Research Article

A Multilevel Point Cloud Classification Method for Underground Tunnels Based on Three-Dimensional Moving LiDAR Measurements

Yanyi Li, Jian Shi, and Zhihua Xiao

College of Surveying and Geo-Informatics, Tongji University, Shanghai 200092, China
Shanghai Dianji University, Shanghai 201306, China

Correspondence should be addressed to Jian Shi; 201801020123@sdust.edu.cn

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Underground tunnel engineering requires complex systematic engineering. A tunnel requires internal measurements after the completion of shield construction to check the real construction quality of the tunnel and provide measurement data for the next tunnel project acceptance team. When measuring a tunnel’s internal construction and performing associated data analysis, it is necessary to accurately count the size and type information of the built tunnel internal structure. In this study, mobile three-dimensional laser scanning technology is used to collect a tunnel’s internal point cloud data, and many unordered point cloud data are collected. Thus, classifying the ground objects inside the tunnel automatically and accurately is a critical problem to be solved in a tunnel construction survey. Additionally, this study proposes a multilayer underground tunnel point cloud classification method that uses the hierarchical clustering structure to deal with the original tunnel point cloud. This method extracts the specific ground objects, such as tracks or roads, platforms, and pipelines, on the tunnel surface and inside the tunnel step by step. Concurrently, the accuracy of the projection plane and the accuracy of point cloud classification are introduced to evaluate the accuracy and finally calculate the statistics of ground object information in the tunnel. To verify the engineering practicability of this method, we first collected the point cloud data of a railway tunnel inside the tunnel using a rail car equipped with high-precision LiDAR and divided the data results into four sample areas for the classification test. To verify the algorithm’s robustness, we used the proposed method to test the highway tunnel data according to the same experimental process. Experiments show that this paper’s multilevel tunnel point cloud classification method can accurately extract these four types of ground objects. The average accuracy of the projection plane in each experimental area is not less than 91.49%, and the average accuracy of point cloud classification is not less than 92.63%. Compared with the other three types of classification methods in the same field, the method in this paper is more suitable for processing tunnel point cloud data and has the advantages of high classification accuracy, strong robustness, and a simple implementation process. The proposed method can also meet the real needs of underground tunnel internal construction surveys.

1. Introduction

1.1. Background and Current Situation. With the continuous development of China’s underground shield technology, the number of underground tunnels has increased markedly. After tunnel construction, safety detection and ground object investigation have become urgent needs [1–3]. The traditional methods for internal tunnel measurement include total station observation, photo shooting, or manual investigation. Due to the long construction mileage of the tunnel, these methods require workers to work in the tunnel for a long time, and the real measured data must be further checked and proofread manually. These shortcomings lead to low work efficiency. Concurrently, the scope and accuracy of the investigation must still be improved [4–6]. With the continuous development of three-dimensional mobile measurement technology [7–10], a three-dimensional laser scanner can measure the internal data of the tunnel, obtain three-dimensional point cloud data, and investigate the construction of the tunnel [11]. Compared with traditional
measurement methods, mobile measurement is more efficient. The spatial accuracy of point cloud data can reach the millimeter level [12], which can fully and properly investigate internal tunnel construction and internal facilities.

However, with a massive three-dimensional point cloud, and considering the disorder of spatial points and the complexity of the internal structure of the tunnel, the point cloud data collected by mobile measurement equipment require a long-time and complex postprocessing [13, 14] so that valuable ground feature information can be analyzed from the point cloud. There are many 3D point cloud classification methods that can primarily be divided into machine learning methods and deep learning methods. The following two aspects are primarily introduced. First, in the point cloud classification field, the traditional machine learning clustering methods include the DBSCAN algorithm, European clustering algorithm, and K-means clustering algorithm [15–17], which are widely used currently. Second, in the field of deep learning, most recent research has investigated the problem of point cloud segmentation. The point-based network directly acts on the irregular point cloud. However, because the point cloud is disorderly and unstructured, it is difficult to use a traditional image deep learning network directly. Therefore, by abstracting the structural features of ground objects in the point cloud, scholars constructed a global feature network for in-depth learning and training and achieved good results. Based on this idea, the latter methods can be roughly divided into point MLP, point convolution, RNN-based, and graph-based methods [18–21]. Among them, the most widely cited is the deep learning network represented by PointNet. Concurrently, PointNet and PointNet++ and their subsequent related networks are also common [22–26]. To improve classification accuracy, scholars have improved and optimized from different angles and proposed a series of classical point cloud classification networks [27–30], including PointSIFT, RandLA-Net, and PointCNN, which can classify specific features in the point cloud.

However, although deep learning has advantages, it does not represent all the methods of managing three-dimensional point clouds. Existing point cloud classification algorithms have been tested on the standard experimental data set and cannot be applied to practical projects. Relevant references are rare for the ground feature classification of the underground tunnel point cloud. How to propose a more engineering-focused and general method that can be expanded and developed, apply different clustering algorithms to the automatic classification of the tunnel point cloud, and evaluate the accuracy of tunnel point cloud classification remains to be solved. Accurately classifying the tunnel’s internal features is also a critical problem to be solved before the final acceptance of the tunnel project.

1.2. Research Progress and Gaps. First of all, Tran et al. [31] carry out point cloud data processing using cylindrical feature fitting [31]. Pitkänen et al. [32] also use the cylinder fitting to process tree point cloud data [32]. On this basis, Duan et al. [33] first apply the cylindrical fitting method to the field of tunnel point cloud modeling [33]. Inspired by this idea, we take the cylindrical fitting method as the first layer of the algorithm. And we apply this method to the classification and extraction of point clouds on the tunnel surface.

In the latest research, Song et al. [34] use the DBSCAN algorithm to extract the characteristics of tunnel point cloud [34]. Our paper refers to this method in designing the second layer algorithm, which is used to extract the track or pavement inside the tunnel point clouds. What’s more, Xiao et al. [35] use the region growth algorithm to extract the plane in point cloud data [35]. Fotsing et al. [36] also use the iterative closest point (ICP) algorithm and region growth algorithm to detect the building plane [36]. And Zhang et al. [37] used the region growth algorithm to extract the railway track in the tunnel point cloud [37], which also provides a practical reference for the third-layer design of our algorithm.

For the European clustering algorithm, Zhou et al. [38] use this algorithm for forest point cloud data processing [38]. And Wang et al. [39] also used this method to extract fine features such as tree point cloud canopy [39, 40]. Additionally, Liu et al. [40] use this algorithm to build the tunnel point cloud model for the mean clustering algorithm. Combining the characteristics of the two algorithms, we completed the development of the fourth layer algorithm, which is used to extract the pipeline point cloud inside the tunnel.

All in all, the contribution of this paper is to propose a multilevel classification method for the tunnel point cloud. This method integrates cylinder fitting algorithm, DBSCAN algorithm, region growing algorithm, European clustering algorithm, and K-means clustering algorithm. Different from the previous research work, we apply these algorithms to the tunnel point cloud feature classification problem. And the adaptation of these algorithms is also one of the potential contributions of this paper. However, there is little research on applying the above methods to the problem. The differences between the method used in this paper and the traditional algorithms are mainly reflected in the following:

(1) The cylindrical fitting algorithm extracts the point cloud on the tunnel surface, and the characteristic cylindrical parameters are designed.

(2) This paper uses the optimized KT-DBSCAN algorithm to improve the efficiency of point cloud data retrieval, which is faster than the traditional DBSCAN algorithm.

(3) This study uses the region growth algorithm to extract the plane in the tunnel point cloud. We expand the application field of the traditional region growth algorithm to enable it to process the tunnel point cloud.

(4) This research combines the Euclidean and K-means clustering algorithms to extract the pipeline feature points in the point cloud. It applies these two traditional algorithms to tunnel point cloud processing.

The above characteristics are the innovative applications of the algorithm in tunnel point cloud data processing. In the
second part, we introduce the specific implementation of these algorithms in the above order.

1.3. Content and Structure. Focusing on the above-mentioned problems, this study primarily focuses on underground tunnel point cloud data processing using a multilevel point cloud classification method to process the point cloud inside the tunnel. The method proposed in this study can primarily be divided into five layers. The first four layers classify and extract different ground objects in the tunnel, and the last layer accounts for the complexity of the internal structure of the tunnel in the future. The development part is reserved in the previous layer. The design can achieve nested processing between different algorithms, improve and upgrade the following methods, and reflect the structural characteristics of high cohesion and low coupling.

To test the multilayer underground tunnel point cloud classification method proposed in this study, the research team used a three-dimensional laser scanner to collect the tunnel point cloud data under the real engineering scene. Accurate engineering data will be used to test the method.

This study’s content and structure are as follows. The first part introduces the research status in tunnel point cloud processing and explains relevant existing literature. The second part presents the specific structure of the multilevel tunnel point cloud classification method and introduces the principle of each algorithm in detail. The third part uses the real data to test the method’s feasibility and yields a series of conclusions and discussions. Finally, the research prospects in this field are summarized and discussed.

2. Multilevel Tunnel Point Cloud Classification Method

2.1. Method Basic Architecture Design. The method used in this study can primarily be divided into five levels, and the specific structure is shown in Figure 1. To improve the compatibility of the methods used in this study, an external function interface is designed at level 5 to expand subsequent algorithms further. The description will not be developed in this study, but the primary algorithm principles of the first four levels will be introduced.

The primary clustering algorithm based on the unit cylinder space equation is the first level. After preprocessing the tunnel point cloud obtained by mobile scanning, this algorithm is the first-level clustering algorithm. The point cloud on the tunnel surface can be extracted through this algorithm. Second, through the optimized KT-DBSCAN clustering algorithm of the second level, and based on the clustering of the first-level algorithm, this algorithm is used to accurately segment and extract the track point cloud in the tunnel. Third, through the clustering algorithm based on the region growth algorithm in the third layer, the point cloud data of the internal platform are accurately extracted based on the data processing of the first two layers. In this study, the inner platform refers to the personnel evacuation platform inside the tunnel in the real scene. Finally, at the fourth level, the K-means clustering algorithm based on Euclidean distance is used to accurately extract the pipeline point cloud data inside the tunnel. After processing these components of the proposed method, the tunnel surface, rail, internal platform, internal pipeline, and five other types of ground objects are classified, and semantic matching is performed according to the real tunnel interior scene image.

To improve the efficiency and reliability of this method, cohesion and coupling are considered in the combination of each layer algorithm. The method in this paper can improve cohesion through the following measures. (1) Only a unique interface is reserved between each layer of algorithms. (2) Deleting the intermediate algorithm processing layer will not affect the work of other processing layers. (3) We ensure that the transmission data structure between layers does not change. In addition, the method in this paper reduces the coupling degree through the following measures. (4) This method is not applicable to global variables. (5) Class inheritance is not used. (6) We configure an independent header file library for each layer of methods. In practice, the algorithm in this paper is written in C++ as the primary programming language, follows the C++ 14 Standard, and is designed according to the standard of high cohesion and low coupling. The number of operation layers can be reasonably adjusted according to the number of ground object types extracted to improve the data processing efficiency. The multilayer algorithm design may also indirectly increase the complexity of data processing. However, each layer algorithm is only responsible for extracting one type of ground object. As a data postprocessing method, the proposed method has no real-time requirements; thus, this part will not be discussed further.

2.2. Method Basic Architecture Design. Considering that the underground tunnel presents the geometric characteristics of the internal cylinder during the shielding process, the clustering algorithm based on the spatial equation of the unit cylinder is used to segment the point cloud [41–43], and the point set conforming to the spatial cylinder distribution characteristics is extracted as the point cloud data of the tunnel surface.

First, the cylindrical spatial equation is written as shown in formula (1):

\[
(x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 - r^2 = \frac{[l(x - x_0) + m(y - y_0) + n(z - z_0)]^2}{l^2 + m^2 + n^2}.
\]

(1)

In a rectangular coordinate system, the coordinates of the points that comply with the above formula will be strictly distributed on the regular cylindrical plane. These coordinates can be filtered by judging whether the points comply with the cylindrical distribution form of formula (1). In the space rectangular coordinate system, we will build a standard unit cylinder as shown in Figure 2.

As shown in Figure 2, when building a unit cylinder, seven-cylinder parameters must be extracted: \((x_0, y_0, z_0)\) represents a point on the cylinder axis, \((l, m, n)\) represents the direction vector of the unit cylinder axis, and \(r\) represents...
the radius of the cylinder. Thus, data processing is performed according to the process shown in Table 1.

2.3. Optimized KT-DBSCAN Secondary Clustering Algorithm. DBSCAN is a density-based clustering algorithm that is robust to noise, does not require a specified number of categories, and can use arbitrary shape clustering in spatial data. Because the point cloud data processed by the first-layer algorithm have higher spatial disorder and noise, the proposed algorithm is used for further processing. To explain the basic principle of the algorithm more clearly, several parameter variables must first be defined: $\varepsilon$ is the neighborhood distance; minPts is the minimum number of points contained around the core point, which is the point with at least minPts neighborhood points in the neighborhood as the core point. Concurrently, three concepts must be defined: direct density reachability, density reachability, and density connection. Natural density reachability refers to that for a given set sample $D$, given that a series of sample points $q$ is in the $\Phi$ neighborhood of sample point $p$ and taking $p$ as the core object, object $q$ can be reached directly from object $p$. Density reachability means that for a given set of sample $D$ and a given series of sample points, $P_1, P_2, \ldots, P_n$, $p = P_1, q = P_n$, if the density of object $p$ can be reached directly from $q$, then the thickness of object $p$ can be reached from $q$ if the density of $p$ and $q$ connected to the object is the density of $o$ to $q$ connected to the thing.
As shown in Figure 3, where minPts = 4, the red dot is the high-density core point of the rail in the tunnel point cloud, the yellow dot is the boundary point, and the blue dot is the low-density noise point. Red and yellow bubbles form a cluster (cluster). The core points, boundary points, and noise points correspond to different densities, which is why DBSCAN belongs to the density-based clustering method and its antinoise ability. Therefore, this method can mitigate noise in point cloud data from laser scanning inside the tunnel more effectively.

In the traditional DBSCAN algorithm for clustering, the typical process is as follows. First, by traversing all the points in the neighborhood of the data set to determine the core point, the data are clustered through the regional growth method using the core point as the center, issues in the cluster are traversed, and points are classified with a direct density as the same cluster to form the final group. However, this traditional method must traverse the data many times, which decreases the operational efficiency.

Another idea of the DBSCAN clustering algorithm is used in this paper: the first is to traverse point by point. If a point is judged not to be a core point, it will be directly classified into the noise point set, but the noise point may be classified into the cluster by the core point later. If the point is judged to be the core point, a new group will be created, and all neighborhood points will be added to the cluster. For the core points in the neighborhood points, the neighborhood points should be added to the clustering recursively. This process continues until no point can be added to the cluster; the process then considers new points and establishes a new group. The advantage of this process is that all tunnel point cloud data must be processed only once, which improves the algorithm’s efficiency to a certain extent. In essence, the complexity of the DBSCAN algorithm primarily depends on the complexity of the neighborhood point search. The complexity of the traditional direct linear search is \(O(n^2)\). The direct linear search method is generally inefficient; thus, this paper proposes two ideas to improve this method [44, 45].

1. The neighborhood search is performed after pre-calculating the distance matrix, and its complexity is \(O(n^2/2) + O(n \cdot k)\), where \(k\) is the average number of neighborhood points.

2. The index method is used to query neighborhood points. In this study, the kd-tree index method is used for management, and its complexity is \(O(n \cdot \log(n) + k \cdot \log(n) \cdot n)\), in which \(k\) is the average number of neighborhood points. The first item represents the time complexity of building a kd-tree, and the second item describes the domain search complexity.

Compared with idea (2) above, idea (1) requires additional complexity based on traditional methods. In this study, idea (2) can achieve better results in theory. Because the improved algorithm uses kd-tree for data management, it is called the KT-DBSCAN algorithm in this paper. The processing flow of the algorithm is shown in Table 2.

To describe the improved effect more clearly, we compare the traditional DBSCAN algorithm with the KT-DBSCAN algorithm, and the pcl: EuclideanClusterExtraction clustering function in the PCL point cloud database also participates in the comparison to comprehensively describe the algorithm advantages of KT-DBSCAN. This part will be described in detail in the third part of this paper. In addition, after completing the first layer of algorithm processing, the remaining point cloud data are further processed by the algorithm in this section. As the point cloud on the tunnel surface has been extracted, only ground objects such as railway tracks have apparent clustering degrees among the remaining point clouds near the ground. Therefore, according to the algorithm process in this section, the point cloud of railway tracks and other ground objects can be extracted quickly.

### 2.4. Three-Level Clustering Algorithm Based on Region Growth Algorithm

After the first two layers of data clustering, the tunnel and rail point cloud were extracted. The region growth algorithm removes the internal platform point cloud from the remaining data. Because an evacuation platform is typically placed inside the tunnel, among the point clouds collected by the laser LiDAR sensor, the point cloud of the Mobile Information Systems 5
3.1. Experimental Platform and Conditions. Our team independently designed a scanning rail car that can operate automatically in the tunnel to facilitate carrying high-precision LiDAR for mobile measurement. Its essential operation is shown in Figure 4.

The data used in the test in this paper are the tunnel point cloud data obtained from the actual measurement. Firstly, we conducted the feasibility test of our algorithm. The processing process and data results are shown in Figures 5–10. And this part uses railway tunnel data. It is the point cloud data measured later in constructing a subway tunnel in Jiangsu, China. The measuring equipment is a measuring rail car equipped with LiDAR. The measuring time is September 2020. Additionally, the tunnel length taken in the experiment is 25 m, and the estimated shield diameter is 5.4 m.

To test the algorithm’s robustness and further prove that the algorithm in this paper can be used for different types of tunnels, we additionally take the highway tunnel data. The processing process and results are shown in Figures 11 and 12. These data are collected from a mountain crossing highway tunnel in Qingdao, Shandong, China. The measuring equipment also adopts LiDAR. The measuring time is May 2019. The tunnel length taken in this experiment is 54 m, and the estimated shield diameter is 14 m.

The above data are processed by the algorithm developed in this paper. The main development and processing software is visual studio 2017. The algorithm is tested by C++ program language, and our point cloud visualization software displays the results as shown in Figure 13.

3.2. Data Acquisition and Preprocessing. To verify the algorithm’s effectiveness, we consider some tunnel point cloud data from an underground shield project in China. The data acquisition equipment of this part is a Z + F 9012 LiDAR scanner, which is carried by a rail car inside the tunnel for mobile measurement. The basic setup of the equipment is shown in Figure 14 and achieves a high-precision ranging capability and a 360° scanning field of view. Its scanning rate exceeds 1 million points/s, and the maximum scanning speed is 200 rpm. Due to the short distance between scanning sections, they can scan at high speed, which is suitable for tunnel point cloud data acquisition tasks.

The tunnel investigated in this study is a subway tunnel. The real acquisition scene is shown in Figure 15, which describes the internal conditions of the tunnel measured by the experiment and four types of ground objects inside the tunnel, including the tunnel surface, rail, internal platform, and internal pipeline. Therefore, we also investigate the extraction of these four types of ground object point clouds. Tunnels with many different structural components are generally selected when selecting the experimental area. The point cloud collected by this tunnel type can better classify and extract ground objects.

According to the characteristics of the multilevel classification algorithm of the tunnel point cloud proposed in this paper, the tunnel point cloud scanned by LiDAR is processed according to the following steps:

1. Perform data preprocessing on the original data and preliminarily denoise some noticeable noise as shown in Figure 5.
Table 2: Pseudocode of KT-DBSCAN secondary clustering algorithm.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Read the point cloud data, judge the core points, and temporarily classify the non-core points as noise points.</td>
</tr>
<tr>
<td>2</td>
<td>If the point is the core point, create a new cluster.</td>
</tr>
<tr>
<td>3</td>
<td>Establish kd-tree index, search neighborhood points, and classify the surrounding neighborhood points into the cluster.</td>
</tr>
<tr>
<td>4</td>
<td>If there are also core points in the neighborhood searched in the previous step, create a new cluster and judge the relationship.</td>
</tr>
<tr>
<td>5</td>
<td>The points in the neighborhood around the core points are divided according to different clusters.</td>
</tr>
<tr>
<td>6</td>
<td>Step 5. And so on, until no points can be classified, the remaining points are classified as noise points.</td>
</tr>
</tbody>
</table>

Table 3: Pseudocode of three-level clustering algorithm based on region growth algorithm.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Set an empty seed point sequence and an empty cluster array, select the seed point (the point with the minor curvature), and add it to the seed point sequence.</td>
</tr>
<tr>
<td>2</td>
<td>Search the neighborhood points of the current seed point, calculate the included angle between the normal of the neighborhood point and the normal of the current seed point, and add the neighborhood points less than the smoothing threshold to the current region.</td>
</tr>
<tr>
<td>3</td>
<td>The curvature of each seed in the neighborhood is less than the current threshold, and the new seed is added to the neighborhood to delete the new seed curvature.</td>
</tr>
<tr>
<td>4</td>
<td>Repeat the above growth process until the seed point sequence is empty. At this point, a region is grown and added to the cluster array.</td>
</tr>
<tr>
<td>5</td>
<td>Repeat the above steps for the remaining points until all points are traversed.</td>
</tr>
</tbody>
</table>

Table 4: Pseudocode of K-means clustering algorithm based on Euclidean distance.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Initialize the prototype specify K values and K clustering centers.</td>
</tr>
<tr>
<td>2</td>
<td>Clustering. Traverse all data points and calculate the Euclidean distance to the K cluster centers from each data point.</td>
</tr>
<tr>
<td>3</td>
<td>Each data point is assigned to the category of the nearest cluster center until the last data point.</td>
</tr>
<tr>
<td>4</td>
<td>Update the cluster center. That is to calculate the centroid of each class and compare the calculated cluster center with the previous cluster center.</td>
</tr>
<tr>
<td>5</td>
<td>If all clustering centers do not change, stop. If there is any change, take the current cluster center as the new cluster center, and repeat the above processes 2, 3, and 4 until all cluster centers do not change.</td>
</tr>
</tbody>
</table>
Figure 4: Workflow of tunnel internal movement measurement.

Figure 5: Data preprocessing diagram.

Figure 6: Sample division diagram of tunnel point cloud data.
Figure 7: The first-layer clustering algorithm extracts the point cloud of the tunnel surface.

Figure 8: The second-layer clustering algorithm extracts the orbital point cloud.
(2) The representative part is intercepted from the overall point cloud data for the experimental test.

(3) Feature extraction is performed layer by layer according to a multi-level classification algorithm.

(4) We sort the classification results, calculate the evaluation indices, and evaluate the methods.

3.3. Algorithm Data Processing at All Levels. To facilitate data processing and testing, the original tunnel point cloud data are evenly divided into four samples according to the length as shown in ABCD in Figure 6. This part of the paper discusses classifying the above four samples and makes statistics and evaluations on relevant indicators.

First, after the primary clustering algorithm based on the unit cylinder space equation, the classification results of point cloud data are shown in Figure 7. The tunnel surface data are extracted from the original point cloud data.

After completing the first layer of clustering, the orbital point cloud is extracted from the remaining point cloud data and divided into four sample areas of ABCD for testing. The effect is shown in Figure 8.
After completing the second layer of data processing, the remaining point clouds are processed by the third-layer clustering algorithm to extract the point cloud data of the internal platform. In this study, the region growth algorithm is primarily used for processing. Because the point cloud of the inner platform has apparent characteristics in the normal direction, it can be easily distinguished from the other point cloud data. The classification effect is shown in Figure 9.

After the first three layers of algorithm clustering, the pipeline data must be extracted from the remaining point cloud data; thus, it must be applied to the K-means clustering algorithm based on Euclidean distance to automatically extract the pipeline point cloud data inside the tunnel as shown in Figure 10.

Finally, the remaining point clouds are classified as other point clouds, and some data did not contribute to the classification of features. Therefore, this part of the point cloud will not be considered later. If it is necessary to refine the clusters further and segment the tunnel point cloud, the confidential information in this part of the data can be used for future mining.

3.4. Evaluation of Classification Effect of This Method. This paper uses the multilevel point cloud classification method. A four-level clustering algorithm processes the original tunnel point cloud, and the ground objects inside the tunnel are accurately classified by multilevel clustering. The classification effect is shown in Figure 16.

To evaluate the classification accuracy of the multilevel classification method in tunnel point cloud data processing more accurately, we evaluate these data using two indicators: the coincidence rate of the projection plane and the classification accuracy of the point cloud. Before the evaluation, the original tunnel point cloud data are finely classified by the manual method. The manual acceptable classification results will be used as standard evaluation data to compare the classification accuracy with this paper’s multimorphographic classification method. The comparison indicators are as follows.

3.4.1. Accuracy of the Projection Plane. The accuracy of the projection plane is to project each category onto the same rectangular coordinate plane and compare the overlapping area with the projection of standard classification [46]. The calculation formula is shown in the following equation:

\[ \text{overlap} = \frac{S_{\text{Algorithm classification}}}{S_{\text{Standard classification}}} \times 100\%, \]  

(2)

where overlap is the accuracy of the projection surface, \( S_{\text{Algorithm classification}} \) is the projection area of the point cloud automatically classified by the algorithm in this paper, and \( S_{\text{Standard classification}} \) is the projection area of the point cloud manually typed. We report statistics on the data indicators in different sample areas of ABCD and select the projection according to as shown in Figure 17.

As shown in Figure 17, when using the proposed method to classify the internal features of the railway tunnel, the accuracy of the projection plane is not less than 90.75%. The highest value in this figure is the extraction of rail, followed by the extraction of tunnel surface, the extraction of the internal platform, and the lowest in this figure is the extraction of the internal pipeline. Because the structural characteristics of the internal pipeline and internal platform are more complex than the other two types of ground features, it is expected that the index value is marginally lower.

3.4.2. Accuracy of Point Cloud Classification. The accuracy of point cloud classification is measured by the ratio of the points correctly classified to the points in the standard classification point cloud [47]. The calculation formula is shown in the following equation:

\[ \text{accuracy} = \frac{N_{\text{correct}}}{N_{\text{all}}} \times 100\%, \]  

(3)

where accuracy is the accuracy of point cloud classification, \( N_{\text{correct}} \) is the number of points in the correct point cloud classified by the proposed multilevel clustering method, and \( N_{\text{all}} \) is the number of points in the standard classification point cloud manually classified. Statistics are calculated for the data indicators in different sample areas of ABCD as shown in Figure 18.

As shown in Figure 18, when using the method in this paper to classify the internal features of the railway tunnel, the point cloud classification rate is not less than 87.21%. The highest value in this figure is the extraction of the tunnel surface, followed by the extraction of the rail, and followed by the extraction of the internal pipeline. The lowest in this figure is the extraction of the internal platform. From the numerical perspective, the accuracy of this index (in Figure 18) is lower than that of the projection surface (in Figure 17), which shows that the proposed method is more accurate when classifying the internal structures of the tunnel and that the effect of extracting the point cloud of the corresponding ground object is also good.

The second-layer algorithm uses the KT-DBSCAN algorithm in classification. This algorithm is an improved version of the DBSCAN algorithm combined with KD tree optimization. Compared with the traditional algorithm and the current mainstream Euclidean cluster extraction algorithm, this algorithm dramatically reduces the operation time before ensuring accuracy. This effect is shown in Table 5, which compares the average overlap and average accuracy of rail point cloud data extracted after processing four ABCD samples and compares the average operation time under the same operating platform environment.

As shown in Table 5, the improved KT-DBSCAN algorithm improves the two indicators of average overlap and average accuracy. The average overlap index of the KT-DBSCAN algorithm is 6.01% higher than that of the DBSCAN algorithm and 0.11% higher than that of the Euclidean-cluster-extraction algorithm. Concurrently, the average accuracy index of the algorithm is 5.05% higher than that of the DBSCAN algorithm and 0.43% higher than that of the Euclidean-cluster-extraction algorithm. In terms of processing
efficiency, the processing speed of the KT-DBSCAN algorithm is approximately twice that of the DBSCAN algorithm, which is equivalent to that of the Euclidean-cluster-extraction algorithm.

3.5. Algorithm Comparison and Subsequent Testing

3.5.1. New Type of Highway Tunnel Point Cloud Is Used to Test the Algorithm. To verify the reliability and robustness of the multilevel classification method used in this paper, we continue to use the highway tunnel point cloud data to test the algorithm, and the basic process of feature classification is consistent with the process described above. This part of the experiment is used to show that this algorithm still has strong processing abilities for highway tunnel point cloud data.

The data processing sequence is shown in Figure 12. After the first layer of the algorithm is processed, the tunnel surface point cloud is extracted. After the second layer of the algorithm is processed, the outlet surface point cloud is extracted. After the third layer of the algorithm is processed, the internal platform point cloud is extracted. Finally, after the fourth layer of the algorithm is processed, the internal pipeline point cloud data are extracted.

The final classification effect is shown in Figure 19. The algorithm in this paper classifies all types of ground objects accurately and can meet the real needs of the project. According to the accuracy of the projection plane and point cloud classification, the data results of point cloud data processing for highway tunnels are also counted as shown in Figures 20 and 21.

3.5.2. Comparison with Other Classification Methods. In this section, we compare the algorithm in this paper with several other types of algorithms and evaluate the effect of the algorithm using the two proposed indicators of projection plane accuracy and point cloud classification accuracy. This study compares the traditional region growing point cloud clustering algorithm [41], the machine learning point cloud classification method SVM [42], the deep learning classification method PointNet++ [43], and the proposed classification algorithm. The point cloud data of the railway tunnel and highway tunnel are considered, and the test area is counted according to the four samples of A B C D. Therefore, in the comparison, other algorithms are used to process four samples of the two types of data and analyze each type of ground object’s classification effect.

After comparison, the proposed multilevel tunnel point cloud classification method is shown to have marked advantages compared with other methods. In the point cloud data processing for railway tunnels, as shown in Figure 22, the proposed method performs well when classifying four types of ground objects. The SVM algorithm has the same effect as the proposed method when classifying internal platforms. When classifying other types of ground objects, the two indicators are lower than the method in this paper. In addition, the comparative region growth algorithm and PointNet++ algorithm have a poor effect on the classification of ground objects. In the point cloud data processing for highway tunnels, as shown in Figure 23, the proposed method performs better than the other three methods. For the two types of tunnels, after the point cloud data are processed by the four methods compared in this section, the average accuracy of the projection plane of the method in this paper is more than 92.07%. The accuracy of point cloud classification can be maintained at more than 90.12%, which is better than the other three methods.

The accuracy of this method is 2% ~ 10% higher than that of the SVM method, 11% ~ 26% higher than that of the region growth algorithm, and 9% ~ 19% higher than that of the PointNet++ method. The accuracy of this method is 3% ~ 11% higher than that of the SVM method, 12% ~ 21% higher than that of the region growth algorithm, and 5% ~ 11% higher than that of the PointNet++ method. Thus, the proposed algorithm has certain advantages when classifying various types of tunnel point clouds and ground objects.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Mean-overlap (%)</th>
<th>Mean-accuracy (%)</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBSCAN</td>
<td>90.33</td>
<td>91.39</td>
<td>21.45</td>
</tr>
<tr>
<td>EuclideanClusterExtraction</td>
<td>96.23</td>
<td>96.01</td>
<td>13.21</td>
</tr>
<tr>
<td>KT-DBSCAN</td>
<td>96.34</td>
<td>96.44</td>
<td>13.01</td>
</tr>
</tbody>
</table>

Table 5: Comparison table of DBSCAN algorithm before and after optimization.

Figure 11: Schematic diagram of highway tunnel point cloud data.
Figure 12: Continued.
4. Conclusion and Further Discussion

4.1. Conclusion. First, this paper systematically proposes using a multilevel classification method for underground tunnel point cloud data processing, obtains a laser point cloud through real measurements, performs an algorithm test, and obtains more ideal results. The tunnel point cloud data used in the test can be roughly divided into four sample areas of ABCD according to the distance of the central axis, and the proposed methods are tested for the tunnel point cloud in different regions. From the experimental results, the following conclusions can be drawn:

(1) The proposed multilevel point cloud classification method can extract the characteristic features in a tunnel point cloud layer by layer more effectively and accurately classify the four critical elements of the tunnel surface, rail, internal platform, and internal pipeline. For railway tunnels, the extraction accuracy of each type of ground feature is more than 86%. The average accuracy of the projection plane in each experimental area is not less than 95.00%. The average accuracy of point cloud classification is not less than 92.63%. For highway tunnels, the average accuracy of the projection plane in each experimental area should not be less than 92.56%, and the average accuracy of point cloud classification should not be less than 91.11%. This precision can meet the needs of automatic ground feature investigation and classification using the point cloud inside the tunnel.
Figure 14: Data acquisition equipment diagram.

Figure 15: Tunnel internal measurement scene.

Figure 16: Effect of multilevel clustering method on tunnel point cloud classification.
For each sample area, the accuracy of the projection plane and point cloud classification are counted according to the above four types of ground objects. The statistical results indicate that when using the multilevel classification method in this paper to classify the point cloud of the tunnel surface and rail, the accuracy of the projection surface is generally 3% ~ 5% higher than that of extracting the internal platform and pipeline. The accuracy of point cloud classification is generally 7% ~ 11% higher than that of removing internal platforms and pipelines.
(3) The accuracy of the projection plane of each type of sample is marginally higher than that of point cloud classification, and the accuracy of the projection plane and point cloud classification of the railway is the highest compared with the other three types of features.

(4) The accuracy of the projection plane of the point cloud classification of the internal platform and internal pipeline of the tunnel is low, among which the point cloud classification accuracy of the internal platform is the lowest compared with the other three types of ground objects, followed by the internal pipeline of the tunnel. Generally, the proposed method has marked advantages when classifying the point cloud of a tunnel surface and railway track.

(5) Compared with the region growth algorithm, SVM machine learning algorithm, and PointNet++ deep learning algorithm, the proposed multilevel point cloud classification method achieves the highest accuracies of the projection surface and point cloud classification, which shows that the proposed method is more suitable for classification tasks with tunnel point cloud ground objects.
Statistical chart of classification accuracy

Figure 21: Statistical chart of point cloud classification accuracy.

Statistical chart of classification effect evaluation indicators

Figure 22: Statistical chart of classification effect evaluation index of railway tunnel.
4.2. Further Discussion. Based on these conclusions, some discussion points can be made. The proposed multilevel classification method achieves good performance when extracting tunnel surface point clouds and railway tracks because these two parts of ground objects are extracted from the original tunnel point cloud earlier in the processing sequence. Concurrently, the geometric features of the cylinder are used to classify the point cloud on the tunnel surface. After extracting the track surface, the railway track has more distinct geometric features in space than other ground objects; thus, the accuracy of these two types of ground objects is higher. The two different types of parts are extracted from the remaining tunnel point clouds based on these two types of extraction. After the first two-layer clustering algorithm, there are more noise points in the remaining point cloud; thus, it is difficult to extract the internal plane and pipeline of the tunnel. Concurrently, the spatial size of these two parts is much smaller than the tunnel surface and rail. Therefore, it is more difficult to accurately extract the internal plane and pipeline of a tunnel with a relatively small size from a large tunnel point cloud, which also leads to low extraction accuracy. In this study, the KT-DBSCAN algorithm is used to classify railway tracks.

The comparison results between this algorithm and the other two algorithms show that the optimized KT-DBSCAN algorithm dramatically speeds up the operation speed to ensure high accuracy, which is the advantage of using kd-tree index structure optimization. Therefore, in the latter two-layer clustering algorithm, the kd-tree index structure of the second layer is retained by default to improve the operation efficiency. From the numerical perspective, the accuracy of the projection plane and point cloud classification of the four types of ground objects in the four samples of ABCD are different. Overall, the accuracy of the projection plane is higher than that of point cloud classification. This phenomenon is because the accuracy of the projection plane is more concerned with the coincidence degree of the two-dimensional graphic area of ground objects on the same projection plane; projection along the z-axis direction is used in this study. This index measures the classification accuracy of the algorithm when classifying ground objects. If the point cloud identified by the algorithm is of the same class, the projection area of this part of the point cloud should be consistent with that of the reference classification point cloud: the higher the accuracy of the projection surface is, the more accurate the classification of the algorithm.

![Figure 23: Statistical chart of classification effect evaluation index of highway tunnel.](image-url)
However, the accuracy of point cloud classification is to classify the attributes of each point; thus, this index judges the detailed gap between the point cloud distinguished by the algorithm and the standard classification point cloud: the higher the accuracy of point cloud classification, the more complete the details of the point cloud classified for this type of feature. Therefore, the accuracy of the projection plane describes the accuracy of classification, and the accuracy of point cloud classification represents the integrity of the clustering point cloud. The former is macro, and the latter is micro. Therefore, the former will be marginally higher than the latter, which also shows that the proposed method aims to classify ground features in the tunnel point cloud, which can ensure the correctness of the classification and ensure the integrity of different ground feature point clouds.

Finally, because the features classified in this paper include the tunnel surface, rail, internal platform, and internal pipeline, these four types are the most common and essential for different underground tunnels. However, they may not be available in all underground tunnels. Therefore, in this method’s design, the fifth layer’s public interface is reserved to facilitate the connection of different subsequent ground feature extraction algorithms. In future research, we can refer to the clustering methods in different fields [48, 49] and perform secondary development on this public interface to ensure that the proposed method can adapt to more complex practical projects. Concurrently, this paper tests the point cloud classification of highway tunnels and obtains competitive results using the proposed method.

5. Summary and Prospect

5.1. Summary. This study proposes a multilevel feature classification method for underground tunnel point cloud data processing. By constructing a multilayer clustering algorithm, the tunnel point cloud is classified layer by layer. First, the point cloud on the tunnel surface is accurately classified by the primary clustering algorithm based on the unit cylinder space equation. Then, the rail point cloud (or road point cloud) is quickly extracted by the improved KT-DBSCAN secondary clustering algorithm. Concurrently, the classification accuracy of this part of the point cloud is more than 95.15%.

Thus, the platform point cloud inside the tunnel is classified by the three-level clustering algorithm based on regional growth. Finally, the pipeline point cloud inside the tunnel is extracted using the K-means clustering algorithm based on regional growth. After this process, four ground objects (the tunnel surface, rail (or road), internal platform, and internal pipeline) are accurately classified. By processing the point cloud data of railway and highway tunnels and comparing other methods in the field of point cloud classification, the proposed method obtains competitive results.

5.2. Expectation. Future research should consider identifying the ground feature types inside the tunnel from the image through the deep learning method, taking these as the a priori semantic information, and combining ground feature type semantics and the classified point cloud by constructing the matching mapping to automatically improve the category information of the point cloud inside the tunnel.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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