HYPERSPECTRAL TREE SPECIES CLASSIFICATION WITH AN AID OF LIDAR DATA

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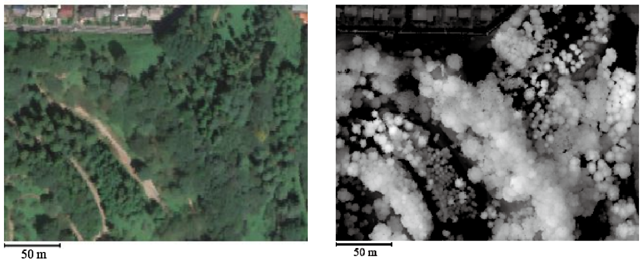
ABSTRACT

Classification of tree species is one of the most important applications in remote sensing. A methodology to classify tree species using hyperspectral and LiDAR data is proposed. The data processing consists of shadow correction, individual tree crown delineation, classification by support vector machine (SVM) and postprocessing by a smoothing filter. The authors applied this procedure to the data taken over Tama Forest Science Garden in Tokyo, Japan and classified it into 16 classes of tree species. As a result, the authors achieved classification accuracy of 79 % with 10 % training data, which is 17 % higher than what is obtained by using hyperspectral data only. Shadow correction and morphological processing derived from LiDAR data increase the accuracy by 3 % and 14 %, respectively.

Index Terms— classification, forest, hyperspectral data, LiDAR, data fusion

1. INTRODUCTION

Tree species classification is an important issue on the study of land cover or forest management. Periodic field surveys by experts cost a large amount of time and human resources. Since remote sensing can provide wide area observation at one time, its contribution to tree species classification is expected. During the past years, many researches have worked on classification or identification of tree species. Since hyperspectral sensors have hundreds of observation bands and high spectral resolution, we can obtain a continuous spectrum that enables more detailed analysis. In addition to spectral data, light detection and ranging (LiDAR) data is very informative to obtain canopy height models (CHMs). In recent years, fusion of these two data for classification has been studied [1]. Many researchers used LiDAR data as preprocessing or raw height data. Morphological information, such as tree shape, obtained from LiDAR-derived CHMs is expected to be more useful. In this work, we propose a methodology to classify tree species by coupling hyperspectral and LiDAR data. In the methodology, we extract spectral and morphological information and input them to its classifiers. We apply the procedure to a challenging tree species classification problem and show its effectiveness.



(a) RGB image (b) Canopy height model

Fig. 1. Study area

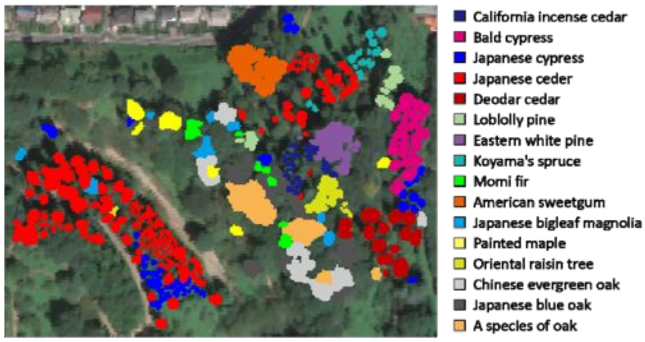


Fig. 2. Ground truth

2. STUDY AREA

The study area is Tama Forest Science Garden in Tokyo, Japan. Fig.1 shows the RGB image derived from hyperspectral data and the CHM derived from LiDAR data. The CHM is the difference of the digital elevation model (DEM) and the digital surface model (DSM), which represents the height of trees excluding terrain effects. These data are taken by airborne sensors on 10 September, 2009 and provided by Japan Space Systems. The ground sampling distance of the both data is 1 m. The observation wavelength of the hyperspectral sensor ranges 400 – 1050 nm with 72 bands. Field survey has been carried out in this area tree by tree. Fig. 2 shows the distribution of the ground truth. The species and the crown shapes of some trees are investigated by experts. There are more than 90 species of trees in this area. However, most of species occupy few pixels. We choose major 16 species that have enough ground truth data. Tab. 1 shows the class names and the number of samples. This is the typical mixed forest of conifers and broad leaved trees.

Tab. 1. Major class names

	English name	Scientific name	Samples
1	California incense cedar	Calocedrus decurrens	304
2	Bald cypress	Taxodium distichum	927
3	Japanese cypress	Chamaecyparis obtusa	875
4	Japanese ceder	Cryptomeria japonica	3327
5	Deodar cedar	Cedrus deodara	833
6	Loblolly pine	Pinus taeda	332
7	Eastern white pine	Pinus strobus	579
8	Koyama's spruce	Picea koyamae	267
9	Momi fir	Abies firma	282
10	American sweetgum	Liquidambar styraciflua	733
11	Japanese bigleaf magnolia	Magnolia obovata	380
12	Painted maple	Acer pictum	403
13	Oriental raisin tree	Hovenia dulcis	361
14	Chinese evergreen oak	Quercus myrsinifolia	948
15	Japanese blue oak	Quercus glauca	1083
16	A species of oak	Quercus serrata	987

3. METHODOLOGY

The proposed method consists of four parts: (1) shadow correction for hyperspectral data, (2) individual tree crown delineation from LiDAR-derived CHMs, (3) classification by support vector machine (SVM), and (4) postprocessing. Fig. 3 shows the classification flow.

3.1. Shadow correction

There are many shadows in forest, which affect classification results. Therefore, shadows in hyperspectral data need to be modified for accurate classification. We used the unmixing-based approach for de-shadowing of reflectance data [2]. First, the shadow is defined as a "black" (zero reflectance) endmember. Next, endmember spectra, which are thought to be non-shadowed, are selected by vertex component analysis (VCA). Abundance fractions are estimated using the fully constrained least squares (FCLS) method satisfying sum-to-one and non-negativity constraints. The reflectance spectra are approximately de-shadowed by dividing the spectra by (1 – shadow abundance fraction). Fig. 4 (a) shows the de-shadowed image of the study area.

3.2. Individual tree crown delineation

Individual tree crown delineation is one of the important techniques to extract information of forest. Many researchers have investigated individual tree crown delineation methods [3]. We used a region growing method

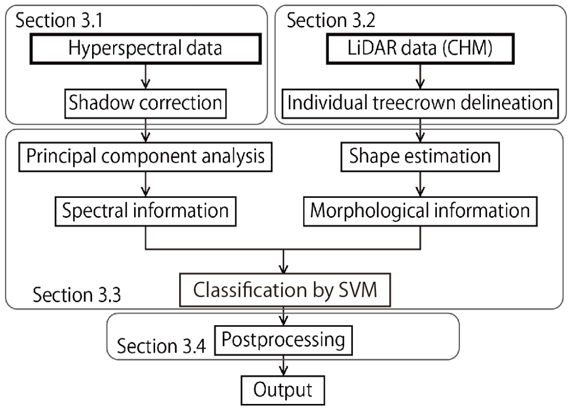


Fig. 3. Classification flow

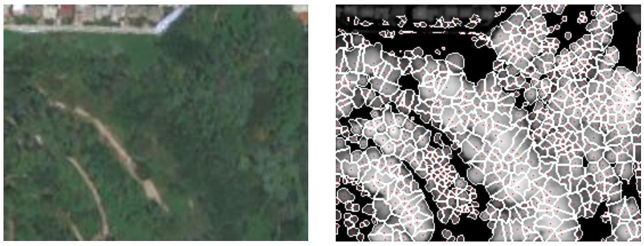
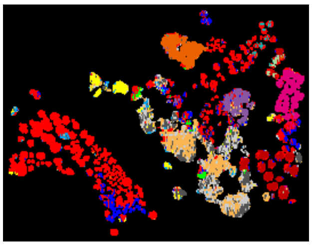

(a) De-shadowed RGB image (b) Individual tree crown delineation

Fig.4. Preprocessed image.

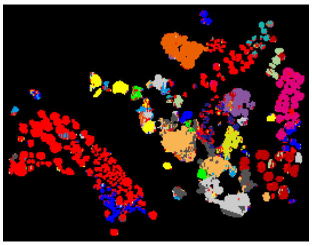
for LiDAR derived CHMs [4]. First, to reduce noise, we apply a Gaussian smoothing filter with the kernel size of 3 pixels to the CHM, which is determined not to miss small trees. Then, we find local maxima of the smoothed image. They include non-tree objects. Thus the local maxima whose normalized difference vegetation indices (NDVI) are lower than 0.5 or heights are lower than 1 m are excluded. The rest of them correspond to the tops of trees. Regions corresponding tree crowns grow from the local maxima. If the neighboring pixels satisfy some conditions, regions grow and the neighboring pixels become the next starting pixels. The conditions are set that the height of the neighboring pixel is lower than that of the starting pixel and higher than 1 m so that regions do not expand to the ground. This growing step is repeated until there is no starting pixel. After the growing step, each region is adjusted to be star-shaped, by which we exclude the pixels that locate out of the region centered by treetop [4]. Finally, overlapped regions are assigned to the region of the nearest local maxima. Fig. 4 (b) shows the result of the delineation. The red dots represent the tops of trees.

3.3. Classification by SVM

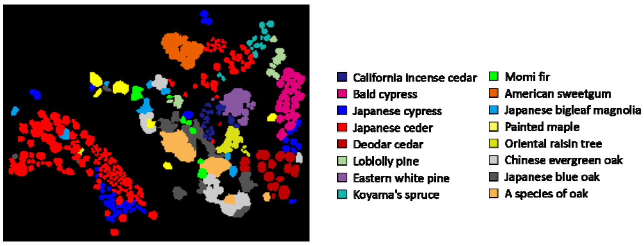
We classify data using SVM with the radial basis function (RBF) kernel to deal nonlinear distribution. The input data are spectral information and morphological information. The dimension of the hyperspectral data is 72 but the latent



(a) Hyperspectral-only



(b) Proposed method



(b) Ground truth

Fig. 5. Classification map

dimension is lower. Therefore, the spectral information is principal components of the modified hyperspectral data. We input 15 principal components that represent more than 99.5 % of the whole data. Then, the canopy height, size and curvature are used for the morphological information. The height and the size are defined by the highest value of CHM and the number of pixels in each crown, respectively. The curvature is estimated by fitting function defined as $z = H - ar^{c}$, where we assume axial symmetry and use cylindrical coordinates (*r*, *z*). *H* denotes the height of the tree, and *a* and *c* are estimated values. If a pixel is not included in any crowns, the height is its own value, the size is 1 and the curvature is 0. The bandwidth is decided by cross-validation. We coded this method in MATLAB with LIBSVM, which is the library for support vector machine [5]. It supports multi-class classification using one-against-one method.

3.4. Postprocessing

Since the spectra are different depending on the pixels even in the same crown, the classification map becomes noisy. We apply a crown-preserving smoothing filter as postprocessing. The filter is based on a Gaussian filter and weights depending on crowns segment. If filtered pixels belong to the same crown, the weight is 1. Otherwise, the weight is smaller than 1. Since the classification results are categorical values, we re-classify the data to the class in which score is highest after smoothing.

4. RESULT

We applied our method to the hyperspectral and LiDAR-derived CHM taken over forest areas. The training set, whose size is given as a percentage to all ground truth, was randomly selected and commonly used for comparison methods in one test. Fig. 5 shows the classification map when the training set size is 10 %. Here, the classification accuracy is evaluated only in the regions with ground truth. The accuracy of the proposed method is better than that obtained by spectral information only. Since the proposed method uses morphological information, we can use information on crown segment, and thus less noisy result is achieved. Furthermore, the proposed method improves the result of the central area and Koyama's spruce in the northeast area. Fig. 6 shows the accuracy of each class, which is obtained by averaging the result of multiple tests. The accuracy of the proposed method is higher than hyperspectral-only method in most of the classes. The overall accuracy is shown in Fig. 7, in which the training set size was changed from 1 % to 30 %. It is compared with three methods, i.e. original (non-modified) spectral information only, shadow corrected spectral information only, and original spectral and morphological information. It is found that shadow correction increases the accuracy by 3 % and morphological information increases it by 14 %.

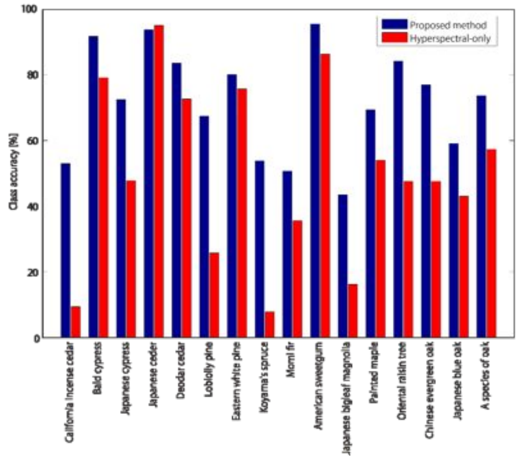


Fig. 6. Class accuracy

Fig. 8 shows the results of postprocessing including the region where ground truth data do not exist. It is compared with majority voting in each crown. The proposed filter can smooth results preserving smaller structures than majority voting. Moreover, applying the proposed filter multiple times can smooth results strongly preserving crown edges. Fig. 9 shows the overall accuracy with postprocessing. Majority voting makes the results worse on average. In contrast, the proposed filter improves the results. Applying the smoothing filter multiple times increases the accuracy. These results depend on the delineation but the proposed filter can preserve small structures even if the delineation is incomplete. This work shows that hyperspectral data with morphological information is effective for tree species classification in Japanese forests, in which conifers and broad leaved trees make complex biodiversity.

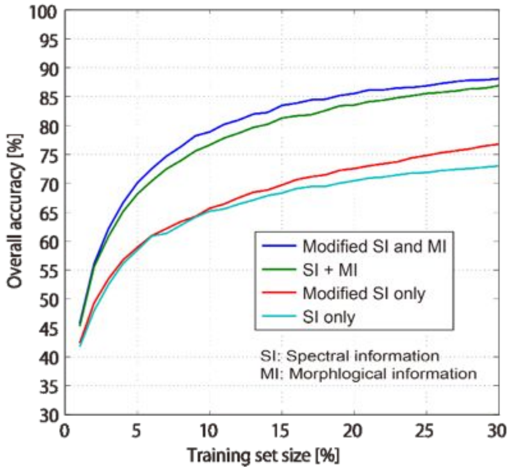


Fig. 7. Overall accuracy

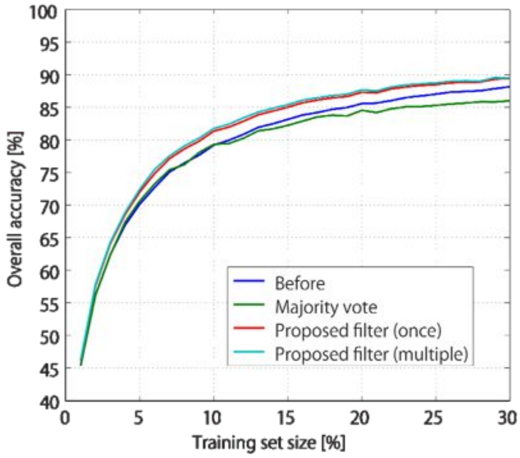
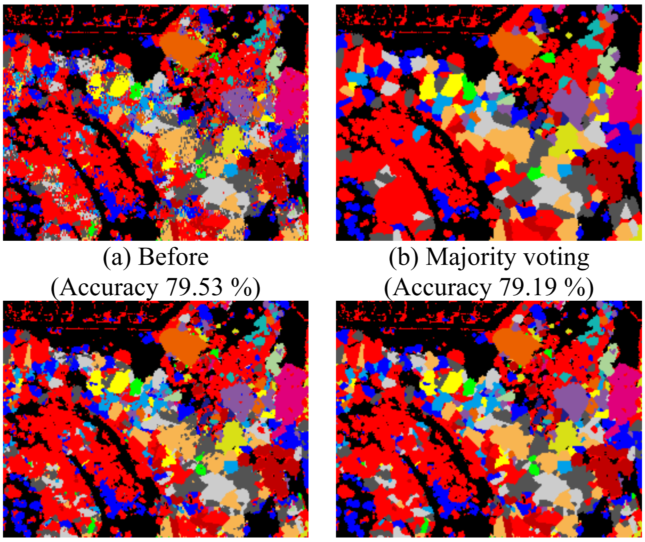


Fig. 9. Overall accuracy (postprocessing)



(a) Before (Accuracy 79.53 %)

(b) Majority voting (Accuracy 79.19 %)

(c) Proposed filter (once) (Accuracy 80.47 %)

(d) Proposed filter (multiple) (Accuracy 81.97 %)

Fig. 8. Classification map (postprocessing)

5. CONCLUSION

We proposed the methodology to classify tree species using hyperspectral data and LiDAR-derived CHMs. We applied it to the data taken over Tama Forest Science Garden in Tokyo, Japan and classified the data into 16 classes. The proposed method shows higher performance than the method using hyperspectral data only. It is found that shadow correction and morphological information are useful for tree species classification, showing the importance of height data. Furthermore, the crown-preserving smoothing filter as postprocessing improves the classification results.

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6. REFERENCES

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