A Streamlined Laser Scanning Verticality Check Method for Installation of Prefabricated Wall Panels

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Abstract

Installation quality check is essential for ensuring the construction quality of prefabrication construction. The existing techniques for assessing the installation quality of prefabricated wall panels heavily depend on manual inspection and contact-type measurements, which is labour intensive and slow. Laser scanning was previously adopted in construction quality check, however, few studies have focused on using laser scanners to assess the verticality of prefabricated wall panels, and no method has been developed for effective practical implementation. This study proposes a streamlined laser scanning approach for onsite verticality check of prefabricated wall panels. Based on systematic experiments of using the point cloud data collected by different types of laser scanners, and 25 prefabrication wall panels of four shapes, this study validates the proposed method and compares the use of different laser scanners. To facilitate an effective streamlined process for practical use, this study identifies the point cloud segmentation parameters under different laser scanning datasets and suggests suitable parameters for these case scenarios. These parameters can be adopted directly or used as references for practical application of the proposed laser scanning method in the installation verticality check. This study contributes to improving the efficiency of installation quality check of prefabrication construction, and facilitating the digital evolution of the construction industry.

Keywords: Quality Check, Verticality Check, Laser Scanning, Prefabricated Wall Panel, Region Growing Segmentation, Point Cloud Segmentation

Practical Applications

Checking the verticality of the installed prefabricated wall panels is crucial in construction quality control. However, traditional methods for assessing the installation quality of prefabricated wall panels heavily depend on manual inspection and contact-type measurements, which is labour-intensive, slow and costly, especially for project involves a large number of same or similar type of prefabricated construction elements, the repetitive work causes human fatigue and in-efficiency. This paper proposes a laser scanning method to streamline the quality check process for the installation of prefabricated wall panels. By systematically experimenting with the point cloud data collected by different types of laser scanners for various wall panels of different shapes, this study validates the effectiveness of the proposed method. Another major contribution of this research is pre-identification of optimal segmentation parameters for laser scanning point cloud. This means construction professionals can use these parameters directly or as references for identifying suitable segmentation parameters for other projects. The streamlined laser scanning method contributes greatly to improving the efficiency of installation quality check of prefabrication construction practice, especially when large number of identical or similar elements are used.

Introduction

Prefabrication wall panels (PWPs) are widely used in construction projects, and verifying their verticality is essential in the construction process. Currently, manual inspection method, which uses traditional tools like T-type measuring tools and 2-meter inspection rulers, is time-consuming (Wang et al. 2021). Laser scanning technology can capture geometric data of existing structures quickly and accurately (Li et al. 2020), and has gradually gained popularity in prefabrication construction.

Existing studies on quality check using laser scanning are mainly based on the detection of variations between Building Information Models (BIM) and point cloud datasets. For example, Guo et al. (2020) detected the geometric quality of prefabricated electrical and plumbing elements from laser scanning data by matching with the as-design BIM. Rausch et al. (2017) conducted the quality check of dimensional deviation for prefabricated elements through the comparison between laser scanning point cloud and BIM model. Tan et al. (2020) proposed a method to conduct geometric quality inspection by using BIM model and laser scanning data, which could be applied to prefabricated structural elements, and prefabricated mechanical, electrical and plumbing elements. Li et al. (2020) and Bosché and Guenet (2014) developed quality check methods for flatness inspection of building surfaces by computing the deviations between the as-design BIM and laser scanning data. Xu et al. (2020) proposed a quality control approach for the surface defects evaluation for prefabricated elements. The geometric data is extracted from laser scanning point cloud and the quality information is obtained by comparing with BIM model. However, although using the as-design BIM model can detect all the deviations of the actual building from the design, it is not applicable for the early stages of construction as the available BIM is of the completed building. Therefore, these BIM-based quality check methods are not suitable for installation quality check during the construction process.

There are some previous studies attempted using laser scanning to conduct quality check of buildings without BIM. For example, Wang et al. (2015) proposed a quality check method for existing structures using Terrestrial Laser Scanning (TLS), which focuses on checking the verticality of indoor environments for house projects. Li et al. (2022) proposed a flatness and verticality quality assessment for indoor acceptance testing based on TLS.

For quality check during construction process, Wang et al. (2021) proposed a framework for installation quality check of wall panels using the datasets collected by one type of laser scanner, BLK360. The time efficiency of using laser scanning is reported in comparison with the traditional method (Wang et al. (2022). However, the proposed method has limited use of one specific laser scanner, for one type of wall panels, and the method is not streamlined and still requires manual tuning of segmentation parameters in processing the point cloud data, which can be time consuming. Therefore a streamlined installation quality check method needs to be developed for practical applications.

To streamline the laser scanning method for installation quality check, accurate identification of wall panels from laser scanning datasets is crucial. Previously, studies have focused on processing indoor datasets of complete buildings, for example, Pan et al. (2022) proposed a method to recognize the building elements using laser scanning and photogrammetry technologies based on training point cloud datasets from the Technical University of Munich and Stanford 3D Indoor Scene Dataset (S3DIS) dataset. Chen et al. (2019) proposed an approach for object recognition from indoor point cloud scenes based on training using S3DIS point cloud dataset. However, few studies have applications in construction process or on outdoor object detection and segmentation (Rao et al. 2022).

Segmentation of point cloud data removes irrelevant objects and is used to identify wall panels. There are four main approaches for plane segmentation proposed in previous research (Biosca and Lerma 2008; Xu et al. 2018): (1) model fitting-based, which is also a parameter-based approach, such as Random Sample Consensus (RANSAC) algorithm and Hough Transform; (2) region growing-based; (3) feature clustering-based, and (4) global energy optimisation-based. Some point cloud processing software like Leica Cyclone or CloudCompare offers mature packages or plug-ins for plane segmentation using region-growing algorithms and RANSAC (Girardeau-Montaut 2011; Leica Geosystems 2022). The region-growing segmentation is commonly used due to its simplicity and low computational load (Martínez et al. 2016). However, fine-tuning its parameters for different PWPs is time-consuming (Wang et al. 2021) and this is a barrier for practical use of laser scanning method for onsite verticality check.

Therefore identifying patterns of optimal segmentation parameters and validating their use in different scenarios are essential for practical implementation (Biosca and Lerma 2008). In practice, usually a variety of different types of prefabricated wall panels are used and it is important to validate the laser scanning method in these different scenarios.

In another aspect, different laser scanners are available in the market (Becerik-Gerber et al. 2011; Tóth and Živčák 2014). These scanners offer different specifications, such as scanning range, speed, point accuracy, and resolution (Nurunnabi et al. 2016; Poux et al. 2022). It is necessary to compare and discuss the use of different types of laser scanners and select the most appropriate ones for construction practice (Becerik-Gerber et al. 2011).

In summary, this research proposes an effective and practical verticality check method using laser scanning. Based on previous research, the following research objectives are established: (1) Developing a streamlined laser scanning method for verticality check and validation of the proposed method using the point cloud data collected by different types of laser scanners and prefabrication wall panels; (2) Systematic experiments of point cloud segmentation and predefining the segmentation parameters under different datasets to properly identify the

PWPs; and (3) Assessing the practicality of using different laser scanners and providing guidance on selecting appropriate laser scanners for various projects.

The major contribution of this paper is the development of a streamlined laser scanning method for installation quality check of prefabricated wall panels, and validation of the method across diverse conditions, including various laser scanner and different types of wall panels. As appropriate point cloud segmentation parameters need to be used in the data analysis to enable a streamlined process to produce the quality check outcome, this study also suggests optimal segmentation parameters after systematic experimenting for some specific cases. These parameters can be adopted directly or used as references for practical application of the proposed laser scanning method on installation verticality check. This advancement enables the streamlined procedure to deliver timely quality check results in practical scenarios.

Laser scanning technology

In civil projects, two commonly adopted types of laser scanners are TLS and mobile laser scanning (MLS) (Gollob et al. 2020). TLS is frequently used for quality checks of prefabricated concrete elements, including geometry quality assessment (Guo et al. 2020), detection of surface defects and flatness (Wang et al. 2016), and displacement monitoring of mechanically stabilised earth (MSE) walls (Oskouie et al. 2016). TLS could generate dense data and capture more details of the construction site, such as the rebars, supporting elements, and waste materials. Previous studies have primarily employed TLS for quality inspection of prefabricated elements.

MLS is commonly used for road and tree detection in urban environment analysis (Yadav et al. 2021), tunnel underground inspection (Cui et al. 2019), and displacement monitoring of MSE walls as well (Al-Rawabdeh et al. 2020). It is rarely used for quality checks due to its relatively low accuracy. However, MLS has rapidly advanced in recent years, providing high quality point cloud data and considerably reducing scan time (Ellmann et al. 2022; Singh et al.

2021). With the development of simultaneous localization and mapping (SLAM) technology, the accuracy of point clouds collected by MLS has improved (Alsadik and Karam 2021; Kim et al. 2018). For example, Trzeciak et al. (2023) and Trzeciak and Brilakis (2023) developed a prototypic handheld scanner for accurate point cloud collection. This technique improved the accuracy and density of multiple individual lidar scans by utilizing additional geometric constraints inferred from the predicted feature maps in the corresponding images. Therefore, as MLS's accuracy increases, it also has the potential to be adopted for quality inspection.

In some aspects, MLS outperforms TLS in creating data more complete, efficiently, and easily, particularly in complex construction sites (Nurunnabi et al. 2018). While most TLS devices have higher accuracy, they require a technical operational process, and the scanning position is fixed (Gollob et al. 2020; Sepasgozar et al. 2018). Prefabrication construction sites often have many supporting elements for PWPs, which create occlusions of the point cloud data generated by TLS. The incompleteness of the collected data decreases the accuracy of the checking results. MLS offers great flexibility in capturing data comprehensively. Moreover, MLS is more convenient and time-efficient for use on construction sites, making it easier for construction practitioners to implement in practical scenarios. Therefore, MLS is included in this research to explore their potential in the verticality check of installing PWPs.

Research Design and Methodology

Overview

This research follows a three-step research design, as illustrated in Figure 1. Firstly, the quality checking approach was developed. The identification process of PWPs from point cloud and quality check process were designed in the approach. The second step included the collection of the point cloud datasets used for validating the approach. Three different types of scanners, Leica BLK360, FARO Focus X330 and GeoSLAM ZEB, were adopted to collect onsite point cloud data. A real case was selected for the validation, and it contained 25 different PWPs.

Finally, systematic experiments of the collected point cloud data were carried out to identify suitable parameters in different scenarios. Validation of the method was carried out through comprehensive comparison and validation.

Proposed laser scanning approach

The proposed laser scanning approach for the verticality check is shown in Figure 2. After data collection, data registration is performed to combine data collected by different scans into one dataset using the open-source software, CloudCompare (Girardeau-Montaut 2011; Xia et al. 2020). The manual step is conducted using CloudCompare, as it simply involves cropping out the irrelevant construction site area from the raw point cloud dataset and reducing the ground points, which is a process only takes a few minutes. Ground points can be removed from the datasets to reduce computational costs and processing time. The Cloth Simulation Filter (CSF), a plugin in the CloudCompare software, is used to separate ground points and off-ground points (Zhang et al. 2016). The parameters of CSF are determined based on previous research (Štroner et al. 2022; Wei et al. 2013). These pre-processes are conducted using CloudCompare 2.12.0 version.

Following data pre-processing, the critical step is to identify wall panels from point cloud data. Region growing is adopted for segmentation, and the suggested parameter values will be provided in this study. After segmentation, each segment is fitted with a plane using the RANSAC algorithm, which efficiently computes a fitted plane (Li et al. 2020; Wang et al. 2021). The plane equation and the points contained within each segment are obtained (Goebbels and Pohle-Fröhlich 2020). The parameters in the RANSAC algorithm are set as confirmed by Wang et al. (2021). The obtained information for each PWP includes computed plane equations, inliers, normal vectors, and heights, which will be used for the verticality check of each fitted plane.

A further filtering process is developed after segmentation and RANSAC to remove unnecessary points of other construction materials, such as supporting poles and background points. This process differentiates PWP segments from other segments based on their vertical status and heights. The differences between PWP segments and other segments are their verticality and heights. Firstly, the PWPs are vertical, while the supporting elements are always oblique. In this case, the angles of the fitted planes with the ground plane can be used as a constraint for removing the supporting elements. Based on the tests of removing support elements, the threshold can be set as 89^{o} which could remove all the supporting elements. Secondly, some construction materials on the construction site could also be in the point cloud data after segmentation. Their heights are usually lower than the height of PWP. The segments with a height lower than 2 metres could be removed. Algorithm 1 summarises the process for filtering unnecessary fitted planes to extract PWPs.

In Algorithm 1, W includes all fitted wall panels after RANSAC, E_i is the mathematical plane equation of each wall based on RANSAC plane fitting. The normal vector of each wall is extracted from E_i and is then used for filtering the support elements. RANSAC also identifies the inliers of each fitted wall panel, allowing the height of each wall panel to be computed based on the estimation of the z attributes of each wall. After RANSAC fitting and Algorithm 1, planes that do not correspond to any walls can be effectively removed based on a comparison of their vertical angles and heights.

The final step is to conduct the verticality check. This involves calculating the normal vector of each panel and then calculating their vertical angles. Algorithm 2 summarises the process of the verticality check. The output of Algorithm 1 comprises the PWPs after filtering, which serve as the inputs for Algorithm 2. Similar to Algorithm 1, the vertical angles and heights of PWPs are computed. Subsequently, the vertical deviation of each PWP is calculated. Based on a comparison with the quality threshold of 0.005m, the PWPs that do not meet the quality criteria can be automatically and accurately selected after Algorithm 2.

Algorithm 1. Filtering process.

```
Input
    $W=\{w_0, w_1,\ldots, w_n\}$  fitted wall planes
    $Cluster_i$  inliers of $w_i$
    $p_{ij}$  $point_j$ in the $Cluster_i$
    $z_{ij}$  z attributes of the points $p_{ij}(x_{ij},y_{ij},z_{ij})$ in the $cluster_i$
    $E_i$  mathematic equations of fitted wall planes $w_i$
Output
    W'  wall planes after filtering
    for point $p_{ij} \in Cluster_i$
        normal vector of $w_i = v(E_i)$
        $\cos\theta=(v(E_i), <0, 0, 1>)$
        angle set $D_i$= degree(acos(cosθ))
        if $D_i<D(threshold)$
            remove $w_i$ from W
        end
    end
    for point $p_{ij} \in Cluster_i$
        max height set $H(max)_{ij}= z_{ij}(max)$ in $Cluster_i$
        max height set $H(min)_{ij}= z_{ij}(min)$ in $Cluster_i$
        $Height(threshold)= min(H(min)_{ij})+2$
        if $H(max)_{ij} < Height(threshold)$
            remove $w_i$ from W
        end
    end
```

Algorithm 2. Verticality check process.

```
Input
    $W'=\{w_0', w_1',\ldots, w_n'\}$  wall planes after filtering
    $Cluster_i'$  inliers of $w_i'$
    $p_{ij}$  $point_j$ in the $Cluster_i'$
    $D_i'$  angle set of wall planes $w_n'$
    $E_i'$  mathematic equations of fitted wall planes $w_i'$
Output
    $\chi\{w_i':\delta_i\}$  dictionary of verticality angles
    $\phi\{w_i':\Delta_i\}$  dictionary of deviations
    $\psi\{w_i':Cluster_i'\}$  dictionary of point cloud set of panels need rectification
    for point $p_{ij} \in Cluster_i'$
        compute wall height set $h_i=z_{ij}(max)-z_{ij}(min)$
        $V_i = h_i * \tan[90^\circ - D_i']$
        if $V_i > 0.005$
            add $w_i'$ to $\psi$
        end
    end
```

Point cloud datasets for experiments

The point cloud datasets used to validate the proposed approach were collected by different laser scanners. Commonly used TLS include Leica and FARO scanners, such as FARO Focus X330 (Wang et al. 2016; Yang et al. 2020), Leica BLK360 (Badenko et al. 2019; Wang et al. 2021), and Leica RTC 360 (Allegra et al. 2020; Jingli 2020). Popular MLS scanners are GeoSLAM scanners, such as Zeb1 or ZebRevo (Gollob et al. 2020; Nikoohemat et al. 2020). For this study, TLS including Leica BLK360 and FARO Focus X330 are used for validating the effectiveness of the proposed quality check method (Focus3D X330 2022; Leica Geosystems 2022). MLS including GeoSLAM ZEB horizon is selected for comparison with TLS regarding the time efficiency(GeoSLAM ZEB Horizon 2022). Table 1 presents the specifications of these laser scanners. These scanners can generate laser scanning datasets with different levels of accuracy and point cloud densities.

In this research, the BLK360 scanner was used for data collection at standard resolution (10 mm at 10 m). For comparison with the BLK360 dataset, the FARO X330 scanner was set with 1/8 resolution (12 mm at 10m) and 2x quality. Average point spacing (*APS*) is a feature defined by Xu et al. (2014) for classification and can be used to roughly represent the density (Martínez et al. 2016). *APS* describes the distance between each point and its adjacent points. The estimation of the *APS* is as follow:

$$APS = \frac{1}{N}\sum_{P=1}^{N} min\left(dis(p,q)\right), q = 1,2,\ldots,N, p \neq q$$

Where *N* is the number of point cloud data, $dis(p,q)$ represents the distance between point *p* and other point q, min $\left(dis(p,q)\right)$ represents the minimum distance between point *p* with its neighboring points.

Point density and spacing are directly related. Lower point cloud spacing enables more specific details. A smaller *APS* indicates dense point distribution, while a larger *APS* suggests sparser points and lower density. Point density may be inconsistent due to varying scanning distances and positions (Calders et al. 2020; Tóvári and Pfeifer 2005).

Design of Experiments

To minimise the impact of other factors, such as data incompleteness (Wang et al. 2021), the quality of different laser scanning datasets is pre-tested before conducting experiments. This process aims to identify low-quality issues, such as occlusion or inconsistent density in the datasets, which may lead to over-segmentation or under-segmentation problems. The completeness of the collected data is checked first to identify potential occlusions that could cause one panel to be split into two segments during segmentation.

To address variations in segmentation results for panels with the same shapes, further checks are conducted. Over-segmentation or under-segmentation issues resulting from these variations are challenging to resolve through parameter tuning. This process aims to confirm that tuning segmentation parameters is less influenced by such issues. As a result, the segmentation experiments exclude PWPs with low-quality data to ensure the reliability of the results.

The critical step to identify all PWPs from point cloud data is finding optimal segmentation parameters. For region growing point cloud segmentation, five parameters need to be set, including K search (*KS*), number of neighbours (*NN*), minimum clusters (*MC*), smoothness threshold (*ST*), and curvature threshold *(CT*) (Dong et al. 2018), as listed in Table 2. The factors that need to be fine-tuned in the proposed approach are *KS* and *NN* (Wang et al. 2021).

Lower values of *KS* and *NN* could cause over-segmentation while higher values may result in under-segmentation (Stewart et al. 2002). To reduce over-segmentation and under-segmentation problems caused by inappropriate parameter values, systematic experiments are conducted with varying values of *KS* and *NN* (Xu et al. 2018). *KS* is tested in the range of 35 to 50 to avoid over-segmentation issues previously observed from 15 to 35 (Deschaud and Goulette 2010; Wang et al. 2021). *NN* is tested over a larger range to reduce the influence of noise. Two rounds of testing are designed: the first round with a parameter interval of 15 to find the rough range, and the second round with an interval of 5 for more refined tests.

The general guideline for tuning the values of *KS* and *NN* is to increase their values if over-segmentation occurs and decrease them if under-segmentation is observed. Some under-segmentation with adjacent rebars or supporting elements is acceptable and can be further addressed in subsequent processes. However, over-segmentation is not acceptable.

While the manual check is the widely used method in the industry and is accurate for most construction projects, the streamlined laser scanning method aims to improve time efficiency. Lin et al. (2019) and Tang et al. (2022) also validated the effectiveness and accuracy of laser scanning point-cloud techniques using manual checks. The time spent using the streamlined method is a critical concern for industry practitioners (Guo et al. 2020; Wang et al. 2022).

Experiments and validation

In this section, a real case of a prefabrication residential building is selected for validation of the laser scanning approach. Data collected by three laser scanners is used for this purpose, and pre-tests are conducted on the datasets to ensure the reliability of the experiment results. These suggested values will be predefined in the proposed method for further utilisation of the proposed method under different scenarios.

Case background

The case study was undertaken in Shanghai, China, as seen in Figure 3(a). This building has sixteen floors, with the selected floor being the sixteenth floor. The scanned area covered approximately 300 m^2. The construction site layout is shown in Figure 3(b), and a total of 25 PWPs were present on this floor. These included 14 solid panels, 5 panels with a window frame hole, 3 panels with a door frame hole, and 3 bay window panels, as given in Table 3. The position information of these PWPs is provided in Figure 3(b), while their shape information is depicted in Figures 3(c), (d), (e), and (f).

Data collection and pre-tests

After the installation of all PWPs, the construction site was scanned using the selected MLS and TLS. Three experienced surveyors were involved in the scanning process to ensure accuracy and efficiency. One surveyor used the GeoSLAM to walk around the construction site and collected point cloud data in approximately 4 minutes, as seen in Figure 4(a). The scanning processes using the BLK360 scanner and FARO X330 scanner were carried out by two other surveyors as shown in Figure 4(b) and Figure 4(c), taking around 3 minutes and 4 minutes per scan, respectively. The scanning positions of the two scanners were not the same but both captured the whole construction site. The total data collection time for BLK360 was approximately 20 minutes, and for FARO X330, it was about 22 minutes, including the setup time for the built-in parameters. Simultaneously, manual measurements were conducted as shown in Figure 4(d), and it took approximately 100 minutes to complete the manual checks.

Table 4 presents the information of the three datasets after pre-processing, revealing significant variations in point numbers and density. The GeoSLAM dataset has an *APS* of 6.486 mm with approximately 9,841,610 points. The BLK360 dataset has an *APS* of 3.433 mm with around 17,013,765 points for the same area. The FARO X330 dataset contains the highest number of points, approximately 31,230,427, with an *APS* of 2.869 mm. The ranging accuracy of FARO X330 is 2 mm, while BLK360 ranges with a 4 mm accuracy. In contrast, the ranging accuracy of GeoSLAM is 10-30 mm. In summary, the FARO X330 dataset is the densest and most accurate, followed by the BLK360, while the GeoSLAM dataset has the lowest density and accuracy.

Different from MLS, the BLK360 dataset and FARO X330 dataset were obtained through multiple scans, and their density maps are given in Figure 5. In the BLK360 dataset, the point cloud densities of most panels range between 46,196 points/m^2 and 75,808 points/m^2, as seen in Figure 5(a). In the FARO X330 dataset, the densities of most wall panels exceed 90,614 points/m^2, with only a few panels having densities smaller than 75,808 points/m^2, as seen in Figure 5(b). Both the BLK360 and FARO X330 datasets exhibit varying point cloud densities for different wall panels. This variation is mainly caused by differences in scanning distances, scanning angles, and overlapping scans. Consequently, even with the same scanner equipment, it is common and unavoidable to encounter varying point cloud densities in TLS datasets.

Based on pre-tests on the GeoSLAM dataset, it was found that BP1 was consistently over-segmented, while BP2 and BP3 were properly segmented. The density map of the GeoSLAM dataset, shown in Figure 6(a), indicated that the density of BP1 was above 28000 points/cm^2, while other panels had densities around 15000 points/cm^2. The higher density of BP1 was due to it being the starting point of the scanning, capturing more points compared to other wall panels, as shown in Figure 6(b). The red colour represents the scanning route of the mobile scanner, indicating that BP1 took longer to scan compared to other wall panels. Therefore, the segmentation result of BP1 was excluded from the segmentation assessment.

Based on pre-tests of the BLK360 dataset, it was observed that DP2 was consistently over-segmented. Further examination revealed that the point cloud of DP2 was incomplete due to the occlusions of supporting elements and some workers, as seen in Figure 6(c). Those occlusions separated DP2 into several pieces, making it difficult to cluster the points as a whole segment even with adjustments to the segmentation parameters. Thus, the segmentation result of DP2 in the BLK360 dataset was excluded from the segmentation assessment.

During pre-tests of the FARO X330 dataset, it was noticed that five PWPs were consistently over-segmented. Further examination revealed that the point cloud data of four PWPs are incomplete, including SP4, WP4, DP1, and DP2, as shown in Figure 7(a), (b), (c) and (d). For DP3, its point spacing is 6.0 mm, which was much higher than the *APS* of 2.89 mm, indicating a much lower density. These issues mainly resulted from improper scanning processes, where some areas were not scanned thoroughly. Consequently, the segmentation results of these five PWPs were excluded from the performance assessment.

In summary, based on the pre-tests of the three datasets, the PWPs that will not be assessed during the segmentation tests are listed in Table 5. These low-quality data issues mainly resulted from improper scanning processes, such as occlusions of elements and workers on the construction sites, as well as variations in scanning times for each PWP. The pre-test processes were conducted to ensure the accuracy of the experimental dataset and results, thereby improving the reliability and effectiveness of the predetermined parameters. Once the parameters are determined, the proposed method can then be streamlined and used for other cases without repeating the pre-test processes.

Tests of segmentation parameters

The segmentation tests for the three datasets were conducted. The results for the GeoSLAM dataset are presented in Table 6 and Figure 8. When the *KS* was set as 35 and the *NN* was tested from 35, it resulted in over-segmentation, as seen in Figure 8(a). When the *NN* was set as 95, the point cloud data was under-segmentation as shown in Figure 8(b). When *NN* as set as 65, most of the PWPs were properly separated, as seen in Figure 8(c). When *KS* was set as 95, WP3 was under-segmented, as seen in Figure 8(d). Finally, it was found that setting *KS* as 50 and *NN* from 65 to 75 resulted in a good segmentation result for the GeoSLAM dataset.

Table 7 presents the results of segmentation tests on the BLK360 dataset. When the *KS* was set as 35 and the *NN* was tested from 35, it led to over-segmentation, as seen in Figure 9(a). Setting the *NN* as 80 resulted in under-segmentation of the point cloud data, as shown in Figure 9(b). With *NN* set as 65, most of the PWPs were properly separated, as seen in Figure 9(c). When *NN* was set as 80, DP1, BP1, WP4 and SP4 were under-segmented, as seen in Figure 9(d).

Finally, it was found that setting *KS* as 50 and *NN* from 55 to 65 resulted in a good segmentation result for the BLK360 dataset.

The results of segmentation tests on the FARO X330 dataset are shown in Table 8. When the *KS* was set as 35 and the *NN* was tested from 35, it resulted in over-segmentation, as seen in Figure 10(a). When the *NN* was set as 80, the point cloud data was under-segmentation as shown in Figure 10(b). When *KS* was set as 50 and *NN* as 65, SP7 and BP1 were under-segmented, as seen in Figure 10(c). Setting *NN* as 80 caused many panels to be under-segmented, as seen in Figure 10(d). when *NN* was set as 65, most of the PWPs were properly separated, as seen in Figure 10(e). Setting *NN* as 70 resulted in under-segmentation, as shown in Figure 10(f). Finally, setting *KS* as 45 and *NN* as 60 or 65 led to a good segmentation result. Based on the tests on the three datasets, the suggested values for segmentation parameters for using each scanner are summarised in Table 9. The obtained segments are fitted with a plane using RANSAC. The planes after the filtering process are show in Figure 11(a), (b), and (c), representing the PWPs in the GeoSLAM, BLK360, and FARO X330 datasets respectively.

Comparison of verticality check results

The verticality results using the laser scanning approach are computed and compared with the that of the conventional manual method. The manual check method is still the widely used and accepted method in the industry, and it could be used to assess the effectiveness of the proposed streamlined method. In manual checking, two quality inspectors were required. One inspector places the top end of the measuring tool, a 2 m inspection ruler, against the wall panel and adjusts the tool to be vertical. The second inspector measures and records the distance of the bottom end to the wall panel (If this distance is zero, it means that the wall is perfectly vertical to the ground). During this process, the inspectors must ensure that the ruler is perpendicular to the ground. This process needs manual handling with great care, therefore it is time-consuming when large number of wall panels need to be checked. The manual checking results were used to validate the consistency of the results computed by using the laser scanning method, and the comparison of these results is given in Table 10. Based on the manual check, the panels that need to be rectified are SP1, WP2, WP4. The results obtained using BLK360, FARO X330, and the manual method are consistent with each other. The validation results demonstrate that using BLK360 and FARO scanners can correctly identify the PWPs that need to be rectified. In conclusion, the effectiveness of the proposed approach is validated using TLS.

Table 11 presents the time costs for using the laser scanning approach and the manual method. The total time for the manual method to check all 25 panels is approximately 100 minutes, with an average time of around 4 minutes per PWP. The time cost of using different laser scanners is also provided. Among the laser scanners, GeoSLAM is the quickest, taking 0.684 minutes per PWP and 17.1 minutes in total, followed by the BLK360 with 1.484 minutes per PWP and 37.1 minutes in total. Although FARO X330 has the highest accuracy, it is also slower than other laser scanners, taking 2.068 minutes per PWP and 51.7 minutes in total.

Based on the results of the case study, the proposed laser scanning approach is effective in computing the verticality using TLS. Using BLK360 and FARO X330 successfully identified all types of PWPs that need to be rectified, including solid panels, panels with a door frame, panels with a window frame, and bay window panels. All point cloud datasets and code used in this study are openly accessible on request, and the Code and Data Availability Statement is added at the end of the paper.

In real-world scenarios, some PWPs may exhibit uneven and non-flat surfaces, as depicted in Figure 12 (a) and (b). Placing a measurement tool on such uneven areas can lead to inaccuracies in the obtained measurements. The traditional method relies on the assumption that PWP surfaces are flat, and it requires careful handling by workers to achieve accurate results (Wang et al. 2018). Moreover, manual measurements are limited to covering only specific surface areas of the PWP, making them inconsistent and less reliable. In contrast, laser scanning provides a more accurate and reliable method for capturing the geometry information of PWPs. Analysing the entire point cloud with laser scanning reduces the inconsistency in inspection results, resulting in higher accuracy and reliability compared to the traditional method (Oskouie et al. 2016; Rashidi et al. 2020).

Discussion of experiment results

Recommended segmentation parameters for different PWPs

To achieve streamlined and rapid verticality check results, having pre-defined segmentation parameters is crucial. This ensures efficiency in obtaining accurate results. This section analyses the patterns of fine-tuning segmentation parameters. Firstly, Table 12 shows that the optimal values of *KS* vary for different scanners. Additionally, few studies have explored the determination of *NN* value for *NN*. This study provides suggested *NN* values for different scanners in Table 12. Secondly, prefabrication projects may contain various types of PWPs. Based on Table 6, 7 and 8, the optimal values for good segmentation of different PWP types are summarised, as seen in Table 12. The suggested values to identify each shape of PWP are provided for each scanner, indicating that different shapes of PWPs will influence the selection of segmentation parameter values.

In summary, tuning segmentation parameters should consider the shape of the PWPs. For solid panels, *KS* values of 35 or 50 are recommended, and *NN* can be set equal to or larger than *KS*. Parameter tuning is more straightforward for datasets with lower density, like those collected by the GeoSLAM scanner, allowing for a larger range of parameters. While for datasets with higher density, such as using the FARO X330 scanner, the tuning of parameters is more challenging and the optimal range for *NN* is narrower: (1) For MLS data with *APS* around 6.5 mm, *NN* could be effective at around 30-60 larger than *KS* when *KS*=35 and 15-25 larger than

KS when *KS*=50m (2) For TLS data with *APS* about 3.5 mm, setting *NN* in the range of 0 to 45 larger than *KS* could yield good segmentation results, (3) For TLS data with *APS* about 2.9 mm, it is suggested to set *NN* in the range of 15-35 larger than *KS*.

In this study, systematic experiments were conducted to ensure the reliability of the pre-defined segmentation parameters for the specified case scenarios (or very similar situations). The selected project contains some common shapes of PWPs in construction practice, including solid panel, panel with window frame, panel with door frame and bay window panel. This study covers the commonly available laser scanners in the market, too. For high-precision laser scanners with accuracies of 1-2 mm, the values adopted for the FARO laser scanner could be referenced. For scanners with accuracies of 3-5 mm, the BLK 360 scanner could be taken as a reference. The optimal segmentation parameters in Table 12 could be adopted for the three types of laser scanners and the specific type of wall panels. For other cases, the streamlined laser scanning method and the segmentation parameters, can be reproduced following the procedures presented in the Methodology section. Some potential limitations are acknowledged, such as variations in experimental conditions, which may influence the reliability of using the pre-defined segmentation parameters for other cases.

Table 10 demonstrates the results of verticality checks in real-life practices. In comparison with the conventional manual method, both BLK360 and FARO X330 could identify all PWPs that need to be rectified. However, as noted in Table 10, the GeoSLAM dataset was not able to properly identify some panels. This might be caused by the low accuracy of the scanner, typically ranging between 1 cm to 3 cm. Therefore, the case study validation demonstrated that the proposed laser scanning method could accurately carry out the quality check in practice with appropriate laser scanners. Additionally, the quality check results are compared with manual check results, validating the reliability of implications in real practice. However, there is a limitation regarding the lack of validation of vertical deviations of the PWPs computed using the proposed method with the ground truth results from the laser scanning data.

In many prefabrication construction projects, such as high-rise residential buildings, a large number of identical elements are installed, and their verticality needs to be checked after each floor completes. The parameters suggested in this research can be adopted directly for the prefabrication projects with similar wall panels and scanned with the same type of scanning devices. For projects with different types of panels or using other scanning devices, these suggested values provide good references for a starting point, and will save the "trial and error" effort in the tunning process. In practical application, laser scanning can be carried out when the first typical floor is completed, and segmentation parameters can be determined by referencing the suggest values in this paper (if the PWPs are of the similar size and shape, and using the same type of laser scanners), or further adjusted/tuned to obtain the optimal value, then the segmentation parameters can be used in the installation verticality check for all remaining floors. This will greatly improve the efficiency of the onsite quality check.

Practical implications

This section provides a comprehensive discussion of the practical implementation of the laser scanning method. A detailed comparison of the three available laser scanners is presented. When considering the practical implementation of a technology, it is important to take into account its perceived usefulness and perceived ease of use (Igbaria et al. 1994; Venkatesh and Davis 2000). In this research, perceived usefulness is defined by the accuracy and efficiency of the laser scanning method, and as such, the time needed to use different scanners and their accuracy were compared. Perceived ease of use is related to the effortlessness of using the scanners on a construction site. To this end, the comparison of the three scanners was conducted, and the results of the case study are given in Table 13.

MLS's low accuracy makes it unsuitable for quality checks. However, it has advantages in obtaining more complete datasets and reducing occlusion issues caused by onsite supporting elements. The study also found that tuning segmentation parameters for GeoSLAM is the easiest, with a larger range of optimal parameters compared to the other two scanners. If technology advancements improve MLS's accuracy in the future, its convenience and time-efficiency for collecting onsite data could make it an effective tool for practical use.

In summary, combined with the consistency of the checking results again manual check method, using BLK360 and FARO X330 have been validated to carry out effective and practical installation quality checking in the real project. Compared with the manual checking method with 4 minutes for checking each PWP, the proposed streamlined laser scanning method is considerably more efficient than the conventional method.

This research is particularly pertinent to high-rise buildings characterised by many repetitive floors or projects comprising multiple identical buildings. Using prefabrication construction for these projects will involve installation of a large number of identical wall panels. Therefore once the segmentation parameters are pre-determined in a specific situation, i.e., using the same laser scanner and for the same type of wall panels, the process can be streamlined to produce quality check results in a much more efficient manner comparing to the manual method.

Conclusion

This study proposes a streamlined laser scanning method for onsite verticality check of PWPs, aiming to improve the efficiency of quality inspection in prefabrication construction. The contribution includes the development of a streamlined process to use laser scanning to carry out the onsite verticality check, and validation of the method in various conditions including different laser scanners and wall panels of different shapes. Another major contribution of this research is pre-identification of optimal segmentation parameters for laser scanning point cloud processing after systematic experimenting for some specific cases. These parameters can be adopted directly or used as references for practical application of the proposed laser scanning method on installation verticality check, which allows the streamlined process providing timely outcomes in practical situations. The major research findings are summarised below.

Firstly, different TLS were utilised to validate the proposed method on prefabrication construction with varying types of PWPs. The verticality check results were compared with that of manual inspection, and it is found that using TLS can accurately identify the PWPs that need rectification. The two TLS devices, BLK360 and FARO X330 scanners were significantly faster than the traditional manual method, taking around 1.5 and 2 minutes per PWP, respectively, in comparison with the traditional manual method, which takes approximately 4 minutes per PWP. When there are large quantities of PWPs, laser scanning method will take even less time per PWP, while manual method will become slower due to human fatigue.

Secondly, the study conducted systematic experiments to fine-tune point cloud segmentation parameters for PWPs of different shapes. The patterns of optimal segmentation parameters were identified by analysing the experiments involving 25 PWPs scanned with three different laser scanners. The results revealed that both the shape of PWPs and the type of scanner used significantly influence the values of the segmentation parameters. The study summarised the optimal segmentation parameters for datasets with different *APS* and different types of wall panels in Table 12.

The proposed method has the potential to be generalised to diverse cases. For the other cases or prefabricated concrete elements, the parameters used could be referenced from Table 12. The selected project contains the most common shapes of PWPs in construction practice, including solid panel, panel with window frame, panel with door frame and bay window panel. These PWPs were scanned using three scanners with different specifications. These parameters can be adopted directly for the other prefabrication projects with similar wall panels. For the projects with more different types of panels or using other scanning devices, these suggested values serve as good references in the tuning process. In summary, this streamlined method has the potential to be adopted in different construction projects with varying type of wall panels. Finally, the study assesses the practicality of using different laser scanners and suggests suitable laser scanners for various projects. Tuning segmentation parameters for datasets of higher density proves to be more challenging compared to lower density datasets, with a smaller range of optimal values. Consequently, high-resolution scanners like FARO X330 are recommended for projects with higher installation quality requirements, especially those involving identical repetitive wall elements and regular shapes. In such cases, the optimal segmentation parameters can be determined relatively quickly, or they may already be pre-defined. On the other hand, for projects with a diverse range of wall elements, lower resolution laser scanners like BLK360 are more time efficient. Testing and identifying the optimal values for segmentation parameters are simpler, and the accuracy of these scanners remains satisfactory for the project's needs. This research also highlights the practicality of employing MLS for quality checks, particularly in light of the continuous advancements in the accuracy of this technology.

This study has some limitations. Firstly, the approach could be influenced by incomplete datasets, especially in prefabrication building projects with occlusions caused by supporting elements, notably in TLS datasets. To overcome this, a comprehensive scanning plan should be devised beforehand to prevent data incompleteness and address occlusion-related issues. Considering the incompleteness of the datasets, data imputation techniques could be adopted to complete the dataset. There are some current point cloud completion algorithms that could be used to infer the complete geometries for missing regions of 3D objects (Han et al. 2017; Wen et al. 2020). The quality checking results could be improved with more accurate geometry of the wall panels. Additionally, the research focuses on a specific set of construction projects. Future studies could cover a wider range of construction projects from different regions and building scales, as well as a wider range of laser scanners with varying years in duty and to identify optimal segmentation parameters so the proposed approach can be used in more extensive situations. Future research could also integrate automated segmentation algorithms to improve the efficiency of the tuning process and adapt the method to different case scenarios in a more automatic way (Poux et al. 2022).

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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