SCAN-VS-BIM FOR REAL-TIME PROGRESS MONITORING OF BRIDGE CONSTRUCTION PROJECT

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ABSTRACT:

New transport infrastructure construction can stimulate the growth of economy as well as improving the public citizen welfare. However, with the rising number of mega infrastructure projects, the low project performance, such as project delay and cost escalation, are challenging the traditional Architecture, Engineering, and Construction (AEC) industry. Traditional Construction progress monitoring methods rely on manual data collecting and paperwork reporting which can be labor-intensive, time-consuming and error-prone. Therefore, it is necessary for the involved stakeholders to introduce advanced technologies which facilitates assessing the construction performance automatically and ensures the projects to be delivered on time. The application of building information modeling (BIM) provides involved parties an accurate understandable single source of truth that can improve the interoperability of project information. Nevertheless, current 'Scan-to-BIM' workflow cannot support the demand for real-time data analysis and status reporting. This paper presents a semi-automatic construction progress monitoring framework that evaluating the project performance of the infrastructure in real-time. It introduces Hausdorff distance which transmits the 3-D geometrical information contained by as-built point cloud to virtual point cloud directly, to avoid the drawbacks of space partitioning algorithms. The Poisson surface reconstruction utilizing volume as criterion to improve the robustness of progress determination. In addition, the application of 2D polygon fitting provides a potentially feasible method to identify the installation of pre-cast components of the bridge construction. The results indicate that the proposed framework can effectively monitor the geometric increment of road bridge construction project.

1. INTRODUCTION

Transport infrastructures are responsible to distribute products, resources, and labor nationally, contributing to the economy growth and public welfare of citizens (Costin et al., 2018). As the pre-requisite factor affecting the efficiency of land physical distribution, it is defined as the backbone of country's economy. The construction and renovation of transport infrastructures, such as highway and bridge, can offer work opportunities as well as promoting the growth of gross domestic product (GDP) (Kim et al., 2015). In some developing countries, logistics contributes more GDP than the construction projects in transport sector (Chia et al., 2014). Hence, there is a huge interest in investment of realigning current and constructing new transport network. Since the planned service life of transport infrastructures are from 50 to 100 years, the asset management, which is used to ensure the structures in good conditions, is more important and costly for the owners. However, the performance of construction project contributes to the reliability and durability of the structures during their service life. A successful progress monitoring cannot only guarantee a timely delivery of the construction projects with a less construction error and high quality, but also reducing the delay cost and alleviating the public troubles.

AEC industry is challenging by project delay and budget overrun occurring frequently in mega projects, such as harbor, airport, and transport system, regardless of the level of development worldwide (Vick and Brilakis, 2016, Patel et al., 2021). Flyvbjerg et al. (2003) found that about 90% of infrastructure construction projects have experienced delay. In 2015, it was reported that over 77% of infrastructure construction projects have about 29% cost escalation all over the world (Salling and Leleur, 2015). The conventional progress monitoring methods require the project managers to collect data manually and summary multi sources document as a written report. Hence, the manners are labor-intensive, time-consuming and error-prone. In addition, the weekly or monthly surveying and reporting cannot present the issues to involved parties on time. It means a timely corrective decision cannot be made and then, project delay will occur. Therefore, it is necessary to introduce the digital technologies and to monitor the construction progress in real-time which aims at minimizing the project delay and its effects.

Thanks to the rapid development of digital technologies in recent years, the research emphasis of progress monitoring has shifted from improving strategy based methods to the digitalization since 2007. (Patel et al., 2021). Those technologies, such as BIM, are widely adopted in the AEC industry during the design and asset management phases, since they can improve the interoperability and visualization of vital information, facilitate communication between the stakeholders, and promote the understanding of the building structures (Liu et al., 2019, Sloot et al., 2019). Previous research of BIM focus on the design and management stages with the static external conditions rather than the inspection of the dynamic site. Moreover, since current methodologies cannot

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support a real-time Scan-to-BIM process on site, it is not capable of conducting a progress monitoring timely and accurately as required (Czerniawski and Leite, 2020). Scan-vs-BIM offers an alternative to monitor the construction site and determine the construction productivity in real time. Different from Scan-to-BIM, it detects the geometric discrepancy by comparing as-is point cloud with as-design BIM (Bosché et al., 2015). Since the comparison can be conducted between as-built point cloud and as-planned BIM directly, the efficiency of the construction progress monitoring is far more improved by avoiding introducing Scan-to-BIM modeling process. It means daily progress monitoring activity becomes feasible and effective. Hence, this timely supplementary reporting activity can also be used to support decision-making for corrective actions. Then, the results of progress monitoring can be utilized to mitigate issues caused by project delay.

This paper aims to present a semi-automatic bridge construction progress monitoring framework that are used to assess the project performance in real-time. Hausdorff distance and Poisson surface reconstruction are introduced to improve the tolerance and universality of framework as well as avoid the weakness of 2D algorithm, such as convex hull and coverage calculation, in some specific cases. 2D polygon fitting is utilized to detect the installation of pre-cast elements. It plans to verify the feasibility of combining 2D and 3D Scan-vs-BIM criteria in progress tracking and outputting a series of understandable results for involved stakeholders without expertise. The remainder of this paper are structured as follows: Section 2 presents the literature review of reality capture and construction progress monitoring. Section 3 discusses the details of proposed methodology. Then, a case study of Kapooka bridge is showed in the section 4. Finally, the conclusions are described in the last section.

2. LITERATURE REVIEW

The methodology of real-time construction progress monitoring is developed from the concept of Scan-vs-BIM. It also includes ideas from reality capture and construction progress monitoring. Then, the previous research that related to above fields will be generally reviewed to determine the research gaps and reveal the innovation of proposed methodology.

2.1 Reality Capture Techniques

The conventional reality capture methods, such as camera and naked eyes inspection, relie on the information contained by a series of red, green, blue (RGB) pixels (Hajian and Becerik-Gerber, 2009). To achieve the visualization, 3D models can also be created via Structure from Motion (SfM) methods and RGB images with high overlap rate (Westoby et al., 2012). To improve the efficiency, it is commonly to introduce machine learning to the processes of object recognition and information extraction. Huang et al. (2021) develop a computer-vision based method to automatically recognize workers' activities from site photos and update BIM via current construction activities. However, the data quality of optical sensors is vulnerable to the external conditions, including brightness, obstruction, and shooting angle (Che et al., 2019). It means the survey for construction site must be seriously planned and additional data pre-processing technologies should be applied to eliminate the effects of above issues. Other active data acquisition approaches, including Radio Frequency Identification (RFID), Thermal Camera (Infrared Camera), and Ultra-Wideband (UWB), are used as main or supplementary methods in previous research. Fang et al. (2016) present a case study that introducing RFID and reader to localize the position of workers in indoor environment. Similarly, UWB can also be applied to track the location of construction materials which enables project managers to adapt the supply chain and infer the construction progress (Furlani and Pfeffer, 2000). Nevertheless, the installation of tags used in RFID and UWB is time-consuming and unsuitable for the large-scale applications. Furthermore, the accuracy of progress tracking based on those indirect inferring cannot satisfy the requirements for construction schedule update.

To overcome above issues, light detection and ranging (LiDAR) have been introduced to capture the geometric information which can reflect the construction progress accurately. As an active sensor, LiDAR has a broad application in the field of computer vision, remote sensing and engineering (Che et al., 2019, Patel et al., 2021). Although LiDAR can effectively reduce the distortion and details loss during the 3D reconstruction, the point cloud processing is still impeded by occlusions and noise generated during the survey (Armeni et al., 2016). To validate the feasibility of proposed methodologies, most of the prior research were confined to the static indoor environment which means terrestrial laser scanner (TLS) is the best option for the research. Therefore, some raw date pre-processing algorithms are specially developed for merging and registering the date from TLS (Che et al., 2019). In Nguyen's research, a group of eighteen TLSs were applied to track the construction progress of a stadium and the three fourths of the stadium was merely captured (Nguyen et al., 2020). It means the capacity of TLS cannot satisfy the requirement for data collection of a large-scale structure, although it has the highest accuracy within the scanner family. To this end, laser scanners are mounted on the mobile platforms, such as car, unmanned ground vehicle (UGV) and unmanned aerial vehicle (UAV), to create mobile laser scanner (MLS). It improves the efficiency of data acquisition as well as reducing the requirement for the operators and the sensors. However, comparing with TLS, MLS captures point cloud with a various density, large data size and relatively low accuracy. It means the researchers should balance the efficiency and accuracy in data processing procedures.

2.2 Construction Progress Monitoring

Construction progress monitoring is a construction performance assessment process with highly repetitive and cyclical activities which aims to reduce the risk of project delay and budget overrun (Mantel and Meredith, 2009). Derived from control theory, it consists of data collecting, data analysis and status reporting processes. Hence, a successful progress monitoring activity can continuously evaluate and improve the performance of an on-going construction project. The conventional management based progress monitoring strategies are gradually replaced by the digital technologies, such as BIM, Digital Twin (DT), and Machine Learning (Mani et al., 2009). To improve the level of automation, the research emphasis has been shifted to application of BIM since 2007 (Patel et al., 2021). In general, the progress monitoring methods can be sorted into direct (spatial) method and indirect (non-spatial) method (Vick and Brilakis, 2016, Patel et al., 2021). The former indicates capturing the details of target structure and measure the physical progress based on geometric features, such as volume and overlapping rate. Nguyen et al.

(2020) presented a volume measurement case study to determine the construction progress of the superstructure of a stadium. Scan-vs-BIM presented in mechanical, electrical and plumbing (MEP) components inspection can also be defined as a direct progress tracking method (Bosché et al., 2015). Some researchers collect point cloud via helmet mounted LiDAR to record construction activities and time stamp, and then, merge all data to monitor construction progress (Pučko et al., 2018). The latter utilizes information collected from sensors on site, such as camera, and RFID to infer the construction progress (Omar and Nehdi, 2016). Montaser and Moselhi (2014) use RFID to track the location of material delivery trucks and estimate the progress via consumption of materials.

2.2.1 Scan-vs-BIM: Scan-vs-BIM indicates the comparison between as-design BIM and as-built point cloud (Bosché et al., 2015). It enables surveyors to monitor the construction in both qualitative and quantitative ways in theory (Chen and Cho, 2018, Bosché and Guenet, 2014). This concept improves the efficiency of construction progress monitoring by avoiding introducing the Scan-to-BIM whose efficiency is seriously affected by the level of automation of segmentation and object recognition processes. Czerniawski and Leite (2020)'s review reveals that current automatic object recognition methodologies based on machine learning can only recognize the main structures of the buildings accurately and it is vulnerable to the components with various features, such as window. Hence, Dawod and Hanna (2019) explores the feasibility of introducing as-design BIM into object recognition via geometric features fitting. The mainstream of Scan-vs-BIM methodologies includes point-to-surface and point-to-point comparison. Bosché et al. (2015) present a point to surface comparison method to monitor the construction progress of MEP components. Chen and Cho (2018) conduct a case study via point-to-point comparison for a large-scale steel frame structure. In their research, the triangular cell of mesh on the model surface will be marked as 'detected', if at least one point can be found within it. Then, they compared the tags on the surface of as-design and as-built models to determine the level of compliance. Nevertheless, their method can only provide binary results which indicate the status of structure as 'finish' or 'not finish'. Vick and Brilakis (2018) design a new space partitioning method called 'Bricktree' that is used to detect the point cloud near the design surface of the pavement. This method classifies the surface materials via thickness and determine construction progress for incremental construction. His method cannot handle the case when error larger than the thickness of the design layers. Hence, Ellinger et al. (2021) improved his method by introducing a machine learning based material classifier to correct the final outputs. The Scan-vs-BIM offers researchers an alternative that tracking the construction progress without converting as-built point cloud to as-built BIM. Although this concept is still affected by the quality of scanning data, it does improve the efficiency of construction progress monitoring (Rebolj et al., 2017).

2.2.2 Horizontal Construction and Vertical Construction: It was found that previous research did not emphasize on monitoring the construction of transport infrastructures which are defined as horizontal construction. Most of the research focused on applications of BIM and progress monitoring of the buildings (vertical construction) due to the shortage of relevant data and high computational capacity requirement. The status of vertical construction can be simply captured by TLS and many available opensource data set can be applied for the machine learning training. Only a few of research explored the possibility that tracking the construction progress of the horizontal structures. Bügler et al. (2013) present a volumetric measurement based method to support the pavement construction on site. A method utilizing aerial images to recognize the progress of horizontal infrastructure construction is proposed by Behnam et al. (2016). Then, Vick and Brilakis (2018) develop a new space partitioning method to determine surface material for progress monitoring. After that, Ellinger et al. (2021) improved Vick's method by combining it with Convolutional Neural Network (CNN). In addition to highway construction, Puri and Turkan (2020) conduct progress monitoring for road bridge construction via point-to-point filtration and convex hull algorithm. In general, the progress monitoring of vertical construction prefers to choose volume as the criterion to determine the progress in percentage. On the contrary, the horizontal construction uses surface area as optimal metric in the case of horizontal incremental expansion. However, since the transport infrastructures consist of both vertical and horizontal components, these two criteria should be interchangeable and combined in the construction project.

3. METHODOLOGY

A closed loop project performance improving system is proposed which consists of data acquisition, data analysis and status reporting modules (Figure 1). In this paper, a real-time semi-automatic construction progress monitoring framework is developed to support the project performance assessment system for road bridge construction project covering its first two modules (Figure 2). The construction progress is tracked by determining the geometric discrepancy between as-built point cloud and as-design BIM. Since the bridge has been finished before the survey, additional steps will be introduced to segment and manipulate the as-built point cloud of the bridge manually to simulate the whole construction sequence.

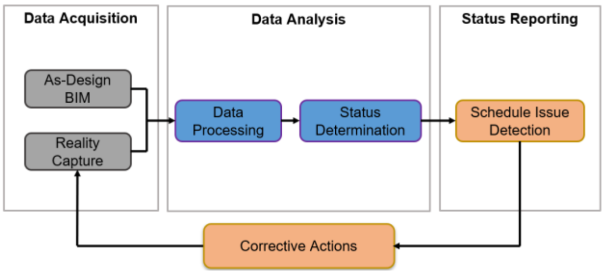

Figure 1. The modules of proposed system.

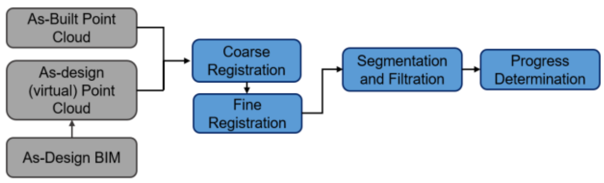

Figure 2. The developed framework.

The proposed workflow aims to determine the completion of the components in percentage. Four steps are involved in to evaluate the construction progress of infrastructure's elements. Firstly, the as-design (virtual) point cloud will be generated based on the as-design BIM which is developed by Autodesk Civil 3D. Then, the coarse and fine registration are applied respectively to align the as-design (virtual) point cloud with the as-built point cloud. Registration is followed by segmentation and filtration to remove the noise and determine the as-is status. Finally, the construction progress will be determined via calculating the ratio between the numerical results of as-is and as-design point cloud which represent their geometric statuses.

3.1 Data registration

The registration process is proceeded in open-source software CloudCompare. During the coarse registration, four points are picked manually as reference points in both virtual and as-built point cloud. This process can overlap two sets of point roughly and prepare them for the following fine registration. The fine registration is conducted via Iterative Closest Point (ICP) algorithm. It will align a pair of point sets via minimizing the transformation error between the corresponding point sets during iterative calculation (Rusinkiewicz and Levoy, 2001). It means the relative distance between virtual and as-built point cloud set will be minimized after introducing the fine registration. Then, virtual point cloud is ready for the following data segmentation and filtration which will sample virtual point cloud via utilizing as-built point cloud as the benchmark.

3.2 Data Segmentation and Filtration

Initially, the k-nearest neighbor (k-NN) is planned to be applied as main data filtration and segmentation algorithm. This method can effectively pair the corresponding points in virtual and as-built point cloud within the given threshold. It enables point cloud segmentation and object recognition to be proceeded simultaneously. However, in this case, due to the low quality of point cloud, Hausdorff distance sampling replaces k-NN point to point filtering algorithm to mitigate the effects of quality issues. Hausdorff distance is used to measure the distance between two point sets. Equation (1) presents its conceptual formulae. Its visualized output is a similarity heat map which can used to filter the point cloud with low similarity out automatically. In this case, virtual point cloud is sampled utilizing as-built point cloud as the benchmark which means the sampled virtual point cloud depicting the as-is status. Comparing with as-built point cloud, the sampled virtual point cloud distributes evenly along the surface of infrastructure's element which is more suitable for Poisson surface reconstruction in the following step.

$$d_H(X,Y) = \max\{\sup_{x\in X} \inf_{y\in Y} d(x,y),\ \sup_{y\in Y} \inf_{x\in X} d(x,y)\} \quad (1)$$

where $d_H(X,Y)$ = the maximum distance between two mesh
$d(x,y)$ = distance between point in X and Y
sup = sampled mesh
inf = reference mesh

3.3 Progress Determination

In this step, the construction progress of the target elements will be determined by comparing numerical outputs derived from as-is status and schedule. Equation (2) shows the formulae used to determinate the progress based on the comparison of volume. This criterion is commonly used in vertical construction for the main components, such as wall, roof, and floor. In this case, it is applied to measure the progress of bridge elements constructed vertically, such as abutment, retaining wall, pier, and pier cap beam. Different from convex hull algorithm focusing on the surface area comparison, this criterion can effectively handle the case which structure is not constructed in longitudinal direction.

$$P = \frac{V_{ab}}{V_{ad}} \quad (2)$$

where P = construction progress in percentage
V_{ab}= as-built volume
V_{ad} = as-design volume

The construction progress of precast and prefabricated elements, such as T-girders and barrier wall, can be easily identified by comparing their geometric features with the designed values. For instance, if the half of the bottom surface area of a T-girder can be detected, we can define this girder as installed in place. Hence, 2D polygon facets fitting is the optimal choice in this case. It fits polygons on the given area , and then those fitting results can be used to calculate the surface area.

4. CASE STUDY

In this case study, the selected bridge is located at North-East of Kapooka area as a part of the Olympic highway realignment project near Wagga Wagga, New South Wales 2650, Australia (Figure 3). The total length of bridge is 99 meters which consists of 3 equal length spans, with a skew angle of 53 degrees. To accelerate the highway realignment project, the contractor company decided to introduce the precast concrete structures to simplify the road bridge replacement project. Hence, four main components of Kapooka bridge, including abutments, retaining walls, girders and parapet road barriers, are manufactured off site.

Figure 3. The side view of Kapooka bridge.

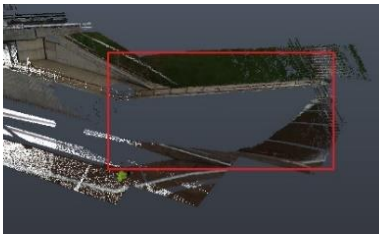

Figure 4. The occlusion of point cloud on the retaining wall.

The construction of Kapooka bridge is completed before the survey starts. Hence, the raw point cloud data cannot record the consecutive construction progress as required. The as-built point cloud is collected with two terrestrial laser scanners. Since no traffic control was conducted, two laser scanners were set on the side of alignment under the slope. Hence, serious occlusions could be observed in the as-built point cloud (Figure 4). In addition, due to the geo-reference issues, the raw data of two scanners were not fully registered and merged, and, as a result, two layers of as-built point cloud could be found on the surfaces of the bridge (Figure 5). To simulate the construction progress of the road bridge, piers, pier cap beams and girders which were constructed in order, are chosen as the validating targets.

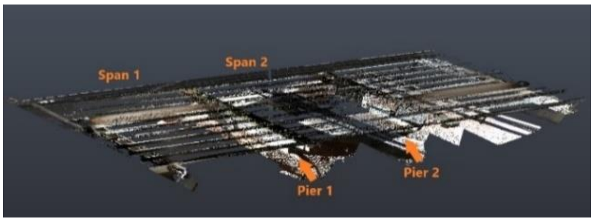

Figure 5. An overview of the Kapooka bridge (white and shadow point cloud are from two different laser scanners).

The geometric details of Kapooka bridge were acquired by measuring as-built point cloud with Autodesk ReCap. Then, the BIM was developed by Autodesk Civil 3D and exported as stereolithography (STL) format (Figure 6). As-design point cloud is generated in opensource software CloudCompare with halved point number of the as-built point cloud. In this case study, we assume that the BIM derived from as-built point cloud is identical to the as-design BIM. The manual manipulation of as-built point cloud simulates the construction sequence of the Kapooka bridge.

4.1 Progress Monitoring of Piers and Pier Cap Beams

Although some occlusions could be found on the surface of Pier 2, the point cloud of two piers and their cap beams are the most intact in this laser scanning data (Figure 5). Hence, point cloud registration and segmentation were conducted on them to filter the as-built status for the volume calculation. Since the reinforced concrete pier and its cap beam is finished by pouring concrete into the formwork, three cases were considered in this case study. (1) The top surface of the pier reaches the top surface of the pier bent. (2) The pier is finished (3) The pier cap beam is finished.

4.1.1 Data Registration: Due to the quality issues of the as-built data mentioned before, the as-built point cloud is manually segmented to simulate the construction progress. Two piers and corresponding pier cap beams were segmented and manipulated for three cases. To mitigate the effects of geo-referencing error in raw data, the registration process was applied for Pier 1 and 2 separately. Firstly, the coarse registration is conducted by picking four reference points in both virtual and as-built point cloud with opensource software CloudCompare. This process can overlap virtual and as-built point cloud set roughly. Then, the virtual point cloud is finely registered with as-built point cloud via ICP algorithm with 98% final overlap (Figure 7). The match rate was set as 98%, since the geometries of virtual point cloud are not completely identical to as-built point cloud due to the manual measurement error and quality issues.

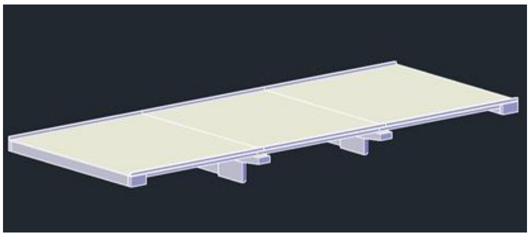

Figure 6. An overview of the BIM of Kapooka bridge.

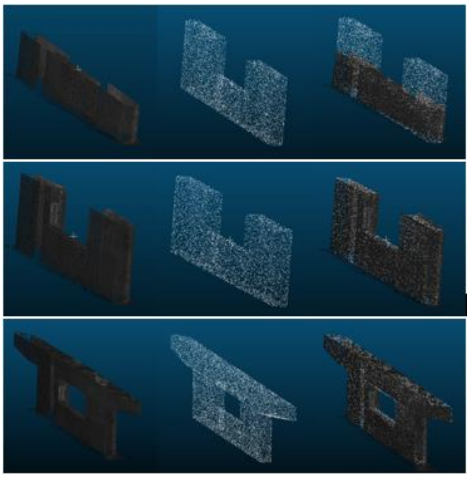

Figure 7. The as-built point cloud, virtual point cloud and registration results for case 1, 2 and 3 of Pier 1 (Left to right, top to bottom respectively).

4.1.2 Data Segmentation and Filtration: Due to the measurement error mentioned before, the point-to-point filtering method, such as k-NN, cannot be applied in this case. Hence, the Hausdorff distance sampling was introduced to detect the geometric discrepancy between virtual and as-built point cloud. Since Hausdorff distance in MeshLab is one-side Hausdorff sampling, choosing virtual point cloud or as-built point cloud as benchmark will generate the different visualized outputs. Due to the limitation of Poisson surface reconstruction, as-built point cloud is used as benchmark to sample the virtual point cloud. The sampled virtual point cloud has a evenly distributed point cloud layer which can form a closed mesh via 3D reconstruction. The similarity between virtual and as-built point cloud is showed by heat map in MeshlLab (Figure 8). After this process, the virtual point with the highest similarity (red) are kept for the following as-is volume calculations.

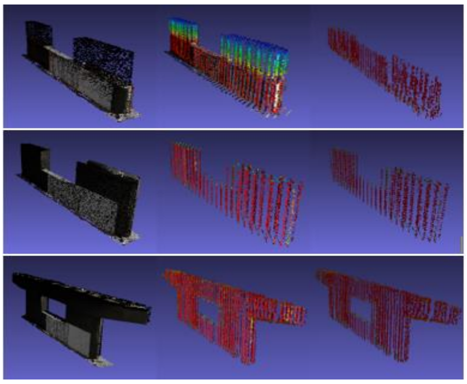

Figure 8. The registration results, Hausdorff distance sampling heat map and simpling results for 3 cases of Pier 1 (Left to right, top to bottom respectively).

4.1.3 Volumetric Calculation and Progress Determination: Two volume calculating methodologies are available for filtered virtual point cloud in CloudCompare. The first one is 2.5D volume calculation which resembles rasterization theory, and it calculates the volume between two selected parallel cross section with a given height. However, this method can only be applied to the point cloud with the continuous cross section change in the z-direction. Since the discrete cross section variation in z-direction could be identified in case 2 and 3, multi sliced surfaces are required for this method. Hence, Poisson surface reconstruction is applied to filtered virtual point cloud and then, a closed mesh is constructed for volume determination. Nevertheless, the results of Poisson surface reconstruction are seriously affected by the distribution and quality of the point cloud. Although the filtered virtual point has a more regular and smoother facade than as-built point cloud, some reconstruction error could be observed in heat map with blue color (Figure 9). In case 1, additional volume on the top of pier bent will be subtracted manually. For case 2 and 3, the uneven surface will be balanced itself resembling the uniform distribution which contributes a relatively accurate result. Then, the construction progress is determined by calculating the ratio between as-built volume based on sampled virtual point cloud and as-design total volume.

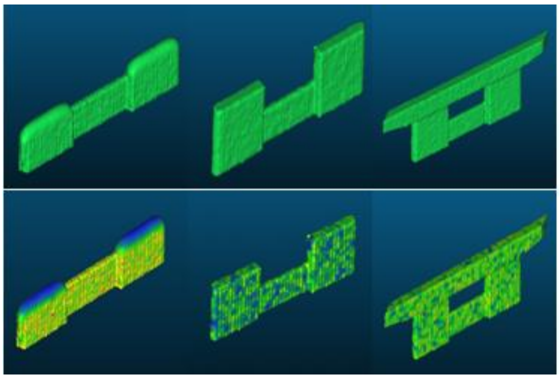

Figure 9. Poisson surface reconstruction results and their quality heat map for 3 cases of Pier 1.

4.1.4 Results of Pier 1: In this case, as-built volume of Pier 1 is calculated based on the filtered virtual point cloud. A-design volume indicates the volume of as-design BIM. However, to keep consistence with the filtered virtual point, the virtual volume was calculated based on the results of Poisson surface reconstruction of virtual point cloud before sampling. It can be observed that the results based on 3D reconstruction is larger than the volume of as-design BIM. It caused by additional facets on the uneven mesh surface. Then, the progress is determined by the ratio between as-built volume and virtual total volume. Since the sampled virtual point cloud has a smoother surface comparing with as-built point cloud, the difference of results between as-built and as-design results is less than 5%. The positive discrepancy indicates that Poisson surface reconstruction will create a closed uneven mesh with a larger volume with less point guiding after sampling.

Pier 1	Case 1	Case 2	Case 3
As-built Volume (m³)	86.13	149.13	295.81
As-design Volume (m³)	82.65	146.65	292.87
Virtual Volume (m³)	83.47	147.39	293.75
As-planed Progress (%)	28.22	50.07	100.00
As-built Progress (%)	29.32	50.77	100.70
Discrepancy (%)	1.10	0.70	0.70
Absolute Discrepancy (%)	1.10	0.70	0.70

Table 1. The numerical results and construction progress in percentage for Pier 1.

4.1.5 Results of Pier 2: Pier 2 has more serious occlusions at the back of the pier (Figure 10). Then, during the Hausdorff distance sampling, the virtual point cloud is less influenced by the as-built point cloud benchmark which means the filtered virtual point cloud need to remove more points with low similarity after sampling. It results in a smoother mesh on the occlusion area after the 3D reconstruction. Hence, the difference between as-design and as-built is smaller than the results of Pier 1 (Table 2).

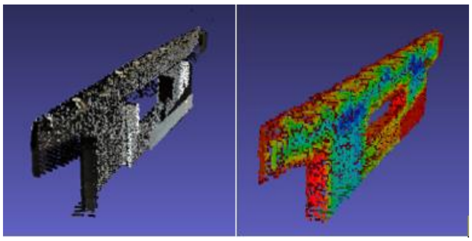

Figure 10. The occlusion on the surface of pier (Left) and the quality heat map after Hausdorff distance simpling (Right).

Pier 2	Case 1	Case 2	Case 3
As-built Volume (m³)	85.50	122.43	268.81
As-design Volume (m³)	82.65	121.05	267.29
Virtual Volume (m³)	83.34	121.51	268.60
As-planed Progress (%)	31.83	45.58	100.08
As-built Progress (%)	30.92	45.29	100.00
Discrepancy (%)	0.91	0.29	0.08
Absolute Discrepancy (%)	0.91	0.29	0.08

Table 2. The numerical results and construction progress in percentage for Pier 2.

4.2 Progress Monitoring of Girders

As mentioned in section 4, the scanning is conducted on the side of alignment under the slope. Hence, only the bottom surfaces of the T-girders are captured. In addition, the precast T-girder is a sort of precast element, and then it is meaningless to measure the construction progress of them. Hence, the area of bottom surface is measured to determine whether T-girder is installed in place or not. To achieve this purpose, 2D polygon facet is fitted to the as-built point cloud of girder's bottom surface. By comparing the as-built surface area with the designed bottom surface area, the installation status of girders can be determined. For each girder, if 50% of its bottom area can be detected, we can conclude that it is installed in position. However, due to the geo-reference registration issues between two terrestrial laser scanners, the bottom surface area can only be segmented and measured individually without registration. Since the point cloud of two laser scanners are not fully overlapped, the observed bottom surface area of single girder is larger than as-design one.

4.2.1 Girder Span 1: In Span 1, the point cloud of girders shows the most intact bottom surface (Figure 11). Hence, the results show a smaller area difference in this span (Table 3). However, all the as-built bottom surface areas are larger than the designed ones due to the merging issue discussed in section 4.2. Although the as-built areas are larger than the designed ones, these values still could be used to determine the status of T-girders. It could be concluded that all girders were installed in place.

Span 1	As-built (m^2)	As-design (m^2)	Area Difference (m^2)	Absolute Value (%)
G1	31.10	25.82	5.28	20.45
G2	29.56	25.82	3.75	14.51
G3	27.08	25.82	1.26	4.87
G4	33.29	25.82	7.47	28.93
G5	27.69	25.82	1.87	7.24
G6	29.66	25.82	3.84	14.89
G7	27.68	25.82	1.86	7.19
G8	33.39	25.82	7.57	29.33
G9	30.22	25.82	4.40	17.05
G10	28.32	25.82	2.50	9.69
G11	28.60	25.82	2.78	10.77

Table 3. Results for eleven girders in Span 1.

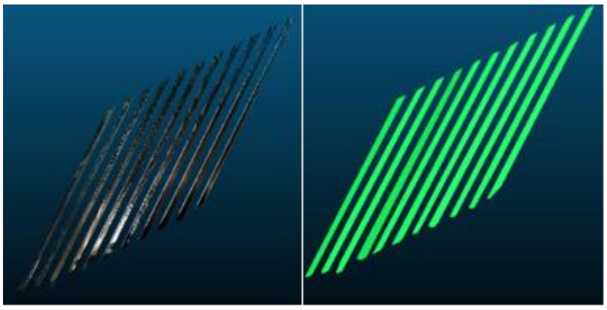

Figure 11. The as-built point cloud for eleven girders in Span 1 and their 2D polygon fitting results.

4.2.2 Girder Span 2: Different from Span 1, the bottom surface of girders in Span 2 was obstructed by Pier 1 during the scanning process. Hence, some occlusions could be found in the as-built point cloud. However, the results of bottom area indicate that the occlusion does not reduce the surface area of 2D fitting. Indeed, the merging issue increases results seriously (Table 4). Since Span 2 is far from the location of two terrestrial scanners, the 2D polygon fitting results show a more serious distortion in x-y plane comparing with Span 1. It contributes the higher value difference of bottom surface area.

Span 2	As-built (m^2)	As-design (m^2)	Area Difference (m^2)	Absolute Value (%)
G1	34.10	25.82	8.28	32.07
G2	26.17	25.82	0.35	1.35
G3	29.42	25.82	3.61	13.97
G4	38.66	25.82	12.85	49.76
G5	37.65	25.82	11.83	45.82
G6	27.77	25.82	1.95	7.57
G7	28.13	25.82	2.31	8.95
G8	36.03	25.82	10.21	39.56
G9	31.86	25.82	6.05	23.42
G10	32.30	25.82	6.48	25.09
G11	33.09	25.82	7.27	28.16

Table 4. Results for eleven girders in Span 2.

5. CONLUSIONS

This study verifies the feasibility of proposed framework that are used to monitor construction progress of the bridge in real time. By introducing Hausdorff distance sampling and Poisson surface reconstruction, the Scan-vs-BIM process transmits the geometric information from as-built point cloud to as-design point cloud directly avoiding the limitations of space partitioning algorithm in some specific cases. The volumetric criteria, which is preferred in the buildings construction progress tracking in the previous research, can accurately determine the construction progress in percentage for piers and their pier cap beams during the bridge construction. Moreover, the 2D polygon facets fitting is feasible in the precast concrete elements recognition. In overview, this research presents a real-time construction progress monitoring framework for road bridge construction and verified its feasibility based on the data of Kapooka bridge replacement project. The results indicate that introducing Scan-vs-BIM theory into the infrastructure construction progress monitoring can effectively improve its accuracy.

In future study, a serious data collecting plan will be introduced to cover the whole construction project and ensure the quality of raw data. Then, the point based filtration and segmentation methods can be applied to increase the level of automation of the construction progress monitoring framework. Moreover, the alternative of 2D polygon fitting, such as convex hull algorithm, can be combined with methods used in this case study to improve the accuracy and efficiency in determining the progress of both vertically and horizontally constructed components.

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