Measurement of displacement of petroglyphs of Bangudae Terrace in Daegok-ri, Ulju, using edge and region extraction

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Abstract

Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju are the world's oldest whale hunting petroglyphs and are located on a cliff in Daegokcheon. It was designated as South Korea's National Treasure No. 285, and was listed as the 'Daegokcheon Petroglyph Group' on the 'Priority List', a list of UNESCO World Heritage candidates.

When stone cultural assets such as the Petroglyphs of Bangudae Terrace are damaged, it is very difficult to restore them to their original state. Therefore, it is very important to predict risk factors in advance and regularly manage them for preservation.

In this paper, we will use two Deep Learning models such as PiDiNet, and DexiNed to extract edges and legions. And then we will measure the contours and areas of the extracted areas. In terms of area, both 'Cavity' and 'Joint separation' showed the highest values in the first quarter. Additionally, looking at the change from the second quarter to the fall, the numbers appear to be stable in the case of 'Cavity'.

In the future, we will continue to conduct experiments to improve the accuracy of edge and area extraction and to present a reference point for whether displacement has occurred through additional experiments so that we can automatically determine that displacement has occurred-

Keywords

Petroglyphs of Bangudae Terrace, Displacement, PiDiNet, DexiNed, Deep Learning.

1. Introduction

Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju are the world's oldest whale hunting petroglyphs and are located on a cliff in Daegokcheon. It was designated as South Korea's National Treasure No. 285, and was listed as the 'Daegokcheon Petroglyph Group' on the 'Priority List', a list of UNESCO World Heritage candidates selected by the Cultural Heritage Administration (CHA) of the South Korea [1]. However, due to the Sayeon Dam located downstream of Daegokcheon, the water volume decreases during the dry season when rainfall is low, but when rainfall increases, the water level rises rapidly, causing the petroglyphs to be submerged, gradually accelerating damage due to encroachment or erosion [2].

When stone cultural assets such as the Petroglyphs of Bangudae Terrace are damaged, it is very difficult to restore them to their original state [3, 4]. Therefore, it is very important to predict risk factors in advance and regularly manage them for preservation [5]. However, such regular monitoring and management has many limitations in terms of resources, information processing, and expertise, therefore various studies are being conducted to automatically monitor and manage cultural assets using Deep Learning technology [6, 7].

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We will use two Deep Learning models, including, PiDiNet [6], and DexiNed [7], as Deep Learning architectures to extract edges and legions [8]. And then we will extract 'Cavity' and 'Joint separation' using them, and measure the contours and areas of the extracted areas over time to monitor trends in displacement.
This paper is structured as follows. Chapter 2 will describe the data collection process for Petroglyphs of Bangudae Terrace, datasets for experiments, and labeling methods. Chapter 3 will describe the Deep Learning Neural Network used for edge extraction. Chapter 4 will present the preprocessing process and results of displacement measurement and analyzes the experimental results. And we will conclude in Chapter 5.

2. Dataset and preprocessing

The monitoring image is data taken from a telephoto camera located 200m across from Petroglyphs of Bangudae Terrace, and is captured once a day at the same time. Since it is impossible to capture the entire area at once, the horizontal area is divided into 12 areas and then filmed by rotating the camera angle. The original data is saved as a JPEG image, the standard is 4912 x 7360, and the data capacity is approximately 20 to 35 MB per image.

2.1. Labeling Method

Labeling data for learning has the same file name as the original data, but is saved as PNG with a different extension. Additionally, the dimensions of 4912 x 7360 horizontal and vertical are the same as those of the original data. This is tailored to an open source-based Deep Learning algorithm for learning. The learning data is divided into 'Joint separation' areas, 'Cavity' areas, and areas containing both 'Joint separation' and 'Cavity' according to the type of displacement (See Figure 1). And depending on the labeling method, it is divided into 'Linestrip', 'Polygon', and 'Linestrip & Polygon' (See Figure 2).

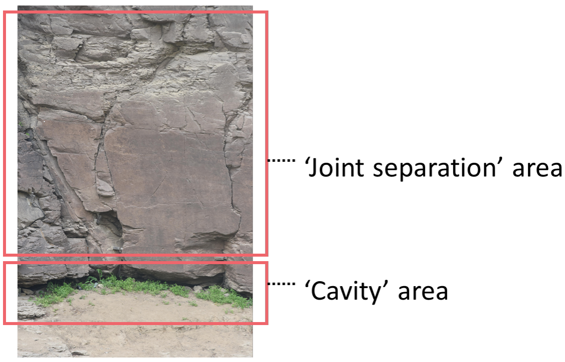


Figure 1: Displacement type

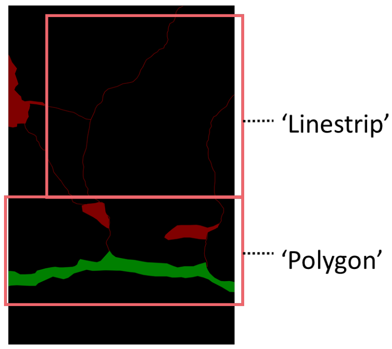
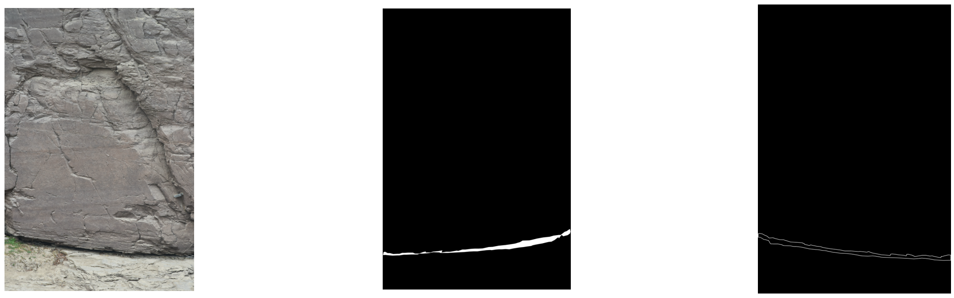


Figure 2: Labeling method

2.1.1. 'Cavity' labeling

The cavity is located at the bottom of the Petroglyphs of Bangudae Terrace, and is an empty space naturally created by water flow and erosion over a long period of time. We used a labeling tool called Labelme to label the 'Cavity' area and labeled it with 'Linestrip' or 'Polygon' type (See Figure 3). In the case of 'Cavity', unlike 'Joint separation', they have a simple shape, so the labeling method of 'Linestrip & Polygon' was not applied.

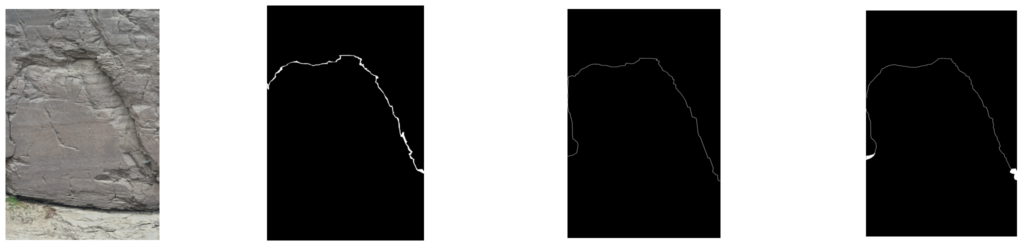


(a) Original data (b) Labeling by 'Polygon' (c) Labeling by 'Linestrip'

Figure 3: Labeling of 'Cavity' area

2.1.2. 'Joint separation' labeling

The main rock surface of the Petroglyphs of Bangudae Terrace has various types of 'Joint separation' developed, including vertical separation, diagonal separation, and complex separation. We used a labeling tool called Labelme to label the 'Joint separation' area and labeled it with 'Linestrip', 'Polygon', and 'Linestrip & Polygon' (See Figure 4).



(a) Original data (b) Labeling by 'Polygon' (c) Labeling by 'Linestrip' (d) Labeling by 'Polygon'&Linestrip'

Figure 4: Labeling of 'Joint separation'

2.1.3. 'Cavity & 'Joint separation' labeling

We labeled the 'Cavity' and 'Joint separation' areas in the same manner as described in the previous section to experiment with images containing both of them (See Figure 5).

(a) Original data (b) Labeling by 'Polygon' (c) Labeling by 'Linestrip' (d) Labeling by 'Polygon'&Linestrip'

Figure 5: Labeling of 'Cavity' & 'Joint separation'

2.2. Data normalization

To normalize the learning data, we converted the labeling data to a binary image with pixel values from 0 to 255 (See Figure 6-(a)). And the sizes of both the original image and the labeled image were normalized to 1,280 x 720. In this process, a comparative experiment was conducted using two different methods: cropping and reducing the image size to 1/10 and resizing it to 491 x 736 (See Figure 6-(b)).

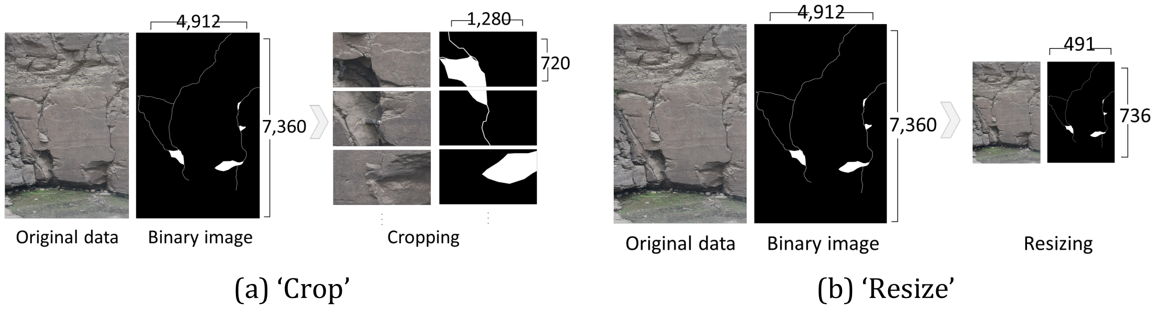


Figure 6: Normalization of training data

3. Deep Learning Networks for Edge Detection

In this paper, we utilize an Open Source-based pre-trained Deep Learning model based on CNN. After labeling the original image of the Petroglyphs of Bangudae Terrace, it goes through preprocessing processes such as black-and-white processing and normalization, and uses this as learning data to extract edges.

Based on this result, we can determine the detection area for 'Cavity' and 'Joint separation', and detect or predict whether displacement will occur by analyzing the change patterns of displacement values in time series. Figure 7 shows the overall research and development flow chart for the method proposed in this paper.

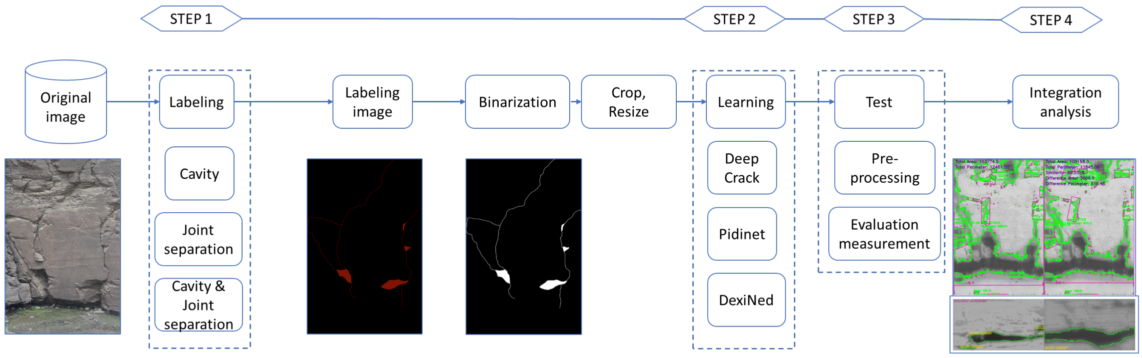


Figure 7: Research and development flow chart

We used two Artificial Intelligence Neural Networks, including PiDiNet, and DexiNed, to detect the displacement of the Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju, South Korea and measure the amount of displacement in this research. PiDiNet is specialized in detecting details in images [6] while DexiNed is optimized for boundary edge detection [7].

3.1. PiDiNet

The PiDiNet model uses a deep and wide separable Neural Network structure for fast inference and easy learning [9] (see Figure 8). PiDiNet do not use any normalization layers for simplicity since the resolutions of the training images are not uniform and replace the vanilla convolution in the 3 × 3 depth-wise convolutional layer in the residual blocks with Pixel Difference Convolution (PDC) [6].

It learns rich edge representations through side structures and effectively generates edge-maps [10]. It generates a lot of multi-scale edge information through many Compact Dilation Convolution based Module (CDCM) and removes background noise using Compact Spatial Attention Module (CSAM). Then, it combines single edge maps with a sigmoid function to generate the final edge map.

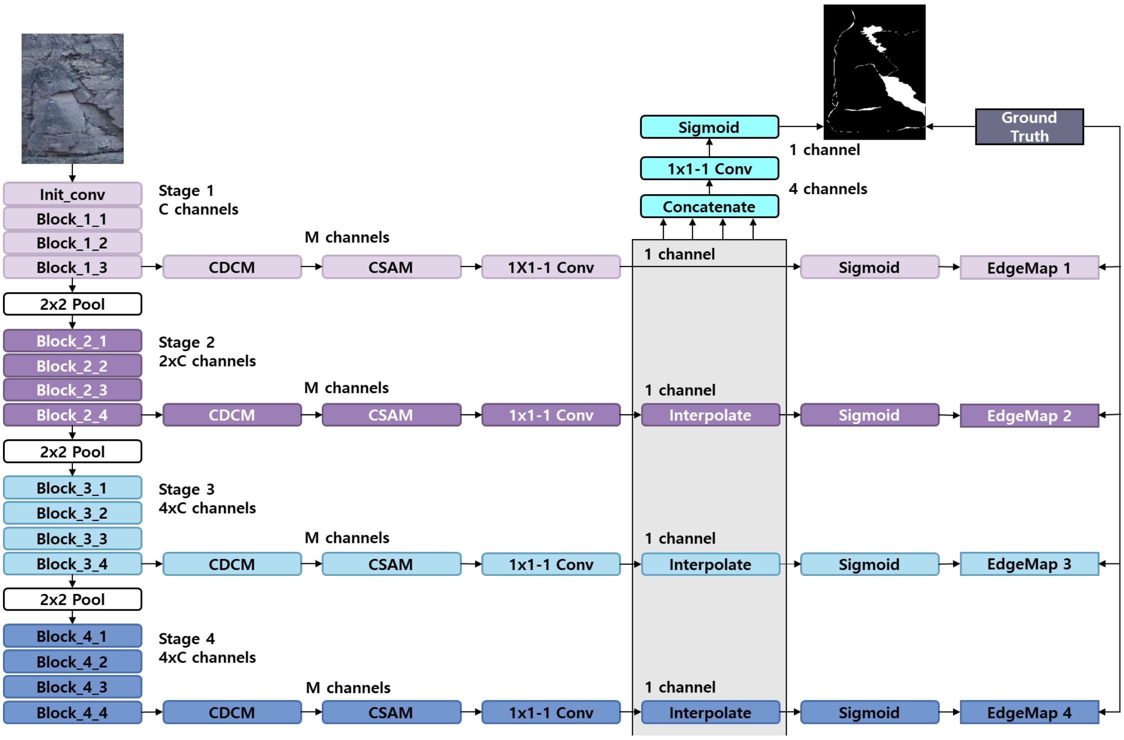


Figure 8: Architecture of PiDiNet

3.2. DexiNed

The DexiNed model consists of two subnetworks: Dexi and USNet (see Figure 9). The Dexi network consists of six blocks that act as encoders, and each block consists of sub-blocks with multiple neural network layers and skip-connections [11, 12].

It generates edge maps combined with the learned filter for each block, and finally creates one edge map by combining the features generated from each edge map. USNet passes the feature maps from the Dexi network through two blocks. In the first block, a kernel of size 1 x 1 is used to process it through the ReLU activation function, and then a kernel of size

s × s, where s is the input feature map size, is used to create a feature map of the same size as the predicted answer value [7].

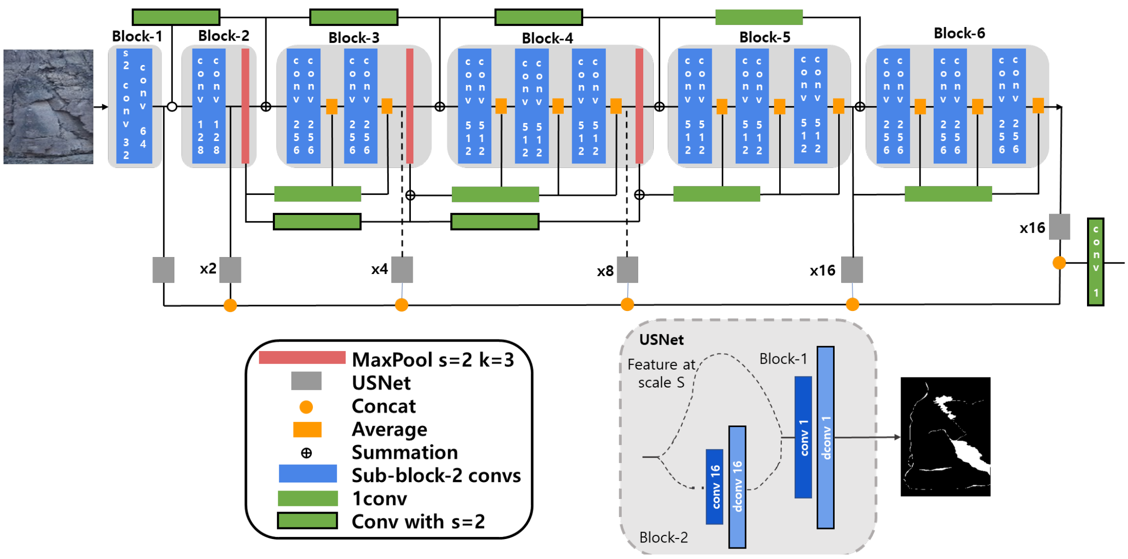
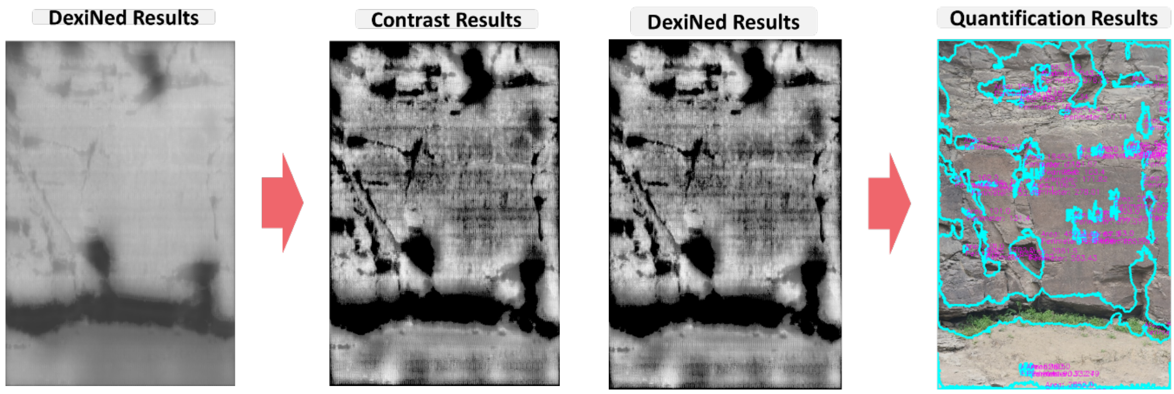


Figure 9: Architecture of DexiNed

4. Experiment results and analysis

4.1. Preprocessing and evaluation measurement

When the 'Joint separation' or 'Cavity' areas of the edge-extracted image were not clear, we went through the process of increasing the contrast to make the areas clearer. Figure 10-(a) shows the result of adjusting the brightness intensity to increase the contrast of the image contrast, making the 'Joint separation' area clearer. Figure 10-(b) shows the results of finding the contour line for each joint area detected after preprocessing and calculating the area and length for the corresponding contour area.



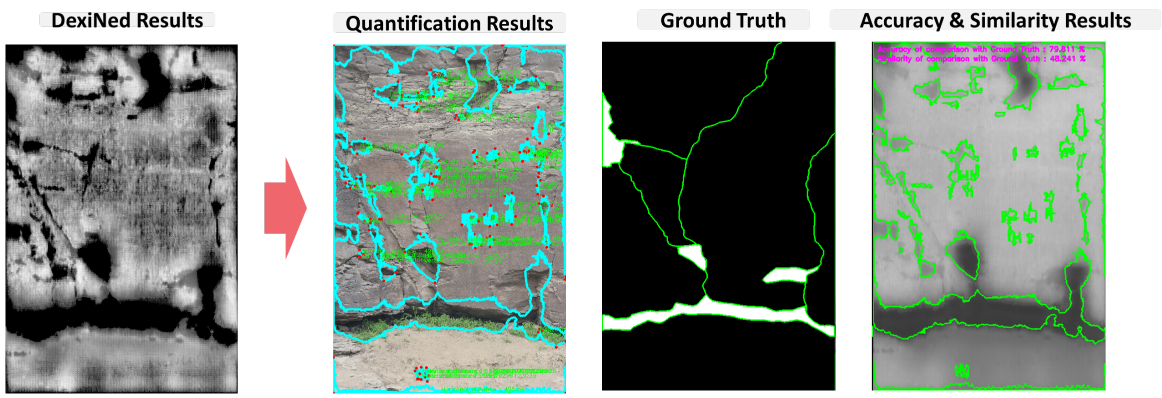
(a) Contrast enhancement (b) Displacement measurement

Figure 10: Contrast enhancement and displacement measurement results

The red dots in Figure 11-(a) are the horizontal and vertical endpoints of each 'Joint separation' area detected in the resulting image. Using these points, we can find the maximum distance between the horizontal end points and the maximum distance between the vertical end points of the 'Joint separation'

Performance evaluation of the Deep Learning architecture used in the experiment can be done through accuracy and structural similarity index.

Accuracy is obtained as a ratio of how well the 'Joint separation' area of the ground truth image binarized into black and white matches the 'Joint separation' area extracted from the image to be evaluated (see Figure 11-(b)). The structural similarity index (SSI) is obtained using the structural similarity, such as luminance, contrast, and pixel value, of the two images being compared.



(a) Maximum horizontal and vertical distance measurement (b) Accuracy and Similarity

Figure 11: Maximum distance and measurement accuracy

4.2. Measurement of displacement of 'Joint separation'

When looking at the displacement of 'Joint separation' by season using the PiDiNet model, which shows the best general performance, the contour area showed values of 1,312, 1,606, 1,660, and 1,014 in spring, summer, fall, and winter, respectively. and the contour lengths showed values of 365, 381, 383, and 342, respectively (see Table 1).

If we only look at the amount of change in the area value, we can assume that there has been a somewhat significant change, but if we look at the change in the length value, we may conclude that there is no significant change. Therefore, it is necessary to comprehensively review the amount of change in area and length to determine whether there has been a significant change.

Table 1

Seasonal 'Joint separation' displacement measurement results

Result				
Date	April 1, 2022	June 26, 2022	Sep. 22, 2022	Dec. 15, 2022
Season	spring	summer	fall	winter
Area	1,312	1,606	1,660	1,014
Contour	365	381	383	342

4.3. Measurement of displacement of 'Cavity' and analysis

In the case of the 'Cavity', the contour area showed values of 13,827, 13,263, 14,392, and 8,468 in spring, summer, fall, and winter, respectively, and the contour length showed values of 2,361, 2,273, 2,886, and 2,255, respectively (see Table 2). This also showed similar aspects to the 'Joint separation' analysis results.

Table 2

Seasonal 'Cavity' displacement measurement results

Result				
Date	April 1, 2022	June 26, 2022	Sep. 22, 2022	Dec. 15, 2022
Season	spring	summer	fall	winter
Area	13,827	13,263	14,392	8,468
Contour	2,361	2,273	2,886	2,255

4.4. Integrated analysis of joint and cavity displacement measurements

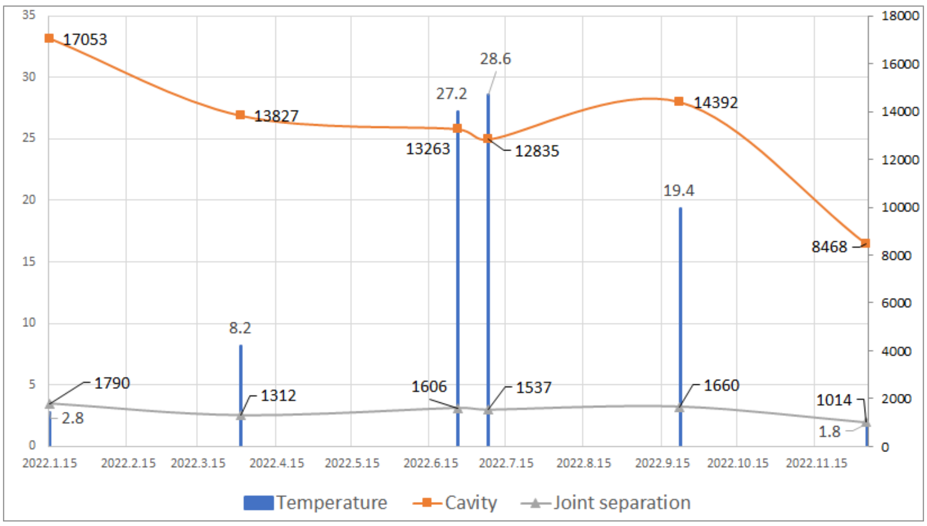


Figure 12: Area changes in 'Cavity' and 'Joint separation' according to temperature

In terms of area, both ‘Cavity’ and ‘Joint separation’ showed the highest values in the first quarter (See Figure 12). Additionally, looking at the change from the second quarter to the fall, the numbers appear to be stable in the case of ‘Cavity’. In the case of ‘Joint separation’, there is some change, but the value appears to be stably maintained between 1,312 and 1,660.

Changes in the contour path showed slightly different characteristics in cavities and joints, as shown in Figure 13. In the case of cavities, the contour length had the greatest value in fall, and in the case of joints, the difference was large between the first quarter and spring, and then showed stable values from the second quarter to fall. Comparatively, the deviation between area and contour length was larger in the cavity, and the contour length of all joint joints was more stable than the area.

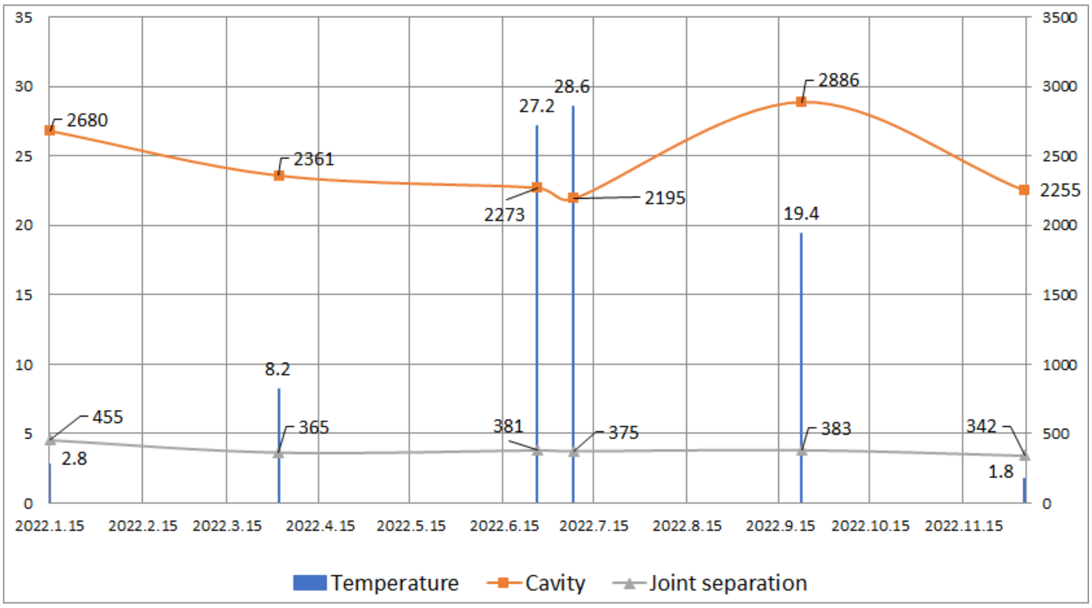


Figure 13: Contour changes in ‘Cavity’ and ‘Joint separation’ according to temperature

According to the comprehensive survey research report on the Daegokcheon petroglyph group [2], the ‘Cavity’ and ‘Joint separation’ of the Petroglyphs of Bangudae Terrace undergo rapid displacement during the spring thaw, but after April, the measured values showed a stable value and showed a slight divergence in the negative direction. It is assumed that the gap narrowed due to thermal expansion of the rock, and this trend is consistent with the results of this research. In addition, it was reported that the correlation between temperature and displacement is inversely proportional, which is also found to show a similar pattern to the results of this research. However, in winter, area and contour length were directly proportional to temperature. We analyzed that in the case of year of 2022, unlike 2019 when the comprehensive research report was written, there were many abnormal climates, and the light and dark in the photo may have had an effect.

5. Conclusion

Petroglyphs of Bangudae Terrace in Daegok-ri, Ulju are designated as National Treasure No. 285 of the Republic of Korea, and are listed as the 'Daegokcheon Petroglyph Group' in the 'Priority List', a UNESCO World Heritage candidate list selected by the Cultural Heritage Administration (CHA). However, they are submerged in water due to the Sayeon Dam located downstream of Daegokcheon Stream, and damage from erosion is gradually accelerating.
In this paper, we presented a method to measure and automatically monitor the amount of displacement of Petroglyphs of Bangudae Terrace using Deep Learning technology. Using

PiDiNet and DexiNed Deep Learning models, we were able to automatically extract edges and areas and detect whether displacement occurred by measuring changes in the outline length and area of the extracted area.
In terms of area, both ‘Cavity’ and ‘Joint separation’ showed the highest values in the first quarter. Additionally, looking at the change from the second quarter to the fall, the numbers appear to be stable in the case of ‘Cavity’. In the case of ‘Joint separation’, there is some change, but the value appears to be stably maintained. In terms of contour length, the contour length of ‘Cavity’ had the greatest value in fall, and in the case of ‘Joint separation’, the difference was large between the first quarter and spring, and then showed stable values from the second quarter to fall.
In the future, we will continue to conduct experiments to improve the accuracy of edge and area extraction and to present a reference point for whether displacement has occurred through additional experiments so that we can automatically determine that displacement has occurred.

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