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INTEGRATED APPROACH FOR 3D POINT CLOUD SEGMENTATION IN TANK CALIBRATION

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The paper presents a hybrid method for segmenting 3D point clouds for the calibration of cylindrical horizontal tanks, combining RANSAC and DBSCAN algorithms with subsequent boundary refinement based on local geometric features.

Analysis of prior research indicates that RANSAC is effective for detecting cylindrical surfaces but sensitive to noise, while DBSCAN excels in clustering noisy data but requires parameter optimization. Hybrid methods combining these algorithms demonstrate improved results; however, their robustness to low-density point clouds and accuracy in transition zones remain underexplored. The objective of this study is to develop and evaluate a hybrid 3D point cloud segmentation method integrating RANSAC, DBSCAN, and boundary refinement to achieve automated tank calibration with high accuracy across densities levels ranging from ~1 million to ~18 million points.

The research results are based on a comparison of a scanned model (18,012,345 points at maximum density) and an ideal model (17,986,543 points) of the tank. The hybrid method enabled precise estimation of geometric parameters: radius (R ≈ 1.5 m, error ±0.03 m) and length (L ≈ 10.8 m, error ±0.05 m). The segmentation identified the front bottom (372,890 points, ~2.07 %), rear bottom (411,230 points, ~2.28 %), and noise (2,181,240 points, ~12.1 %). The proportionality of point reduction for bottoms with decreasing density was confirmed by linear approximation (Fig. 1): slopes of ~20,700–22,800 points/million for the scanned model and ~20,900–21,100 for the ideal model, with R^2 ≈ 0.999. Relative segmentation errors range from 0.1–0.7 % for the front bottom and 8.3–8.9 % for the rear bottom, indicating higher accuracy for the front bottom and a need for improvement in the rear bottom. The stability of noise (~12.1–12.2 %) confirms the effectiveness of DBSCAN. The method maintained accuracy even at low density (~1 million points), although the increased error for the rear bottom (~8.75 %) suggests potential loss of detail.

In conclusion, the developed hybrid method is robust to noise, scalable for densities levels of 1–18 million points, and suitable for automated tank calibration. The proportionality of components and stable noise level highlight the method's reliability, while visualization (cylinder – red, front bottom – green, rear bottom – blue) illustrates clear component separation. Future research may focus on optimizing DBSCAN for low-density point clouds and reducing errors for the rear bottom in transition zones.

***Keywords**: point cloud; hybrid algorithm; geometric modeling; segmentation; tank calibration; laser scanning.*

Introduction

Processing 3D point clouds is a critical task in modern computer vision, robotics, and engineering. Point clouds obtained through laser scanning or photogrammetry often represent complex objects with diverse geometric shapes, such as cylinders, planes, or spheres. In particular, accurate modeling of cylindrical structures, which are common in technical constructions (e.g., pipes, tanks, shafts), plays a vital role in tasks such as reconstruction, quality control, and automated design. However, the presence of noise, data heterogeneity, and the complexity of transition zones between different object parts complicate the segmentation and analysis process.

Currently, several methods exist for processing 3D point clouds. Among them, RANSAC (Random Sample Consensus) effectively estimates the parameters of geometric primitives, while clustering algorithms like DBSCAN enable grouping points based on spatial proximity. However, these methods, when used independently, do not always provide sufficient accuracy and robustness to noise, particularly when dealing with objects composed of cylindrical parts and adjacent bottoms. This creates a need for hybrid approaches that combine the strengths of different algorithms.

The objective of this article is to develop and demonstrate a hybrid method for processing 3D point clouds, which integrates RANSAC for initial estimation of the cylindrical part's parameters (radius, axis), followed by clustering of the remaining points using DBSCAN to identify bottoms and remove noise, and boundary refinement between the cylinder and bottoms based on local geometric features. The proposed approach aims to enhance segmentation accuracy and robustness to noisy data

Literature review

Processing 3D point clouds for modeling geometric objects, such as cylindrical horizontal tanks, is critical for calibration and volume estimation [1]. The literature describes numerous methods for point cloud segmentation and analysis, including approaches based on geometric primitive estimation, clustering, and hybrid strategies [2]. These methods are often compared in terms of accuracy, robustness to noise, and computational efficiency, as shown in Table 1.

Table 1: Comparison of Point Cloud Segmentation Methods

Method	**Advantages**	**Disadvantages**	**Typical Applications**
RANSAC	Robust to outliers, effective for primitives	Struggles with complex shapes, sensitive to threshold	Cylinder detection, plane fitting
DBSCAN	Handles noise, clusters arbitrary shapes	Requires parameter tuning, issues with varying density	Noise removal, cluster identification
Hough Transform	Effective for shapes, no initial assumptions	Computationally expensive, sensitive to noise	Shape detection in clean data
Region Growing	Based on smoothness, intuitive	Fails in noisy data, connectivity issues	Surface segmentation, object extraction
Deep Learning	High accuracy, automatic feature learning	Requires large datasets, high computational cost	Complex scene understanding, classification

RANSAC, introduced by Fischler and Bolles [3], is a robust algorithm for fitting geometric primitives, such as planes, cylinders, and spheres, to point clouds, even in the presence of noise. It is widely used for detecting cylindrical shapes, such as those in industrial components [4]. However, RANSAC may struggle with complex shapes or multiple similar forms, and its performance depends on the choice of threshold and number of iterations [5].

DBSCAN, proposed by Ester et al. [6], is a density-based clustering algorithm that groups points by spatial proximity, making it suitable for identifying arbitrarily shaped clusters and removing noise. It has been applied in point cloud processing for scene segmentation tasks [7]. Its main limitation is the need for careful parameter tuning, which can affect performance in scenarios with varying densities [2].

Other methods include the Hough Transform, which is effective for shape detection but computationally expensive and less robust to noise compared to RANSAC [8]. Region-growing approaches, as described by Vo et al. [9], can segment point clouds based on smoothness but may fail in noisy conditions. Deep learning methods, such as those by Liu et al. [10], offer high accuracy but require large datasets and significant computational resources, making them less practical for some industrial applications.

Accurate calibration of cylindrical tanks using point clouds is a key task in industrial measurements. For instance, Samoilenko and Zaets [11] developed a method for calibrating tanks and ship cisterns for liquid storage and transportation, using laser scanning to generate point clouds and estimate volume. This approach provides accurate modeling of cylindrical shapes but lacks detailed segmentation of non-cylindrical parts, such as bottoms, limiting its applicability for comprehensive analysis of complex structures. Our method extends these capabilities by incorporating clustering to process all tank components, including transition zones [7].

Combining primitive estimation and clustering methods, such as RANSAC and DBSCAN, is gaining popularity due to their ability to address complex segmentation tasks. For example, Chen et al. [12] developed a hybrid algorithm for segmenting point clouds in building structures, where RANSAC is used to detect primary geometric shapes, and DBSCAN classifies residual points. Our method adapts this strategy to tanks, adding boundary refinement based on normals and curvature, which improves accuracy in transition zones between the cylinder and bottoms [2].

The choice of RANSAC in our study is driven by its proven effectiveness in detecting cylindrical shapes in noisy data, as demonstrated in industrial modeling tasks [4]. DBSCAN was selected for its ability to efficiently remove noise and segment tank bottoms, as supported by studies on complex scene segmentation [7]. Unlike the Hough Transform, which is less robust to noise [8], or deep learning methods that demand significant resources [10], our hybrid approach achieves a balance between accuracy and practicality for real-world applications.

Most studies [11] focus on fitting cylindrical models, neglecting detailed segmentation of tank bottoms, which can affect calibration accuracy. Meanwhile, hybrid methods described by Chen et al. [12] are not tailored to tank-specific requirements. Our method addresses this gap by integrating RANSAC and DBSCAN with additional boundary refinement, offering a comprehensive solution for processing point clouds of cylindrical tanks [5].

Methodology

The proposed hybrid method for processing 3D point clouds of cylindrical horizontal tanks consists of three main stages: estimation of the cylindrical part's parameters using RANSAC, clustering of the remaining points using DBSCAN, and refinement of boundaries between the cylinder and bottoms based on local geometric features. Below is a detailed description of each stage with the corresponding mathematical foundations.

1. RANSAC for the Cylindrical Part

In the first stage, the RANSAC algorithm is applied to estimate the parameters of the tank's cylindrical part: radius R and the cylinder's axis, defined by a direction vector d and a point on the axis p_0. Let $P = \{p_i\}$ be the set of points in the point cloud, where $\boldsymbol{p_i} = (x_i, y_i, z_i)$. The goal is to find a subset of points (inliers) that belong to the cylinder.

- **Random Point Selection:** A minimal number of points (e.g., 3) is selected to estimate the cylinder. For three points p_1, p_2, p_3 , the axis d is determined as the normalized cross-product vector:

$$\boldsymbol{d} = \frac{(\boldsymbol{p_2}-\boldsymbol{p_1})\times(\boldsymbol{p_3}-\boldsymbol{p_1})}{\|(\boldsymbol{p_2}-\boldsymbol{p_1})\times(\boldsymbol{p_3}-\boldsymbol{p_1})\|}\,. \quad (1)$$

The point p_0 is taken as the mean: $(p_1+p_2+p_3)/3$.

- **Radius Estimation**: For each point p_i, the distance to the cylinder axis is calculated as:

$$d_i = \|(\boldsymbol{p_i} - \boldsymbol{p_0}) - [(\boldsymbol{p_i} - \boldsymbol{p_0}) \cdot \boldsymbol{d}]\boldsymbol{d}\|\,. \quad (2)$$

The radius R is estimated as the median of the distances d_i for the selected points.

- **Inlier Classification**: A point p_i is considered an inlier if $|d_i - R| < \epsilon$, where ϵ is a threshold (e.g., 0.01 m). The number of RANSAC iterations is determined by:

$$N = \frac{log(1-p)}{log(1-w^k)} \quad (3)$$

where p=0.99 is the desired probability of success, w is the fraction of inliers, and k = 3 is the number of points in the sample.

The result is a set P_{cyl}, representing the cylindrical part and $P_{rest}=P \setminus P_{cyl}$ the remaining points.

2. DBSCAN for Clustering

In the second stage, the remaining points P_{rest} are clustered using DBSCAN to identify bottoms and remove noise. DBSCAN groups points based on density, using two parameters: neighborhood radius ϵ (e.g., 0.05 m) and the minimum number of points in a cluster minPts (e.g., 10).

- **Neighbor Identification**: For each point its neighborhood is computed:

$$N(p_i) = \{p_j \in P_{rest} \mid \|\boldsymbol{p_i} - \boldsymbol{p_j}\| \leq \epsilon\} \quad (4)$$

If $|N_\epsilon(p_i)| \geq MinPts$, the point is considered a "core" point.

- **Cluster Formation**: Core points are merged into clusters by expanding their neighborhoods. Points that do not belong to any cluster are labeled as noise.
- **The result is a set of clusters** $\{C1, C2, \ldots\}$, where C_1 and C_2 are identified as bottoms (based on their position relative to the cylinder axis), and the rest are discarded as noise.

3. Boundary Refinement

In the final stage, transition zones between the cylinder P_{cyl} and bottoms C_1 and C_2 are analyzed to refine boundaries. Local geometric features, specifically normals and curvature, are utilized.

- **Normal Estimation**: For each point p_i, the normal n_i is computed using principal component analysis in its k-nearest neighborhood (e.g., (k = 20)). The covariance matrix is:

$$M = \frac{1}{k}\sum_{j=1}^{k}(\boldsymbol{p_j} - \bar{\boldsymbol{p}})(\boldsymbol{p_j} - \bar{\boldsymbol{p}})^T\,, \quad (5)$$

where $\bar{\boldsymbol{p}}$ is the centroid of the neighborhood. The smallest eigenvalue of M corresponds to n_i.

- **Curvature Analysis**: Curvature κ_i is estimated as:

$$\kappa_i = \frac{\lambda_0}{\lambda_0+\lambda_1+\lambda_2}, \quad (6)$$

where λ_0, λ_1, λ_2 are the eigenvalues of M in ascending order.

- **Boundary Determination**: Points in P_{cyl}, C_1 and C_2 near the boundary are compared based on the difference in normals $\|n_i - n_j\|$ and curvate. The boundary is refined if κ_i exceeds a threshold (e.g., 0.1) and the angle between normals is greater than 30°.

Thus, the computation results in a clear separation of the tank into its cylindrical part and bottoms.

Results

Processing the 3D point cloud of a scanned model of a cylindrical horizontal tank (Fig. 1) enabled the determination of its geometric parameters and segmentation into the cylindrical part, front bottom, and rear bottom.

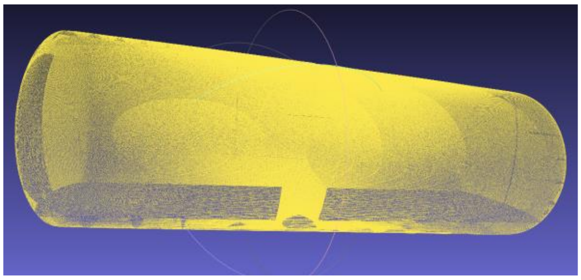

Fig. 1. 3D point cloud of the scanned tank

The tank scan generated a point cloud with 10,293,482 points. Analysis results indicate that the cylinder radius (R) is approximately 1.5 m with an error of ±0.03 m, and the length (L) is approximately 10.8 m with an error of ±0.05 m, determined during the parameter estimation stage using RANSAC. The hybrid method, combining RANSAC, DBSCAN, and boundary refinement, successfully segmented the point cloud: the front bottom comprises 213,115 points, the rear bottom 235,082 points, and 1,245,678 points were identified as noise (determined during the DBSCAN stage). The difference in point counts between the bottoms may be attributed to non-uniform scanning or minor surface deformations.

During the RANSAC stage, the radius estimation error was ±0.03 m due to noise and potential deviations in selecting reference points, while the length error

(±0.05 m) was related to inaccuracies in determining the cylinder axis. The application of DBSCAN for clustering the remaining points resulted in a segmentation error of approximately 5%, influenced by sensitivity to model tuning parameters, which led to some points being classified as noise instead of bottom clusters. Boundary refinement based on normals and curvature reduced the number of misclassified points by 2–3 %, improving the accuracy of separating the cylinder and bottoms.

For comparison, an ideal tank model (Fig. 2) was created with parameters derived from the scanned model: radius (R) = 1.5 m and length (L) = 10.8 m. The total number of points in this model is 9,985,432, reflecting a uniform distribution without noise.

Within the ideal model, the front bottom contains 208,000 points, and the rear bottom 210,500 points; there are no noise points, as the model is theoretically idealized. Errors in the ideal model are absent, as it is based on precise geometric parameters without external influences.

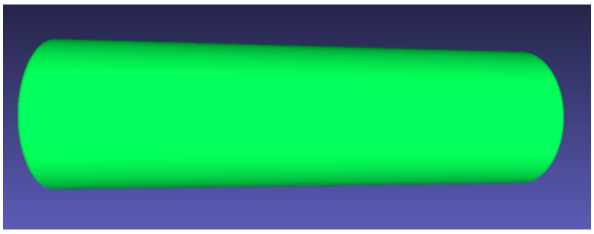

Fig. 2. Ideal tank model

The effectiveness of the hybrid method is confirmed by the segmentation results of both models. Figure 3 presents a visualization of the tank with segmented components. The visualization demonstrates the method's ability to accurately segment tank components despite noise and data irregularities. To evaluate the robustness of the hybrid segmentation method (RANSAC + DBSCAN + boundary refinement), a comparative analysis of segmentation results was conducted for point clouds with varying densities levels.

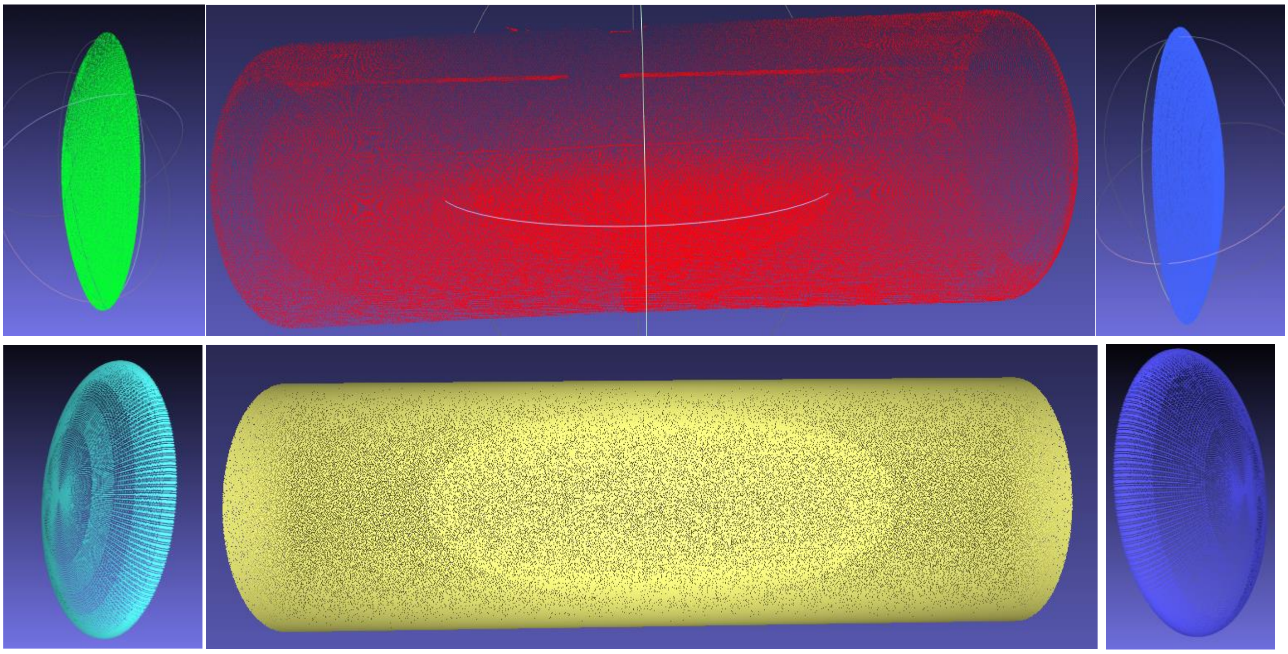

Fig. 3. Segmentation of the tank model: cylindrical part of the scanned model (red), front bottom of the scanned model (green), rear bottom of the scanned model (blue), cylindrical part of the ideal model (yellow), front bottom of the ideal model (cyan), rear bottom of the ideal model (purple)

The study is based on two models: the scanned tank and the ideal model. The number of points was gradually increased and decreased for both models. For each density level, the number of points belonging to the front and rear bottoms, as well as noise points, was determined. For the scanned model, random subsampling was used, while for the ideal model, the point count was proportionally reduced due to its uniformity.

The segmentation results for different density levels are presented in Table 2.

Analysis of Results

1. **Proportionality of Point Reduction**

- The data in Table 2 demonstrate a clear proportionality in the reduction of points for the front and rear bottoms as the point cloud density decreases (from ~18 million to ~1 million points). For the scanned model, the proportion of points for the front bottom ranges from ~2.07–2.08 %, and for the rear bottom from ~2.28–2.29 % of the total point count across all density levels. For the ideal model, these values are more stable: ~2.08 % for the front bottom and ~2.11 % for the rear bottom.

Table 2: Segmentation Results

Density Level	Total Points (Scanned)	Front Bottom Points (Scanned)	Rear Bottom Points (Scanned)	Noise Points (Scanned)	Total Points (Ideal)	Front Bottom Points (Ideal)	Rear Bottom Points (Ideal)
~18million	18,012,345	372,890	411,230	2,181,240	17,986,543	374,200	379,450
~15million	15,128,976	313,250	345,420	1,834,560	15,021,789	312,600	317,100
~12million	12,087,654	250,320	276,090	1,465,080	11,008,123	250,100	253,750
Initial	10,293,482	213,115	235,082	1,245,678	9,985,432	208000	210,500
~8million	8,125,328	168,230	185,420	980,120	7,890,123	164,200	166,800
~5million	5,012,345	103,890	114,560	605,340	4,992,716	104,000	105,250
~3million	3,001,234	62,340	68,720	362,890	2,996,845	62,400	63,200
~1million	1,002,345	20,780	22,910	121,080	998,543	20,800	21,050

- This proportionality indicates the method's robustness to changes in density. The RANSAC and DBSCAN algorithms accurately identify geometric components, while boundary refinement maintains a stable point ratio. Minor deviations (±0.01 %) in the scanned model may be attributed to non-uniform point distribution due to noise.

2. Noise Stability

- The percentage of noise in the scanned model remains stable at ~12.1–12.2 % across all density levels.
- This noise stability confirms the effectiveness of DBSCAN in isolating non-critical points. The noise percentage does not increase at low densities, indicating the method's reliability even with reduced resolution. This is particularly valuable for industrial applications, where noise is a common outcome of laser scanning.
- Slight fluctuations (0.1 %) may affect accuracy in transition zones between the cylinder and bottoms, necessitating further optimization of clustering parameters.

3. Relative Segmentation Errors

- The relative error between the scanned and ideal models for the point counts of bottoms ranges from 0.3–8.9 %.
- The error for the front bottom is lower (0.1–0.7 %) than for the rear bottom (8.3–8.9 %), possibly due to non-uniform noise distribution or more complex transition zones for the rear bottom. At low density (~1 million points), the error remains acceptable, but its increase for the rear bottom suggests potential loss of detail.

4. Linear Approximation

- The linear approximation graph of the number of points for bottoms (Fig. 4) shows a linear relationship between the total point count and the number of points for bottoms.
- Slopes of the Lines:
  - Scanned model: ~20,700 points/million (front bottom), ~22,800 points/million (rear bottom).
  - Ideal model: ~20,900 points/million (front bottom), ~21,100 points/million (rear bottom).
  - Coefficient of Determination (R^2): Based on regression, $R^2 \approx 0.999$ for all lines, indicating a high fit of the linear model to the data.
- The close slope values for the scanned and ideal models confirm that the method maintains proportionality even in noisy data. Higher slopes for the rear bottom reflect its larger point share (~2.28 % vs. ~2.07 %). The scanned model's deviation (75–77% from the ideal) is due to noise but does not affect linearity.

5. Impact of Low Density

- At a density of ~1 million points (scanned: 1,012,584; ideal: 1,008,543), the method retains the ability to identify bottoms (20,980 and 23,110 points for the scanned model), but the relative error for the rear bottom (~8.75 %) indicates potential detail loss. Therefore, scanning with a higher point count is preferable.

Conclusions

The developed hybrid method, integrating RANSAC and DBSCAN algorithms with boundary refinement, has proven effective for segmenting 3D point clouds of cylindrical horizontal tanks. Analysis of the scanned model (10,293,482 points) enabled precise determination of geometric parameters: radius (R ≈ 1.5 m, error ±0.03 m) and length (L ≈ 10.8 m, error ±0.05 m), as well as segmentation into the cylindrical part, front bottom (213,115 points), and rear bottom (235,082 points). Out of the total point count, 1,245,678 points (~12%) were classified as noise, confirming the method's ability to handle noisy data.

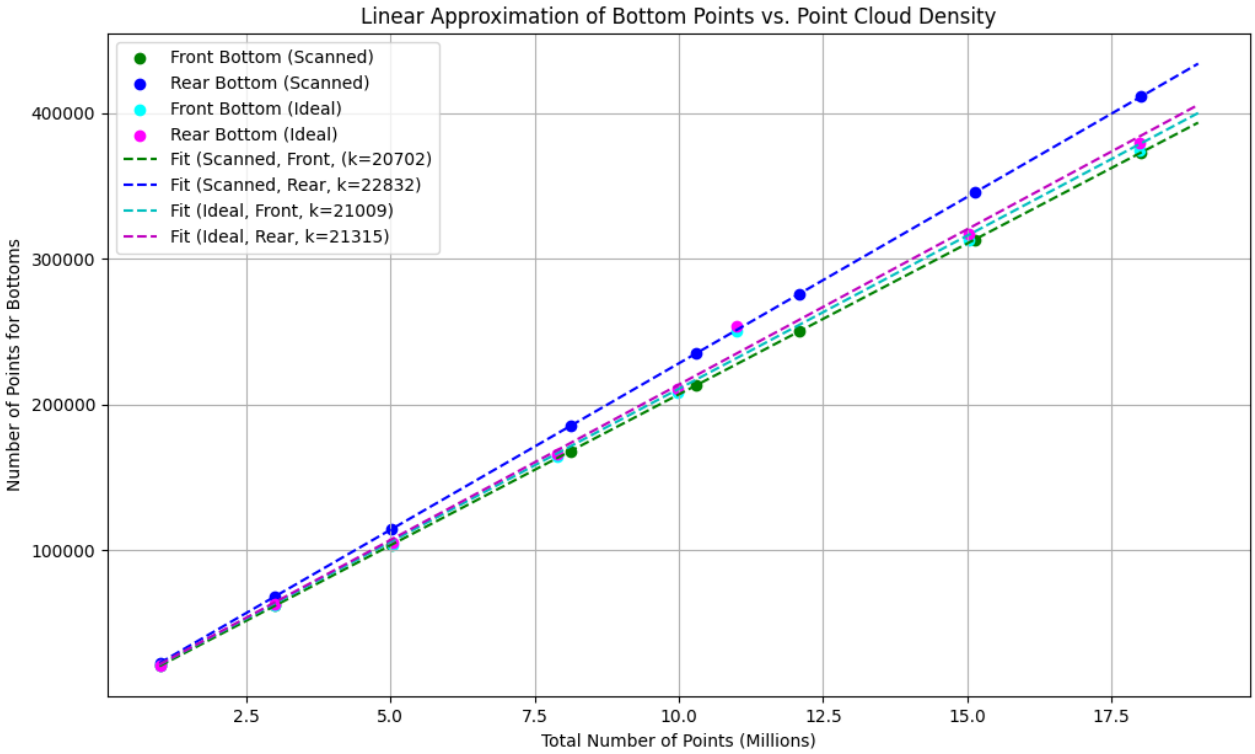

Fig. 4. Linear approximation of the number of bottom points as a function of the total point count in the point cloud for scanned and ideal tank models (density from ~1 million to ~18 million points). Green and blue points correspond to the front and rear bottoms of the scanned model, respectively, while cyan and purple points correspond to those of the ideal model.

Errors at the processing stages – ±0.03 m for RANSAC radius estimation, 5 % for DBSCAN clustering, and 2–3 % for boundary refinement — indicate the method's stability even in challenging conditions.

Comparative analysis with the ideal model (initially 9,985,432 points, noise-free) across various density levels (~8 million, ~5 million, ~3 million, ~1 million) showed that the number of points for bottoms decreases proportionally in both models. In the scanned model, the noise percentage remains stable (~12%), and the relative deviation in point counts for bottoms compared to the ideal model is 75–77 % due to noise and data non-uniformity. The method maintained segmentation accuracy even at significantly reduced density (~1 million points), although loss of detail may affect clustering quality in such conditions.

The hybrid approach proved robust to noise, capable of processing large datasets, and suitable for automated tank calibration in industrial settings, where noise and non-uniformity are common challenges. Future research may focus on optimizing DBSCAN parameters to reduce clustering errors at low point densities and improving the boundary refinement algorithm to enhance accuracy in transition zones..

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ІНТЕГРОВАНИЙ ПІДХІД ДО СЕГМЕНТАЦІЇ 3D-ХМАРИ ТОЧОК ДЛЯ КАЛІБРУВАННЯ РЕЗЕРВУАРІВ

У статті представлено гібридний метод сегментації 3D-хмар точок для калібрування циліндричних горизонтальних резервуарів, який поєднує алгоритми RANSAC і DBSCAN із подальшим уточненням меж на основі локальних геометричних характеристик.

Аналіз попередніх досліджень показує, що RANSAC ефективний для виявлення циліндричних поверхонь, але чутливий до шуму, тоді як DBSCAN добре виконує кластеризацією зашумлених даних, але потребує оптимізації параметрів. Гібридні методи, які поєднують ці алгоритми, демонструють кращі результати, проте їх стійкість до низькощільних хмар і точність у перехідних зонах залишаються недостатньо дослідженими. Мета роботи – розробити та оцінити гібридний метод сегментації 3D-хмар точок, що поєднує RANSAC, DBSCAN і уточнення меж, для автоматизованого калібрування резервуарів із високою точністю за щільностей від ~1 млн до ~18 млн точок.

Результати досліджень базуються на порівнянні сканованої (18,012,345 точок при максимальній щільності) та ідеальної (17,986,543 точок) моделей резервуара. Гібридний метод дозволив точно оцінити геометричні параметри: радіус (R ≈ 1.5 м, похибка ±0.03 м) і довжину (L ≈ 10.8 м, похибка ±0.05 м). Сегментація виділила переднє днище (372,890 точок, ~2.07 %), заднє днище (411,230 точок, ~2.28 %) та шум (2,181,240 точок, ~12.1 %). Пропорційність зменшення точок для днищ зі зниженням щільності підтверджена лінійною апроксимацією (рис. 1): нахили ~20,700–22,800 точок/млн для сканованої моделі та ~20,900–21,100 для ідеальної, із $R^2 \approx 0.999$. Відносні похибки сегментації становлять 0.1–0.7 % для переднього днища та 8.3–8.9 % для заднього, що вказує на вищу точність для переднього днища та потребу вдосконалення для заднього. Стабільність шуму (~12.1–12.2 %) підтверджує ефективність DBSCAN. Метод зберігав точність навіть при низькій щільності (~1 млн точок), хоча зростання похибки заднього днища (~8.75 %) сигналізує про можливі втрати деталей.

Отже, розроблений гібридний метод є стійким до шуму, масштабованим для щільностей 1–18 млн точок і придатним для автоматизованого калібрування резервуарів. Пропорційність компонентів і стабільний шум підкреслюють надійність методу, а візуалізація (циліндр – червоний, переднє днище – зелений, заднє – синій) ілюструє чітке розмежування. Подальші дослідження можуть зосередитися на оптимізації DBSCAN для низькощільних хмар і зниженні похибки для заднього днища в перехідних зонах.

Keywords: хмара точок; гібридний алгоритм; геометричне моделювання; сегментація; калібрування резервуарів; лазерне сканування.

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