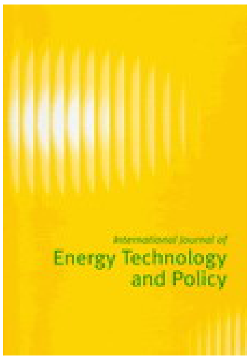

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Xuan Qi, Honglin Yan, Xiao Tu*, Yinying Liu and Weihua Ding

Construction Branch,
State Grid Jiangsu Electric Power Co., Ltd.,
Nanjing, 210000, Jiangsu, China
Email: qxa2008@139.com
Email: yanhl1028@163.com
Email: wyturx@163.com
Email: yayaliuying@163.com
Email: dingwh001@163.com
*Corresponding author

Abstract: To address the inefficiency in feature point extraction and registration caused by the complex structure of power transmission towers, this study proposes a feature registration strategy incorporating curvature feature. Given the critical role of power transmission infrastructure in smart grid systems, accurate and efficient tower modelling is essential for ensuring structural safety and operational reliability. First, an algorithm based on normal vector angles is employed to obtain an initial set of feature points. Subsequently, high-curvature points rich in geometric information are identified and retained through Gaussian curvature analysis. This approach enhances feature distinctiveness compared to uniform sampling or intensity-based selection methods. To further enhance registration efficiency, Gaussian curvature parameters are introduced into the random sample consensus (RANSAC) algorithm for preliminary matching. This integration significantly reduces the number of incorrect correspondences compared to standard RANSAC implementations. Additionally, a symmetric objective function optimises the iterative closest point (ICP) algorithm to achieve precise registration across surfaces with varying characteristics. Unlike conventional ICP, which assumes consistent surface normals, the proposed method handles asymmetric structures more effectively. Finally, by using 3D inspection software to compare the registered point cloud with a standard model, accurate quality assessment data for power transmission towers are obtained.

Keywords: iterative closest point; ICP; power transmission; Gaussian curvature; random sample consensus; RANSAC; 3D inspection.

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Biographical notes: Xuan Qi received his Bachelor's degree from Hohai University, China. Currently, he works at State Grid Jiangsu Electric Power Co., Ltd., Construction Branch. His research interests include new technologies for electric power and electrical equipment.

Honglin Yan received his Master's degree from Hohai University, China. Currently, he works at State Grid Jiangsu Electric Power Co., Ltd., Construction Branch. His research interests include new technologies for electric power and electrical equipment.

Xiao Tu received his Bachelor's degree from Southeast University, China. Currently, he works at State Grid Jiangsu Electric Power Co., Ltd., Construction Branch. His research interests include new technologies for electric power and electrical equipment.

Yinying Liu received her Master's degree from Tongji University, China. Currently, she works at State Grid Jiangsu Electric Power Co., Ltd. Construction Branch. Her research interests include new technologies for electric power and electrical equipment.

Weihua Ding received his Bachelor's degree from Shanghai University of Electric Power, China. Currently, he works at State Grid Jiangsu Electric Power Co., Ltd., Construction Branch. His research interest includes new technologies for electric power and electrical equipment.

1 Introduction

Power transmission towers are essential components of the electricity delivery network, playing an irreplaceable role in ensuring stable power transmission. Consequently, regular quality inspections are crucial for preventing failures and maintaining grid safety (Baik and Valenzuela, 2019; Xiao et al., 2020). To enhance the efficiency and accuracy of these inspections, virtual assembly technology has been extensively integrated into modern inspection processes. Unlike traditional physical assembly methods, which require time-consuming and resource-intensive field testing, virtual assembly enables the simulation of assembly and inspection procedures within a digital environment. This approach allows engineers to test various components and configurations without physical prototypes, significantly reducing costs and material waste. Furthermore, by facilitating iterative digital testing of designs, the virtual assembly provides greater flexibility and helps identify potential issues before physical assembly begins. Laser point cloud technology, which enables high-precision 3D scanning, is widely adopted in virtual assembly systems owing to its efficiency and non-contact measurement characteristics (Fang et al., 2021; Kim and Lee, 2023; Mo et al., 2024). Consequently, achieving higher accuracy in point cloud registration is a key issue in quality inspections.

Point cloud registration aligns data models captured from different locations and times into a unified coordinate system to achieve an accurate representation of physical structures (Zhao et al., 2024b). For models with complex geometries, the initial scans often generate extremely large point cloud datasets. Feature-based registration methods are widely employed to address these challenges, as feature points exhibit high stability and effectively capture key model attributes.

Common methods for feature point extraction include normal vector angle-based feature points, intrinsic shape signatures (ISS) feature points, and scale-invariant feature transform (SIFT) feature points (Ran and Xu, 2020). By computing the normal vectors for each point in the point cloud and analysing the angular variations between the normal vectors of neighbouring points, geometrically distinctive positions can be identified (Zhu et al., 2024). Feng et al. (2020) utilised the ISS algorithm to quantify the morphological characteristics of points and their neighbourhoods, thereby identifying feature points with significant morphological distinctions, which in turn facilitates the simplification of point cloud models. In Gan et al. (2024), the SIFT algorithm constructed a scale-space pyramid to detect invariant feature points to scale and rotation, ensuring consistency of features across different viewpoints and resolutions.

For the obtained feature point cloud, feature descriptors are utilised to characterise the local geometric properties within the point cloud, which are subsequently employed for registration purposes (Yang et al., 2020). Wu et al. proposed a method that establishes a local coordinate system for each feature point, representing the geometric characteristics of its neighbourhood through histograms, thereby effectively capturing the feature information of the point cloud (Wu et al., 2020). Peng et al. (2024) introduced an approach that divides the spherical neighbourhood around each feature point into multiple subspaces and computes the histogram of normal angle features for each subspace, based on the signature of histograms of orientations (SHOT) method. Tang et al. proposed a novel descriptor termed the signature of geometric centroids (SGC), which enables direct shape matching between scans without requiring preprocessing steps such as denoising or mesh conversion (Tang et al., 2017).

To achieve optimal registration results, the registration process is typically divided into two stages: coarse registration and fine registration. Coarse registration provides an approximate estimation of the positional transformation between two point clouds, initially aligning the data and offering a good starting point for the subsequent fine registration. Fine registration then refines the alignment by optimising a distance-based objective function, adjusting the relative position and orientation of the point clouds to achieve optimal alignment (Zhang et al., 2024; Wang et al., 2021). Random sample consensus (RANSAC) estimates transformation parameters by repeatedly randomly selecting the minimal necessary subset of points, ultimately choosing the model with the highest number of consistent points as the best estimate (Shen et al., 2023). To address challenges such as computational complexity and noise susceptibility, the multiscale iterative normal distribution transform (MI-NDT) was developed based on a multiscale iterative optimisation framework (Shen et al., 2024). Xu et al. (2019) improved the 4-point congruent sets (4PCS) by embedding multiscale sparse features, facilitating efficient global registration of terrestrial laser scanning point clouds.

The classical iterative closest point (ICP) algorithm, commonly employed in fine registration, iteratively minimises the Euclidean distances between corresponding points of two point clouds to achieve optimal alignment (Gao et al., 2024; Bolea-Fernandez et al., 2024). The point-to-plane objective function was employed to minimise the distance between a point and a plane defined by the matching point and its normal, thereby improving the ICP registration algorithm with faster convergence and greater accuracy (Splietker and Behnke, 2023). A symmetrical objective function is introduced to enhance the ICP registration algorithm, providing improved convergence speed and a wider convergence basin while retaining the simplicity of point-to-plane optimisation (Rusinkiewicz, 2019). Neural networks are also widely used in registration, with Liu et al. (2021) using an iterative neural network based on the inverse compositional algorithm to complete the final registration transformation.

Due to the intricate geometric structure of power transmission towers and the extensive volume of source point clouds, the registration process can impose considerable computational demands (Pleterski et al., 2024). Traditional methods such as the RANSAC coarse registration algorithm rely heavily on random sampling and iterative validation, which significantly increases time complexity and reduces efficiency, especially. Moreover, conventional feature selection strategies often lack sufficient sensitivity to critical structural features, leading to suboptimal registration performance in terms of both accuracy and speed.

Therefore, Gaussian curvature is employed to streamline computations. In the fields of 3D geometry processing, Gaussian curvature is a vital metric for shape analysis, favoured for its ability to precisely capture local geometric properties of object surfaces (Tang et al., 2023). Motivated by the above characteristics, we propose a power tower point cloud extraction strategy based on Gaussian curvature. Compared to normal vector-based feature extraction methods, the approach proposed in this paper incorporates Gaussian curvature, which is particularly effective at identifying sharp edges and turning points that contain rich structural information. By applying Gaussian curvature to evaluate the initially extracted feature point cloud data, we are able to select points with higher curvature values, thereby enhancing the accuracy and representativeness of the feature points. Compared to RANSAC-based methods proposed by Pleterski et al. (2024) and Gao et al. (2024), our approach achieves more efficient and reliable coarse registration by focusing on structurally significant points, thereby enhancing both performance and robustness in handling complex 3D point cloud data of power transmission towers.

The registered point cloud model accurately reflects the actual condition of the power tower, providing a solid foundation for subsequent model quality inspection. By comparing the point cloud model with a high-precision standard 3D model, a series of critical geometric error measurements can be obtained, which are used to evaluate and ensure the structural integrity and safety of the power tower. Common 3D model quality inspection methods often involve the use of specialised software such as CloudCompare or Geomagic Control, which offer robust data processing capabilities and enable complex comparisons between models. Through dense point-to-point or surface-patch alignments, these tools accurately calculate the deviation distributions between the actual and design models.

To address the limitations of existing virtual pre-inspection technologies for transmission towers, this paper proposes an efficient and precise scanning method along with a point cloud data processing solution. Current approaches using 3D laser scanning are underdeveloped, particularly in geometric feature extraction and virtual inspection. Our study develops and successfully applies a complete technical procedure in practical scenarios, offering a comprehensive solution for the virtual pre-inspection of transmission towers.

2 Related work

The complex geometric structures of power transmission towers pose significant challenges to efficient feature extraction and registration. To address this limitation, this study proposes a novel feature registration strategy incorporating curvature-based features. Before detailing this approach, it is essential to contextualise it within current technological developments. Recent methods have focused on improving data quality and reducing computational complexity. For instance, Zhao et al. (2024a) rapidly filtered invalid point clouds by constructing a K-D tree for neighbourhood searches combined with plane fitting and statistical analysis. Similarly, Mo et al. (2024) integrated height and curvature data for dimensionality reduction, converting point clouds into images to streamline feature extraction. While these preprocessing techniques effectively remove noise and simplify data, they predominantly address global characteristics or dimensionality reduction. In contrast, the method proposed here specifically leverages Gaussian curvature during feature point selection. This approach intrinsically reduces data complexity while concentrating on structurally rich regions of the transmission towers, thereby targeting more representative points for registration.

For feature point detection, the central point of the point cloud was selected as the feature point, and the predicted distances were utilised as the feature information (Liu et al., 2025). The principal component analysis method was employed to estimate and normalise normal vectors on unstructured point cloud data, thereby obtaining optimised point cloud information (Yao et al., 2025). Furthermore, dynamic graph convolutional neural networks were used to extract hybrid features that integrate spatial coordinates and global characteristics from point cloud data (Liu et al., 2025). While these methods extract points or features based on centrality, normals, or learned representations, the approach in this work explicitly targets geometrically salient features by applying Gaussian curvature analysis to points initially selected via normal vector angles.

In terms of coarse registration, line features were used as constraints to construct a spatial transformation objective function, enabling the estimation of transformation-related parameters and achieving initial alignment (Li et al., 2024). A multi-neighbourhood feature descriptor was leveraged to achieve initial alignment between the target and template point clouds (Wang et al., 2025). Additionally, multiple planar geometric constraints were computed, and the globally optimal constraint was selected to determine the final rotation matrix (Luo et al., 2024). These coarse registration methods utilise various geometric constraints. The proposed method enhances RANSAC-based coarse registration by introducing a curvature-guided pre-filtering step, which prioritises structurally similar point pairs and improves efficiency.

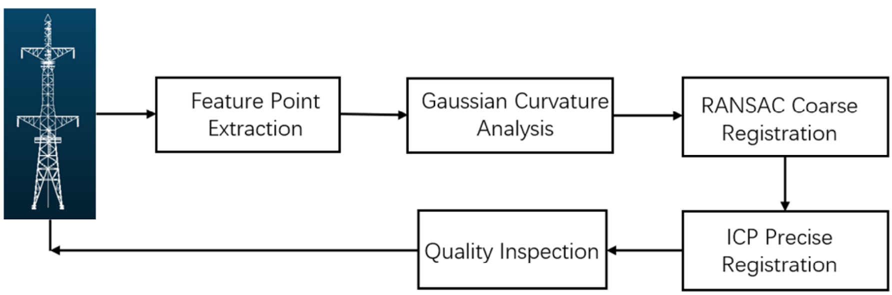
A lightweight deep learning-based registration method was proposed to capture features from multiple perspectives for the prediction of overlapping points (Jiang et al., 2025). A novel knowledge transfer mechanism guided by historical information was introduced during both the coarse and fine registration stages, effectively adjusting the search behaviour of the fine registration process (Ding et al., 2024). Moreover, the Kullback-Leibler divergence was applied to mitigate the influence of non-overlapping regions, thereby improving both registration efficiency and accuracy (Li et al., 2025). While learning-based and information-theoretic approaches show promise, the present study focuses on enhancing the classical ICP algorithm. A symmetric objective function that considers normals from both source and target point clouds is introduced to provide a wider convergence basin and potentially more accurate final alignment.

This study proposes a feature registration strategy incorporating curvature feature, which effectively addresses the challenges posed by complex geometric structures in power transmission towers. By leveraging Gaussian curvature and enhancing classical registration algorithms, the method achieves improved accuracy and efficiency without relying on deep learning or extensive preprocessing.

3 Methods

To address inefficiencies in feature point extraction and registration for power transmission towers, our proposed approach incorporates curvature feature to enhance both accuracy and efficiency. Initially, an algorithm based on normal vector angles extracts a preliminary set of feature points. Subsequently, Gaussian curvature parameters are incorporated into the RANSAC algorithm, enabling robust initial matching. For further precision, a symmetric objective function is integrated into the ICP algorithm, ensuring a more accurate registration across different surfaces of the transmission tower. In the final stage, 3D inspection software is utilised to compare the registered point cloud with a reference standard model, enabling a comprehensive quantitative assessment of the structural quality of the power transmission towers. This approach directly addresses the control goal by ensuring high registration precision and efficiency, even for complex tower structures. Figure 1 provides an overall system design block diagram.

Figure 1 System design block diagram (see online version for colours)



3.1 Feature point cloud extraction

Due to the complexity of point clouds associated with power transmission towers, performing a comprehensive fine registration requires addressing significant challenges. Given that feature points effectively capture critical characteristics and structural information, we opted to utilise these points for local fine scanning. After achieving precise local registrations, the resulting registration matrices enable overall fitting technology, ensuring a coherent and accurate alignment across the entire structure.

The normal vector represents a core geometric property of point clouds, exhibiting robust invariance under rotational and translational transformations. Curvature feature within local surface regions can be inferred by analysing angular differences between the normals of sample points and their neighbours. Leveraging this intrinsic property, we employ normal angle variance as the criterion for identifying and extracting salient feature points from point clouds.

Gaussian curvature is a crucial metric for characterising the local geometric shape of a three-dimensional surface, particularly excelling in revealing the sharpness of the surface. By calculating the Gaussian curvature of sampled points, we can identify those with prominent geometric features and richer information content. This screening process not only improves the quality of the selected feature points but also enhances the computational efficiency of downstream algorithms by reducing the overall computational complexity.

The specific process of the point extraction integrated with Gaussian curvature is as follows:

1. initial feature point extraction: compute the normal vector for each point and select those points with significantly varying normal vectors as the initial feature points
2. Gaussian curvature filtering: calculate the Gaussian curvature values of the initial feature points, retaining only those points whose Gaussian curvature exceeds a predefined threshold
3. feature point optimisation: remove isolated points and perform local geometric consistency checks to ensure the quality and uniform distribution of the feature points.

3.1.1 Initial feature point extraction

The computation of normal vectors for point cloud data typically involves two methods: least squares fitting and principal component analysis (PCA). Given the computational complexity and inefficiency associated with least squares methods, this paper selects the PCA method. PCA utilises the relationship between points and their neighbourhoods to construct a covariance matrix, where the eigenvector corresponding to the smallest eigenvalue of this matrix can be approximated as the normal vector of the point cloud. For the sampled points p_i, the covariance matrix E_i is constructed based on the k nearest neighbour points P_{ij} ($j = 1, 2, \ldots, k$).

$$E_i = \frac{1}{k}\sum_{j=1}^{k}\left(P_{ij} - \overline{p}_i\right)\left(P_{ij} - \overline{p}_i\right)^T,$$

where $\overline{p}_i$ is the centroid of the k neighbouring points.

The properties of eigenvalues yield the relationship between the eigenvalues and eigenvectors of the covariance matrix E_i:

$$E_i \cdot v_m = \lambda_m \cdot v_m,$$

where λ_m denotes the m^{th} eigenvalue of the covariance matrix E_i, with v_m being the corresponding eigenvector. If the computed eigenvalues satisfy $\lambda_0 \leq \lambda_1 \leq \lambda_2$, then the eigenvector v_0 corresponding to λ_0 can be considered the normal vector n_i for the sampled point p_i.

However, the direction of the normal vector cannot be determined, necessitating the use of the following formula to ascertain its direction (Zhan et al., 2020):

$$n_i = \begin{cases} n_i, & n_i \cdot \left(v_0 - p_i\right) \geq 0, \\ -n_i, & n_i \cdot \left(v_0 - p_i\right) < 0, \end{cases}$$

where v_0 denotes the origin of the coordinate system.

The curvature of a local surface can be characterised by the angle between the normal vectors of sampled points and their neighbouring points, with a larger angle indicating a higher degree of surface curvature. Thus, the curvature of the local plane around the sampled point p_i can be determined based on the angle between the sampled point and its neighbouring points ϕ_i:

$$\phi_i = \frac{1}{k}\sum_{j=1}^{k} \arccos\left(\frac{n_i \cdot n_{ij}}{|n_i| \cdot |n_{ij}|}\right),$$

where n_{ij} is the normal vector of the p_{ij}.

Based on the computation of the angles between the normal vectors of all sampled points and their neighbouring points, a suitable normal vector angle threshold ϕ_d can be set. If the angle ϕ_i between a sampled point p_i and its neighbours ϕ_{ij} exceeds this threshold, the sampled point is retained as a preliminary feature point. In threshold design, the use of adaptive thresholds can better accommodate various datasets, thereby enhancing the robustness and generality of the feature point detection process. For each set ϕ_i, calculating the mean μ and standard deviation σ allows for setting an adaptive normal vector threshold.

$$\phi_d = k_d(\sigma + \mu),$$

where k_d is an adaptive coefficient, typically a positive value.

3.1.2 Feature point optimisation

Although normal vectors can effectively reveal the local orientation and curvature characteristics of a point cloud surface, their ability to describe prominent features such as sharp angles, edges, and variations in concavity and convexity in complex geometric structures is limited. Therefore, introducing Gaussian curvature to further refine the initially obtained feature values is particularly critical.

Gaussian curvature, as a fundamental concept in differential geometry, quantifies the product of curvature along two orthogonal directions at a given point, thereby reflecting the local convexity and sharpness characteristics of that point. By applying Gaussian curvature analysis to the initially selected set of feature points for secondary refinement, it is possible to more accurately identify and retain those feature points with high geometric information content, thereby enhancing the recognition and representation capabilities of the feature set.

Gaussian curvature, calculated as the product of the two principal curvatures at a sampling point, can be obtained by performing singular value decomposition on the covariance matrix of the surface formed by the sampling point and its neighbours (Fu et al., 2022):

$$k_{1,2} = \frac{1}{2}\left(\lambda_0 + \lambda_1 \pm \sqrt{(\lambda_0 - \lambda_1)^2 + 4\lambda_2^2}\right),$$

where ± represents two distinct values, corresponding to different principal curvatures.

The Gaussian curvature corresponding to the sample point p_i is K_i, and $\underline{K_i} = k_1 \cdot k_2$. For sampled points, higher Gaussian curvature values indicate more prominent geometric features and richer information (Xu et al., 2019). A Gaussian curvature threshold K_d is set. If the Gaussian curvature of a feature point exceeds K_d, the point is retained. The Gaussian curvature values K_i for the initial feature points are computed, and the corresponding mean σ_k and standard deviation μ_k are determined to design an adaptive Gaussian curvature threshold.

$$K_d = c_d(\sigma_k + \mu_k),$$

where c_d is an adaptive coefficient, typically a positive value.

By focusing on feature points, the proposed method improves both the accuracy and robustness of point cloud registration, while simultaneously reducing computational complexity and processing time. The localised approach efficiently manages large and intricate datasets, simplifying the identification and correction of misalignments. Additionally, this scalable solution adapts to various structural complexities, making it ideal for applications requiring high precision and efficiency in point cloud registration.

3.2 Feature descriptor construction

The FPFH feature descriptor encodes the geometric information of a point cloud neighbourhood into a 33-dimensional histogram to describe feature points. The specific process of the feature descriptor construction is as follows:

1. Construction of local reference frames: based on the normal vectors and nearest neighbour information of each point, local reference frames are constructed to ensure the rotational invariance of feature descriptors and provide a unified coordinate system.
2. Computation of FPFH feature descriptors: utilising the established LRFs, FPFH descriptors are computed for each point. High-dimensional feature vectors that characterise the geometric properties are generated.
3. Optimisation and preparation for application: the FPFH feature descriptors undergo dimensionality reduction or normalisation to enhance computational efficiency and matching accuracy.

First, a local coordinate system is established based on the feature point p_i, its neighbouring points $\underline{P_{ij}}$ ($j = 1, 2, \ldots, k$), and their corresponding normal vectors n_i and P_{ij} ($j = 1, 2, \ldots, k$), as illustrated in Figure 2.

The coordinates of the local coordinate system can be expressed as:

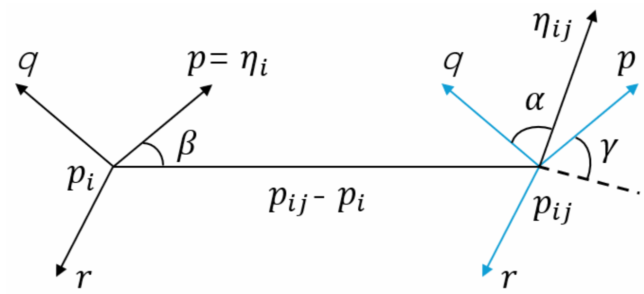
$$\begin{cases} p = n_i, \\ q = p \cdot \dfrac{p_{ij} - p_i}{\left\| p_{ij} - p_i \right\|}, \\ r = p \cdot q. \end{cases}$$

In the established local coordinate system, the angle (α, β, γ) represents the positional relationship between the feature point and its neighbouring points, and the angle (α, β, γ) is defined as:

$$\begin{cases} \alpha = q \cdot n_{ij}, \\ \beta = p \cdot \dfrac{p_{ij} - p_i}{d_{ij}}, \\ \gamma = \arctan\left(r \cdot n_{ij},\ p \cdot n_i\right), \end{cases}$$

where d_{ij} is the Euclidean distance between the feature point p_i and its neighbouring points p_{ij}.

Figure 2 Local coordinate system (see online version for colours)



The angular features (α, β, γ) between the feature point p_i and all neighbouring points P_{ij} ($j = 1, 2, \ldots, k$) are computed. Each angular feature is divided into multiple subspaces and represented as a histogram, resulting in the initial simplified point feature histogram (SPFH). The final FPFH descriptor is computed by weighting the SPFH values of all feature points and their neighbourhood points, and it takes the form of (Peng et al., 2023):

$$\text{FPFH}(p_i) = \text{SPFH}(p_i) + \frac{1}{k}\sum_{i=1}^{k}\frac{1}{d_{ij}}\text{SPFH}(p_{ij}).$$

To balance the detail of feature description with computational efficiency, FPFH divides each angular dimension (α, β, γ) into 11 subspaces, resulting in a 33-dimensional feature vector that describes the characteristics of the sampled points.

3.3 RANSAC coarse registration

The essence of RANSAC lies in random sampling and model hypothesis verification. It begins by randomly selecting a minimal subset of data points from the dataset to construct an initial mathematical model for registration. Subsequently, according to predefined error thresholds, the fit of the remaining data to this initial model is evaluated. Data points within an acceptable deviation range are labelled as inliers, while those with larger discrepancies are classified as outliers. Repeating the aforementioned steps, the model with the largest number of inliers is ultimately identified as the coarse registration model.

The randomness of RANSAC allows it to handle diverse data and improves its noise resistance. However, the process requires repeated sampling and model fitting. This typically demands many iterations, with each involving model construction and evaluation, which increases computational costs. To reduce RANSAC's computational demands, we employ curvature feature, incorporating Gaussian curvature, for initial matching point screening. By comparing the Gaussian curvatures of randomly selected surface feature points, this initial filtering improves matching reliability and efficiency.

Let the sets of source and target point clouds be denoted as S_{fp} and D_{fp} respectively. The point cloud sets are randomly divided into a source point cloud $S_c \in S_{fp}$ and a target point cloud $D_c \in D_{fp}$, where the point pairs can be represented as $\{(s_i, d_i) | s_i \in S_c, d_i \in D_c, i = 1, 2, \ldots, N\}$, with N being the number of corresponding points. Select an appropriate threshold ζ. Let $K(s_i)$ denote the Gaussian curvature value of the source point cloud s_i, and $K(d_i)$ denote the Gaussian curvature value of the target point cloud s_i. If the condition is met:

$$\left|\frac{K(s_i)-K(d_i)}{K(s_i)+K(d_i)}\right| \leq \zeta.$$

Then, the point pair (s_i, d_i) can be considered to satisfy the constraints of the curvature feature parameters and can serve as an initial mathematical model. If the point pair (s_i, d_i) does not satisfy the curvature feature parameter constraints, then suitable point pairs are re-elected.

The specific process of the RANSAC algorithm integrated with Gaussian curvature is as follows:

1 Three sets of elements (s_i, d_i) ($i = 1, 2, 3$) are randomly selected from the set of corresponding points (S_c, D_c), where any two sets must satisfy the above equation. If they do not, the selection process is repeated. The required rigid transformation matrix T is then calculated based on the three sets of corresponding points.

2 Using the calculated rigid transformation matrix T, the source point cloud samples S_c are transformed to obtain the sample set S_v.

3 The distances between the transformed point set S_v and the corresponding points in the target point cloud set D_c are calculated. If the distance is below a threshold, the point pair is considered an inlier. Otherwise, it is deemed an outlier.

4 The process is repeated until the predefined number of iterations is reached, and the model with the most inliers is selected as the optimal model. At this point, the source point cloud has been transformed using the rigid transformation matrix, achieving coarse registration of the point clouds.

3.4 ICP precise registration

The traditional ICP algorithm has two primary variants: one minimising point distance (point-to-point), and other incorporating normal vectors for point-to-plane matching. Point-to-point ICP aligns models by minimising the total sum of Euclidean distances between each source point and its closest target point. Point-to-plane ICP uses geometric surface information more deeply. It aligns each source point along the normal direction of the target surface, improving surface conformity between the models. By using normal vectors, point-to-plane ICP can better adapt to subtle structures and variations in the target surface during alignment. This enhances the algorithm's robustness and accuracy when matching complex shapes. The specific steps for ICP precise registration are as follows:

1 Initial registration: select initial corresponding point pairs from the source and target point clouds and calculate the distance error between each pair using a symmetric objective function.

2 Based on the aforementioned distance errors, compute the optimal rigid transformation matrix by minimising a symmetric objective function, and apply this transformation to align the source point cloud accordingly. This iterative process is repeated until either the preset convergence criteria are satisfied or the maximum

number of iterations is reached, thereby achieving high-precision point cloud registration.

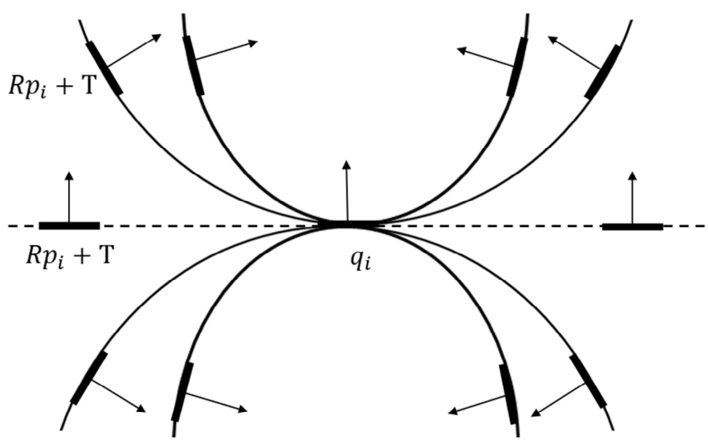
The objective function ε_{plane} is as follows:

$$\varepsilon_{plane} = \left\| (Rp_i - q_i) \cdot n_q \right\|^2,$$

where R and T represent the rotation and translation transformation matrices respectively. (p_i, q_i) is a set of corresponding point pairs. n_q is the normal vector of the point q_i.

By using normal vector information from each point in the target point cloud, the point-to-plane ICP algorithm significantly improves registration accuracy and robustness. However, this requires a better initial alignment of the point clouds, so the algorithm's convergence basin becomes narrower. This limitation is especially evident when dealing with curved surfaces. The error only approaches zero when corresponding points lie within truly flat, local regions. For points on curved surfaces, the traditional point-to-plane ICP objective function may fail to find their correct correspondences accurately, leading to alignment errors.

Figure 3 Symmetric objective function-based ICP principle



Therefore, considering the surface normal of the source and target point clouds, a symmetric objective function ε_{symm} is designed to account for a broader range of alignments for precise registration, thereby achieving precise registration. This approach, as illustrated in Figure 3, enables the point clouds to undergo slight adjustments along their surfaces without incurring additional errors. By incorporating the surface normal into the objective function, the method ensures that the alignment process considers not only positional data but also the orientation of points, leading to more accurate and robust registrations. The use of a symmetric objective function minimises errors in both directions, enhancing the overall accuracy of the matching process.

The objective function ε_{symm} takes the form of:

$$\varepsilon_{symm} = \left\| (R \cdot p_i - q_i) \cdot (n_p + n_q) \right\|^2,$$

where n_p is the normal vector of point p_i.

The proposed symmetric objective function considers the normals of both point clouds, measuring not only the alignment error from the source to the target point cloud but also the error from the target to the source point cloud. This bidirectional consideration ensures symmetry in the registration process and simplifies computational complexity.

4 Results

To demonstrate the effectiveness of the Gaussian curvature-integrated point cloud registration and quality inspection strategy designed in this paper, the following engineering examples are conducted. In the engineering application of power transmission towers, the process begins by extracting feature points using an algorithm based on normal vector angles. These points are then used in the RANSAC algorithm, where Gaussian curvature parameters are integrated to achieve a robust preliminary match. To refine the accuracy, the ICP algorithm with a symmetric objective function is applied for precise registration across the tower surfaces. Finally, CloudCompare software is used to compare the registered point cloud with a standard model, enabling a comprehensive quality inspection of the tower.

Compared to the classic normal vector angular feature detection algorithm, this paper leverages the advantages of Gaussian curvature in describing the local characteristics of complex geometric surfaces. By introducing Gaussian curvature as a selection criterion, the proposed method can more accurately identify feature points rich in geometric information while eliminating redundant or less informative points.

The experimental platform is based on the Ubuntu 18.04 operating system, with PCL version 1.9.1 integrated as the point cloud processing framework. For the software environment, CloudCompare 2.13.2 is selected as the tool for evaluating point cloud model quality. The entire experiment is conducted on a hardware platform equipped with an NVIDIA RTX 4060 graphics card, to support efficient point cloud data processing and visualisation tasks.

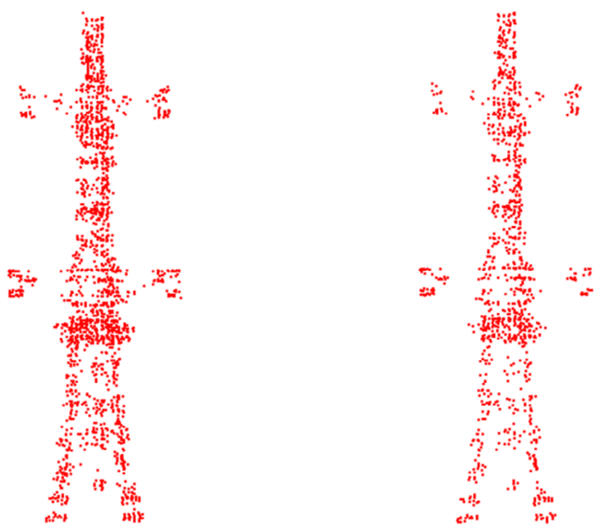
The designed parameters are chosen as: $k = 20$, $d_d = 0.5$, $c_d = 0.5$, $\zeta = 5$. Table 1 presents the criteria for parameter selection and provides a detailed explanation of how the parameters affect the designed point cloud recognition strategy.

Table 1 Parameter selection strategy

	Parameter selection strategy
Step 1	Initially, when using the PCA method to obtain the normal vector values of the point cloud, k is used to determine the number of neighbouring points. A larger k can yield more accurate normal vectors, but it also brings a higher computational burden.
Step 2	During the normal vector selection process, by setting a threshold value k_d and a Gaussian curvature threshold c_d the normal vector values of each point cloud are computed. As the value of k_d and c_d increase, the resulting set of preliminary feature points gradually decreases. However, a larger k_d and c_d value may also lead to the omission of important point cloud data.
Step 3	The parameter ζ is then selected to determine the accuracy of the coarse registration. Before performing RANSAC-based coarse registration, the Gaussian curvature threshold ζ is used for preliminary filtering. A higher threshold can improve the accuracy of the coarse registration, but it may also result in some point clouds failing to register.

Figure 4 Diagram of normal vector feature points (see online version for colours)

Figure 5 Diagram of Gaussian curvature feature points (a) the case with an adaptive coefficient of 1 (b) the case with an adaptive coefficient of 0.5 (see online version for colours)



(a) (b)

4.1 Extracted point cloud feature points

Figure 4 illustrates the feature points obtained using the normal vector angle feature extraction method. As shown, the number of extracted feature points is abundant, providing comprehensive coverage of the entire power tower structure. As we show in code file 2, Figure 5 presents the results of the normal vector angle feature detection algorithm after incorporating Gaussian curvature. With this algorithm, the number of feature points is significantly reduced, and these points are primarily concentrated at key locations such as the top of the power tower, the crossbars, and the insulators. This result validates the effectiveness and advancement of using Gaussian curvature for feature point selection. Notably, the final number of feature points varies significantly based on different adaptive settings for the Gaussian curvature parameter. With an adaptive parameter set to 1, the number of feature points extracted was 1,154. However, when the adaptive parameter was set to 0.5, the quantity of feature points increased to 1,752. Given that a higher number of feature points can more comprehensively capture the critical structural details of the power transmission towers, the final choice was to use the adaptive parameter setting of 0.5.

4.2 Registration results of point clouds

After extracting feature points, the RANSAC coarse registration algorithm using Gaussian curvature can make better initial point pair selections. Specifically, by comparing the Gaussian curvature values of candidate point pairs, we can quickly filter out geometrically incompatible matches. This significantly reduces ineffective random sampling attempts, improving the algorithm's efficiency. To more fully demonstrate the performance enhancement of the RANSAC coarse registration algorithm through the integration of Gaussian curvature, we conducted comparisons using the same number of iterations, setting the iteration count to 8,000. Figure 6 shows the coarse registration results of the classical RANSAC algorithm. It can be observed that the point clouds have achieved initial alignment, but there remains a significant deviation. Figure 7 presents the results of the RANSAC coarse registration enhanced with Gaussian curvature. With the same number of iterations, a significantly improved alignment of the point clouds is evident, with key structures such as crossbars and connection nodes achieving more precise positional alignment.

In the fine registration process, a symmetric objective function-based ICP algorithm is designed to simultaneously consider the normal information of both the source and target point clouds. This effectively expands the convergence range of the algorithm, thereby significantly enhancing registration efficiency while ensuring registration accuracy. Figure 8 shows the fine registration results for the power tower, demonstrating the precise alignment of the main body structure. These results demonstrate that the proposed method is capable of accurately registering complex surface geometries.

Figure 6 The RANSAC coarse registration results (see online version for colours)

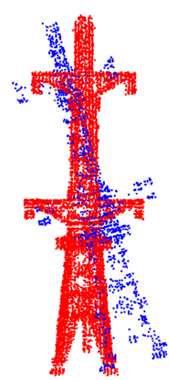


Figure 7 The RANSAC coarse registration results integrated with Gaussian curvature (see online version for colours)

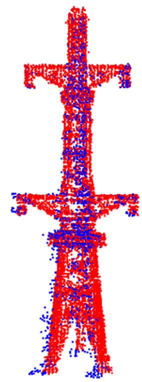
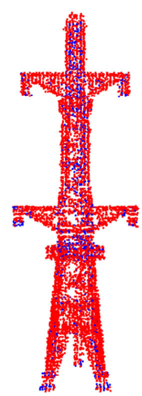


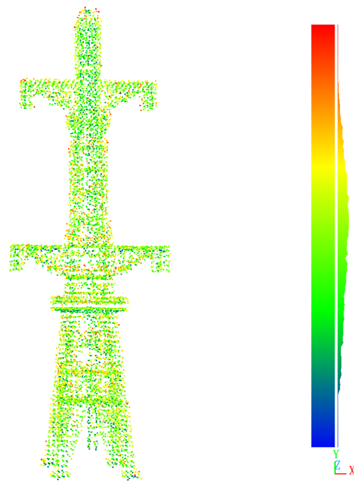
Figure 8 Precision registration results on power transmission tower (see online version for colours)



4.3 The results of the quality inspection

Ultimately, after performing fine registration, we achieved precise alignment between the LiDAR point cloud scans and the standard model. Subsequently, we utilised specialised quality assessment software, CloudCompare, to compare the aligned point cloud model with the standard geometric model, thereby generating quality evaluation difference maps. As shown in Figure 9, the error colour map on the right illustrates the error distribution, where green indicates smaller errors and red denotes larger errors. The difference map intuitively illustrates the error distribution across various structural components, with particular emphasis on regions exhibiting more pronounced degradation. Specifically, areas displaying a higher concentration of red indicate greater discrepancies at the edges of the power tower, suggesting increased susceptibility to damage and a corresponding reduction in structural integrity.

Figure 9 Quality assessment difference map of point cloud models (see online version for colours)



The experimental results indicate that the proposed point cloud registration algorithm significantly improves registration efficiency and effectively alleviates computational pressure. After registration, we successfully conducted quality assessments of the power tower models using three-dimensional model quality inspection software.

5 Conclusions

This study addresses the challenge of efficiently and accurately processing complex 3D point cloud data of power transmission towers. By integrating Gaussian curvature feature with an ICP algorithm based on a symmetric objective function, a novel solution is provided. Using Gaussian curvature's ability to capture distinct surface features, we select highly descriptive feature points from an initial set based on normal vector angles. The geometric information of the extracted feature points is described using the FPFH feature descriptor. Then, a Gaussian curvature-enhanced RANSAC algorithm performs coarse registration to estimate an initial transformation matrix between point clouds. For surfaces with non-zero curvature, we design a symmetric objective function to optimise the classical ICP algorithm. Finally, we compare the registered point cloud model with the standard model using quality inspection software to evaluate the power transmission tower. This approach combines advanced feature extraction with robust registration, significantly improving efficiency and accuracy. However, the point cloud recognition strategy proposed in this study operates independently across different segments, which may lead to the accumulation of errors. In the future, reinforcement learning methods may be considered to improve the current strategy.

Declarations

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All authors declare that they have no conflicts of interest

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