Tracking Secondary and Temporary Concrete Construction Objects Using 3D Imaging Technologies

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ABSTRACT

Recent research efforts to improve construction progress tracking has focused on employing emerging technologies such as three dimensional (3D) imaging, including digital photogrammetry and 3D Terrestrial Laser Scanning (TLS). Previous research has shown that “Scan-vs-BIM” object recognition systems, which fuse 3D TLS and 4D project BIM, provide valuable information for tracking structural works. However, until now these systems have focused on tracking progress for permanent structures only; none of them has considered progress of secondary or temporary structures. In the context of structural concrete work, temporary structures include formwork, scaffolding and shoring, while secondary components include rebar. The value of tracking temporary and secondary elements is that it would add veracity and detail to the progress tracking process, and consequently to billing. This paper presents two different techniques for detecting concrete construction secondary and temporary objects in TLS point clouds, one of which is based on a Scan-vs-BIM object recognition system. Both techniques are tested using real-life data collected from a reinforced concrete building construction site. The preliminary experimental results show that it is feasible to detect and track secondary and temporary objects in 3D TLS point clouds with high accuracy. This will help to improve progress estimation and tracking.

Keywords: **Construction progress tracking, Laser scanning, BIM, Object recognition, Temporary objects, Secondary objects**

INTRODUCTION

Accurate and effective progress tracking is a must for successful management of construction projects as it allows corrective decisions to be made in a timely fashion. Traditional construction progress tracking methods involves manual data collection and data extraction from different construction documents which is tedious and time consuming. Recent research efforts to improve progress tracking are mainly focused on employing technologies such as three dimensional (3D) imaging including digital photogrammetry (Golparvar-Fard et al. 2009; Wu et al. 2010) and 3D laser scanning (Cheok et al., 2000; Bosché and Haas 2008; Turkan et al. 2012). However, none of these systems report progress of secondary or temporary structures, i.e. their focus is mainly on tracking permanent structure's progress. Nonetheless, secondary and temporary structures' progress would add veracity and detail to the progress tracking process. Temporary construction objects such as formwork, scaffolding, and shoring are the largest cost components of a concrete building's structural frame (Hurst, 1983; Peurifoy and Oberlender, 2011). Together with the secondary objects such as rebar, total cost of temporary and secondary objects constitute a significant portion of a concrete building's structural frame's cost (Jarkas and Horner, 2011). Therefore, it is important to track these elements to increase the accuracy of progress tracking and also better support billing.

This paper describes two techniques for recognizing concrete construction secondary and temporary objects in TLS point clouds, one of which based on an object recognition system developed by Bosché and Haas (2008) that uses a "Scan-vs-BIM" framework. Both techniques are tested using real life data that is obtained from a reinforced concrete building construction.

LITERATURE REVIEW

The literature review revealed that at present there are only a limited number of studies on using 3D imaging technologies for automated detection and tracking of secondary and temporary construction objects. Two relevant research works have been identified by the authors. One is by Lee et al. (2010) who developed an image-based technique for calculating the quantity of formwork installed from construction site images. Although high recognition values were reported in this work (as much as 90%), there are issues with sunlight, shadow, obstructions etc. The second relevant research is the work by Ishida et al. (2012) who developed a system to inspect the quality of a reinforced concrete structure using 3D point clouds obtained with TLS. Essentially, they used a shape recognition technique to detect steel rebars in reinforced concrete structures. Their system successfully identified the rebars in the 3D point clouds, and was able to count the number of column ties and vertical ties.

The Automated Object Recognition System: One of the secondary and temporary element recognition techniques described herein is built upon the object recognition algorithm proposed by (Bosché and Haas, 2008) to recognize designed 3D model objects in TLS point clouds. This "Scan-vs-BIM" system and its experimentally validated performance are detailed in (Bosché and Haas, 2008; Bosché, 2010). A brief review is given below:

Registration of TLS Point Clouds with Building 3D Model: An initial coarse registration is performed, for example by manually matching n pairs of points selected in the 3D model and in the scan using commercially available cloud processing software. A robust Iterative Closest Point (ICP) based algorithm using the point-to-plane framework (Chen and Medioni, 1991; Rusinkiewicz and Levoy, 2001) is then employed to perform the fine registration of the TLS point clouds with the building 3D model. Following that for each scanned data point, a matching model point is calculated as the closest of the orthogonal projections of the data point on the objects' triangulated facets. For ensuring robustness of the matching and consequently registration with respect to outliers, point pairs are rejected when:

(1) The Euclidean distance between two matched points is larger than a threshold τ_D .We typically use τ_D =20mm for structural elements.

(2) The angle between the normal vectors to two matched points is larger than a threshold τ_A. We typically use $\tau_A = 45^o$.

The ICP iterative process is stopped when $\Delta MSE < 0.05 mm^2$, where ΔMSE is the improvement in Mean Square Error (MSE) between the current iteration and the previous one.

Recognition of 3D Model Objects in TLS point clouds: At the end of the registration process, the project 3D model and TLS point clouds are optimally registered. Because it is known to which object points were matched at the last iteration, each model object can be assigned a corresponding as-built point cloud. The analysis of the as-built point cloud can then lead to the recognition of the object itself using a surface-based recognition metric (Bosché, 2010). The percentage of recognition $\%_{recognized}$ is calculated as:

$$\%_{recognized} = \frac{S_{recognized}}{S_{recognizable}} = \frac{S_{recognized}}{S_{planned} - S_{occluded}} \qquad [2]$$

where $S_{planned}$, $S_{occluded}$ and $S_{recognized}$ are the planned, occluded and recognized surfaces. $\%_{recognized}$ and $S_{recognized}$ are used to infer the recognition of each object. We typically use the rule:

If ($\%_{recognized}$ >50% or $S_{recognized}$ >1000cm^2),

then the object is considered recognized.

TECHNIQUES FOR CONCRETE CONSTRUCTION TEMPORARY AND SECONDARY OBJECTS RECOGNITION AND TRACKING

We describe two techniques here for recognizing concrete construction secondary and temporary objects in 3D TLS point clouds.

Technique 1: The first technique simply changes the default point matching metrics in the approach of Bosché and Haas (2008). It is hypothesized that formworks and rebar could be detected by searching for matching points that are slightly further away than the default τ_D value. Furthermore, the τ_A ~~τ_A~~threshold is discarded to enable the recognition of formworks used for forming the faces of walls or columns hidden from the scanner's location. The recognition of column formwork (and rebar) and columns themselves should then be differentiable by analyzing the variation of $\%_{recognized}$ over a range of values of τ_D, e.g. between 10mm to 60mm (Figure 1). A completed column should present high recognition levels for most values of τ_D (10-20mm). Formworks typically have thicknesses of 30mm and more, while the concrete cover in an RCC column and beams is typically 40mm (1.5in) (Nunnally, 2004). As a result, formworks and rebar should lead to low recognition levels for low τ_D values, and higher recognition levels only for large τ_D values. However, because rebar has a visible surface that is smaller than the finished object, recognition levels for larger τ_D values should be lower than for formworks. Technique 1 can be applied to detect formwork and rebar, but cannot be used for shoring.

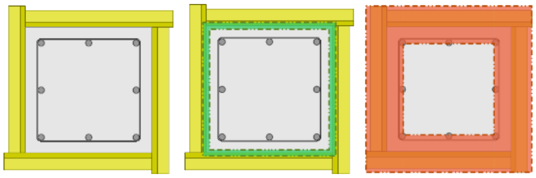
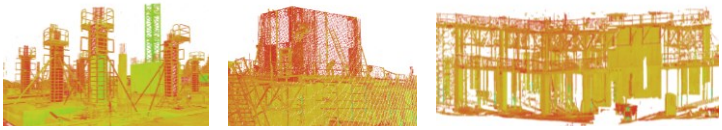


Figure 1: Formwork and rebar recognition using Technique 1: (a) top view of a concrete column showing the reinforcement and formwork; (b) Recognition of finished concrete using a small value of τ_D e.g. 20 mm (green volume) (c) Recognition of rebar and formwork using a large value of τ_D, e.g. 50mm, (red volume)

Technique 2: An "open space" volume is an empty 3D space volume in the 3D model. For example, the open space volume for floor slab shoring can be defined as the cubic space surrounded by four columns. Given an open space volume, the total number n of TLS data points contained within that volume can be calculated, and the number of points per cubic meter η inferred. Then, if $\eta > \eta_{\min}$, shoring can be considered detected. This technique can be applied to detect shoring. Its advantage for shoring is simplicity and effectiveness (as shown later). However, its disadvantage is the necessity to run a routine on the 3D model which can interpret it automatically to create the volumes to be analyzed. This should be generally straight forward, but complex design geometries could present challenges.

EXPERIMENTS

In order to evaluate the performance of the proposed secondary and temporary construction object recognition techniques, experiments were conducted using a 3D model obtained for the Engineering V Building site at the University of Waterloo, Canada and eleven different TLS point clouds acquired on eleven different days over a seven month period (Figure 2). The 3D laser scans were acquired using a Trimble® GX 3D laser scanner that uses time-of-flight technology.



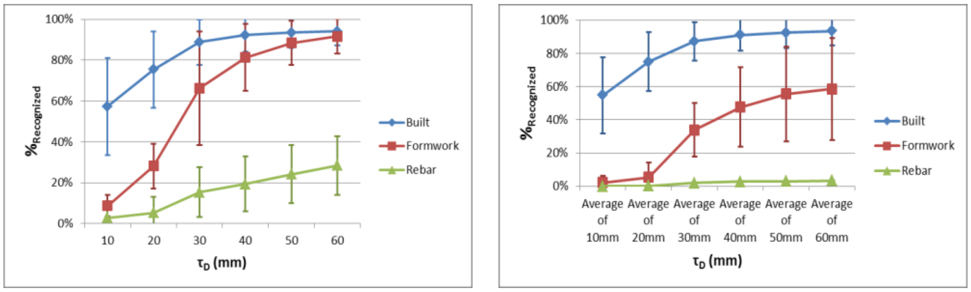
(a) **(b)** **(c)**

Figure 2: Temporary and Secondary objects at E5 Building site: (a) column formworks – July 25, 2008; (b) Rebar – September 19, 2008; (c) Slab formworks and shoring – October 9, 2008.

Recognition of Completed Objects (Step 1): In order to recognize secondary and temporary structures, the algorithm of Bosché and Haas (2008) is first run using its default settings, i.e. τ_D =20mm, $\%_{recognized}$ =50% and $S_{recognized}$ =1,000cm^2. This step leads to the recognition of all completed elements, and subsequently the removal from the TLS point clouds of all the points matched to the recognized elements.

Recognition of Formwork and Rebar (Step 2): As a second step, Bosché and Haas' (2008) algorithm is run with values of τ_D ranging from 10mm to 60mm in order to identify whether rebar and formwork could be distinctly differentiated from completed objects. Five of the TLS point clouds were used here which collectively contain data from 111 column, floor and wall objects in different construction states, namely: "built" (i.e. completed), "formwork" and "rebar". The experiment results are summarized in Figures 3 for columns and walls respectively. Overall, it appears, as expected, that recognition levels for objects in "formwork" state show very low $\%_{recognized}$ for values of τ_D <30mm, but then clearly increase from 30mm onwards. Objects in "rebar" state show similar patterns as those in "formwork" state but do not reach as high recognition levels for larger values of τ_D, which was also expected. Therefore, it can be concluded that the analysis of the variation of $\%_{recognized}$ over the suggested range of values for τ_D can be used to distinguish the different construction states of concrete structures.

Figure 4 shows an example of the results obtained for a scan after the first two steps are successively applied.



(a) **(b)**

Figure 3: Recognition performance for different values of τ_D and at different construction stages. The curves show the average and standard variation of $\%_{recognized}$: (a) columns (b) walls

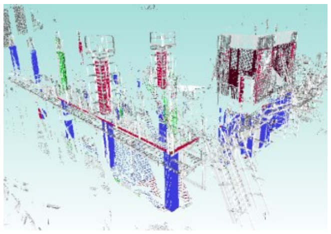


Figure 4 Illustration of the recognition of concrete structure elements in state “built” (blue), “formwork” (red) and “rebar”(green).

Recognition of Shoring (Step 3): In order to recognize shoring in TLS point clouds, a simple technique based on the analysis of points contained within open spaces defined by design objects, is tested. Trimble® Realworks® manual segmentation tool was used to select sets of points from the point cloud by defining boundaries using its polygonal framing function; the tool reports the number of points in the defined volume. Separately, the corresponding volume of the defined volume is calculated using the structural BIM model and commercial BIM software (Autodesk® Revit® was used here). While our experiment performs this task manually, full automation is feasible. 50 open spaces that have shoring and another 50 open spaces that do not have shoring were selected from the TLS point clouds of the Engineering V Building. Figure 5 shows that the number of points per cubic meter varies between 20 and 40 if there is no shoring, and between 60 and 100 if there is shoring in the selected open space volume (these results were obtained with a relatively constant scanner-volume distance so that the scanning resolution does not significantly impact the results). Using a threshold of 50 points per cubic meters would lead to a 100% recall and 100% precision. The proposed technique seems to be a good indicator of the presence of shoring, although wrong classification of open volumes could still happen, with both false positive and false negative results. Reducing the risk of false positives would require that the organization of the identified points within the volume be further analyzed (e.g. geometry or color analysis). The risk of false negatives (mainly due to occlusions) could be addressed by developing an algorithm that would estimate the “visible open volume” and thus infer a level of confidence in the result.

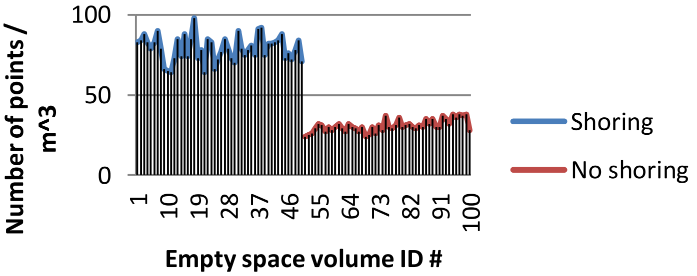


Figure 5 Distribution of number of points per cubic meter in the volumes that have shoring and no shoring.

CONCLUSIONS

In this paper, two techniques for recognition of concrete construction secondary and temporary objects in TLS point clouds are proposed. Both of these techniques have shown good potential for recognizing formwork, rebar and shoring using real life data obtained from the Engineering V Building construction site. The first technique leverages the automated object recognition system of Bosché and Haas (2008). It requires analyzing the level of recognition $\%_{\text{recognized}}$ within a range of values of τ_D from 10mm to 60mm. Experimental results have shown that it is feasible using this approach to distinguish whether concrete structure objects are in state "built", "formwork" and "rebar". Different settings may be necessary depending on the type of object (columns, walls or floors), as the type of object impacts formwork thickness or rebar cover. The second technique is an application of a simple metric to open spaces defined by design objects and aims at recognizing shoring. The experimental results have shown that it is feasible to differentiate spaces that have shoring and no shoring using this simple metric. It is however acknowledged that the current simple metric, while being a good indicator of the presence of shoring, is not robust and should be extended with additional processing. For example, to ensure the recognition of shoring, algorithms can be developed that would more actively recognize individual shores within the point clouds contained in each open space using techniques such as the Hough transform for 3D edge detection.

Overall, while the seemingly simple approaches (considering the complex foundational software developed to support them) tested in this paper have shown potential, future research is required to explore techniques that could strengthen the recognition of these objects. The integration of color information within the recognition framework has good potential since rebar formwork and shoring typically have colors that are quite different from finished concrete. Analyzing the geometry of points, as investigated by Ishida et al. (2012) for rebar, would further strengthen the recognition performance. Finally, studies remain to be conducted to integrate these results within progress tracking systems (such as the one described in (Turkan et al., 2012)) and measure the resulting improvement in progress tracking.

REFERENCES

Bosché F. and Haas C.T. (2008). “Automated retrieval of 3D CAD model objects in construction range images.” Automation in Construction, 17 (4), 499-512.

Bosché F. (2010). “Automated recognition of 3D CAD model objects and calculation of as-built dimensions for dimensional compliance control in construction.” Advanced Engineering Informatics, 24 (1), 107-118.

Chen Y. and Medioni G. (1991). “Object modeling by registration of multiple range images.” Proceedings of the International IEEE Conference on Robotics and Automation in Sacramento, CA, USA, pp. 2724-2729.

Cheok, G.S., Stone W.C., Lipman R.R., and Witzgall C. (2000). “Ladars for construction assessment and update.” Automation in Construction, 9 (5), 463-477.

Golparvar-Fard M., Peña-Mora F., Arboleda C. A., and Lee S. H. (2009). “Visualization of construction progress monitoring with 4D simulation model overlaid on time-lapsed photographs.” Journal of Computing in Civil Engineering, 23 (6), 391-404.

Hurst, M.P. (1983), Formwork, Construction press, Longman Group Limited, New York, NY.

Ishida K., Kano N. and Kimoto K. (2012). “Shape recognition with point clouds in rebars.” Gerontechnology Journal, 11(2), 89-96.

Jarkas, A. and Horner, M. (2011). “Revisiting the applicability of learning curve theory to formwork labour productivity.” Construction Management and Economics, 29 (5), 483-493.

Lee, S., Oh, S., Hong, M., Choi, J. (2010). “An Investigation of an Image Processing Application for Measurement of a Quantity Estimate of Euro Form Installed in Construction Sites.” Proceedings of the IEEE 5th International Conference on Ubiquitous Information Technologies and Applications in Hainan, China, pp. 1-5.

Nunnally, S.W. (2004). Construction Methods and Management, Pearson Prentice Hall, New York, NY.

Peurifoy, R.L. and Oberlender, G.D., (2011). Formwork for concrete structures, McGraw-Hill Professional, New York, NY.

Rusinkiewicz S. and Levoy, M. (2001). “Efficient Variants of the {ICP} Algorithm.” Proceedings of the International Conference on 3D Digital Imaging and Modeling (3DIM) in Quebec City, Canada, 2001, pp. 145-152.

Turkan Y., Bosché F., Haas C.T., Haas R. (2012). “Automated Progress Tracking Using 4D Models and 3D Sensing Technologies.” Automation in Construction, 22 (1), 414-421.

Wu Y., Kim H., Kim C. and Han S.H. (2010). “Object Recognition in Construction-Site Images Using 3D CAD-Based Filtering.” Journal of Computing in Civil Engineering, 24 (1), 56-64.