Application of Liar Remote Sensing Forest Leaf Area Index Extraction Method Based on Big Data Network

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Abstract. In the past, liar was mainly used to study forest ecosystem flight time. So far, the ecological application of SLR is mainly to use one-dimensional index to characterize the canopy height. A new 3D analysis method of liar waveform is proposed. Many models developed before are scale dependent and need to be fitted and then applied with the same scale or pixel size. A method of scale invariant estimation of forest biomass based on liar data is proposed. Two equivalent biomass models were proposed: linear biomass model and linear biomass model. The development of sensors and algorithms is evaluated. The specific areas discussed include the selection of analysis units (grid units, segments or individual trees), canopy height model and point based analysis, the role of multiple benefits and benefit intensity, and the comparison of common algorithms. The results showed that the highest biomass of bark was 0.2645, the lowest biomass of above ground was 0.0267, and the biomass of branch was 0.021 higher than that of trunk.

Keywords: Big Data, Network, Liar Remote Sensing, Forest

1. Introduction
With the continuous progress of science and technology, big data technology has become an indispensable part of our life. For a long time, canopy structure has been considered to affect the productivity and ecological dynamics of tropical forests by changing the availability of leaves to light. However, there is still a lack of theories and methods to link detailed quantitative observation of canopy structure with forest dynamics.

With the development of information technology, there are more and more researches on remote sensing of forest leaf area using liar. For example, some research groups in China have studied extracting key forest structure parameters from multi-purpose remote sensing data, and established and tested predictive models for estimating photosynthetic pigment concentrations in broad-leaved and coniferous plantations using airborne imaging spectrometer and liar instruments. A prediction model of wood volume, trunk volume, above ground biomass and basal area based on canopy structure, site and liar characteristics was proposed. This new modeling method does not use the standard stepwise regression method, but uses a series of height measurements obtained from airborne liar. According to
the information difference among different echo types of airborne LiDAR discrete point cloud data, the airborne LiDAR point cloud data is used to dilute the point cloud data, and the average forest height is estimated by linear regression model. Based on the energy information of Airborne LiDAR point cloud, the point cloud is stratified according to the height of the point cloud, and the total energy of each layer is calculated. According to the distribution of point cloud energy with point cloud height, the maximum point cloud energy height $h$ and canopy energy height $h$ were proposed, and the extracted variables were modeled by RBF neural network to predict Forest Above ground biomass. The correlation factors of slope and aspect are extracted from DEM by point cloud filtering, and the linear and nonlinear combination parameters are extracted from Landsat. Established multiple regression model and BP neural network model for biomass estimation, and discussed the best model construction method in this study area [1]. Some experts have studied the remote sensing estimation and analysis of forest biomass in Northeast Forest Region, analyzed the forest distribution in the study area, which can better estimate the biomass, and verified it according to the measured data and the estimated data of validation samples. Compared with the regression model, the accuracy of this method is greatly improved [2]. In addition, some experts have studied the application of 3D imaging LiDAR remote sensing technology in forestry, introduced the research status of airborne full waveform LiDAR data, and used the barometrically growth equation, litter sampling analysis or optical remote sensing data to calculate indirectly. Using LiDAR data to estimate LAI can obtain LAI at any position of LiDAR data coverage area, and select the most relevant structural parameters from the three types of structural parameters to monitor forest tree species diversity. Combined with individual tree separation results and canopy scale conversion, the effects of thunderstorm shrub and canopy structure on individual tree spectral characteristics were excluded. For example, the time and scope of data acquisition and the basic indicators of the scanning system can fully confirm the authenticity and reliability of the research data [3]. Although the research on LiDAR remote sensing of forest leaf area is quite fruitful, the research on LiDAR remote sensing of forest leaf area index extraction method based on big data network is still insufficient.

In order to study the LiDAR remote sensing forest leaf area index extraction method based on big data network, the LiDAR remote sensing technology is studied, and the radar equation is found. The results show that the LiDAR remote sensing technology based on big data network is conducive to the extraction of forest leaf area index [4].

2. Method

2.1 LiDAR Remote Sensing

(1) LiDAR remote sensing

Due to the lack of reliable estimation of biophysical properties of forest canopy and stand structure, it can not meet the data and information needs of forest, landscape and global ecologists. It measures and samples the earth's surface and its characteristics point by point. Therefore, LiDAR can provide spatial explicit measurement of canopy height. LiDAR topographic mapping remote sensing technology is a new scientific mapping technology widely used, which plays an active role in engineering, scientific research and other fields. Hyper spectral remote sensing data are mainly used to monitor forest species diversity. The first one is based on Hyper spectral classification technology to monitor forest species diversity through tree species identification. The second one is based on spectral vegetation index calculated from hyper spectral data of specific bands to detect biochemical components of vegetation to distinguish different tree species. Hyper spectral data can provide detailed spectral information of forest tree species, and airborne LiDAR data can provide structural parameters of forest tree species. The combination of LiDAR and hyper spectral data for forest species diversity monitoring is the mainstream of forest species diversity remote sensing monitoring [5].

(2) Application of LiDAR in remote sensing

At present, the research progress of airborne radar in foreign countries far exceeds that in China. For example, the UAV detection system, as we all know, is to apply its technology to the UAV, so that
the airborne radar can detect the target area through remote control, so as to improve the detection flexibility [6]. Through airborne, it greatly expands the depth and height of the detection, improves the work efficiency, and uses airborne to quickly capture the movement between the city and the places that are difficult for people to reach. This kind of controllable airborne radar can be used in all kinds of harsh environments, and in the actual operation process, it can repeatedly measure some places that are difficult to determine, so as to further improve the accuracy of its surveying and mapping data. In addition, airborne radar can also sample some underwater relics. (2) Space borne radar. The main purpose of space borne radar is to apply its radar mapping system to the satellite system, so as to capture the space environment and obtain the corresponding data. At present, it has been widely used to monitor the activities of the moon, Mars and outer space, providing more detailed information for people to study its activities. Generally speaking, when mapping, space borne radar will rotate and circle through the relevant settings, so as to record the terrain, geological characteristics, atmospheric activities and other data of the planet surface, and obtain the relevant information through the linkage with the ground control system. (3) Horological mapping. In addition to topographic mapping, in the process of ground detection, horological detection has gradually become a new application, especially in recent years, through the combination of computer network technology and GPS positioning system, horological environment monitoring gradually gets rid of the past history of manual measurement [7]. In addition, for large-scale horological natural disasters, through long-term monitoring, early warning can be issued in time to avoid personnel and local economic losses. For suspicious places, we can track them in real time until the hidden danger is eliminated [8].

2.2 Radar Equation

The radar equation is the expression of the physical relationship between the echo signal power received by the antenna and the parameters of the sensor and the target. Without considering the influence of atmosphere, the echo power received by the antenna can be expressed by formula (1):

$$P_R = \frac{P_T G_T(\theta)\lambda^2}{(4\pi)^3 R_T^2 R_R^2} \sigma A$$

(1)

When electromagnetic wave propagates in space, when it encounters obstacles, the propagation direction and intensity of electromagnetic wave will change with the physical characteristics of chatters. It is shown in formula (2-5):

$$E_s(\vec{r}) = E_i(\vec{r}), r \in V$$

(2)

$$E(\vec{r}) = \frac{k^2}{4\pi r^2} \int \int E_{in}(\vec{r})dV, \quad r \lambda \gg 1$$

(3)

$$E_s(r, \theta, \varphi) = \frac{e^{-jkr}}{4\pi R} E_s(\theta, \varphi)$$

(4)

$$\sigma = \frac{4\pi R^2 |E_s|^2}{|E_i|}, \quad R \to \infty$$

(5)
3. Experience

3.1 Experimental Object Extraction

There will inevitably be gross errors, errors or irrelevant information in the original data. For example, the reflection signal or echo signal hole problem caused by the occlusion of birds, poles and other targets, and the jumping information caused by local terrain mutation. Because the existence of outlines will affect the establishment of ground model and canopy model, so the original data are removed manually. In order to establish the ground model, the point cloud filter is used to separate the ground points and non-ground points, that is, the ground points and vegetation points. Point cloud data are distributed irregularly in space in the form of three-dimensional coordinates. For the bare ground and the roof, the laser signal does not extend down to the ground, there is only one echo, and the signal recorded by the sensor is regular. When the signal propagates in the vegetation area, the pulse will be transmitted and refracted. The sensor will record multiple echoes and the point clouds will gather together. If the vegetation coverage is high, the laser echo signal will be more complex. The first echo received by the sensor comes from the vegetation canopy, then from the lower branches, and the last echo usually comes from the ground. According to the characteristics of the echo, it can be used as a criterion to distinguish the ground point from the vegetation point. BP neural network model is a multilateralism forward neural network based on error back propagation algorithm. It was originally proposed by power ship, but it has not been well promoted. It is a mathematical model of information processing with distributed parallel method. Its characteristic is to achieve the purpose of information processing by adjusting the relationship between internal nodes. Traditional biomass estimation methods need to establish accurate estimation models. Because of the internal relationship between biomass parameters, this method is difficult to describe accurately. Neural network modeling method has the characteristics of large-scale parallel processing, adaptive and fault-tolerant. At present, this nonlinear intelligent prediction algorithm has become a hot spot in forest biomass estimation [9].

3.2 Experimental Analysis

Forest horizontal structure parameters can describe the structure information and distribution of vegetation in horizontal direction. The traditional method of extracting forest horizontal structure is to use optical remote sensing data directly through remote sensing physical model. However, the surface reflectance of optical data is easily affected by atmospheric conditions and canopy structure, which affects the extraction accuracy of forest horizontal structure parameters. Airborne liar data has the advantages of all-weather and high penetration, which can overcome the atmospheric conditions to obtain high-precision horizontal structure parameters [10]. In terms of horizontal structure parameters, the canopy width, canopy coverage and Lai were extracted from airborne liar data. Among them, canopy size reflects the growth state of forest vegetation through the exchange of material and energy with the outside world through photosynthesis, transpiration and transpiration. Firstly, the single tree point cloud is segmented and the crown width is extracted. Taking CHM as data source, the filtered point cloud data and classified point cloud data are interpolated to generate DSM and DEM, and then CHM is obtained according to the difference between them. Then, the grid CHM is segmented according to the watershed segmentation algorithm, and the crown width is directly extracted according to the area surrounded by the crown edge. Canopy coverage refers to the degree of canopy covering the ground, which is an important indicator of stand structure and density. Lai is one of the important parameters to characterize the total canopy area and net photosynthetic point [11].

4. Discussion

4.1 Above Ground Biomass Statistics

The above ground biomass of each plot can be determined by the relative growth equation of trees, mainly by DBH and tree height. The above ground biomass of trees can be obtained by certain empirical formula, including total biomass, leaf biomass, stem biomass (stem + bark) and branch
biomass. As shown in Table 1.

Table 1. Metrical growth diagram of biomass

| Biomass       | MSE  |
|---------------|------|
| Above-ground  | 0.0267 |
| Stem biomass  | 0.1643 |
| Bark biomass  | 0.2645 |
| Branch biomass| 0.1853 |

It can be seen from the above that the above ground biomass is 0.0267, the trunk biomass is 0.1643, the bark biomass is 0.2645, and the branch biomass is 0.1853. The results are shown in Figure 1.

Figure 1. Metrical growth diagram of biomass

It can be seen from the above that the highest value of bark biomass is 0.2645, the lowest value of above ground biomass is 0.0267, and the branch biomass is 0.021 higher than the trunk biomass.

4.2 Application of Small Spot Liar in Forest Classification

Radiometric correction of liar data, standardization of intensity classification rules, acquisition of full waveform data and effective decomposition of waveform data are still the main factors restricting the application of small spot liar data in forest classification [12]. With the development of multi-purpose remote sensing data, the combined application of data sources can improve the accuracy of tree species classification, which is an aspect of future research. As shown in Table 2.

Table 2. Examples of forest classification using small spot liar

| Classified tree species | result |
|-------------------------|--------|
| Mature pine             | 26%    |
| Immature pine           | 35%    |
| Mature broad leaved tree| 39%    |

It can be seen from the above that the proportion of mature pine trees is 26%, the proportion of immature pine trees is 35%, and the proportion of mature broad-leaved trees is 39%. The results are shown in Figure 2.
5. Conclusion
In recent years, as an active remote sensing technology, LiDAR has shown great potential in this work because it can accurately measure above ground biomass and canopy height. Terrestrial laser scanning (TLS) uses tiny laser footprints to analyze three-dimensional structure quickly and accurately, which provides a new opportunity for ecosystem research. However, its practical application largely depends on the effectiveness of LiDAR analysis method. In order to better use TLS to describe forest canopy characteristics, we established a methodology paradigm, combining physics and statistics, and obtained leaf profile, leaf area index (LAI) and leaf angle distribution (LAD): established a probability model of laser vegetation interaction, and developed maximum likelihood estimation (MLE) vegetation parameters of laser vegetation interaction. LiDAR enhances the rendering ability of remote sensing leaf area index (LAI) and improves the rendering accuracy. This paper discusses the application potential of LiDAR data in stand parameter estimation.

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