

Review of Noise Filtering Algorithm For Photon Data

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ABSTRACT:

As a continuation of Ice, Cloud, and Land Elevation Satellite-1 (ICESat-1)/Geoscience Laser Altimeter System (GLAS), the Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2), which is equipped with the Advanced Topographic Laser Altimeter (ATLAS) system, was successfully launched in 2018. Since ICESat-1/GLAS has facilitated scientific results in the field of forest structure parameter estimation, how to use the ICESat-2/ATLAS photon cloud data to estimate forest structure parameters has become a hotspot in the field of spaceborne photon data application. However, due to the weak photon characteristics of the ICESat-2/ATLAS system, the system is extremely susceptible to noise, which poses a challenge for its subsequent accurate estimation of forest structural parameters. Aiming to filter out the noise photons, the paper introduces the advantages of the spaceborne lidar system ICESat-2/ATLAS than ICESat-1/GLAS. The paper summarizes the research of the simulated photon-counting lidar (PCL) noise filtering algorithm and noise filtering on spaceborne.

1. INTRODUCTION

Forest structural parameters have been listed as one of the important indicators for monitoring forest carbon by the International Union of Forest Research Organizations (IUFRO). How to quickly and accurately quantificate the forest structure parameters of the study area is great significance for monitoring forest carbon (Jandl, 2019 and Golshani, 2019). In the process of forest monitoring, forest structural parameters (such as canopy height, et al.) directly reflect the growth of forests, and have become one of the most commonly used bases in forest ecological research (Wu, 2019). Traditional forest monitoring methods are mostly acquired by manual field measurement. Although the measurement is accuracy, it has a long working cycle and low efficiency and not applicable complete large-scale, multi-scale for forest structure parameter monitoring (Piermattei, 2019).

In recent years, with the development of remote sensing technology, remote sensing technology has become a key technology for monitoring carbon, and has been identified as a monitoring method that complies with the “Kyoto Protocol” (Lefsky, 2002). Different from optical remote sensing image (Mohd, 2018) and synthetic aperture radar (SAR) (Zhang, 2019) by cloud and biomass saturation, spaceborne Light Detection And Ranging (LiDAR) technology

overcomes the above problem from the perspective of data source, and has been widely used with its efficient and accurate ranging capability. In order to acquire large-area, multi-scale, multi-temporal forest monitoring data, studies used the spaceborne lidar data to retrieve forest structural parameters. So far, two spaceborne lidar could provide scientific data, include Ice, Cloud, and Land Elevation Satellite (ICESat-1) launched by the NASA in 2003, (Wang, 2019, Hu, 2019 and Lefsky, 2010), and Ice, Cloud, and Land Elevation Satellite (ICESat-2) (Neuenschwander, 2019) successfully launched in 2018, respectively. ICESat-2 is a continuation of the ICESat-1 scientific mission, planning to provide scientific and accurate photon data for global forest biomass (Sawruk, 2018 and Markus, 2017). However, because the ICESat-2 system has the characteristic of photon-counting, the signal photons emitted and received are weak signal photons, which are greatly affected by background noise (solar background noise, system dark noise, et al.). Therefore, how to effectively filter noise photon is the hotspot in photon data processing and application (Li, 2018, Huang, 2019 and Moussavi, 2014).

In order to advance the progress of the spaceborne photon noise filtering algorithm, this paper will introduce the advantages of the spaceborne lidar system ICESat-2 and its relative ICESat-1/GLAS, and

summarize the simulated photon data noise filtering algorithm. The research prospect the trend of photon data noise filtering algorithm.

2. MAIN BODY

2.1 ICESat-2/ATLAS and ICESat-1/GLAS

ICESat-2 was successfully launched on September 15, 2018. The system is equipped with Advanced Topographic Laser Altimeter (ATLAS). The system adopt photon-counting technology, which has the characteristics of high repetitive frequency and low energy (Moussavi, 2014), the laser emission mode of the system is multi-beam emission mode, the emission mode is 3 pairs laser beam and in each pair of beams with the ratio of 4:1. This multi-beam laser emission method can increase the observation data of the same route, and can provide more information for the slope and vegetation coverage of the study area. (Molly, 2019 and Montesano, 2015). The laser emission frequency is 10 kHz. Combined with the satellite orbital altitude and satellite operating speed, the footprint size is 17m (nominal) and the footprint spacing is 0.7m. This high-frequency transmission could obtain approximate continuous information, and since ATLAS has a smaller footprint diameter than the Geoscience Laser Altimeter System (GLAS), the small footprint can more clearly describe surface features than the footprint. The small footprints are less affected by the terrain, and improving the accuracy of the measurement. These features will continue the ICESat-1/GLAS mission, providing more accurate and scientific data for global canopy height (Kelly, 2019, Christopher, 2019 and Lana, 2019).

Limited to the hardware characteristics of the ICESat-1/ATLAS system, the laser emission mode of the system is single beam transmission mode, the laser emission frequency is 40Hz, combined with the satellite orbital height and the satellite running speed, the footprint size is 66m. The spacing of 170m along the track makes the GLAS system unable to obtain continuous information. Because of the large footprint, ICESat-1/GLAS contains more ground information, which is more susceptible to information such as terrain slope (Yang,2019, Moussavi,2014 and

Yang,2019). Unlike the waveform technology used in the ICESat-1/GLAS system, the ICESat-2/ATLAS system will use photon-counting technology. The GLAS laser has high pulse energy, low frequency, and measured target information by waveform. The ICESat-2/ATLAS has low pulse energy and high frequency. The recorded target information is determined by recording the returned photon time tag information. The ICESat-2/ATLAS system has three advantages over the ICESat-1/GLAS system. Firstly, its photon density is denser than the ICESat-1/GLAS system (ATLAS is 0.7m along the foot footprint, GLAS is 170m along the foot footprint), could acquire continuous information, and the information of the measured target can be more accurately described, which is significance for improving the extraction of forest structure parameters. Secondly, the ICESat-2/ATLAS system is a multi-beam transmission method, and could acquire more observation information under the same orbit. Thirdly, the ICESat-2/ATLAS system has a smaller footprint diameter (17m for ATLAS and 70m for GLAS), which reduces the impact of slope on spot information acquisition.

2.2 Review of Simulated Photon LiDAR Noise Filtering Algorithm

In order to simulate the ICESat-2/ATLAS spaceborne photon data noise filtering algorithm, the noise filtering algorithm concentrated on single photon radar (SPL) and Multiple Altimeter Beam Experimental LiDAR (MABEL), Slope Imaging Multi-Polarization Photon Counting Lidar (SIMPL), MATLAS data. Xia et al (2014) and Xu. et al (2014, 2017) used the MABEL data under night conditions as the experimental data. The algorithm firstly projects the photon data to the local coordinate system and converts the plane coordinates of the photon data into the orbital distance, thus generating a 2-dimensional elevation photon data profile. Then calculating the total distance of each photon to the k^{th} -nearest photons and statistics the frequency histogram of the local total distance. Finally, the noise photon is removed by setting the threshold. The noise filtering result indicates that the algorithm can effectively eliminate most of the noise photons under nighttime observation

conditions. However, the study data is nighttime photon data, which is less affected by solar background noise, so noise filtering can filter noise photon data by threshold statistics.

Wang et al. (2016) used MABEL data as the research data, and proposed the probability distribution function of k-th nearest neighbors (KNN) to judge the distance of each photon cloud, and then applied Bayesian probability theory to calculate signal photons. The noise filtering results show that the algorithm can effectively distinguish between noise photons and signal photons. However, the noise photons distribution are relatively random and are closely related to the observation target. It is difficult to accurately determine the photon property only by the probability of detection.

Yu. (2016) used the photon-counting laser data of the laboratory platform as the research data to analysis the noise filtering performance of the moving surface fitting method and the mathematical morphology filtering algorithm. The processing targets are hypothetical targets. Combining the advantages and disadvantages of the two methods, an improved noise filtering algorithm is proposed based on improved mathematical surface morphology. The experimental results show that the noise filtering algorithm can filter noise photon data in the laboratory platform, but manually setting the threshold is the key to noise filtering algorithm.

Magruder et al. (2012) proposed three methods for noise filtering photon data, such as Canny Edge Detection (CED) algorithm, Probability Distribution Function (PDF) and local angle mapping method. The result proves that the CED algorithm in the forest research area has better noise filtering ability, but the signal photon loss event is prone to occur in the gridding process, which will reduce the effectiveness of noise filtering.

Tang et al. (2016) proposed a new voxel-based spatial filtering method based on SPL data as experimental data, and determined the optimal voxel size for the optimal filter by testing different voxel sizes. It is finally determined that Garrett algorithm is the optimal algorithm for the experimental data, and

$3\text{m}\times 3\text{m}\times 0.2\text{m}$ is the optimal voxel size of the test data.

This method effectively filters the noise photon of the smooth surface while maintaining the spatial integrity of the SPL data, but the algorithm has filtered less photon in the research area with forest cover on the surface, and the SPL data is high density photon cloud data. There is a significant difference between the SPL data and the ATLAS photon data, so the voxel-based spatial filtering algorithm is not necessarily applicable in the ATLAS photon data.

Nie et al. (2018) proposed a local statistical analysis algorithm based on strong beam laser type MATLAS data as experimental data. The algorithm establishes the frequency histogram based on the elevation of all photon data. Then uses the waveform analysis method to identify the peak location of the frequency histogram, set a reasonable elevation threshold range near the peak location. Then, the statistics and normalize the photon density. Finally, the local distance statistical algorithm is used to filter noise photons. Experiment results show that the algorithm can effectively remove noise photons in the photon data. However, this type of algorithm needs to manually change the threshold parameters of local statistics according to different study area, which reduces the applicability of the noise filtering algorithm.

Zhu et al. (2018) proposed an improved elevation frequency histogram noise filtering algorithm. Firstly, the method calculates the photon search region in a horizontal elliptical shape, density of each photon and the maximum of each photon. Then, algorithm generates the local photon density distribution histogram by the calculated photon density. Since the signal photon density is much higher than the noise photon density, the low-density photon can be regarded as a noise photon. The photon density threshold is set by fitting the noise peak and the signal peak using Gaussian curve to classify the original photon into signal photons and noise photons.

Based on the different characteristics of noise photon density and signal photon density, scholars have chosen different density spatial clustering algorithms as noise filtering algorithms into photon data. Among

them, Herzfeld et al. (2014) used statistical classification parameters and feature type hyper-parameters as auxiliary parameters, and proposed a photon denoising algorithm using spatial statistics and discrete mathematical concepts. The experimental results show that the algorithm can effectively identify the signal photons in the photon data and provide the data basis for photon feature classification. Herzfeld et al. (2017) proposed a Density Dimension Algorithm (DDA), which calculates the Radial Basis Function (RBF) under anisotropic conditions. The weighted density of the data aggregation form and the concept of considering the density additional dimension is introduced as the auxiliary of the adaptive threshold determination. The photon noise filtering experiment is completed by the low pass filter. The results show that the algorithm has better adaptive ability. It can effectively distinguish noise photons and signal photons. However the algorithm does not have the ability to effectively identify signal photons with forest cover complex terrain.

Popescu et al. (2018) used MABEL data as experimental data to filter noise based on integrated moving window and clustering algorithm. Firstly, the terrain reference range is defined by the auxiliary digital elevation model (DEM), the noise photons far away from the surface are removed by the hard threshold method, and then the noise photon is filtered by the clustering algorithm with log likelihood function. Finally, the residual abnormal noise photons are removed by a Confidence Interval (CI) filter. The results show that the algorithm can identify the background noise in the flat study area and preserve the signal photons in the original data, however, the algorithm does not have the ability to effectively identify signal photons with forest cover complex terrain.

Due to the ICESat-2/ATLAS photon density characteristics, the photon density in the horizontal direction is higher than the vertical direction. Therefore, Zhang et al. (2014) proposed an improved density spatial clustering algorithm modified Density Based Spatial clustering of Applications with Noise

(mDBSCAN), for each photon object in the same cluster, the number of samples contained in the neighborhood Eps of a given radius cannot be less than a certain threshold MinPts as the cluster basis. Based on the clustering of photon objects with density connection properties. In the original photon data set, clustering can continue as long as the density of photon data exceeds MinPts. These photon objects are identified as signal photons, otherwise, these photons are identified as noise photons. The algorithm uses the horizontal elliptical shape to calculate the distance between photons, which makes the algorithm have better noise filtering effect in the flat test area. On the basis of this research, Chen et al. (2019) proposed the distance between photons by using vertical elliptical shape, horizontal elliptical shape and circular shape. The algorithm is completed under the condition of strong beam laser type. The results show that the horizontal ellipse search domain is more suitable for the flat photon cloud noise filtering algorithm.

3. CONCLUSIONS

According to the research, it is recommended to pay attention to the following problems in the future study: 1) The photon noise filtering algorithm has high precision on smooth surfaces, while in the forest coverage area, due to noise photons distributed over the canopy, inside the canopy and below the ground, which seriously affects the accuracy of the noise filtering algorithm. 2) The above research only selects one type of airborne route. The simulated PCL data is not analysis noise filtering by laser pointing and strong and weak type, lacking comprehensive analysis and evaluation of noise filtering effect. 3) Most algorithms need to manually adjust the parameter of the noise filtering algorithm. It also limits the adaptability of the algorithm. Therefore, how to improve the noise filtering effect of the spaceborne photon data in the forest coverage area by an adaptive way is the technical difficulty in photon data processing.

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