Machine Learning for Construction Process Control: Challenges and Opportunities

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Abstract -

One of the primary drivers of inefficiencies plaguing construction projects world over is the lack of efficient process control in the construction process. This paper explores the idea of construction process control through BIM based quality control. It discusses the challenges of practically implementing BIM based quality control on a construction site and the opportunities for innovation in this space using state-of-the-art Machine Learning methods.

Keywords -

BIM; 3D Machine Learning; Laser Scanning; Process Control

1 Introduction

Construction, one of the worlds largest industries is also one of its most wasteful and inefficient [1, 2]. One of the major reasons the industry is unable to curb its waste and inefficiencies is because there is no quick and easy way to compare what is being built (reality) to what was designed (BIM). In industrial manufacturing settings this method of comparison is termed *Manufacturing Process Control* [3] whereas in construction settings it is called *Project Control* [4]. This inability to do process control in construction, limits the ability to reduce waste and inefficiency. This article proposes a paradigm for construction process control (project control) which compares the BIM to the onsite construction process using reality capture and machine learning (ML). In the rest of the paper, the general problem of process control, the challenges associated with the data inputs in construction, and the potential opportunities to deploy ML based solutions are addressed.

2 Process control in construction

The process of building construction is a specialized form of onsite manufacturing where a 3D model is recreated in physical space using machines, material and labour. Though construction bears many similarities to other onsite manufacturing processes like automotive, electronics, etc.; there exist stark differences between these processes and construction that affect the practical implementation of efficient process control.

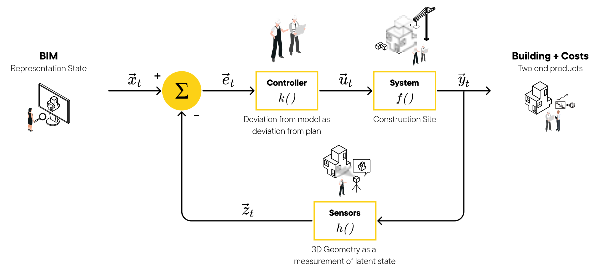

Figure 1: BIM based construction process control

List of Constraints

- Extremely **non linear state evolution** of the building under manufacture due to lack of correlation between states in the state vector. For example, the state (stage of construction) on floor A seldom informs the state on a different floor B within the same building.
- The **lack of correlation** results in different parts of the building having **different rates of evolution**, making the process model extremely complex.
- As the building is also the warehouse, it becomes an **open system for process control**, that is plagued with clutter and other detractors. This results in the building state being only **partially observable**.

These issues make the problem of implementing process control in construction challenging. Section 2.1 will discuss how one can implement process control in construction by measuring variables that can capture the complex latent state space of the construction process that involves material, machines, labour and schedule, without directly measuring them.

2.1 Construction process control via proxies

Since the actual state of the construction process is not directly measurable, one can use the constructed onsite geometry of the building as a proxy for the construction process. It is reasonable to assume that if the physical geometry of the constructed structure is incorrect (not in accordance with the BIM), the underlying process has not

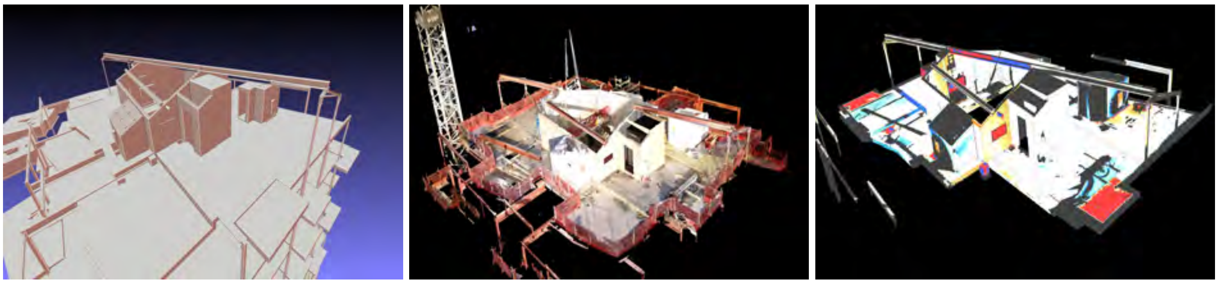

Figure 2: From left to right figure shows the idealized BIM model, the reality captured on the construction site using laser scanning and the point wise divergence between BIM and reality. The laser scans from the construction site are susceptible to both low and high frequency noise.

evolved accurately. Leveraging the BIM, one has access to a 4D signal (3D building geometry evolving over time) of how the ideal construction process should evolve. This can be used as a reference signal for the construction process control problem. For the actual signal of the construction process, one can measure the onsite constructed geometry using laser scanners or similar devices. This process is illustrated in Fig 1.

With this raw information, the physical 3D geometry of the built structure can be reconstructed using structure from motion techniques [5] like SLAM [6]. This 3D geometry once transformed into the reference coordinate space of the BIM, provides a canonical form for comparing the BIM to reality. The divergence between the BIM and reality can be used as the feedback error signal to perform process control on the construction site. This error signal contains both the error in the constructed geometry and the location of this error within the built structure (state space of construction). This error is illustrated in Fig 2.

3 Challenges with the quality of data

This section highlights how input data quality can be a detriment for implementing process control. Both the reference signal (BIM) and the onsite process signal (reality capture) are generally corrupted and noisy.

3.1 Divergence between BIM and reality

Though the difference between the BIM and reality can be used as a representation of divergence in the construction process, this is seldom the case in the real world. BIMs are generally not good reference signals as in practice they are seldom an exact representation of the intended on site geometry [7, 8]. Most practical implementations utilize a **LOD** 200 or 300 (level of detail) which is often a best case approximation of the constructed geometry. This results in situations where differences between the BIM and reality are not always errors in construction. Some reasons of divergence are:

- Prefabricated elements have a different level of manufacturing detail than their CAD modeled counterpart. This is highlighted via an architectural section drawing in left most figure in Fig: 3, where the constructed element is circular (represented by red lines) but BIM element is a low polygon CAD element.

- Elements during installation may differ entirely from the BIM, or not be represented at all in the model geometry. For example, in the center Fig: 3, a generic sewer placeholder prism is modeled in the BIM that does not match its location in reality.

- Construction elements often suffer *organic* forces and changes, which result in plastic deformations that are not represented in the CAD model. For example in the rightmost figure Fig: 3, non rigid deformations are encountered in concrete slabs due to flexion forces.

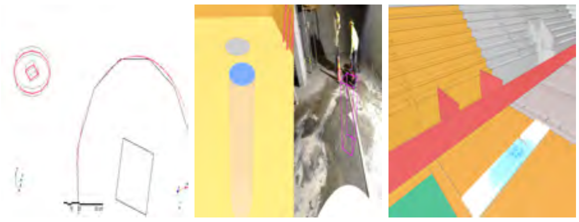

Figure 3: The figures above portray common divergences between the BIM and reality. From left to right the figures show the divergence between BIM and prefabricated elements, the installation differences between BIM and reality, and the divergence due to plastic deformations

3.2 Domain specific low frequency noise

Unlike an industrial manufacturing site, a construction site is also its warehouse. Construction sites, by nature are scenes with a significant amount of clutter, tools, auxiliary props, etc. These onsite artefacts naturally translate to occlusions and spurious measurements in the pointclouds captured by reality captured devices as shown in Fig: 4.

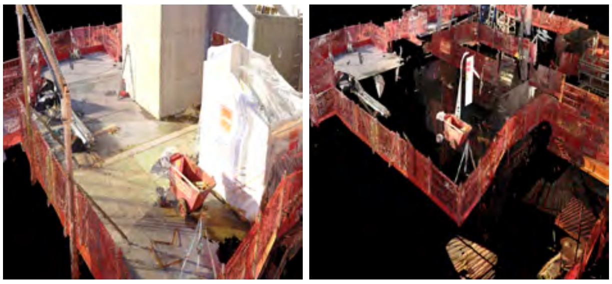

Figure 4: Original pointcloud and the segmented low frequency noise: segmented clutter, props, tools, etc

This unmodeled low frequency noise can easily lower the quality of data. The final sparse signal (pointcloud) after filtering low and high frequency noise is shown in Fig: 5.

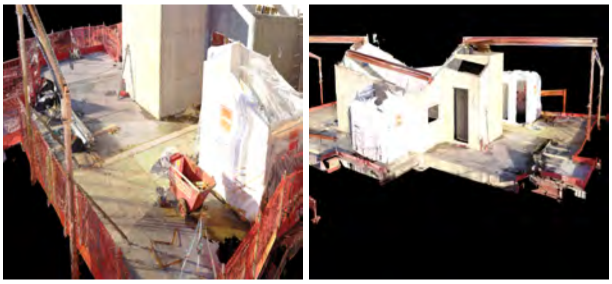

Figure 5: Original pointcloud and the filtered signal cloud that can be used to compare to BIM after segmentation

3.3 Into-the-wild sensor acquisition

Another stark contrast between industrial manufacturing settings and a construction site is that, given the open nature of the environment, a construction site is susceptible to uncontrolled events such as bad weather (rain, snow, etc.); bad illumination conditions (Fig: 6) and exposure to materials (glass and reflective surfaces) that cannot be measured with current depth sensors. This degrades the onsite data captured for comparison to the BIM. An example of snow affecting data capture is show in Fig: 7

Figure 6: Examples of construction sites with bad illumination conditions due to the nature of the environment

4 Challenges with the quality of labels

This section will highlight the issues related to label quality in the input data.

4.1 Lack of reliable ground truth

Building reliable ML models requires access to accurate ground truth (BIM vs Reality). A practical problem that plagues the acquisition of accurate ground truth labels on construction sites is the hierarchical risk management profile within the industry. Asset owners hire general contractors who hire subcontractors to execute on-site work. This incentivizes risk being pushed down the value chain which results in a feedback mechanism where no single entity on a construction site can provide accurate information (ground truth) regarding the state of the construction project. Resulting in very inaccurate mappings between the BIM and reality.

4.2 Lack of consistent semantics

Another source of poor label quality is the lack of reliable and consistent semantics between the BIM and onsite processes. For example, a semantic label such as "wall under construction", can have multiple different geometrical interpretations depending on the type of wall. These poorly defined semantics have distinctly different outcomes when measuring the divergence between the BIM and reality. Moreover domain experts also tend to commonly disagree on the semantics of these divergences.

5 Opportunities for ML in Construction Process Control

Despite the challenges discussed in Sec 3, 4, the problem of process control in construction reveals significant opportunities to employ ML based techniques by exploiting peculiarities in the input data or the problem structure.

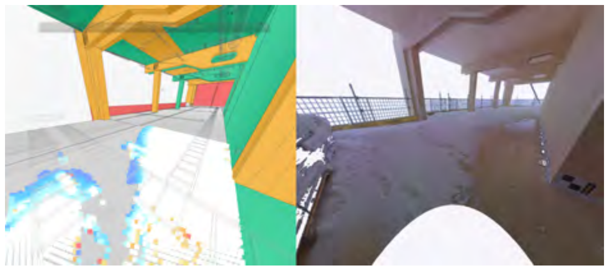

Figure 7: Environmental effects on captured onsite data. The onsite snow interferes with laser returns

5.1 Equivariant learning for construction process control

The lack of consistent semantics discussed in Sec 4.2 are consequences of descriptive characteristics of BIM elements being subject to various transformations such as shift, rotation, scaling etc. This results in the divergence (BIM vs reality) being subject to similar transformations. ML models that are equivariant to group operations can account for such variations. These models can handle variation within the mesh representation of a single element in a BIM or in the entire building graph structure represented by the BIM. At *Scaled Robotics*, we use deep learning models such as PointNet and its extensions [9, 10] to handle equivariance with respect to the point set. We also utilize graph neural networks [11] to model equivariance with regards to the building graph structure.

5.2 Localizing insights for efficient process control

Insights regarding the divergence between BIM and reality also need to be geometrically localized to specific surfaces within BIM elements. As shown in Fig 2, the divergence specific to a BIM element can have its own unique semantic meaning. We extend attention models [12] to work with geometric data to capture these insights.

5.3 Applications for Unsupervised Learning

Construction process data is extremely high dimensional, with non trivial correlations between the inputs. This makes the data domain ripe for the application of unsupervised learning [13] and dimensionality reduction techniques. At *Scaled Robotics*, we utilize both techniques to cluster the divergence to extract specific insights to inform the process control problem.

6 Conclusion

This article introduces the problem of process control in construction and a potential solution to the problem involving BIM to reality comparison using reality capture and machine learning. It also underscores the issues with data and label quality for implementing ML based solutions for construction process control. Finally the article highlights opportunities for exploiting particular threads in ML research that can benefit construction process control.

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