Comparative Analysis of Forest Ecological Parameters based on Small Spot Lidar

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Abstract: In order to better analyze the characteristics of forest ecological parameters, the comparative analysis method of forest ecological parameter characteristics based on small-spot lidar is proposed through the research and analysis of relevant investigation results at home and abroad. Combined with the least square method, the input and output collection of deleted ecological parameter characteristics is carried out, and the inversion and classification processing are carried out according to the collection results. Finally, the effective comparison of forest ecological parameter characteristics under different types of parameters is realized. Finally, the experiment proves that the comparative analysis method of forest ecological parameter characteristics based on small spot lidar is more practical than the traditional method.

Keywords: Small light spot; Lidar; Forest ecology; Parameter characteristics

1. Introduction

Human activities affect and change the earth's ecosystem on which life depends at an unprecedented speed and intensity, resulting in worldwide ecological environment problems, such as global climate change, loss of biodiversity, reduction and degradation of ecosystem services, etc. resulting in serious threats to the earth's sustainable development capacity [1]. Real-time, rapid and accurate monitoring and analysis of forest ecosystem parameter characteristics is helpful to correctly evaluate the role of human activities in environmental changes, so that decision-making departments can effectively manage and control. The rapid development of lidar technology, especially the emergence of airborne small-spot waveform lidar, provides a new technical means for the extraction of forest ecological parameters and a favorable guarantee for the automation and scientific management of forest resources survey [2]. Forest parameters retrieved by high-precision lidar can also be used as training data and verification data for other remote sensing methods. Although lidar technology has shown strong advantages in forest resources investigation, its mechanism, data analysis and remote sensing application need to be further improved compared with traditional optical remote sensing, which has a long development time and more mature theory and application [3]. In view of the rapid development of small-spot lidar system and the huge demand of forestry application, the processing algorithm of small-spot lidar data and the estimation method of forest ecological key parameters are studied, the characteristics of forest ecological parameters are analyzed, the decomposition and calibration algorithm of forest spot data are developed, the classification and comparison of ground objects are carried out by using waveform characteristic parameters, and the methods and estimation processes of forest leaf area index and forest single wood ecological characteristic parameters based on waveform data are developed, so that the comparative analysis of forest ecological parameter characteristics based on small-spot lidar is realized.

2. Definition of Forest Ecological Parameters Based on Small Spot Lidar

Forest ecological parameter is an important index to measure the productivity of ecosystem, and is also an important foundation to study the material circulation of forest ecosystem. As the main body of terrestrial biosphere, the characteristics of forest ecological parameter are of great significance to the study of global climate change [4]. Traditional forest ecological parameter characteristic statistics are based on measured data and require a large number of field investigations. The workload is large and the cycle is long. When estimating the ecological characteristic parameters of large-area stands, it is often difficult to obtain the measurement data per wood of the stand to be measured. With the rapid development of small-spot lidar technology, multi-source remote sensing data including aerial photographs, optical remote sensing images, microwave radar and lidar have been applied to the monitoring and information extraction of forest types, distribution and structural characteristics, providing a fast, economical and convenient way for large-scale forest ecological characteristic parameter estimation and long-term dynamic change research.

The study of forest ecological parameter characteristics using optical remote sensing data started earlier, but its signal penetration was poor, so the horizontal structure information of forest was mainly recorded [5].Synthetic

Aperture Radar (SAR) operating in a specific wavelength range has certain penetrating ability to vegetation and can estimate ecological characteristic parameters by backward scattering [6]. However, microwave is greatly disturbed by topographic relief and is easily saturated when vegetation canopy is closed or ecological characteristic parameters are high, thus limiting its application in estimation of regional ecological characteristic parameters. Lidar is an active remote sensing technology developed rapidly in recent years. It has strong penetrating ability to forests and has significant advantages in obtaining forest structural parameters. However, the small spot lidar also has some limitations such as high cost, limited coverage and large amount of data, which limits its application in extracting spatial structure information of large area forests [7]. The small-spot lidar with complete waveform can describe the spatial structure information of forest canopy, record the energy value of light spot changing with time, acquire more forest canopy information than the small-spot lidar, and theoretically have the ability to acquire global data. At present, the new technology represented by small spot lidar has gradually become an important measure in forest ecological parameter measurement, and is playing an incomparable advantage [8]. At present, it is a hot spot to fuse small spot lidar data with other optical or microwave remote sensing data to study the characteristic parameters of forest ecological parameters, which has great development potential.

3. Research Method of Forest Ecological Parameter Characteristics Based on Small Spot Lidar

3.1 Characteristic collection of forest ecological parameters

This is also the key difficulty in estimating forest canopy density using the pixel binary model based on vegetation index, i.e. how to determine the two threshold values of NDVI NDVInon-crown is different from NDVIsoil, which is slightly changed under the influence of atmosphere and surface humidity, but the range is generally controlled between -0.1~0.2; However, NDVInon-crown is also affected by undergrowth vegetation, and this effect will vary greatly depending on the forest type. Therefore, different thresholds should be set for different forest types instead of fixed NDVIcrown and NDVInon-crown values to improve the estimation accuracy of the model. According to the frequency statistics of NDVI data, the frequency cumulative value of NDVI data is calculated, and NDVI values at four locations with distances of 2%, 1%, 0.5%, and 0.2% are set as corresponding NDVIcrown and NDVImin-Crown values [9]. At the same time, the measured forest canopy density value is verified and compared with the canopy density estimated based on each threshold value to obtain the optimal threshold value N of each forest ecological type, and then the regional inversion parameter I of forest canopy density in the research area is carried out on AcrGIS platform [10]. For the prediction effect of the model, the determinable coefficient y and the root mean square error yi are used to test, and the algorithm is as follows:

$$R^2 = \sum_{i=1}^{n} (\hat{y}_i - \bar{y}) / \mathrm{NDVI} \sum_{i=1}^{n} (y_i - y)^2 \tag{1}$$

$$RMSE = (\mathrm{NDVI}_{\mathrm{crown}} - \mathrm{NDVI}_{\mathrm{non-crown}}) \sqrt{\sum_{i=1}^{\mathrm{n}} R^2 / (n-1)} \tag{2}$$

Due to the operation of parameter acquisition, the acquired data are not at the same time, and changes in different weather conditions or equipment performance will lead to differences in the echo energy data acquired at different times [11]. Therefore, in order to make the data acquired at different times comparable, the waveform data are standardized by using the formula.

$$V_R = \sum_{i=1}^{n=554} RMSE \cdot (V_{\mathrm{i}} + V_n) \tag{3}$$

Where Vi is the capability value and Vn is the standard waveform parameter. According to the above algorithm, the forest ecological parameter waveforms collected by lidar can be obtained through standardization, as shown in the figure below:

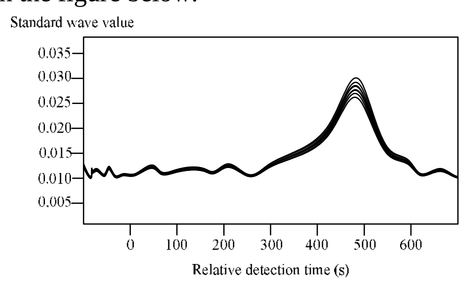

Figure 1. Waveform of forest ecological parameters

According to the above figure, noise is collected from forest ecological parameters. Effective noise removal can improve the accuracy and speed of data processing [12]. According to the characteristics of noise in forest waveform data collected by small-spot lidar lidar, the waveform data is converted to the frequency domain for processing, and the low-value part with higher frequency is taken as the judgment standard of noise level, so as to effectively and dynamically judge the noise level [13]. At the same time, the second derivative method is used to effectively judge the initial values such as the number, position and amplitude of the initial waveform. Finally, the nonlinear least square method is used to fit the original data. So as to effectively complete the collection of characteristic parameters.

3.2. Inversion of forest ecological parameters

Echo data received by small-spot lidar is affected by many factors. In order to correctly evaluate the response of ground objects to laser pulses, the influence of these factors must be eliminated [14]. Compared with discrete lidar data, waveform data can not only provide the three-dimensional coordinate information of the target, but also faithfully record the echo signal after the launch pulse and the target act. The characteristic information of the target can be obtained through the processing of echo data, and an important role of this information is to classify the target [15]. On the basis of Gaussian decomposition and relative radiation calibration of waveform data, this paper adopts the method of rasterizing original data to study the ability of waveform data to classify ground objects [16]. On the basis of single wood separation, the waveform characteristic parameters of forest ecology are extracted and the recognition accuracy of characteristic parameters and the influence of relative calibration on classification results are quantitatively evaluated in combination with field survey data.

After the data collection is completed, the collected data are classified and integrated, and the division method mainly adopts a multiple linear regression method of backward type, and the best ecological characteristic parameter estimation model is determined by comparing the determinability coefficient R2 and RMSE(R2 is the largest and RMSE is the smallest) of each regression model [17]. At the same time, the index factor introduced in this model is the result of variable screening. It is found that the more parameters are introduced, the better the accuracy of the model is not necessarily. On the contrary, the appropriate index factor model has the highest accuracy and good stability [18]. The classification model algorithm is as follows:

Class A feature type:

$$\text{Biomass}\ (A) = SLAVI * V_R * H_A - fcover(A) * MSR * \text{NDVI}_{\text{non-crown}} + WI * \text{NDVI}_{\text{crown}} - LAI \tag{4}$$

Class B feature type:

$$\text{Biomass}\ (B) = SLAVI * V_R * H_B - fcover(B) * MSR * \text{NDVI}_{\text{non-crown}} + WI * \text{NDVI}_{\text{crown}} - 2LAI \tag{5}$$

Class C feature type:

$$\text{Biomass}\ (C) = SLAVI * V_R * H_C - fcover(C) * MSR * \text{NDVI}_{\text{non-crown}} + WI * \text{NDVI}_{\text{crown}} - 3LAI \tag{6}$$

Among them, Biomass is the ecological characteristic parameter in the forest ecological environment in each detection period, WI is the humidity index, MSR is the ratio vegetation index corrected by mid-infrared, fcover is the canopy canopy density, LAI is the leaf area index [19].

3.3. Comparison of forest ecological parameters

Comparing the multiple linear regression model of ecological characteristic parameters of each forest type with the corresponding regression model of ecological characteristic parameters based on the maximum canopy height, it can be found that the simulation accuracy of each forest type model is better than that of the latter, indicating that the stand height model has been significantly improved after the spectral information is integrated [20]. By comparing the prediction ability of the model with independent verification data, it can also be found that the measured values of ecological characteristic parameters of various forest types keep good consistency with the predicted values of the model. Therefore, the ecological parameters of the fused spectral information and canopy height information are used to invert the ecological parameters of the jet, and the waveform characteristic parameters of the small-spot lidar are used to study the characteristic classification parameters of the forest ecological parameters. The specific characteristic comparison algorithm is as follows:

$$N(x, y) = \begin{cases} Biomass(A) * w_1 p_{x-1,y-1} \\ Biomass(B) * w_2 p_{x-1,y-1} \\ Biomass(C) * w_3 p_{x+1,y+1} \end{cases} \tag{7}$$

The above algorithm is used to demonstrate the principle of feature comparison, as shown in the following figure:

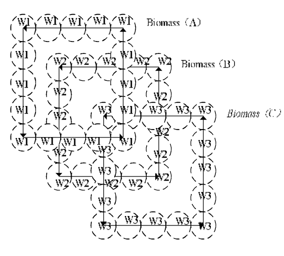

Figure 2. Comparison principle of forest ecological parameter characteristics

Combined with the above methods, the noise removal of waveform data is an important research content in waveform data processing [21]. Effective noise removal can improve the accuracy and speed of data processing. According to the characteristics of noise in the waveform data, the waveform data is converted to the frequency domain for processing, and the low value part with higher frequency is taken as the judgment standard of noise level, so as to effectively and dynamically judge the
noise level [22]. At the same time, the properties of concave-convex curves are studied. The second derivative method is used to effectively judge the initial values such as the number, position and amplitude of initial waveforms. Finally, the nonlinear least square method is used to fit the original data.

Waveform data is affected by many factors relative to echo data received by radiation calibration lidar [23]. In order to correctly evaluate the response of ground objects to laser pulses, the influence of these factors must be eliminated. On the basis of introducing the lidar equation, this paper analyzes the influencing factors of lidar waveform data. In the process of relative radiometric calibration, the influence of the change of emission pulse energy and the change of distance between the laser and the target on the echo is considered. At the same time, the description of different scattering targets in the radar is introduced, the corresponding physical meaning of different correction factors based on distance is explained, the final calibration formula is given, and the calibration results are compared and evaluated by using the data in the research area. On the basis of Gaussian decomposition and relative radiation calibration of waveform data, the ability to classify waveform data into ground objects is studied by rasterizing the original data. Based on the separation of single wood, the waveform characteristic parameters of single wood are extracted and combined with field work. The survey data are used to compare and analyze the accuracy of tree species identification and the influence of relative calibration on classification results.

4. Research Progress at Home and Abroad Based on Characteristics of Forest Ecological Parameters

Traditional statistics of forest ecological characteristic parameters are based on measured data and require a large number of on-site investigations. The workload is large, the cycle is long, and certain damage is caused to the physical objects. When estimating the ecological characteristic parameters of large-scale stands, the data of each wood gauge of the stand to be measured are often difficult to obtain. With the rapid development of remote sensing technology, a fast, economical and convenient way is provided for the estimation of large-scale forest ecological characteristic parameters and the study of long-term dynamic changes.

At present, people can investigate the forest ecosystem through optical remote sensing, microwave radar, laser radar and other sensors, thus forming a variety of remote sensing data to be applied to the estimation of forest ecological characteristic parameters, greatly improving the accuracy and rapidity of estimation, without damaging on-site organisms, being capable of estimating forest ecological characteristic parameters in a long-term, dynamic and continuous manner, and having irreplaceable advantages in large-scale forest ecological characteristic parameter estimation.

Starting from the current main remote sensing data sources, remote sensing estimation methods and research progress of forest overground ecological characteristic parameters are discussed in detail, and their respective advantages and disadvantages are pointed out. In particular, the importance of retrieving forest overground ecological characteristic parameters by combining multi-source remote sensing data is emphasized. In recent years, many remote sensing researches focus on the relationship between spectral response and forest structure parameters, and indirect estimation of forest ecological characteristic parameters such as base area, canopy density, tree height, DBH and leaf area index are measured by TM and other sensors. In addition, traditional multispectral remote sensing is only a few discrete bands, and images are acquired with different band widths (usually 100~200 nm), thus a large amount of spectral information about the features of ground objects is lost. However, the width of hyperspectral remote sensing waveband is generally less than 10 nm, which can subdivide the spectral waveband in a specific spectral domain to obtain detailed and continuous "atlas integration" information. These spectra can well describe vegetation characteristics.

Hyperspectral remote sensing mainly uses derivative spectrum to estimate and analyze vegetation index and ecological characteristic parameters. The application of narrow-band hyperspectral Hyperion data and wide-band IKONOS, ALI and ETM＋+in estimating ecological characteristic parameters of tropical rain forests in Africa is compared. It is found that wide-band data can only explain 13%-60% of information, while narrow-band data can explain more. APAR and ecological characteristic parameters of absorbed photosynthetic active radiation were estimated by hyperspectral analysis.

Using the satellite EO-1 Hyperion hyperspectral remote sensing data for forest type identification and canopy density quantitative estimation, good results have been obtained. The hyperspectral vegetation index calculated by Hymap data has a significant correlation with the ecological characteristic parameters of mangrove sample plots, but the regression model obtained by hyperspectral vegetation index has a weak consistency between the estimation of mangrove ecological characteristic parameters and the measured ecological characteristic parameters, indicating that the existing hyperspectral vegetation index still has many defects in the feasibility of estimating forest ecological characteristic parameters, and how to mine effective information from a large amount of information to estimate ecological characteristic parameters is the key. At present, optical remote sensing images have certain advantages in obtaining horizontal structural parameters, but due to their poor penetrability, they still have a certain distance to be applied to the inversion of vertical structural parameters, and are prone to saturation and poor sensitivity in obtaining forest ecological characteristic parameter information.

5. Summary and Prospect

5.1. Result analysis

In order to verify the accuracy of comparative analysis of forest ecological parameter characteristics based on small-spot lidar, comparative experiments were carried out. The extracted original spectrum and correlation analysis results of vegetation index and measured forest canopy density were compared with the accuracy of traditional parameter acquisition and the effectiveness of parameter acquisition based on small-spot lidar. The comparison results are as follows Figure 3.

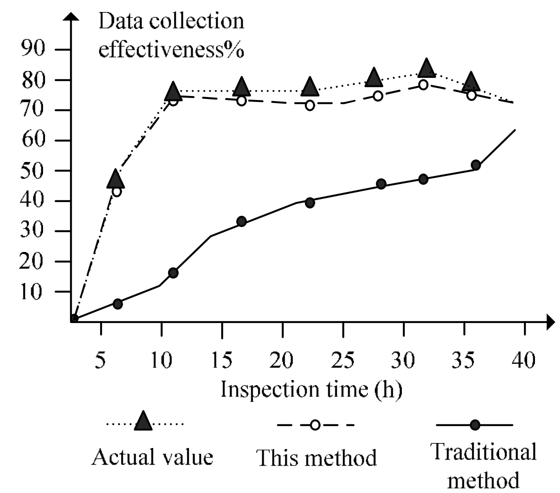

Figure 3. Comparison test results of data acquisition effectiveness

In order to further detect the comparative analysis effect of forest ecological parameter characteristics based on small spot lidar, the accuracy of the two methods is compared. The results are as follows Figure 4.

Investigation shows that in the process of detecting the accuracy of forest ecological parameter feature comparison, the denoising effect has a direct impact on the accuracy, and the better the denoising performance is, the higher the accuracy of feature comparison is. On this premise, it is not difficult to find that the comparative analysis method of forest ecological parameter characteristics based on small-spot lidar proposed in this paper is far superior to the traditional method in terms of data collection and accuracy of data analysis, compared with the traditional method.

5.2. Conclusion

The characteristics of forest ecological parameters are collected and analyzed by using small-spot lidar technology, and index remote sensing inversion calculation is carried out by combining multiple linear regression and least square method. Research shows that the partial method can be used for large-scale leaf area feature collection and index inversion with high prediction accuracy. Experiments prove that its detection junction is obviously superior to the traditional method.

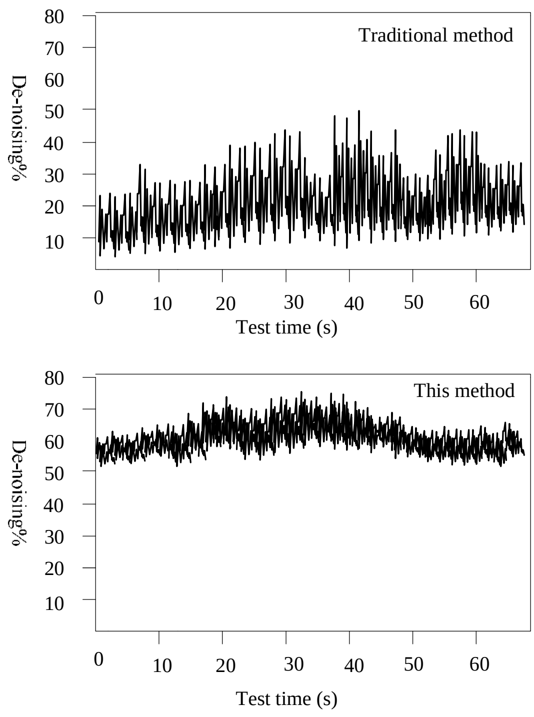

Figure 4. Denoising detection results

However, there are still some problems in this study, that is, due to thick cloud cover and no good matching of remote sensing images in the detection process, considering that the changes for forests are not very large, the remote sensing data of 2017 in the same period are selected for research and analysis. At the same time, in order to reduce the influence of atmospheric effect on remote sensing image data as much as possible, the MORTRAN4+ radiation transmission model is corrected based on FLAASH atmospheric correction, thus achieving the goal of image correction.

Research shows that for complex forest ecosystems, it is difficult to achieve the need of modeling and retrieving LAI by only relying on a single band or vegetation index, and the integration of various index factors can better improve the accuracy of remote sensing estimation. The study also found that the introduction of terrain index did not improve the prediction effect of the model. Judging from the inversion capability of the model, no matter the multiple linear regression method or the partial least square method, the more complex the structure, the greater the spatial difference, and the more difficult it is to accurately grasp the change characteristics of forest community structure. However, due to the limitation of manpower, material resources and financial resources, the measured data of field forest sample plots are not very abundant, so the method and the lecture conclusion need to be further optimized.

5.3. Prospect

The characteristics of forest ecological parameters are compared with small-spot lidar technology. From the pretreatment of data collected from field sample plots, such as atmospheric correction, radiation correction, geometric correction, interpretation and classification, leaf area index, canopy density inversion, to the realization of GLAS complete waveform data processing algorithm, the maximum canopy height estimation model suitable for complex terrain conditions is constructed, and then the spatial expansion of forest canopy height and ecological characteristic parameters at the regional scale is carried out, and a complete and systematic exploration is carried out.

However, due to the shortage of measured data, the complexity of terrain conditions and the spatial heterogeneity of forest vegetation at different scales, currently, the accuracy of retrieving regional forest canopy height and ecological characteristic parameters from multi-source remote sensing data is not accurate enough, and a series of researches need to be continued: Under complex terrain conditions, both optical remote sensing images and large spot lidar data will be affected by terrain effects. Spectral information directly affects the retrieval precision of vegetation physiological structure parameters, while GLAS waveform data is affected by terrain, the light spot range becomes larger, and more non-vegetation information is integrated, which affects the extraction of key parameters and tree height inversion. Therefore, how to reduce the impact of terrain is the focus of future research in mountain areas, and how to effectively use GLAS waveform data in areas with large slope impact is also the key problem of current research.

At present, most researches are still based on the correlation between remote sensing data or its index and vegetation physiological structure parameters to establish empirical models for regional scale spatial inversion. However, the empirical model has its inherent disadvantages and poor temporal and spatial portability. Although the artificial intelligence algorithm has high precision, it is not easy to explain the mechanism. Therefore, it is more potential to develop radiation transmission models or to integrate remote sensing data with ecosystem process models for inversion of ecological characteristic parameters.

6. Concluding Remarks

The processing of small spot waveform lidar data is the premise of its forestry application, and is also the basic work of leaf area index inversion and ecological characteristic parameter inversion. This chapter first introduces the composition and working principle of lidar system, the development of waveform lidar system, the characteristics of waveform data and its application advantages in forestry. It is inconvenient to directly use waveform data, which needs further processing. The non-linear least square method is used to process the waveform data by Gaussian fitting. The workflow and important processing steps of waveform decomposition are described in detail. Using waveform data for data classification is one of its important advantages. However, using uncalibrated data for classification often has certain problems. Therefore, on the basis of Gaussian decomposition, relative radiometric correction is carried out on the decomposed data to improve the accuracy and precision of classification results. Finally, the decomposition results and the relative radiation calibration results are analyzed.

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