IEICE TRANSACTIONS

on Fundamentals of Electronics, Communications and Computer Sciences

DOI:10.1587/transfun.2024EAP1121

Publicized:2024/12/06

This advance publication article will be replaced by the finalized version after proofreading.

A PUBLICATION OF THE ENGINEERING SCIENCES SOCIETY

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PAPER

Optimization Strategy for Electric Vehicle Charging Port Identification and Location based on Improved Point Cloud Registration

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SUMMARY
With the rapid rise of the electric vehicle industry, the gap between electric vehicle ownership and available charging pile is becoming increasingly large. In order to ensure the automatic charging efficiency of electric vehicles, it becomes crucial to achieve identification and location of electric vehicle charging ports efficiently and accurately. However, existing technologies face numerous challenges, such as noise interference, large data volumes, and low registration efficiency, which lead to suboptimal performance in charging port identification and positioning. Existing point cloud data noise reduction, feature point extraction and registration techniques for charging port identification and location have problems such as low noise reduction accuracy, poor quality of extracted points and low registration efficiency. Therefore, this paper proposes an optimization strategy for electric vehicle charging port identification and location based on improved point cloud registration. Firstly, the adaptive K-dimensional tree (K-D Tree) method is used to reduce the noise for point cloud data by dynamically selecting the optimal splitting dimension and value. Next, using the geometric feature information of the point cloud data, high quality feature key points are extracted by clustering analysis. Then, a feedback updating mechanism based on the registration loss function is proposed, which updates the K-D Tree model in real-time by the calculation results of the loss function to improve the registration efficiency as well as the charging port identification accuracy. Finally, simulation experiments are conducted to verify the performance of the proposed method in the identification and location of electric vehicle charging ports. The simulation results indicate that, compared with baseline 1 and baseline 2, the intersection over union (IOU) of proposed algorithm is increased by 43.54% and 55.46%, respectively.
key words: *electric vehicle; point cloud registration; identification and location; K-D Tree*

1. Introduction

New energy electric vehicles and hybrid rechargeable vehicles are already leading the way in automotive innovation, thanks to their remarkable environmental friendliness and high level of technological integration [1]–[4]. The gap between electric vehicle ownership and available charging piles is huge. How to charge efficiently and safely has been an issue of great concern in the electric vehicle sector [5]–[8]. To ensure automatic and efficient charging of electric vehicles, the first crucial step is accurately pinpointing the three-dimensional spatial location and direction of the vehicle's charging port. This information serves as the foundation for the subsequent operations such as precise positioning, charging port navigation, and automatic docking [9], [10]. Due to the limited field view of the sensor, complex geometry of the scanned target, and occlusion reasons, it is necessary to collect electric vehicle charging port data multiple times in different directions [11]–[13]. How to unify the data from multiple scans under the same coordinate for obtaining complete electric vehicle charging port three-dimensional information is a major challenge for electric vehicle charging port identification and location.

Point cloud registration aligns the charging port data of electric vehicles captured from different viewpoints or different moments, unifying multiple scans into a single coordinate system to create a complete and coherent three-dimensional model of the charging port. This enables high-precision identification and positioning of the charging port, playing a crucial role in the recognition and positioning of electric vehicle charging ports [14]–[16]. In current studies on aligning point clouds, the data are typically pre-processed with appropriate methods prior to registration. In [17], Wu *et al.* proposed a correlation entropy-based point cloud data processing method for source and target point cloud registration with large noise and outliers. In [18], Shi *et al.* incorporated a filtering step into the registration workflow, with simulation results showing reduced and more stable errors thereafter. In [19], Yang *et al.* used the branch bounding principle to resist the noise, which achieves better registration in low noise situations. The above literature focused on using different data processing methods to process the point cloud data. However, these data processing methods cannot solve the fast indexing problem, the data processing efficiency is not high, which complicates fulfilling the time-sensitive needs for identifying and locating electric vehicle charging ports.

A K-dimensional tree (K-D Tree) serves as a data structure that stores points within K-dimensional space for rapid retrieval [20], [21]. There have been many studies applying K-D Tree to point cloud data noise reduction. In [22], Zhang *et al.* introduced a denoising approach for point cloud models using KD-Tree spatial indexing and uniform sampling, significantly enhancing the efficiency of noise removal. In [23], Hong *et al.* searched planes, removed outliers and reduced noise based on KD-Tree and bilateral filtering. In [24], Liu *et al.* used KD-Tree for outlier removal of segmented point clouds, followed by mathematical morphological filter-

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ing for noise reduction of labeled point clouds. However, the above methods use a pre-defined sequence for selecting the split dimensions during the construction of the K-D Tree, which may lead to tree imbalance problems when dealing with different distributions of datasets.

The substantial volume of acquired point cloud data significantly affects its subsequent processing, storage, and manipulation [25], [26]. Consequently, registering these point clouds requires extracting a limited set of stable, high-quality feature key points to enhance registration efficiency. In [27], Xiong *et al.* introduced a technique using point feature histograms to encapsulate key details of a point cloud's feature points. This method generates a multidimensional histogram by weighting the distances to neighboring points within a specified radius, capturing their spatial relationships. In [28], Kleppe *et al.* identified feature points based on curvature and searched for correspondences in order to speed up subsequent registration, but the search for correspondences was more time-consuming and susceptible to noise. In [29], Sofien *et al.* firstly extracted the scale-invariant feature points, and then completed the point correspondence by considering the normal-vector pinch relation of the feature points. However, the above methods require high initial position and do not consider the geometric feature information of the point cloud data, resulting in slow convergence, low efficiency and low accuracy.

Despite the existing research progress in point cloud registration, there are still some technical challenges that need to be addressed. Firstly, when noise reduction is performed on point cloud data by the K-D Tree method, the traditional K-D Tree construction process usually uses a predefined sequence to select the splitting dimensions, e.g., according to the dimension rotation sequence. However, this approach may lead to tree imbalance problems when dealing with datasets with different distributions, failing to provide better input data for following point cloud registration. Then, traditional methods for extracting key feature points often overlook the geometric characteristics of point cloud data. As a result, the quality of the extracted feature points is poor, leading to inefficient and slow point cloud registration. The conventional method does not update the K-D Tree model according to the registration loss function after location, which cannot improve its registration convergence efficiency and identification accuracy of charging ports.

To address the above problems, this paper proposes an optimization strategy for electric vehicle charging port identification and location based on improved point cloud registration. Firstly, when constructing the K-D Tree, the noise reduction model for point cloud data based on adaptive multi-dimensional binary tree is used to dynamically select the split dimension and the split value to avoid tree imbalance caused by the uneven distribution of point cloud data. Secondly, the adaptive K-D Tree is traversed to determine and remove discrete noise points based on the Euclidean distance method which provides better quality input data for the following point cloud registration algorithm. Next, the geometric feature information of the points is used for feature analysis, after which the feature key points are extracted by clustering the central key points. At last, the extracted feature key points are used for point cloud registration. The loss function is calculated based on the registration results, which is applied to the K-D Tree model update to improve the noise reduction accuracy of the point cloud data of the adaptive multi-dimensional binary tree, ensuring the accuracy of the identification for charging cover and charging port. Moreover, simulations demonstrate the efficiency and reliability of the proposed method in the identification and location of electric vehicle charging ports. The primary contributions are summarized below.

- **Adaptive K-D Tree based noise reduction for point cloud data:** We propose an adaptive K-D Tree based noise reduction method for point cloud data, where each point coordinate in the point cloud data is feature extracted to construct an adaptive split-dimension K-D Tree. At each node, an optimal splitting dimension and splitting value are dynamically selected based on the feature distribution of points within the node, which improves the quality of point cloud data.
- **Feature keypoint extraction method based on geometric feature information classification:** We propose a feature key point extraction method based on geometric feature information classification by calculating seven geometric features of points in point cloud data as feature information sets. Moreover, we use Euclidean distance for clustering analysis and extract the centroid of each cluster as the feature key point, which improves the stability and quality of key point selection and effectively reduces the search time for a large number of point pairs.
- **Feedback update method based on registration loss function:** We propose a feedback update method based on the loss function of the registration result. At the end of the location phase, we enhance the search efficiency of the K-D Tree model by calculating the registration loss function and applying the feedback information to the K-D Tree model update which ensures the identification accuracy of the charging port.

2. Point Cloud Data Noise Reduction Method based on Adaptive K-D Tree

The identification of electric vehicle charging ports faces challenges due to illumination, surface reflections, and artifacts. Sensor and device limitations further contribute to noise and outliers in the collected point cloud data, inevitably degrading its accuracy [30]. To enhance the quality and precision of high-point cloud data, preprocessing is vital. This involves removing noise and outliers while preserving features, mitigating noise impact, and simplifying computational complexity. The refined data then serves as optimal input for subsequent point cloud registration algorithms [31], [32]. The principle of point cloud data noise reduction based on adaptive K-D Tree is shown in Fig. 1, and the implementation steps include feature extraction, adaptive multidimensional binary tree construction and point cloud data denoising.

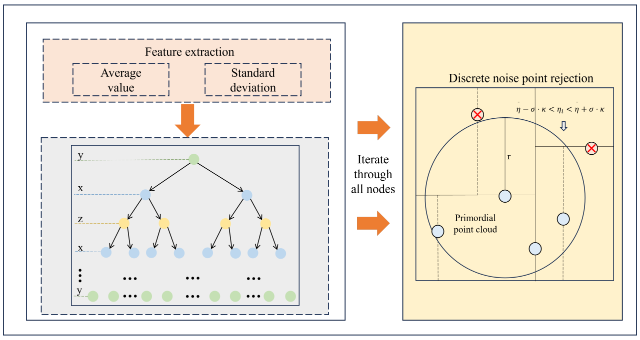


Fig. 1 The principle diagram of point cloud data noise reduction based on adaptive K-D Tree.

2.1 Construction Method of Adaptive Multidimensional Binary Tree

Traditional K-D Trees typically use a predefined order to select split dimensions during noise reduction [33]. However, this approach can lead to unbalanced trees when dealing with data sets with different distributions, which in turn affects the noise reduction efficiency [34]. To address the issue of original point cloud data containing high noise ratios and numerous discrete values, an adaptive multidimensional binary tree point cloud data noise reduction model is proposed. When constructing K-D Tree, split dimensions and split values are dynamically selected to avoid tree imbalance caused by uneven distribution of point cloud data.

For the point cloud data collected from the same object under different viewing angles, there is a rigid transformation relationship between them. Therefore, the essence of point cloud registration is to find a spatial coordinate transformation method to make the corresponding points in two sets of point cloud data coincide as much as possible. Assume that the set of the target point cloud and the on-time point cloud to be configured are $\{\mathbf{O}_i = [x_i^{\mathrm{o}}, y_i^{\mathrm{o}}, z_i^{\mathrm{o}}]^{\mathrm{T}}\}$ and $\{\mathbf{U}_i = [x_i^{\mathrm{u}}, y_i^{\mathrm{u}}, z_i^{\mathrm{u}}]^{\mathrm{T}}\}$, respectively.

First, the coordinates of each point in the original point cloud data are extracted. In point cloud data, the feature dimension is $M = 3$. Set the number of points on the node to be split as I. The set of eigenvalues of point cloud data in feature dimension $m = 1$ is $\{c_{1,i} = x_i^{\mathrm{u}}\}$. The set of eigenvalues on the eigendimension $m = 2$ is $\{c_{2,i} = y_i^{\mathrm{u}}\}$, and the set of eigenvalues on the eigendimension $m = 3$ is $\{c_{3,i} = z_i^{\mathrm{u}}\}$.Then, the average value and standard difference of point cloud data on the feature dimension m can be expressed as

$$\mu_m = \frac{1}{I}\sum_{i=1}^{I} c_{m,i}, \tag{1}$$

$$\sigma_m = \sqrt{\frac{1}{I}\sum_{i=1}^{I}(c_{m,i} - \mu_m)^2}. \tag{2}$$

In order to ensure the tree stability, when determining the splitting dimension, the dimension with wider data distribution and greater dispersion is selected as far as possible, i.e., the feature dimension with the largest standard deviation is selected as the splitting dimension of the node, which can be expressed as

$$\hat{m} = \underset{m\in\{1,2,3\}}{\arg\max}\ \sigma_m, \tag{3}$$

where $\hat{m}$ is the selected split dimension. After the splitting dimension is determined, the eigenvalue $\{c_{\hat{m},i}\}$ of the point set inside the node is sorted on the splitting dimension, and the median is selected as the splitting value. Based on the adaptive splitting dimension method, the original cloud point data are split until all the point cloud data are built on the node of the K-D Tree.

2.2 Point Cloud Data Denoising Model based on Adaptive Multidimensional Binary Tree

Step1. Once the indexing structure of the K-D Tree is constructed, the adaptive K-D Tree is traversed. For each node, it is determined whether it is a discrete noise point. The specific process is as follows: Let $\mathbf{U}_i = [x_i^{\mathrm{u}}, y_i^{\mathrm{u}}, z_i^{\mathrm{u}}]$ be an arbitrary node on the K-D Tree. Search for other nodes within a sphere centered at $\mathbf{U}_i$ with radius r, denoted as $\mathbf{H}_i$, which contains V_i nodes. Calculate the Euclidean distance between the center node $\mathbf{U}_i$ and the other V_i nodes as

$$d_{i,v} = \sqrt{\left(x_i^{\mathrm{u}} - x_v^{\mathrm{u}}\right)^2 + \left(y_i^{\mathrm{u}} - y_v^{\mathrm{u}}\right)^2 + \left(z_i^{\mathrm{u}} - z_v^{\mathrm{u}}\right)^2}, \tag{4}$$

For the node $\mathbf{U}_i$, calculate the mean Euclidean distance to the other V_i nodes, denoted as:

$$\eta_i = \frac{1}{V_i}\sum_{v\in\mathbf{H}_i} \mathrm{d}_{i,v}, \tag{5}$$

Step2. Traverse all nodes on the K-D Tree and repeat Step 1. Calculate the average distance and variance for all nodes, which can be expressed as

$$\bar{\eta} = \frac{1}{I}\sum_{i=1}^{I}\eta_i, \tag{6}$$

$$\sigma = \sqrt{\frac{1}{I-1}\sum_{i=1}^{I}(\eta_i - \bar{\eta})^2}. \tag{7}$$

Step3. Define the standard deviation multiplier κ. The criterion to determine whether a node is a discrete noise point can be expressed as

$$\bar{\eta} - \sigma\cdot\kappa < \eta_i < \bar{\eta} + \sigma\cdot\kappa. \tag{8}$$

If the point $\mathbf{U}_i$ satisfies (8), it is considered not to be a discrete noise point and should be retained. Otherwise, it should be defined as a discrete noise point and removed.

2.3 Complexity Analysis of Construction Process of K-D Tree

The complexity of constructing the K-D Tree is $O(N \log N)$, where N represents the total number of points in the point cloud data, since the algorithm selects the splitting dimension by calculating the mean and standard deviation for all points in the node, which requires $O(N)$ times, and the recursive process involves splitting the dataset along the chosen dimension, reducing its size by half at each level, resulting in a tree height of approximately $\log N$, which leads to the overall complexity of $O(N \log N)$.

3. Feature Keypoint Extraction based on Geometric Feature Information Classification

Based on the aforementioned point cloud denoising method, the denoised point cloud data are obtained. Traditional methods for identifying and locating electric vehicle charging ports rely on point cloud registration using denoised point cloud data. However, due to the large volume of acquired point cloud data and the high complexity of data processing, achieving high-precision identification and localization is challenging [35]. To enhance registration accuracy and reduce computational complexity, a method is proposed that involves feature keypoint extraction based on geometric feature information classification and feedback updating based on loss function. By extracting a small, stable set of high-quality feature keypoints for point cloud registration, the search time for numerous point pairs is reduced, while preserving the point cloud features to obtain an accurate point cloud suitable for further processing. Additionally, the extracted feature keypoints are used for point cloud registration. The loss function is calculated based on the registration results and applied to update the K-D Tree model, improving the denoising accuracy of point cloud data in the adaptive multidimensional binary tree and ensuring the accuracy of identifying the charging cover and charging port.

The principle is illustrated in Fig. 2, and the feature keypoint extraction process based on geometric feature information classification is shown in Fig. 3. Firstly, the point cloud eigenvalues are analyzed by principal component analysis (PCA). Second, seven geometric features including curvature variation, linearity, planarity, scattering, feature entropy, total variance, and anisotropy are extracted. Then, point cloud data is clustered based on Euclidean distance and feature key points are extracted. Finally, K-D Tree model is updated based on the loss function.

3.1 Geometric Feature Information Extraction of Point Cloud Data

To ensure the reliability of keypoint extraction, geometric

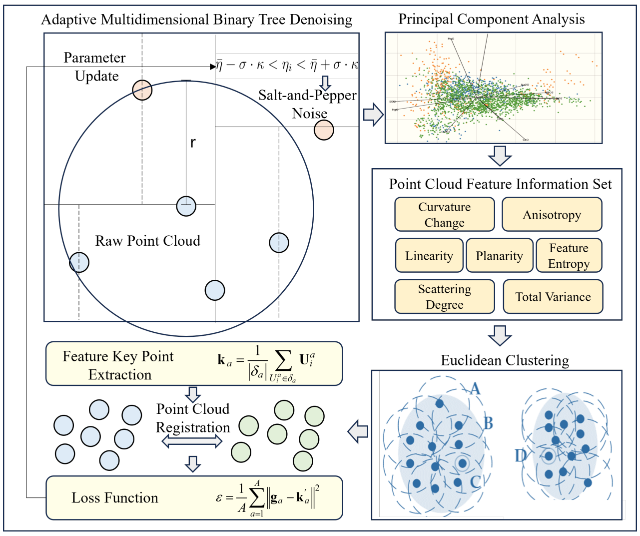


Fig. 2 The principle of feature key point extraction based on geometric feature classification.

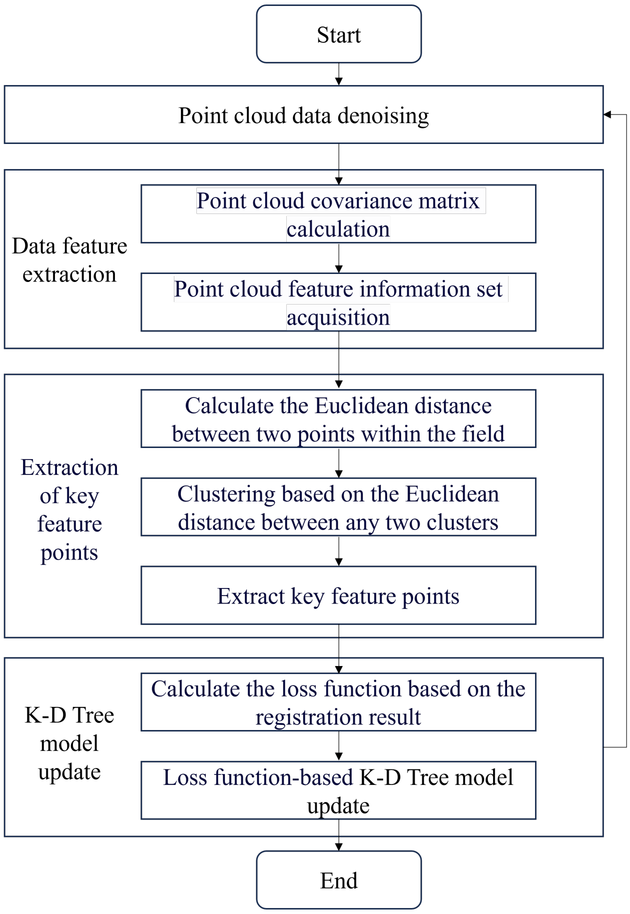


Fig. 3 Flowchart of Feature Key Point Extraction Based on Geometric Feature Classification.

feature information of point cloud data is extracted to construct a point cloud feature information set. PCA is employed to obtain the point cloud eigenvalues. Based on the point cloud eigenvalues, the curvature variation S, linearity L, planarity C, scattering N, feature entropy Z, total variance Q, and anisotropy P are calculated as the seven geometric features that comprise the feature information set.

The covariance matrix of the point cloud is decomposed using PCA to obtain the point cloud eigenvalues. First, the covariance matrix of the point cloud is calculated, denoted as

$$\mathrm{cov} = \frac{1}{I}\sum_{i=1}^{I}\left(\bar{\mathbf{U}} - \mathbf{U}_i\right)\left(\mathbf{U}_i - \bar{\mathbf{U}}\right)^{\mathrm{T}} \tag{9}$$

where $\bar{\mathbf{U}}$ represents the centroid coordinates of the point cloud, i.e., $\bar{\mathbf{U}} = (\bar{x}_i, \bar{y}_i, \bar{z}_i)$. The covariance matrix cov is decomposed using PCA to obtain the eigenvalues sorted in descending order, denoted as β_1, β_2, and β_3. The corresponding eigenvectors are e_1, e_2, and e_3, respectively, with the condition that $\beta_1 + \beta_2 + \beta_3 = 1$.

Based on the point cloud eigenvalues, the curvature variation S, linearity L, planarity C, and scattering N of the point cloud are calculated as follows

$$\begin{aligned} S &= \frac{\beta_3}{\beta_1 + \beta_2 + \beta_3} \\ L &= \frac{\beta_1 - \beta_2}{\beta_1} \\ C &= \frac{\beta_2 - \beta_3}{\beta_1} \\ N &= \frac{\beta_3}{\beta_1} \end{aligned} \tag{10}$$

where linearity L represents the one-dimensional feature, planarity C represents the two-dimensional feature, and scattering N represents the three-dimensional feature.

Feature entropy Z is a measure of the orderliness and disorderliness of the three-dimensional points within the covariance ellipsoid and is calculated as

$$Z = -e_1 \ln(e_1) - e_2 \ln(e_2) - e_3 \ln(e_3) \tag{11}$$

Total variance Q is used to measure the overall distribution of the mean and is calculated as

$$Q = \sqrt[3]{e_1 e_2 e_3} \tag{12}$$

Anisotropy P represents the distribution characteristics of points in different directions within the point cloud and is calculated as

$$P = \frac{e_1 - e_3}{e_1} \tag{13}$$

3.2 Point Cloud Data Clustering and Feature Keypoint Extraction based on Euclidean Distance

To effectively extract feature keypoints from point cloud data, clustering is performed based on the point cloud feature information set, followed by the extraction of feature keypoints. The Euclidean distance clustering method is used, where a given point is considered as the center, and points within a specified Euclidean distance range are grouped into the same category. Its advantage lies in the ability to effectively identify and aggregate points that are spatially close to each other by calculating the straight-line distance between points, thereby forming a set of feature keypoints [36], [37]. For any given point, the Euclidean distance between two points within the neighborhood is calculated, denoted as

$$\mathrm{dist}\left(\mathbf{U}_i^a, \mathbf{U}_{i'}^{a'}\right) = \sqrt{\sum_{d=1}^{D}\left(\mathbf{U}_{i,d}^a - \mathbf{U}_{i',d}^{a'}\right)^2} \tag{14}$$

where $\mathbf{U}_i^a$ represents the coordinates of point $\mathbf{U}_i$ in cluster a, $\mathbf{U}_{i,d}^a$ denotes the d-dimensional coordinate of point $\mathbf{U}_i$ in cluster a, $\mathbf{U}_{i'}^{a'}$ represents the coordinates of point $\mathbf{U}_{i'}$ in cluster a', and $\mathbf{U}_{i',d}^{a'}$ denotes the d-dimensional coordinate of point $\mathbf{U}_{i'}$ in cluster a'.

To determine whether to merge any two clusters based on the Euclidean distance between them, the criterion is expressed as

$$\mathrm{dist}\left(\delta_a, \delta_{a'}\right) = \frac{1}{|\delta_a|\,|\delta_{a'}|}\sum_{\mathbf{U}_i^a \in \delta_a, \mathbf{U}_{i'}^{a'} \in \delta_{a'}} \mathrm{dist}\left(\mathbf{U}_i^a, \mathbf{U}_{i'}^{a'}\right) \tag{15}$$

where δ_a and $\delta_{a'}$ represent clusters a and a', respectively, and $|\delta_a|$ and $|\delta_{a'}|$ denote the number of elements in clusters a and a', respectively. Define a distance threshold $\mathrm{dist}_{\min}$ and a cluster number threshold A. If $\mathrm{dist}(\delta_a, \delta_{a'}) < \mathrm{dist}_{\min}$ and the number of clusters is greater than A, then clusters a and a' are merged. If the number of clusters equals A, clustering is stopped.

After clustering is completed, the center point of each cluster is extracted as the feature keypoint, denoted as

$$\mathbf{k}_a = \frac{1}{|\delta_a|}\sum_{U_i^a \in \delta_a} \mathbf{U}_i^a, \tag{16}$$

where k_a represents the feature keypoint of cluster a.

3.3 K-D Tree Model Update based on Loss Function

The K-D Tree model is updated based on the loss function to improve denoising performance. Feature keypoints of the target point cloud are obtained using the aforementioned keypoint extraction method. The iterative closest point (ICP) method is employed for point cloud registration, where the feature keypoints of the test point cloud and the target point cloud are used as inputs. The best rotation transformation matrix between the point clouds is iteratively solved, and the loss function is calculated based on the registration results, denoted as

$$\varepsilon = \frac{1}{A}\sum_{a=1}^{A}\left\|\mathbf{g}_a - \mathbf{k}_a'\right\|^2 \tag{17}$$

where $\mathbf{g}_a$ represents the a-th feature keypoint of the target point cloud, and $\mathbf{k}'_a$ denotes the corresponding feature keypoint of the test point cloud after iterative rotation and translation adjustments.

The loss function is applied to update the K-D Tree model. A higher loss function value indicates lower registration accuracy, necessitating a reduction in the standard deviation multiplier in the K-D Tree model. This adjustment reduces the tolerance for discrete noise points, increases the denoising strength on the original point cloud data, and enhances the accuracy of point cloud denoising. This, in turn, ensures the accurate identification of the charging cover and charging port, as expressed by

$$\kappa \leftarrow (1-\varepsilon)\kappa \tag{18}$$

3.4 Complexity Analysis of Update Process of K-D Tree

The complexity of updating the K-D Tree is $\mathrm{O}(N)$, since the update process depends on the feedback from the registration loss function, which adjusts the splitting criteria or noise handling for specific nodes. While calculating the loss function may involve examining a limited number of feature points, the actual updates typically impact only a small portion of the tree structure, thereby ensuring that the overall time complexity remains linear, or $\mathrm{O}(N)$, during the update phase.

4. Simulation

To demonstrate the feasibility and effectiveness of the proposed algorithm, this paper focuses on the electric vehicle charging port, employing a three-dimensional laser scanner to capture its initial point cloud. The experimental platform is Intel (R) Core (TM) i57200U@2.50 GHz 2.70GHz processor, 16GB running memory, windows10 64-bit operating system. Baseline algorithm 1 is a method which extracts macroscopic and microscopic structures to represent shared features of virtual and real models. In combination with the multi-constraint registration algorithm, virtual prior knowledge is used to register invisible 3D objects to achieve high-precision virtual and real registration tasks. However, feature point extraction is not carried out, resulting in low noise reduction efficiency and failure to dynamically adjust noise reduction model parameters according to registration results [38]. Baseline algorithm 2 is a 3D point cloud registration algorithm based on interval segmentation and multidimensional features. It performs internal segmentation of source and target point clouds, establishes multidimensional feature vectors based on curvature features and fast point feature histogram, and solves the transformation matrix accordingly to improve registration accuracy, but does not consider point cloud data noise reduction and feature point extraction [39].

Fig. 4 shows the variation of loss functions of different algorithms with registration times. Compared with baseline 1 and baseline 2, the loss function of the proposed algorithm

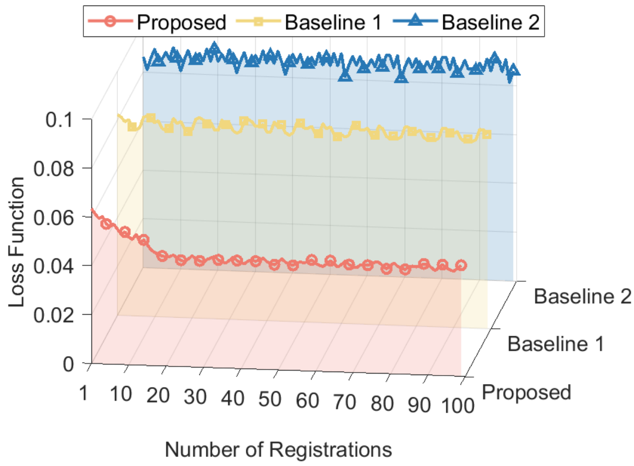


Fig. 4 The variation of loss functions of different algorithms with registration times.

is reduced by 58.73% and 66.89%, respectively. This is because the proposed algorithm extracts the features of each point coordinate in the point cloud data and constructs a K-D Tree with adaptive splitting dimensions. On each node, the optimal splitting dimension and splitting value are dynamically selected according to the feature distribution of points within the node, so as to improve data quality and high cloud registration accuracy.

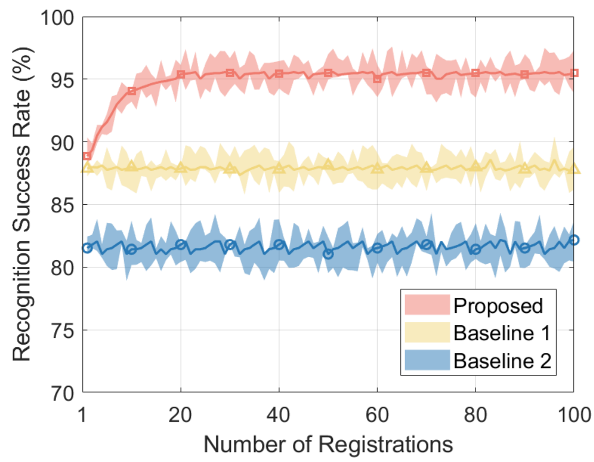


Fig. 5 The recognition success rate varies with the number of registrations.

Fig. 5 shows the change of recognition success rate with registration times. Compared with baseline 1 and baseline 2, the recognition success rate of the proposed algorithm is improved by 21.28% and 33.70%, respectively. This is because the proposed algorithm updates the K-D Tree model based on the registration result loss function. After the positioning stage, the registration loss function is calculated, and the feedback information is applied to the K-D Tree model update, so as to improve the search efficiency of the K-D Tree model and ensure the identification accuracy of the charging cover and charging port.

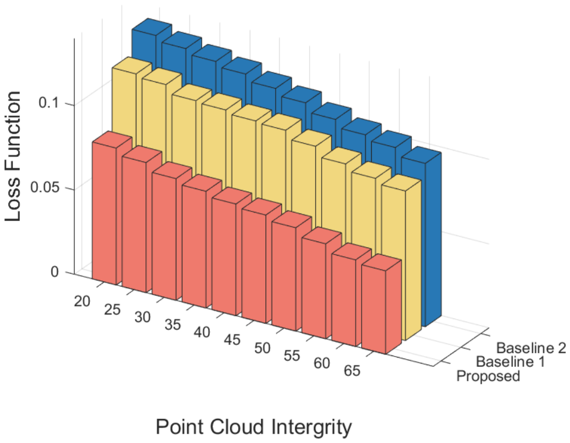
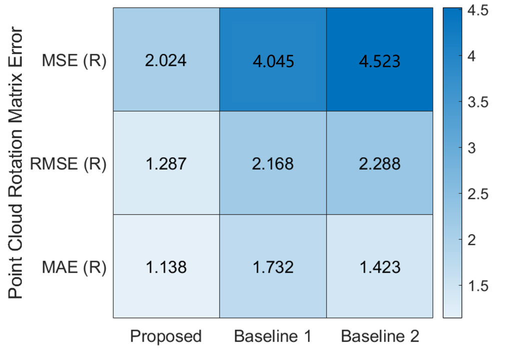


Fig. 6 The loss function of different algorithms varies with the point cloud integrity.

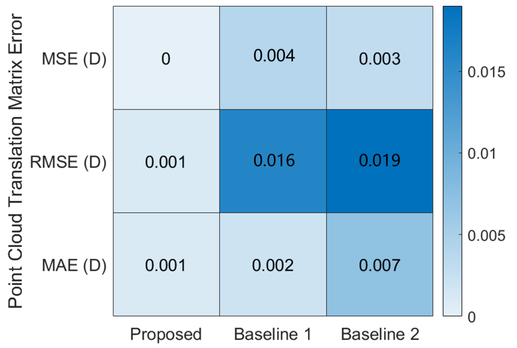
Fig. 6 shows the variation of loss functions of different algorithms with point cloud integrity. Compared with baseline 1 and baseline 2, when the point cloud integrity is 65%, the loss function of the proposed algorithm is reduced by 57.34% and 63.85%, respectively. In practical application scenarios, the obtained point cloud data may be incomplete due to the limited viewing angle of the sensor or the occlusion of the electric vehicle charging port. This is because the proposed algorithm calculates the loss function based on the registration results, and applies the loss function to the K-D Tree model update to improve the noise reduction accuracy of the adaptive multidimensional binary tree point cloud data, and improve the accuracy and reliability of the high-point cloud registration.

Fig.7 describes the trust evaluation of different algorithms. Mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) are mainly used to measure the error between the real value and the predicted value. Obviously, the MSE, RMSE and MAE of the translation matrix and rotation matrix predicted by the proposed algorithm are smaller than those of the baseline. This is because the proposed algorithm dynamically selects an optimal splitting dimension and splitting value based on the feature distribution of each point in the point cloud. Then it updates the K-D Tree model through the point cloud registration results. After that, it adjusts the noise reduction efforts of the original point cloud data and improves the noise reduction accuracy of the high point cloud data. Therefore, it ensures the identification accuracy of the charging cover and charging port. The formulas of MSE, RMSE, and MAE are given by

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(l_n - \hat{l}_n\right)^2 \tag{19}$$



(a) Point cloud rotation matrix errors of different algorithms



(b) Point cloud translation matrix errors of different algorithms

Fig. 7 Registration performance of different algorithms

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(l_n - \hat{l}_n\right)^2} \tag{20}$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|l_n - \hat{l}_n\right| \tag{21}$$

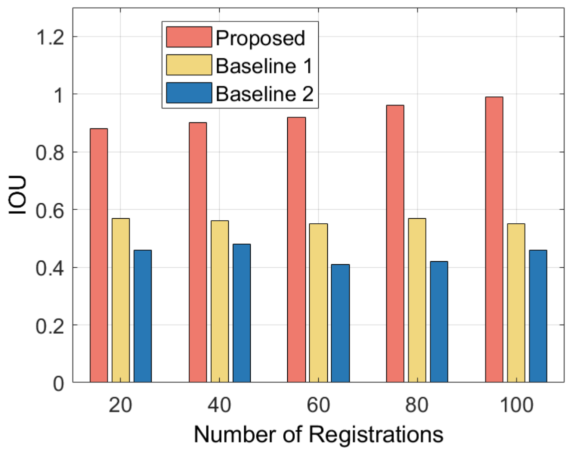


Fig. 8 IOU varies with number of registrations.

Fig. 8 shows the change of intersection over union

(IOU) varies with number of registrations. IOU stands for the intersection over union which represent the overlap rate between the target point cloud and the on-time point cloud to be configured. Compared with baseline 1 and baseline 2, the IOU of the proposed algorithm is increased by 43.54% and 55.46%, respectively. This is because the proposed algorithm dynamically selects an optimal split dimension and split value according to the feature distribution of points within the node in order to improve the high point cloud data quality. At the same time, it updates the K-D Tree model based on the loss function to adjust the noise reduction of the original point cloud data and improve the noise reduction accuracy of the high point cloud data. Therefore, it improves the identification accuracy of the charging port. The formulation of IOU is given by

$$IOU = \frac{W_{O\cap U}}{W_{O\cup U}}, \tag{22}$$

where $W_{O\cap U}$ represents the intersection area of the target point cloud and the scheduled point cloud and $W_{O\cup U}$ represents the union area of the target point cloud and the target point cloud.

Table 1 summarizes the performance analysis of the proposed algorithm, baseline 1, and baseline 2.

Table 1 Summary of simulation results

Performance index	Improvement compared to baseline 1	Improvement compared to baseline 2
Loss function versus registration times	58.73%	66.89%
Recognition success rate	21.28%	33.70%
Loss function versus point cloud integrity	57.34%	63.85%
IOU	43.54%	55.46%

5. Conclusion

Addressing the challenge of automatically identifying and accurately locating electric vehicle charging ports, this paper develops a refined strategy, leveraging advancements in point cloud registration to enhance the precision and reliability of detection and positioning. By using the adaptive K-D Tree method to reduce the noise of point cloud data, this paper effectively solves the problem of tree imbalance that may occur when the data sets are unevenly distributed in the traditional method, and improves the quality of point cloud data. In addition, this paper uses the geometric feature information of point cloud data to extract high-quality feature key points through cluster analysis, which significantly improves the efficiency and stability of the registration algorithm. Further, a feedback updating mechanism based on registration loss function is proposed, and the K-D Tree model is updated in real time through the calculation results of the loss function, which not only improves the accuracy of the charging port identification, but also enhances the model's adaptability to the point cloud data under different conditions. The simulation results show that compared with the baseline algorithms, the proposed algorithm is significantly improved in terms of loss function, recognition success rate, and integrity and accuracy of point cloud data. In the future, we will explore the integration of advanced machine learning techniques to further enhance the accuracy and efficiency of point cloud registration and electric vehicle charging port identification.

Acknowledgments

This research was funded by Science and Technology Project of State Grid Shandong Electric Power Company under grant number SDDD-2024-03, titled "Research and Application of Autonomous Charging Robots Based on Deep Reinforcement Learning and Compliant Control Technology".

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