A Brief Discussion on the Overall Classification Algorithm of Airborne LiDAR Point Cloud

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Abstract

Point cloud classification is the most important problem in airborne LiDAR point cloud data processing. In recent years, classification strategies with new theoretical background keep emerging, so it is urgent to make a more systematic and detailed summary of existing point cloud filtering algorithms, so that relevant researchers can have a more macroscopic and clear understanding of various algorithms and their advantages and disadvantages. Based on the characteristics of airborne LiDAR point cloud data, this paper combs the general process of point cloud classification. This paper summarizes the current mainstream classification methods and analyses their application effects in different scenarios, aiming at exploring and customizing suitable point cloud classification methods according to specific purpose objectives or industry standards. The point cloud classification is classified into three-level classification strategy. The first-level classification is gross error elimination, the second-level classification is point cloud filtering, which is to distinguish ground points from non-ground points. The third-level classification is to extract thematic point clouds from non-ground points according to application requirements. At present, the primary and secondary classification methods are relatively diverse and mature, reaching a certain level of application, while the tertiary classification is still in the initial stage of exploration, and large-scale application is not widespread.

1. Introduction

Airborne Light Detection And Ranging combines Global Positioning System (GPS), Laser Scanning System (LS) and Inertial Navigation System (INS). As a means of active mapping and mapping of surface spatial information, it has the advantages of fast all-day acquisition of three-dimensional coordinates, rich data information and high precision, safe operation, and certain penetration of ground vegetation, etc. At present, it has been widely used in many fields of geospatial information disciplines such as digital ground model acquisition (Hui Zhenyang, et al., 2018; Huang Zuowei, et al., 2018), road extraction (Cheng Xiaojun, et al., 2018), power line extraction (Lin Xiangguo, 2017), forest parameter estimation (Zhao Zongze, et al., 2016), three-dimensional city model establishment (Yang Wei, et al., 2018), point cloud classification (Lin Xiangguo, 2017; Zhang Aiwu, et al., 2016). In China, the research and application development of this technology is slightly late, and the relevant data processing methods need to be further explored and improved.

The key point of point cloud data processing and application is the classification of point cloud. The main task of point cloud classification is to use a suitable classification algorithm to extract the point cloud that meets the business application. Early ISPRS proposed point cloud filtering algorithms based on slope, irregular triangulation, mathematical morphology, segmentation and other six algorithms, recently also appeared such as surface fitting, cluster segmentation, fabric simulation, deep learning and other algorithms. Therefore, this paper analyzes the characteristics of airborne LiDAR point cloud data, sorts out the airborne LiDAR point cloud classification process, summarizes and compares the advantages and disadvantages of several popular algorithms, aims to explore customized and applicable airborne laser point cloud classification methods according to specific purposes or industry standards, and summarizes the three-level strategy of overall point cloud classification.

2. Airborne LiDAR Point Cloud Characteristics

Point Cloud is a massive point set that expresses the spatial distribution and surface characteristics of the target under the same spatial reference frame (Li Lanlan, 2010), and the spatial coordinates of each sampling point on the surface of the object are called "point cloud". Las format is the industry standard format of LiDAR point cloud data, and the specified point cloud recording format includes three-dimensional coordinate information (x, y, z), reflection intensity, multiple echo information, the number of echoes of the specified pulse, classification information, the range of scanning angles, GPS time, RGB and other information. The difference in surface medium and elevation leads to the difference in reflectivity and echo intensity, and the laser receiver can record multiple echo information of a pulse. When a laser beam propagates to the ground, it inevitably encounters obstacles, resulting in different degrees of laser reflection; The first is the laser signal returned by the top surface of the structure, power lines, tree crowns and other uppermost ground objects, which is called the first echo; The unreflected beam continues to propagate downward until it encounters medium-height vegetation such as leaves, branches, and shrubs again, at which time it returns the second echo, and so on, the third and fourth echoes are the laser signals returned by the low ground objects contacted for the third and fourth times, and the last echo is likely to be the laser signals returned by the ground or grass, and a maximum of five echoes can be returned. Generally, 1-3 echoes are the most common (Li L, 2014), and the ground only reflects one echo signal. The first echo is the sum of the entire surface, the DSM; Intermediate echo is helpful to separate vegetation data of different levels. The last echo approximates the topographic surface, which is the basis of DEM production. Therefore, as a collection of

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massive discrete three-dimensional data on the surface of the real world, point cloud has no obvious definition domain in space, and it cannot be filtered and classified in a unified and solidified form. In other words, the point cloud is not a function, and for the actual complex three-dimensional scene, the x, y and z are not defined by some law or some numerical relationship, and the connection between horizontal and vertical coordinates cannot be established. Point clouds are widely distributed and irregular in space, so it is the most difficult to establish the mutual position relationship between points. Therefore, the current point cloud classification relies on geometric information and attribute information such as echoes and reflectance, rather than numerical relationships.

3. Airborne LiDAR Point Cloud Classification Process

In general, the original point cloud obtained by airborne LiDAR needs to be classified after flight data inspection, unified spatial coordinate system and normal height transformation, and pre-processing such as strip merging, strip redundancy elimination, and data segmentation. Point clouds include surface normal (also known as noise points, coarse handicap). Point cloud classification is to distinguish which are normal point clouds, which are abnormal points, which are ground points in normal point clouds, which are non-ground points above the ground, that is, ground points such as houses, roads, trees, etc. In this paper, according to the different stages of point cloud data processing and classification purposes, a hierarchical classification strategy is designed: the first-level classification is gross error elimination, which is mainly to filter abnormal point clouds; the second-level classification is to distinguish ground points and non-ground points (ground object points), which is called point cloud filtering; the third-level classification is to extract thematic point clouds of specific ground objects from non-ground points according to application requirements. According to the degree of automation of classification, point cloud classification can also be divided into computer classification and manual classification. All computer classifications require, to a greater or lesser extent, human involvement in the fine classification. The overall classification process of airborne LiDAR point cloud is shown in Figure 1.

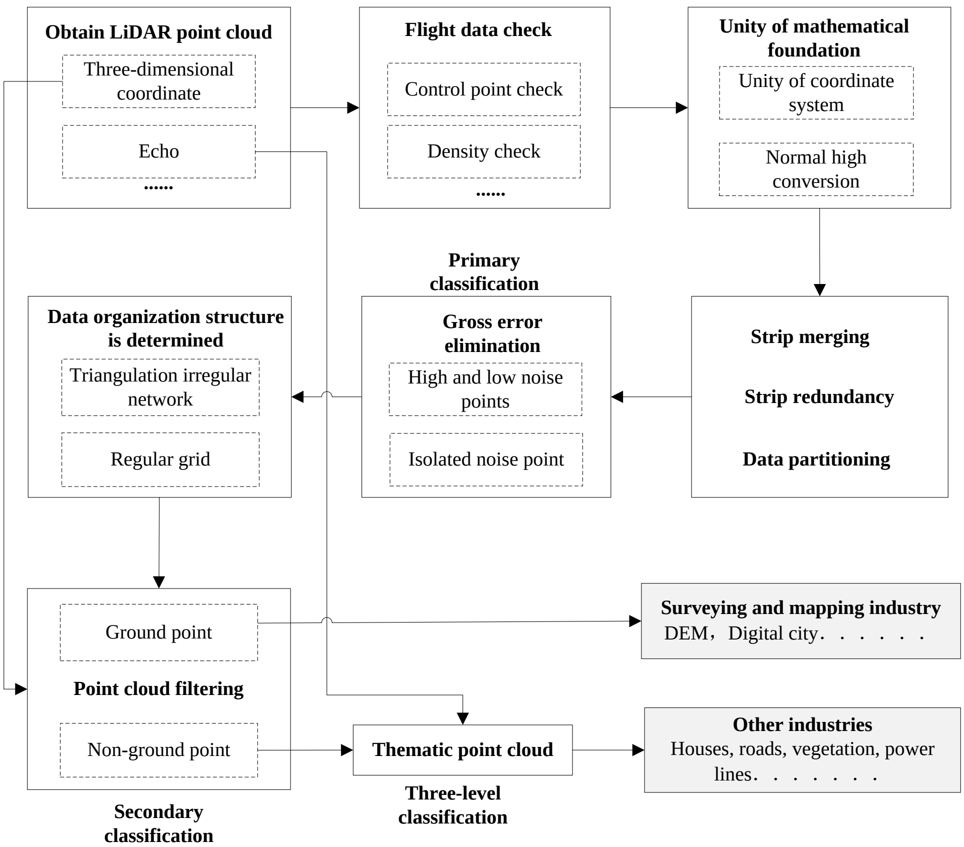

Figure 1. Airborne LiDAR point cloud classification process.

4. Airborne LiDAR Point Cloud Classification Method

4.1 Gross Error Elimination (First-Level Classification)

Airborne LiDAR point cloud outliers refer to points caused by LiDAR multipath effects, systematic errors, airborne flying objects (such as birds), and floating objects, which are often significantly higher or lower in elevation than their neighboring points or are relatively isolated in geometric relations (Meng X L, et al., 2009), also known as noise points and coarse approximations. Gross error elimination is the prerequisite and key to realize the classification algorithm, that is, automatic filtering, also known as noise point filtering, denoising, etc., is a first-level classification of point clouds. If these points are not removed, it will not only cause uncertain interference to the subsequent filtering work of the point cloud, but also affect the overall quality and classification accuracy of the point cloud classification results. Rough handicap is roughly divided into two categories: extremely high and very low noise points and outlier isolated noise points. The point cloud after gross error removal can generate DSM.

Vosselman and Maas (2001) proposed to use the maximum height difference erosion function to extract the gross handicap. Jiang et al. (2008) used K nearest proximity method to judge the rough handicap. Leslar et al. (2010) discussed the mobile fixed-interval smoothing method based on α-β-γ filter and the quadratic polynomial surface fitting method to detect and remove abnormal noise points. Dong Jing et al. (2010) found the gross handicap through the visual elevation histogram. Badino et al. (2011) used the median filtering method to eliminate the influence of noise points. Li Lian (2013) studied the elevation mean deviation method and the adaptive moving box denoising method. The number of noise points is generally not large, and most commercial software on the market can get a relatively ideal gross error elimination effect.

4.2 Point Cloud Filtering (Second-Level Classification)

4.2.1 Assumptions And Existing Problems of Point Cloud Filtering: When LiDAR point cloud filtering, it is necessary to establish a rule to distinguish ground points and non-ground points (ground object points) in normal point clouds, which is the second-level classification of point clouds, and this rule is a prerequisite for filtering algorithms. All filtering algorithms need one or more assumptions as the basis for classification and recognition. At present, the main assumptions are as follows: (1) Non-ground points in DSM are higher than ground points, that is, the lowest point of laser scanning (excluding rough handicap) is a sufficiently accurate ground point, and almost all filtering algorithms take this as the premise (Huang Xianfeng , et al., 2009); (2) The change of ground slope will not be too great, and the change of natural terrain slope is always within a certain limit, and the slope of non-terrain features will exceed this limit (Vosselmang, 2000; Axelsson P.E, 2000; Kraus K, et al., 1998). The laser will always penetrate the forest to reach the ground, but it will produce multiple echoes (Liu Shanshan, 2018). It should be noted that the road and the ground are at the same elevation, and the phenomenon of sudden change in the real world is very common, and whether the laser can penetrate the forest depends on the density of the forest on the one hand, and the point cloud density on the other hand.

Common Filtering Algorithms: In practical applications, appropriate classification algorithms are usually selected according to specific needs and data characteristics. In addition, in order to improve the accuracy and robustness of classification, different algorithms can also be combined or integrated to form a hybrid classification method.

1. Mathematical Morphological Filtering Algorithm

As early as 1993, Professor Lindenberger in Stuttgart, Germany, used mathematical morphology to perform open operations on point cloud data. The principle of the algorithm is to set a certain size of filtering window in the local area, and use morphological operation to eliminate points higher than the ground to get a surface of the approximate terrain. Dilatation, corrosion, closing operation and opening operation are the four formulas that constitute mathematical morphology operation. The elevation of non-ground points of point cloud will change greatly after morphological operation. The points whose height difference is greater than the threshold value are classified as ground object points and filtered out. The advantage of this method is that it is intuitive and has a ready-made theoretical basis, but the disadvantage is that it is easy to be affected by the size of the filter window, and the processing effect is not good for the region with drastic terrain changes.

2. Filtering Algorithm Based on Irregular Triangulation Network

The algorithm of progressive encryption triangulation irregular network was proposed by Axelesson (Axelsson P., 2000) in 2000, which is referred to as PTD filtering algorithm. The core content of the algorithm is to first determine the key seed points on the ground, construct the irregular triangulation network from the seed points, calculate the plane distance and Angle from the remaining points to the triangulation network, and perform iterative encryption on the points that meet the conditions until the remaining points do not meet the iterative threshold. PTD algorithm is the most robust filtering algorithm in recent years, and it performs well in various complex terrain. Its disadvantage is that it requires high computer memory, and when the amount of point cloud data reaches a certain level, the calculation time is longer. It is not sensitive to very low coarse handicap, and it is easy to misreport it as a ground point; In addition, the initial constructed TIN has a significant impact on the subsequent classification results.

3. Cloth Simulation Filtering Algorithm

Cloth Simulating Filtering (CSF) was proposed by Zhang et al. (Zhang W M , et al., 2016). The algorithm works like this: If a soft piece of fabric falls on the ground due to gravity, it will stick to the ground surface, and the shape of the fabric in three-dimensional space is DSM. When the shape is reversed in the vertical direction, the z in the point cloud coordinate becomes -z, and then the fabric particles fall due to the influence of gravity. By analyzing the relationship between the fabric node and the corresponding LiDAR point cloud, the final position of the fabric particles is determined, so as to determine the final shape of the fabric (DEM), and achieve the purpose of point cloud filtering. Compared with other filtering algorithms, CSF algorithm has the following advantages: (1) it can be applied to steep slopes, discontinuous areas and narrow terrain; ② Other filtering algorithms need to set complex filtering parameters, and the filter parameters of cloth simulation are less set; (3) Other algorithms need to debug the algorithm parameters to find the optimal terrain value for different terrain, which requires high experience of operators, while CSF only needs to switch to select different terrain, and more people can participate in this work.

4. Filter Algorithm Based on Machine Learning

Machine learning-based filtering algorithms often regard point cloud filtering as a binary classification problem of LiDAR point cloud (Hui Zhenyang, et al., 2018). Through machine learning algorithms, such as conditional random field, support vector machine, Adaboost, etc., the training sample is trained to obtain a training model, and then the training model is used to mark the point cloud with 0 and 1 (0 represents ground points, 1 represents non-ground points), so as to achieve point cloud filtering (Hui Zhenyang, et al., 2018). Lu et al. established a conditional random field model based on discrete and continuous implicit random variables. Jahromi et al. proposed a point cloud filtering algorithm based on artificial neural network (ANN). Hu and Yuan used convolutional neural networks (CNN) to implement point cloud filtering through deep learning of point clouds. Point cloud filtering based on machine learning can obtain the best filtering accuracy of existing filtering algorithms. However, the filtering algorithm based on machine learning still has the following problems: (1) it requires a lot of manpower to train samples; (2) The training sample involves all terrain features and has greater difficulty;

Machine learning is premised on high time costs and sufficient computer resources.

Application scenario: Applicable to various terrain and ground object types, especially when the point cloud data has enough characteristic information.

Advantages: The characteristic information of point cloud data can be fully utilized, and the classification accuracy is high. Through training, the model can adapt to different environments and feature types.

Disadvantages: A large amount of training data is required, and the training process of the model can be complex. In addition, for some special feature types, it may be necessary to manually adjust the feature parameters or select other algorithms.

5. Classification based on threshold:

Algorithm description: Set threshold values based on some basic attributes of point cloud data (such as height, intensity, etc.), and classify point cloud data into different categories.

Application scenario: Simple distinction between ground points and non-ground points.

Advantages: Simple calculation and fast speed.

Disadvantages: For complex scenarios, a single threshold may not be accurate enough.

6. Classification based on Deep learning:

Algorithm description: The deep learning model (such as CNN, PointNet, etc.) is used to process the point cloud data, and the automatic classification of the point cloud is realized through multi-layer feature extraction and classifier.

Application scenario: Applies to point cloud classification in complex scenarios, such as urban environments and forests.

Advantages: Ability to automatically learn complex feature representations, high classification accuracy.

Disadvantages: A large amount of labeled data is required for training, and computing resources are consumed.

7. Rules-based classification:

Algorithm description: Formulate a series of rules according to expert knowledge or experience, and divide point cloud data into different categories through rule judgment.

Application scenario: It is suitable for scenarios with clear prior knowledge, such as the extraction of specific ground objects.

Advantages: Can be combined with professional knowledge and experience for targeted classification.

Disadvantages: The formulation of rules may be affected by subjective factors, and it is difficult to cope with complex and changing scenarios.

8. Classification based on clustering:

Algorithm description: The point cloud data is divided into different clusters by clustering algorithm (such as K-means, DBSCAN, etc.), and each cluster represents a category.

Application scenario: Applicable to the classification of ground objects with no obvious boundary but similar internal point cloud features.

Advantages: The ability to automatically discover structural information in the point cloud without the need to pre-set the number of categories.

Disadvantages: Sensitive to noise and outliers, post-processing may be required to optimize clustering results.

9. Classification method based on semantic segmentation

This method is a technique to classify point cloud data into different semantic categories. The core concept of this algorithm is to assign a semantic label to each point cloud data point, such as road, building, tree, etc., so as to realize the semantic understanding of the entire point cloud data.

Application scenario: It is suitable for situations where the semantic information of point cloud data has high requirements, such as automatic driving and urban planning.

Advantages: The ability to accurately segment point cloud data into areas with the same semantics, such as roads, buildings, vegetation, etc. For complex urban environment, semantic segmentation method has better classification effect.

Disadvantages: A large amount of training data and computing resources are required, and the model training time is long. In addition, semantic segmentation method has high requirements for preprocessing and feature extraction of point cloud data, and needs a certain technical basis.

10. Morphological classification

Morphological classification mainly depends on the geometric and topological characteristics of point clouds. It constructs morphological features of point cloud data, such as height, intensity, roughness, etc., and uses these features to perform threshold judgment or region growth algorithm to achieve classification.

Application scenario: Morphological classification is often used to identify and extract ground objects with obvious geometric features, such as roads, buildings, rivers, etc. This method is especially suitable for flat or more regular terrain areas.

Advantages:

(1) Simple and intuitive: By using the morphological characteristics of point clouds, such as size, shape, connectivity, etc., it is easier to identify and classify ground objects.

(2) High computational efficiency: Morphological operations are usually relatively fast and suitable for processing large-scale point cloud data.

(3) It is robust to noise and local changes: morphological operations can smooth data to a certain extent and reduce the impact of noise and local changes on classification results.

Disadvantages:

(1) Poor adaptability to complex terrain: The effect of morphological classification may not be good for areas with large relief or irregular shape of features.

(2) Morphological parameters need to be manually set: Morphological classification often requires the manual setting of some parameters, such as the size and shape of structural elements, which may affect the accuracy of the classification.

11. Classification of statistical models

Classification of statistical models is a method of classification based on the statistical characteristics of point cloud data. It assumes that point cloud data in the same category are statistically consistent, while data in different categories show significant differences.

Application scenario: Statistical model classification is applicable to the situation where the point cloud data has obvious statistical rules, such as vegetation cover area and water body. This method can describe the distribution characteristics of point cloud data by establishing a statistical model, so as to classify it.

Advantages:

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(1) High accuracy: Statistical model classification can be modeled using the statistical characteristics of point cloud data, so as to obtain more accurate classification results.

(2) High flexibility: The statistical model can be adjusted and optimized according to different data characteristics, and is suitable for different ground objects and scenes.

Disadvantages:

(1) Large sample size required: In order to build an effective statistical model, a large number of training samples are usually required, which may be difficult to achieve in some cases.

(2) Sensitivity to noise: Statistical model classification is usually sensitive to noise and outliers, which may affect the accuracy of the classification.

It should be noted that the advantages and disadvantages of the above classification algorithms are not absolute, and they will be affected by a variety of factors in practical applications, such as data quality, algorithm parameter Settings, computing resources, etc. Therefore, when selecting the classification algorithm, it is necessary to make comprehensive consideration according to the specific needs and data characteristics.

4.3 Thematic Point Cloud Classification (Three-Level Classification)

Thematic point cloud refers to laser points that express a specific category of ground objects, such as building points, vegetation points, wire points, etc. (Xie Lijuan., 2019). After reviewing the existing literature, the current research and practice of thematic point cloud mainly focus on the extraction of ground objects such as buildings, roads, vegetation and power lines. In addition to the three-dimensional coordinate information recorded in the point cloud data, there are also attribute information such as reflectivity, echo intensity and echo frequency. The first and second level classification of point cloud mainly relies on coordinate data and geometric information, and the third level classification not only uses coordinate and geometric features, but also mines more information contained in reflectivity and echo.

Many domestic and foreign scholars (Zuo Zhiquan, et al., 2012; Donoghue D N M, et al., 2007; Orka, H.O, et al., 2007; Moffiet T, et al., 2005; Rottensteiner F, et al., 2002] have conducted a lot of studies on echo intensity, trying to use the average echo intensity and intensity changes to simply identify a certain type of ground object, or for subsequent direct classification and indirect guidance classification (Li L, 2014). Professor Zhang Xiaohong (Zhang Xiaohong, et al., 2007) of Wuhan University calibrated the echo intensity of media by studying the reflectance of different media (Li L, 2014). In the extraction of thematic ground objects, Li Feng classifies urban road surface point clouds according to the corresponding relationship between the reflectance and reflection intensity values of urban roads and the characteristics of adjacent point clouds in urban streets, and according to the regional growth method. Zhang et al. (2006) used plane fitting method and regional growth method to distinguish buildings and vegetation from normalized DSM (nDSM). Demir and Baltsavias (2012) summarized and implemented five building detection methods.

The difficulty in the implementation of thematic point cloud classification lies in the fact that social construction is changing with each passing day, and features such as the shape and contour of ground objects are becoming more and more diversified. Especially in urban areas, the vertical cross-distribution of ground objects in the surface space is becoming more complex, and the materials of ground objects are also developing in a diversified way, making it increasingly difficult for automatic classification algorithms to adapt to the complexity and variability of point clouds. After automatic classification, more workload needs manual intervention, and the degree of automation needs to be improved (Xie Lijuan., 2019).

5. Conclusion

Feature extraction is the key step of point cloud classification algorithm. It extracts useful information of point cloud data by calculating geometric, statistical and topological features of point cloud. These features include point coordinates, normal vectors, curvature, distance, etc., as well as higher-level features such as the shape, size, texture, etc., of the point cloud. After extracting effective features, it is crucial to select a suitable classifier for point cloud classification. Common classifiers include support vector machine (SVM), Random Forest, convolutional neural network (CNN) and so on. Which classifier to choose depends on the characteristics of the data, the complexity of the classification task, and the limitations of computational resources. After the classifier is selected, it needs to be trained using labeled point cloud data and evaluated by validation sets to evaluate the classifier's performance. During the training process, the parameters of the classifier should be adjusted to optimize its classification effect. The use of validation sets can help us understand how a classifier behaves on previously unseen data.

Performance evaluation is the key step to evaluate the quality of point cloud classification algorithm. Commonly used performance metrics include Accuracy, Precision, Recall, and F1 scores. By comparing the performance metrics of different algorithms, we can choose the algorithm that is most suitable for a particular task. Based on the results of performance evaluation, we can optimize and improve the algorithm. This may involve adjusting the parameters of the classifier, improving feature extraction methods, trying different classifiers, or combining multiple algorithms for ensemble learning, etc. Through continuous optimization and improvement, we can improve the performance and robustness of high cloud classification algorithms.

Although there are many researches on point cloud classification theory and algorithm, and each has its own strengths, compared with airborne LiDAR point cloud data classification technology and its application requirements, it is still relatively backward, lacking of simple operation, truly efficient, accurate and universal algorithms, and relevant research and practice still need to be further explored. At present, the algorithms of the first and second classification are relatively diverse and mature, and have reached a certain level of application. The third classification is still in its infancy, and the scale application is still very limited. From the current development of point cloud classification theory and the status quo of data processing platforms at home and abroad, there is still a wide range of relevant research space. At present, most experimental conclusions are based on the standard sample data provided by ISPRS, rather than the actual project data. More research should be based on the actual application of a wider range of data, make full use of the spatial and physical attributes of point clouds, optimize existing algorithms, and innovate, find a point cloud classification method that meets specific uses and industry standards, develop a point cloud classification platform, and achieve the purpose of automatic and efficient classification with as few parameters as possible. Moreover, the research on point cloud classification algorithm for complex terrain and features (such as urban areas) should be carried out extensively.

Point cloud classification algorithm has been widely used in many fields, such as unmanned driving, automatic navigation, 3D modeling and so on. Different application scenarios have different requirements on point cloud classification algorithms, such as real-time, accuracy, and stability. Therefore, for different application scenarios, we need to choose the appropriate algorithm and carry out the corresponding adjustment and optimization.

With the continuous development of deep learning and computer vision technology, point cloud classification algorithms will also usher in more innovation and development. Future trends may include the use of more complex neural network structures for feature learning and classification, the introduction of more contextual information to improve classification accuracy, and the use of unsupervised learning methods for pre-training. In addition, with the increase in hardware computing power and the expansion of data sets, we are also able to handle larger scale point cloud data and further improve classification performance.

To sum up, point cloud classification algorithm is a complex and challenging task. By summarizing the main steps and trend prospects of the existing algorithms, we can better understand and apply the point cloud classification algorithm, and lay a foundation for future research and application.

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