Forest Stand Delineation Using a Hybrid Segmentation Approach Based on Airborne Laser Scanning Data

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Abstract. Forest stand delineation is an important task for forest management. Traditional manual stand delineation based on aerial color-infrared images is a labor intensive process and its results are partially subjective. These images are also highly affected by weather conditions and imaging parameters. In this work, we applied a hybrid segmentation approach on Airborne Laser Scanning (ALS) data to delineate forest stands. The ALS data was firstly pre-processed to extract a three band feature image, containing tree height, density, and species information, respectively. Then the image was segmented by the mean shift algorithm to generate raw stands, which were refined by the Spectral Clustering (SC) algorithm in the following stage. In the SC algorithm, we also estimated the number of stands based on eigengap heuristics. We tested our method on real ALS data acquired at Juuka in Finland, and compared the results with the manually delineated result visually and numerically, as well as results based on previous methods. The experimental results showed that our method worked well for the forest stand delineation based on ALS data, and return better results in most cases when compared to previous methods.

Keywords: forest stand delineation, forest stand segmentation, LiDAR, ALS, spectral clustering, mean shift, hybrid segmentation.

1 Introduction

Forest management is an important operation in maintaining forestry resources. The conventional way to collect data for forest management is based on forest stand level field inventories. Forest stand delineation, therefore, is a critical and fundamental task, and also of great interest for practical applications. Forest stands are homogeneous forest areas that have different characteristics with their adjacent areas [1]. Forest stands are usually manually delineated based on aerial images and field surveys. However, manual forest delineation is time consuming, and requires professional foresters' manual work that may result in partially subjective delineation results [2].

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Therefore, several automatic forest stand delineation methods have been proposed with aerial images, such as clustering methods with tree crown information [3].

Recently, Airborne Laser Scanning (ALS), also known as Light Detection and Ranging (LiDAR), have been increasingly used in several forestry applications, since it provides abundant high spatial resolution data on the vertical structure of forests. The ALS data is relatively stable in various weather conditions when compared to aerial Color-Infrared (CIR) images. However, few studies were done on ALS based forest stand delineation [4-7]. That may due to the fact that the ALS data lacks the clear information on tree species. Alpha shape concept [8], a computational geometry technique, was employed to construct metrics from ALS data to describe tree species information [9]. By using these metrics as well as tree size and density that are all solely derived from ALS data, the performance of forest stand delineation was improved when compared to only using tree size and density information [5].

The methods used in previous studies on ALS based forest stand delineation are usually based on conventional region growing approaches and the watershed method [4-7]. Popular segmentation methods, such as Mean Shift (MS) algorithm [10] and Spectral Clustering (SC) algorithm [11], are seldom used in this task. The MS algorithm is a non-parametric density estimate technique, looking for local maxima of a density function. It, however, usually returns over-segmented results and thus needs a segment merging process in image segmentation tasks. The SC algorithm is a relaxation of the graph partitioning problem by eigen-decomposition of Laplacian matrix derived from data. It needs to first construct similarity matrix between each data point. This results in storage and computational problems in image segmentation tasks, due to the large number of pixels in one image. To solve these problems, recently MS and one type of SC, Normalized Cut (NC), were combined together as a hybrid method to do color image segmentation [12]. The MS is firstly applied to segment the image, whose results are then used to do region based segmentation with NC to generate the final segmentation results. The MS algorithm can automatically detect the number of segments. However, the number of segments is required to be known for SC. To detect the number of segments for SC, Eigengap heuristics could be used as a quality criterion [13]. It can be computed efficiently, only computing the difference between each adjacent eigenvalue of Laplacian matrix that have been already obtained during the eigen-decomposition process in SC.

In this work, we studied the forest stand delineation based on ALS data with a hybrid segmentation method. The hybrid segmentation method mainly follows the work in [12]. However, we added the estimation of the number of forest stands based on eigengap heuristics. In addition, instead of NC, we used the SC algorithm in [11]. The flowchart of our forest stand delineation process is shown in Fig. 1. Firstly, three features, Tree Size Indicator (TSI), Forest Density Indicator (FDI), and Tree Species Indicator (TSI), were generated from raw ALS data based on [5] and then concatenated into a three band image. An example of this three band feature image rendered in pseudo colors is shown in the left upper part of Fig. 1. Secondly, the feature image was segmented by MS into raw forest stands. Thirdly, in every raw stand, the mean values of all pixels were computed, and then processed with Feature Expansion (FE). In the FE process, the mean values were replicated several times to generate the new feature. In the end, the new feature was segmented by SC with the stand number estimation process to obtain the final forest stands. We tested our method on the real ALS data acquired at Juuka in Finland and compared the results with previous methods as well as manually delineated forest stands by a professional forest. The experimental results showed that our method worked well for the forest stand delineation based on ALS data, and return better results in most cases compared to previous methods. In addition, it showed that the correct estimation of the number of forest stands is critical in ALS based forest stand delineation and highly affects the results in our method.

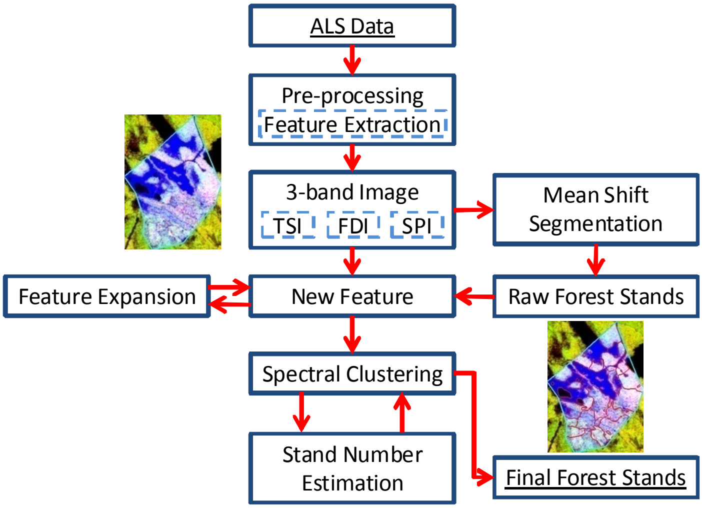


Fig. 1. Processing flow of our ALS data based forest stand delineation

2 Airborne Laser Scanning Data Preprocessing

The raw Airborne Laser Scanning (ALS) data is usually a set of point clouds based on irregularly distributed x, y, z coordinates. The features extracted from ALS point clouds highly affect the quality of forest stand delineation. First, we followed the conventional approach to create a Canopy Height Model (CHM) based on Digital Terrain Model (DTM) derived from raw ALS point clouds. Then instead of traditionally using CHM as the single feature, other useful features were also extracted in order to improve delineation accuracy.

2.1 Canopy Height Model Creation

The ALS point clouds were firstly divided into two classes: ground points and other points, based on the method in [14]. Then a raster DTM with a spatial resolution of 2.5 m × 2.5 m per pixel was generated as the mean values of the ground points within each raster cell. For pixels with no ground points, their values were calculated based on bilinear interpolation. Based on the DTM, a CHM was created as the difference between the z-values of the ALS data and the DTM values.

2.2 Feature Extraction

Three features were exacted from CHM and ALS point clouds in this work: Tree Size Indicator (TSI), Forest Density Indicator (FDI), and Tree Species Indicator (SPI), following the work in [5]. The first two features represent the size and density of trees. TSI was set to be 85% of CHM values with a spatial resolution 4 m × 4 m per pixel. FDI is the proportion of non-ground hits in all ALS data points within each 4 m × 4 m cell. The last feature, SPI, gives information on tree species [5]. It is the first principal component from Principal Component Analysis of several 3D alpha shapes. These shapes are generated by using the alpha shape technique [8] from ALS data [5]. An alpha shape is a polytope that is derived from the Delaunay triangulation of the point set. Its level of details is controlled by the parameter alpha. Every simplex of the triangulation will be removed, if the simplex has an empty circumsphere whose squared radius is larger than the predefined alpha value. As the same with [5], several alpha shapes were generated from ALS data with different height levels (95%, 80%, 70%, 65%, and 55% relative height) and alpha values (0.5, 2, and 4) to extract volume and number of solid components (the number of separate components needed to generate the shape with one specified alpha value) in our work. Based on these three features, TSI, TDI and, SPI, a three band image was generated with each feature on each band.

3 Hybrid Segmentation for Forest Stand Delineation

We used a hybrid image segmentation approach in forest stand delineation based on the three-band image derived from ALS data. The segmentation approach mainly follows the work in [12] of color image segmentation. We combined two popular image segmentation methods, mean shift [10] and spectral clustering [11]. In addition, we added a method to estimate the number of segments (forest stands), based on the eigengap heuristic [13].

3.1 Raw Forest Stand Segmentation Based on Mean Shift

The Mean Shift (MS) algorithm, a non-parametric density estimator based on Parzen window technique, is a popular feature-space analysis method that has been successfully used in color image segmentation tasks [10]. The MS procedure is an adaptive gradient ascent method, discovering local maxima in feature-space by moving towards them incrementally based on the MS vector. With local maxima, the data points can be grouped into clusters. MS based image segmentation is a merging process of clusters obtained from MS procedure performed in the joint spatial-range domain with a predefined kernel, usually Epanechnikov kernel or Gaussian kernel. Epanechnikov kernel was used in our work. In addition, the minimum number of pixels in each segment is often predefined to eliminate small segments. Therefore, with MS image segmentation algorithm [10], the feature image is segmented into k raw forest stands $S^R = \{S_1^R, \ldots S_k^R\}$.

3.2 Forest Stand Refinement Based on Spectral Clustering with Feature Expansion

The raw forest stands S^R generated by the MS segmentation algorithm is usually over-segmented. Some post-processing is necessary to merge the small stands to generate the final forest stands. We followed the work in [12] to use the mean values of every pixel in each raw forest stands as new features. However, instead of normalized cut used in [12], we employed Spectral Clustering (SC) algorithm in [11] to obtain the final forest stands. The SC algorithm, a relaxation of the graph partitioning problem, is based on the eigen-decomposition of the Laplacian matrix derived from data [11]. The eigenvectors induce a new data representation of the original one. By using this new representation, the dataset can be easily clustered with some clustering algorithm.

Define the feature derived from raw forest stands S^R to be $S = \{s_1, \ldots, s_k\}$ where $s_l \in \Re^3$ is the mean value of each pixel in S_l^R with $l = 1, \ldots, k$. Instead of directly using S in SC, we applied the same multiple child node technique on S as in [12] to generate new features by simply replicating C times each element in S. We call this procedure as Feature Expansion (FE). With the FE process, some inappropriate cluster partitioning can be avoided [12]. Thus the new feature Z could be written as

$$Z = \{\underbrace{s_1, \ldots, s_1}_{\text{C Elements}}, \underbrace{s_2, \ldots, s_2}_{\text{C Elements}}, \ldots, \underbrace{s_k, \ldots, s_k}_{\text{C Elements}}\}, \tag{1}$$

where $Z = \{z_1, \ldots, z_p\}$ with $Z_m \in \Re^3$, $m = 1, \ldots, p$ and $p = k \times C$.

Based on Z, we applied the SC algorithm proposed in [11] to generate the final forest stands. In our work, the similarity matrix W was computed by Gaussian similarity function. Matrix W contains element w_{uv} with $u = 1, \ldots, p$ and $v = 1, \ldots, p$ that is the similarity between each pair of elements in Z and can be defined as

$$w_{uv} = \begin{cases} \exp\left(-\dfrac{\|z_u - z_v\|^2}{2\sigma^2}\right) & \text{if u and v are adjacent} \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

where $\|\cdot\|$ is the Euclidean norm, and σ is the scaling parameter controlling the rapidity of the decay of w_{uv}.

3.3 Forest Stand Number Estimation

It is not a trivial task to predefine the number of forest stands which is needed in the SC algorithm to do forest stand refinement. We adopted the eigengap heuristic to estimate the number of stands. Here, eigengap is the difference between a^{th} and $(a+1)^{th}$ eigenvalues of Laplacian matrix in SC. It can be regarded as a measurement of the performance of SC and as a quality criterion for SC to automatically choose the number of clusters [13]. In addition, eigengap can be easily computed in our case, since the eigen-decomposition of Laplacian matrix is one step of SC. Therefore, by computing the eigengap of all eigenvalues and then choosing the largest one between a^{th} and $(a+1)^{th}$ eigenvalues, the number of forest stands could be estimated to be a.

4 Experiments

We tested our method in forest stand delineation with real ALS data. The ALS data was first preprocessed to generate an 8-bit three-band feature image. Then the hybrid segmentation method was applied. We firstly studied the effects of the parameters in our method. Then the results were analyzed and compared with manually made delineation by a professional forester and results from previous methods.

4.1 ALS Dataset and Field Data

The ALS data was acquired on July 13, 2005 at Juuka in eastern Finland over a 67 ha commercial forest property owned by United Paper Mills and managed in a manner typical of Scandinavian conditions. The Optech ALTM 3100C sensor was used with nominal average point density 0.6 pulses/m^2, varying in the range of 0.5-1 pulses/m^2. The average flight altitude is 2000 m above ground level and the field of view is 30 degree, with a 60 cm beam footprint. Four returns were recorded by the sensor, and the first and last pulses were attributed.

In order to do validation, 729 sample plots were set in the same area of the ALS data. These plots were systematically distributed with 30 m distance between each adjacent plot. Only 683 plots were measured, due to some of the plots are non-forested lands, giving a plot density of 9.6 plots/ha. In each plot, forest characteristics were assessed by tree species and by canopy layers. Plot center locations were measured with a pathfinder ProXRS GPS device with real-time differential correction.

4.2 Experimental Setup

Parameter Setting. There are five parameters in the hybrid segmentation method, three for the Mean Shift (MS) algorithm, one for the Feature Expansion (FE), and one for the Spectral Clustering (SC) algorithm. We first studied the effects of these parameters on the final forest stands. Then based on these studies, we chose parameters to generate the optimized results and compared with previous methods. Here, we used EDISON system[1] to do the MS segmentation. In SC, we used repeated k-means

[1] http://coewww.rutgers.edu/riul/research/code/EDISON/doc/segm.html

(KM) algorithm to generate the refined forest stands, since the results of KM are highly sensitive to the initial cluster centroids. We repeated running KM 100 times with random initialization centroids and 100 iterations each time. Among the 100 repetitions, the result with the lowest RMSE value between data points and their corresponding cluster centroids was chosen to generate segment labels. Then segment labels were filtered with a 5 × 5 median filter to obtain the final forest stands.

Result Evaluation. The evaluation is based on the field data of plot information, including Basal Area (BA) and Volume (V). We used F values and R^2 statistics, which are the same as previous research [4] [5], in order to do the comparison. Based on the plot information and delineated forest stands, we can write the sum of squares of differences within forest stands SS_{within}, the sum of squares of differences between different forest stands $SS_{between}$, and the total sum of squares of differences SS_{total} as $SS_{within} = \sum_i^K \sum_j^{n_i} (x_{ij} - \bar{x}_i)^2$, $SS_{between} = \sum_i^K n_i (\bar{x}_i - \bar{x})^2$, and $SS_{total} = \sum_i^K \sum_j^{n_i} (x_{ij} - \bar{x})^2$, where K = number of stands, n_i = number of plots in stand i, x_{ij} = forest characteristic variable measured at plot j in stand i, $\bar{x}_i$ = mean of forest characteristic variable measured in stand i, and $\bar{x}$ = mean of forest characteristic variable measured in all plots. Following [4] and [5], F and R^2 values can be defined respectively as

$$F = \frac{SS_{within}}{SS_{between}} \tag{3}$$

and

$$R^2 = 1 - \frac{SS_{within}}{SS_{total}} . \tag{4}$$

Based on these two metrics, different delineated forest stands could be evaluated, so that a better delineation will result from lower F value and higher R^2 value.

4.3 Effects of Parameters

We studied the effects of parameters in our method on forest stand delineation, in terms of the number of estimated stands and the R^2 value of Basal Area (BA).

Mean Shift. First, we explored the effects of kernel bandwidths, h^r and h^s, for range domain and spatial domain, respectively. We fixed the minimum number of pixels M in each segment to be 15, number of expansions E in FE to be 3, and the σ value to be 3 in SC. We tested h^r and h^s in the range [5, 10, …, 50]. The results of the number of raw forest stands from MS, the estimated number of stands from our method, and the R^2 value of BA from different h^r and h^s values, are shown in

Fig. 2 (a) - (c), respectively. We could see that the number of stands is around 1000 when MS is using relatively small values of h^r and h^s. When h^r and h^s were both set to 50, the number of stands is still more than 100. Therefore, the refinement process in our method is necessary to obtain accurate forest stands. From Fig. 2 (b), we can see that the number of estimated stands is much lower than the number of raw stands from MS. When increasing the values of h^r and h^s, stand numbers from MS and our method both have the descendent trends. Based on the R^2 value of BA, the best results came from smaller h^r values, and it seems that the values of h^s do not affect the results significantly.

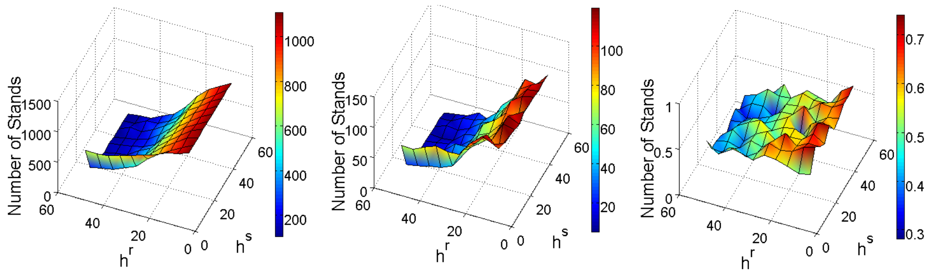
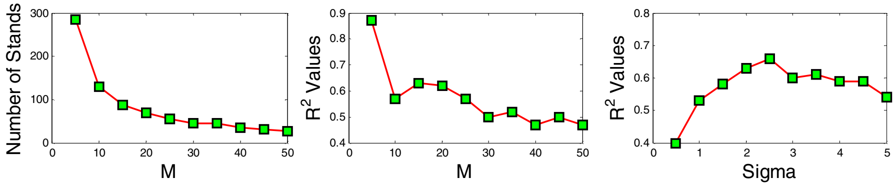


Fig. 2. (a) Surface of numbers of raw stands from MS versus h^r and h^s. (b) Surface of numbers of stands estimated by our method versus h^r and h^s. (c) Surface of R^2 values of BA by our method versus h^r and h^s.

Second, we studied the influence of M on the stand number estimation and the final results. We fixed the values of h^r, h^s, E and σ as 10, 15, 3, and 2. We tested different values of M in the range [5, 10, …, 50]. As shown in Fig. 3 (a), the estimated number of stands will decrease when increasing the value of M. Also R^2 values of BA have the decreasing trend in general as shown in Fig 3 (b).

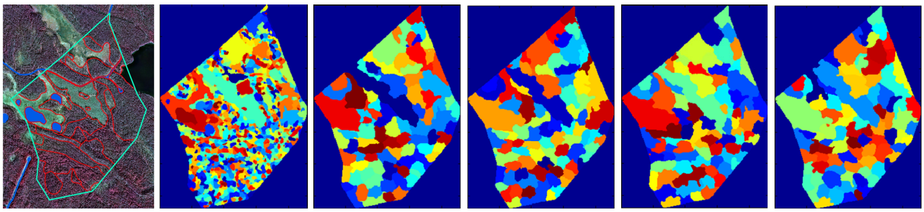
Feature Expansion. We set h^r, h^s, M, and σ to be 10, 15, 15, and 2. And the value of E varied in the set [1,2,…, 5]. When E = 1, it means there is no FE process in our method. In Fig. 4 (a), it shows the forest stands delineated by a professional forester manually with 35 stands whose boundaries are represented by red colors. In Fig. 4 (b) – (f), they are the results of our method with different values of E, where forest stands are shown with pseudo-colors. We could see from Fig. 4 (b) that without FE, the estimated number of stands is 908, which is too large when compared to that of the manually delineated result. This shows it is necessary to include FE in our method to increase the accuracy of stand number estimation and thus improve the final results. Moreover, it seems that the parameter E does not affect the estimation of stand number, since all results have the same number 87. But we can see from Fig. 4 (c) - (f) that there are some slight differences among results.

Spectral Clustering. The values of h^r, h^s, M, and E were fixed as 10, 15, 15, and 3. We tested σ values in the range [0.5, 1, …, 5]. The R^2 values of BA are shown in Fig. 3 (c), which have a peak at σ value 2.5. But they become relatively stable after the peak in the range [3, 3.5, …, 5]. The estimated number of stands is 87 for the σ values in the range [0.5, 1, …, 3.5], and 86 for the values of 4, 4.5, and 5.



(a) (b) (c)

Fig. 3. (a) Estimated number of stands and (b) R^2 values versus the values of M. (c) R^2 values versus the values of σ



(a) (b) (c) (d) (e) (f)

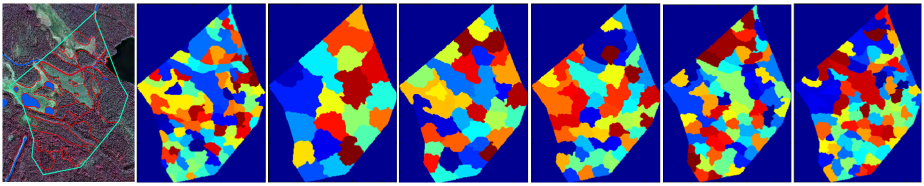
Fig. 4. Visual results of forest stand delineation: (a) manually from the CIR image by a professional forester (35 stands) [6], (b) our method with E = 1, i.e. no FE process (estimated 908 stands), (c) – (f) our method with E = 2, 3, 4, 5, 6 (estimated 87 stands)

4.4 Experimental Result Comparison

Based on the previous experiments in section 4.3, we optimized the parameters h^r, h^s, M, E and σ as 10, 10, 15, 3, and 2. We compared our results with manually delineated results by a professional forester and also previous methods.

Visual Results. The visual results of delineated forest are shown in Fig. 5 (b) – (g) with pseudo-colors representing different forest stands. The manually delineated results from a professional forester based on the Color Infrared (CIR) image of the same study area is shown in Fig. 5 (a) with red lines as the stand boundary on the CIR image. It has 35 forest stands. The result of our method with stand number estimation is shown in Fig. 5 (b). Our method estimated 91 stands, which is almost three times of the result made by the forester. It seems that our method divided the manual made stands into several sub-stands. We also tested our method without stand number estimation but using the same number of 35 stands with the manual one, as well as

20, 50, 65, and 80 stands. For the results with the stand number 35, see Fig. 5 (d), it looks different in some areas, especially the right and bottom parts with large areas of forests, when compared to manual results. This may partially result from the different information given by CIR image and ALS data, since the ALS data contains less information of tree species when compared to CIR image. When the number of stands is relatively low, such as 20, 35, and 50 (Fig. 5 (c) – (e)), their boundaries are quite different from manually delineated results. Also it seems that they are merged by small stands generated by larger stands numbers, such as 91 stands in Fig.5 (b). That may suggest that the number of stands should be higher for automatic stand delineation in order to give reasonable results, compared to manually made segmentation based on CIR images. Thus several segments may correspond to one manual segment, but merge them together is not a trivial task and need more additional information, such as more accurate tree species information.



(a) (b) (c) (d) (e) (f) (g)

Fig. 5. Visual results of forest stand delineation: (a) manually from the CIR image by a professional forester with 35 stands [6], (b) our method (91 estimated stands), (c) – (g) our method with manually set 20, 35, 50, 65, and 80 stands, respectively

Numerical Results. Based on the evaluation metrics introduced in section 4.2, we computed several numerical results and compared our results with previous results [4] [5] for the same study area, and also manual results, as shown in Table 1 and Table 2. In both tables, R1 indicates the results of our method with estimated 91 stands; R_avg is the average results of our method with different h^r and h^s values in the range of [10, 15, …, 30]. As ALS based automatically stand delineation may need higher number of stands than the manual one, we only selected the results whose estimated number of stands is between 70 and 90 to calculate the average. Therefore, we could somehow see the average performance of our method based on some relatively reasonable stand numbers without manually optimizing these parameters.

One thing to note is that the CHM used in our work has much lower spatial resolution of pixel size 4 m × 4 m than that in [4] which is 1 m × 1 m. But we used the same three features derived from ALS data as explained in Section 2.2 with [5].

When compared to the previous results in [4] generated by eCognition software using the region growing method in [15] and also the professional forester, R1 is the best one both for the stand variables BA and V. The average result R_avg is also better in both variables than previous results and manually delineated results. Moreover, we compared our results with [5], which used a region growing and watershed techniques. From Table 2, based on F values, we could see that R1 and R_avg are better than previous results for total tree species and various tree spices of both BA and V. Only for deciduous trees, our method is worse than the previous method in V. It should be noted that R1 is obtained from parameters optimized based on plot information. However, based on the coarse range of correct stand number, we could somehow select the suitable parameters for our method. The results of R_avg showed that our method worked well with correct number of stands, and is better in most cases than previous methods.

Table 1. R2 values of Basal Area (BA) and Volume (V) in the forest stands generated by different methods. R1 is the results of our method with estimated 91 stands. R_avg is the average of the results with estimated stand number between 70 and 90 from different values of parameters h^r and h^s. The results of region growing methods were reported in [4] based on eCognition software based on different data, RGB, CHM, and RGB + CHM, which have higher spatial resolution when compared to features used in our work. Manually delineated results from the CIR image by a professional forester are also from [4].

Stand Variables	R1	R_avg	Region growing method			Manual Delineation
			RGB	CHM	RGB+CHM	
BA	**0.66**	0.61	0.51	0.56	0.57	0.55
V	**0.67**	0.62	0.53	0.61	0.48	0.55

Table 2. F values of Basal Area (BA) and Volume (V) in the forest stands generated by different methods. R1 is the results of our method with estimated 91 stands. R_avg is the average of the results with estimated stand number between 70 and 90 from different values of parameters h^r and h^s. The results of RGW were from [5] based on a region growing and watershed techniques using the same three features as we derived from ALS data.

Metric	Method	Total		Pine		Spruce		Deciduous Trees	
		BA	V	BA	V	BA	V	BA	V
F	R1	**0.55**	**0.50**	**0.63**	**0.49**	**0.45**	**0.46**	**0.45**	0.95
	R_avg	0.65	0.63	0.70	0.58	0.57	0.61	0.57	0.93
	RGW	0.92	0.91	0.88	0.88	0.83	0.81	0.72	**0.73**

5 Conclusion

In this work, we applied a hybrid segmentation approach to delineate forest stands from Airborne Laser Scanning (ALS) data. The ALS data was first pre-processed to generate an image with three features on each band, containing information of tree size, density, and species, respectively. Then the feature image was segmented with the mean shift algorithm to generate raw forest stands. The mean value of all pixels in each stand was computed. Then we replicated each mean value several times in the feature expansion process to generate the new feature for the second stage segmentation. Based on the new feature, we used the Spectral Clustering (SC) algorithm to generate the final forest stands. In addition, we estimated the number of stands in SC by using eigengap heuristics. We applied our method on real ALS data acquired at Juuka, Finland. The results showed that our method worked well for forest stand delineations and return better results in most cases when compared to previous methods. In addition, it was found that the number of stands highly affects the final results in our method. Therefore, more work is needed for parameter optimization and accurate estimation of stand number in order to improve the delineation accuracy.

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