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센서 데이터를 활용한 옹벽 변위 예측 성능 비교

실라* · 박장식**

Comparison of Retaining Wall Displacement Prediction Performance Using Sensor Data

Sheilla Wesonga* · Jang-Sik Park**

요약

구조물 검사의 주요 목적은 주의를 기울이지 않을 경우 구조물의 균열이 심각한 재난으로 이어질 수 있으므로 이러한 구조물을 활용하는 모든 기관의 안전을 보장하는 것이다. 이러한 목표를 염두에 두고 특히 구조물의 옹벽에는 인간 검사자를 보조하는 인공지능(AI) 기반 기술이 필요한다. 본 논문에서는 PR(Polynomial Regressive) 분석 모델과 LSTM(Long Short Term Memory), GRU(Gated Recurrent Unit) 딥러닝 모델을 이용하여 옹벽의 균열 변위를 예측하고 그 성능을 비교한다. 성능 비교를 위해 옹벽의 균열 변위에 영향을 줄 수 있는 온도 및 강수량 데이터를 활용하여 다변수 특성 입력을 적용했다. 훈련 및 추론 데이터는 경사계, 온도계, 우량계 등의 측정 센서를 통해 수집되었다. 그 결과, 다변수 특성 모델의 MAE는 0.00186, 0.00450, 0.00842로, 수행된 평가에서 다항식 회귀 모델, LSTM 모델, GRU 모델에서 각각 0.00393, 0.00556, 0.00929로 단일 변수 특성 모델보다 우수한 성능을 보였다.

ABSTRACT

The main objective of inspecting structures is to ensure the safety of all entities that utilize these structures as cracks in structures if not attended to could lead to serious calamities. With that objective in mind, artificial intelligence (AI) based technologies to assist human inspectors are needed especially for retaining walls in structures. In this paper, we predict the crack displacement of retaining walls using an Polynomial Regressive (PR) analysis model, as well as Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) deep learning models, and compare their performance. For the performance comparison, we apply multi-variable feature inputs, by utilizing temperature and rainfall data that may affect the crack displacement of the retaining wall. The training and inference data were collected through measuring sensors such as inclinometers, thermometers, and rain gauges. The results show that the multi-variable feature model had a MAE of 0.00186, 0.00450 and 0.00842, which outperformed the single variable feature model at 0.00393, 0.00556 and 0.00929 for the polynomial regression model, LSTM model and the GRU model respectively from the evaluation performed.

키워드

Retaining wall, Sensors, Crack Displacement, Prediction
옹벽, 센서, 균열 변위, 예측.

* 경성대학교 박사과정(sheilla2@kyungsung.ac.kr)
** 교신저자 : 경성대학교 전자공학과
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· Corresponding Author : Jang-Sik Park
Dept. of Electronic Engineering, Kyungsung University
Email : jsipark@ks.ac.kr

Ⅰ. INTRODUCTION

The daily innovations in terms of infrastructure calls for maintenance of structures which goes hand in hand with the 40% expected increase in the number of structures the next decade [1]. In regard to structural maintenance, one of the safety points to analyze are cracks. Cracks are some of the outcomes of environmental and internal factors on structures hence shortening their lifespan [2]. This therefore calls for inspection as longevity of structures is dependent on the maintenance for structural safety [3]. Conventional structural crack inspection involves creating an external observation network using a visual inspection by human inspectors and measurement tools such as crack gauges [4]. However, this inspection method is subjective and thus lacks reliability. To increase the objectivity, accuracy, and efficiency of structural crack inspection, research on crack detection and prediction is being actively conducted using techniques such as machine learning [5] and deep learning [6]. Deep learning methods such as convolutional neural networks (CNNs) have recently achieved state-of-art performance in areas such as object detection [7], image recognition [8], image segmentation [9] and sensor-based prediction [10].

The sensor based crack displacement prediction algorithms in this case the long short term memory (LSTM) [10], Gated Recurrent Unit (GRU) [11] predicts the displacement of a crack and we use regression algorithm to determine the effect of factors such as water pressure on the cracks of retaining walls. In this study, a sensor data collection wireless network system was established to observe the condition of the retaining walls in Busan. The collected data required preprocessing before time series analysis. Missing values caused by network communication errors and disconnections, as well as anomalies resulting from sensor malfunctions, are identified and excluded, and the data is reconstructed using linear interpolation for both missing values and anomalies. Since the measurement results of the sensors vary in units and numerical ranges according to their types, Z-score normalization is employed. Pearson Correlation Coefficient (PCC) is used for data correlation analysis [12]. The correlations between each normalized dataset are examined, analyzed through a time series model, and used to predict crack displacements.

Ⅱ. RETAINING WALL ANALYSIS AND CRACK DISPLACEMENT PREDICTION

The framework of this study is as shown in Fig. 1 which represents the sensor based crack prediction.

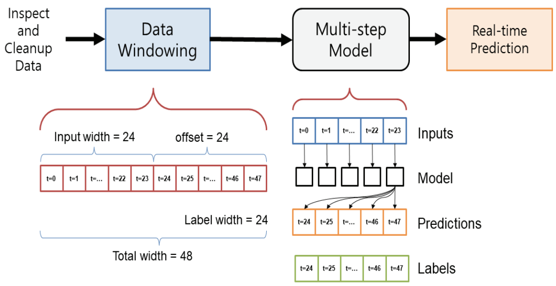


Fig. 1 Our crack prediction framework

2.1 Regression Analysis

In this study, we used the polynomial regression model of the non-linear form [13]. The polynomial regression model of degree m is defined as in equation (1), and its matrix form is as shown in equation (2). By substituting the numerical data collected in the X and Y variables, it becomes the form of a polynomial regression model with only the parameters remaining.

$$y_i = w_0 + w_1 x_i + w_2 x_i^2 + \bullet \bullet \bullet + w_m x_i^m \quad \cdots (1)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \bullet \\ \bullet \\ \bullet \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \bullet & \bullet & \bullet & x_1^m \\ 1 & x_2 & x_2^2 & \bullet & \bullet & \bullet & x_2^m \\ \bullet & \bullet & \bullet & \bullet & & & \bullet \\ \bullet & \bullet & \bullet & & \bullet & & \bullet \\ \bullet & \bullet & \bullet & & & \bullet & \bullet \\ 1 & x_n & x_n^2 & \bullet & \bullet & \bullet & x_n^m \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \bullet \\ \bullet \\ \bullet \\ w_n \end{bmatrix} \Rightarrow Y = XW \cdots \ (2)$$

2.2 LSTM and GRU

The goal of prediction requires the data to be sequential. And for a while now, recurrent neural networks (RNNs) have been widely implemented for this task [14]. However, with growth of the sequence, RNN faces difficulty when carrying information from earlier steps. During the process of back-propagation in RNN, the gradient that necessitates updating the weights of neural networks gradually vanishes which ends up with inefficiency during the network learning process [15]. Therefore, to overcome this issue, a different RNN based network was proposed. The most popular mechanism implemented to overcome the short-term memory problem, LSTM network [10].

The GRU model is a proposed model designed to lighten the computational and memory requirements of LSTM [11]. While the LSTM model uses two separate states: the cell state and the hidden state, the GRU combines these two states using a reset gate layer, leaving only one hidden state. The unified hidden state of the GRU model has values that are semantically more similar to the cell state of the LSTM, thereby reducing memory requirements. Additionally, while the LSTM model differentiates between the forget gate and the input gate, the GRU defines the forget gate to combine the forget gate layer and the input gate layer into an update gate layer.

III. PROPOSED RETAINING WALL MONITORING AND CRACK PREDICTION

3.1 Sensor Dataset Collection Environment

The sensor dataset that we used is a dataset that we collected and is still a work in progress. Different sensors that include rain sensors, ground temperature sensors, outside temperature sensors, crack displacement measurement sensors, to mention just a few were installed in front of a retaining wall to monitor the variations in the cracks as shown in Fig. 2. A wireless network system using LoRa (Long Range) has been established as shown in Fig. 3 to transmit, store, and manage the measured sensor data, allowing users to access the web program and check the sensor data at any time [16][17].

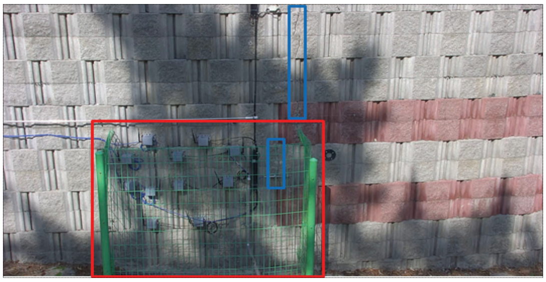


Fig. 2 Sensors (red box) installed on retaining wall with cracks (blue boxes).

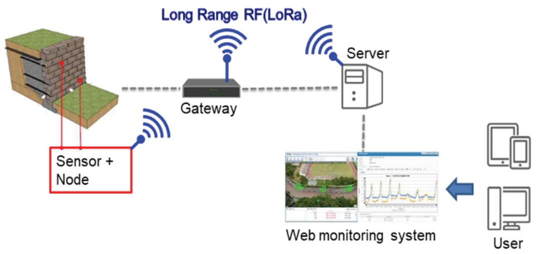
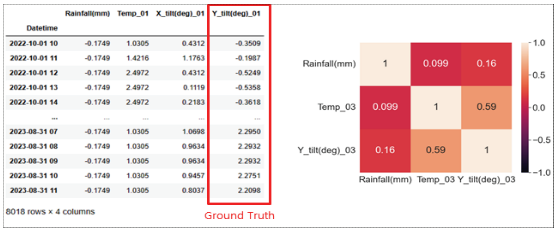


Fig. 3 Wireless network system for sensor data.

3.2 Dataset Configuration

All sensors, except for the rain gauge, measure data at 10-minute intervals, while the rain gauge measures data at 1-hour intervals. In this study, the 10-minute interval measurement data is averaged to produce 1-hour interval data. The experiments were conducted using data collected from October 1, 2022, to August 31, 2023 for region A high sensors, as shown in Fig. 4.



Datetime	Rainfall(mm)	Temp_01	X_tilt(deg)_01	Y_tilt(deg)_01
2022-10-01 10	-0.1749	1.0305	0.4312	-0.3509
2022-10-01 11	-0.1749	1.4216	1.1763	-0.1987
2022-10-01 12	-0.1749	2.4972	0.4312	-0.5249
2022-10-01 13	-0.1749	2.4972	0.1119	-0.5358
2022-10-01 14	-0.1749	2.4972	0.2183	-0.3618
...	...	...	...	...
2023-08-31 07	-0.1749	1.0305	1.0698	2.2950
2023-08-31 08	-0.1749	1.0305	0.9634	2.2932
2023-08-31 09	-0.1749	1.0305	0.9634	2.2932
2023-08-31 10	-0.1749	1.0305	0.9457	2.2751
2023-08-31 11	-0.1749	1.0305	0.8037	2.2098

Fig. 4 Input data columns (left), Pearson Correlation Coefficient (right).

To conduct time series analysis using the LSTM and GRU models, the training dataset was configured as shown in Fig. 5. The model was trained on 7 hours of data from the past to predict the future inclinometer data 1 hour ahead. 90% of the dataset was used for training, 5% for validation, and 5% for testing.

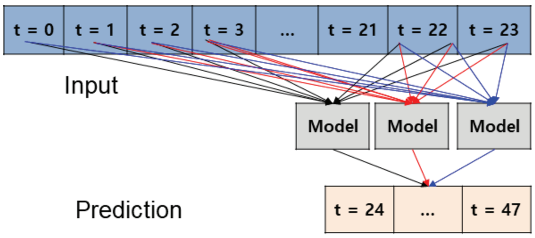


Fig. 5 Time series dataset (input:24, prediction:24)

IV. EXPERIMENTAL RESULTS

The models were evaluated using mean absolute error (MAE) and we compare the model performance as seen in Table 1, first with self prediction (same feature input e.g; Y_tilt, same feature future prediction), and secondly, multi prediction where given 3 features as the input, we make a future prediction of Y_tilt feature. Fig. 6-8 show the visualized prediction of the incline (Y_tilt) for the polynomial regression model, LSTM model and GRU model respectively (red: prediction, blue: ground truth (GT)).

Table 1. Performance comparison based on MAE.

MAE	Regression	LSTM	GRU
single	0.00393	0.00556	0.00929
multi	0.00186	0.00450	0.00842

The Linear regression results for 1 hour crack displacement predictions based on temperature and rainfall are shown in Fig. 6.

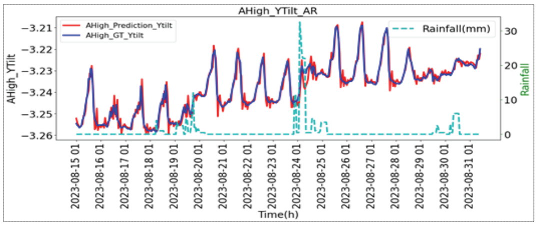


Fig. 6 Regression results for the sensor prediction.

The LSTM results for 1 hour crack displacement predictions based on temperature and rainfall are shown in Fig. 7.

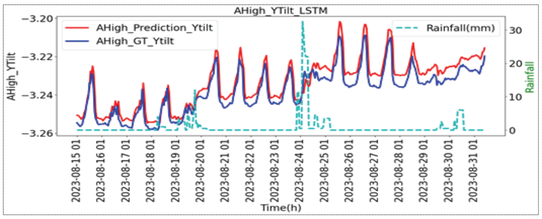


Fig. 7 GRU results for the sensor prediction

The GRU results for 1 hour crack displacement predictions based on temperature and rainfall are shown in Fig. 8. The results in Table. 1 showed us through this study that predicting crack displacement is more viable when we utilize various features compared to the single feature usage as single feature prediction had a lower MAE compare to multi feature usage.

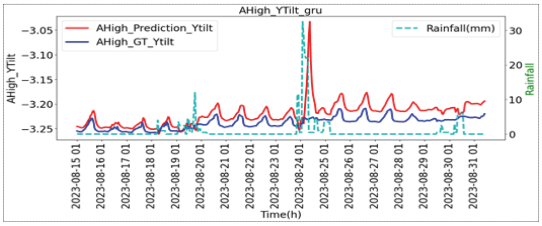


Fig. 8 GRU results for the sensor prediction

Ⅴ. Conclusion

It was confirmed through experiments that it is possible to predict retaining wall crack displacement using sensor data for both single feature and multi feature time series data analysis and prediction models. The retaining wall displacement showed the best performance in the multi feature model and the simplest regression analysis; however, when examining the correlations in the data, it was found that the currently collected data did not show any major crack displacements even with the occurrence of heavy rainfall. Retaining wall crack displacement exhibited a strong linear relationship with temperature, but this is characterized by a daily periodicity due to diurnal temperature variation, which is why the best results were obtained with the multi feature model predictions.

Conversely, in the three-dimensional input with rainfall, temperature, and inclinometer data, the polynomial regression model demonstrated the best predictive performance. Given that rainfall is a major factor contributing to wall failure and that the predictive performance of all three models is within two to three decimal places, this paper determines that the multi feature input prediction models, which showed the best performance are suitable as evaluation resulted in an MAE score of 0.00186, 0.00450 and 0.00842 for polynomial regression, LSTM and GRU respectively.

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저자 소개

박장식(Jang-Sik Park)

1992년 부산대학교 전자공학과 졸업(공학사)
1994년 부산대학교 대학원 전자공학과 졸업(공학석사)
1999년 부산대학교 대학원 전자공학과 졸업(공학박사)
1997년 ~2011년 동의과학대학 전자과 교수
2011년 ~현재 경성대학교 전자공학과 교수
※ 관심분야 : 신호처리, 기계학습, 컴퓨터비전, 심층학습, 임베디드시스템

실라(Sheilla Wesonga)

2017년 음바라라대학교 컴퓨터공학과 졸업(공학사)
2021년 경성대학교 대학원 전자공학과 졸업(공학석사)
2021년 ~현재 경성대학교 대학원 전자공학과 (공학박사과정)
※ 관심분야 : AI, 데이터 분석, 영상 처리