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Idea of AE Separation from Unpredicted Source Area during AE Testing by Autoencoder †

Yoshihiro Mizutani

School of Engineering, Tokyo Institute of Technology, Tokyo 152-8550, Japan; ymizutan@mes.titech.ac.jp

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Abstract: When conducting AE testing, there is an industrial need to separate AE from monitoring area to that from outside of the area in some cases. In this study, usefulness of autoencoder to solve this problem is discussed by simple experiment using an isotropic thin steel ruler. It was shown that a single trained autoencoder can be used for separating AE signals with variety of waveforms from monitoring area to those from outside of monitoring area when setting an appropriate threshold.

Keywords: Acoustic Emission; Artificial Neural Network (ANN); autoencoder; anomaly data separation

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1. Introduction

When conducting AE testing, there is an industrial need to separate AE from monitoring area to that from outside of the area in some cases. When the frequency of AE in monitoring area is different from that in outer area, frequency filter is utilized to separate these AEs. Even if the frequencies of the two AEs are similar, these AEs can be distinguished by using guard sensors. However, when AE testing is conducting for the structures made of anisotropic materials, such as CFRP structures, a large number of guard senor should be attached around the monitoring area as velocity of AE in some propagation path is quite fast compared to other paths. Though it is worth to discuss about other method to separate these AEs without using large number of guard sensor. On the other hand, use of artificial neural network (ANN) in engineering field including NDT field is widely discussed in recent years. Autoencoder [1] is one of the major ANN used for anomaly detection [2,3].

In this study, usefulness of autoencoder to solve this problem is discussed by simple experiment using an isotropic thin steel ruler.

2. Experimental Setup

Figure 1 shows experimental setup. AE sensors of Ch. 1 to 4 were attached on the metal scale at the 200, 250, 750 and 800 mm. The scale was assumed as one of the thin structural components of machines or structures in this study. Ch.1 and 4 are AE sensors (PAC, Type: R15) with 150 kHz resonance, Ch.2 and 3 are piezoelectric buzzers (muRata, Type: 7BB-20-6L0) with 6.3 kHz resonance, and used as AE receiver in this study. The area between 300 to 400 mm on the scale was categorized as “left area” and 600 to 700 as “right area”. In this study AEs generated at “left area” are assumed as AEs from monitoring area. On the other hand, AEs at “right area” are assumed as AEs from outside of monitoring area. For the generation of AEs, the tip of the driver (hereinafter referred to as “driver”) and the rubber part for erasing the ballpoint pen (hereinafter referred to as “ballpoint pen”) were used as an impactor. Various artificial AE were generated at the “left area” or “right area” by changing the impact force, impact tools and impact position. The outputs of sensors were digitized with a sampling interval of 7.9 μsec and sampling size of 256 points via a digitizer (pico technology, Type: 5442 A). In all experiments, the trigger channel was set to channel 1, and data acquisition was set to be started when the signal output exceeded a certain threshold value. One hundred and sixty AE signals were measured in each of the four conditions (left + driver, left + ballpoint pen, right + driver, right + ballpoint pen), respectively. Figure 2 shows example of detected AEs for each condition. As you can see from the figure, high frequency components are obtained in AEs generated by the driver compared to those by the ballpoint pen. As a result, waveforms are quite different for AE with driver and ballpoint pen. When AEs are generated at the left area, AEs reach at ch.1 and 2 first. On the other hand, when AEs are generated at the right area, AEs reach at ch.3 and 4 first.

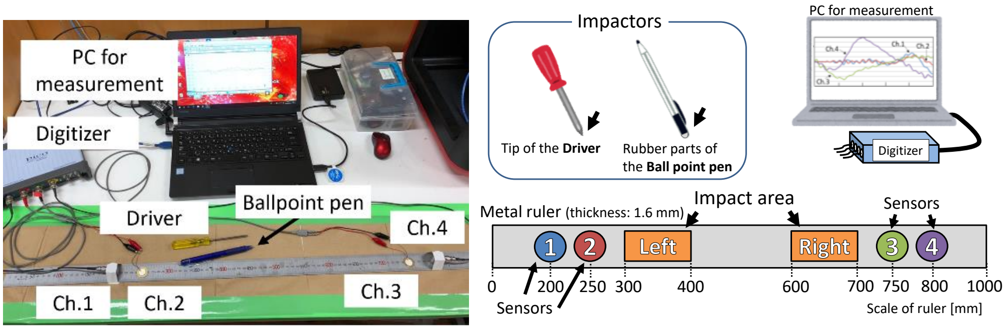


Figure 1. Experimental setup to detect AE. Four AE sensors are attached along the metal ruler. AEs were generated at any position of the "left area" or the "right area" by using the driver or ball point pen by changing impact force.

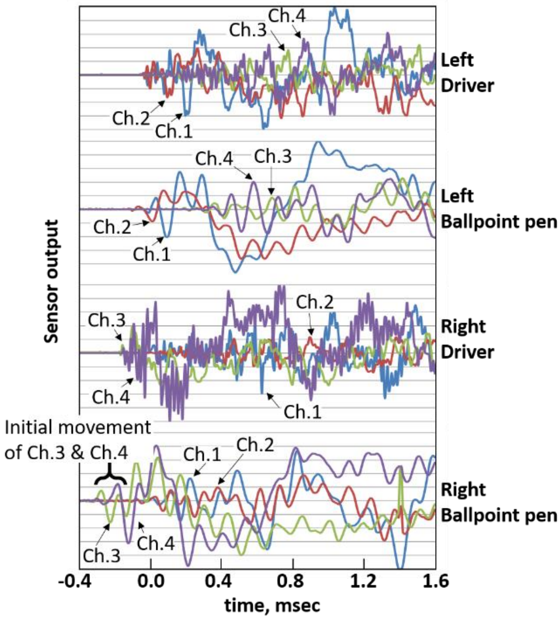


Figure 2. Example of detected AEs. Example of the detected AEs under the conditions of "Left + Driver", "Left + Ballpoint pen", Right + Driver", and "Right + Ballpoint pen" are shown in order from the top.

3. Autoencoder

An autoencoder is known as a type of artificial neural network (ANN) of unsupervised manner. The autoencoder is used for various purposes, and anomaly detection is a one of the typical ways to use it. In this study, the autoencoder is trained only on AEs generated at "left area" in Figure 1 and assume AEs generated at "right area" as anomaly AEs such like AEs from outside of AE monitoring area.

Figure 3 shows the simplest structure of an autoencoder and used for this study. The left structure in the figure shows an autoencoder. Input data for this ANN are AEs of four channel with 256 sampling sizes (256 × 4). Though the size of the input data becomes 1024. 1024 input data is encoded and the size of the data reduced to 32 (about 3 %). After that, reduced data is decoded by decoder and AEs are decoded (reconstructed). Root mean square error (RMS error) is calculated by using input data and decoded data. During the training of this structure, only the AEs generated at "left area" were used. The 80 % of the data was used for the training and the other is used for the validation. During the validation, AEs of "right + driver" and "right + ballpoint pen" are also used and discuss if autoencoder is useful to separate anomaly AEs (AEs from "right area"). We use neural network console [4] to realize autoencoder in this study.

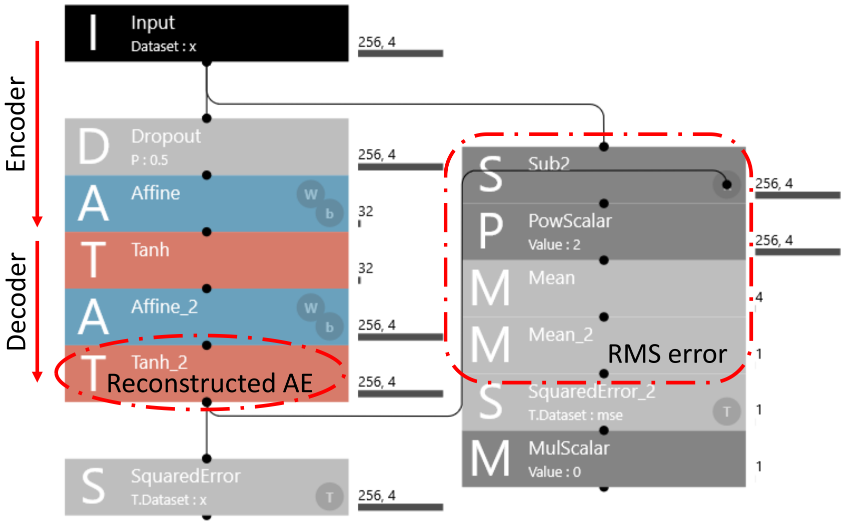


Figure 3. Structure of autoencoder used for this study. AE signals generated at "left" area are used for the training. After the training, AEs at "right" area (anomaly AE) are added as input data and discussed if the autoencoder can separate "right" AEs from "left" AEs.

4. Results and Discussion

Figure 4 shows Comparison of input AEs and decoded AEs during validation of ANN for AEs generated at "left" area. The top two are AEs generated by "driver" and the bottom two are AEs generated by "ballpoint pen".

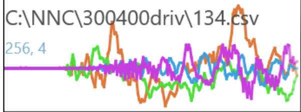
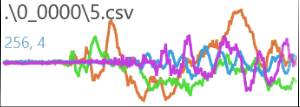
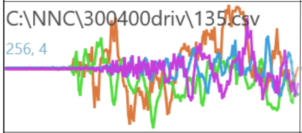
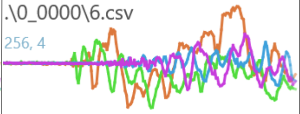
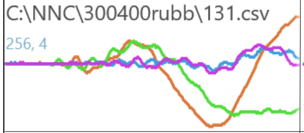
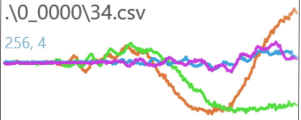
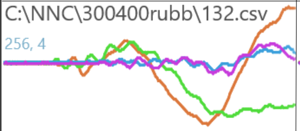
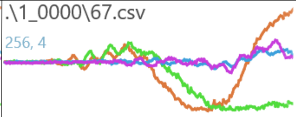
Input AEs：x	Decoded AEs：x'	RMS error
C:\NNC\300400driv\134.csv 256, 4 	.\0_0000\5.csv 256, 4 	0.0062
C:\NNC\300400driv\135.csv 256, 4 	.\0_0000\6.csv 256, 4 	0.0056
C:\NNC\300400rubb\131.csv 256, 4 	.\0_0000\34.csv 256, 4 	0.0049
C:\NNC\300400rubb\132.csv 256, 4 	.\1_0000\67.csv 256, 4 	0.0031

Figure 4. Comparison of input AEs and decoded AEs during validation of ANN for AEs generated at "left" area. These AEs are assumed as AE of normal AEs (AEs from monitoring area) and the waveforms of decoded area are resembled to those of input AEs.

These AEs are assumed as AE of normal AEs (AEs from monitoring area) in this study and the waveforms of decoded AEs are resembled to those of input AEs. It is noted that each AE signal is compressed from 256 points to 8 points during the process in Figure 3, although, decoded waveforms quite resembles to the input waveforms. It is also noted that characteristics of AEs generated by "driver" and "ballpoint pen" are quite different, although, a single trained autoencoder can be utilize to decode the AEs. This result shows possibility to use autoencoder to extract features of AE signals.

Figure 5 shows Comparison of input AEs and decoded AEs during validation of ANN for AEs generated at "right" area. The top two are AEs generated by "driver" and the bottom two are AEs generated by "ballpoint pen". These AEs are assumed as AE of anomaly AEs (AEs from outside of monitoring area) in this study. Decoded waveforms are quite different from those of input AEs. RMS errors are shown in the table in the figure. The error is larger compared to the error for normal data in Figure 4

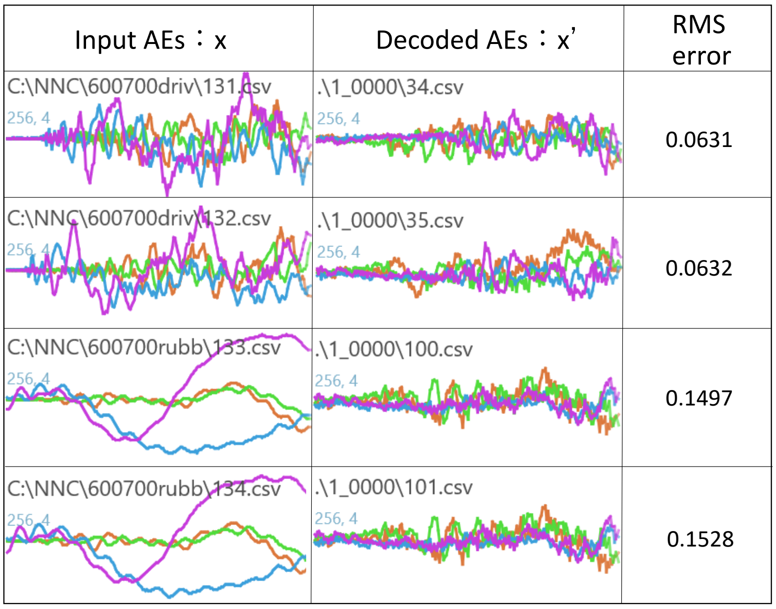


Figure 5. Comparison of input AEs and decoded AEs during validation of ANN for AEs generated at "right" area. These AEs are assumed as AE of anomaly AEs (AEs from outside of monitoring area). Decoded waveforms are quite different from those of input AEs.

Figure 6 shows Frequency of error in decoded area. The data for the normal data (AEs at "left") and anomaly data (AEs at "right") is shown in orange bar and blue bar in the figure respectively. This result shows that the two data can be distinguished by setting an appropriate threshold.

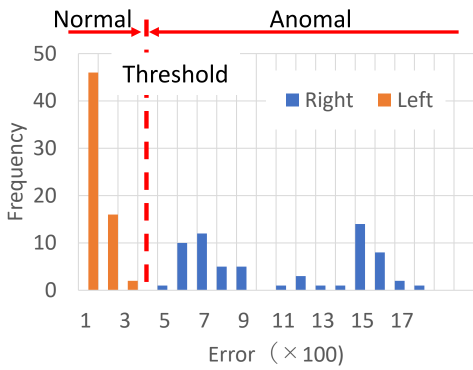


Figure 6. Frequency of error in decoded area. The data for the normal data and anomaly data is shown in orange bar and blue bar in the figure respectively. This result shows that the two data can be distinguished by setting an appropriate threshold.

5. Conclusions

In this study, usefulness of autoencoder to separate AE from monitoring area (normal data) to that from outside (anomaly data) is discussed by simple experiment using an isotropic thin steel ruler. It was shown that a single trained autoencoder can be used for separating AE signals which characteristic are quite different (generated by "driver" and "ballpoint pen") by setting an appropriate threshold.

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