UPDATING CADASTRAL MAPS USING DEEP CONVOLUTIONAL NETWORKS AND HYPERSPECTRAL IMAGING

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ABSTRACT: Cadastral maps are maps showing the boundaries and ownership of land parcels. Surveying and updating cadastral maps is typically performed using several conventional methods such as field work and remote sensing (RS) based on aerial and satellite images. While field surveying is accurate, it is time-consuming and impossible when access to remote areas is difficult due to harsh weather conditions or other restrictions. Therefore, RS is often preferred to field survey. To update a cadastral map, land use information on how people use the landscape is required. However, land use cannot be determined using RS imaging. RS imaging can only generate land cover information detailing how much of a region is covered by forests, wetlands, impervious surfaces, and other land types. In this study, we employed hyperspectral images and a deep learning network to efficiently use RS imaging for updating a cadastral map. The classes output by the network trained on hyperspectral images were reorganized according to the cadastral categories to update the map. Through this process, it was possible to extract the areas requiring updating, and update their attribute information. The results demonstrated that hyperspectral images could be effectively classified, allowing to update the considered cadastral map.

1. INTRODUCTION

Cadastral maps represent boundaries and unique identification of each land parcel and include information on land tenure, use, and value. Updating cadastral maps is crucial for recording land ownership and property division changes in a timely manner (Ali et al., 2012). However, ensuring that cadastral maps provide the latest information is not an easy task. Cadastral maps consist of spatial data (such as boundaries and shapes of parcels) and non-spatial data (such as ownership and land use type). Many studies have been conducted on how to update the spatial data of cadastral maps. Analyzing satellite and airborne images is a common method for surveying cadastral information. Satellite images over wide areas can provide historical records about these areas by supplying images repeatedly and economically. Hence, satellite images are often used for preparing and updating cadastral maps (Corlazzoli and Fernandez, 2004; Jacobsen et al., 2008). Aerial images offer rapid and cost-effective means of extracting topographic information (Barnes et al., 1994). In recent years, unmanned aerial vehicles (UAVs) have been used for various RS applications such as creating and updating cadastral maps. Surveys conducted using UAVs are rapid, efficient, low-cost, and flexible (Crommelinck et al., 2016). There have been many attempts to use UAV images for cadastral mapping (Crommelinck et al., 2016; Puniach et al., 2018; Sim and Song, 2015).
The majority of studies has been focused on updating the boundaries and shape of each parcel and used multi-spectral sensors consisting of three to four bands. However, while there may be no changes in parcel boundaries and shapes, land and properties may be subject to other changes such as changes in land use type. Therefore, it is important to identify parcels that require their land information to be updated. In this study, hyperspectral images and deep learning were used to classify the land information of cadastral maps and compare the results of classification with actual cadastral maps.

2. METHOD

In this study, hyperspectral images providing detailed spectral information were used to extract land information, while a deep learning network was employed to classify hyperspectral images accurately based on limited training data. After that, the classes of the cadastral map were reassigned according to the classes of land cover maps obtained from hyperspectral classification. Finally, areas having the attributes consistent with those of existing cadastral maps were extracted to update the cadastral map in question (Fig. 1).

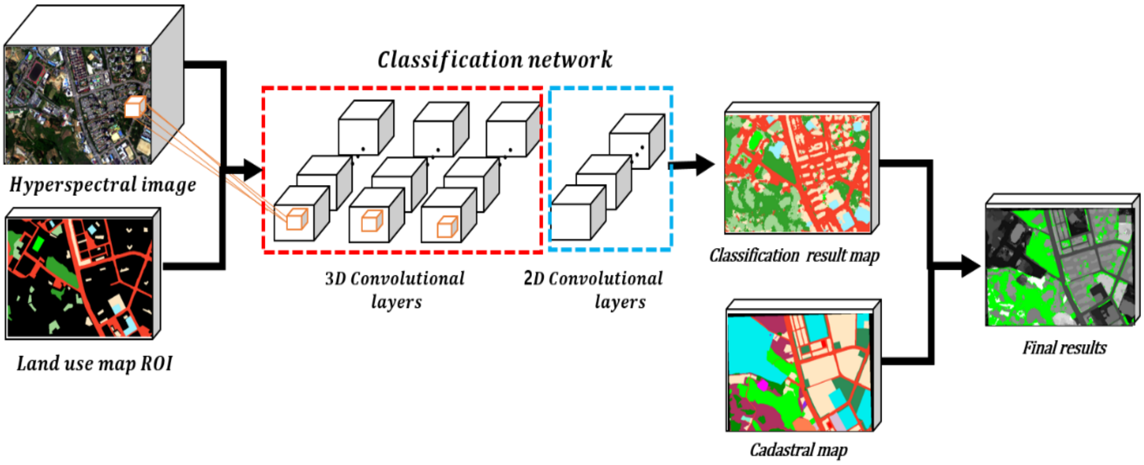


Figure 1. Flow chart of the proposed method for updating cadastral maps

2.1 Classification of hyperspectral images using a deep learning network

Hyperspectral images include hundreds of spectral bands and provide more detailed spectral signatures compared to multi-spectral images. Therefore, hyperspectral images allow distinguishing similar spectral properties and can be useful for classifying various crop types and other materials. However, hyperspectral imaging has problems such as high-dimensionality and computational cost. Deep learning has demonstrated its effectiveness in analyzing high-dimensional data. In this study, a convolutional neural network including three-dimensional (3D) and two-dimensional (2D) kernels was used for extracting spatial and spectral information of hyperspectral images (Roy et al., 2019). Training and test data were necessary to train and test the network. Training data should be reliable and include all important land cover classes within hyperspectral images to avoid wrong allocations of pixels to the classes of interest. However, it is difficult to obtain accurate training data without prior knowledge of experimental sites. For example, there may be similar land types such as those covered with needleleaf trees and broadleaf trees, or natural pastures and paddy fields, which are difficult to distinguish using visual analysis. A land use map generated by the Ministry of Environment of Korea was used to select training data for this study. Since there was a difference between the time of acquiring hyperspectral images and the land use map production, only unchanged areas were used as training data. Furthermore, areas that could be classified as criteria for the land cover were selected. The classes that could not be specified on the land use map such as buildings were manually selected.

2.2 Comparison between the cadastral map and restructured land use map

In this study, overlay analysis was performed after mapping the land use classes identified in the training hyperspectral images with the land categories on the cadastral map. Table 1 shows the result of organizing the land categories matched to the classes of land use employed in this study. The relationship between the land uses and land categories listed in Table 1 is investigated in other studies on the Korean cadastral mapping system (Sung and Lim, 2008; Hong, 2010; Kim and Kwon, 2010; Yoo et al., 2013).

Table 1. Relationship between land use classes and land categories

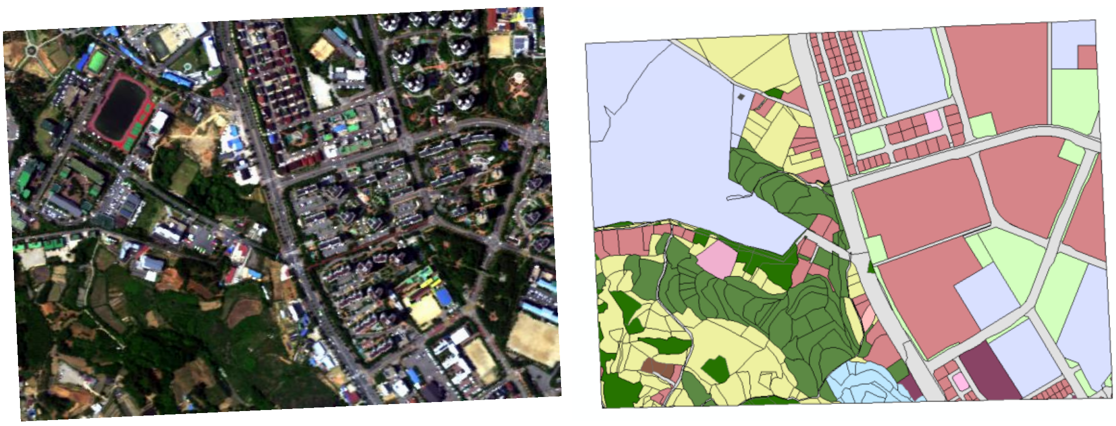
Land use classification	Land categories of the cadastral map
Urban or built-up land with roads	Building site, school site, road, cemetery, site for religious use, site for gas station, parking lot

Urban or built-up land with buildings	Building site, school site, cemetery, site for religious use, site for gas station, parking lot, site for sports
Agricultural land with low vegetation	Paddy field, park site, field, cemetery, amusement park, miscellaneous land
Pasture (grass)	Park site, school site
Forest land	Park site, forest, cemetery, amusement park, miscellaneous land
Barren land	Building site, paddy field, school site, field, cemetery, amusement park, miscellaneous land, site for religious use, site for gas station, parking lot, site for sports

To acknowledge the inconsistency between the cadastral map and the actual land use, a land use map (LUM) was created. The geometry of the LUM was derived from the boundaries of parcels on the cadastral map, while the attributes of the generated map was the result of land use classification through deep learning. Based on ‘the Act on the Construction and Management of Spatial Information’, the land categories of the cadastral map were determined according to the major uses of the parcels. The same criteria were applied when the LUM was constructed. When several land use classes existed in a parcel, the class with the largest area was assigned as the attribute value for the main use. After overlaying the constructed and cadastral maps, the land category and land use class of the same parcel could be compared to analyze the discrepancy through a spatial join.

3. CASE STUDY

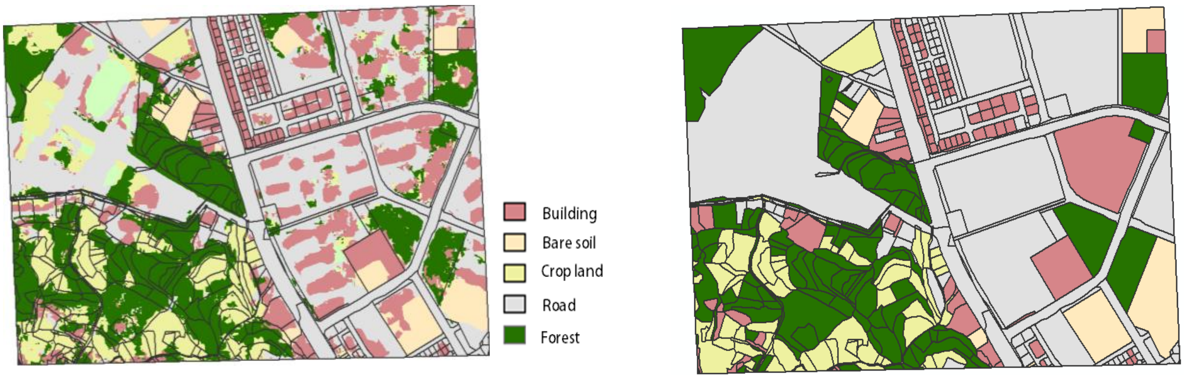
The test area was Jeonju in South Korea. Hyperspectral images were obtained from an airborne sensor. The cadastral map consisted of 14 categories: building site, paddy field, park site, school site, road, field, forest, cemetery, amusement park, miscellaneous land, site for religious use, site for gas station, parking lot, and site for sports (Figs. 2(a) and 2(b)). Hyperspectral images were classified using a deep learning network and the resulting classes were reorganized to compare with the cadastral map.



(a) (b)

Figure 2. Study site (a) hyperspectral image (b) cadastral map

Figure 3 represents the generated LUM for the test area. Areas for the same use per parcel were combined using multipart polygons. Then, the major use was extracted for the land use value by calculating the ratio of the area by use.



(a) (b)

Figure 3. Generated land use map (LUM); (a) including all uses (b) including major uses

Table 2 shows the inconsistencies between land use classification results and land categories of the cadastral map for the test area. As a result, parcels for which the registered land category and actual land use were inconsistent based on the mapping table were detected as they could cause difficulties in land management. Each column in Table 2 shows the number of parcels according to the land use values, taking into account the proportion of the area by use in parcels. It was confirmed that the rate of inconsistency can be reduced when comparing not only the main use but also secondary use. In contrast, the inconsistency ratio was high when comparing the major use only. These results indicate that there is a limit in matching between the land category system and the land use classes, and it is necessary to improve the land category system to reflect the actual land use.

Table 2. Result of inconsistency analysis (CM stands for cadastral map, CR stands for classification result)

Land category	Land use class	All for major use		over 50% area for major use		over 60% area for major use	
		Number of parcels on CM	Number of parcels in CR	CM	CR	CM	CR
Building site	Urban land with buildings and roads, barren land	139	131	124	119	108	104
Paddy field	Agricultural land with low vegetation, barren land	70	20	67	19	58	15
Park site	Agricultural land with low vegetation, pasture (grass), forest land	24	4	22	3	20	3
School site	Urban or built-up land with buildings and roads, pasture (grass), barren land	11	8	8	5	5	4
Road	Urban land with roads	67	38	65	35	56	35
Field	Agricultural land with low vegetation, barren land	110	41	90	36	74	31
Forest	Forest land	42	17	39	16	34	15
Cemetery	Urban land with buildings and roads, agricultural land with low vegetation, forest land, barren land	2	2	2	2	1	1
Amusement Park	Agricultural land with low vegetation, forest land, barren land	12	9	11	8	10	8
Miscellaneous land	Agricultural land with low vegetation, forest land, barren land	3	2	2	1	2	1
Site for Religious use	Urban land with buildings and roads, barren land	3	3	3	3	3	3

	Site for Gas station	Urban land with buildings and roads, barren land	1	1	1	1	0	0
	Parking lot	Urban land with buildings and roads, barren land	2	2	2	2	1	1
	Site for Sports	Urban land with buildings, barren land	1	1	0	0	0	0
Total			487	279	436	250	372	221

4. CONCLUSION

This study was conducted to update a cadastral map using its hyperspectral image. The image was classified using a deep learning network composed of 2D and 3D convolutional layers. The result of classification was reorganized to compare with the cadastral map. Classification errors were identified for the paddy field, forest, field, and road classes. This is because it is difficult to distinguish between a crop land and a forest, and a road and a building. In further study, the classification accuracy should be improved. In particular, a more sophisticated inconsistency analysis can be attempted by performing the classification based on parcel units. In addition, the detection accuracy of the mismatched areas can be improved by providing a more accurate comparison between the LUM and the cadastral map by refining the mapping between the land categories and detailed land use classes.

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