Experimental Data Generation using StyleGAN-like Architecture

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1. Introduction

Recently, as deep learning technology has rapidly advanced and interest in smart factories has increased, there has been a growing trend of applying deep learning technology to anomaly detection. Similarly, there is a growing demand for applying deep learning technology to detect anomalies in plant pipes. To develop a model using deep learning technology to detect anomalies in plant pipes, a large amount of high-quality data is needed. However, abnormal state data is very rare in actual plant environments, making it difficult to collect abnormal state data. Furthermore, in actual plant environments, it is difficult to artificially induce abnormal states because in most cases significant damage occurs when abnormal states occur.

For these reasons, most of deep learning models are trained by collecting experimental data in a testbed environment. However, obtaining experimental data requires a considerable amount of time and effort, and it is impossible to collect experimental data for all possible cases that may occur. To address these difficulties, this paper introduces a technique for generating new experimental data using the collected experimental data and deep learning technology. In this paper, we introduce an experimental data generation model using the Generative Adversarial Network (GAN), one of the representative deep learning-based generative models, and specifically introduce the method of generating data using StyleGAN.

2. Data Generation using StyleGAN-like Architecture

Variational autoencoder and GAN[1] are representative generative models based on deep learning technology. There has been significant research on using GANs for image generation due to the common issue of low quality data generated through autoencoders.

The simplified structure of GAN is shown in Fig. 1, where G represents the generator network and D represents the discriminator network. G is trained to generate data that is similar to real data in order to deceive D into being unable to distinguish it. Then, G generates data that is similar to real data from an input random noise vector. On the other hand, D is trained to successfully distinguish between generated data from G and real data. However, a drawback of GAN is that when input random noise is given, it is not guaranteed what specific characteristics the generated data will have.

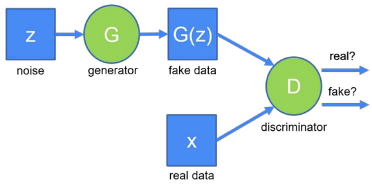

Fig. 1. Simplified architecture of GAN.

In 2019, StyleGAN[2] was proposed to control detailed elements (gender, hairstyle, expression, etc.) when generating human face images. The key idea of StyleGAN is the mapping network. Unlike GAN structure shown in Fig. 1, an input random noise vector is passed through the mapping network to learn features and generate data, as shown in Fig. 2. The advantage of this structure is that the noise is learned as features in the latent space through the mapping network. This allows us to adjust vectors in the latent space to generate the desired data. For instance, using StyleGAN, it is possible to generate a sequence of human face images with gradually changing facial expressions.

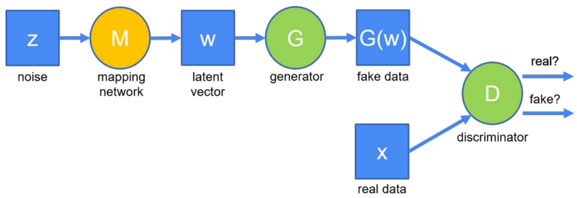

Fig. 2. Simplified architecture of StyleGAN.

We generate experimental data using StyleGAN-like architecture in Fig. 2, and data generation using the proposed data generation network in Fig. 2 proceeds as follows:

i. Train the mapping network, generator network, and discriminator network using the training dataset.
ii. Generate a latent vector corresponding to the data using the mapping network and generator network.
iii. Linearly Interpolate the latent vectors between two different data and generate data from the generator network using the interpolated vector.

3. Experimental Results

We validate the proposed method using impact signal data of metal materials for the beam structure shown in Fig. 3. The impact signal was collected using an accelerometer sensor. In this experiment, we generate impact data at positions 2, 3, and 4 using impact data at positions 1 and 5. Hence, in this paper, impact data from positions 1 and 5 are used as training data, while impact data from positions 2, 3, and 4 are used as validation data.

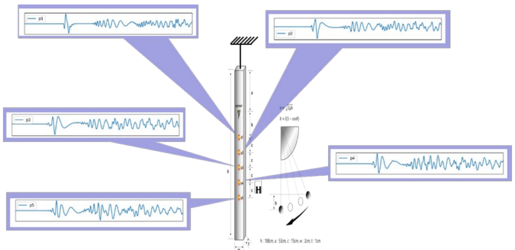

Fig. 3. A beam structure used in experiments and actual impact signal data of metal materials for the beam structure.

The latent vectors that generate the impact data at positions 1 and 5 are shown in the rightmost images of Fig. 4 and 5. The leftmost images in Fig. 4 and 5 are actual impact data, while the middle images are the data generated by the generation network when the latent vector is given. As shown in Fig. 4 and 5, the impact data from positions 1 and 5, which were used for training, are generated to be similar to the actual impact data..

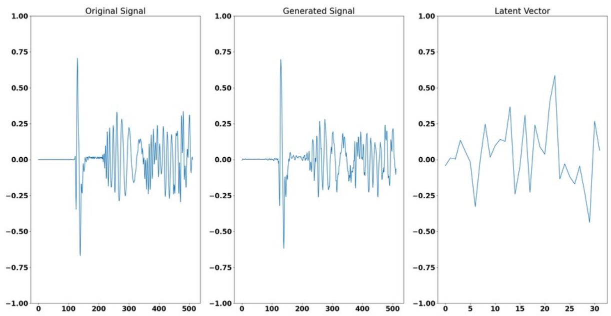

Fig. 4. Impact data, generated data, and latent vector at position 1.

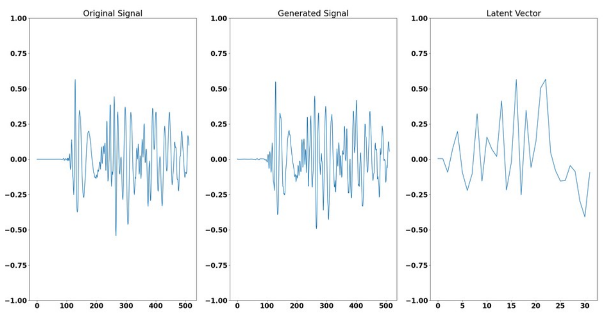

Fig. 5. Impact data, generated data, and latent vector at position 5.

In Fig. 6 and 7, the actual impact data and the generated impact data for positions from 1 to 5 are presented from top to bottom, respectively. For the generated data for positions 2, 3, and 4, the overall signal characteristics appear to be reflected in the generated data, but high-frequency noise is observed in the generated data.

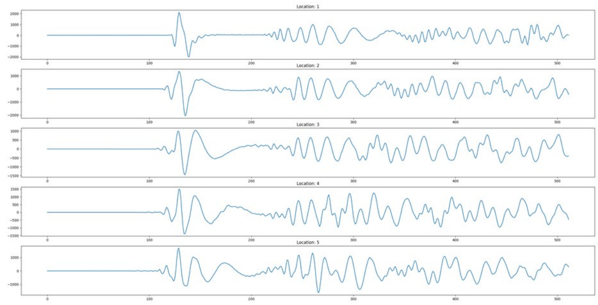

Fig. 6. Actual impact data at position from 1 to 5. (From top to bottom)

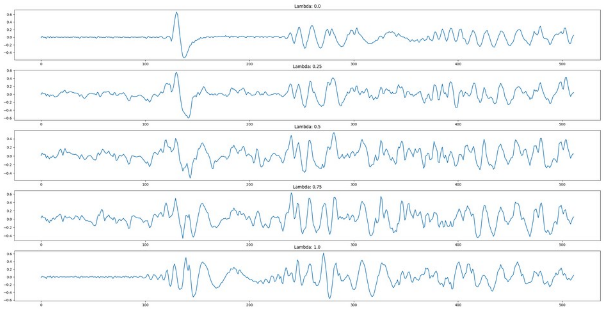

Fig. 7. Generated impact data at position from 1 to 5. (From top to bottom)

4. Conclusion

We proposed a data generation model using StyleGAN-like architecture. We trained the mapping network, generation network, and discrimination network using the training dataset, and then generated a latent vector corresponding to the data using the mapping network and the generation network. Next, we linearly interpolated the latent vectors of two data and generated interpolated data using the generation network and the interpolated vector. We verified the proposed method using the impact signal data of metal substances in beam structures collected using an acceleration sensor. The generated data appears to reflect the overall characteristics of the actual signal, but high-frequency noise was added to the generated data. Additional research is needed to reduce this high-frequency noise and improve the quality of generated. Moreover, the paper lacks a quantitative metric for evaluating the quality of the generated data. To address this, we are considering using commonly-used performance metrics for generative models such as Frechet Inception Distance (FID) in GANs. Additionally, as mentioned in the paper, we plan to evaluate the quality of the generated data by using a subset of the experimental data that was not used for training, as the test data.

ACKNOWLEDGEMENT

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