3-Dimensional Spatial Analysis of Parking Lot Wall Scratch Using Mobile Point Cloud Data

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Abstract

This study investigates the application of point cloud data for identifying and analyzing scratch patterns on walls within underground parking lots. As parking demands increase, narrow passages, intricate turns, and suboptimal layouts in parking facilities heighten minor collision risks, leading to substantial financial and operational costs. Conventional assessment methods, relying on on-site surveys and video surveillance, often fail to capture accurate spatial details and minor wall damages. This research employs high-precision point cloud data, complemented by image data, to precisely model and analyze parking lot layouts and scratch-prone areas. A novel approach integrating YOLOv10 object detection and PTv3 point cloud processing algorithms is developed to detect and localize scratches, while spatial analysis evaluates design factors affecting scratch distribution. Using handheld SLAM scanning devices, point cloud data was efficiently collected from five representative underground parking lots. The analysis of these datasets, which captured 327 wall scratches, reveals that structural layout and lighting conditions significantly influence scratch occurrence patterns, highlighting the potential of point cloud data in improving safety-oriented parking facility design.

1. Introduction

Parking lot accidents, particularly minor scrapes and collisions, occur frequently and pose significant safety risks. The likelihood of such incidents has increased due to multiple factors: the rising number of vehicles, growing demand for parking, and poor parking lot designs with narrow passages, complex turning angles, and inefficient layouts. While these accidents may not result in consequences as severe as major traffic collisions, their high frequency makes them a notable concern. According to the National Safety Council research report, parking lot accidents account for 20% of all vehicle collisions in the United States, resulting in approximately 60,000 injuries and an estimated 500 fatalities annually (Council, 2023). In China, despite typically low vehicle speeds in these areas, 15.9% of child traffic accidents occur in parking lots, and roadside parking zones (Bureau, 2022). Therefore, implementing well-planned parking lot designs and efficient spatial layouts is crucial for enhancing traffic safety. Moreover, there is a practical necessity to evaluate and optimize existing parking facilities to address these safety concerns.

Currently, parking facility assessment primarily relies on field surveys (Akai et al., 2021), surveillance camera data (Shih and Tsai, 2014), and vehicle trajectory analysis (Rahmani-Andebili et al., 2018). However, traditional evaluation methods often lack precision in capturing spatial details, particularly when assessing minor damages such as wall scratches, making it challenging to fully understand the actual environmental conditions under which accidents occur. These methods also provide limited insight into the three-dimensional spatial characteristics of parking facilities, failing to accurately reflect the spatial relationships between walls, obstacles, and vehicles. Such limitations often prevent potential issues from being identified and resolved during the design phase or early operational stages.

In recent years, with the advancement of three-dimensional laser scanning technology, point cloud data has emerged as a powerful tool for parking facility design and assessment (Gong et al., 2019). Point cloud data provides high-precision three-dimensional information, enabling accurate spatial coordinate representation of structural elements, walls, and obstacles within parking facilities. Compared to traditional two-dimensional data or image analysis, point cloud technology offers deeper insights into the spatial characteristics of parking facilities and aids in identifying accident-prone areas and their relationships with the surrounding environment through geometric analysis. The integration of point cloud data with image information effectively addresses many challenges in parking facility environmental assessment, demonstrating particular advantages in identifying wall scratches and analysing spatial constraints.

This study aims to employ an integrated approach combining point cloud data and imagery to identify existing wall scratches in parking facilities and conduct a detailed analysis of the surrounding features in affected areas. Through data collection and analysis from five different parking facilities, we seek to reveal the spatial characteristics that contribute to scratch formation and propose recommendations for optimizing parking lot design to reduce similar incidents in the future.

2. Related work

Methods for three-dimensional modeling of indoor parking lots have evolved into a robust and comprehensive technical system (Kang et al., 2020). Regarding data acquisition, point cloud data is primarily collected using Terrestrial Laser Scanners (TLS), handheld laser scanners, or Mobile Laser Scanning systems (MLS). Data quality is further enhanced through preprocessing steps including point cloud registration, noise filtering, and downsampling. The modeling methods are commonly classified into three categories:

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The first category comprises modeling methods based on plane extraction, such as RANSAC algorithms, region growing methods, and Hough transforms, which are particularly suitable for identifying and processing regular planar features, like walls and floors in parking facilities (Yang et al., 2022). The second category involves modeling methods based on semantic segmentation, which employ deep learning networks (e.g., PointNet++ and DGCNN) or traditional machine learning approaches (such as Random Forest and SVM) for point cloud semantic segmentation, enabling accurate identification and preservation of component classification information (Qi et al., 2017, Wang et al., 2019). The third category consists of parametric modeling methods, primarily using BIM and CAD-based parametric modeling, which are capable of generating standardized models in compliance with engineering specifications (Tang et al., 2010, Volk et al., 2014). Each method offers unique applications and advantages, necessitating careful selection or combination based on specific project requirements.

The spatial structure analysis of indoor parking facilities based on three-dimensional models has matured into a systematic research methodology. In spatial topology analysis, researchers have developed graph-theory-based approaches to study connectivity between functional areas and characterize spatial organization (Stephan et al., 2021). For accessibility analysis, space syntax modeling evaluates inter-regional accessibility, providing a foundation for traffic flow optimization (Ma and Xue, 2020). In terms of visibility analysis, viewshed analysis methods examine drivers' field of vision and blind spot distribution, focusing especially on visual obstructions at corners and around columns (Ma et al., 2022). For evacuation path analysis, personnel evacuation simulation technology assesses emergency evacuation efficiency, offering essential reference points for safety design (Young-Joo and II-Chean, 2019). The comprehensive application of these analytical methods provides a scientific basis for optimizing the spatial design of parking facilities.

Research on accident characteristics and layout impact factors in indoor parking facilities has revealed significant underlying safety concerns. Regarding accident types, these primarily include vehicle-to-vehicle collisions and scratches, reverse parking accidents, and vehicle-pedestrian conflicts, with high occurrence rates at turns, entrances/exits, ramps, and near columns (Zhang et al., 2023). Layout factors affecting parking facility safety can be categorized into three types:

The first type includes geometric factors, such as parking space dimensions and shapes (considering varied vehicle turning radii), aisle width (accommodating two-way traffic), turn radius (affecting sight distance and turning safety), ramp gradient (related to driving stability), and clearance height (for various vehicle types). The second type encompasses environmental factors, including lighting systems (requiring uniform illumination and adequate brightness), ventilation (influencing visibility), signage (necessitating clarity and visibility), and anti-slip measures (especially on ramps and turns). The third type involves traffic organization factors, covering one-way or two-way traffic flow, vehicle-pedestrian separation, entry/exit quantity and placement, and traffic signage arrangement. The scientific design and optimization of these factors play a crucial role in enhancing parking facility safety and must be carefully considered during the planning and design stages (Douissembekov et al., 2014).

3. Methodology

The technical workflow for analyzing wall scratches in parking facilities using three-dimensional point cloud data is illustrated in Figure 1.

The data collection process was initiated with a Simultaneous Localization and Mapping (SLAM) device capturing point cloud data while multi-angle cameras simultaneously gathered image data. During the data preprocessing phase (Step 1), the point cloud data underwent noise reduction and downsampling, while the image data was enhanced through histogram equalization and edge enhancement. In the wall scratch recognition phase (Step 2), a deep learning model was employed to identify and classify scratches. Following this, in Step 3, an interior feature analysis was conducted to measure the spatial structures in scratch-affected areas and evaluate lighting conditions within these zones. Finally, in the correlation analysis phase (Step 4), features were aligned, and a clustering algorithm was applied to analyze scratch distribution patterns. This comprehensive analysis has revealed environmental factors' impact on scratch formation, providing data-driven support for design optimization of parking facilities. The detailed workflow steps are as follows:

3.1 Data preprocessing

Data acquisition was performed using the Feima SLAM-100 three-dimensional laser scanner, which employs SLAM technology to enable simultaneous scanning and mapping while in motion, with a scanning accuracy of ±3cm@10m, measurement range of 0.1m-100m, and scanning speed of 430,000 points per second. Operators carried the handheld device while walking through the parking facilities at a constant speed of 1m/s along predetermined paths, ensuring uniform point cloud coverage. During data collection, real-time SLAM positioning and mapping technology was employed, eliminating the need for manual target placement. The collection device integrated an IMU (Inertial Measurement Unit) sensor, which automatically compensated for posture changes during the collection process, enhancing acquisition accuracy. After collection, trajectory optimization was performed using the device's built-in SLAM loop closure detection functionality, achieving a loop closure detection accuracy better than 5cm. Within each parking lot, the planned collection paths covered all driving lanes and major structural areas, with total path lengths varying according to the parking lot area.

Point cloud data preprocessing: Initially, the Statistical Outlier Removal (SOR) algorithm was applied to remove noise from the point cloud data. This algorithm identifies and removes anomalous points by analyzing the statistical characteristics of each point's neighborhood, making it particularly suitable for processing indoor LiDAR point cloud data (Rusu et al., 2008). In practice, setting the number of neighboring points K=50 and the standard deviation threshold to 2.0 effectively removed measurement noise.

Subsequently, Voxel Grid Filter was employed for downsampling, which simplifies data by replacing all points within each voxel with the voxel center point, better preserving the geometric features of the point cloud (Elseberg et al., 2013). During downsampling, the voxel size was set to 0.05m, reducing data volume by approximately 70% while maintaining geometric features.

Image data preprocessing: The image data underwent histogram equalization and edge enhancement to improve the visibility of scratch areas.

The Feima SLAM processing software was utilized to integrate the image and three-dimensional point cloud data, enabling color information to be mapped onto the point cloud. This fusion process enhanced the point cloud data by displaying precise color details from the images on the three-dimensional structure, thereby improving the visualization and interpretability of environmental features within the parking facilities.

3.2 Scratch Detection

Scratch Detection in Image Data: This study established a comprehensive detection process based on a deep learning-based object detection algorithm, aiming at the automated detection and analysis of scratches on parking lot walls. During the dataset preparation phase, the research team randomly selected 5,000 high-resolution images of parking lot walls from the collected images, each with a resolution of 2592×1944 pixels. To ensure consistency and reliability in labeling, strict scratch identification criteria were developed (Figure 2). Specifically, scratches visible under standard parking lot lighting with a linear damage length exceeding 5 cm and a width ranging from 0.5 mm to 5 cm were defined as valid scratch samples. Moreover, to account for the varied forms of scratches, damage types were subdivided into three categories: deep scratches (penetrating to the base material), surface scratches (affecting only the paint layer), and impact damage (characterized by circular or irregular patterns). For model training and evaluation, the dataset was divided into a training set (70%) and a test set with the remaining 30%, ensuring a balanced representation of each scratch type in both subsets.

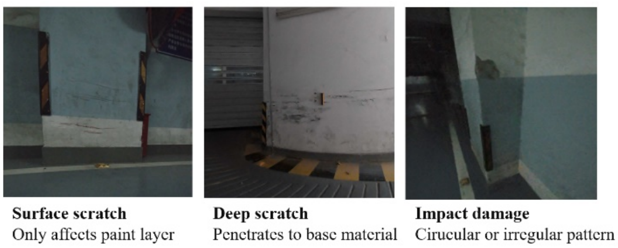

Figure 2. Visual identification criteria and classification of wall scratches

Model Development: YOLOv10 was selected in this study with CSPNet (Cross Stage Partial Network) as the backbone network (Wang et al., 2024). Considering variable lighting conditions and viewing angles in parking lots, data augmentation strategies were introduced in the preprocessing stage. These included uniformly resizing input images to 1280×1280 pixels, applying random rotations of ±15°, brightness adjustments of ±20%, and horizontal flips. The model was trained using mini-batch stochastic gradient descent with a batch size of 32, an initial learning rate of 1e-4, and a cosine annealing strategy for dynamic adjustment. To prevent overfitting, training was limited to 100 epochs, with early stopping implemented at a patience of 15 epochs. Additionally, the confidence threshold for inference was set at 0.5, and the non-maximum suppression (NMS) threshold at 0.4, balancing detection accuracy with recall.

Scratch Localization in 3D: To achieve 3D localization of scratch center points, this study mapped the scratch center from 2D image space to 3D point cloud through coordinate transformation. Initial correspondences between 2D image features and 3D point cloud coordinates were established via SIFT-based feature matching between image projections and point cloud views. Using intrinsic camera parameters and extrinsic data from the Feima SLAM100 sensor, scratch center coordinates were transformed from 2D to 3D space. To enhance accuracy, the RANSAC algorithm optimized the transformation matrix, and bundle adjustment minimized reprojection error, ensuring precise 3D positioning of scratches.

3.3 Spatial feature Analysis

To analyze indoor features around scratch locations, detailed analysis was conducted on wall structures, spatial layouts, and lighting conditions in scratch-affected areas.

Spatial Structure Extraction: Considering the structured characteristics of parking lot environments, we employed Point Transformer V3 (Wu et al., 2024) pre-trained on the Stanford Large-Scale 3D Indoor Spaces (S3DIS) dataset, which provides high-quality annotations for walls, columns, and ground surfaces among its 13 semantic classes. Point Transformer V3 demonstrates state-of-the-art performance on S3DIS through its improved self-attention mechanism and efficient local aggregation strategy. We directly utilized the pre-trained weights of their released model, which achieves 74.5% mean IoU on the S3DIS Area 5 test set, ensuring robust performance on structural element recognition. The model effectively processes point clouds using its hierarchical vector attention and local vector self-attention modules, operating at multiple scales to capture both fine-grained geometric details and global structural information.

Spatial Structure and Obstacle Analysis: Through semantic analysis of the point cloud, spatial constraints in scratch areas were analyzed. Wall-to-column distances were calculated as the minimum distance between the scratch wall W and the centreline of the nearest column C:

$$d_{W,C} = \min_{p_w \in W} \left| \frac{(\overrightarrow{c_2} - \overrightarrow{c_1}) \times (\overrightarrow{c_1} - \overrightarrow{p_w})}{|\overrightarrow{c_2} - \overrightarrow{c_1}|} \right| \qquad (1)$$

where $\overrightarrow{p_w}$ is a point on the scratch wall, $\overrightarrow{c_1}$ and $\overrightarrow{c_2}$ are two points defining the column centreline.

The wall angle α at scratch location was measured as the deviation from horizontal line:

$$\alpha = \arccos\left(\frac{\overrightarrow{n_w} \cdot \vec{h}}{|\overrightarrow{n_w}||\vec{h}|}\right) \cdot \frac{180}{\pi} \qquad (2)$$

where $\overrightarrow{n_w}$ is the wall surface normal vector at scratch location, and $\vec{h} = [1,0,0]$ is the horizontal reference direction. The resulting α is in degrees, representing the wall’s horizontal curvature at scratch position.

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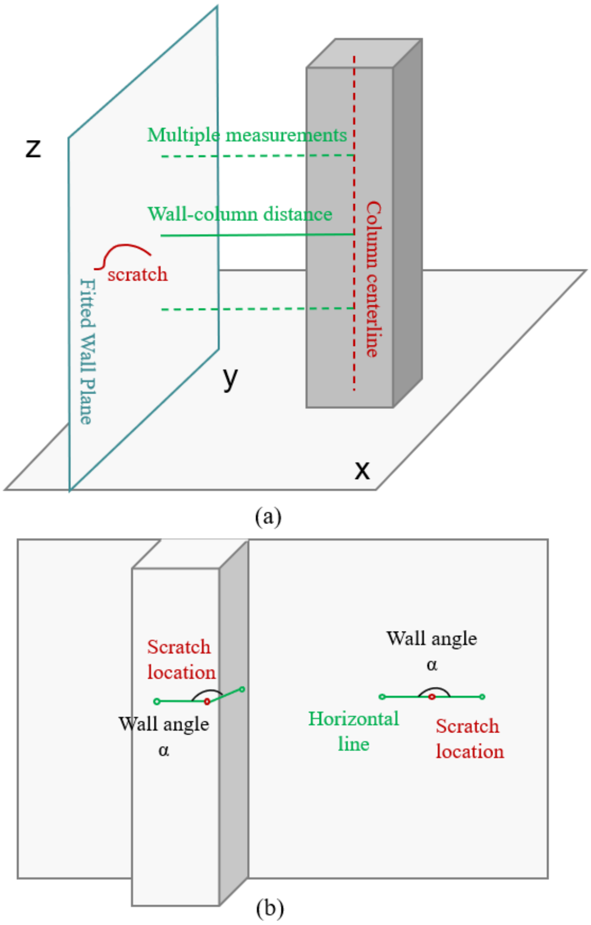

Figure 3. Schematic Diagram of Spatial Structure and Obstacle Analysis: (a) wall-column distance calculation, (b) scratch wall angle calculation.

Lighting Condition Analysis: For each image containing scratches, an image processing tool (Python's OpenCV library) was used to convert the color image to a grayscale image, followed by calculating the average grayscale value of all pixels within the image, serving as an indicator of the local light intensity.

To convert the grayscale value to physical illuminance (lux), an empirical grayscale-to-lux conversion relationship was established. In an experimental setting, a light meter (Delixi 1802) measured the actual light intensity at multiple points, and images of the corresponding areas were taken. Five representative measurement points were selected, covering low, medium, and high illuminance levels, including 25 lux, 50 lux, 100 lux, 150 lux, and 200 lux. At each point, the actual illuminance and the corresponding average grayscale value of the image region were recorded. Using these data points, a mapping relationship from grayscale values to lux was developed through linear or polynomial regression. This conversion relationship was then applied to transform the average grayscale value of each scratch image into the corresponding illuminance value, supporting subsequent analysis of the relationship between illuminance and scratch occurrence.

After obtaining the illuminance value for the scratch area in each image, the illuminance values of all images were grouped into intervals, with each interval spanning 25 lux (e.g., 0-25, 25-50, …). Then, within each illuminance group, the number of images containing scratches was counted, yielding the scratch frequency across different illuminance intervals.

3.4 Correlation Analysis of Scratches with Spatial Features

To investigate the relationship between scratch distribution and indoor architectural elements, advanced image analysis techniques were employed to examine correlations between scratch locations and the design of parking facilities. The DBSCAN clustering algorithm was applied to evaluate the spatial distribution patterns of scratches, pinpointing high-frequency scratch zones. Additionally, by integrating spatial features such as wall-to-column distances and corner angles, a statistical analysis identified key environmental factors contributing to scratch formation.

4. Experiments

4.1 Datasets

To validate the proposed methodology, we collected point cloud data from five diverse parking lots, ensuring a representative dataset (Table 1).

Table 1. Characteristics of Five Parking Lot Datasets

Dataset	Number of Points (Million)	Area (Square Meters/Level)	Collection Path Length (Meters)	Collection Duration (Seconds)
# P1 (Residential parking lot)	126	5236 2 floors	477	642
# P2 (Office building parking lot)	176	3595 3 floors	837	1034
# P3 (University parking lot)	237	2,375 2 floors	704	1160
# P4 (University parking lot)	127	3,091 1floor	441	620
# P5 (Office building parking lot)	72	Only entrances and exits	273	502

These parking lots were strategically selected to encompass a range of urban scenarios. P1 represents a residential complex parking lot with two floors, characterized by relatively dim lighting and a complex layout tailored to long-term parking needs. P2 and P5 are located within commercial office buildings; P2 is a modern, three-floor garage with well-maintained facilities and sufficient lighting, whereas P5 is a gated facility with data focused primarily on high-traffic entrance/exit areas. The dataset further includes two university parking lots (P3 and P4), each with unique designs: P3 is a two-floor underground structure with limited lighting, and P4 is a single-floor open lot. This selection ensures a comprehensive dataset that reflects a variety of architectural layouts, lighting conditions, and usage patterns. The office building parking lots (P2, P5) generally feature superior facilities and lighting systems, while P1, P3, and P5 exhibit more challenging lighting environments. The diverse internal layouts and structural designs across these parking lots enhance our

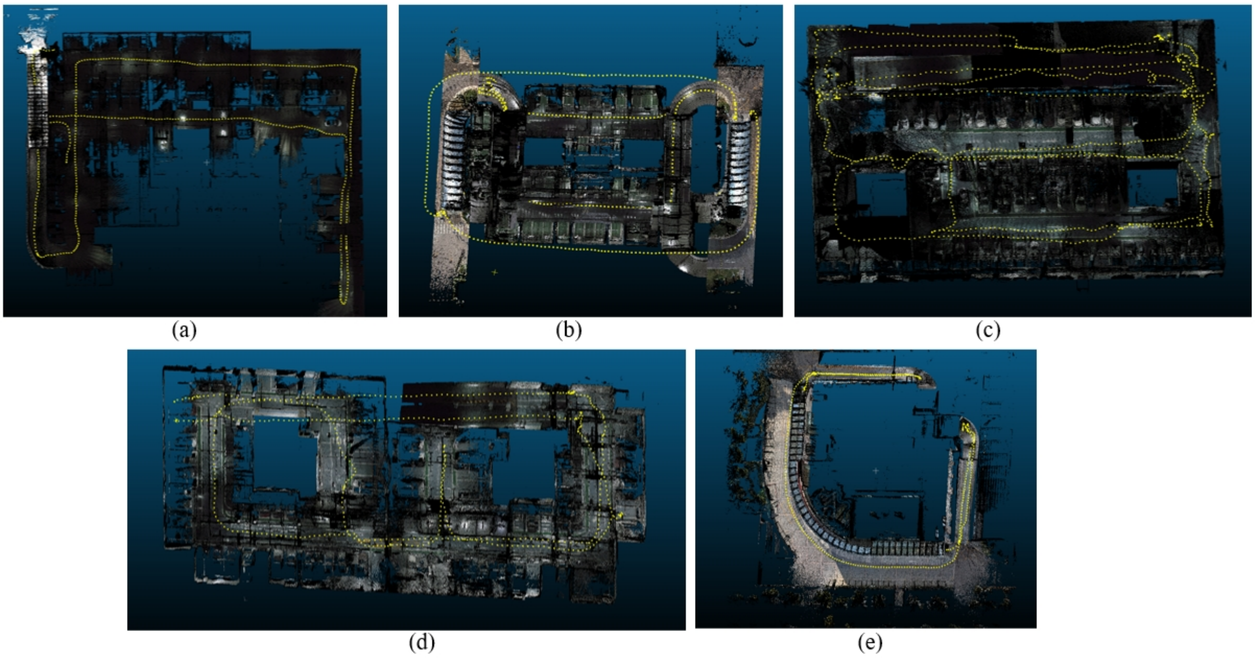

Figure 4. Top-view point cloud and collection trajectory visualizations for parking lots P1–P5, with subfigures (a)–(e) representing each lot respectively.

ability to assess the method's robustness across different spatial configurations.

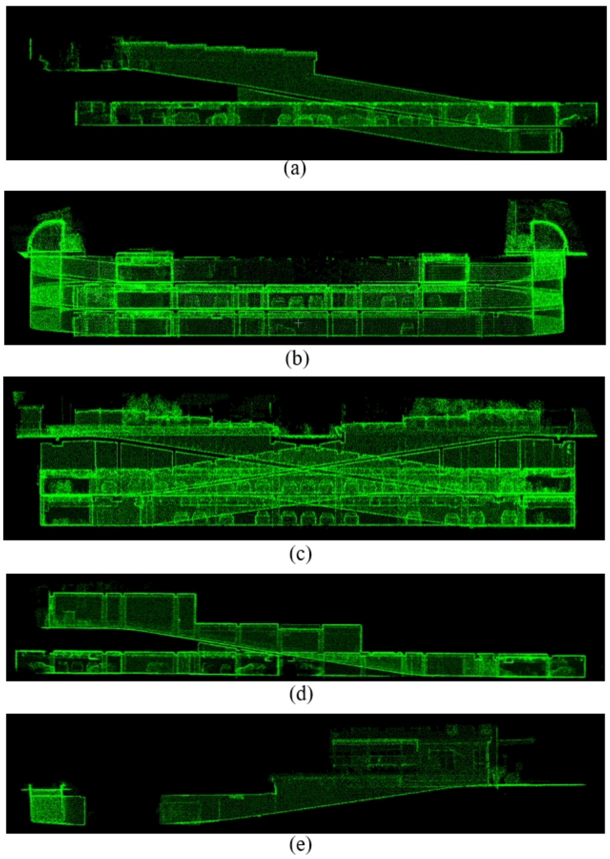

Figure 5. Cross-sectional point cloud visualization of parking lots P1-P5, with subfigures (a)-(e) representing each lot respectively.

The final 3D point cloud model integrates image data, providing top-view and cross-sectional perspectives of the dataset, as illustrated in Figures 4 and 5. Across the five parking facilities, a total of 181 wall sections and 441 columns were identified, excluding the restricted entrance in P5. These parking facilities exhibit diverse structural characteristics: ceiling heights range from approximately 2.5 meters to 4.2 meters, and column spacing varies from 5 to 6 meters, depending on the design of each facility. All structures feature concrete walls, with surface roughness and flatness differing significantly across the facilities. This diversity of characteristics aids in validating the algorithm's adaptability and robustness across various structural configurations.

4.2 Results and discussions

4.2.1 Validation of Scratch Detection Algorithm

This study employed the Confusion Matrix and its derived metrics for quantitative evaluation of the proposed scratch detection algorithm (Table 2). The overall accuracy reached 94.4%, indicating that 119 out of 126 samples were correctly classified - this measures the proportion of all correct predictions. In terms of precision, which represents the proportion of true positive predictions among all positive predictions, 89.5% of all samples identified as scratches were true scratches, demonstrating a low false positive rate. Regarding recall, which indicates the proportion of actual positives correctly identified, 91.9% of all actual scratch samples were successfully detected, showing a low false negative rate.

Table 2. Confusion Matrix Results of the Scratch Detection Algorithm

		Prediction	
		Scratches	Non-scratches
Ground-truths	Scratches	34（91.9%）	3（8.1%）
	Non-scratches	4（4.5%）	85（95.5%）

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4.2.2 Visualization of Experimental Results

Through systematic identification, a total of 327 valid scratches were detected, comprising 196 surface scratches, 97 deep scratches, and 34 impact damages. This dataset provides robust quantitative evidence for assessing wall damage in parking facilities.

The spatial analysis revealed that 90-degree corner areas exhibited the highest concentration of scratches, accounting for 42% of the total, followed by other wall angles at 35%—primarily observed at turning entrances and exits—while straight wall areas showed relatively fewer scratches, accounting for only 23% (Figure 6). This distribution pattern highlights the differing levels of collision risk across areas within the facility. 90-degree wall intersections had notably higher scratch incidences than straight wall sections, with the former showing twice as many scratches as the latter. In narrow spaces where the distance to columns was less than 6 meters, scratch density was approximately twice as high as in more open areas.

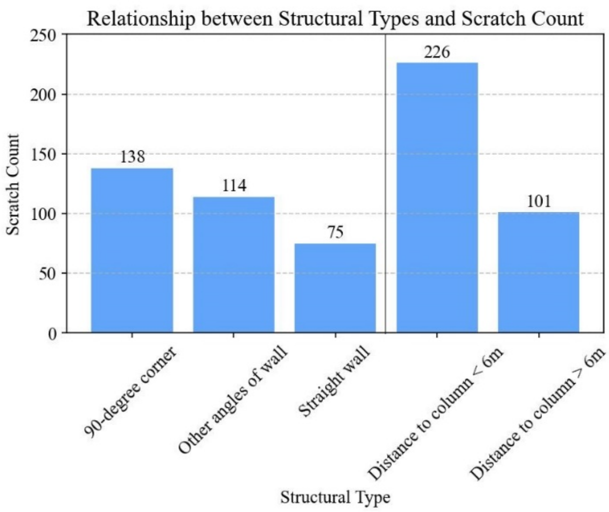

Figure 6. Impact of Lighting Conditions on Scratch Incidence

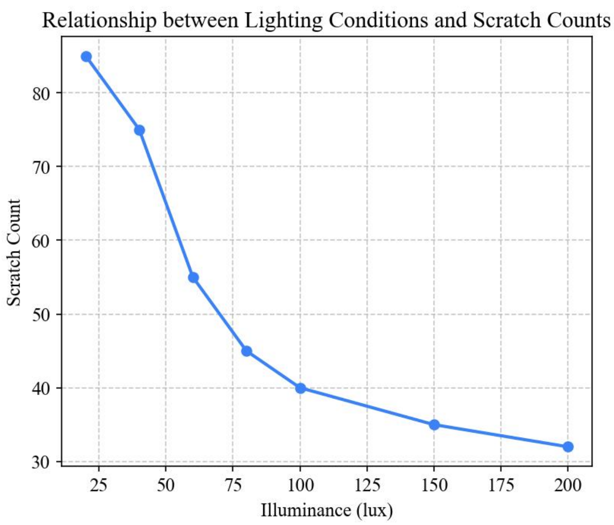

Figure 7. Scratch Incidence by Structural Type and Proximity to Columns

Correlation analysis between environmental factors and scratch distribution demonstrated that lighting conditions significantly impact scratch formation (Figure 7). In poorly lit areas (illuminance below 50 lux), the frequency of scratches was 2.3 times higher than in well-lit areas. Moreover, areas with high lighting contrast exhibited approximately 35% more scratches. These findings suggest that enhancing lighting conditions could be an effective strategy for reducing scratch occurrence in parking facilities.

5. CONCLUSIONS AND FUTURE WORK

This study proposed and validated a method combining three-dimensional point cloud data with image data for identifying parking lot wall scratches and conducting in-depth analysis of 3D spatial characteristics. Through the application of advanced deep learning algorithms including YOLOv10 and PTv3, modeling and analysis were performed on data from five different types of parking facilities. Results indicate that scratch distribution in parking facilities is closely correlated with spatial layout and lighting conditions. Particularly in narrow passages and corner areas, scratch frequency increased significantly, providing scientific evidence for improving parking facility design and effectively reducing risks in high-incident areas. The innovation of this study lies in combining high-precision three-dimensional modeling of point cloud data with image recognition technology, providing new tools for parking facility design and safety management, overcoming limitations of traditional planar data or surveillance footage in detail capture and spatial relationship analysis.

The primary limitations of this study arise from data collection challenges specific to indoor parking facilities. In particular, the unpredictable lighting conditions caused by motion-sensor lighting systems significantly impacted data quality, as low lighting levels could result from lights being inactive. Additionally, restricted access to gated indoor parking lots, as encountered with P5 parking lot in our experiment, limited our ability to gather comprehensive spatial data. These constraints affected both the quantity and quality of the collected point cloud data, potentially influencing the robustness and reliability of our analysis.

Future research could aim to develop advanced methodologies to overcome the current limitations in data collection, particularly addressing challenges related to variable lighting conditions in indoor environments. Implementing vehicle-mounted sensing technologies could simulate real-world driving experiences and enable synchronized data collection. Additionally, expanding the research scope to incorporate obstacle detection and more comprehensive 3D spatial analysis would deepen our understanding of parking facility layouts. This expanded analysis would include vertical circulation patterns, multi-level spatial relationships, and the distribution of structural elements across different floors. Such a holistic spatial analysis would offer valuable insights into the organizational efficiency of parking facilities, supporting more informed design decisions. These advancements would not only mitigate current methodological limitations but also contribute to a more nuanced understanding of parking facility spatial characteristics, ultimately enhancing the practical applicability of the proposed methodology in the design and management of modern parking infrastructure.

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