

Article

Point Cloud Data Processing Optimization in Spectral and Spatial Dimensions Based on Multispectral Lidar for Urban Single-Wood Extraction

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Abstract: Lidar can effectively obtain three-dimensional information on ground objects. In recent years, lidar has developed rapidly from single-wavelength to multispectral hyperspectral imaging. The multispectral airborne lidar Optech Titan is the first commercial system that can collect point cloud data on 1550, 1064, and 532 nm channels. This study proposes a method of point cloud segmentation in the preprocessed intensity interpolation process to solve the problem of inaccurate intensity at the boundary during point cloud interpolation. The entire experiment consists of three steps. First, a multispectral lidar point cloud is obtained using point cloud segmentation and intensity interpolation; the spatial dimension advantage of the multispectral point cloud is used to improve the accuracy of spectral information interpolation. Second, point clouds are divided into eight categories by constructing geometric information, spectral reflectance information, and spectral characteristics. Accuracy evaluation and contribution analysis are also conducted through point cloud truth value and classification results. Lastly, the spatial dimension information is enhanced by point cloud drop sampling, the method is used to solve the error caused by airborne scanning and single-tree extraction of urban trees. Classification results showed that point cloud segmentation before intensity interpolation can effectively improve the interpolation and classification accuracies. The total classification accuracy of the data is improved by 3.7%. Compared with the extraction result (377) of single wood without subsampling treatment, the result of the urban tree extraction proved the effectiveness of the proposed method with a subsampling algorithm in improving the accuracy. Accordingly, the problem of over-segmentation is solved, and the final single-wood extraction result (329) is markedly consistent with the real situation of the region.

Keywords: Houston; multispectral lidar; target classification; intensity interpolation processing; urban single wood extraction; region growing algorithm



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1. Introduction

In recent years, intensive urban development and economic activities have increased energy consumption and have led to serious greenhouse gas emissions [1,2]. Urban trees significantly impact environmental quality and human health because they can absorb carbon dioxide and store excess carbon in biomass [3,4]. Protecting carbon storage and improving green space infrastructure in urban areas present significant environmental benefits [5]. Therefore, estimating and monitoring urban carbon storage and green space is critical. The airborne lidar system is an accurate remote sensing technology for monitoring biological carbon and has been widely used in surface condition research and land cover classification [6]. In the aspect of vegetation state monitoring, multispectral lidar systems have also been widely used [7,8]. With the increasing demand for more accurate land cover classification and urban biomass monitoring, the frequency of lidar use is also

increasing. Multispectral lidar has been carried out in many laboratories. Lidar has achieved satisfactory results in many fields of application and developed rapidly from single-wavelength to multiple spectra and high spectrum thereafter [9–25]. Although multiple spectra and hyperspectral lidar have shown better capabilities for land cover and forestry, they cannot be mass-produced, have no airborne implementation results, and are unable to be used in large-scale applications. In terms of the system, higher spectral resolution results in large systems. Therefore, in terms of practicability, two- or three-wavelength lidar are more suitable for large-scale research. In 2014, Optech released its first commercial multispectral airborne lidar system, introduced the system's outstanding land and extremely shallow water mapping capabilities, and demonstrated new applications for realizing its multispectral capabilities [26].

At present, there have been many mature research methods for land cover classification of Titan data. Many studies convert point cloud data into raster images to achieve the land cover classification of multispectral Titan data [27,28]. Some research classifies data by constructing characteristics [29,30]. Some research uses morphology to improve the accuracy of classification [31]. In forestry, many studies have verified the high potential and advantages of airborne multispectral lidar in forest and urban vegetation detection and single-tree extraction [32–39]. Subsequent studies have also demonstrated lidar's ability to estimate tree biomass and carbon content [40–48]. Moreover, the accurate extraction of individual trees in complex urban environments remains challenging.

The Titan sensor is used to obtain multispectral point clouds from three groups of single wavelength point clouds with spatial and spectral differences. Moreover, the intensity of point clouds should be interpolated in the preprocessing stage to convert them from single wavelength to multispectral point cloud data. The traditional method aims to interpolate the original point cloud directly. Weinmann developed software that searches the other two-channel point clouds within a 1 m radius of the point cloud and assigns the intensity value to the searched point cloud [49]. Ekhtari used a large point cloud search radius to exclude the case that the corresponding channel has no point cloud [50]. However, because of the close distance between ground objects, the edge intensity interpolation of ground objects is inaccurate. Therefore, we need to improve the accuracy of interpolation of the point cloud intensity to properly obtain the spectral information of urban vegetation.

To address the geometric and spectral inconsistencies of the Titan data, we propose an improved method for multispectral lidar point clouds. Firstly, the preprocessed point cloud is divided by the proposed method. Secondly, we set the bands according to the complexity of urban features in the classification. The spectral indices are selected to improve the extraction of trees in the city. Then, the down-sampling method is adopted in the subsequent single-wood extraction to effectively eliminate errors, which is caused by the scanning geometry. Compared with other methods, our method improves the spectral information completion accuracy of the multispectral point cloud [49,50] and optimizes the geometry distribution of the point cloud [51,52]. Meanwhile, the quality of airborne multispectral lidar point cloud data for urban single-wood extraction is enhanced [32,33,36,37].

2. Materials and Methods

2.1. Study Area and Point Cloud Data

2.1.1. Study Area

The flight area dataset was acquired using the Airborne Multispectral Lidar System OT of the University of Houston in Houston, Texas, USA (Wikipedia) (29° 43' 09.68" N, 95° 21' 12.72" W) (Figure 1). The study area is a subset of the flight dataset which is located at the intersection of Wheeler Avenue and Scott Street and centered on the residential west side of the University of Houston.

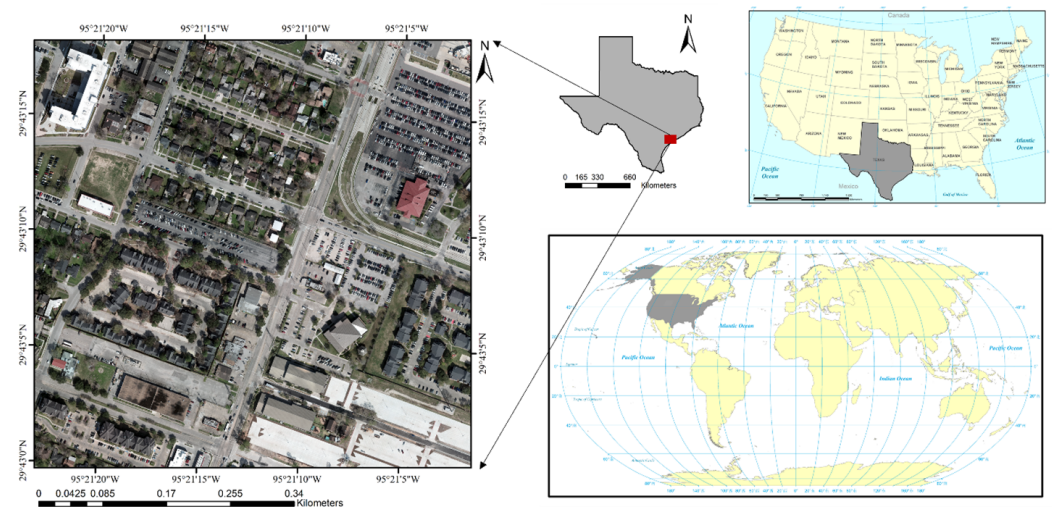


Figure 1. Study area location and RGB images.

2.1.2. Data Introduction

The data used are igASS2018. The three channels of Titan are scanned at different angles: the 1550 nm, 1064 nm, and 532 nm channels are scanned vertically downward, 3.5° forward, and 7° forward, respectively. Therefore, point cloud files collected through the three channels will produce some geometric inconsistencies. The numbers of points in the three channels are 4,436,481, 4,801,267, and 4,739,643 and the average point cloud density is 6.3 points per m^2 . Data include point source ID, user data, flight line edge, sweep angle, echo times, echo intensity, and details other than coordinate information. We also obtain the true value of single trees in the region through images provided by Titan and point cloud data after elevation rendering. This area contains many independent houses and 308 trees. We refer to some other articles on classification using Titan data [21,53]. Considering the presence of several parking areas and many cars in the scene, we took cars as a separate category in combination with RGB images and point cloud data. For non-residential buildings, we also refer to RGB images and point cloud data. It is found that in the three bands of the point cloud studied, non-residential buildings exhibit spectral characteristics that are different from other ground features. Therefore, we classified non-residential buildings as a separate category. We manually divide target objects into eight categories: roads, low vegetation, high vegetation, cars, bare land, housings, non-residential buildings, and wires (Figure 2d) (all point clouds were displayed by cloudcompare software). The number of multispectral point clouds corresponding to these categories is shown in Table 1.

Table 1. Reference points for the eight classes.

Class	Wire	Car	Road	Low Vegetation	High Vegetation	Bare Land	Housing	Non-Residential Building
Number of Points	790,066	284,271	3,329,665	4,824,554	2,368,410	408,167	1,697,271	114,987

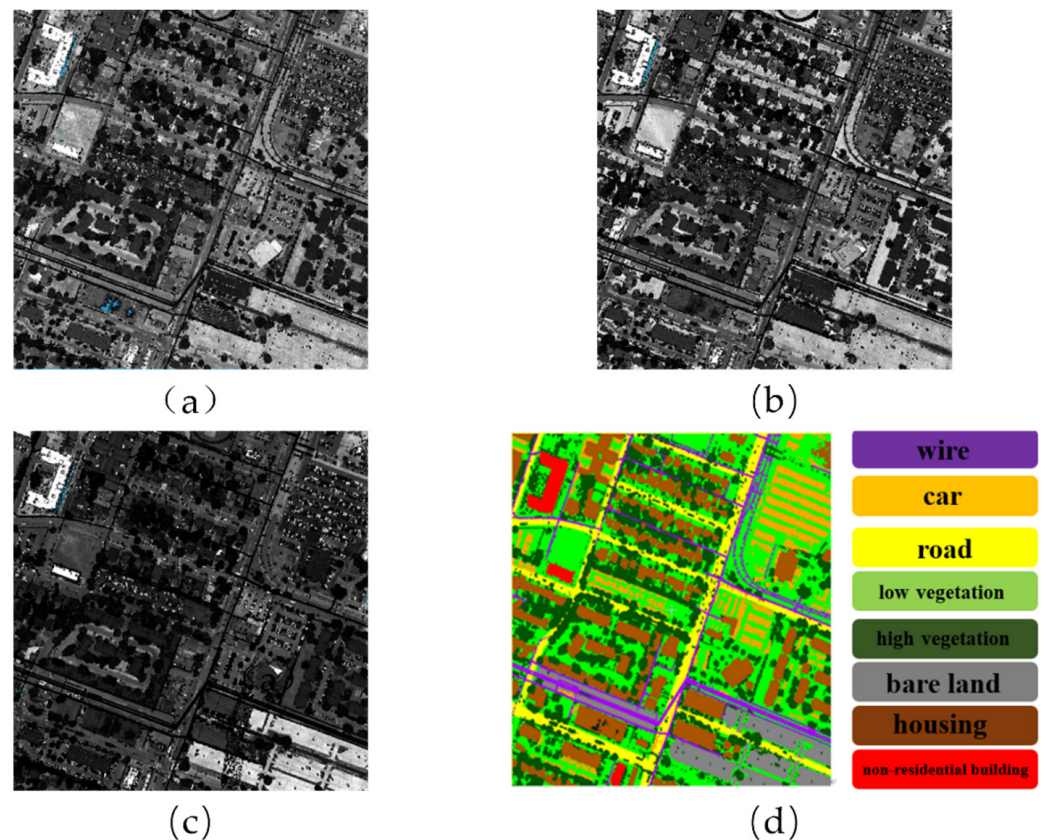


Figure 2. (a) The 532 nm channel point cloud intensity; (b) the 1064 nm channel point cloud intensity; (c) the 1550 nm channel point cloud intensity; (d) multispectral lidar point cloud rendered by ground truth value.

2.2. Methods

The proposed method for land cover classification using Titan multispectral lidar data is presented in the flowchart (Figure 3). Firstly, we segmented the single-wavelength point cloud, and on the basis of the segmentation, we carried out intensity interpolation for the point cloud and improved the quality of spectral information by using the information advantages of the spatial dimensions of the point cloud. After the point cloud intensity interpolation, we obtained the multispectral point cloud data. By constructing the spectral index, we classified the point cloud. We obtained the tree point cloud in the classification result. To optimize the spatial distribution of tree point clouds, we conducted drop sampling for tree point clouds. Finally, we carried out single-wood segmentation for tree point clouds and evaluated the accuracy of the classification and single-wood segmentation results according to the ground truth value. The details of the method are presented in the following subsections.

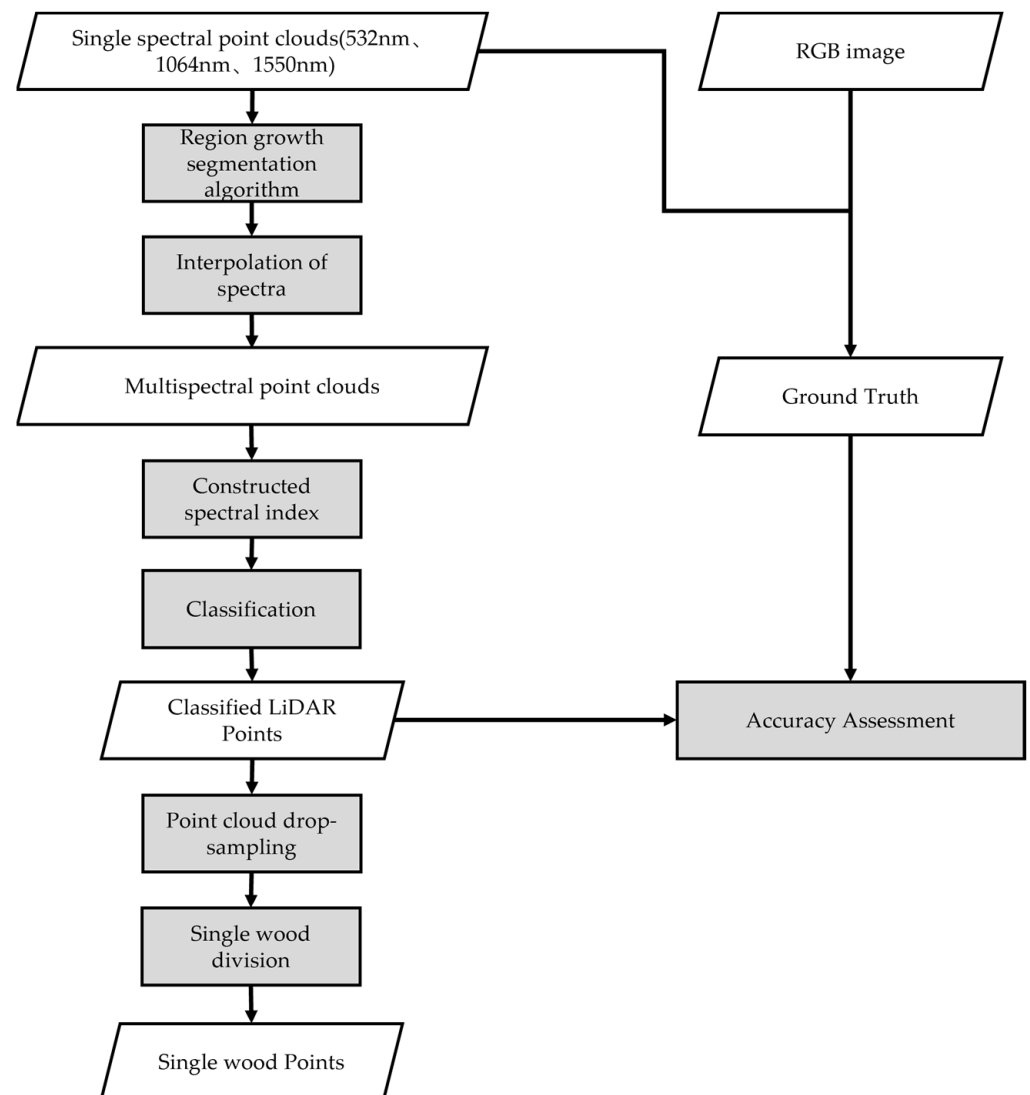


Figure 3. Flowchart detailing the methodology.

2.2.1. Spectral Interpolation Based on Space Information Enhancement

The three point-cloud datasets have their geometric information in a single wavelength with a single channel backscattering lidar point cloud, owing to the geometrical inconsistencies of the three channels of Titan. The red point cloud in the figure is the point cloud obtained by the 1550 nm NIR channel, the green point cloud in the figure is the point cloud obtained by the 1064 nm NIR channel, and the blue point cloud in the figure is the point cloud obtained by the 532 nm green light channel (Figure 4). Thus, our first step is the three channels containing different spectral information, which have geometrical inconsistencies of the lidar point cloud data processing for multiple spectral point clouds. Traditional point cloud interpolation methods include the nearest point, bilinear, and inverse distance weight interpolation methods. We need to interpolate the intensity of the single-wavelength point cloud. When we use the traditional method to interpolate multispectral point clouds for classification, we find that the classification results at the edges of different ground objects are not particularly ideal. Considering the spectral information used in classification, we are convinced that the point cloud at the edge of the ground object may have acquired the intensity information of other categories of point clouds during interpolation. Therefore, we propose a method of point cloud segmentation before intensity interpolation to effectively improve the accuracy of point cloud interpolation. We obtain different types of point cloud

blocks after point cloud segmentation. Interpolation in a single point cloud block can effectively avoid point cloud intensity from other ground objects.

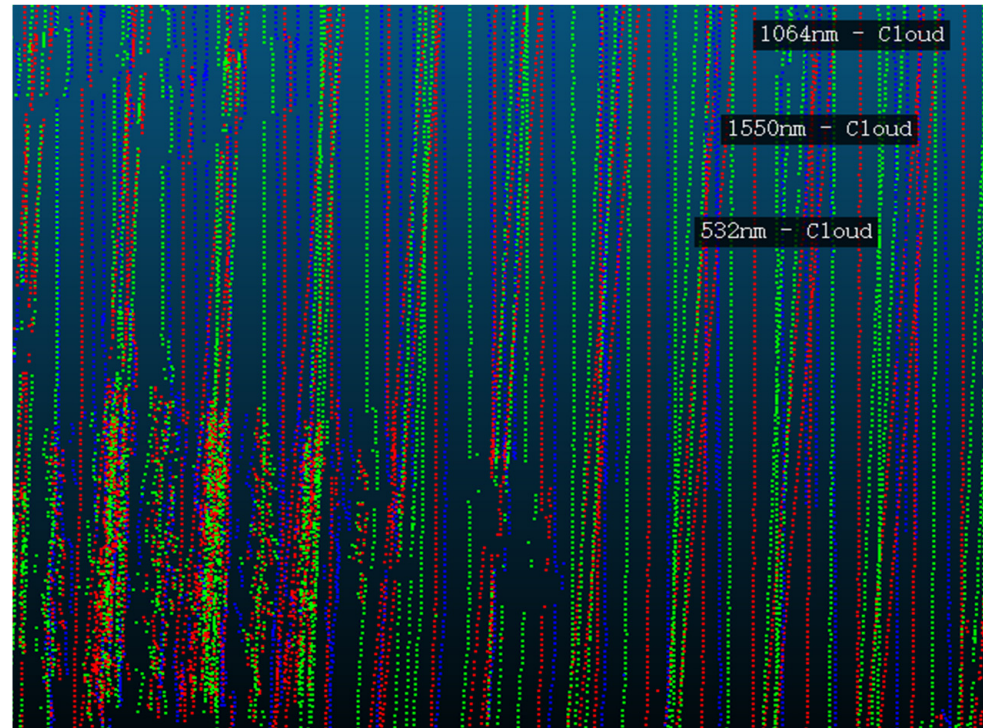


Figure 4. Single-wavelength point cloud with three different channels (the points of the 1550 nm channel are red, the points of the 1064 nm channel are green, and the points of the 532 nm channel are blue).

The calculation method of point cloud curvature is as follows. Here, $\vec{n}$ is a normal vector, A is the infinitesimal region around p , $diam(A)$ is the diameter of this region, ∇ is the gradient operator with respect to point p , and α_{ij} and β_{ij} are the opposite angles connecting sides p_i and p_j . When the mean curvature x_n of point p on a surface is calculated, x_n is satisfied:

$$2x_n\vec{n} = \lim_{diam(A) \rightarrow 0} \frac{\nabla A}{A} \quad (1)$$

The formula is discretized to get:

$$x_n(p_i) = \frac{n}{4A_{min}}\gamma \quad (2)$$

$$\gamma = \sum_{j \in N_i} (\cot\alpha_{ij} + \cot\beta_{ij})(p_i - p_j) \quad (3)$$

We choose the region-growing segmentation algorithm in the segmentation. In this method, the point with the least curvature is used as the seed point to start growth. Using such an approach can reduce the total number of regions. We calculate the angle between the normal of the neighborhood point and the normal of the current seed point, the domain points smaller than the smoothing threshold are added to the current area. Then we check the curvature value of each field point, and add the seed point sequence to the field points less than the curvature threshold. Point cloud normal vector calculation, smoothing threshold, curvature threshold, and all subsequent methods are implemented by PCL (Point Cloud Library).

In the subsequent intensity interpolation method, we refer to the tool developed by Weinman that is used to search the other two-channel point clouds within a 1 m radius of the point cloud and assign the intensity value to the searched point cloud [49]. When there is no corresponding point cloud in other channels, the intensity value of 0 is assigned to all point clouds. Thus, all point clouds are assigned two intensity values. Ekhtari used a large point cloud search radius to exclude the case that the corresponding channel has no point cloud [50]. To search all point clouds, this study uses the existing interpolation method as a basis to search all point clouds. We search for point clouds in other channels by the ten closest to each point cloud, not by the radius of the point cloud. By using this method, we can effectively solve that the point cloud strength value is zero, and search the point cloud according to the distance to weight calculation of intensity. The calculated intensity value is given. Lastly, the point cloud interpolation of the other two channels is performed. The three groups of multispectral point clouds obtained are also merged to increase point cloud density and reduce interpolation error.

2.2.2. Spectral Index Analysis Based on Land Cover Classification

One of the difficult tasks in urban areas is to accurately distinguish complex ground object categories merely by relying on the intensity characteristics and geometric features of a single wavelength of lidar point cloud data. Many studies have used the spectral advantages of Titan data as bases, whether in terms of spectral dimension or exponential construction, to demonstrate the advantages of the spectral aspects of datasets for the classification of point clouds [29,30,50,54–57].

For feature categories for regions with traditional urban features, compared with other classification methods, using the method of spectral index indicative is strong as it can effectively monitor and distinguish the corresponding feature, and analyzing the classification results also helps to study the laws of spectral characteristics and features of ground object classification for further contribution to the study. To build a suitable spectrum index for the classification of choice before we build a larger contribution to the classification results of two groups of band selection, we classify the point cloud by combining bands in pairs and adding the geometric information of the point cloud. Lastly, we determine the two bands with maximum influence on the classification results according to the results of the three classification groups and the classification results of adding all spectral and geometric information. We select six groups of spectral features (Table 2) suitable for distinguishing vegetation, buildings, vehicles, wires, and other ground objects according to the study area's characteristics. After determining the two bands, we analyze the feature contribution degree of spectral features according to the classification results.

In the analysis of the contribution degree of spectral features, we calculate the influence of each spectral index on the final classification results by adding all spectral indices and not adding spectral indices together with a single set of experiments. We likewise analyze the influences of different bands and spectral indices on the accuracy of the final feature classification.

Table 2. Spectral exponential framework formula.

Spectral Indices		Formula	Reference
<i>DVI</i>	Differential vegetation index	$I_{532} - I_{1064}$	[58]
<i>NDVI</i>	Normalized differential vegetation index	$\frac{I_{1064} - I_{532}}{I_{1064} + I_{532}}$	[59]

Table 2. Cont.

	Spectral Indices	Formula	Reference
<i>RNDVI</i>	Ratio normalized difference vegetation index	$\frac{I_{1064}^2 - I_{532}^2}{I_{1064} + I_{532}^2}$	[60]
<i>SR</i> ²³	Simple ratio index	$\frac{I_{1064}}{I_{532}}$	[61]
<i>SAVI</i>	Soil-adjusted vegetation index	$\frac{(1+0.5) \times (I_{1064} - I_{532})}{(I_{1064} + I_{532} + 0.5)}$	[62]
<i>EVI2</i>	2-band enhanced vegetation index	$I_{532} \frac{I_{1550} - I_{1064}}{I_{1550} + (6 - \frac{7.5}{2.08}) I_{1064}}$	[63]

For accuracy verification, a confusion matrix is created to ensure that the overall accuracy (OA) and kappa statistics are calculated. Overall accuracy is the ratio of the number of correctly classified point clouds in the category to the total number of point clouds in the category, the kappa statistics represents the proportion of errors reduced by a classification compared to a completely random classification. Here, i represents the category of ground objects, and a_i is the correct classification number of categories i . x_i and y_i is the number of category i ground object samples in the ground truth label and predicted label, respectively. N is the total number of samples and C is the number of categories.

$$OA = \frac{\sum_{i=1}^C a_i}{N} \quad (4)$$

$$Kappa = \frac{N \sum_{i=1}^C a_i - \sum (x_i y_i)}{N^2 - \sum (x_i y_i)} \quad (5)$$

2.2.3. Single-Wood Extraction Based on Point Cloud Density Homogenization

Trees are divided after classification to obtain individual urban trees. At present, a significantly mature method of single-wood extraction uses airborne lidar. A similar local maximum algorithm is used to identify the crown reuse area for extraction by the growth algorithm [64]. The casting algorithm, empirically based tree shape assumption, and canopy edge detection are combined [65]. The k-means clustering algorithm is used to segment individual trees from the point cloud [66]. A new algorithm is developed to segment individual trees from the small footprint discrete return airborne lidar point cloud. Different from forest trees, trees in cities are mostly artificial, sparsely distributed, and fewer in number. The single-wood segmentation method based on point clustering is used in this study. The point spacing is about 0.15 m and the row spacing is irregular, 0.45 m in width and 1.1 m long, owing to the influence of the scanning mode of airborne lidar. Therefore, some single-wood segmentation results are linear. We sample the point cloud under the voxel before segmentation. The octree down-sampling method is utilized to reduce the point cloud density to one-fifth, and the point closest to the center of the voxel is used as the sampling point. Characteristics of the original point set are preserved as extensively as possible to reduce the impact of uneven distribution of point cloud data (Figure 5). The segmentation result of the point cloud after down-sampling is close to the real tree.

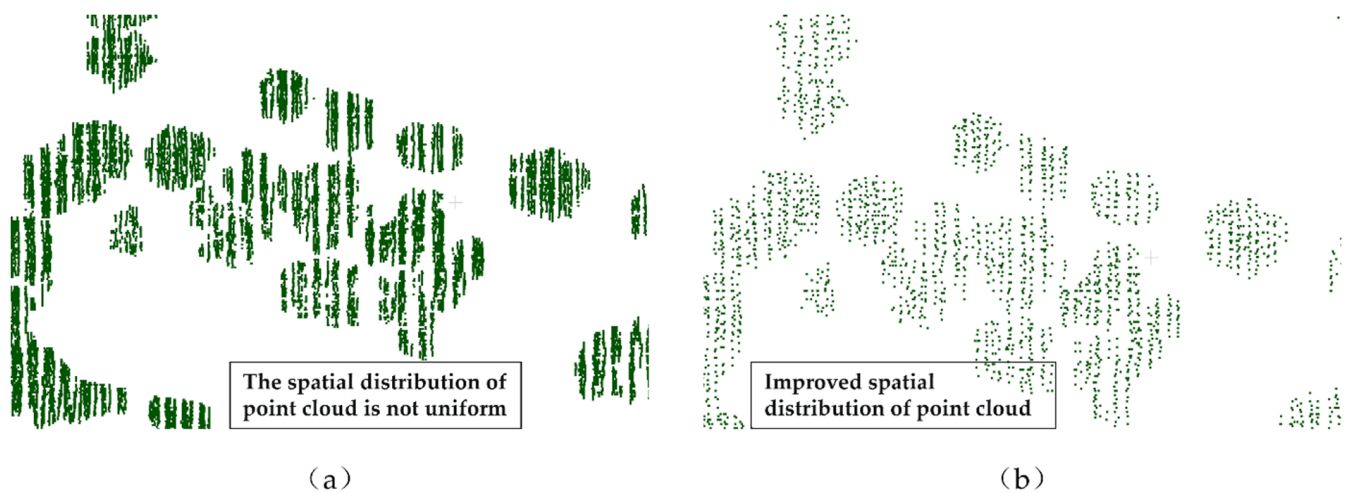


Figure 5. (a) Point cloud of trees before down-sampling (the gap between scan lines is too large). (b) Point cloud of trees after down-sampling (less affected by scan lines).

3. Result

3.1. Effect Evaluation of Improved Point Cloud Interpolation Method

We obtain many individual objective point cloud data, number them, interpolate the intensity of different objects, and fuse all interpolated data to obtain the final multispectral point cloud data after dividing three groups of single-wavelength point cloud data. It can be intuitively seen that the intensity obtained by the undivided multispectral point cloud data at the edge of the object will be affected by other nearby ground objects through the three-dimensional false color display of the object (Figure 6a,b).

We are convinced that the influence of adjacent ground objects can be relatively eliminated when interpolating the segmented objects. However, although the influence of alien features is eliminated, the error of similar features in different positions remains. Hence, this study focuses on a single object interpolation, considers the incident angle of laser scanning and multiple echo intensity caused by the error, chooses the interpolation to search to the point cloud according to the distance to weight calculation of the intensity, and combines multiple adjacent point weighting intensity values. Moreover, our demand for the accuracy of spectral information is also met.

In order to verify the effectiveness of the method, we divide the whole area into four small areas. In order to divide the same feature into the same area, we divided the area along the street, and we test this method in four small areas (Figure 7). We use the random forest method to classify according to the spectral information of point clouds. The directly interpolated multispectral point cloud and the interpolated multispectral point cloud after segmentation processing are classified. The results show that under the same condition, the classification results of point cloud data with segmentation before interpolation are improved in all areas. Area (d) showed the highest improvement (3.9%). Area (c) showed the lowest improvement (3.46%) (Table 3). We consider there are more buildings and trees in area (b) and area (d). Segmentation makes it easier to distinguish such large features and makes our method optimize more points.

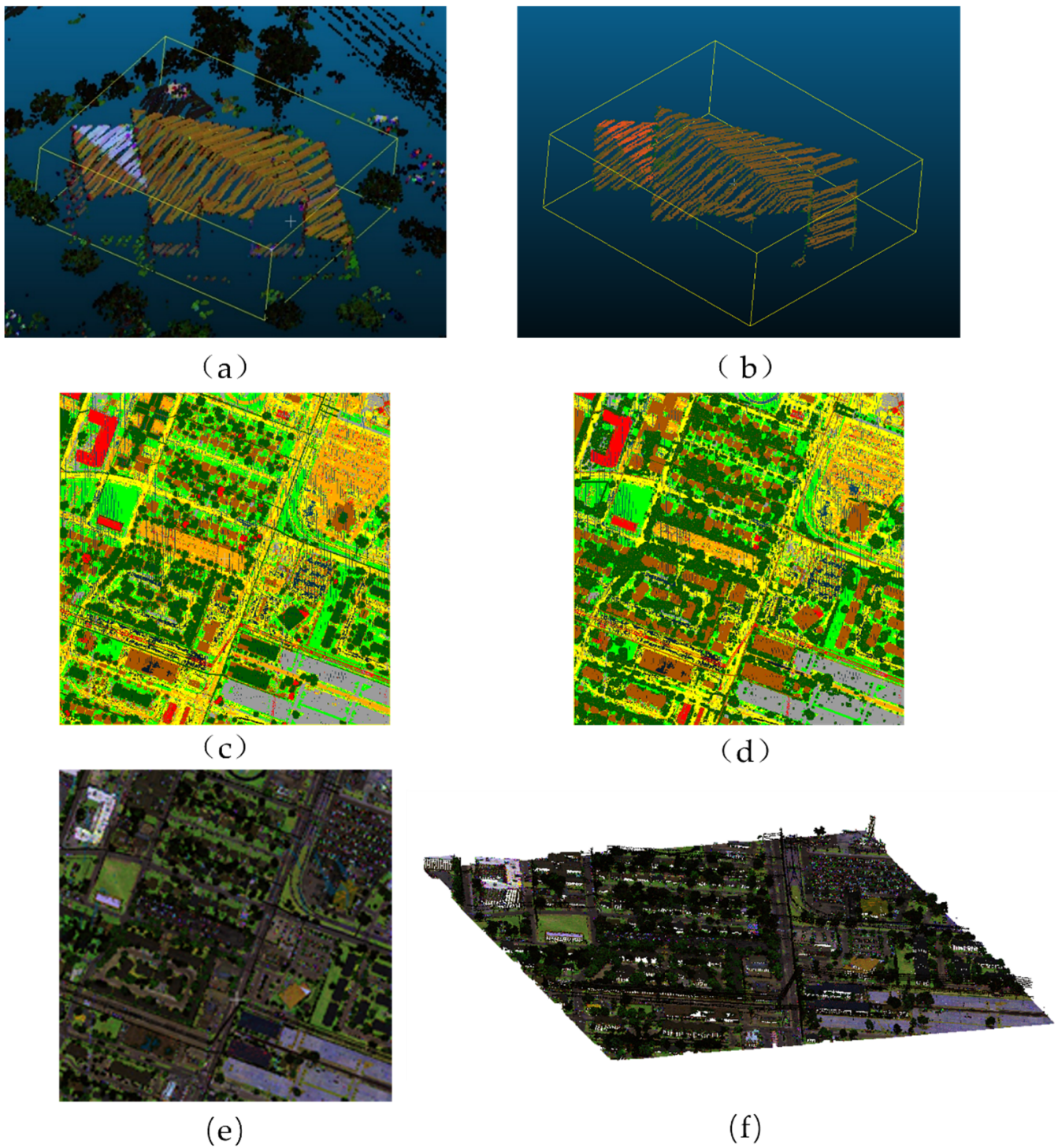


Figure 6. (a) Pseudo-color display of conventional processing methods, (b) pseudo-color display after segmentation, (c) classification results of conventional processing methods, (d) classification results after segmentation, (e) pseudo-color image by merging the three spectral intensity images, and (f) pseudo-color image by merging the three spectral intensity images for 3D representation.

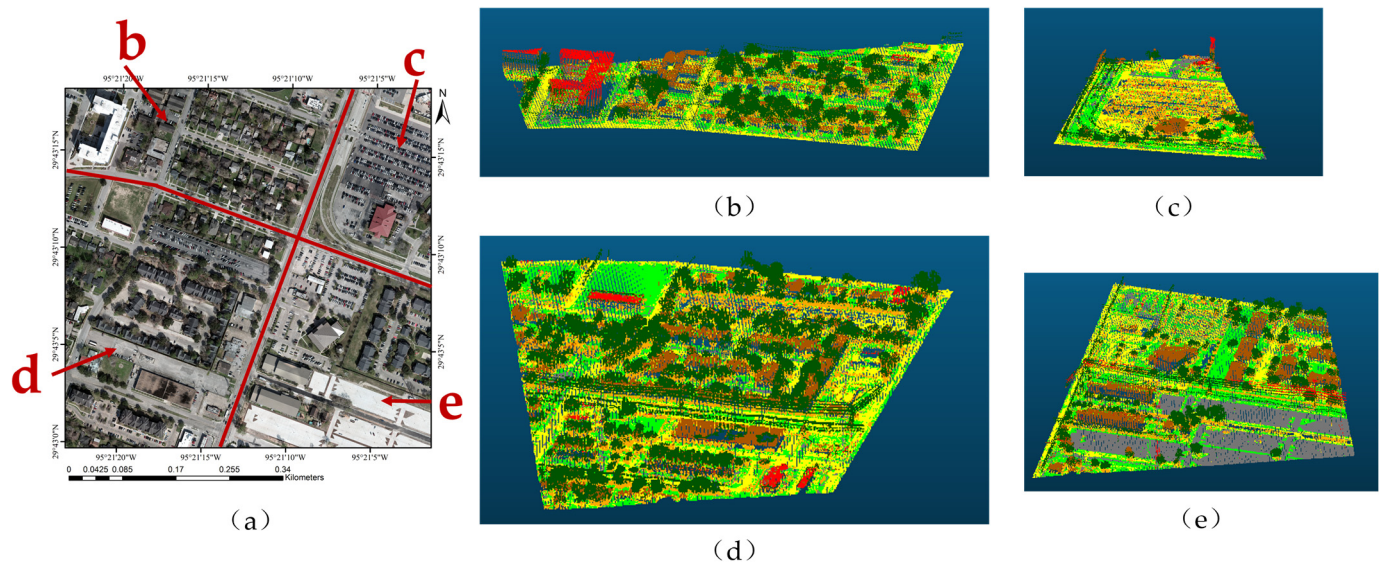


Figure 7. (a) The whole area is divided into four small areas, (b) the classification result of area (b) after segmentation processing, (c) the classification result of area (c) after segmentation processing, (d) the classification result of area (d) after segmentation processing, and (e) the classification result of area (e) after segmentation processing.

Table 3. Classification results of using improved point cloud interpolation method by the random forest classifier.

	Area (b)	Area (c)	Area (d)	Area (e)
Classification accuracy without segmentation	OA:76.99 Kappa:0.57	OA:73.33 Kappa:0.55	OA:76.49 Kappa:0.57	OA:80.43 Kappa:0.60
Classification accuracy with segmentation	OA:80.25 Kappa:0.60	OA:74.97 Kappa:0.56	OA:80.42 Kappa:0.60	OA:82.11 Kappa:0.61

3.2. Classification Result Based on Spectral Index Construction

The experiment uses k-means and random forest classifiers to divide the point cloud data into eight categories: roads, low vegetation, high vegetation, cars, bare land, housings, non-residential buildings, and wires. We use only small training samples (about 1.1% of the total data) to train the random forest classifiers. The total area contains 13,977,391 points, which are divided into 8 categories. We randomly select 20,000 samples for each type of object according to the category, and a total of 160,000 samples are used as training samples. The remaining 13,817,391 points are used as testing samples.

A difference vegetation index is constructed by combining the two channels with the optimal classification results from the 1064 and 532 nm channels (Figure 8, Table 4).

Table 4. Classification results by the random forest classifier.

	1064 nm and 1550 nm	1550 nm and 532 nm	1064 nm and 532 nm
Total accuracy	OA:62.22 Kappa:0.48	OA:63.91 Kappa:0.50	OA:66.27 Kappa:0.52

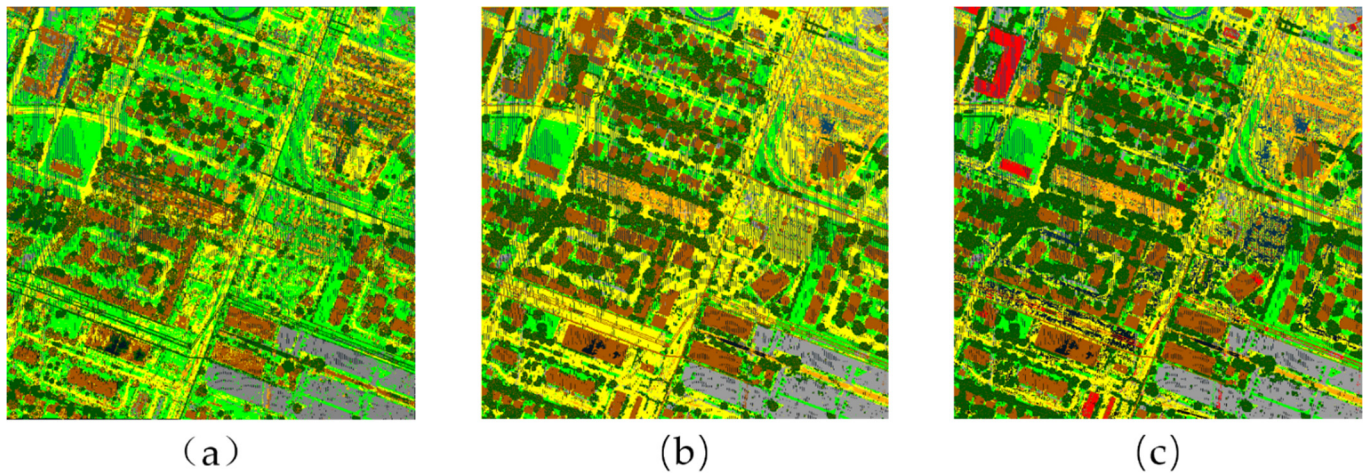


Figure 8. (a) The intensity combination classification results for the 1064 nm and 1550 nm channels, (b) the intensity combination classification results for the 1550 nm and 532 nm channels, (c) the intensity combination classification results for the 1064 nm and 532 nm channels.

We construct six groups of vegetation indices using the 1064 nm and 532 nm channels of spectral information for classification in follow-up experiments. We adopt the k-means (Table 5) and random forest (Table 6) classifiers in the two experiments. Each experiment contains eight groups, and each group of experiments includes geometry and spectral information from the 1064 and 532 nm bands. The first set of experiments added spectral information from only two channels, the second through the seventh experiments each added a spectral index, and the last set of experiments added all the spectral exponents. We can according to the classification accuracy of the six spectrum indexes' contributions to the final classification results. According to the experimental results of joining all the spectral indices, the overall accuracy can be increased by 23% (Figure 9).

Table 5. Classification results using the k-means classifier.

	Spectral Information	Spectral + DVI	Spectral + NDVI	Spectral + RNDVI	Spectral + SR	Spectral + SAVI	Spectral + EVI2	Spectral + All Index
OA	80.91	79.86	73.55	78.88	69.54	72.27	68.04	82.36
Kappa	0.68	0.70	0.61	0.68	0.55	0.60	0.54	0.69

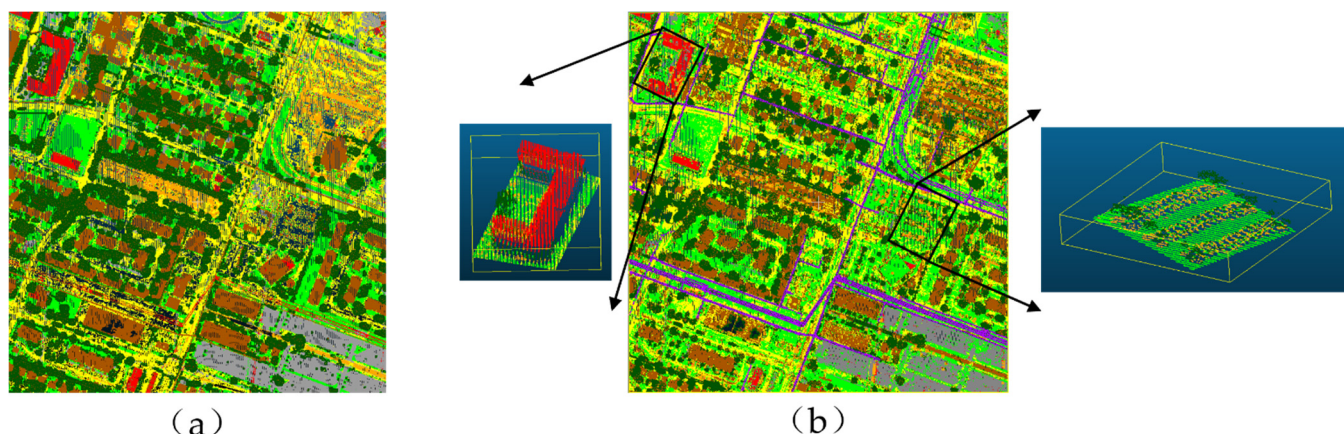
Table 6. Classification results using the random forest classifier.

	Spectral Information	Spectral + DVI	Spectral + NDVI	Spectral + RNDVI	Spectral + SR	Spectral + SAVI	Spectral + EVI2	Spectral + All Index
OA	82.22	80.73	73.29	78.97	72.27	73.09	69.45	85.12
Kappa	0.70	0.70	0.62	0.68	0.58	0.62	0.54	0.72

Adding the spectral index of the experimental results, we can build six spectrum index contributions as follows (Table 7).

Table 7. The contributions of the spectral indexes.

Spectral Indices	Contribution Rate	Cumulative Contribution Rate
<i>DVI</i>	25.02%	64.79%
<i>RNDVI</i>	4.89%	88.09%
<i>EVI2</i>	4.76%	92.85%
<i>NDVI</i>	2.79%	95.64
<i>SAVI</i>	2.35%	97.99%
<i>SR</i>	1.94%	99.93

**Figure 9.** (a) Classification results based on the intensity of the 1064 nm and 532 nm channels; (b) classification results based on all six spectral indices and the intensity of the 1064 nm and 532 nm channels.

3.3. Single Wood Extraction Results

We selected a set of experimental results with optimal classification findings for high vegetation and obtained tree point clouds with a classification accuracy of 92%. In the accuracy assessment, we compared the average value of the five single-wood extraction results with the number of field survey trees to obtain the accuracy. We divide the single trees in the entire area into 377 trees by using a segmentation algorithm. After the single wood is segmented, it will be randomly rendered with colors (repeated colors are not applicable within 20 m). This value is higher than the true value of 308 trees obtained via hyperspectral images using the final segmentation algorithm. The segmentation results indicate that the majority of urban single trees can be effectively extracted, while a few trees gathered together will be under-segmented. In addition, the distance between some scan lines is different owing to the actual scanning situation of Titan. Hence, the over-segmentation of trees appears in the left-center position of the entire region (Figure 10b). After point cloud down-sampling, the segmentation result of 329 trees is generally close to the real value, which indicates the effectiveness of the proposed method in urban tree extraction (Figure 10c). We also compared the single-wood segmentation without the pretreatment stage for point cloud data. Due to the strength of the interpolation with no segmentation, the point cloud interpolation as part of the spectrum information is not accurate, which leads to low classification accuracy. Some other points are classified as trees, so the result of the single-wood quantity is much higher than the real single-wood quantity. In Table 8, we compared the results of single-tree segmentation of point clouds with and without down-sampling. We used the actual number of trees divided by the total number of trees that are segmented as a measure of accuracy. Because the geometry of the point cloud is optimized, it can be seen that the point cloud after down-sampling is more accurate in the segmentation results. In addition, the combination of a passive spectrometer and one-channel lidar is another solution. We combined the hyperspectral data provided by Titan with the point cloud data to obtain the hyperspectral point cloud data. The spectral

coverage of hyperspectral point cloud data is 374.4–1047.1 nm and the spectral resolution is 15 nm. To compare the ability of multispectral lidar data with single-band lidar data and the combination of a passive spectrometer and one-channel lidar in the urban point cloud classification and urban single-tree extraction, we used three single-band lidar data provided by Titan and hyperspectral point cloud data for classification. After classification, the tree point cloud is obtained for segmentation. The results show that the single-tree extraction ability of multispectral lidar data is higher than single band lidar data, and the hyperspectral point cloud data have similar capabilities to multispectral point cloud data (Figure 11, Table 8).

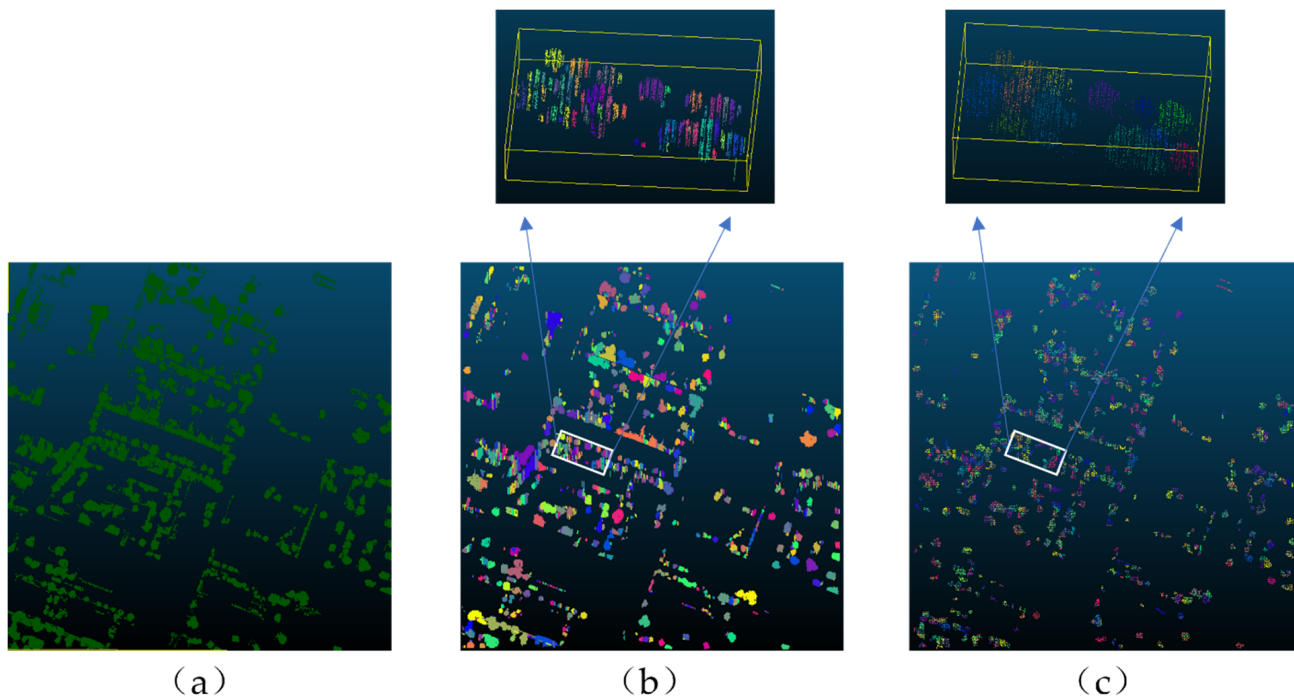


Figure 10. (a) Tree point cloud; (b) single-wood point cloud before down-sampling; (c) single-wood point cloud after down-sampling.

Table 8. Single-wood segmentation accuracy evaluation.

	Number	Accuracy
No. of Field-Surveyed Trees	308	
No. of Lidar-Detected Trees (unsegmented data)	404	76.2%
No. of Lidar-Detected Trees	377	81.7%
No. of Lidar-Detected Trees (after down-sampling)	329	93.6%
No. of Lidar-Detected Trees (532 nm channel lidar data)	451	68.3%
No. of Lidar-Detected Trees (1064 nm channel lidar data)	582	52.9%
No. of Lidar-Detected Trees (1550 nm channel lidar data)	551	55.9%
No. of Lidar-Detected Trees (hyperspectral point cloud data)	335	91.9%

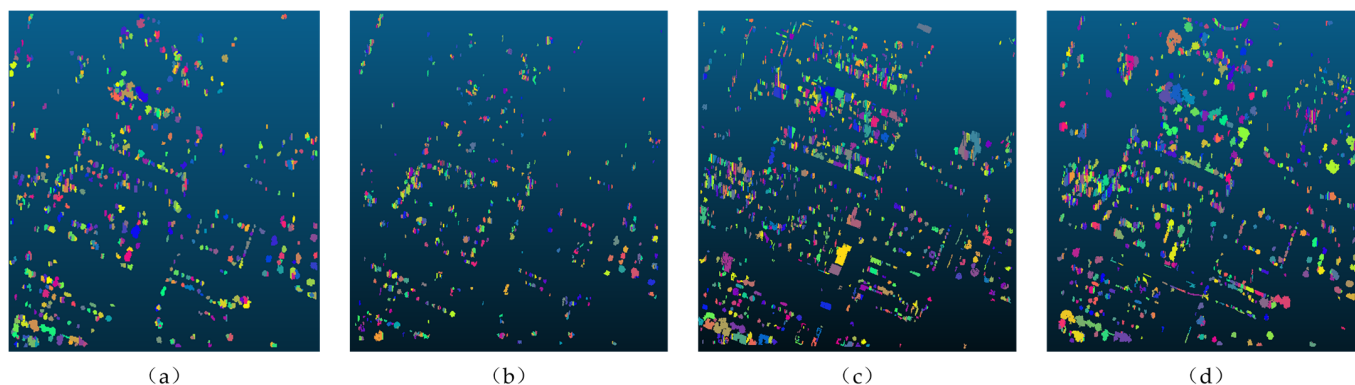


Figure 11. (a) Lidar-detected trees (hyperspectral point cloud data), (b) lidar-detected trees (532 nm channel lidar data), (c) lidar-detected trees (1064 nm channel lidar data), (d) lidar-detected trees (1550 nm channel lidar data).

4. Discussion

The point cloud data provided by the Titan multispectral lidar contain extensive geometric and spectral information. Through in-depth mining of spectral information, the land cover classification ability of point cloud data has been substantially improved. We can effectively obtain different categories of point clouds in complex urban environments and provide effective support for subsequent tree detection.

Based on single-wavelength lidar point cloud data interpolation, we first eliminate point clouds with spectral and geometric position anomalies. Thereafter, studying the segmentation of point clouds enables us to effectively eliminate the adjacent interference features of interpolation. In the subsequent interpolation, we also attempt to use other methods for interpolation. Lastly, we choose to utilize the inverse distance weighting method, but eliminating the search radius did not lower the error of the point cloud. It reduces the incidence angle of laser scanning and intensity error caused by multiple echoes, thereby further improving our demand for the accuracy of spectral information [49,50].

In addition to the categories and features of the target ground objects, we select only six spectral features in consideration of the limitations of the band constructed by part of the spectral index and the influence of data redundancy when constructing the spectral index. We will consider active and passive fusion in subsequent research to improve the number of spectra of point clouds and obtain hyperspectral point clouds. Research on the feature construction of point clouds will also be conducted. The results show that the geometric, spectral, and spectral index information of multispectral lidar can be used to obtain the highest accuracy of classification. The contribution of spectral indices constructed using the 1064 and 532 nm channels to improve the classification accuracy is mainly reflected in the distinction between vegetation and non-vegetation. The classification results indicate that the spectral index can significantly improve the distinction between vegetation and non-vegetation. In addition, the number of our training samples is large enough, and the sample labels have high accuracy when selected manually. Using intensity interpolation, we improve the information accuracy of spectral dimension through the information advantage of data space dimension. This treatment reduces the noise of the sample. Additionally, our parameters are selected, and the number of parameters is small. These reasons all lead to our results not overfitting. The accuracy of tree point cloud extraction can reach 92%. In addition, the vegetation index constructed via the 1064 and 532 nm channels is close to the normalized greenness vegetation index, thereby indicating its satisfactory vegetation discrimination ability. Compared with traditional single-wavelength lidar and hyperspectral sensors, multispectral lidar has shown advantages in ground object classification [56]. In the process of urban single-wood segmentation, considering the distribution and category of urban single trees, we chose the single-wood segmentation method based on point clustering. Lastly, some point clouds continue to exhibit abnormal

intensity and segmentation results, although the proposed preprocessing method can effectively improve the single wood extraction accuracy. So, the optimization in the spatial dimension is taken into account by trying different methods of down-sampling. Finally, the octree descending sampling method, which can preserve the spatial characteristics of the point cloud to the greatest extent, is selected [67]. The over-segmentation phenomenon caused by aerial linear scanning was solved in the process of single wood extraction. In Figure 9 we have circled the areas where the effect is obvious. We also compare the ability of single-channel lidar data and hyperspectral point cloud data (the combination of a passive spectrometer and one-channel lidar) for urban point cloud classification and urban single-tree extraction. The results show that the capability of single-band lidar in this respect is lower than multispectral lidar data. We found that when we extracted tree point clouds by classification, using single-channel lidar makes it difficult to accurately extract tree point clouds. This is slightly better at the 532 nm channel. The results of the hyperspectral point cloud data show similar capabilities to multispectral point cloud data. The accuracy of acquiring tree point clouds in hyperspectral point cloud data is higher than that in multispectral point cloud data theoretically. We consider it to be caused by inaccurate registration during active and passive data fusion.

5. Conclusions

This paper research the optimization of multispectral lidar point cloud data in terms of space and spectrum to improve the accuracy of urban point cloud classification and urban single-wood extraction.

We propose an urban tree extraction method suitable for multispectral lidar point cloud data. By comparing the results before and after the experiment, we reach the following conclusions. We can ensure that all interpolation point clouds are the same object point clouds and eliminate errors through segmentation and interpolation. The final classification result can be improved by 3.7%. The results of the k-means and random forest classifiers showed that the maximum experimental classification accuracy is achieved using geometric, spectral, and six groups of spectral feature information. The increase is about 18.28%. The existing single-wood segmentation algorithm can effectively extract single trees after obtaining the tree point cloud and provide effective data support for the follow-up study on urban biomass and carbon storage. In the process of urban single-wood segmentation, considering the distribution and category of urban single trees, we chose the single-wood segmentation method based on point clustering. Lastly, some point clouds continue to exhibit abnormal intensity and segmentation results, although the proposed preprocessing method can effectively improve the single wood extraction accuracy. The precision of the laser radar-extracted single-wood assessment method, in addition to other important indicators, should be focused on single-wood space position. The reason is that we lack access to accurate field measurement data, and in the results section we only discuss single wood quantity after the split because using multispectral lidar point cloud data to extract a complex scene requires feasibility validation. We will select an appropriate area in a subsequent experiment to verify the spatial location accuracy of single-wood extraction.

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