PERCENTAGE OF COMPLETION OF IN-SITU CAST CONCRETE WALLS USING POINT CLOUD DATA AND BIM

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ABSTRACT:

Progress monitoring of construction sites is becoming increasingly popular in the construction industry. Especially with the integration of 4D BIM, the progression and quality of the construction process can be better quantified. A key aspect is the detection of the changes between consecutive epochs of measurements on the site. However, the development of automated procedures is challenging due to noise, occlusions and the associativity between different objects. Additionally, objects are built in stages and thus varying states have to be detected according to the Percentage of Completion.
In this work, a framework is presented to derive work progress of construction sites based on point cloud data. More specifically, a methodology is constituted to compute the Percentage of Completion of in-situ cast concrete walls. In the literature study, existing methods are evaluated for their ability to track progress even in highly cluttered environments. In the practical study, we perform an empirical analysis on a set of periodic point clouds to establish the obstacles and feasibility of the methodology. This work leads to a better understanding of the progress monitoring paradigm which is still subject of ongoing research and will serve as the basis for the further development of a set of automated procedures.

1. INTRODUCTION

A prominent feature of the Building Information Modeling (BIM) process is the ability to model the available information of a structure during its life-cycle. A major application during the construction phase is the attachment of the construction planning to the physical model. These 4D BIM representations contain detailed information on when specific objects are constructed and are used for construction planning, resource management and financial aspects such as the cost over time of the project (Volk et al., 2014). Also, it allows the tracking of progression of a construction site and whether objects are constructed conform the as-design specifications.

Aside from the advantages for management purposes, the active tracking of a construction site allows for the creation of an as-built BIM model (Son et al., 2015). This model reflect the state of the structure as it was actually built and has numerous applications in terms of project planning, facility management, structural mechanics and so on (Hajian and Becerik-Gerber, 2009). In order to create proper as-built models, dense accurate spatial information, also known as point cloud data, is periodically acquired of the construction site. An additional advantage of this procedure is that there is a measured record of the situation on site which can have legal significance.

It is within the scope of this research to investigate the opportunities of progress monitoring on construction sites. More specifically, the focus of this work is on tracking of in-situ cast concrete walls of building projects. The different types of analysis that can be performed on point cloud data are evaluated and tested for their feasibility. The goal is to provide contractors and construction supervisors with the tools to better manage their projects. The emphasis is on metric information interpretation as it forms the basis for other information sources.

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The remainder of this work is structured as follows. In this chapter, the types of analysis with their respective deliverables and challenges are discussed. The related work is presented in Section 2. In Section 3. the methodology is illustrated. The test design and experimental results are proposed in Section 4. Finally, the conclusions are presented in Section 5.

1.1 Deliverables

Construction site monitoring consists of a wide range of analyses and deliverables. As previously stated, the focus is on the evaluation of basic structural entities such as the walls. However, other objects might also be tracked as they aid in the detection of the walls (Ibrahim et al., 2009). Also, contemporary structures such as supports are considered since these are frequently occurring on construction sites, are a major cost factor and cause serious confusion in the detection of the built entities (Eastman et al., 2011). In this section, the different deliverables are discussed along with the their point cloud specifications and challenges.

Reference It is important to notice that the analysis of progression point cloud data yields different types of information depending on the reference. Both relative and absolute references are considered for the assessment. The former uses consecutive points clouds or subsets of the BIM as reference which reveals the progression of the construction site between two data acquisitions. The latter uses the initial point cloud measurements of the site or the complete BIM to asses the overall progress. While not being a deliverable itself, special attention is given to the reference as it controls which information deliverable an analysis yields.

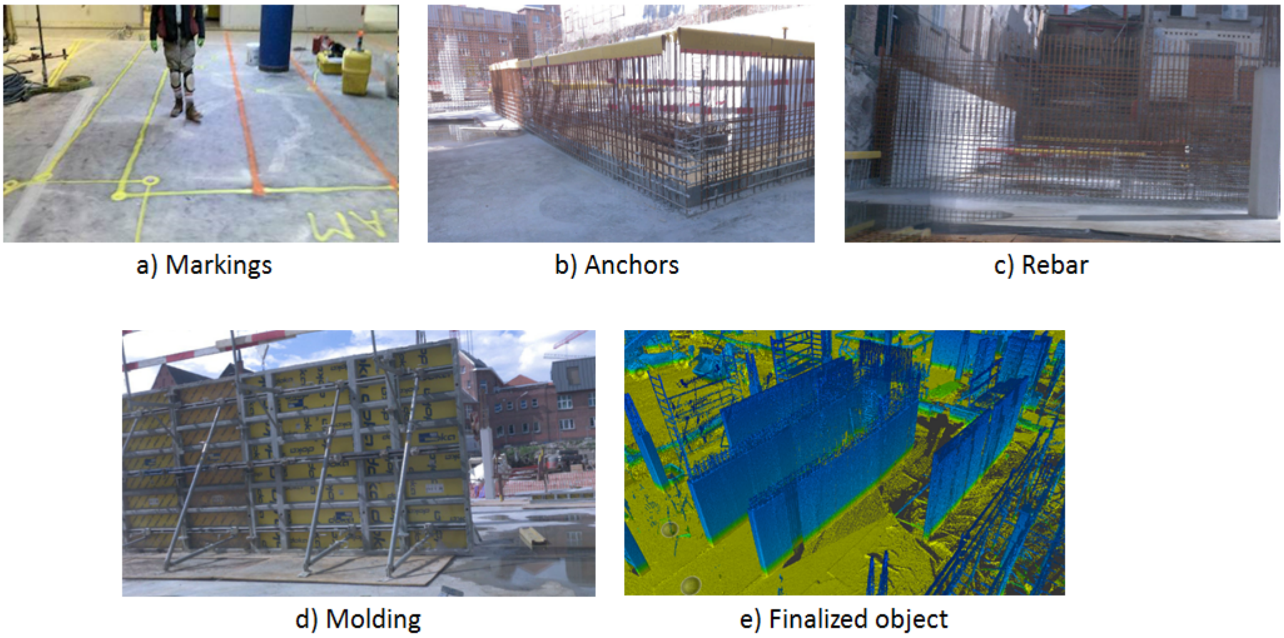


Figure 1: The phases of the Percentage of Completion (PoC) of in-situ cast concrete walls.

Presence A straightforward analysis that can be made is the detection of whether an object is present or not on the construction site given a reference. It is an instance of change detection that assigns a binary value to each object. For instance, the contractor should be warned if an expected structure is not present due to construction delays or erroneous plan interpretation. Similarly, it can be used to flag unexpected objects on site or to locate certain items. To provide any kind of useful information, this evaluation should be robust against the clutter on site. Also, a careful interpretation of the occlusions is mandatory to avoid false positives. Typically, additional information or prior knowledge is incorporated in this detection to improve the detection rate.

Percentage of Completion (PoC) A more detailed instance of change detection is the evolution of the Percentage of Completion of objects. It is a numerical value assigned to each object that reflects its current state of progression (Zhang et al., 2009). For instance, in-situ cast concrete walls progress from their initial survey markings to anchors, rebar, moldings all the way to the finalized object (Fig. 1). It is crucial for further analysis that the PoC is properly determined. For example, a quality assessment should be performed on the appearance of an object and not on its moldings. However, the PoC is challenging to determine since an object's appearance at different stages can look very similar and is prone to occlusions. The difference should therefore be distinguishable in the point cloud data. One approach is to combine the observations of consecutive data acquisitions to establish whether or not there is enough information to determine the PoC and its changes (Gao et al., 2015).

Quantity take offs Resource management is a crucial task that is performed by superintendents. Important resources on a traditional construction site include concrete, steel and moldings. Depending on how much of an object is built, a certain amount of materials is used. It is useful to provide the contractor with detailed information concerning the amount of materials spent on site. For instance, the amount of used concrete should be determined to provide a detailed cost overview and resource planning. However, this information typically cannot be directly observed but is derived from the built objects. Therefore, this evaluation is performed in function of the material type rather than on object level. Additionally, based on the Percentage of Completion, an estimation can be made of the intermediate material usage of larger objects. Similar to the PoC, this analysis suffers from occlusions. Also, the materials of interest for the quantity take-offs often are challenging to observe. For instance, steel rebar and anchors typically are slender objects of which the observations are easily mistaken for clutter or noise. A crucial aspect is the waste of materials which is a driving factor in quantity take-offs but extremely difficult to determine based on remote sensing techniques.

Quality Assessment The quality assessment is an analysis on object level that determines whether an object was built according to the as-design specifications. From a remote sensing perspective, this includes comparing the represented location, orientation and dimensions of an object to its measured geometry. Similar to the absolute and relative references of other analyses, this evaluation yields different information depending on whether an absolute or relative quality assessment is performed. The former is a general evaluation that determines whether an object is built in the correct place with relation to the project coordinate system. The latter is a more detailed analysis that evaluates an object appearance with relation to itself and its immediate surroundings. This is commonly referred to as attribute or feature based deviation detection (Akinci et al., 2006). A major challenge in this analysis is determining which observations to use to measure the deviations. Additionally, aside from occlusions and clutter, the accuracy of the evaluation is highly influenced by the density of the point cloud and its single point accuracy.

As-built BIM Based on the results of the quality assessment, the existing as-design BIM is updated to as-built conditions. This includes relocating the objects and adjusting the dimensions (Gao et al., 2015). This procedure is also referred to as Scan-vs-BIM (Bosché et al., 2014, Rebolj et al., 2017). Careful attention should be given to the modeling specifications since deviations acquired from the quality control can only be determined up to the accuracy and density of the point cloud. Also, minor deviations may not result in design changes since changing the model is labor intensive and has major impact on the rest of the design. Rather than automatically updating the model, it is better to provide detailed information about each object to the BIM manager so they can decide whether or not to update the model.

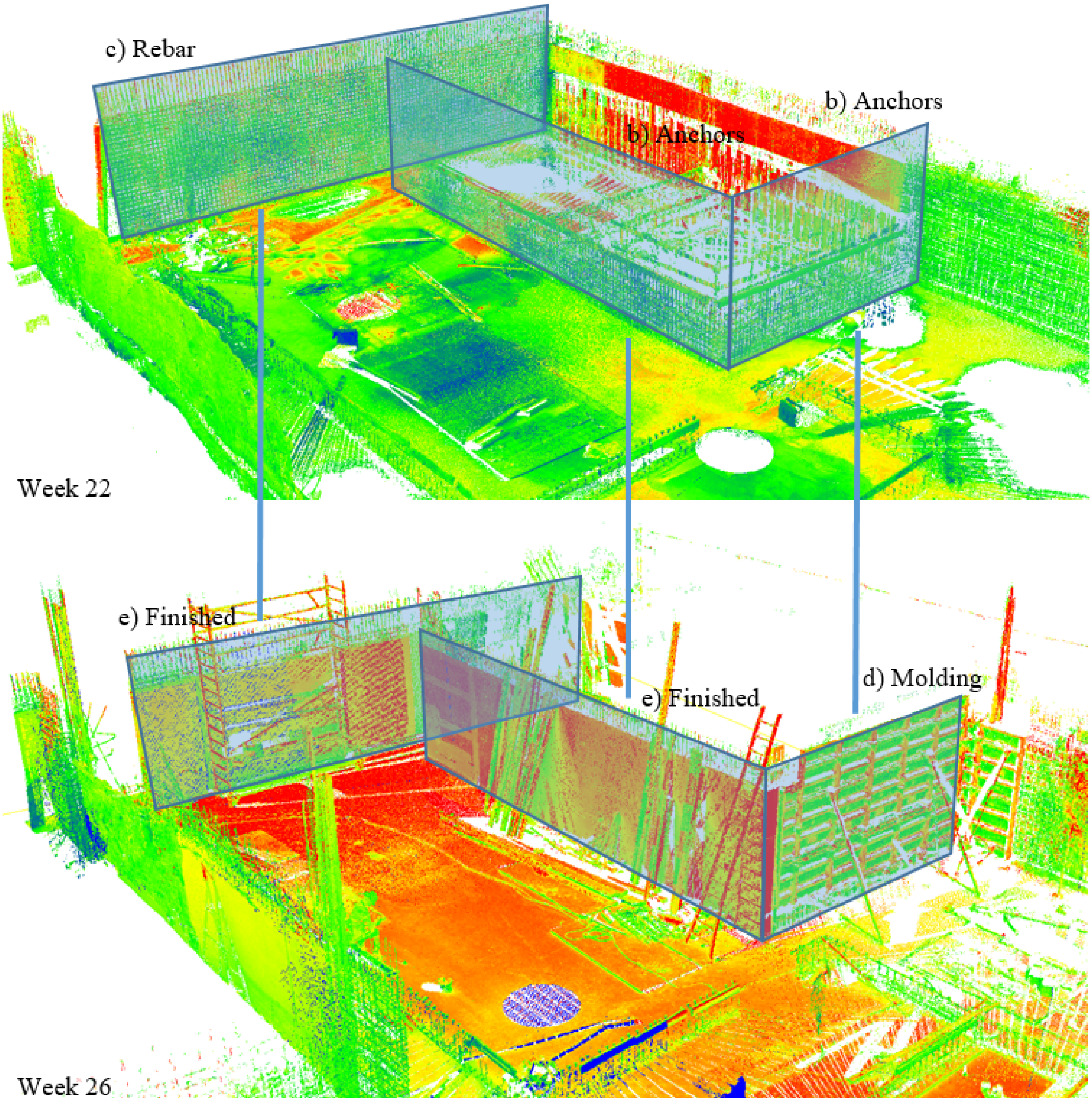


Figure 2: Example of the Percentage of Completion (PoC) of in-situ cast concrete walls in different epochs. 3 walls are depicted with varying PoC's ranging from initial anchors to rebar to moldings and finally to finished structural object. The colorization of the point cloud is based on the SNR value of the scanner and is only used for visualization.

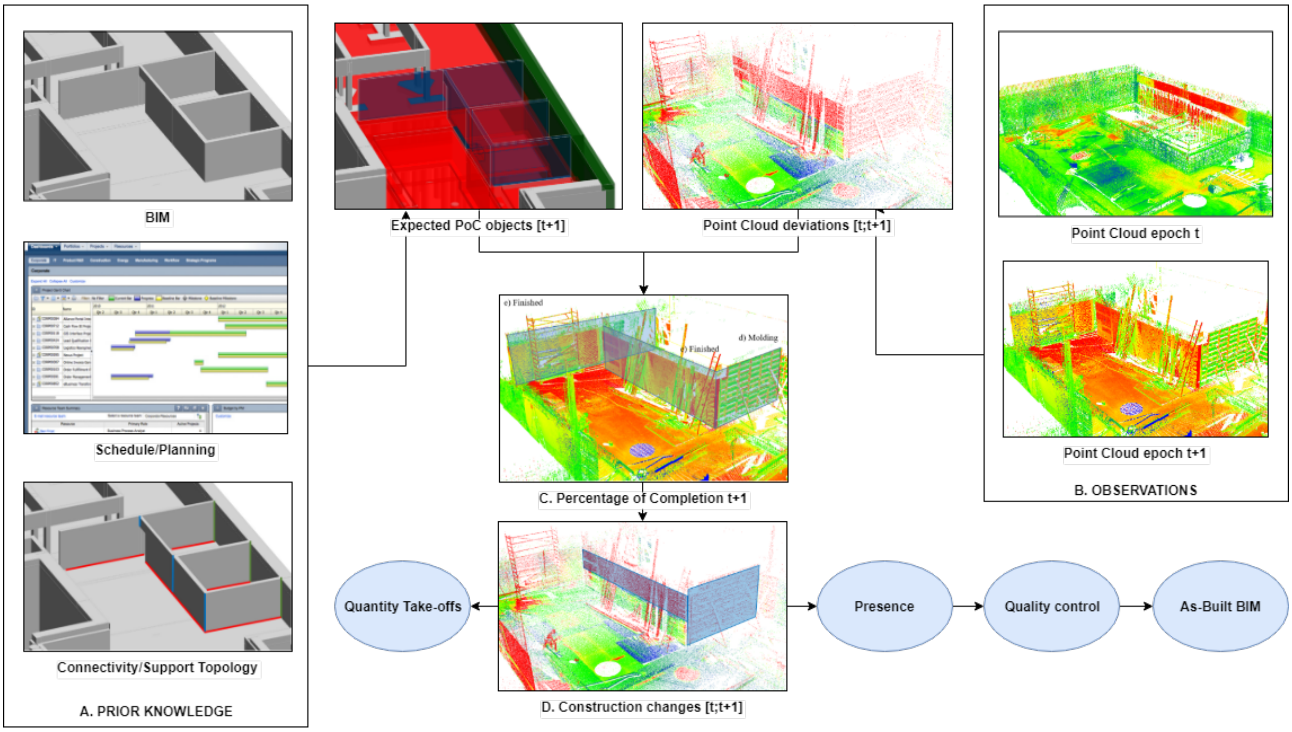


Figure 3: Overview of the workflow to compute the Percentage of Completion (PoC) of in-situ cast concrete walls: (A) the retrieval of the expected PoC objects from 4D BIM including geometry and planning information, (B) the observed geometry from point cloud data and (C-D) the estimation of the PoC from the subsequent epochs.

Aside from the metric deliverables, there are a number of non-metric deliverables that can be indirectly derived from the point cloud analysis. For instance, given the change detection, the project scheduling can be automatically adjusted. This includes a clash detection of the planning and required operations/materials to construct a certain entity. In this research we will focus on the PoC of the objects as it forms the basis for other analyses.

2. RELATED WORK

Currently, progress monitoring is still subject of ongoing research. Typically, the field is divided into two major components, data acquisition and data processing. The former focuses on the production of dense point cloud data of the construction site using imagery, RFID, Terrestrial laser scanners and so on (Zhu and Brilakis, 2009, Bhatla et al., 2012, El-Omari and Moselhi, 2011, Tuttas et al., 2016). The latter focuses on performing analysis on a given a point cloud and providing decision makers with the necessary information to monitor the site and to update the BIM. This work solely discusses this second topic and thus considers the point cloud to be independent of the data acquisition system.

Typically, the paradigm of detecting the presence of an object is defined as determining whether or not a structural object is built. Tuttas et al. (Tuttas et al., 2015) express this information by confirming the presence of BIM objects in consecutive point clouds. They discriminate the geometry of the BIM objects into their boundary surfaces and label each mesh triangle individually based on its Euclidean distance to the point cloud. Converting the as-planned BIM to a point cloud is also considered (Bosche and Haas, 2008, Bosché, 2012). For verification, they compute the percentage of simulated points within a threshold distance after locally aligning the measured point cloud with adapted Iterative-Closest– Point-Algorithm (ICP). In addition to the measurements, prior knowledge is considered. For instance, Kim et al. (Kim et al., 2013a, Kim et al., 2013b, Kim et al., 2013c) use an SVM classifier based on the expected and measured as-built status of object. They state that the sequence of activity execution and the connectivity between components are vital clues in the detection of the as-built status of an object. Braun et al. (Braun et al., 2015a, Braun et al., 2015b) employ a similar detection framework to track the built status of components. They generate a relationship graph from the as-design BIM based on connectivity. Turkan et al. (Turkan et al., 2012) also use schedules and incorporate the detection of secondary objects. Overall, we look to expand their approaches with building logics with structural support sequence knowledge to further enhance the results and compute the PoC of in-situ cast walls.

A common strategy is to perform the change detection once the objects are fully completed. However, in a construction site this is rarely the case as both completed and uncompleted entities are observed on site (Fig. 2). Several approaches have therefore presented to extract progress information and PoC from point clouds of construction sites. A promising work is that of Golparvar et al. (Golparvar-Fard et al., 2015). They use a machine learning scheme to detect physical progress on site. They integrate the as-planned 4D BIM model into an image-based interactive viewer to communicate changes on site. More specifically, they use a Support Vector Machines (SVM) classifier to label the voxel space within the viewer either as progress or no progress. Behnam et al. (Behnam et al., 2016) presents the production of progress maps of infrastructure based on satellite footage. Closely aligned with our work is the research of Kropp et al. (Kropp et al., 2018) who estimate the completion state of objects based on computer vision techniques. Overall, there is still a gap in the research of reliably establishing whether an object is fully completed or not. Our work is focused on this specific evaluation as it is vital for the construction management to get progress information as soon as possible instead of having to wait until the site is completed.

Research has also been performed towards quality control or quality assurance. Anil et al. (Anil et al., 2011) and Akinci et al. (Akinci et al., 2006) present a framework of which parameters are of importance and how to communicate these to the decision makers. They stress the importance of discriminating between deviation detections and defect detections that evaluates the deviations with respect to existing specifications. Bonduel et al. (Bonduel et al., 2017) presents a similar method along with a concrete example of how to assign deviation analysis values to BIM objects. Bosché et al. (Bosché et al., 2013, Bosché et al., 2014) automate the process of quality assessment of the built status of MEP works by matching the point cloud to the as-planned BIM. It is important to notice that the accuracy of the point cloud is a driving factor in the reliability of the assessment. Bhatla et al. (Bhatla et al., 2012) therefore discuss the specifications of the point cloud with relation to certain deviation analyses, revealing that highly dense accurate point cloud data is required to make any sort of assessment. In future work, we look to expand their works, which focus on completed structures, towards the comparison between 4D BIM subsets and periodically acquired data sets.

3. METHODOLOGY

In this paper, a detection framework is proposed that determines the PoC of the expected elements on site. An overview of the general workflow is depicted in Fig. 3. First, a set of built and expected objects is determined given the 4D BIM and additional prior knowledge (Fig. 3a). In parallel, dense point cloud data is acquired from the site (Fig. 3b). Next, a set of operations is conducted to isolate the measurements of the construction changes. These are then evaluated locally to determine the PoC based on geometric features, detected changes and the prior PoC (Fig. 3c). The resulting information is used to compute the construction changes (Fig. 3d). The method is implemented in the Rhinoceros 6 software and extends the Volvox plugin developed in the DURAARK project (Zwierzycki et al., 2016). The consecutive steps are discussed in detail in the following paragraphs.

3.1 Prior Knowledge

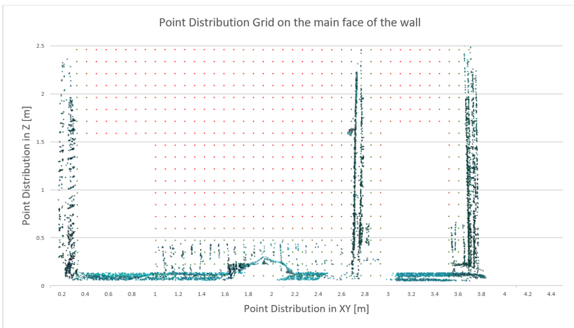
The construction of a building involves the production of hundreds if not thousands of structural objects. The estimation of the PoC of these objects solely based on point cloud data is computationally inefficient and error prone. Therefore, the PoC estimation is limited to those objects that are expected to be built. In this work, we determine the expected objects based on 4D BIM and the building topology. The former is derived from the project's planning, which defines the order in which objects are built. However, the order of the construction progression is typically abstracted to the major phases and thus additional information is required to determine a more detailed order. We propose the use of building topology to narrow the number of objects that should be evaluated within a phase. More specifically, it is our hypothesis that no object can be constructed without its support. In this prototype, we translate this as two rules. First, for every object that is determined as built, its neighborhood is expected. Secondly, the objects supporting (underneath) an object that is determined as built are also considered built. Given the prior knowledge, the expected objects in consecutive point cloud epochs is determined. Once the objects are determined, their mesh geometry is isolated from the BIM model and will serve as a reference for the PoC estimation.

3.2 Observations

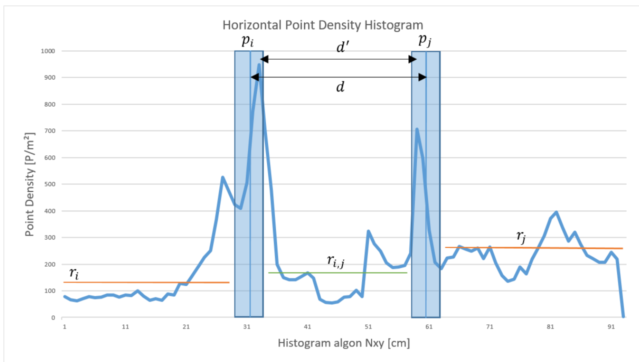
The acquisition of point cloud data from construction sites can be performed with various sensors. Terrestrial Laser Scanning (TLS) is predominantly used for this purpose but alternative methods such as photogrammetry and RGBD sensors are also popular. The result of these methods are either structured or unstructured point clouds. Since it is within our scope to operate sensor-independently, we operate on unstructured point cloud data which can origin from any platform. Currently, we assume the point cloud data to be registered and geolocated. Upon loading a point cloud into Rhino, the Volvox grasshopper plugin restructures the data as a voxel octree for efficient data processing. First, a voxel subsampling of 2cm is employed to create a uniform point density and to compensate for noise. Next, the meshes of the expected geometry are used to segment the data. A buffered geometry is constructed around the objects using offset b, after which it is used to segment the point cloud. The result is a set of points representing the vicinity of each of the expected objects.

3.3 Percentage of Completion

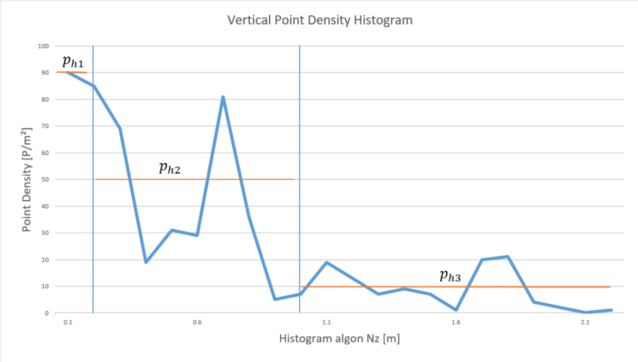
As discussed in the introduction, 5 consecutive states are defined for the completion of in-situ cast concrete objects $y \in \zeta = \{non - existing, anchor, rebar, molding, built\}$. Additionally, we define an "occluded" state to accommodate for walls that are not observed sufficiently to reliably determine their PoC. We consider the estimation of the states Y of the observed walls as a data association problem which can be solved with a classification model. We employ a decision function $P(Y|X)$ with pretrained weights ω developed in previous work (Bassier et al., 2018), that processes a set of features x of each observed wall, and outputs its most likely state y. In the prototype, 10 features are defined. The first is the average point density given the surface area of the walls. Additionally, we consider 3 point density signatures for the other features.



The first signature is based on a rasterized projection of the points on the major face of the walls. First, The voxilized point cloud is projected onto the hearthplane of each wall. Next, a fixed spatial grid is generated on this hearthplane. The second feature is given by the percentage of grid points lying within a threshold t_g of the projected point cloud. The second signature is based on the



point density distribution along the normal of the largest face of the wall. For built walls observed from both sides, it is expected that the histogram contains 2 peaks with little noise in between. Similar conclusions can be drawn for the other states. The 4 features directly derived from the histogram are the noise outside the peaks r_{out} as an average r_i and r_j, the noise within the peaks r_{in} and the height of both peaks p_i, p_j. Additionally, the deviation between the distance between the peaks and the theoretical thickness of the wall is considered an indicator for the PoC. The third



signature is based on the point density distribution along the vertical slope of the wall. For built walls, a consistently high point density in vertical direction is expected. 3 features encode this information as the relative average point density in the lower p_{h1}, middle p_{h2} and top p_{h3} section of the wall. Additionally, the percentage of points below the typical anchor height is stored as a feature. The features are combined in feature vectors which are encoded in such a way that zero indicates low associativity and 1 indicates a high associativity.

The states of observed walls are computed by feeding the feature vectors X to the Random Forests model. The splits of the model are trained by learning them from known observations. A balanced set of features with known states is used to minimize the error of the splits. We bootstrap aggregate a large number of weak learners to significantly lower the variance of the model. The choice of model is driven by the high variance of the inputs and the specificity of the features. The result is the most likely state of each wall.

3.4 Construction changes

Once the state is determined for the observed walls, the construction changes can be derived. In this prototype, we consider the construction process to be feedforward were states can only develop to higher states. For instance, a built wall cannot demode to molding in a subsequent point cloud epoch. An exception is made for the "*occluded*" class were the previously observed state is adopted. Given the construction changes, the progression of work on the site is determined.

4. EXPERIMENTS

The prototype is tested on a construction site in Ghent, Belgium. Three point cloud epochs are observed of a subsection of the site that is under construction (Fig.4a). During each epoch, the site was captured using TLS. The data was not cleaned and contains significant noise and clutter. Over 50 million points were captured of the 32 surrounding walls in different states. As stated in the methodology, a voxel subsampling of 2cm is used which drastically lowers the amount of data. Additionally, the prior segmentation based on the buffered expected geometry is performed with $b = 0.3m$, resulting in a further data reduction. For each of the 32 walls, the 10 features were extracted. For the grid generating, a spatial pattern of 0.1x0.1m was used in u,v direction. As an initial test, we 5-fold cross-validate the Random Forest model for all 32 walls in the three consecutive epochs. Figure 4b depicts the recall and precision matrices of the evaluation. Currently, there aren't sufficient molding observations to provide a reasonable cross-validation and the non-existing and occluded states are merged because of the limited data. The remainder of classes show promising results. On average, 73.3% of the states were correctly determined which is promising despite the presence of noise, clutter and the limited dataset. For the estimation of the built walls, recall values of up to 90% are reported. However, several problems still remain. First of all, there is significant confusion between anchors and non-existing or occluded walls. This is to be expected due to the low point count of these classes and their similar point density signatures. Secondly, there are several circumstances that inherently cause problems in the classification. Figure 4c-f depicts some of the encountered issues such as mixed state occurrences. These are observations of walls that are in multiple states. For instance, a part of a wall is still in rebar while the remainder is already built. This is a temporary issue due to the way walls are constructed and is expected to be mitigated in subsequent epochs. There are also issues with the edges of the construction pit, which are very similar to constructed walls. Model abstractions such as grout walls also inherently cause issues since they are in fact not in-situ cast concrete walls. A final issue we encountered was noise due to the buffered segmentation. Especially for walls that have neighboring walls in different states, the buffer introduces noise which complicates the state estimation.

5. DISCUSSION & CONCLUSION

This paper presents an unsupervised method to estimate the Percentage of Completion of in-situ cast concrete walls on construction sites. More specifically, we propose the use of machine learning decision models to classify the state of the observed walls based on point cloud data. Our approach is sensor-independent and uses point density signatures as features to the decision function. A Random Forests model is employed for the state estimation to target the high variance datasets of construction sites.

In the prototype testing, 3 consecutive point cloud epochs are evaluated. 32 walls in different states are used to train the classification model. The initial cross-validation results indicate promising results for the Percentage of Completion estimation. Especially, the built walls are found with high recall. Several shortcommings will be dealt with in future work. For instance, mixed state occurrences currently cause major confusion in the state estimation. We will solve this through discretizing the input BIM objects. Also, we will further investigate the buffer segmentation to reduce noise. Finally, The prototype will be extended to a full scale test to investigate the robustness and scalability of the method.

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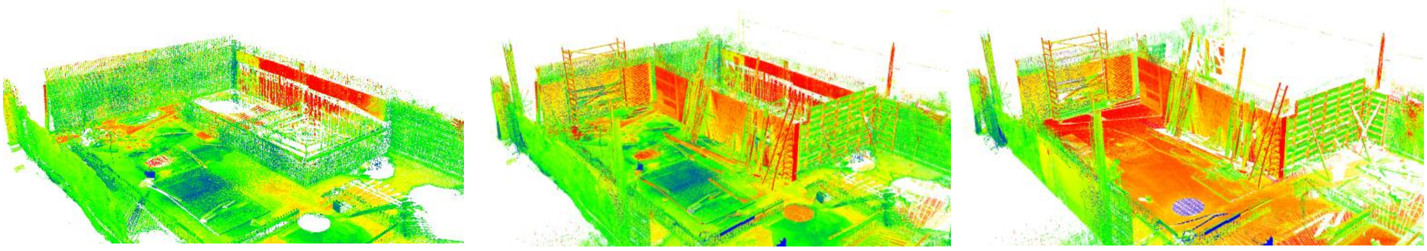

Figure 4a: Point Cloud Data of consecutive epochs at an interval of 2 weeks: (left) week 22, (middle) week 24 and (right) week 26. The point clouds are colorized according to their acquired intensity values. Red indicates poor measurements while blue depicts high quality points.

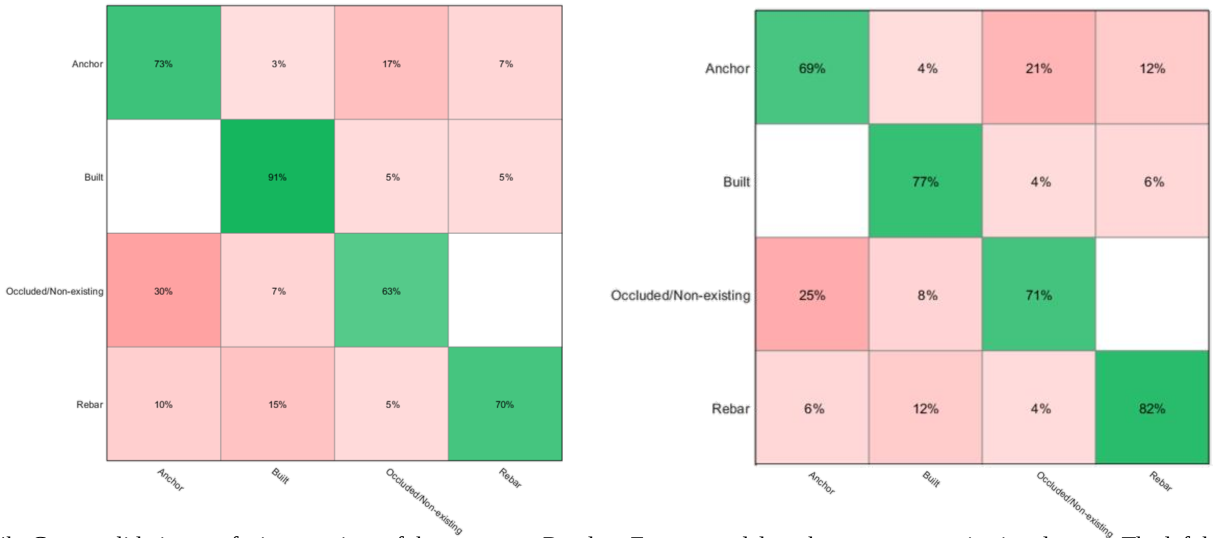

Figure 4b: Cross-validation confusion matrices of the prototype Random Forests model on the progress monitoring data set. The left hand labels are the true classes while the bottom labels are the predicted classes.

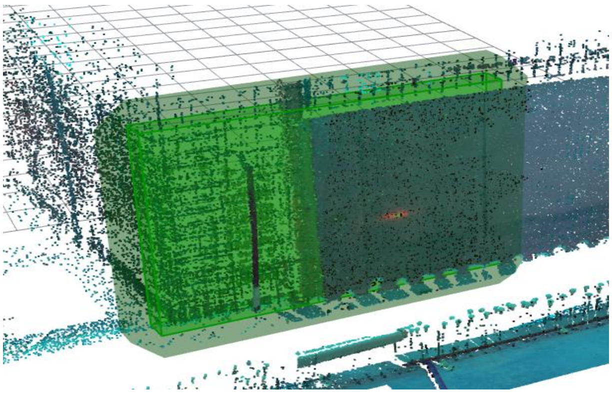

Figure 4c: Mixed state occurrence errors: Walls with parts in different states are inherently prone to misclassification.

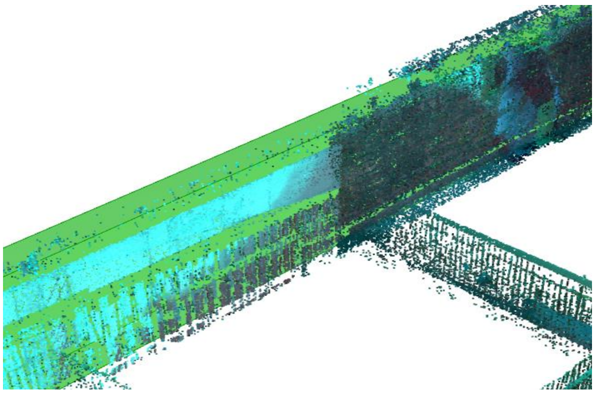

Figure 4d: Modeling abstractions such as grout volumes that were modeled as in-situ cast concrete walls do not correspond to predefined states.

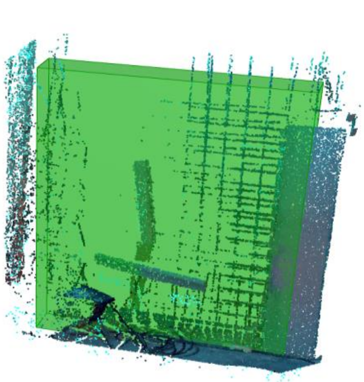

Figure 4e: The buffered point cloud extraction introduces noise especially in the vicinity of neighboring objects.

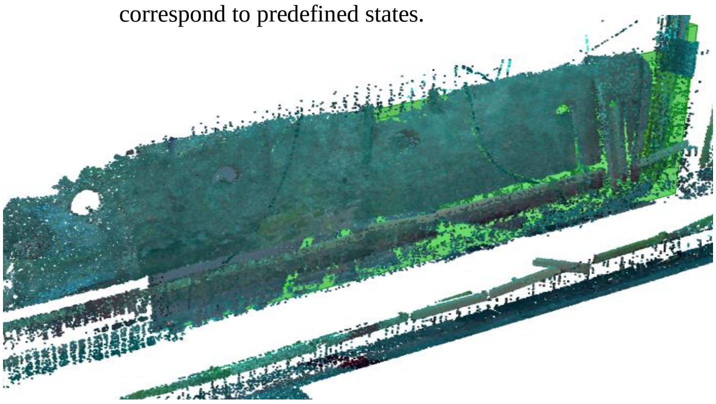

Figure 4f: Observations from the edges of the construction pit introduce confusion in the state estimation of the neighboring walls.

Figure 4: Experimental results of the Percentage of Completion estimation of in-situ cast concrete walls in consecutive point clouds epochs of a construction site.

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