EVALUATION OF 3D MODEL OF REBAR FOR QUANTITATIVE PARAMETERS

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ABSTRACT:

The construction industry practices and processes are evolving constantly, and with the emergence of Industry 4.0, the use of technologies is expanding. Construction progress monitoring is an essential project lifecycle process; project success and timely completion are linked with effective progress monitoring operations and adopted tools. In the domain of automated construction progress monitoring, 3D modeling techniques have been studied a lot, with laser scanning and photogrammetry as two main methods. Although laser scanning provides precise and detailed 3D models, it is an expensive technology. Moreover, the literature reveals that for digitized construction progress monitoring, the major focus has been given to primary reinforced concrete (RC) structures compared to rebar. In contrast, rebar is a key element in RC structures, as structural integrity is dependent on steel reinforcement design, which makes rebar monitoring an essential activity. This study aimed to devise an automated monitoring digital-based methodology for effective and efficient onsite rebar monitoring considering quantitative parameters e.g., rebar length and rebar spacing. The developed module successfully interpreted photogrammetry-based 3D point cloud rebar model for the aforementioned parameters with an overall achieved accuracy ≥ 98%.

1 INTRODUCTION

3D modeling techniques and technologies are gaining popularity among construction industry stakeholders, as 3D reconstruction allows capturing the geometry and appearance of a targeted object or scene. Laser scanning, photogrammetry, and videogrammetry are well-known point cloud reconstruction techniques (Pour Rahimian et al., 2020). Laser scanning is considered a superior technology with the accurate 3D point cloud models. However, photogrammetry is praised due to being relatively less costly, and data collection (images) can be made by any device (drone, camera, CCTV, etc.) (Zhu et al., 2016). However, the attainment of superior quality photogrammetry model is dependent on various aspects, such as object distance, camera specification, capturing angle, image resolution, occlusions, number of images, camera calibration, lighting condition, weather, human intervention, and atmospheric factors (Qureshi et al., 2022c).

The progress monitoring process is the combination of various small functions such as data collection, data interpretation, data interoperability, and data analyses. The generated 3D point cloud contains precise 3D surface geometric details of the targeted object. Moreover, a point cloud consists of a set of 3D points with attributes such as X, Y, Z coordinates and sometimes R, G, B color values (Murtiyoso and Grussenmeyer, 2022; Xu and Stilla, 2021). With the continuous evolution in detection-data acquisition technologies and processes, the usage of advanced techniques such as computer vision (CV) has been applied in the domain of construction progress monitoring (Deng et al., 2020).

In reinforced concrete (RC) structures and elements, rebar is a key element, and its monitoring is critical. The rebar monitoring process requires experienced inspectors, as rebar inspection is meticulous and time-consuming (Wang et al., 2017). In rebar progress monitoring, the inspectors are bound to examine the onsite arrangement of the rebar grid for rebar spacing and rebar dimensions in reference to designed structural drawings during the construction stages. This is an important activity for any construction project, as the bearing capacity of the RC structures is affected by the position and size of the rebar (Ishida et al., 2012). Apart from manual progress monitoring practices, a trend of implementing digital technologies for progress monitoring has also been observed in the construction sector. However, the literature reveals that laser scanning is the most adopted technique, especially for rebar detection, compared to photogrammetry (Alaloul et al., 2021). Moreover, in the domain of rebar progress monitoring, the focus has been given to quality aspects such as shape, positioning, and alignment. Whereas less importance has been given to rebar quantitative parameters, and a few studies have put effort into assessing the rebar spacing and diameters. Nevertheless all of these aforementioned studies have adopted laser scanner technology, which is an expensive option with various operational constraints (Kim et al., 2021, 2020; Lu and Brilakis, 2019; Turkan et al., 2014).

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Rebar monitoring is considered a critical and laborious task with safety hazards (Wang and Kim, 2019), and with the transformation towards digitization culture, there is a need to design and devise safe, economical, and practicable technology-based solutions to motivate construction industry stakeholders towards adoption of smart methodologies (Qureshi et al., 2022b). In light of the above discussion, this study aims to achieve automation in rebar monitoring via photogrammetry for quantification parameters, such as rebar lengths and rebar spacing (center-to-center distance between rebars). This study aims to improve the confidence of industry professionals in the adoption of photogrammetry tools for construction processes in place of expensive detection-data acquisition technologies. Moreover, the developed model would create competition and force the inventors to explore more efficient and effective solutions in terms of cost and time, considering I4.0 theme.

2 METHODOLOGY

This study intended to develop an automated monitoring methodology for inspecting the rebar, covering the quantitative parameters, such as rebar length and rebar spacing. Considering that, the methodology was divided into two main phases. The first phase involved developing the module to interpret the 3D point cloud model for rebar dimensions and rebar spacing (center-to-center distance between rebars). The second phase was testing and validating the developed proposed module for accuracy. Table 1 shows the specifications of the camera and workstation used in this study, i.e., for the module development and validation process. Moreover, for generating a 3D point cloud model, Agisoft Metashape was utilized, as it has been recommended as a suitable tool for the 3D modeling of construction-related processes (Qureshi et al., 2022a).

Items	Specifications & Details
Camera Workstation	Samsung SM-A225F Dell Precision 3630 Tower Intel Xeon CPU 64 GB RAM NVIDIA GeForce RTX 2060

Table 1. Camera and workstation specifications.

2.1 Development of Module

The module was developed in MATLAB, as it provides an effective and suitable environment to work on 3D point cloud models. The algorithm-based MATLAB functions were designed following computer vision (CV) and image processing techniques to interpret 3D point cloud model for desired rebar quantitative parameters. MATLAB, along with various specific designed functions, provides a platform to analyze 3D point cloud models. Moreover, based on provided rules, small function-based algorithms were developed and interconnected as a module to analyze and evaluate rebar 3D point cloud model. Figure 1 shows the working pipeline of the developed module for interpreting the 3D point cloud rebar model.

The module imports the scaled 3D point cloud model, and the plane detection process (pcfitplane) separates the rebar 3D elements from the rest of the plane, i.e., the surrounding environment. Afterward, the module performs the RANSAC-based procedure (pcfitcylinder) and extracts the cylindrical-shaped rebars from the 3D model. Following this, the extracted 3D horizontal and vertical rebar grid were converted into a raster image by projecting them into the 2D space. The projection axis was determined by performing a simple principal component analysis (PCA) computation and taking the major axis formed by the points. The developed raster pixel size is determined by the resolution unit, which for this case was set as 0.5; this value of 0.5 was ascertained after performing some pre-testing. The module reads the developed rebar raster and, by operating via the arrangement of developed functions and designed-MATLAB functions (‘bwlabel’, ‘regionprops’), it separates the horizontal and vertical rebars in raster data. In the end, the designed module evaluated the length of each rebar (horizontal and vertical) separately. Whereas the rebar spacing has been determined by ascertaining the center lines on the rebar grid for each rebar (horizontal and vertical) via ‘conv2’, and by using a combination of various functional features such as ‘regionprops’, ‘PixelList’, and ‘hypot’, the rebar center to center distances were determined.

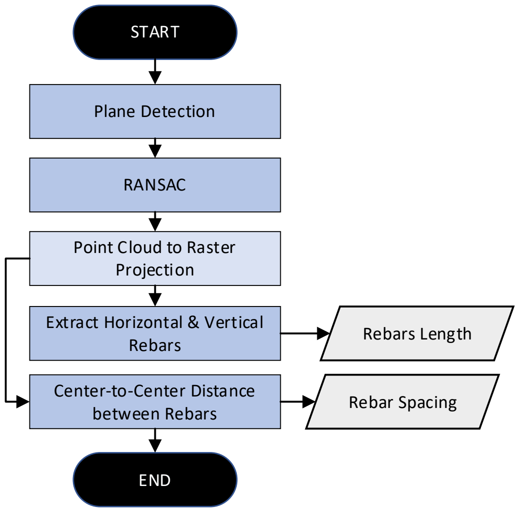


Figure 1. Workflow of module.

The pseudocode of the developed module has been shared as Table 2.

```
SET [model, inlierIdx, outlierIdx] TO pcfitplane(ptCloud,
maxDist, refVector, maxAngDist)
SET plane TO select (ptCloud,inlierIdx)
SET remainPtCloud TO select (ptCloud,outlierIdx)
SET [model,inlierIndices] TO
pcfitcylinder(BotPtCloud,maxDistance,...
SET coeffs TO pca(pcBOT.Location)
CALL min=min(()); max=max(())
DEFINE resolution_pix=0.5
SET raster=zeros(height_pix,width_pix);
FOR i=1:height_pix
   FOR j=1:width_pix
SET TO medfilt2(mask, [1, x]); (mask, [y, 1])
SET bwlabel()
CALL bwconncomp()
CALL regionprops(,'Perimeter','Centroid')
CALL regionprops(,'Area','Perimeter','Centroid')
SET [rows, columns, numberOfColorChannels] TO size()
SET props TO regionprops(, 'Area', 'PixelList')
SET XCrossings TO zeros(,); YCrossings TO zeros(,)
CALL plot(XCrossings(:), YCrossings(:), 'c.', 'MarkerSize', n)
CALL xlocs=conv2(XCrossings,[1,1]/2,'same')
CALL ylocs=conv2(YCrossings,[1,1]'/2,'same')
```

Table 2. Pseudocode of proposed module.

2.2 Module Testing and Validation

For testing and validation of module, a dataset was developed considering the outdoor environment with overall 16 rebars (eight rebars as horizontal rebars and eight vertical rebars). The rebar grid was assembled over an approximate area of 274 cm ×274 cm, i.e., 75,100 sq. cm, and with the length of each rebar approximately 274±2cm in length as ground truth dimensions (GTDs). The center-to-center distance between rebars was kept at approximately 30.48±3cm. The overall GTDs of the developed dataset were noted and using a smartphone camera (Samsung SM-A225F), 50 images were captured, covering all the side views and top views, for the generation of a 3D point cloud model via photogrammetry. Figure 2 illustrates the sample images of the developed rebar grid dataset.

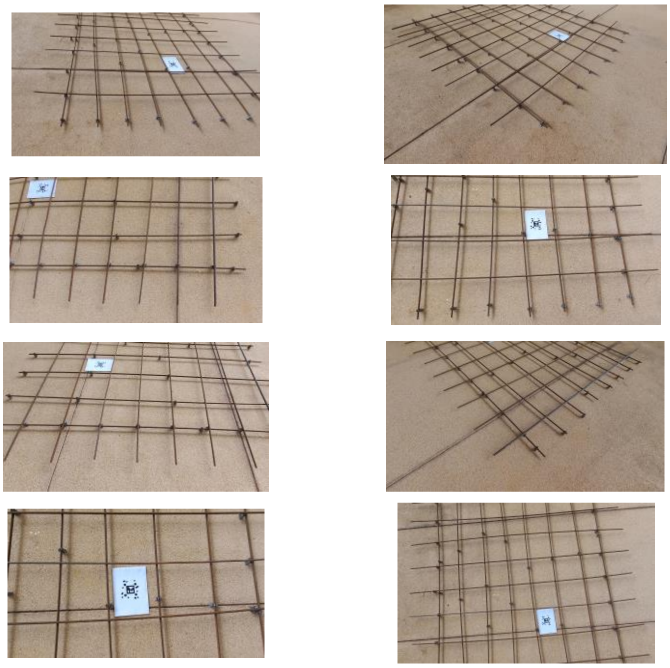


Figure 2. Rebar grid dataset (50 images).

Figure 3 illustrates the GTDs of the developed dataset for its rebar lengths and rebar spacing.

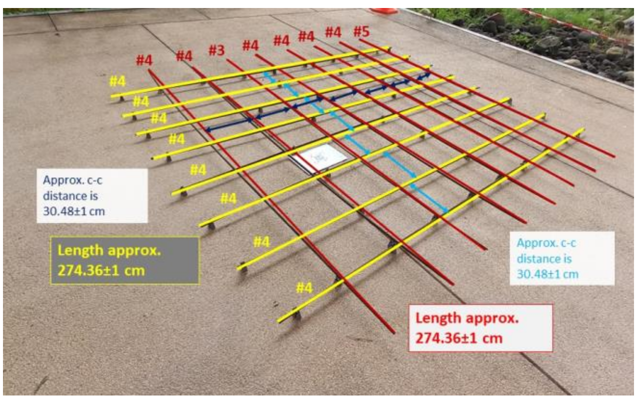


Figure 3. GTDs of rebar dataset.

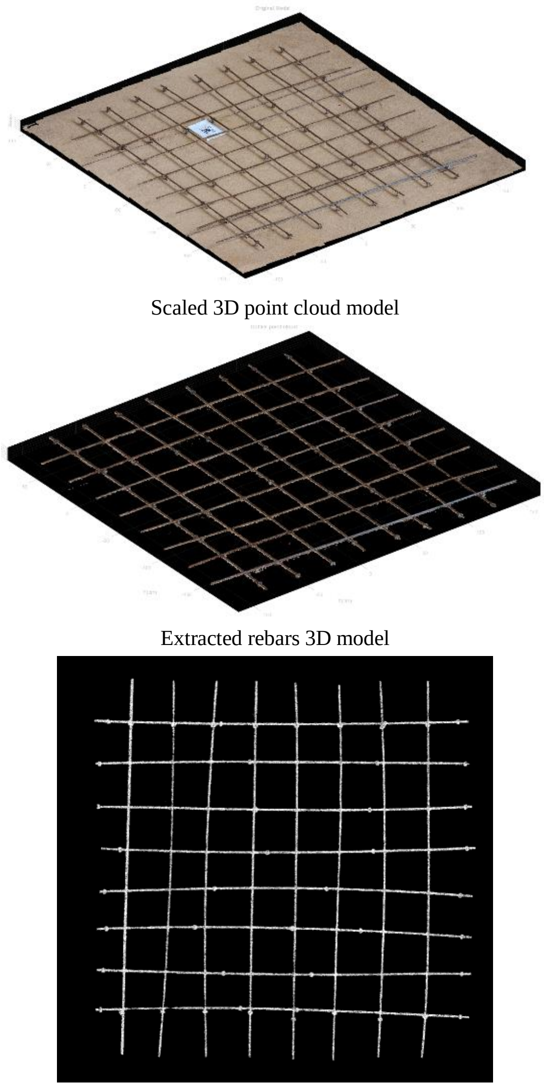


Figure 4. 3D model, extracted elements, and projected raster.

Using the developed image-based rebar grid dataset, a 3D point cloud model was generated using Agisoft Metashape. Moreover, the attained 3D point cloud model was scaled following the GTDs of the rebar grid. The attained scaled 3D point cloud model was imported to the designed module, and its outcomes were compared with GTDs of the rebar grid to assess the accuracy of the designed functions. For the determination of the module accuracy, three analyses were performed, i.e., error mean, percentage (%) error, and % mean error, as shown in Equations 1, 2, and 3.

$$Error\ Mean = \frac{D_1 + D_2 + D_3 + \cdots + D_n}{n} \tag{1}$$

$$D_n = G_n - V_n$$

$$\%\ Error = \%E = \frac{\sum_n^1 D_i}{G_T} \tag{2}$$

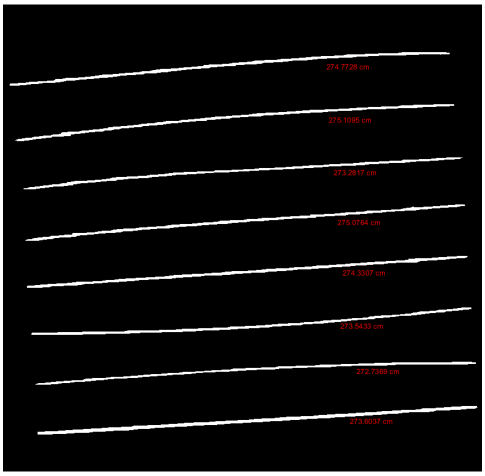
$$G_T = G_1 + G_2 + \cdots + G_n$$

$$\%\ Mean\ Error = \frac{\%E_1 + \%E_2 + \cdots + \%E_n}{n} \tag{3}$$

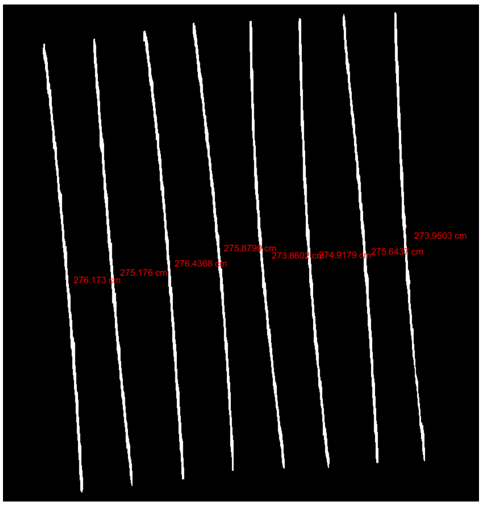
where D_n = deviation between GTD and virtual value
G_n = GTD of element

V_n = virtual/ module-based values of element
G_T = sum of GTDs of all elements in each parameter

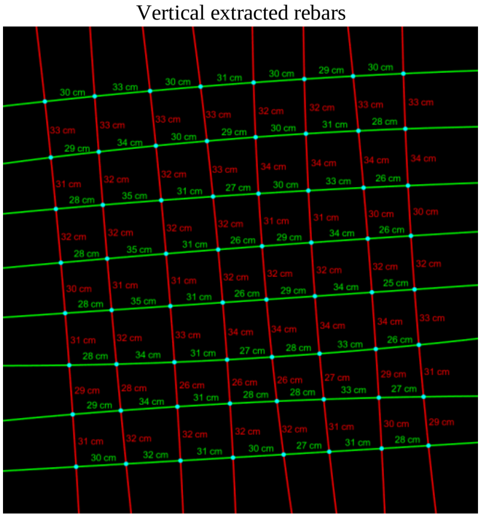
3 RESULTS AND DISCUSSION



Horizontal extracted rebars



Vertical extracted rebars



Rebar spacing

Figure 5. Visual representation of the rebar length and spacing.

The generated scaled 3D point cloud model was imported to the developed module. The module interpreted the 3D point cloud model for rebar lengths and rebar spacing. Figure 4 shows the generated 3D point cloud model from Agisoft Metashape based on an image-based rebar dataset, and the extracted rebars 3D model, along with its projected raster.

It can be seen that the developed module effectively detected the rebar portion from the rest of the model. After plane detection, the algorithm performed an extra check on rebar elements via RANSAC, to detect only cylindrical shape elements and remove any extra objects if necessary.

These cleaned, extracted 3D rebar portion was converted into a raster with the pixel resolution factor set as 0.5. On the successful raster generation, the module extracts horizontal and vertical rebars and evaluates each rebar's length and spacing, respectively. The visual outcomes of the module for horizontal and vertical rebar lengths and rebar spacing have been demonstrated in Figure 5. Table 3 describes the output for a numerical summary of rebar lengths, rebar spacing, and comparison of attained outcomes with GTDs data.

Parameter		GTDs	Proposed module	Remarks
Length of rebars	Horizontal	274±2cm	274.77cm 275.11cm 273.28cm 275.08cm 274.33cm 273.54cm 272.74cm 273.60cm	Acquired length values are approximately within GTDs range, i.e., 272cm to 276 cm.
	Vertical	274±2cm	276.17cm 275.18cm 276.44cm 275.88cm 273.86cm 274.92cm 275.64cm 273.95cm	Acquired length values are approximately within GTDs range, i.e., 272cm to 276 cm.
Rebar spacing	Horizontal	30.48±3cm.	(27.48-33.48) 34.0cm 34.7cm 26.9cm 26.3cm 34.9cm 26.0cm 25.6cm 34.8cm 25.9cm 25.2cm 34.3cm 26.6cm 25.6cm 26.5cm	There were 56 rebar spacing values. Out of which 42 center-to-center distance readings were measured within the given range, i.e., 27.48cm to 33.48 cm. However, 14 readings (highlighted as red) were found to be deviated.
	Vertical	30.48±3cm.	(27.48-33.48) 26.4cm 26cm 26.3cm	53 readings were measured within the given range, i.e., 27.48cm to 33.48 cm. However, 3 readings (highlighted as red) were found to be deviated.

Table 3. Outcomes and comparison with GTDs.

It can be observed from the above outcomes that the proposed module predicted/ evaluated each rebar length and spacing separately for both horizontal and vertical rebar elements. Overall, the developed algorithm's prediction capability is satisfactory. The module successfully measured the rebar lengths, as the predicted lengths were within the defined GTDs range, i.e., 274±2cm. Likewise, for center-to-center distances of rebars, for a few readings, the predicted values deviated (highlighted as red in the table) from the defined range, i.e., 27.48cm to 33.48cm. In the horizontal rebars, 14 readings were found out of the defined range. Whereas, in the vertical rebars, only three readings were found to deviate. Whereas the overall deviation was close to GTDs defined values.

Based on the obtained data and to explore the precision of the module, analyses were performed by computing error mean, % error, and % mean error for each parameter category, i.e., length of horizontal rebar, length of vertical rebar, horizontal rebar spacing, and vertical rebar spacing. The aforementioned analyses were achieved by adopting Equations 1, 2, and 3 for the dataset. Table 4 summarizes the analyses for rebar lengths, and Table 5 shows the analysis of rebar spacing.

Rebar Lengths	Error Mean (cm)	% Error
Horizontal rebars	0.77	0.28%
Vertical rebars	1.30	0.48%
% Mean Error	0.38%	

Table 4. Analysis summary for rebar lengths.

Rebar Spacing	Error Mean (cm)	% Error
Horizontal rebars	1.07	3.65%
Vertical rebars	0.24	0.79%
% Mean Error	2.22%	

Table 5. Analysis summary for rebar spacing.

From Tables 4 and 5, it can be observed that module was more effective for determining the rebar lengths as the error means range lie under 1.5 cm with a % error mean of 0.38%, which is exceptional prediction accuracy. Whereas % error for horizontal rebars was more than for vertical rebars, making % mean error up of rebar spacing up to 2.22%, which is satisfactory. However, there is a need to improve the algorithm for rebar spacing to mitigate this inconsistency. Overall, the results are acceptable as an automated monitoring rebar tool. Moreover, this model also demonstrates that using the right CV techniques allows rebar monitoring to be effectively managed via low-cost photogrammetry tools.

4 CONCLUSION

The study devised a CV vision and image processing algorithms-based module for interpreting the 3D rebar point cloud model. The module was developed by using the MATLAB platform, and various functions were designed as per the requirement of rebar monitoring for the quantitative aspects, i.e., rebar length and rebar spacing. Moreover, for 3D point cloud generation via photogrammetry, Agisoft Metashape was utilized. Overall, it was observed that the designed module effectually evaluated the 3D point cloud model of the developed rebar dataset. The evaluation was performed for computing rebar length and rebar spacing via performing various functions such as plane detection, RANSAC, extraction, and measurement. It was noted that the outcomes of the developed module were more precise for rebar lengths, i.e., more than 99% accuracy with 0.38% as % mean error for GTDs and attained virtual outcomes. However, the accuracy for rebar spacing was found to be near to 98% with % mean error as 2.22%. Overall, the results were satisfactory, and the methodology is practicable and economical compared to other similar technologies available in the market.

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