Basic investigation on estimation of land cover classification conforming to the ASJ RTN-Model using hyperspectral imaging data

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1. Introduction

Numerical simulations in three dimensions for outdoor acoustic propagation situations have become possible in actual areas because of recent developments of computer technology and simulation techniques [1,2]. In addition, spatial evaluation of noise is becoming general [3,4]. Comprehensive geographic information data are necessary to address outdoor acoustic propagation situations. Thousands of labor hours must be expended to obtain geographic information data firsthand from field observations. Therefore, the use of digital map data and remote sensing data are regarded as valuable in obtaining geographic information data. However, the data intended for use in acoustic simulations, particularly geographic information such as land cover classification, have not been discussed to any great degree. Practical use has been reported, in our previous work, of geographic information data such as polygonal edges of buildings on a two-dimensional digital map of building plans, and digital surface model (DSM) data in remote sensing data such as the heights of buildings and altitude [1]. In that study, the land cover classification was treated as a rigid surface (complete reflection surface) without exception because no existing database provides land cover classification to set individual land cover classification in detail. Other groups have also used rigid surface models for numerical acoustic simulation [2].

Much work in the fields of resource development, agriculture, and disaster prevention has been conducted to estimate the land cover classification using remote sensing data. Among well-known studies is that of a method using multispectral imaging data [5]. The multispectral imaging data consist of the spectrally resolved reflectance of visible and infrared electromagnetic radiation. Recently, hyperspectral imaging data, which consist of a more highly resolved spectral reflectance of electromagnetic radiation than in the multispectral imaging data, are beginning to be used in some works for estimating land cover classification [6,7]. However, no report of estimation using hyperspectral imaging data suitable for outdoor acoustic propagation situations (e.g., classification focused on effective flow resistivity or acoustic impedance) has yet been published. Therefore, a land cover classification estimation technique is necessary for outdoor acoustic propagation simulations.

A final goal of this study is the establishment of an estimation technique of land cover classification suitable for outdoor acoustic propagation simulations. In this report, we present a possible land cover classification estimation technique specialized for acoustic simulations using high-accuracy hyperspectral imaging data through a case study using a Nagaoka sample.

2. Hyperspectral imaging data

Figure 1 presents hyperspectral imaging data for Nagaoka, Niigata, in a grayscale (wavelength: 661 nm). The image was obtained by PASCO Corp. on 5 June 2004 using the Airborne Imaging Spectroradiometer for Application (AISA), which is a hyperspectral sensor with a 1 m spatial resolution developed by Spectral Imaging Ltd. The image data comprise 67 bands, covering both the visible and a part of near-infrared wavelengths from 400 nm to 1,000 nm. Spectral band widths are equally spaced by 8–9 nm. The spectrum value at each picture element indicates a normalized spectral reflectance, which is calculated based on the spectral radiance of the ground surface and the sun observed simultaneously. Each data element is quantized by 16 bits (unit: 0.01 percent).

Figure 2 shows the average and standard deviation of the spectral reflectance for each land cover classification (Table 1) extracted from hyperspectral imaging data at training areas (Fig. 1, as will be described hereafter in detail). The averages of spectral reflectance differ among land cover classifications. The reflectance in the visible region of the spectrum (400–700 nm) is uniformly lower than those in the higher wavelength region in the classification of compacted soil. The reflectance values of loose soil vary widely among all regions; those of the grassland and trees vary widely in the regions longer than 700 nm. The variance is thought to be the main cause of the mixed pixel problem owing to the spatial
resolution (1 m × 1 m) [8]. However, the reflectance values of the rice field and compacted soil are the same in all regions. We attempt to estimate the land cover classification suitable for outdoor acoustic propagation simulations using such characteristics of hyperspectral imaging data.

3. Estimation of land cover classification

3.1. Classification categories

The land cover classification that should be estimated is determined by referring to ASJ RTN-Model 2008 [9] in the first step to discuss classification methods. ASJ RTN-Model 2008 defines land cover classifications of four categories: loose soil (soft farmland and furrowed rice fields), grassland (lawn, rice fields, and grassland), compacted soil, and concrete and asphalt. The corresponding effective flow resistivities are, respectively, 75, 300, 1,250, and 20,000 kPa s/m².

In this report, the land cover classification that must be estimated is decided from five categories (Table 1). The category “Others,” a reflecting surface, contains expansive land cover, e.g., concrete, asphalt or trees. Therefore, a picture element that has not been classified as an absorption surface (category in which effective flow resistivity is less than 1,250 kPa s/m² in Table 1) is classified as a reflecting surface in “Others.” In numerical acoustic simulations, edge polygons of buildings on a two-dimensional digital map is used to identify building areas [1]. Therefore, it is not necessary to classify buildings using hyperspectral imaging data.

Table 1 Effective flow resistivity for each land cover category used in this study.

| Land cover category | Flow resistivity [kPa s/m²] |
|---------------------|-----------------------------|
| Loose soil          | 75                          |
| Grass               | 300                         |
| Rice field          | 300                         |
| Compacted soil      | 1,250                       |
| Others              | 20,000                      |

3.2. Estimation technique

Three widely known supervised classification techniques using training data sets of each land cover category are employed for estimating the land cover classification: maximum likelihood method (ML), minimum Euclidean distance method (MED) [10], and shape difference method (SD) [11]. Furthermore, Oki et al. proposed a new method for classifying land cover categories using hyperspectral imaging data, combining the characteristics of the MED method and the SD method (MED-SD method) [6]. Consequently, the accuracy of the MED-SD method is higher than those of the other three methods. Therefore, the MED-SD method is used in this study. The MED-SD method normalizes each value calculated from the MED method and the SD method. The chosen category of land cover is the smallest value of the discriminant function fi,x, as in
where $D$ [m] and $\theta$ [rad] respectively represent the distances calculated using the MED method and the angle calculated by the SD method. The subscripts “min” and “max” respectively indicate the minimum and maximum values among all data elements for each land cover classification $i$ ($i = 1-4$). The value of $f_{i,x}$ indicates the degree of similarity between the averaged spectrum of land cover classification $i$ and the spectrum of data element $x$. The value can be 0–2. A smaller value of $f_{i,x}$ indicates greater similarity.

### 3.3. Training area and data

The MED-SD method is a supervised classification method. Therefore, it is necessary to set the training area for each category. The spectra for each data element included in each training area are extracted; then the spectra are averaged to obtain the supervised spectrum data for each category. Here, the training areas are set up as presented in Fig. 1 on the basis of high-resolution digital aerial photographs and field investigations, where the observation area included an area of the hyperspectral imaging data. The average and the standard deviation of the spectrum in the training areas for each category have already been presented in Fig. 2.

Figure 3 presents the results of the identification of land cover classification in the training areas. The percentage of correct identifications for the category of loose soil is the lowest (36%) because of the great variation in spectral reflectance (see Fig. 2). The correctness for the tree category is also lower (52%), and the percentage of incorrect identifications as grassland is about 34%. On the other hand, the percentages of correct identifications for the categories of grassland, rice field, and compacted soil are greater than 80%. Therefore, it can be said that these categories are estimated accurately.

In order to identify an element $x$ that is not applicable to any absorption category as “Others,” it is necessary to set an identification threshold for each category, so the lowest 5% of $f_{i,x}$ is regarded to be outlier. Therefore, the 95 percentile value of $f_{i,x}$ is adopted as the threshold (hereafter called $f_{0.95}$) in this report. Data element $x$ is identified as category $i$ when $f_{i,x}$ is less than $f_{0.95}$. Table 2 shows $f_{0.95}$ for each category. The $f_{0.95}$ of loose soil, which has the lowest accuracy, is a maximum of 0.241.

### 4. Estimation results

The land cover classification is estimated in the test area surrounded by the heavy solid line in Fig. 1, using the supervised average spectrum (Fig. 2) and the threshold $f_{0.95}$. Figure 4 illustrates the identification result. It can be said that the land cover classifications can be accurately identified,
but some incorrect estimations are recognized between trees and grassland, and rice field and loose soil. The mistakes between trees and grassland would be reduced using the digital elevation model (DEM) and DSM data (the height difference between the DEM and the DSM data should be larger for a tree than for grassland). The mistakes between rice field and loose soil would invite overestimation of noise attenuation, which is unsafe for noise prediction. Therefore, it is necessary to suggest some improvement method for that point. In addition, incorrect estimation between compacted soil and loose soil is apparent. It would not lead to the overestimation of noise attenuation, but it must be improved to enable high-accuracy numerical acoustic simulations. As observed above, useful land cover classification data can be generated using hyperspectral imaging data for outdoor acoustic simulations, although some incorrect estimations exist.

5. Conclusions

In this report, we presented a preliminary land cover classification estimation technique using hyperspectral imaging data with the final goal of establishing a technique that is suitable for use with outdoor acoustic propagation simulations. Consequently, the usefulness of estimation by the MED-SD method using hyperspectral imaging data was indicated, despite some incorrect estimations.

Our future studies will be conducted to reduce incorrect estimations, particularly those between rice field and loose soil, and grass and trees. Additionally, more detailed field investigations to obtain more reliable supervising data for unbiased verification and identical investigations in other seasons to obtain changes in the land cover acoustical characteristics with the passing of the seasons are important for general knowledge.

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