Study on the grasp of forestry situation using IKONOS data and airborne LiDAR data

Yuka Takahashi, Tetsuro Sakai
Biosphere informatics department of Social Informatics Kyoto University
Kyoto 606-8501, Japan
yukat@bre.soc.i.kyoto-u.ac.jp

Abstract: We have examined the performance of forest type classification using IKONOS data and LiDAR data. In order to cover a wide forest region, DEM (Digital Elevation Model), which provides various information including altitude, elevation difference and inclination and which derives from airborne LiDAR offering better understanding of geographical features, is considered to be particularly important. IKONOS data, on the other hand, can observe surface of the earth at a high resolution, and also offers not only spectral information but also the texture and the shape analysis. In this study, with spectral feature obtained from IKONOS data, tree height from LiDAR data, and texture feature, forest was classified into two types, such as natural and artificial forest. Tease results showed that spectral feature, tree height and texture feature are effective for classification of forest types.

Keywords: IKONOS, LiDAR, texture futures, forest type classification, fusion analysis.

1. Introduction

Forest is a place of production activity of forestry, and its importance as a place of preventing global warming, a regulator absorbing carbon dioxide, and a habitat of a variety of living things is drawing attention in recent years. However, the situation surrounding forestry in Japan is severe, and deterioration of the function of forest due to an increase in poorly controlled forests is feared. Therefore, it is requested to manage forests efficiently by fewer costs, and the use of high-resolution remote sensing tools which can collect detailed data of the large area is anticipated. So, the possibility of extracting woods such as estimation of the density and the height etc. by combining these data is examined as well. There are not many researches conducted using both data and, so, it is significant to develop a new method with these data. As researches utilizing remote sensing data, land cover classification [1] and tree species classification [2] using satellite images, and single tree extraction based on LIDAR height information [3] have been proposed. Researches combining satellite images and LIDAR data utilizing the respective features include the attempt of extracting single tree using the trunk extraction technique known as nearest color exploration [4][5] and construction of 3-dimensional model of trees in urban areas [6]. However, there are not many researches in which photogrammetry such as satellite images and height information are integrated. Thus, in this study, we examined algorithm that forest was classified into two types, such as natural and artificial forests with spectral feature obtained from IKONOS data, tree height from LiDAR data, and texture feature.

2. Study area and data

We selected Kitaku and a part of Sakyoku, Kyoto, which include various land uses such as forests and residential areas, Kyoto International Conference Hall and Kyoto University Kamigamo Experimental Station. Kamigamo Experimental Station is located in 35°04'N and 135°46'E and 109-225 m above the sea. The annual mean temperature is 14.6 and the annual rain fall is 1,582 mm. A snowfall of a few centimeters is observed several times every winter. A natural forest consisting of Japanese cypress and Japanese red pine mixed with broadleaf trees accounts for 65% of the total area while 28% is covered by artificial woods consisting mainly of foreign tree species and 7% by sample woods, nurseries and buildings. Broadleaf trees include Quercus serrata, Ilex pedunculosa, Lyonia neziki, Clethra barbinervis, Eurya japonica, Rhododendron reticulatum, Rhododendron macrosepalum, and so on.
The data used are as follows.

A) **Satellite image:** IKONOS satellite image taken on October 19, 2000, was used. It is a pansharpen image of a multispectral image and the data with surface resolution of 1 m x 1 m was used (Figure1).

B) **LIDAR data:** The airborne LiDAR (Light Detection And Ranging) is an instrument that determines the distance to a target by measuring the time taken for the light to travel out to the target and back to the LiDAR. The target area in this study is the area in Kamigamo district where Kamigamo Experimental Station, suburban woods and urban areas are included. Laser measurement was performed on May 13, 2001. The data was obtained at 2,500 m in height and 203.687 m in flight speed and the scanning angle was 18 degrees.

C) Numerical map of 1:25,000: An image data issued by Geographical Survey Institute based on the measurement taken on October 1, 1999, was used.

D) Forest type map: We used Forest type map [7] to examine the accuracy of classification. Figure2 shows forest type map I classified using it.

Figure 1. IKONOS data

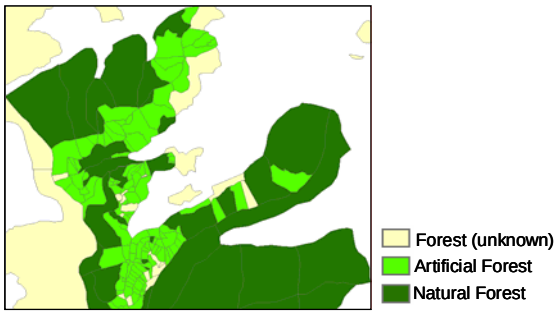


Figure 2. Forest type map

3. Method

Figure 3 shows the flow chart of the analysis used for forest type classification using the IKONOS data and LiDAR data. First, we extracted spectral features from IKONOS data, and calculated tree height by surface point extracted from LiDAR data. Then, we calculated texture feature from these data, and performed cluster analysis with all these variables.

1) Calculation of tree height

The filtering technique of airborne LiDAR data was used to calculate the tree height of the study area. In filtering, the following two indices are defined.

Concave Index: The ratio amount from the object point to the point where the altitude value is the highest in 10 m×10 m rectangular district with the object point at the center is shown. (Figure 4) The larger the ratio amount is, the lower the point is as compared to the surroundings, and it is highly possible that the object point is a surface point.

Convex Index: TIN is prepared by using the surface point, and height (h) of the object point from TIN divided by horizontal distance (x) from the closest surface point shows quotient (h/x) (Figure 5). It is a numerical value to show the deviation from the ground level and the smaller the value is, the higher the possibility that the object point is the surface point is. Not the distance from TIN but height was used because the inclination was considered.

The processing technique of filtering is as follows. In process 1, a rectangular district of 30 m×30 m represents one unit, which subdivided into 9 meshes of 10 m. In process 2, the point at which Concave Index is the maximum is selected in each 10m mesh. Therefore, nine points are selected in each rectangular district of 30 m×30 m. In process 3, 0.84% of the maximum Concave Index is assumed to be a threshold in each 30 m×30 m rectangular district and the points with the values greater than the threshold are regarded as the surface points. The purpose of this is to extract surely the surface points that make TIN used in the next process. In process 4, the points with a Convex Index below the threshold are regarded as surface points. The processing starts from the point of 2nd pulse or more with a high possibility of being the surface point. Thus,

(1) second to fifth pulses were processed 3 times taking the threshold as 0.20,

(2) first to fifth pulses were processed 3 times taking the threshold as 0.20,

(3) the points with no surface point in the surroundings of 10 m were processed twice taking the threshold as 0.35.

When the surface points were extracted by the process 4, TIN was changed as well as Convex Index and it was necessary to repeat the processing again. TIN was prepared by using the surface points finally extracted, and compared with 57 points of the ground truth. As a result, a vertical error margin was 0.00 m in average, and standard deviation was 0.98 m. It was found that the surface points were extracted automatically using this filtering technique.

Then, the tree height was calculated from the difference between TIN value connecting coordinate points judged as surface points and other coordinate points. The minimum value was 0 m, and the maximum value was 32.4 m.

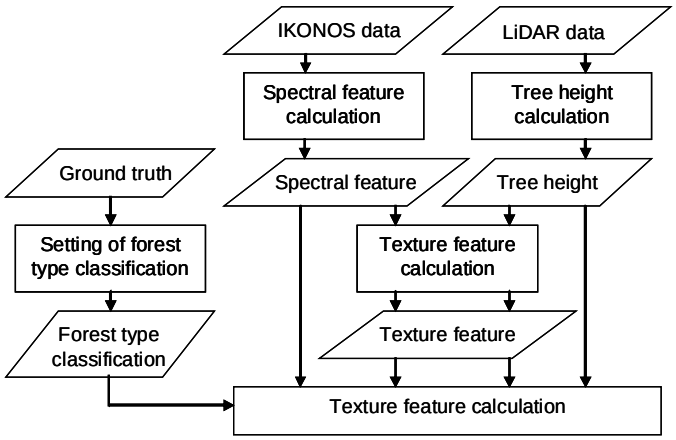


Figure 3 the flow chart of analysis

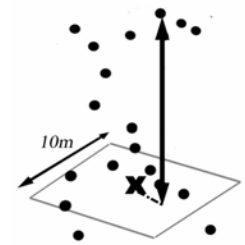


Figure 4 Concave Index

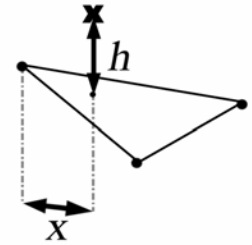


Figure 5 Convex Index

2) Calculation of texture features

We tried texture analysis for the value of IKONOS data and LiDAR data. The texture calculated were five variables, such as the average, the contrast, decentralization, energy, and entropy. The method to calculate the texture features measured from the density histogram was as follows.

- The density histogram H (l)(0,1,2,…,L-1) was calculated from the imagery where texture features were to be determined.
- Frequency H (l) at each density level was divided by the number of pixels of imagery, and it was normalized so that the number of total pixels becomes 1.0.
- The purpose of normalization is to make the texture features independent from the area of the imagery.
- The normalized value was assumed as P (l).

Moreover, the expression of each variable and the feature of each expression are as follows. Expression (1) shows the average of the density level. Expression (2) shows a large value if the distribution is biased at the high level. Expression (3) shows a large value if a lot of pixels deviate from the average. Expression (4) shows a large value when the pixels concentrate at particular density level (approaching 1). Expression (5) shows a large value when a lot of error margins at density level exist (approaching 1).

$$\text{Mean} = \sum_{l=0}^{L-1} lP(l) \qquad (1)$$

$$\text{Contrast} = \sum_{l=0}^{L-1} l^2 P(l) \qquad (2)$$

$$\text{Variability} = \sum_{l=0}^{L-1} (1-MEN)^2 P(l) \qquad (3)$$

$$\text{Energy} = \sum_{l=0}^{L-1} P^2(l) \qquad (4)$$

$$\text{Entropy} = -\sum_{l=0}^{L-1} P(l)\log P(l) \qquad (5)$$

Here, the texture was calculated. As 5 variables, such as the average, the contrast, variability, energy, and entropy were calculated from 5 variables as R, G, B, Nir, and NDVI that were spectral information on the IKONOS data, 25 variables were adopted for IKONOS data. Moreover, 5 variables were adopted for LiDAR data because the texture was calculated to the tree height obtained from the LiDAR data. In addition, when the texture was calculated, the following rules were applied to each value of IKONOS data and LiDAR data.

A) The section between the maximum and the minimum in the histogram of the original data was divided in equal sections. The values were converted by dividing into five or seven sections in this study.

B) Four sizes of 3×3, 5×5, 7×7, and 9×9 were set for windows.

C) Two windows of a rectangle and a diamond were set for the windows in (2). Figure 6 shows the rectangle and the diamond windows of 3×3. The values in the surrounding cells are put in the central cell. For 3×3 window size, for example, the number of cells in a rectangular window is nine pixels in total and the diamond window becomes five pixels.

When data had been converted by the rules (A) to (C), 16 data was calculated for one data. Then, each data was classified into 30 classes, and the most effective data was examined for the accuracy of classification with the forest type map. Here, the texture features applied to the Kamigamo examination station are considered. Energy, the contrast, and the average were allocated in RGB and displayed. First of all, the texture features of R, G, and B band of the IKONOS data were drawn. The residential area was expressed more satisfactorily than the forest area. It is difficult to classify the forest area into the natural forest and the artificial forest, but roads and houses seem to be classifiable. Especially, the texture of B band was displayed well without the effect of geographical features or the shadow (Figure 7). Next, the texture feature of Nir band was influenced by shadow (Figure 8). The appearance of forest was quite different between the north side of the mountain (upper part) and the south. In addition, the accuracy of the classification of the residential area (right side of figure) and the forest (left) was also low. However, meadows such as golf ground and fields were displayed relatively well unlike the three mentioned above. In the four bands mentioned above, ponds (lower right of figure) and forests were displayed equally. Finally, the texture features of NDVI are shown in Figure 9. Forests and houses were displayed well, and the influence of the shadow was less than Nir. Pond was displayed clearly. Therefore, it was considered that NDVI band among 5 bands classified land uses accurately covering all features.

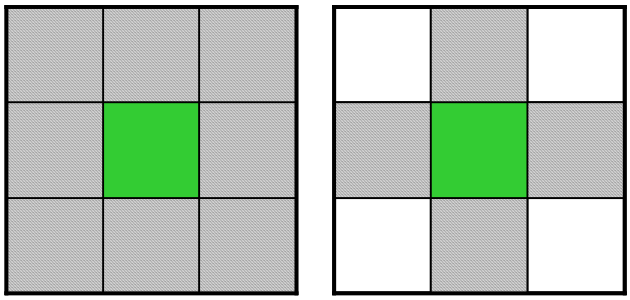
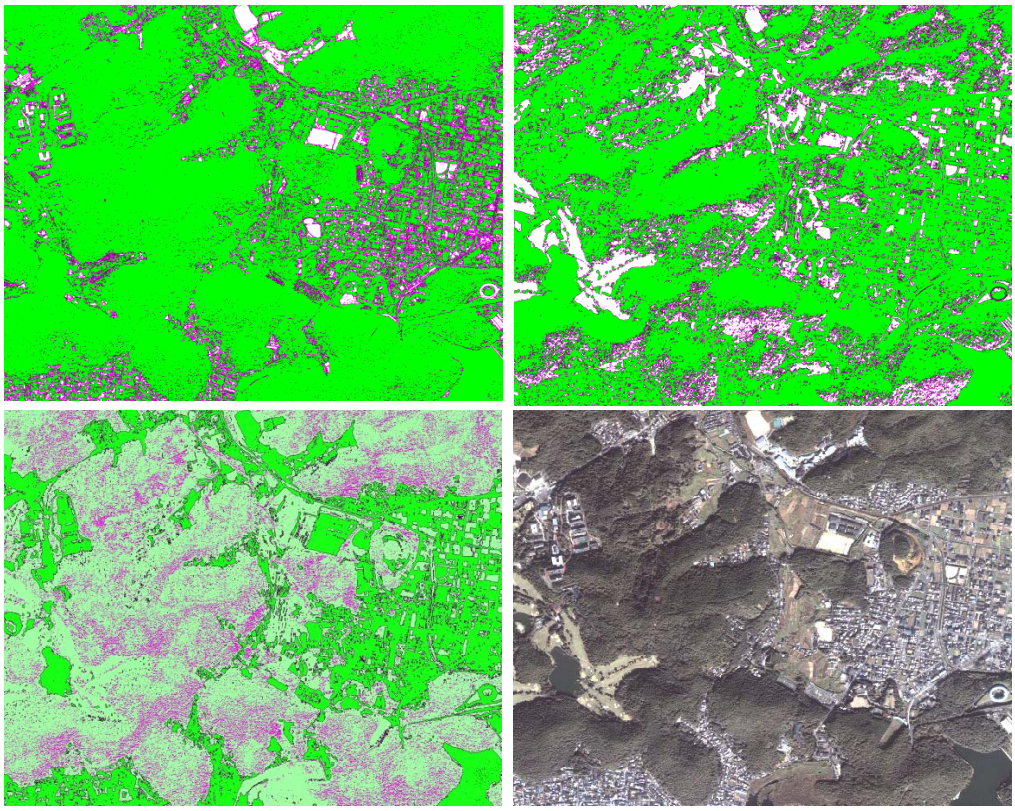


Figure 6. The rectangle and the diamond windows of 3×3 (left)

Figure 7. B band (upper left)
Figure 8. Nir band (upper right)
Figure 9. NDVI band (lower left)
Figure 10. IKONOS imagery (lower right)



4. Result and discussion

1) Analysis of spectral feature and tree height

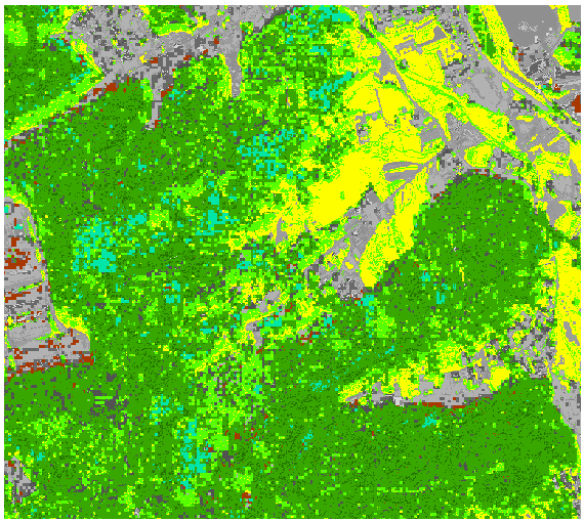
The cluster analysis was performed using six variables of the tree height from LiDAR data and five variables, such as R, G, B, Nir, and NDVI from IKONOS data, and LiDAR. The number of classes was set 30, which were classified into non-forest, natural forest, and artificial forest. Figure 11 shows the result of cluster analysis and Table 1 shows the classification error matrix. The ratio of area classified into natural forest was 80.5% and that classified into artificial forests was 36.9%. Although classification was relatively satisfactory, the field was classified into the same class as the artificial forest.

2) Analysis of texture features obtained IKONOS data and LiDAR data

The cluster analysis was performed using 30 variables consisting of 25 variables from IKONOS data and five variables from LiDAR data. The number of classes was set 30 classes which were classified into non-forest, natural forests and artificial forests. When the rules explained in 3.2 section were applied to the analysis, it was found that an increase in the window size of a diamond window improved the accuracy of classification of both natural and artificial forests. It is thought that an increase in the window size gathers surrounding information into the center. In future, it will be necessary to examine the comparison results of the number of texture divisions, because it varied in each size of the window. Moreover, since many variables were strongly correlated among 30 variables, we performed the cluster analysis by converting them to 12 variables which had the average and entropy with weak correlation to each texture feature. Figure12 shows the result of data conversion in the diamond size of 9×9 with five divisions. The ratio classified into the natural forest was 88.8% and the artificial forest became 18.3%. The accuracy of the natural forest was improved, but it was decreased for artificial forest. Moreover, the edge of the mountain was classified into one class alone.

3) Fusion analysis - Spectral feature, tree height and texture features obtained IKONOS data and LiDAR data

The cluster analysis was performed by 18 variables used in 3.1 and 3.2 sections. Figure 13 shows the result of classification. All accuracy is shown in Table 2. The ratio classified into the natural forest was 85.5% and the artificial forest became 23.1%. They were classified well and most evenly among the three data above, but the expectation that the result of fusion analysis was best failed.



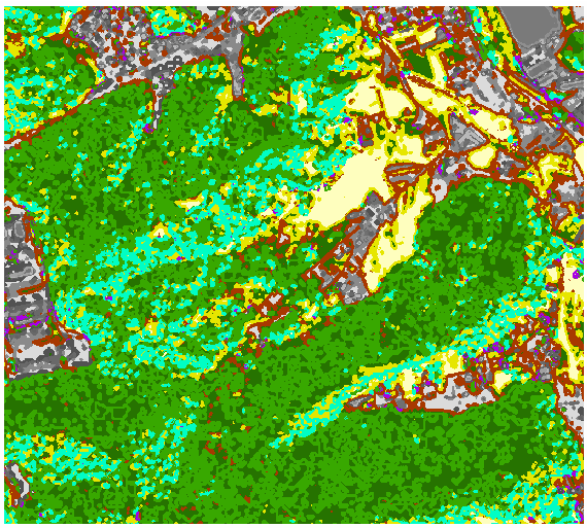


Figure11. Analysis of spectral feature and tree height (Left)
Figure12. Analysis of texture features obtained IKONOS data and LiDAR data (right)

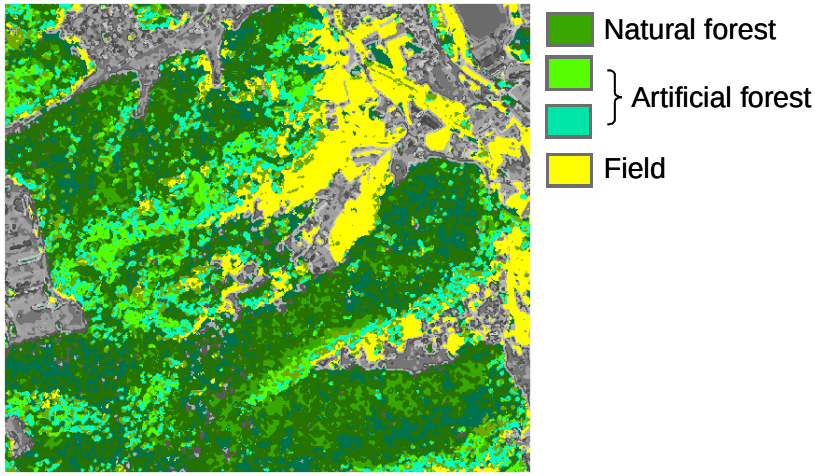


Figure13. Fusion analysis

Table 1. the classification error matrix of spectral feature and tree height

	Land use(nuber of pixel)					
	non forest	forest(unknown)	natural forest	artificial forest	total	accuracy of classidfication(%)
non forest	171,108	9,449	17,502	7,333	205,392	83.3
forest(unknown)	0	0	0	0	0	0
natural forest	43,992	102,404	272,277	65,857	484,530	21.1
artificial forest	167,841	43,314	48,282	42,841	302,278	14.1
total	382,941	155,167	338,061	116,031	992,200	38.5
accuracy of classidfication(%)	44.6	0	80.5	36.9		

Table 2. all accuracy of classification (%)

	forest	natural forest	artificial forest
Fusion analysis	69.5	85.5	23.1
Analysis of Spectral feature and tree height	68.5	80.5	33.2
Analysis of texture features	70.8	88.8	18.3

4. Conclusion

The purpose of this study was to classify forest types, but high accuracy of classification was not necessarily obtained. The superiority of fusion analysis was not demonstrated clearly, either. As a reason, it is given that the natural forest is a mixed forest. In the figure, in fact, , it seems that kinds of trees such as conifers are classified accurately. Therefore, it will be necessary to give priority whether conifers and the broadleaved trees are distinguished in future instead of discriminating between natural forests and artificial forests. Moreover, as the technique for improving accuracy, we consider the use of fuzzy clustering means, FCM, rather than the crisp analysis. We will examine the use of FCM, which expresses the degree of belonging of an individual to clusters fuzzily assuming that some individuals belong to two or more clusters besides the situation that a certain individual belongs solely to one cluster.

References

[1] Kenji Ynagida, Yousuke Yasuda and Mitsuharu Tokunaga: The land covering classification using satellite picture IKONOS data, JSPRS Journal of the Japan Society of Photogrammetry and Remote Sensing, 2004.
[2] Kazuaki Iida and Nobuyuki Abe: Determination of species of broadleaf trees based on the brightness in high-resolution satellite images. ,JFS Japanese Forestry Society, 2004.
[3] Koumei Takahashi: Extraction of the single tree parameter by airborne LiDAR, the115th JFS, p.572, 2004.
[4] Ryotaro KOMURA, Mamoru KUBO and Ken-ichiro MURAMOTO: Crown Analysis with Local Fractal Dimension Using an Aerial Image, SPRS, vol.42, no.4, pp.27-37, 2004.
[5] Masaki Teraoka, Masahiro Setoshima, Yasuaki Imai and Yoshihumi Yasuoka: Single trees extraction using a satellite photograph and LIDAR data, JSPRS, 2004.
[6] Yosuke YAMAGISHI, Tao GUO and Yoshifumi YASUOKA: 3D City Modeling Using Remote Sensing Data, JSPRS, 2004.
[7] http://fserc.kais.kyoto-u.ac.jp/kami/
[8] Katsuhiko Yonezu, Filtering method of airborne LiDAR data suitable for extraction of the surface points in forests, the115th JFS, 2004