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Analysis of dryness in cement-based mixture via spectral imaging and dimensionality reduction

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Dryness in cement-based mixture can be systematically analyzed using hyperspectral imaging and dimensionality reduction techniques. In this study, we captured the spectral images of cement-water mixture in the near-infrared range and obtained the spectrum as a function of time. The temporal evolution of the spectrum data was analyzed using dimensionality reduction techniques to determine the dryness of cement-water mixture. Since it was found that the standard deviation in each dimension of the dimensionality reduction results decreased with the moisture content, the product of standard deviations also decreased up to 97.7% until the perfect drying of water in the cement-water mixture. The proposed dryness analysis method provides a nondestructive and efficient real-time method for determining dryness of cement-based materials at construction sites.

Dryness in cement-based mixture directly affects the safety of concrete-based buildings. The moisture content of cement-based mixture is related to its thermal conductivity and hardness. As the moisture content in cement-based mixture increases, its thermal conductivity increases, and in severe cases, excessive heat can cause the cement structure to explode[1,2]. Furthermore, as the moisture content in cement-based mixture increases, its hardness decreases, which can result in the collapse of buildings if construction is continued using such cement[3]. On the contrary, if the moisture content in cement-based mixture is not enough, the adhesiveness of mixtures gets weak, and it also makes the strength of constructed-building weak[4]. Therefore, dryness of cement-based mixture must be measured at every step of building construction. Dryness of cement-based mixture is commonly measured by directly crushing concrete and measuring its water content (weight of water per unit weight of cement, sand, gravel etc.)[5]. However, cement grinding is a destructive process, and it cannot be used in real-time measurement. Non-destructive moisture-measurement techniques are a nuclear magnetic resonance (NMR) spectroscopy such as H NMR, liquid-state NMR, and solid-state NMR, and a neutron radiography (NR) that measures the intensity of transmitted neutron beam, and to measure an attenuation of electromagnetic radiation such as ground penetrating radar (GPR), and time-domain reflectometry (TDR)[4–6]. NMR and NR methods have advantages of giving detailed information on the internal structure of materials non-destructively, but disadvantages of rigorous sample preparation, slow test speed, safety issue for the environment and human, and difficulty in operation[5]. GPR and TDR are very fast and real-time measurement with them can be possible, but obtained results are very huge and systematic analyze should be introduced[5]. In another method that is electrical impedance spectroscopy, surface resistivity is measured by directly establishing contact among several probes on the surface of cement-based materials. Measuring resistivity is a nondestructive method for determining the moisture content of cement-based mixture, but the measurable area is limited[7–10]. (See Supplementary Information 1)

Herein, we propose a method for determining dryness in cement-based mixtures using a hyperspectral camera in the near-infrared (NIR) range and a dimensionality reduction technique, as shown in Fig. 1(a) and (b). The proposed method is nondestructive and allows real-time measurements over a large area. To obtain the desired properties of materials nondestructively, spectral imaging is adopted in various fields, such as agriculture, environment, art, military, and medicine[11–15]. Compared with color imaging, which generally utilizes only red, green, and blue bands in the visible range, spectral imaging uses several tens to hundreds of bands in the ultraviolet or NIR range. However, because spectral images contain more spectral bands than color images, the data are numerous, complex, and difficult to analyze. Therefore, it requires techniques reducing data while sustaining important information in large volumes of data, which are called as dimensionality reduction techniques[16]. The dimensionality reduction technique transforms data from a high-dimensional space into a

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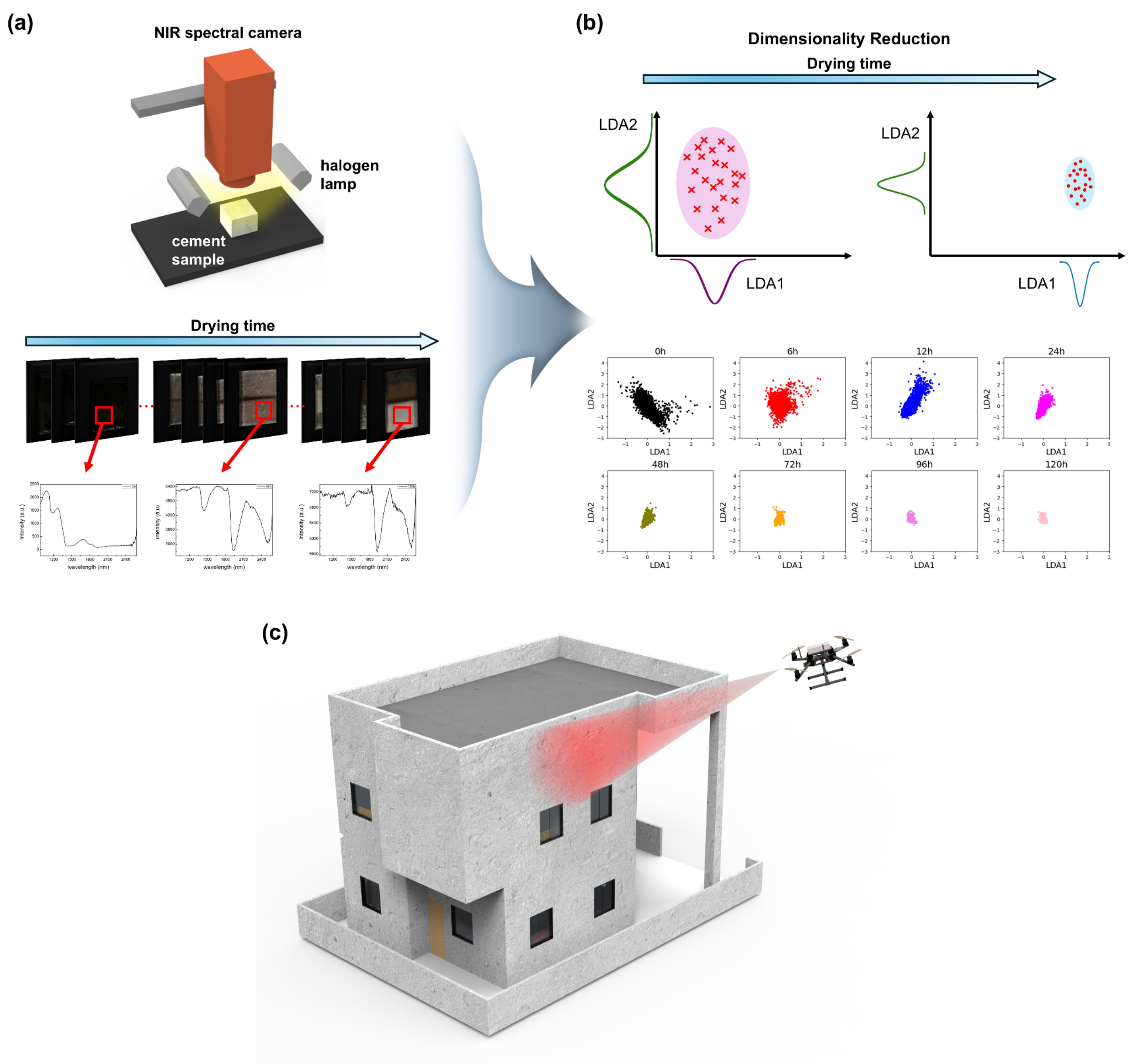

Fig. 1. (**a**) Schematic illustration of spectral imaging for dryness of cement-based mixture. (**b**) Schematic illustration of dimensionality reduction processes on spectral images (top) and graphs of dimension-reduction analysis representing as a drying time goes (bottom) (**c**) Schematic of real-time monitoring on the status or dryness of cement-based building using a drone with a hyperspectral imaging apparatus.

low-dimensional space to remove unnecessary information or noise while preserving important information as shown in Fig. 1(b). Many dimensionality reduction techniques exist, such as principal component analysis (PCA) and linear discriminant analysis (LDA). Meaningful results can only be obtained by adopting the dimensionality reduction technique that is the most suitable for each situation.

In this study, we continuously captured spectral images of drying cement-based mixture over time using an NIR spectral camera (Spectral Camera SWIR; SPECIM) as shown in Fig. 1(a) in order to find an indicator showing status that is drying water in cement-based mixtures as time goes by. This kind of time series hyperspectral imaging techniques are actually used in wide applications that monitor time-varying status such as food quality evaluation, analysis of chemical components, surface damage assessment in heritage constructions etc[17–20]. Subsequently, a dimensionality reduction technique is applied to a large amount of data obtained from spectral imaging to determine dryness of cement-based mixture[20-23]. Among various dimensionality reduction techniques, we adopted the LDA method to reduce the amount of hyperspectral-image data. The LDA method is widely used in the supervised learning of artificial intelligence (AI), primarily for the classification of data classes by maximizing the variance between classes and minimizing the variance within classes[24–29].

By applying the LDA method to the spectra of cement-water mixtures obtained from the time series NIR spectral images, we could transform 3-dimensional data into 2-dimensional data and plot them in 2-dimensional graphs over time. The reduced results confirmed that as the cement-water mixture dried over time, the data obtained

Time (h)	Temperature (°C)	D ($=\sigma_x \cdot \sigma_y$)	Water content (%)
0	22.6	1	100.0
6	23.0	0.354	80.2
12	23.6	0.223	74.1
24	22.7	0.112	56.0
48	22.6	0.095	25.9
72	23.5	0.026	3.4
96	23.3	0.023	0
120	23.3	0.023	0

Table 1. Temperature conditions, water contents, and *D* parameters in drying-sample experiment.

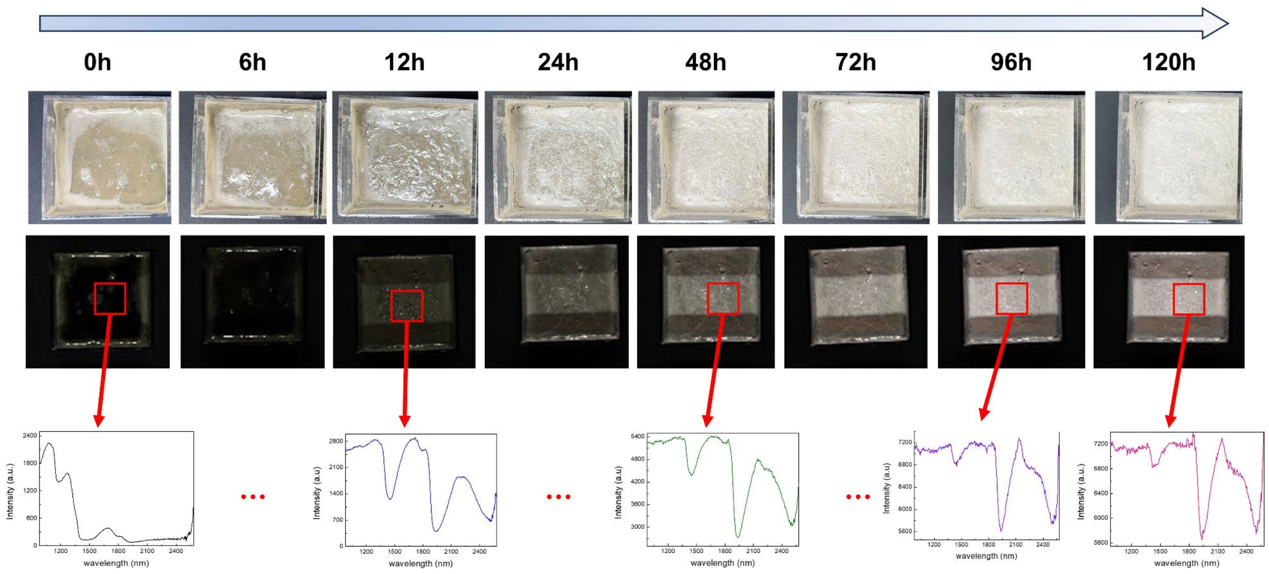

Fig. 2. Visible (top) and near infrared images (middle) captured using spectral camera. Spectrum (bottom) at a certain time was obtained at central point of image.

using the LDA method became spatially concentrated, and the dispersion became extremely narrow. Therefore, we set the product of standard deviations in reduced dimensions as the indicator for the dryness of cement-water mixture. By comparing this data with the moisture content of actual cement-water mixture obtained by directly measuring the weight of dried cement-water mixture, we were able to determine the quantitative correlation between cement-water mixture dryness and spectral images. Proposed dryness-measurement method using hyperspectral imaging and a dimensionality-reduction technique is non-destructive, fast, and efficient in cost and time, compared with the existing methods. When combined with recent-developed autonomous vehicles such as drones, emerging AI technologies, and computing resources as like in Fig. 1(c), it is expected to give us useful methods for monitoring and evaluating the surface condition of very large concrete structures such as bridges, dams, and buildings or under construction in real time.

Experiment and analysis
Spectral imaging
We prepared samples (Sampyo, Korea) mixed cement powder with water at a ratio of 3:1 (cement: water) in a transparent acrylic box and captured their spectral images while drying them at a constant temperature, as shown in Table 1. (See Methods: Sample Preparation) The prepared samples were continuously measured over the drying period using an NIR spectral camera, which comprised 289 spectral bands within the range of 1000–2500 nm. On the first day, the prepared samples were measured at 2-h intervals because they initially dried rapidly; as the drying time decreased considerably after one day, the samples were measured at 6-h intervals from the second day onwards, as shown in Fig. 2. Figure 2 shows the visible and NIR images of the drying samples. Changes in the NIR images became more evident over time.

The spectrum in the wavelength range of 1000–2500 nm was obtained from the central area of the measured NIR image of the sample. The obtained spectrum confirmed that dips at wavelengths of 1450 and 1950 nm deepened over time. As the dryness increased, the intensity of the spectrum increased gradually, thus confirming that the reflectivity of the sample increased. Changes in the spectrum over time showed a complex pattern, with dips deepening in specific bands, whereas the reflectivity, which corresponds to the background level, increased. Therefore, the obtained spectrum could not be analyzed easily because it contained multidimensional data. Hence, we reduced the dimensionality of the spectral data and removed the complexity of the multidimensional data to obtain a quantitative indicator related to dryness of cement-based mixture.

Dimensionality reduction

We reduced the spectral data by performing LDA, which is a linear dimensionality reduction method, as mentioned in the Introduction. When dimensionality is reduced using LDA, each class is distinguished based on the target setting. The data reduced via LDA maximize the gap between classes categorized by the set target and clarify the distinction between classes while minimizing the variance within the class. Therefore, to determine cement dryness over time, dimensionality reduction was performed using the drying time as the setting target. Subsequently, LDA was performed to minimize the dispersion of spectral data at a specific time and simultaneously maximize the dispersion of spectral data over time. (See Supplementary Information 2) Based on Fig. 3, the dispersion of the dimensionality-reduced spectral data decreased over time. The intensity decreased at a specific wavelength, and the increase in the average intensity of the spectral data results caused the dispersion to decrease continuously after dimensionality reduction. As shown in Fig. 3, the spectral and dimensionality-reduced data after 96 and 120 h remained almost unchanged; thus, we considered 96 h to be the time at which the cement-water mixture completely dried. Therefore, we confirmed that the dryness of cement-water mixture is highly correlated with the dimensionality-reduced data, and that the narrow spatial distribution of the dimensionality-reduced data can be used as an indicator of cement-water mixture dryness. To numerically quantify changes over time in dimensionality-reduced data, we introduced D ($D = \sigma_x \cdot \sigma_y$, where σ_x and σ_y are the standard deviations of dimensionality-reduced data in the x- and y-axes, respectively) as a figure of merit for the spatial distribution of the data.

Correlation analysis

Assuming that water evaporates as mass decreases, the dryness of cement can be expressed by Eq. (1), which can be obtained by measuring the weight of the cement-water mixture sample after a certain period[30]:

$$\text{moisture content } (\%) = \frac{(w_i - w_f)}{w_f} \cdot 100 \tag{1}$$

$$w_f \ : \ weight\ of\ cement, \ \ w_i \ : weight\ of\ cement\ after\ i\ hours\ pass$$

A constant sample weight indicates that all moisture had evaporated, and the sample had completely dried. To determine whether the product of the standard deviations in each axis of the dimensionality-reduced spectral data is related to the dryness of the cement-water mixture, the weight of the sample was measured each time to calculate the moisture content. By comparing the data measured using these different methods, we obtained a relationship between dimensionality-reduced spectral data obtained from the spectral image of the sample and the dryness of the sample. The measured D value and moisture content are plotted as a function of drying time in Fig. 4(a). The D value, which is the product of the standard deviations of the dimensionality-reduced data in each axis and the moisture content measured simultaneously, decreased as time progressed. Based on these results, a clear correlation between the two measurements was confirmed.

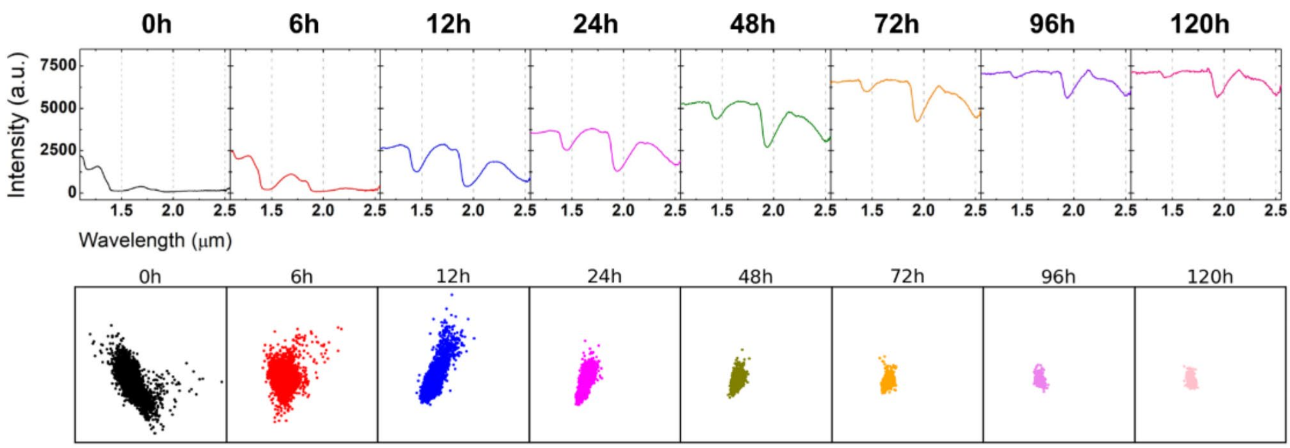

Fig. 3. Spectrum of drying cement (top) and plot of dimensionality-reduced data achieved via linear discriminant analysis (LDA) (bottom).

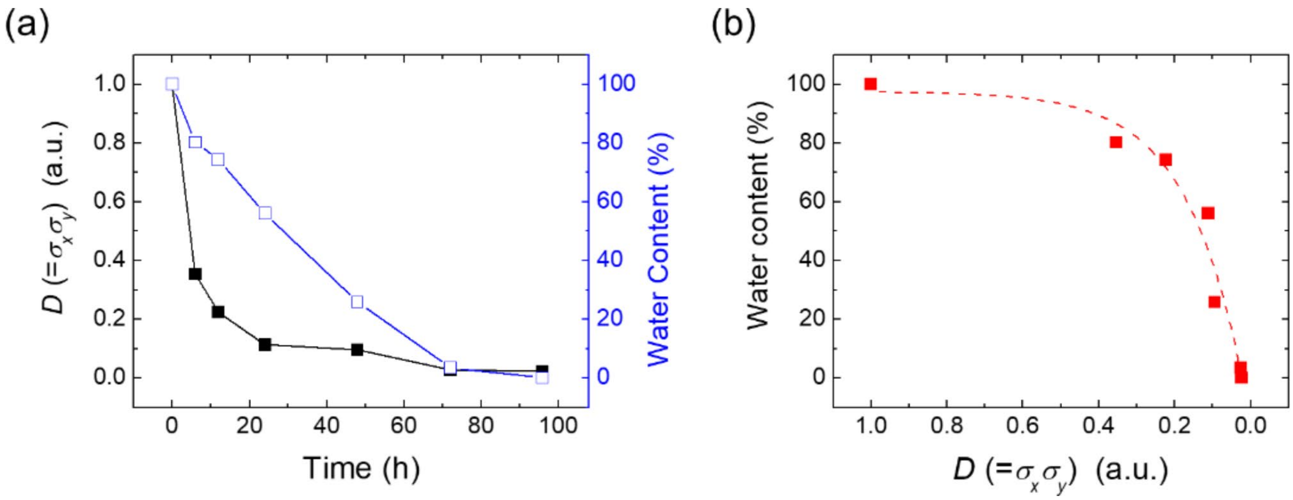

Fig. 4. (**a**) Plot of *D* parameter (product of x- and y-standard deviations) and water content in cement-water mixture sample as a function of drying time. (**b**) Plot of water content in cement-water mixture sample t as a function of D parameter.

The moisture content was plotted as a function of *D* to determine the exact relationship between the two measured values, as shown in Fig. 4(b). Based on this graph, we can conclude that the *D* value and moisture content exhibit a clear exponential decay relationship. Thus, we obtained the following equation as a fitting value:

$$W\,(\%) = -112.95\exp\left(-\frac{D}{0.15}\right) + 97.44 \tag{2}$$

We extracted the spatial *D* value from the NIR spectral image of cement-water mixture sample with spatially different moisture contents via LDA and estimated the moisture content of the sample using Eq. (2). The *D* value of 0.14 obtained from the wet region in Fig. 5 corresponded to a water content of 53.34%. We can see two peaks with around 1,400 and 2,100 nm from the spectrum obtained from the dry region of sample shown as a red line in the graph of Fig. 5. Because we did not find these peaks in the spectrum of wet region shown as a blue line in the graph of Fig. 5, it could be guessed that these peaks may be related with cement itself. From Fig. 4 of ref.[31], we could find two peaks with 1450 nm and 1950 nm, which are similar with two peaks in spectrum obtained by us[31]. From this comparison, it could be concluded that two peaks shown in the spectrum of dried sample came from the cement itself, and it let us know again that the sample was fully dried.

Discussion

The proposed method for measuring the dryness of cement-based mixture has advantages of fastness, effectiveness in cost and time, and possibility of real-time monitoring, but has some limitations and should be improved. Cement-based materials used in the construction have complex components and internal structures depending on the construction purpose. Therefore, it is necessary to measure internal status of cement-based materials besides surfaces. Generally, as the wavelength of light gets longer, there is a trend that the penetration depth into materials gets larger[32]. Even though spectral imaging with NIR range used in this experiment gives us drying information on the surface of the cement-based materials, spectral imaging with longer wavelengths such as mid wavelength infrared (MLIR) or long wavelength infrared (LWIR) can give us information on the internal status of cement-based materials and research in these regions should be executed more in the future. Additionally, dryness or status of cement-based materials is very sensitive in surrounding environment. For example, drying speed of cement-based materials is different on the day or night, season, and position of the construction. Therefore, spectral imaging experiments on the cement-based materials with various conditions should be done and obtained data should be analyzed more-in-depth. As data with various conditions are collected more, AI technology can be trained with more data and gets more useful and efficient, resulting the improvement of proposed method to measure the dryness of cement-based materials.

Conclusion

We proposed and experimentally demonstrated a method to measure dryness of cement-based mixture while avoiding the disadvantages of existing dryness measurement methods. By performing NIR spectral imaging, we obtained the dryness spectrum over a large area in a nondestructive and real-time manner. Based on the spectral data obtained, we confirmed that a characteristic dip appeared in a specific wavelength range and introduced a dimensionality reduction method to determine the quantitative indicator of cement-based mixture dryness. We experimentally confirmed that the standard deviation of the dimensionality-reduced spectral data of sample was related significantly to the moisture content of cement-based mixture and suggested it as a standard indicator for cement-based mixture dryness. Our proposed dryness measurement method using NIR spectral imaging and

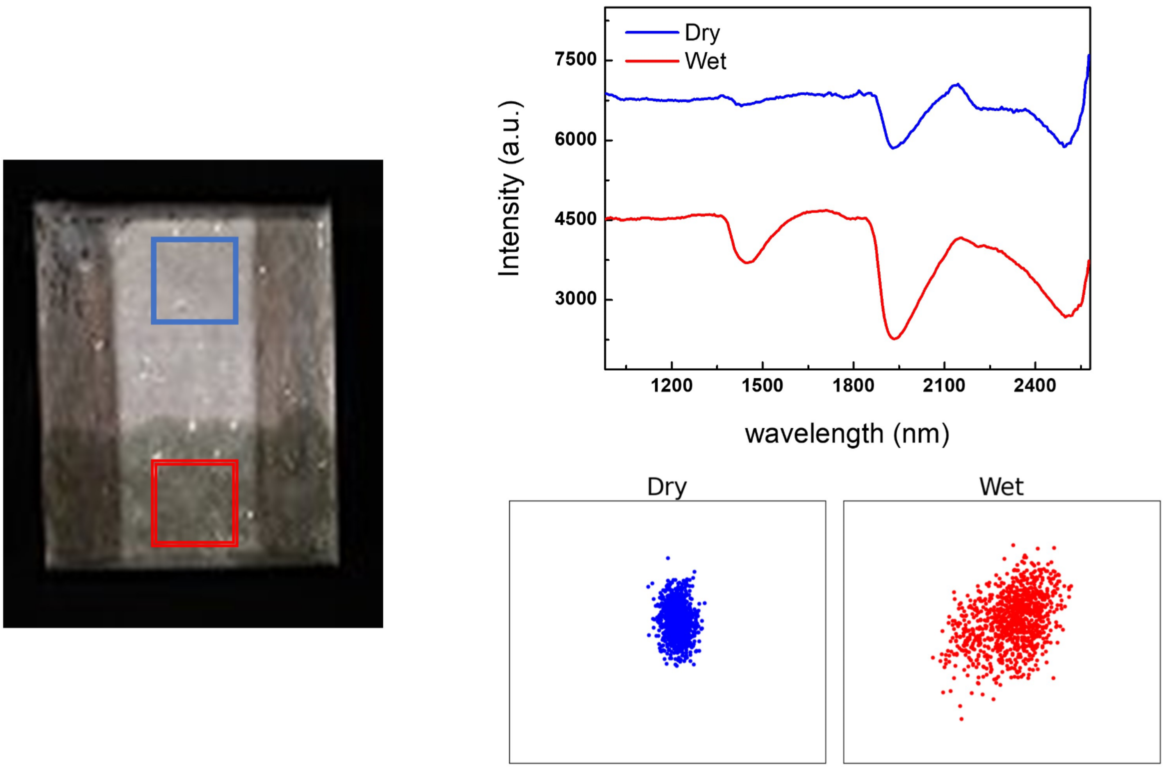

Fig. 5. (Left) NIR image of sample with different moisture contents at top and bottom. (Right-top) Spectra obtained from measured image. (Right-bottom) Data dimensionally reduced via LDA. Data obtained from wet region (red), which deviate slightly from those obtained from dry region (blue).

a dimensionality-reduction technique is nondestructive and can determine dryness of cement-based mixture with high precision in real time. Therefore, it is expected to be more useful than existing methods at actual construction sites.

Methods

Sample preparation

To make a cement-water mixture sample for the analysis, cement powder and water were mixed at a reference ratio of 3:1, which mixing ratio was calculated by calculating the weight ratio of the water indicated from the cement product. In order to take spectral images of the mixture with a hyperspectral camera, the cement-water mixture was poured into acrylic boxes that are transparent from visible to near-infrared range, and dried in the environment with controlled conditions. Before drying samples, we measured the weight of samples to use as the references. The weight of the cement-water mixture sample was measured over time, and we calculated the moisture content of the sample by using the lost weight of samples. Since drying status of samples is sensitive to environment such as temperature and humidity, samples were stored in a laboratory where temperature and humidity were maintained to continuously obtain uniform data, while measuring the temperature and humidity every day. We are about to investigate effect of environment to the dryness of cement-based mixture as the next experiment because it would be that the dryness of cement-based materials is affected much by environment in real construction sites. The cement-water mixture contained sample was fixed on the table and the hyperspectral camera was moved to scan the sample. To obtain the data with the most uniform condition, we used data extracted from the center part of the picture taken by the spectral camera. The time interval for measuring spectral images of samples was set as the time interval that showed well the dryness of samples when multiple cement samples were made and measured. When the cement-water mixture was almost completely dried, no change was observed in the spectral images and spectra.

Data availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

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Author contributions

H.-J. K. and C.K. executed measurement. S.C. and G.S.K. prepared samples. H-J.K., W.J. and J.Y. analyzed data. S.J.O. and Y.P. conceived and conducted experiment. H.-J.K. and Y.P. wrote the main manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

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