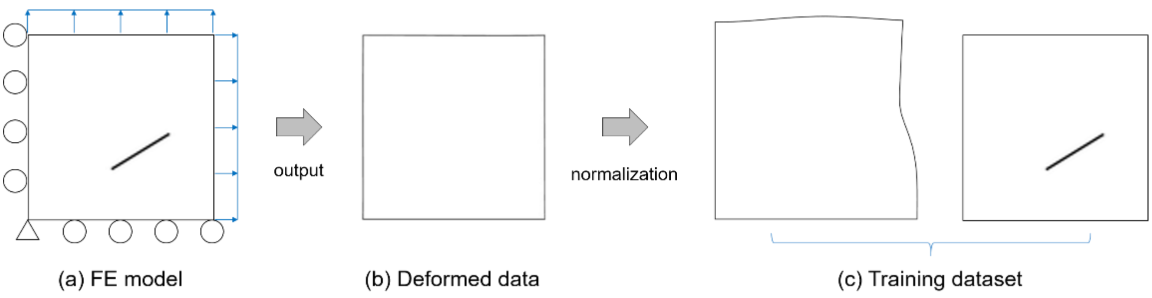

Fig. 1 (a) Finite element model; (b) Deformation data; (c) Training dataset

2.2 Variational encoder and decoder network

VAE is one of the generative models, consisting of an encoder network and a decoder network. The encoder network uses variational inference to approximate high-dimensional data with a certain probability distribution. The decoder network reproduces high-dimensional data through sampling from the distribution obtained from the encoder network. In general, VAE is intended to reproduce the input data, and thus the input and output are the same. The training progresses so that latent variables follow a specific probability distribution while minimizing the error between input and output. In this study, the goal is to detect the crack shape from the deformed shape. We designed the variational encoder and decoder network to obtain a new output by modifying the input / output structures of VAE. In this study, our network consists of CNN and ANN. The detailed structure is shown in Fig. 2.

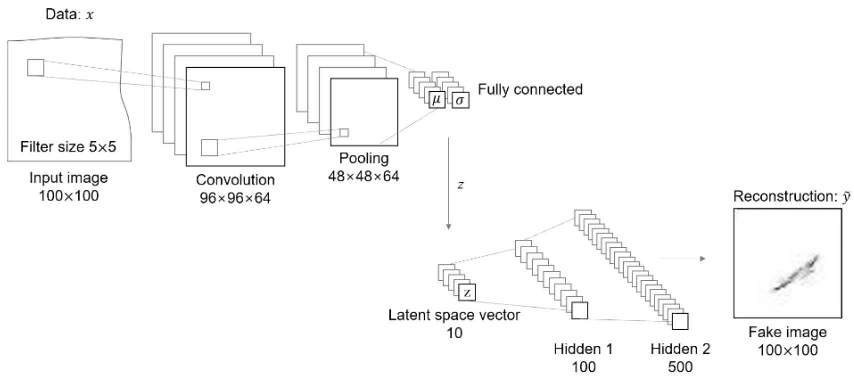

Fig. 2 Detail of the variational encoder and decoder network

At this time, the crack image is a simpler form than the deformation image. Therefore, we designed the encoder and decoder as different neural networks to reduce training time. For the supervised learning of the VAE structure, the computation proceeds with minimizing the difference between the real cracks and the generated cracks. As a result, as shown in Fig. 3, we were able to plot cracks from the new deformation images that are not in the training dataset.

Fig. 3 Result of variational encoder and decoder network

2.3 Adversarial encoder and decoder network

Adversarial autoencoder (AAE) is a combination of VAE and GAN (Makhzani 2015). GAN is designed to reduce the difference between the actual distribution of data and the distribution created by the generator. Using GAN, AAE complements the disadvantages of VAE that require only normal distribution. The VAE structure of AAE acts as a generator, and the added discriminator network distinguishes the latent variables sampled from the fake distribution and the latent variables sampled from the target distribution. In general, AAE is designed to reproduce the input data and has the same input and output. However, the goal is to generate the crack shape from the deformed shape. Therefore, we designed the adversarial encoder and decoder network by modifying the input and output of AAE to plot the crack as an image when the deformation image is input. In this study, the network consists of CNN and ANN to reduce training time. The detailed structure is shown in Fig. 4.

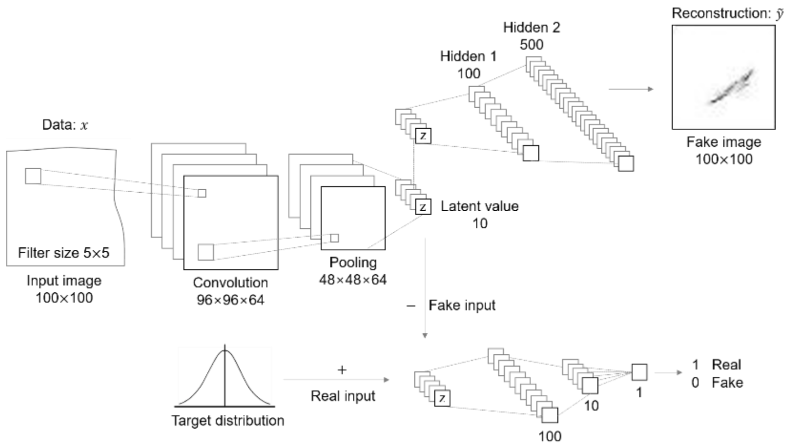

Fig. 4 Detail of the adversarial encoder and decoder network

We used the following methods to guide the training of the AAE structure. First, we update the encoder and decoder parameters to minimize the difference between the real crack image and the crack image is generated by the network. Next, the discriminator parameters are updated to minimize the difference between the fake distribution of the encoder and the target distribution. We then update the encoder parameter so that the discriminator can distinguish the fake crack image as the real crack image. The results are shown in Fig. 5.

The results of the variational encoder and decoder network as shown in Fig. 3 are expressed as a combination of training data and tend to be smooth and blurry. In other words, the variational encoder and decoder network has characteristics that are dependent on training data and tend to overfitting. Fig. 5 shows the results of the adversarial encoder and decoder network. The 3rd and 8th results, which belong to well-trained cases, can be seen to be less blurry compared to another network. In other words, we can see that the adversarial encoder and decoder network generates new images that are not in the training dataset. However, due to the characteristics of GAN, which has difficulty in training, most test cases did not have good results compared to another network.

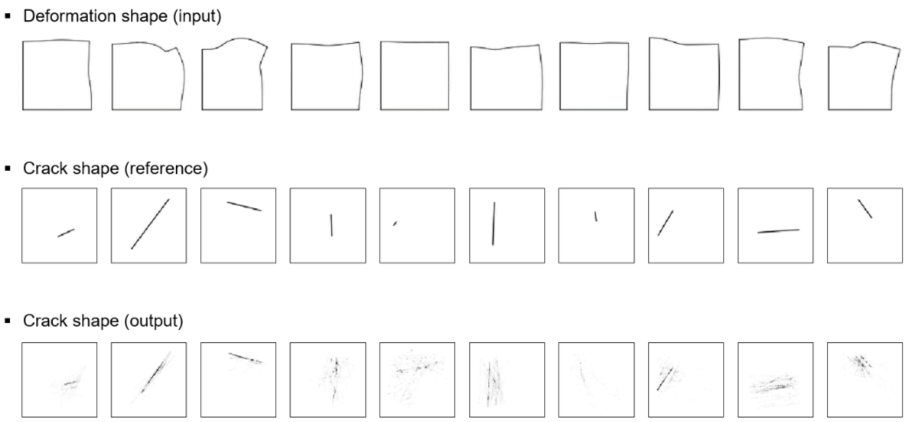

Fig. 5 Result of adversarial encoder and decoder network

3. CONCLUSIONS

We modified VAE to build a network to detect the crack shape corresponding to the deformed shape. From the results, we can confirm that crack detection is possible from data that does not exist in training data. However, we can see that the result is represented by a combination of training data. We also designed the new network by modifying AAE that combines GAN with VAE to enable crack detection for new data.

There are a number of limitations that need to be overcome in order to apply this methodology to real problems. First, we need to use 3-dimensional data to detect internal cracks, which was the goal of our research. Also, in real world problems, deformation is not easy to measure. We are going to carry out a follow-up study using vibration data generated by using 3-dimensional finite element analysis. During the deformation normalization process, the size information of the crack in the training data was ignored. We plan to modify the data or network in order to consider the size information of the cracks. In this study, we used CNN and ANN together to reduce training time, but we will use CNN-only networks in future studies. We will also use GPU computing to shorten training time. If we overcome these limitations, we expect that it is possible to detect the internal cracks of structures with only finite element analysis data without using experimental data.

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