Object Based Hyperspectral Image Analysis for Cadastral Mapping

Kangjoon Cho (1), Yongil Kim (1), Taehong Kwak (1)

[1] Seoul National Univ., 1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Korea
Email: chris091@snu.ac.kr; yik@snu.ac.kr; mwsa302@snu.ac.kr

KEY WORDS: OBIA (Object Based Image Analysis), Cadastral map, Hyperspectral Image, Change Detection

ABSTRACT: Several studies have focused on using hyperspectral sensors for various applications. Hyperspectral images have the advantage of having more spectral resolutions than multispectral sensors, which is advantageous because they can be usefully used for cadastral classification. However, most hyperspectral image classification methods focus on pixel analysis, and the pixel classification cannot be suitable for object based cadastral mapping. In this study, the segmentation of AISA FENIX hyperspectral aerial images was performed in the city of Jeonju city using object analysis to overcome the disadvantages of existing pixel classification and analysis in order to update the cadastral map. On the basis of this method, a subdivision of the parcel was carried out and was used to estimate the change of the cadastral map.

1. INTRODUCTION

In the field of cadastral mapping, many attempts have been made using various sensors and platform (Wang *et al*, 2017; Puniach *et al*, 2018) Hyperspectral images have the advantage of having more spectral resolutions than multispectral sensors, which is advantageous because they can be usefully used for cadastral classification (Akar, 2017). In particular, the utilization of hyperspectral image which have a number of bands is increasing. These hyperspectral images can also be used to update and maintain cadastral maps. Obtaining updated land use or parcel data is crucial in management of cadastral mapping (Akar, 2017). However, most hyperspectral image classification methods focus on pixel analysis, and the pixel classification cannot be suitable for object based cadastral mapping. In this study, hyperspectral image was taken from aerial hyperspectral sensor, AISA FENIX which have 450 spectral bands from 400 nm to 2500 nm wavelengths. The segmentation of hyperspectral aerial image was performed in the city of Jeonju city using object analysis to overcome the disadvantages of existing pixel classification and analysis in order to update the cadastral map.

2. METHOD

Figure 1 represents the flowchart of this study. First, applying the principle component analysis (PCA) transformation reduces the number of dimensions. This is the process performed to increase the efficiency of the segmentation. This study selected 10 bands from the bands obtained through PCA conversion to perform object segmentation. Second, creating segmented objects through the Multi-Resolution Segmentation (MRS) method. The final procedure is to perform a comparison analysis with the cadastral map based on the estimated object segmentation and select candidates that need updating for unmatched parcel information.

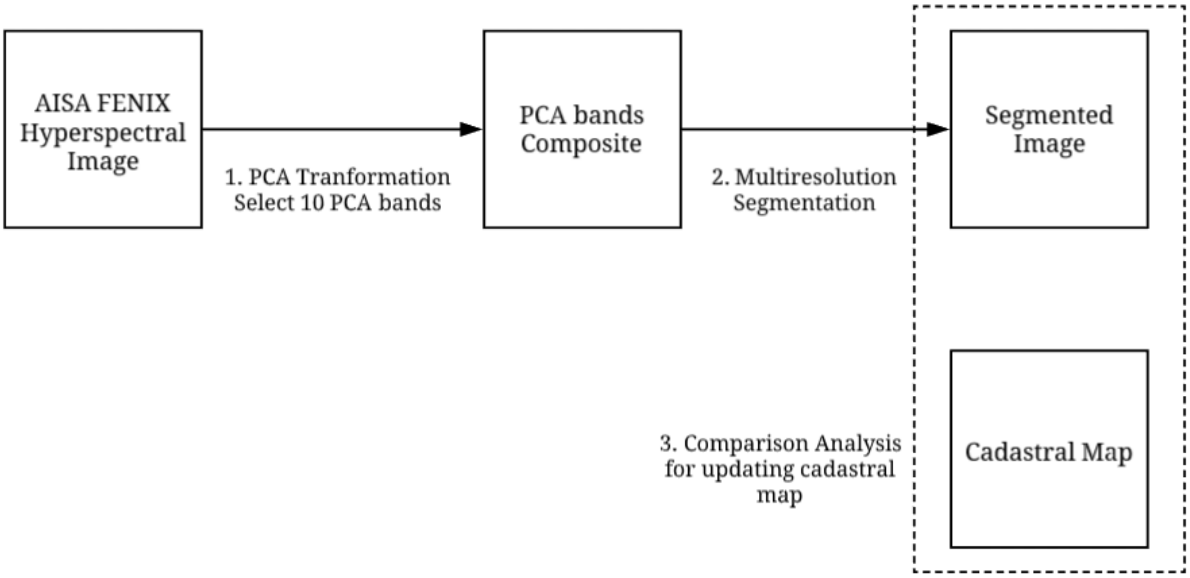

Figure 1. Flowchart of this study

2.1 Principle Component Analysis

Principle component analysis (PCA) is a method to convert an original image to an independent set of variables, and can also effectively reduce dimension of hyperspectral image. Applicability of PCA in hyperspectral data results from mathematical properties based on eigenvalue decomposition of data covariance matrix (Σ). Transformation from raw image to PC bands is based on the eigenvalue decomposition as follows:

$$\Sigma = \mathrm{A}\Lambda A^T \tag{1}$$

where $\mathrm{A} = (a_1, a_2, \ldots, a_N)$ is the eigenvectors matrix, Λ is the diagonal matrix composed of the eigenvalues. The first K eigenvectors of A can be used to calculate a transformed pixel vector z_i from an original image pixel vector x_i via the following equation:

$$z_i = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_K \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{K1} & \cdots & a_{KN} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix} \tag{2}$$

The transformed PC bands are independent of each other by the property of eigenvectors. Because hyperspectral imagery has continuous spectral response functions, neighboring bands may have the redundancy problem. PCA can remove this correlation through the dependency of the PC bands. Variance explained by the first few PC bands is calculated as:

$$\frac{\sum_{i=1}^{K} \lambda_i}{\lambda_1 + \lambda_2 + \cdots + \lambda_N} \tag{3}$$

Since the first PC band can explain the highest variance of information, and explained variance is decreasing, the appropriate number of PC bands needs to be determined for efficient dimension reduction of hyperspectral imagery.

2.2 Multiresolution Segmentation

The result of the image segmentation affects the final result for application (Maboudi *et al*, 2018). In this study, image segmentation was performed by MRS algorithm, which uses spectral information and morphological characteristics. The MRS is a bottom up region merging image segmentation method that considers each pixel as an object and merges adjacent objects to minimize heterogeneity in the fusion factor. The fusion factor is expressed as a weighted sum of the heterogeneity of color and the heterogeneity of shape as following equation:

$$f = W_{color}h_{color} + W_{shape}h_{shape} \tag{4}$$

where h is heterogeneity and W is weight of the heterogeneity. For the heterogeneity of color is represented by the following equation:

$$h_{color} = \sum_{b=1}^{B} W_b n_m \sigma_{b,m} - (n_1\sigma_{b,1} + n_2\sigma_{b,2}) \tag{5}$$

where n is number of pixels, σ is standard deviation of object's spectral value, B is cardinality of the bands set and 1, 2, m means first, second, and merged object respectively. the heterogeneity of shape is represented as a weighted sum of smoothness heterogeneity and compactness heterogeneity.

$$h_{shape} = W_{smooth}\left\{n_m\frac{l_m}{p_m} - \left(n_1\frac{l_1}{p_1} + n_2\frac{l_2}{p_2}\right)\right\} + W_{comp}\{l_m\sqrt{n_m} - (l_1\sqrt{n_1} + l_2\sqrt{n_2})\} \tag{5}$$

where l is factual length of the object and p is perimeter of minimum bounding box.

3. EXPERIMENTAL RESULT

3.1 Study Area

In this study, aerial hyperspectral images taken in May at Jeonju city were acquired. The acquired images are shown in Figure 2, and the characteristics of the land cover pattern are evenly distributed about urban and agricultural land cover. The hyperspectral image used in this experiment was taken by AISA FENIX sensor, and detailed specifications are shown in Table 1. AISA FENIX images were taken with a spatial resolution of 2 m and a total of 450 spectral bands ranging from 380 nm to 2500 nm. AISA FENIX sensors can acquire visible light, near-infrared and short-wave infrared images, and have spectral resolutions of 3.5 nm and 12 nm, respectively. Finally, cadastral reference map of Jeonju city was used for comparison analysis of object-based analysis (Figure 3).

Table 1. Specification of airborne hyperspectral image

Specification	Hyperspectral Image
Sensor	AISA FENIX
Spatial resolution	2 m
Spectral resolution	3.5 nm (VNIR), 12 nm (SWIR)
The number of band	450 bands
Spectral range	380-2500 nm (VNIR, SWIR)
Radiometric resolution	12 bits (VNIR), 16 bits (SWIR)

Figure 2. RGB color composite of study area. The study area was chosen Jeonju city and image was acquired by AISA FENIX hyperspectral sensor

Figure 3. Cadastral map of Jeonju city for comparison analysis

3.2 Experimental Result and Discussion

The color composite of bands 1, 2 and 3 obtained through PCA transformation are shown in figure 4. In the PCA image, the value is indicated by alternatively designating the axis where the variance is maximum, which contains a lot of information about the object-based analysis. Next, the MRS method was applied to the PCA image. In the MRS technique, the scale factor was set to 200, the shape factor to 0.5 and the compactness factor to 0.6. The scale factor is a measure of the number of objects created and the number of objects is determined by the ratio between the objects and the total number of pixels. In the case of the shape factor, the shape of parcel is important in the cadastral map. As a result, the reflection of the spectral information has been slightly reduced by reflecting the value of the high shape factor. In the case of the compactness factor, the rectangular compatibility value of 0.6 was applied since the parcels were composed of many rectangles. Figure 5 shows that the result of applying the MRS method.

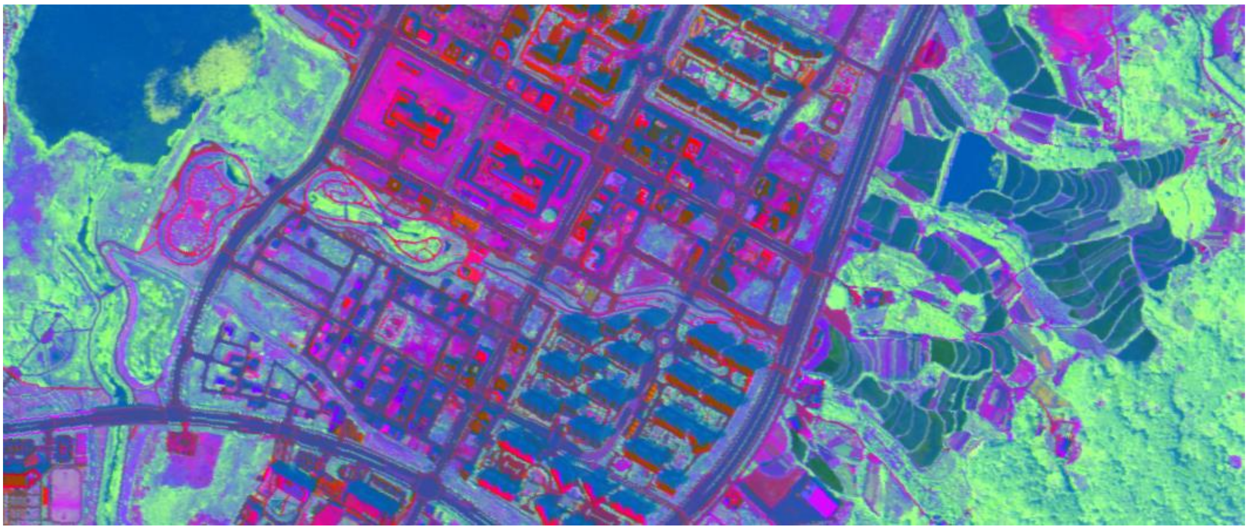

Figure 4. PC 1,2 and 3 color composite as result of PCA transformation

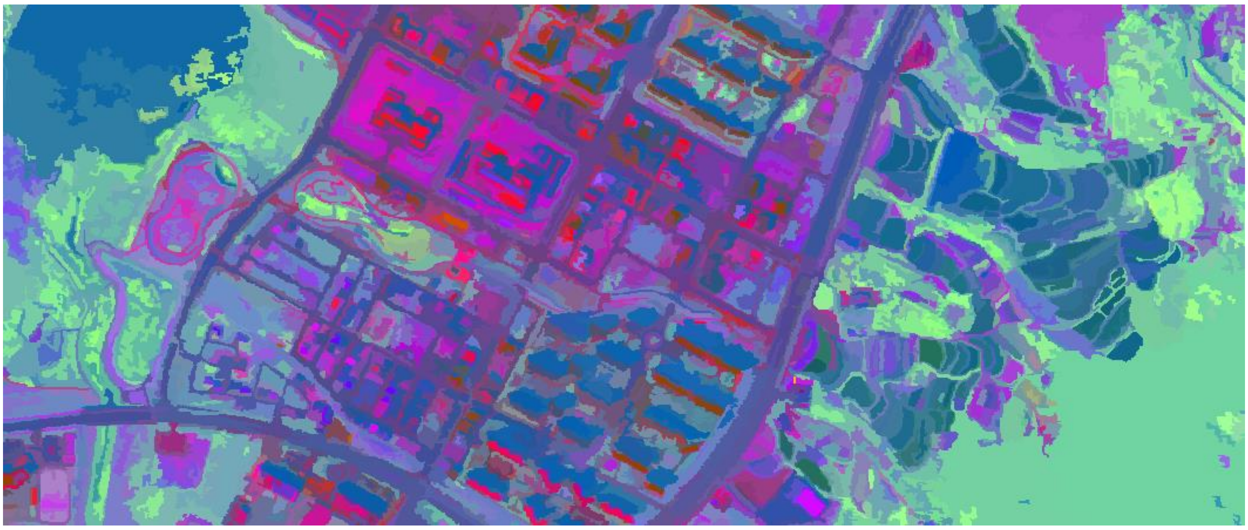

Figure 5. The result of MRS method, object mean value color composite of PC 1, 2 and 3 bands

For urban cover, agricultural cover and forest cover, the comparison with cadastral map was performed. First of all, for the agricultural cover, the result of the object segmentation proved to be in agreement with the parcel appearing on the cadastral map (Figure 6). However, there is a difference between the segmentation result and the parcel in forest land cover because the forest areas are all homogeneous due to their unclear boundaries.

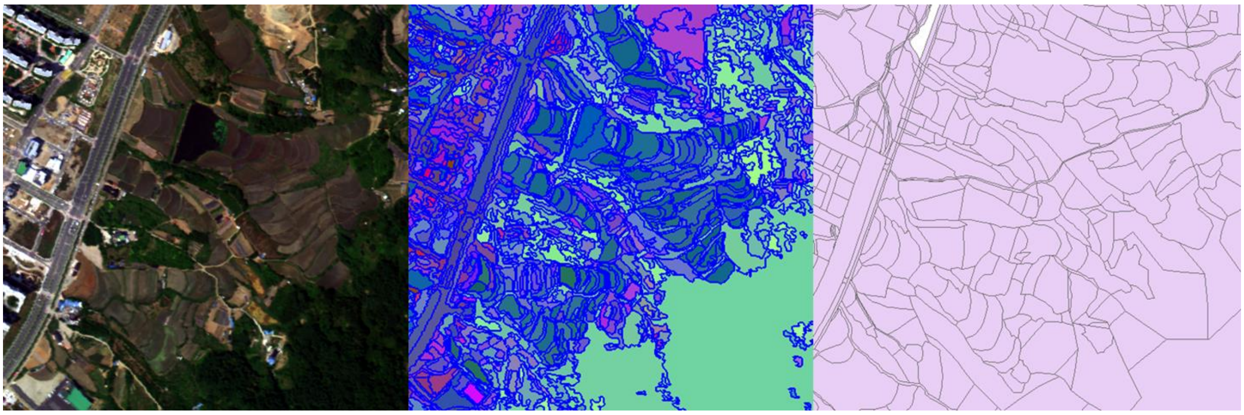

Figure 6. Subset for comparison analysis between segmentation result and cadastral map

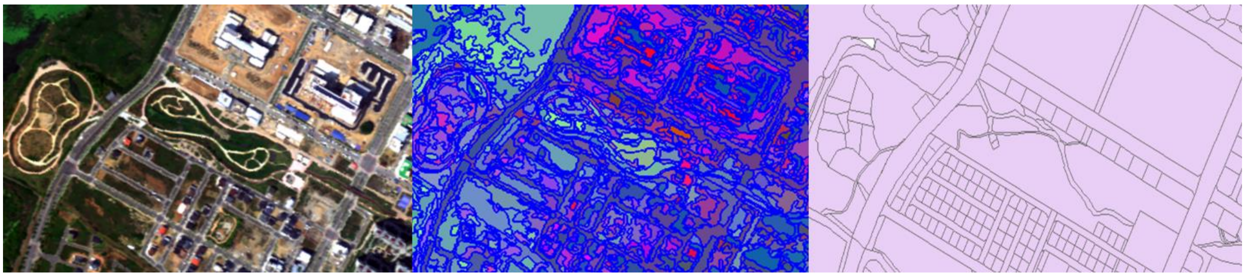

Figure 7. Subset for comparison analysis between segmentation result and cadastral map

For urban land cover, figure 7 shows the comparison results in urban areas. The number of segmented objects tends to be greater than the number of parcels. That means the results of the segmentation reflect the results of the detailed land cover, while the areas represented by the parcel have a high correlation with the land use patterns, resulting in differences in the results. Therefore, to use the object-based analysis method in the cadastral map of the urban area, it is also necessary to reduce the number of objects by introducing a fusion technique that reflects the characteristics of objects appearing in a parcel.

4. CONCLUSION

In this study, parcels were acquired using the MRS method and compared it to the parcel of the existing cadastral map. The segmentation of AISA FENIX hyperspectral aerial images was performed in the city of Jeonju city using object analysis to overcome the disadvantages of existing pixel classification and analysis in order to update the cadastral map. As a result, parcels with specific boundaries, such as agricultural areas, are well aligned with segmentation results and cadastral maps. On the other hand, because of the difference between the concept of parcels and objects in urban areas, segmentation results are not immediately available for updating parcel information. Therefore, it is necessary to reduce the number of objects by introducing a fusion technique that reflects the characteristics of objects representing in a parcel.

ACKNOWLEDGEMENT

This research was supported by the research and development program funded by Spatial Information Research Institution of Korea Land and Geospatial Informatix Corporation.

References from Journals:

Akar, Ö ., 2018. The Rotation Forest algorithm and object-based classification method for land use mapping through UAV images. Geocarto international, 33(5), pp. 538-553.

Maboudi, M., Amini, J., Malihi, S., & Hahn, M., 2018. Integrating fuzzy object based image analysis and ant colony optimization for road extraction from remotely sensed images. ISPRS journal of photogrammetry and remote sensing, 138, pp. 151-163.

Puniach, E., Bieda, A., Ćwiąkała, P., Kwartnik-Pruc, A., & Parzych, P., 2018. Use of Unmanned Aerial Vehicles (UAVs) for updating farmland cadastral data in areas subject to landslides. ISPRS International Journal of Geo-Information, 7(8), pp. 331.

Wang, Z., Du, B., Zhang, L., Zhang, L., & Jia, X., 2017. A novel semisupervised active-learning algorithm for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 55(6), pp. 3071-3083.