Damage Detection Approach for a Mooring Line on an Offshore Structure Using Convolutional Auto-Encoder

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***Abstract*—This study presents a machine learning-based approach to detect damage in mooring lines supporting a floating offshore platform that is installed to collect submarine crude oil. The proposed approach for damage detection using a convolutional auto-encoder can be implemented in three steps: data acquisition, model learning, and model update. The time series data used for damage detection are measured from the environment and the floating offshore platform but not mooring lines due to affordability and efficiency of both installation and maintenance of the sensors on the offshore structure. Therefore, it is expected that the approach proposed in this study can be applied using only data obtained from the structure in an actual environment.**

***Index Terms*—damage detection, offshore, mooring lines, convolutional auto-encoder**

I. Introduction

Floating offshore platforms, which are one of infrastructure installed mainly for extraction of crude oil buried in the sea floor, are located above the sea and move continuously due to currents and wind. To minimize this movement, floating offshore platforms are fixed on the seabed using mooring lines. These mooring lines are an important factor for the safety of floating offshore platforms, thus their damage should be monitored in real time.

In order to secure the safety of mooring lines, there are two approaches, which are used to directly detect damage to mooring lines using images and videos [1, 2], as well as indirectly by analyzing the acoustic, strain, and displacement data obtained by measuring the motion of mooring lines or the platform [3-5].

Since the mooring lines are installed under the sea, it is difficult to detect internal damage via direct detection. In some cases, it is difficult to estimate external damage if there is a large amount of foreign matter covering the lines. On the other hand, indirect damage detection using measurement data can be used to detect external and internal damage. Therefore, indirect damage detection approaches that monitor measurement data of a floating offshore platform and a mooring line in real time is widely used and studied.

Recently, several techniques for estimating mooring damage based on machine learning were developed to effectively analyze measurement data obtained by monitoring structures [6,7]. These machine learning-based damage detection approaches are mainly based on artificial neural networks (ANNs), which use supervised learning. In general, supervised learning is a method which requires data relating cause and effect, so it requires a lot of data and corresponding labels for training a machine learning model [8].

From the perspective of detecting damage in mooring lines, labels are data that indicate the damage location at the moment when various measurement data are obtained in real time. In particular, training a machine learning model capable of detecting various damage conditions requires a large amount of data that reflect different levels of damage on the mooring line. However, in order to produce such data in a real environment, it is necessary to destroy several parts of the mooring line, which can jeopardize the safety of the structure and, even if possible, it is very costly.

According to this limitation, these machine learning-based damage detection approaches for mooring lines currently use simulation data. However, in the case of a floating offshore platform, which is heavily influenced by unpredictable environmental loads like wind and ocean currents, it is unclear that the machine learning model trained using simulation data can accurately match real data. Therefore, the supervised learning-based damage detection approach which cannot use real measurement data seems to have limitations in its applicability.

This limitation can be addressed by using an unsupervised machine learning-based damage detection approach. Unlike supervised learning, unsupervised learning has the advantage that it can be trained with only measured data from the floating offshore structure. Based on this advantage, this study aims to propose a damage detection approach based on unsupervised learning and convolutional auto-encoder (CAE), an unsupervised machine learning algorithm (i.e., deep learning algorithm).

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II. Convolutional Auto-encoder

A CAE is a deep learning technique that uses a convolutional layer in a convolutional neural network based on an auto-encoder (AE) architecture. In particular, the data used in this study is consists of several variables. For such multivariate data, using the convolutional layer creates and uses many features representing relationships among variables can be useful when developing a deep learning model [8]. Therefore, in this study, CAE using convolution layer based on AE was used for the machine learning algorithm.

Meanwhile, CAE follows the general performance of an AE, thus, this section aims to explain the principle of an AE. An AE uses different methods depending on the application, such as anomaly detection to identify abnormalities in data or de-noising to remove noise in data. The purpose of this study is to detect damage (abnormalities) in mooring lines, thus, we focus on anomaly detection.

An AE uses a neural network designed for unsupervised learning by connecting two artificial neural networks, called an encoder and a decoder, as shown in Fig. 1. The encoder is used to transform the general characteristics of the data by using dimension reduction, and the decoder reconstructs the input data. The working principles of an encoder and a decoder are expressed mathematically in (1) and (2).

$$\mathrm{y} = \mathrm{Wx} + \mathrm{b} \tag{1}$$

$$\mathrm{z} = \mathrm{W'y} + \mathrm{b'} \tag{2}$$

where x is input vector, y is the latent vector calculated by the encoder, z is the reconstructed vector calculated by the decoder, $\mathrm{W}, \mathrm{W'}$ are weight matrices for the encoder and decoder, respectively, and b, $\mathrm{b'}$ are bias vectors of the encoder and the decoder, respectively.

In general, training a neural network model requires that the output data have input data labels to calculate loss (error), which is an important indicator for model training. The most commonly used type of loss for AE training is mean square error, which is defined in (3). However, in the case of AE, the input data is reused as labels so that model training proceeds to confirm how well the input data is reconstructed. This training objective enables anomaly detection.

$$L(x,z) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(z_i - x_i)^2} \tag{3}$$

where, x_i is the i th element of the input vector, z_i is the i th element of the reconstruction vector, and N is the number of elements in the input vector.

The basic principle of anomaly detection based on AE is to identify the difference between normal and abnormal data using the distribution of errors calculated with the AE model. In general, the AE model is trained using normal data. In the view of detecting damaged mooring lines, data from undamaged mooring lines are taken as the normal data, while data from damaged mooring line are taken as abnormal data.

As training progresses, the model becomes progressively more capable of restoring the normal data. Finally, a successfully trained AE model restores the normal data when it comes in as input data, but it does not restore the input data when the input data contains abnormalities. The fact that the input data is not well-restored means that the AE error is relatively large when abnormal data is input. Therefore, the distribution of AE errors when normal data is input and the distribution of AE errors when abnormal data is input can be compared and used to distinguish whether or not the mooring lines are damaged.

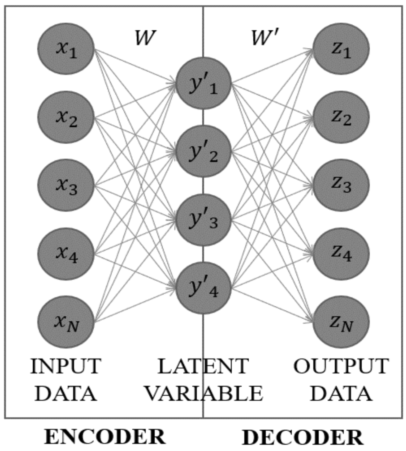

Figure 1. Architecture of an auto-encoder

III. Proposed Damage Detection Approach

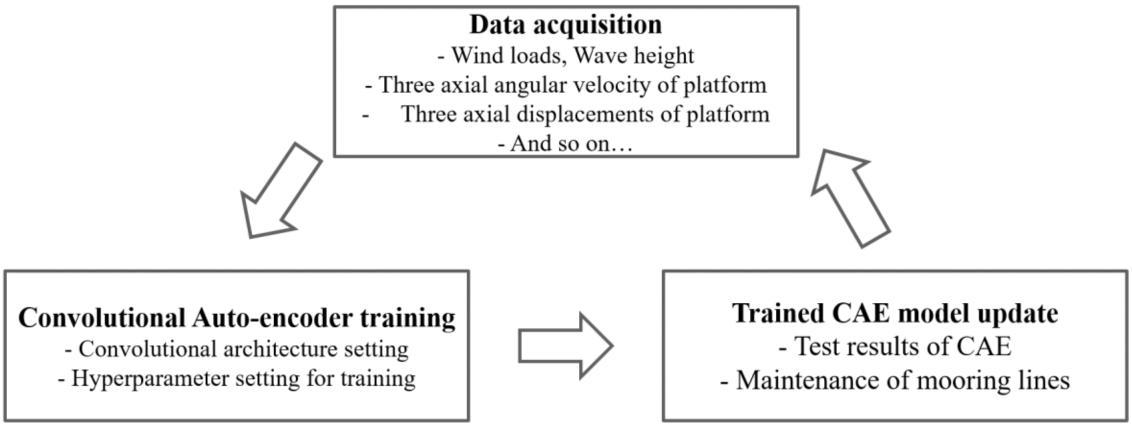

Figure 2. Process of proposed damage detection approach for mooring lines of floating offshore platform

The process for detecting damage in mooring lines installed on a floating offshore platform is shown in Fig. 2. In order to apply this process in a real environment, the data from the undamaged state of mooring lines must be distinguished from the data from the damaged state of mooring lines. However, it is difficult to accurately determine the data from the undamaged state of mooring lines without safety inspection of mooring lines. Therefore, in this approach, it is assumed that 10% (2-2.5 years) of typical design life is the undamaged state.

First, as shown in Fig. 2, the type of data for training the CAE model must be defined in order to reflect the actual installation environment. Table I lists the typical variables of measurement data on a floating offshore platform and the locations obtained the variables. As shown in table1, in views of the locations for measuring variables, it can be divided into three types (variables from the mooring lines, variables from the platform, and variables from the environments). However, since the sensors for the location of mooring lines need to be installed underwater, it is difficult and expensive for installing and maintaining these sensors. Therefore, in this study, the CAE model should be trained without using the mooring line data as this model shows whether the mooring lines are damaged or not.

On the other hand, several sensors showing the behavior of the floating offshore platform have the advantage of being easy to install and maintain. Since the behavior of such a floating structure is affected by damage to the mooring lines, it is possible to trace the presence of mooring line damage using a CAE. Therefore, only the movement of the floating structure, wind, and wave data are used in the proposed approach.

Second, the CAE is trained using the acquired normal data obtained from the undamaged state of mooring lines. Since the acquired data is time series data, the CAE architecture should also be set to match the time series. Fig. 3 shows the concept of proposed CAE architecture in this study. Time series data usually tends to change significantly due to the large white noise over a short period of time. In other words, a short measurement period makes damage detection in mooring lines with a CAE rather difficult. To solve this problem, the maximum sway period of the floating offshore platform can be used to select an appropriate measurement time for the input data to be used in the CAE. Therefore, using time series data with a domain that is larger than the maximum sway period is an easy method for understanding the behavior of the floating offshore platform.

When designing the architecture of the CAE, the maximum sway period of the floating offshore platform should be determined using a fast Fourier transform. The domain of the time series should be longer than the maximum sway period when used as the input data in the CAE. During the CAE model training process, the time series data is used for the input matrix and the output matrix of CAE architecture and the hyperparameter of the CAE architecture needs to be adjusted.

TABLE I. TYPICAL VARIABLES OF MEASUREMENT DATA ON FLOATING OFFSHORE PLATFORM FROM ENVIRONMENTS, PLATFORM, AND MOORING LINES

Location	Variable
Environments	Wind loads
	Wave height
	Ocean currents
	Depth of water
Platform	GPS
	Orientation
	Triaxial accelerations of platform
	Triaxial displacements of platform
Mooring Lines	Tension force
	Triaxial accelerations of each mooring lines
	Triaxial displacements of each mooring lines

Finally, real-time damage detection can be performed using the trained CAE. If a large amount of damage occurs to the mooring lines, the pattern in the measurement data will change, and the CAE error will increase. An alert can be received in real time, allowing worker to inspect the lines for safety and perform maintenance. If the repair work is performed after the safety inspection and maintenance, it is possible to update the CAE based on new data from the 2-2.5 years as normal data.

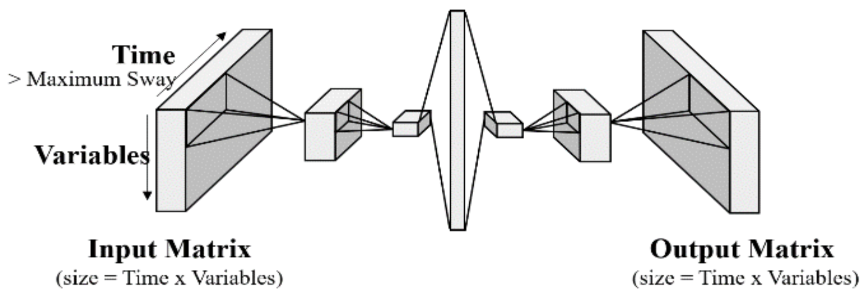

Figure 3. Concept of CAE architecture in the proposed approach

IV. Conclusions

The purpose of this study was to propose an approach for detecting damage in mooring lines supporting floating offshore platforms installed to collect submarine crude oil. In this study, the CAE which is one unsupervised machine learning technique was used for detecting damage of mooring lines. The proposed approach consists of three steps: data acquisition, CAE model training, and model updating. This approach can be employed using only data obtained from offshore platform the actual environment so that it is affordable and efficient to apply this approach in practice. In addition, it has an advantage that it is available for all life cycle of mooring lines.

On the other hand, there is a limitation in that it is impossible to localize damage using the approach proposed in this study. Locations of damage in mooring lines can be identified using latent variables obtained from the encoder in the trained CAE. This study can be considered as a basic study toward the development of damage localization techniques based on unsupervised learning. It is expected that damage localization approach using unsupervised learning can be completed within a short time.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Lee and Jung conceived the presented idea; Lee developed the theory; Shin supervised the project; Lee, Jung, and Shin contributed to the manuscript; Lee, Jung, and Shin had approved the final version of the manuscript.

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