1P2-11

Anomaly detection for split concrete utility poles using autoencoder and Mahalanobis distance

Naoki Furuya [1†], Eiji Iwatsuki [1], Teruyuki Kozuka [1], Takahiro Iwata [1], Masahiro Toyoda [2], and Norio Tsuda[1*]
([1] Aichi Institute of Technology; [2] Honda Electronics. Co., Ltd)

1. Introduction

Utility poles play an active role in Japanese infrastructure, supplying power and communication lines, and being used for road signage. In recent years, split poles, in which poles are divided into multiple sections, have appeared and are gradually increasing in number due to their ease of transportation. However, the collapse of utility poles caused by age-related deterioration and the resulting secondary damage have become a problem.

To achieve the SDGs (Sustainable Development Goals), “#11. Create cities where people can continue to live,” measures must be taken to prevent utility poles from collapsing. In 2008, Japan formulated a plan to promote the elimination of utility poles by undergrounding power lines, however the situation remained poor. According to a survey conducted in 2021, the number of utility poles increased by 46,000 in a year, for a total of 36 million nationwide. Considering the above, it is difficult to eliminate utility poles from Japan, and periodic inspections must be conducted to prevent their collapse.

Generally, inspectors visit utility poles to determine deterioration through visual inspection and sounding. However, there is concern about the shortage of labor owing to the declining birthrate and aging population, necessitating the establishment of a deterioration technology that does not rely on human labor.

In this study, anomaly detection using ultrasonic waves and AI (Artificial Intelligence) was performed on utility poles, especially split poles, particularly split poles, which have increased in number in recent years.

2. Principle

Although there are several nondestructive inspection methods for concrete structures, such as radiation, ultrasonic, magnetic, seepage, and eddy currents, ultrasonic methods were selected for this study because of their compatibility with automation and safety.[1-2)]

For deterioration diagnosis and anomaly detection, we used Python and created a program using autoencoder as an anomaly detection method.

Autoencoder can producing a clear trained image. [3)]

It can perform advanced anomaly detection by determining the difference between the unknown and generated images. Transition learning was used during training to reduce the number of training sheets and make the model lighter. Transfer learning refers to the application of a portion of an already trained model to a new training model, which is expected to improve the learning efficiency and reduce the model weight.

The Mahalanobis distance is calculated by considering the variance of the data in a normal distribution model, and is a practical judgment index in the field of anomaly detection.[4)]

3.Experimental Method

Fig. 1 shows the layout of the experimental apparatus, and **Fig. 2** and **Fig. 3** show examples of STFT (short-term Fourier transform) images used in the experiment. A receiver transducer was installed in the underground embedment, and an oscillator was installed 2 m away in a straight line. Two models were prepared: one with surface defects (hereafter referred to as “deteriorated pole”) and another without defects (hereafter referred to as “sound structural pole”). Forty-three sound structural pole models and two deteriorated pole models were prepared for the experiment. Ultrasonic waves (sine wave, 50 kHz, 60 $V_{p\text{-}p}$, 1 wave) were generated from the ultrasonic transducer using a function generator and a bipolar power supply.

The received waveform was subjected to STFT and imaged as training data.

During verification, loss values were calculated using data other than those used during training and the deteriorated pole data. Two-dimensional data were created using the pixel sum of the generated images and loss values, and anomaly detection was performed using the Mahalanobis distance. A total of 2,000 images, 1,800 of which were not used for training from the data of sound structural poles and 200 of which were used for training from the data of deteriorated poles, were used for accuracy evaluation.

4. Principle results

4.1 Autoencoder

E-mail: †furuya297@gmail.com, *n-tsuda@aitech.ac.jp

The results of the autoencoder for the input STFT images of a sound structural pole and a deteriorated pole are shown below as **Fig. 4** and **Fig. 5**. In the case of a sound structural pole, the image was generated clearly, however, in the case of a deteriorated pole, image generation fails. The loss value for the sound structural pole was approximately 0.00043, whereas that for the deteriorated pole was 0.00201. We can observe the difference between the sound and deteriorated poles.

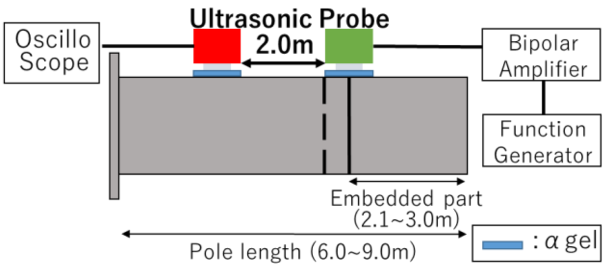

Fig. 1 Experimental layout.

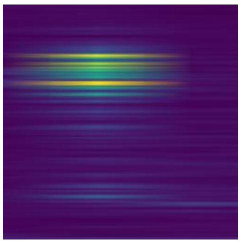

Fig. 2 STFT image of sound structural pole (model 1).

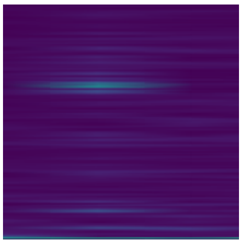

Fig. 3 STFT image of a deteriorated structural pole (model 1).

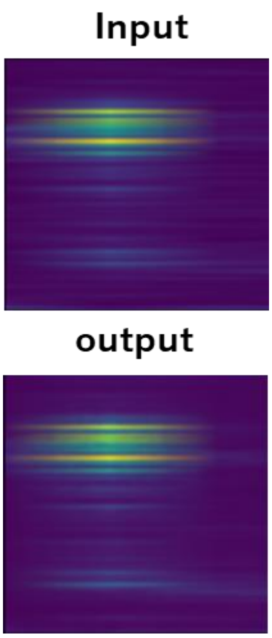

Fig. 4 Results of the autoencoder (input sound structural pole).

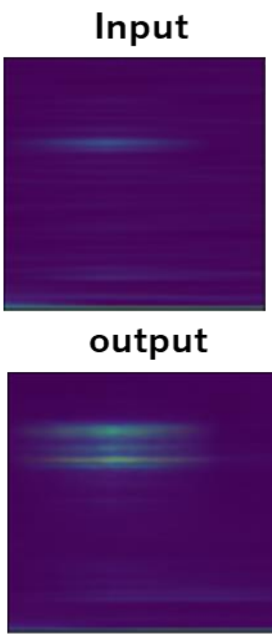

Fig. 5 Results of the autoencoder (input deteriorated pole).

4.2 Anomaly detection

The two-dimensional distribution of the reorganization error and pixel sum is shown in **Fig. 6**, and the results of the anomaly detection by the Mahalanobis distance are shown in **Fig. 7**. In Fig. 6, the black dots represent the data of the sound structural poles, and the orange dots represent the data of the deteriorated poles. The curve in Fig. 7 is a contour line showing the Mahalanobis distance, and the threshold of the Mahalanobis distance was set to 3.5 for anomaly detection. The blue and red dots are True Negative (TN) and True Positive (TP), respectively. In this case, the sound structural and deteriorated poles were correctly separated, and the abnormality was successfully detected.

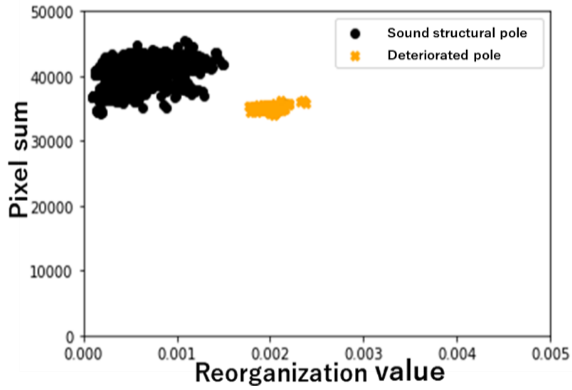

Fig. 6 Two dimensional distribution of each models.

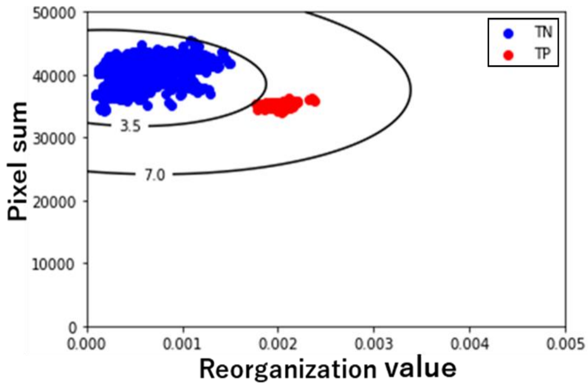

Fig. 7 Results of anomaly detection by the Mahalanobis distance.

References

1) G. Karaiskos, A. Deraemaeker, D. G. Aggelis and D. Van Hemelrijck, Smart Materials and Structures **24**,113001 (2015).
2) C. M. Lee, Y. H. Lee and K. J. Lee, Prog. in Nucl. Energy **49,** 303 (2007).
3) G. E. Hinton and R. R. Salakhutdinov, SCIENCE **313**, 504 (2006).
4) P. C. Mahalanobis, The Indian Journal of Statistics. **80-A**, S1 (2018).