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Reinforcing Bar Segmentation from Depth-Camera-Captured Point Cloud Data

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Abstract

Reinforced concrete, a composite material composed of concrete and rebars, is one of the most widely used materials in buildings. Rebar inspection at construction sites is recommended to mitigate potential risks associated with the omission or improper installation of rebars. However, current rebar inspection conducted on-site is predominantly manual, which is time consuming and labor-intensive. In this study, a new method is proposed to segment the rebar-related point cloud data from depth-camera-captured point cloud data. This method utilizes the normal vectors of tangent planes at each point to segment the rebar-related portions leveraging the directional differences between rebar and floor-related points for effective segmentation. To validate this method, experiments were conducted with six 1.2 m rebars under various experimental conditions. The accuracy of segmentation was assessed by comparing the actual spacing between the rebars and the distances between the segmented rebar points. The results demonstrated that the proposed method can effectively segment rebars and accurately measure the interval instances.

Keywords: rebar inspection, rebar, depth-camera, point cloud data, segmentation, normal vector.

1 Introduction

Reinforced concrete (RC) is a composite-resistant material consisting of concrete and rebars. The tensile strength of concrete is approximately 10% of its compressive strength. Without rebars, it can result in the occurrence of cracks on the tension side or sudden fracture failures. Rebars mitigate the potential risks by compensating for the tensile vulnerabilities of concrete. Therefore, the quantity and spacing of rebars are critical factors in the design and construction of RC structures. Omission or improper installation of rebars can pose significant risks to users. It is recommended that thorough inspections of rebars be conducted by professional supervisors at the construction site [1]. However, rebar inspection currently being carried out at site is highly inefficient. Professional supervisors manually verify the spacing of rebars using tape measure and rulers, and visually confirm the quantity of rebars, making the process extremely labour-intensive. Furthermore, when the construction site is large, conducting a full inspection of the rebars becomes significantly time-consuming. To overcome inefficiencies, the demand for the automation of rebar inspection is increasing [2, 3].

Numerous studies have been conducted to utilize equipment such as cameras, light detection and ranging (LiDAR) sensor or drones to enable more accurate rebar inspection to replace the manual methods [4, 5, 6]. Kim et al. [7] conducted research using Terrestrial Laser Scanning (TLS) to obtain point cloud data and measure the diameter of rebars based on a density-based machine learning model. Additionally, Wang et al. [8] utilized drones to capture images of column's rebars and proposed a model to count the quantity of column's rebars using Faster R-CNN. However, while TLS offers the advantage of obtaining precise point cloud data, its high equipment cost makes practical implementation difficult. Also, using drones to shoot the construction site for imaging may result in inaccurate or incomplete recognition while matching the images to get point cloud data.

Point cloud data are utilized to measure the spacing of rebars, which is one of the items in rebar inspection. A depth-camera is used to obtain the point cloud data of the site. While LiDAR sensor offers the acquisition of accurate point cloud data, it involves a time-consuming process for capturing the site and the equipment is costly. Measuring the spacing of rebars from raw point cloud data is nearly impossible. For higher accuracy, the rebar related point cloud should be segmented from the raw point cloud data.

In this study, a new method was applied to segment the rebar-related parts from the entire depth-camera-captured point cloud data. By analysing the direction of the normal vectors associated with each point's tangent plane in the point cloud data, this study effectively segments rebar-related points. The direction of normal vectors of a tangent plane varies depending on the curvature of surface objects, which distinguishes them from points on flat surfaces, enabling easier and more accurate detection. To evaluate the effectiveness of the proposed method, small-scale experiments were conducted with six 1.2 m rebars evenly spaced at 0.3 m interval on a board. The results demonstrated that the method could practically segment the rebar-related point cloud data without the need for complex machine learning models. Additionally, the accuracy of measuring the rebar spacing varied depending on the location and the angle of shots. Optimal accuracy was achieved when the measurements were taken indoors from a top-down view.

2 Methodology

2.1 Normal Vector of a Plane Method

Normal vector is a line segment perpendicular to the tangent plane. As shown in Figure 1 (a) plane can be made with a specific 3 points. Normal vector can be calculated using Equation (1), taking point P1 as a reference along with points P2 and P3. As depicted in Figure 1 (a), the direction of the normal vector is also illustrated. Figure 1 (b) illustrates the normal vectors calculated for each point within a specific radius around a single reference point, as derived from the initial normal vectors shown in Figure 1 (a). This demonstrates that using the normal vectors from depth-camera-captured point cloud data without further processing can lead to inaccuracies in determining their correct orientations. Consequently, as depicted in Figure 1(c), a new normal vector of a plane (NVP) is calculated by averaging all normal vectors within a designated radius around a single point. The normal vector of a plane can be calculated by Equation 2.

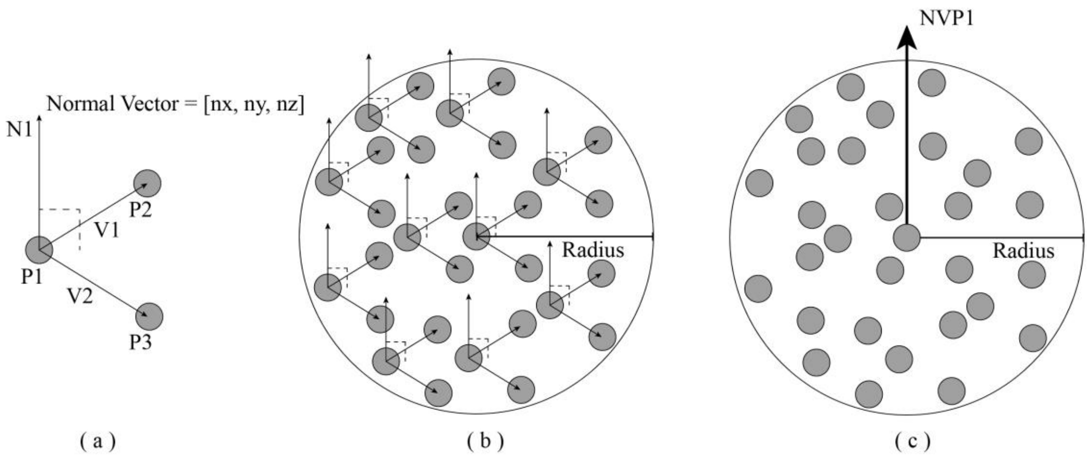


Figure 1: Calculation of normal vector of plane

$$\frac{\overrightarrow{V1} \times \overrightarrow{V2}}{\|\overrightarrow{V1} \times \overrightarrow{V2}\|} = N1 \tag{1}$$

$$\frac{N1 + N2 + N3 + \cdots + Nn}{\|N1 + N2 + N3 + \cdots + Nn\|} = NVP1 \tag{1}$$

In this study, the previously proposed NVP method is utilized to segment object-specific points from point cloud data, which can be acquired via depth cameras or LiDAR sensors. Point cloud data represents the object’s surface with numerous points. The NVP method facilitates the determination of an object's orientation, influenced by the surface’s curvature. For flat surfaces, the NVP consistently points nearly vertically, while for curved surfaces, such as rebar, it diverges. Leveraging these properties, this study introduces an advanced NVP method to selectively segment rebar-related points from depth-camera-captured point cloud data, based on the orientation derived from the normal vector of a tangent plane.

2.2 Experiments

In this study, the NVP method utilizes the divergence characteristics of normal vector of a tangent plane of point clouds. This new approach specifically segments rebar-related points from depth-camera-captured point cloud data, effectively identifying features on curved objects. To assess the accuracy of the segmented rebar-related points, experiments were conducted in four distinct steps.

Step 1: A depth-camera is installed to capture the point cloud data of target object. By considering the shooting locations and angle, the effects of environmental conditions were considered.

Step 2: Crop the target object from depth-camera-captured point cloud. Unprocessed depth-camera-captured point cloud data contains numerous unnecessary data such as noise. By cropping the desired portion needs, this pre-processing step helps in segmenting the desired portion more clearly from the large amount of point cloud data.

Step 3: The NVP method is used on the cropped point cloud data to compute the direction of NVP. points with diverging NVP are separated to detect the object related point cloud data.

Step 4: The spacing of the rebar are determined using the segmented object-related point cloud data. By comparing the result with actual spacing of the rebars, their accuracy is assessed.

This new method is evaluated through a small-scale experiment, as shown in Figure 3 (a). Six rebars, each 1.2 m in length, are arranged as the target object on a board shaped as a square with both horizontal and vertical dimensions of 1.2 m. The rebars are positioned in three vertical and three horizontal orientations, with a spacing of 0.3 m between each. Figure 3 (b) captures the experimental setup, which is photographed indoors at a 45-degree angle.

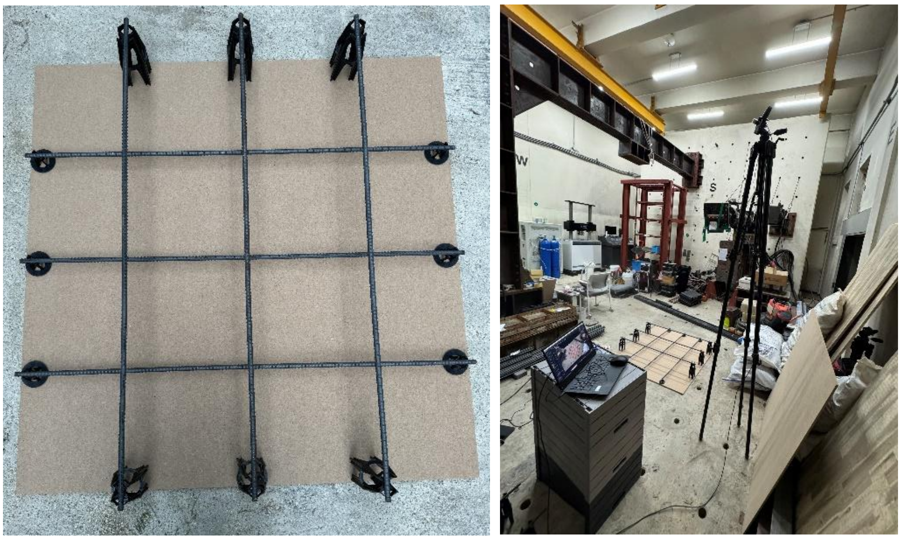
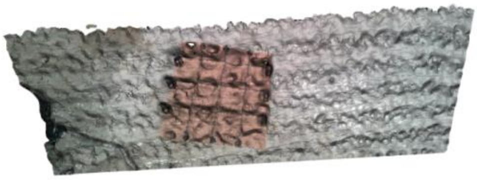


Figure 2: (a) Target object. (b) Experimental setup.

3 Results

In this chapter, the results of segmented rebar-related point cloud data, which were captured using a depth-camera, are presented. The experiments were conducted following the models specified in chapter 2. The depth-camera employed is the Intel Realsense D455 model. The outcomes of the segmentation, performed using the NVP method, are detailed in Section 2.1

Case 1) Shooting location : Outdoor / Shooting angle : 90 degree



(a) Original point cloud data set

(b) Cropped point cloud data set

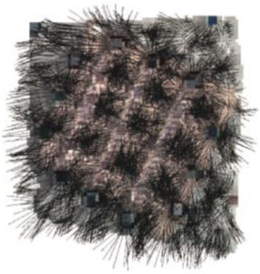
(c) NVP of Cropped point cloud data set

(d) Segmented point cloud data set

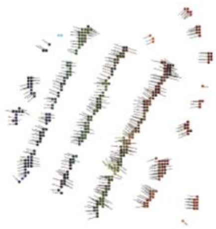
Case 2) Shooting location : Indoor / Shooting angle : 45 degree

(a) Original point cloud data set

(b) Cropped point cloud data set



(c) NVP of Cropped point cloud data set



(d) Segmented point cloud data set

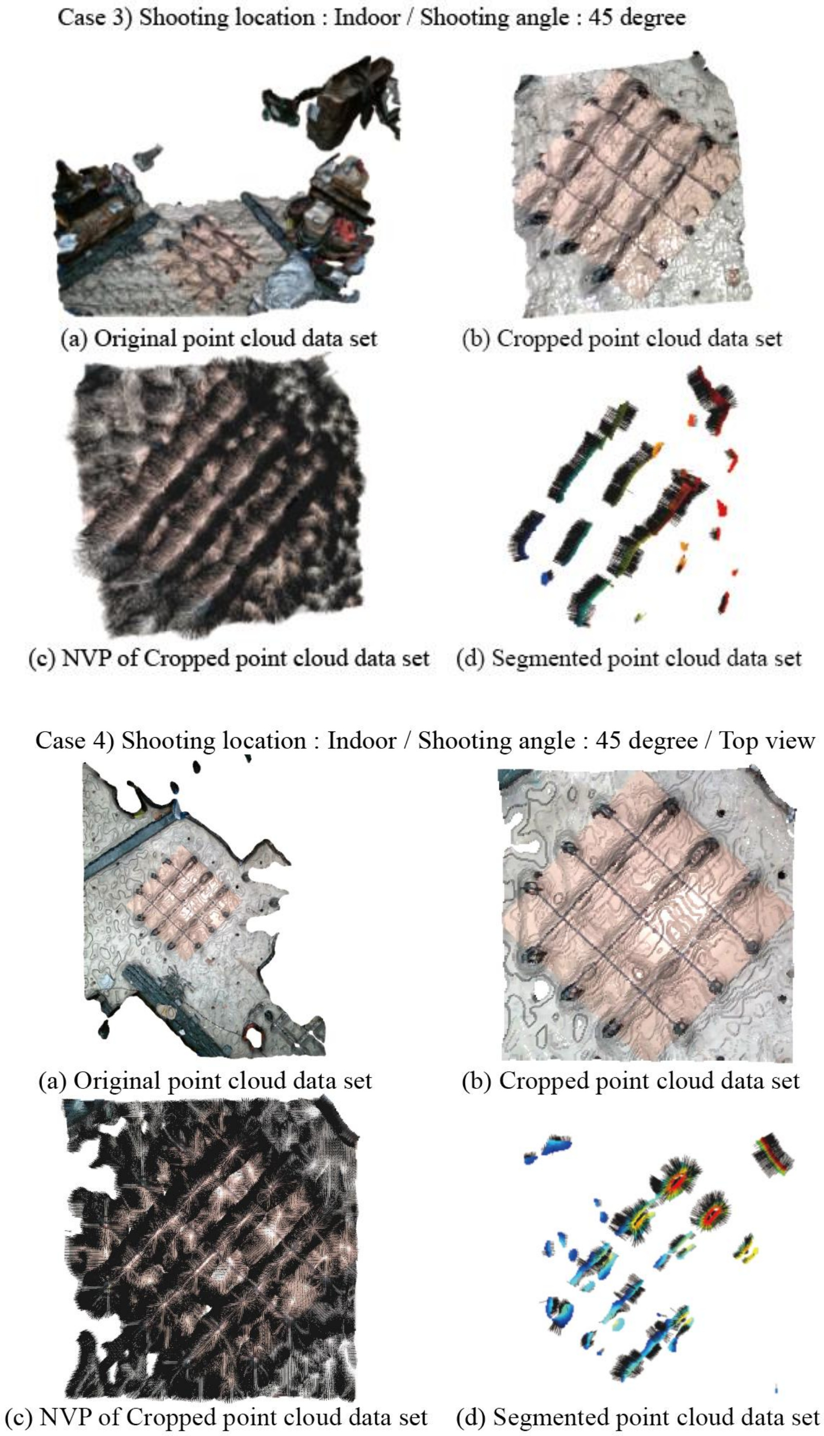


Figure 3: Segmentation using NVP method under various experimental conditions

In Figure 3, cases 1 and 2 are distinguished by the location of the depth-camera captures, with outdoor and indoor settings, respectively, while targeting the same target object. It is evident that the quality of the point cloud data is significantly influenced by lighting conditions. In case 1, which was captured outdoors, the original point cloud data show rippling effects on the ground, leading to less smooth results. Despite these challenges, the rebar was still segmented to a certain extent using the NVP method, although with less precision compared to case 2. In contrast, the point cloud data obtained indoors was much more stable, demonstrating that case 2 provide more accurate data. This highlights the importance of controlled indoor environments for obtaining reliable depth-camera-captured point cloud data. Due to the superior quality of point cloud data achieved through indoor shooting, both cases 3 and 4 were conducted indoors. The primary distinction between these cases is the perspective: case 3 was captured at a 45-degree angle, while case 4 was captured from a top view. Although rebar was clearly segmented in both cases, case 3 demonstrated better segmentation compared to case 4. To evaluate the accuracy of the segmented rebar-related point cloud data, a comparison was made between the actual settings and the distances within the segmented point cloud data. The results of this comparison are summarized in Table 1 below.

Case	Actual Spacing	Average Distance of segmented point		Max
		D1	D2	Error
1	0.3 m	0.3365 m	0.3650 m	21.6 %
2	0.3 m	0.3384 m	0.3370 m	12.8 %
3	0.3 m	0.3357 m	0.3358 m	11.9 %
4	0.3 m	0.3278 m	0.3035 m	9.3 %

Table 1: Accuracy of segmented rebar-related point cloud data using NVP method

4 Conclusions and Contributions

A new approach is proposed that utilizes the normal vector of a tangent plane to the points forming the surface of curved objects like rebar, employing a rule-based method for segmentation. Historically, segmentation of images or point cloud data, particularly for rebar, has often relied on complex machine learning models. To enhance the accuracy of these models requires the creation of extensive datasets, which is not always feasible. In contrast, this novel method does not depend on large datasets and can quickly segment objects by exploiting the directionality of the normal vectors, which varies with the curvature of the object surfaces. This rule-based approach presents a significant advancement over previous machine-learning-dependent techniques. The experimental results verified the accuracy of the segmented rebar-related point cloud data, considering environmental factors such as the location and angle of the depth camera. The quality of point cloud data captured indoors was found to be superior to that obtained at outdoors. Specifically, the error rate for outdoor captures was 21.6%, while indoor captures exhibited a significantly lower error rate of 12.8%. All angle measurements were taken indoors, yielding comparably high accuracy across the board. Among these, the most accurate segmentation occurred when the rebar was captured from a top view, achieving an error rate of only 9.3%. This indicates that both the shooting environment and the camera angle critically influence the precision of segmentation. A limitation of this study was that segmentation was successfully performed only on rebars aligned with the camera's axes, specifically targeting three vertical and three horizontal rebars. Future research aims to enhance the accuracy of this segmentation method. Additionally, the error rate of 9.3% for rebar spacing, although relatively low, still signifies a considerable margin for improvement. Therefore, further studies are necessary to refine the accuracy of rebar spacing measurements.

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References

[1] LIN, Yu-Cheng; CHANG, Jun-Xiong; SU, Yu-Chih. Developing construction defect management system using BIM technology in quality inspection. *Journal of civil engineering and management*, 2016, 22.7: 903-914.

[2] BOUKAMP, Frank; AKINCI, Burcu. Automated processing of construction specifications to support inspection and quality control. *Automation in construction*, 2007, 17.1: 90-106.

[3] Park, Jun Su, et al. "Computer Vision-Based Structural Health Monitoring: A Review." International Journal of High-Rise Buildings, vol. 12, no. 4, 한국초고층도시건축학회, Dec. 2023, pp. 321–333, doi:10.21022/IJHRB.2023.12.4.321.

[4] QURESHI, Abdul Hannan, et al. Smart rebar progress monitoring using 3D point cloud model. *Expert Systems with Applications*, 2024, 249: 123562.

[5] SHIN, Yoonsoo, et al. An image-based steel rebar size estimation and counting method using a convolutional neural network combined with homography. *Buildings*, 2021, 11.10: 463.

[6] PARK, Hyo Seon, et al. A new approach for health monitoring of structures: terrestrial laser scanning. Computer-Aided Civil and Infrastructure Engineering, 2007, 22.1: 19-30.

[7] KIM, Min-Koo, et al. Automated rebar diameter classification using point cloud data based machine learning. *Automation in Construction*, 2021, 122: 103476.

[8] WANG, Seunghyeon, et al. The development of a rebar-counting model for reinforced concrete columns: Using an unmanned aerial vehicle and deep-learning approach. *Journal of Construction Engineering and Management*, 2023, 149.11: 04023111.