DAMAGE DETECTION OF EMBANKMENT USING MACHINE LEARNING

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1. INTRODUCTION

Earth embankments are critical infrastructures that play a vital role in water resource management and flood control. However, these structures are subject to various types of damage, including seismic damage, which can lead to catastrophic failure. Early detection of damage is critical to prevent catastrophic failure and minimize the risk of loss of life and property. Traditional methods for monitoring embankment safety, such as visual inspections and manual measurements, are time-consuming, expensive, and not always reliable. In recent years, machine learning has emerged as a promising approach for detecting and predicting structural damage in various types of infrastructure.

In this study, authors study the use of machine learning techniques, specifically the autoencoder method [1] for detecting damage in the small homogenous embankment. For damage detection, authors assume to use vibration signals from sensors installed at the crest of the embankment which was calculated using TDAP III [2] that is based on the finite element method. Generating response data can be achieved by preparing both the damaged and undamaged embankments. For generating damaged data, authors reduced the Young's modulus of one element (element number1) by 80% but the damage was not detected in the embankment, then increased the damaged elements from one element to four elements as shown in Fig. 1. The autoencoder method, which is classified as the unsupervised learning method, is first trained by healthy state data which is acquired from the healthy state of the embankment model, and then response data from both damaged and undamaged state of the embankment are used as input to the autoencoder.

2. NUMERICAL MODEL AND ANALYSIS

TDAP III software is used to create and analyze a 2-dimensional numerical homogenous small embankment dam model as shown in Fig. 1. The model consists of 25 plane strain elements with the material properties as shown in Table 1. The 2D model was analyzed with the assumption of having a rigid rock foundation and that the structure cannot move or rotate at the base and. For detecting damage, this study used machine learning algorithm.

Table 1. Material properties

Material parameter	Value
Young modulus, E (KPa)	4.5E04
Poisson ratio	0.4
Density (kg/m^3)	1800

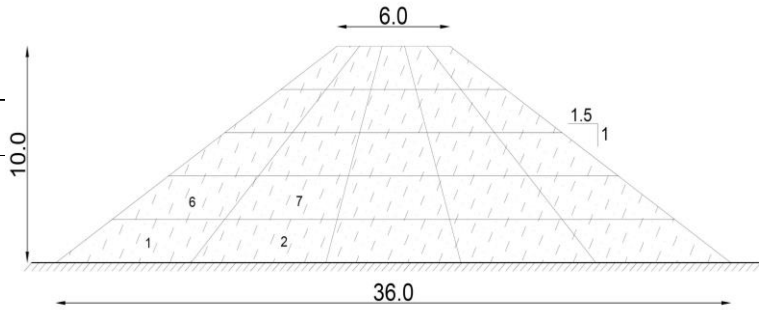

Fig. 1 Embankment model (unit in meter)

3. MACHINE LEARNING

Using the proposed method for damage detection contains three steps. First, the autoencoder was trained using response displacement data from the healthy state of the model, which was generated by analyzing the model giving the earthquake ground motion of El Centro earthquake (NS component) shown in Figure 2 as input. Second, the trained autoencoder was applied to the displacement data shown in Fig. 4 and Fig. 5 calculated from both the damaged and non-damaged state of the model by giving Hachinohe earthquake ground motion shown in Fig 3 as input to the model. Finally, the reconstruction error, which is the difference between the input response data and the reconstructed output response data, was determined. In applying autoencoder, the response time series was divided into partial time series for every 100 data. Therefore, one reconstruction error value is calculated for every 100 data in this study. These reconstruction errors may indicate the presence of damage in the embankment [3]. It should be noted that machine learning was applied to the responses after having the magnitude of the response amplitudes equal. It should also be mentioned that MATLAB and its toolboxes [4] are used for the application of autoencoder in this study.

Keywords: Autoencoder, Damage Detection, Embankment
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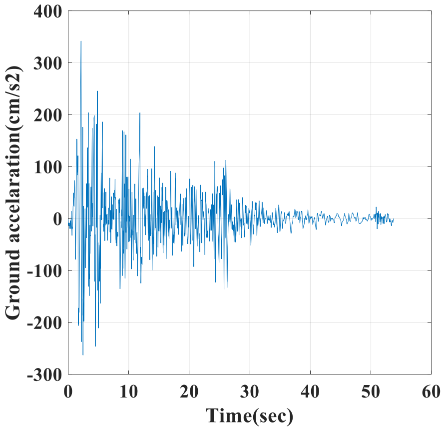

Fig. 2 Elc40 Acceleration time history

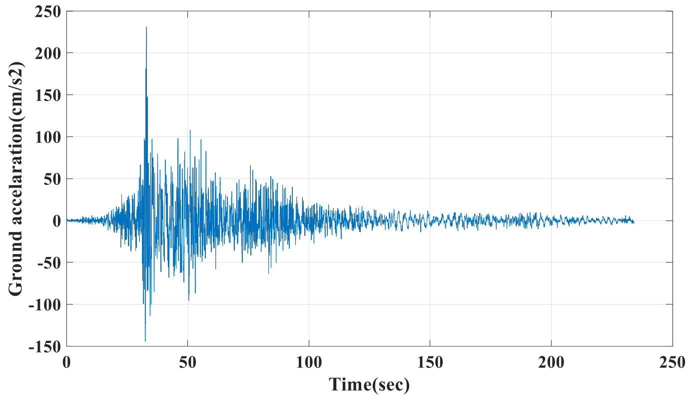

Fig. Hachinohe Acceleration time history

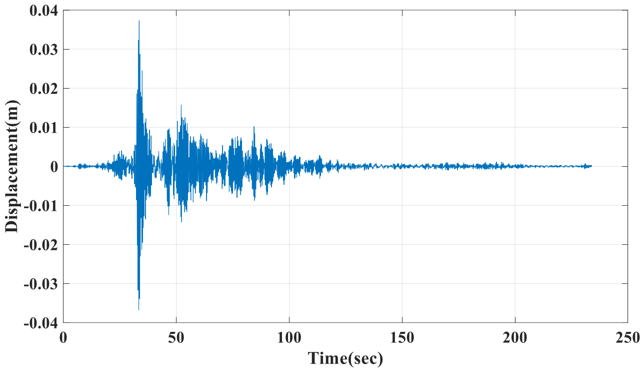

Fig. 4 Non-damaged response displacement

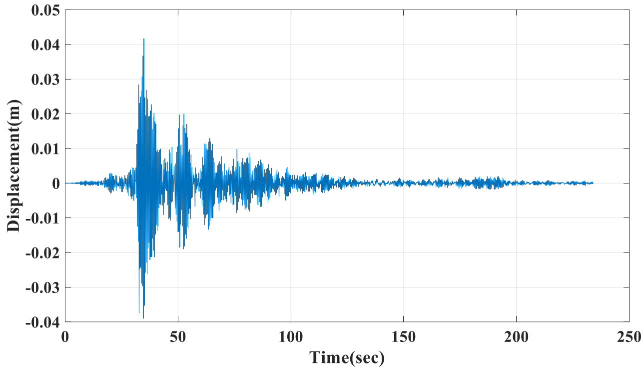

Fig.5 Damaged response displacement

4. RESULT AND DISCUSSION

For damage detection of embankment using machine learning, this study assumed to use vibration signals obtained from sensors installed into the embankment. By preparing damaged and non-damaged data, seismic response data were calculated by using FEM. Autoencoder was trained with non-damaged response displacement data and then the trained autoencoder was applied to the response displacement data of damaged and non-damaged state of model. The results of calculated reconstruction error were shown in Fig.6. It is found that the reconstruction error is generally larger in the case of considering damage. Difference in reconstruction errors indicate that autoencoder method was successfully applied in detecting major damage in homogeneous embankments dam. However, the authors were unable to detect minor damage (for one element).

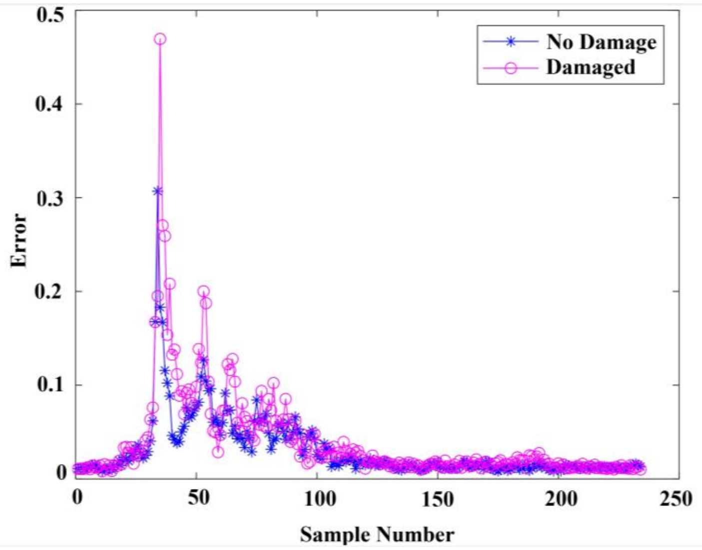

Fig. 6 Reconstruction error

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