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Estimating Soil Moisture Content Considering Environmental Changes Using Thermal Camera

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1. INTRODUCTION

Autonomous construction robots are useful for emergency recovery in natural disaster areas. If the robots drive on wet ground, they can get stuck. For safe and efficient robotic restoration work, technologies are required to determine the soil moisture content. Moisture estimation methods are classified as contact or non-contact. Contact methods have a narrow measurement range and the measurement becomes dangerous. At disaster sites, computer vision solutions that enable wide range and non-contact measurements from a distant place are desirable. Shimano et al. [1] estimated water wetness on object surface based on spectral analysis. The method is inadequate for soils with dry surface and high internal moisture content. Therefore, we aim to estimate moisture content in soils.

2. METHOD

2.1. Measurement of environmental changes

We focus on heat conduction as a non-contact observable quantity that reflects moisture content in soils. Soil with high moisture content has a greater specific heat, resulting in less temperature change compared to dry soil. Based on the relationship between moisture content and temperature change, we propose a method of estimating relative moisture content. To observe heat conduction, an energy change to the soil is required. In a controlled environment with manageable heat sources, it is easy to obtain the energy change. However, it is impractical to control heat sources in a large-scale natural environment. Therefore, we estimate moisture content based on heat conduction resulting from natural environmental changes such as sunlight and wind. We utilize a thermal camera to measure soil temperature. Since it is difficult to estimate the environmental changes directly from temperature measurement, we intentionally prepared a reference object to measure the changes. Figure 1 shows an overview of the proposed method. We estimate relative moisture content from similarity of temperature change between the reference object and target soils. Since the specific heat of water is generally higher than that of soil, water is hard to heat up and cool down. If the temperature change of the target soil is smaller than that of the reference object, the soil has a high specific heat and is wet. Therefore, if the reference object is the same soil as the target with 0% moisture content, the higher the moisture content, the lower the similarity.

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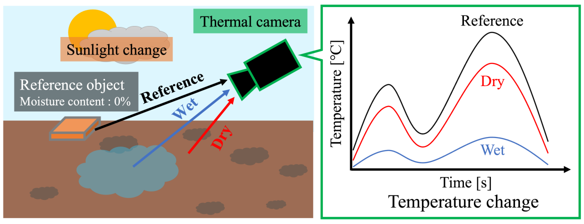


Fig. 1. Overview of the proposed method.

2.2. Estimation of moisture content

We calculate the covariance to evaluate the similarity of the temperature changes. The covariance S is calculated as

$$S = \frac{1}{n}\sum_{k=1}^{n}(T_k - \overline{T})(R_k - \overline{R}), \tag{1}$$

where T is the temperature of the target soil, R is the temperature of the reference object, $\overline{T}$ is average of T during the temperature measurement, and n is the number of sampling times for the measurement. This covariance can be affected by the absolute temperature difference in long-time measurements. To remove this effect, the covariance of the derivative of the temperature S' is also calculated as follows

$$S' = \frac{1}{n-1}\sum_{k=1}^{n-1}(T'_k - \overline{T'})(R'_k - \overline{R'}) \tag{2}$$

where T' is the derivative of T.

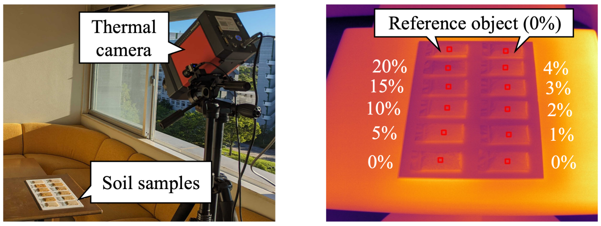
3. EXPERIMENT

3.1. Experimental setup

We placed the soil samples with various moisture contents and the thermal camera (ImageIR 8350) as shown in Fig. 2 and measured the temperature once every 10 seconds for one hour. The samples were small-grained sandy soils with moisture content varying from 0–4% in 1% increments and from 0–20% in 5% increments. The samples were packed in polypropylene bags to keep the moisture content constant during the measurement.

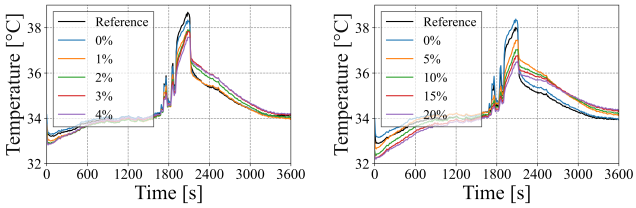
3.2. Measurement of temperature change

Figure 2 (b) is a thermal image and the red squares indicate the measurement areas. The average temperature changes within the red squares are shown in Fig. 3. As the moisture content increased, the temperature change of the target soil was more different from that of the reference object. The correlation between moisture content and magnitude of temperature change was obtained.



(a) Setup (b) Soil samples in thermal image

Fig. 2. Measurement environment.



(a) 0–4% (b) 0–20%

Fig. 3. Temperature change of soil samples.

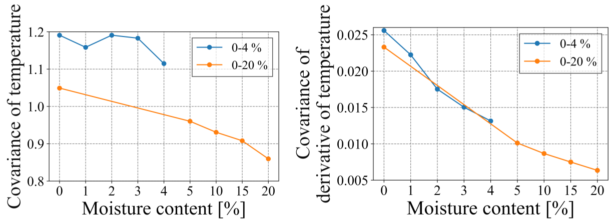
3.3. Covariance with reference object

Figure 4 (a) shows the covariance of temperature change with the reference object. The covariance of 0% was the largest, and tended to become smaller with higher moisture content. However, in the narrow range of 0–4%, it was not monotonically decreasing. Figure 4 (b) shows the covariance of derivative of temperature. The smooth and monotonically decreasing values indicated that this value could be used to estimate the relative moisture content of the soil.

Next, we verified our method by calculating the covariance of derivative of temperature for each pixel, rather than the average of small areas. One thousand points were sampled from each soil sample, and their covariances are shown in the histogram as shown in Fig. 5. If each distribution is small and has little overlap, it indicates high accuracy. Although there were some overlaps, we could see that the peak position for each moisture content was clearly separated. Outliers could be pebbles in the soil samples.

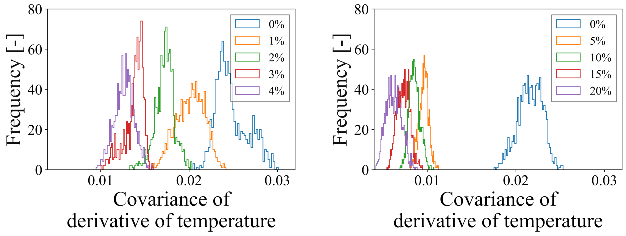
3.4. Moisture map

We conducted an outdoor experiment to estimate the distribution of moisture content on real ground and visualized it as a moisture map. We placed the thermal camera in the room in the tall building as shown in Fig. 6 and measured the ground temperature in the distance once every 10 seconds for one hour. 10 L of water was sprinkled on a 2 m square area. *Wet1* was watered directly, *wet2* was gradually soaked from *wet1*, and *dry* was far from the watered area. The moisture content was *wet1* > *wet2* > *dry* = Reference object (*dry*). Figure 7 (a) shows the temperature change of each region. The temperature changes of the reference object and *dry* were identical. The higher the moisture content, the smaller the temperature change. The covariance of derivative of temperature for each pixel was visualized as the moisture map as shown in Fig. 7 (b). In this map, red areas indicated high moisture content and blue areas indicated low moisture content. We could see that the moisture content could be visualized appropriately for the soil area.



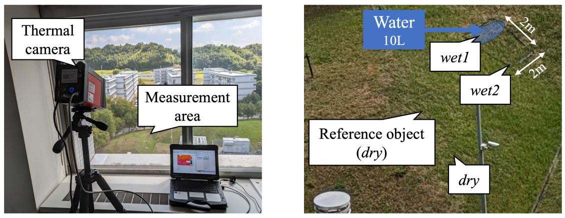
(a) Temperature (b) Derivative of temperature

Fig. 4. Covariance with reference object.



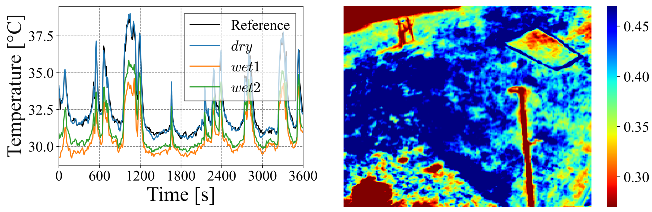
(a) 0–4% (b) 0–20%

Fig. 5. Histogram of covariance with reference object.



(a) Setup (b) Measurement area

Fig. 6. Measurement environment.



(a) Temperature change (b) Moisture map

Fig. 7. Moisture map based on temperature measurement.

4. CONCLUSION

We proposed a method of estimating soil moisture content using a thermal camera. By placing a reference object, we estimated the relative moisture content based on the temperature change of the reference object. The correlation between moisture content and temperature change was confirmed, and the moisture content was estimated by the covariance. In the future, we plan to estimate the absolute moisture content.

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