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AUTOMATED DIMENSIONAL COMPLIANCE ASSESSMENT WITH INCOMPLETE POINT CLOUD

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Abstract: Dimensional compliance assessment of prefabricated assemblies is a critical part of mitigating rework on heavy industrial construction projects. As assemblies become more complex, manual direct contact metrology becomes ineffective at detecting fabrication error and so automated alternatives that offer objective, fast, and continuous data collection must be explored. Nahangi and Haas (2014) developed an automated method for assessing pipe spools through an algorithm that compares as-built laser scans to 3D design files. The tool is capable of automatic and continual monitoring of prefabricated assemblies throughout their lifecycle and enables timely detection and quantification of dimensional non-compliance. In the original publication, the tool was validated using ideal input data. In this paper, the tool is tested for robustness when processing incomplete point cloud input data. Non-ideal input data is a risk associated with unfavorable conditions in the fabrication environment such as random assembly occlusions causing blind spots in sensing setup, budgetary constraints limiting the purchase of sensing equipment/viewpoints, and random hardware or software failures resulting in corrupt data. The tool was found to reliably detect dimensional non-compliance so long as the non-compliance indicator (pipe spool feature distinguishing the non-compliant state from the design state) was not fully occluded. Accuracy of non-compliance quantification was predominantly high, however, loosely proportional to the input point cloud's coverage of the assembly's surface area.

1 INTRODUCTION AND BACKGROUND

1.1 Introduction

As the use of modularization and prefabrication becomes more prevalent within industrial construction, the scope of modularization will expand to include a greater diversity of systems and account for a larger portion of constructed facilities (Chandler 2013). As a result, the effective execution of prefabrication will play an increasingly central role in total cost and schedule management on construction projects.

Prefabrication errors and omissions are considered a significant source of rework (Dissanayake et al. 2003), and so have been the focus of many quality control tool development projects (Bosché 2010; Akinci et al. 2006; Kim et al. 2015). In order to achieve successful deployment in the field, these tools need to be subjected to additional rigorous testing for robustness when operating under non-ideal conditions. In this paper, a series of data inputs of varying quality representing an as-built experimental pipe spool are collected and used for analysis using the tool presented in (Nahangi and Haas 2014). The relationship between input data quality and the accuracy of output fabrication error detection and quantification are explored.

1.2 Rework

In the construction literature, rework is the wasteful effort involved in redoing work that has not yet yielded a product adequately conforming to contractual requirements (Love and Li 2000; Hwang et al. 2009). Rework directly and significantly contributes to cost and schedule overruns on construction projects (Love 2002; Hegazy, Said, and Kassab 2011). Specifically, research published by the Construction Industry Institute (CII) states that rework costs between 2 percent and 20 percent of a typical project's contract amount (Construction Industry Institute (CII) Research Team 252 2011). Using data from 178 construction projects, (Hwang et al. 2009, 187-198) assessed the impact of rework from a contractor's perspective and concluded that it most greatly influenced cost increases on heavy industrial projects. It has been argued that the cause of rework on such projects is attributable to poor construction techniques and poor construction management policies (O'Connor and Tucker 1986). On a mining expansion megaproject in Alberta, it was discovered that errors and omissions in prefabrication and poor workmanship of prefabricated materials was a significant source of rework (Dissanayake et al. 2003). Systematic quality assessment of construction components during their lifecycle is important to reduce rework on projects (Love and Li 2000) and particular attention must be given to processes within prefabrication facilities to ensure they are meeting project requirements and mitigating field rework. Any automated quality assessment tools used for this purpose would need to have the capability of identifying errors and omissions in a timely and accurate manner, while using the most up-to-date design files as many rework situations occur because field changes are not communicated to the fabricator effectively.

1.3 Laser Scanning and Fabrication Process Control

Designers and QC specialists typically utilize standardized dimensional tolerance guidelines such as the systems published by American Society of Mechanical Engineers (ASME) or the International Organization for Standardization (ISO). Currently, the predominant processes for monitoring the critical dimensions outlined in these standards involve manual assessment by certified QC personnel using direct contact measurement devices such as measuring tapes, calipers, custom gauges, squares, and straightedges. These processes can help fabricators evaluate whether basic assemblies are compliant with design specifications, but their effectiveness deteriorates as the assembly's geometrical complexity increases because manual measurement is subjective, time-consuming, costly, and discontinuous. There is a need for automated and systematic dimensional compliance control tools that offer objective, fast, and continuous data collection for reliable quality control on heavy industrial construction projects.

Laser detection and ranging (LADAR) is an increasingly important technology from 3D computer vision used for metrology in the AEC industry (Patraucean et al. 2015). Laser scanners are used to collect spatial data about their surrounding in the form of a 3D point cloud. Compared to contact metrology, laser scanning collects data quickly (up to 976,00 data points per second) allowing for comprehensive coverage of large structures, and with millimeter accuracy (error ± 2mm) (FARO 2015). Considering these capabilities, the feasibility of laser scanning technology for dimensional quality control has been studied by several researchers. (Bosché 2010) proposed an automated method for recognizing 3D CAD model objects in laser scanned data for dimensional compliance control of construction assemblies. (Akinci et al. 2006) proposed a general formalism involving the comparison of as-built laser scans with design CAD models for quality control. (Kim et al. 2015) proposed a holistic approach for dimensional and surface quality assessment of precast concrete elements based on comparing BIM and 3D laser scans.

1.4 Automated Dimensional Compliance Checking in Pipe Spool Fabrication

The increasing complexity of off-site fabricated modules necessitates the implementation of automated dimensional compliance feedback tools capable of comprehensive and reliable measurement. (Nahangi and Haas 2014) presented an automated compliance control method for construction modules that reliably detects the presence of dimensional non-compliance and has consistently quantified the deviations with less than 10% error in experimental studies. The method requires two 3D imaging input files: (1) a 3D model of the as-built assembly generated using a 3D reconstruction technique such as LADAR and (2) the tolerance specifications as represented by the 3D CAD design file. The files are input into a three stage algorithm,

1. Preprocessing: involves converting the input 3D imaging files into a standard point cloud format and object of interest isolation from the as-built cluttered point cloud.

2. Registration: begins by importing the two input point clouds into a common 3D space. Since the input files do not share a common origin, they need to be aligned through a combination of course registration using principal component analysis and fine registration using iterative closest point (Bosché 2012; Besl and McKay 1992)

3. Dimensional non-compliance detection and quantification: analyzes the deviations between the superimposed files using a 3D cube local neighborhood-based metric and outputs discrepancies between the two files in a number of different formats (ex. rotation at joints, extensions/contraction of members) depending on user preference.

The experimental study that validated the method within the paper used ideal as-built data with complete surface coverage of the object of interest.

1.5 Practical Implications of Tool Implementation

Transferring knowledge and technology from universities to industry is extremely challenging because of the inherent gap between basic research at universities and industrial exploitation (Griffiths and Röhrbein 2013). University-industry collaborations attempt to increase and test the robustness of basic laboratory proven technologies to ensure their suitability for application in complex industrial environments. If applied in a fabrication facility, an automated dimensional compliance checking tool would need to be capable of generating meaningful outputs from non-ideal data inputs. Non-ideal data collection conditions and resulting incomplete point cloud inputs are an unfortunate reality because of: random assembly occlusions causing blind spots in sensing setup, budgetary constraints limiting the purchase of sensing equipment/viewpoints, and random hardware or software failures resulting in corrupt data (Seversky and Yin 2012).

In order to progress the tool presented in (Nahangi and Haas 2014) towards application in industry, its ability to accurately detect and quantify dimensional non-compliance from incomplete point cloud inputs should be evaluated.

2 METHODOLOGY AND EXPERIMENT

2.1 Laboratory Setup and Equipment

To evaluate the performance of the methodology proposed in (Nahangi 2015) under incomplete point cloud input conditions, a series of experiments were conducted at the University of Waterloo's Ralph Haas Infrastructure Sensing and Analysis Laboratory. The researchers collected data using a reconfigurable pipe spool (Figure 1), and a FARO LS 840 HE (Table 1). The pipe spool has custom connections that allow controlled displacements and rotations in order to deviate the assembly from its design compliant state.

Two controlled rotations were introduced into the assembly: 2.5 degrees on Branch 1 (B1) and 15 degrees on Branch 2 (B2) (Figure 2). These rotations simulated a state of design non-compliance that was held constant for 7 laser scans. A plan view layout of the locations of the laser scanner for the 7 laser scans can be found in Figure 1.

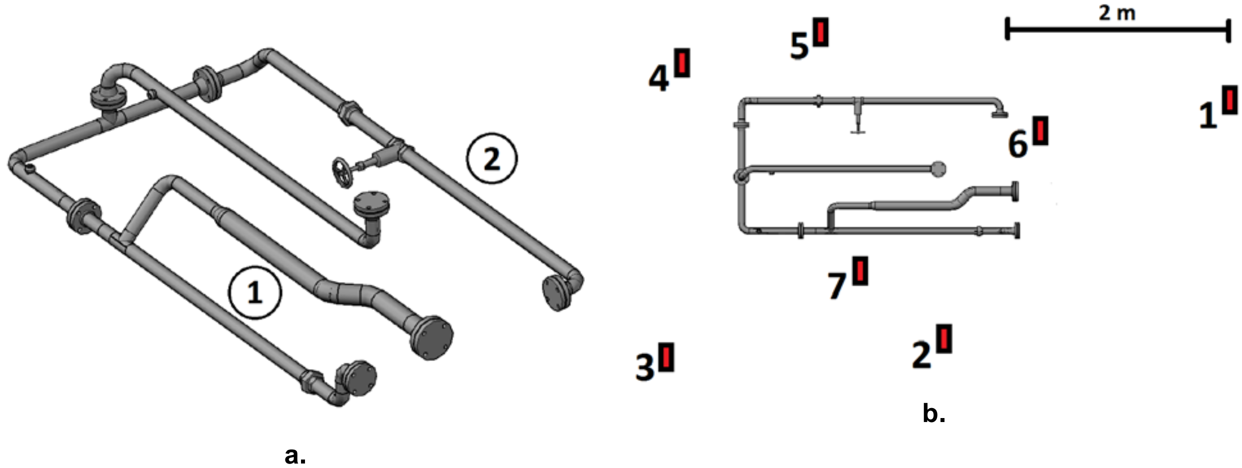

Figure 1: a. Reconfigurable pipe spool with two areas of interest; b. Laser scanner locations relative to pipe spool layout plan view

Table 1: Technical specifications of laser scanner

Laser Properties		
• Power: 10.5 mW • Wavelength: 785 nm • Phase based measurement		
Measurement	**Range**	**Accuracy**
Distance	0.6-40 m	0.6 mm (@ maximum resolution)
Field of View	Horizontal: 360°; Vertical 320°	Horizontal:0.009°; Vertical 0.00076°

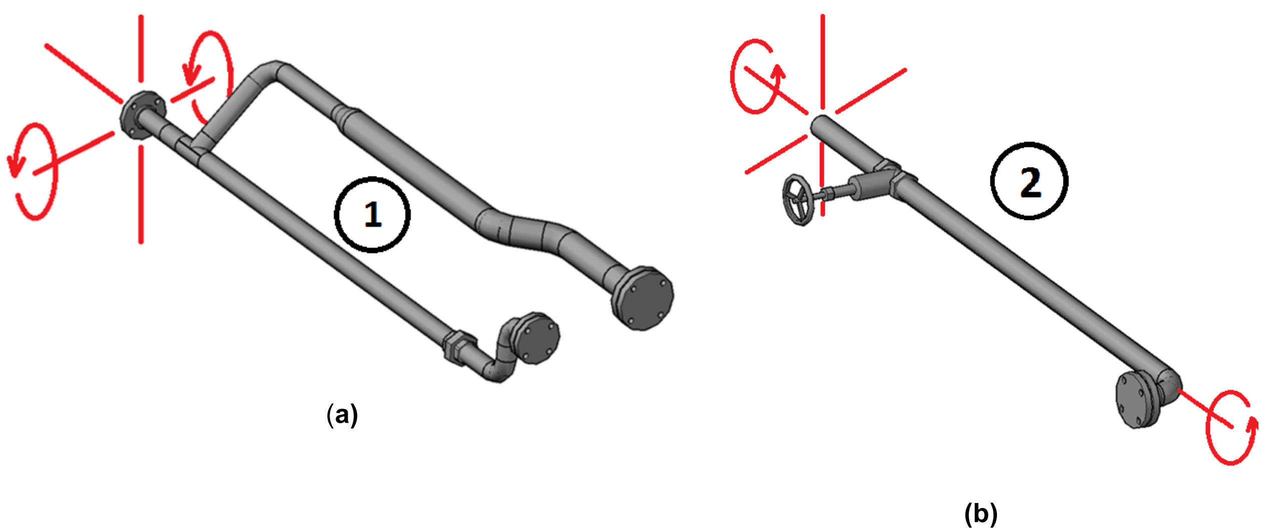

Figure 2: (a) Branch 1 (B1), 2.5 degree branch rotation; (b) Branch 2 (B2), 15 degree branch rotation

2.2 Preprocessing

7 laser scans were collected of the pipe spool in its design non-compliant state. The scans were then merged in different combinations to obtain a set of point clouds with varying pipe spool surface coverage. The point clouds were imported into Meshlab (Cignoni et al. 2014), and through surface reconstruction, a surface area of coverage was calculated and compared to total surface area. Surface coverage is used as a metric for point cloud completeness. The mesh generated from scan 1 data points can be seen in Figure 3. The surface area calculated indicates 44% total pipe spool surface area coverage and 30% surface area coverage of the design non-compliance indicators (NCI) (pipe spool features distinguishing non-compliant state from design state).

Results of preprocessing can be found in Table 2. Total surface coverage ranges from 26% to 100% for the set of point clouds. Point cloud 1 was created by modifying scan 2 to simulate a large obstruction such as a welding screen, occluding half of the pipe spool (Figure 4). In point cloud 3, the NCI for B2 was fully occluded.

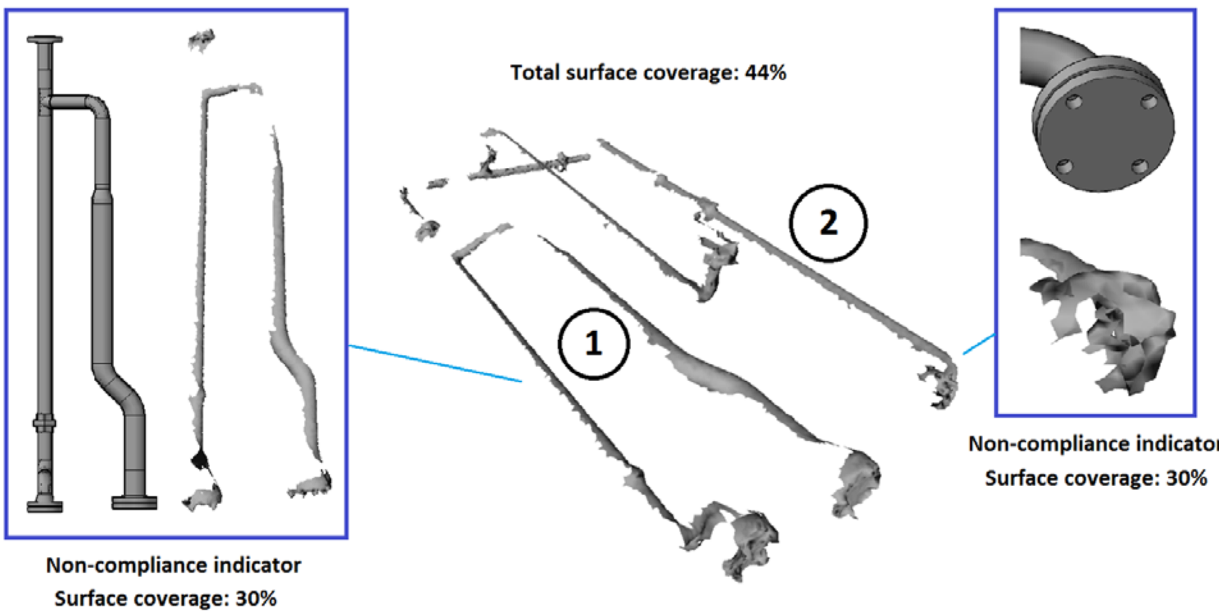

Figure 3: Point cloud 5, scan 1, mesh representing point cloud surface coverage of pipe spool and design non-compliance indicators

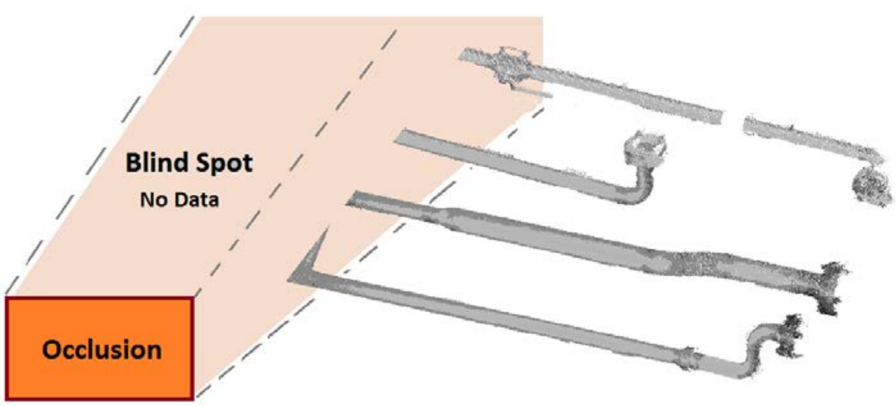

Figure 4: Point cloud 1, scan 2 modified to simulate a large obstruction occluding half of the pipe spool

Table 2: Point cloud surface coverage of pipe spool

Point Cloud	Scan Sources	Surface Coverage: Total	Surface Coverage: B1 Non-compliance Indicator	Surface Coverage: B2 Non-compliance Indicator
1	2 modified*	26%	27%	60%
2	3	33%	13%	30%
3	4	34%	0%	30%
4	2	38%	27%	75%
5	1	44%	30%	30%
6	1,3	55%	52%	61%
7	3,4	57%	16%	67%
8	1,7	58%	52%	84%
9	2,4	60%	27%	80%
10	2,5	66%	34%	65%
11	1,3,4	68%	47%	79%
12	1,2,4	68%	42%	87%
13	2,3,5	74%	53%	88%
14	2,3,6	76%	75%	94%
15	1,2,3,4,5,6,7	100%	100%	100%

*Point cloud 1 modified to simulate a large obstruction occluding half of the pipe spool Figure 4

3 RESULTS

The incomplete as-built point clouds were analysed for dimensional non-compliance using the methodology described in section 2.3. Monitoring both the total surface area coverage and NCI surface area coverage of the pipe pool by the as-built point clouds, the relationship between these factors and the accuracy of the corresponding dimensional compliance assessments was explored. As seen in Figure 5, the detection rate of the controlled rotation in B1 was 100% (i.e. all point cloud instances were able to detect the presence of the rotation). As well, the quantification of the controlled rotation in B1 ranged from 2.41 to 2.53 degrees, representing a maximum error of 4% for point cloud from a single scan, 1.6% from two scans, and 3.2% from three scans (relative to the quantification from Point Cloud 15, 2.51 degrees).

The detection rate of the controlled rotation in B2 was 93%. The point cloud which was unable to detect the rotation had 0% surface area coverage of the B2 NCI and was not included in the quantification stage of the methodology. The quantification of the controlled rotation in B2 ranged from 8.61 to 28.63 degrees representing a maximum error of 90% for point cloud from a single scan, 42.9% from two scans, and 20.9% from three scans (relative to the quantification from Point Cloud 15, 15.08 degrees). All data suggests an inverse correlation between error of non-compliance quantification and surface coverage by point cloud.

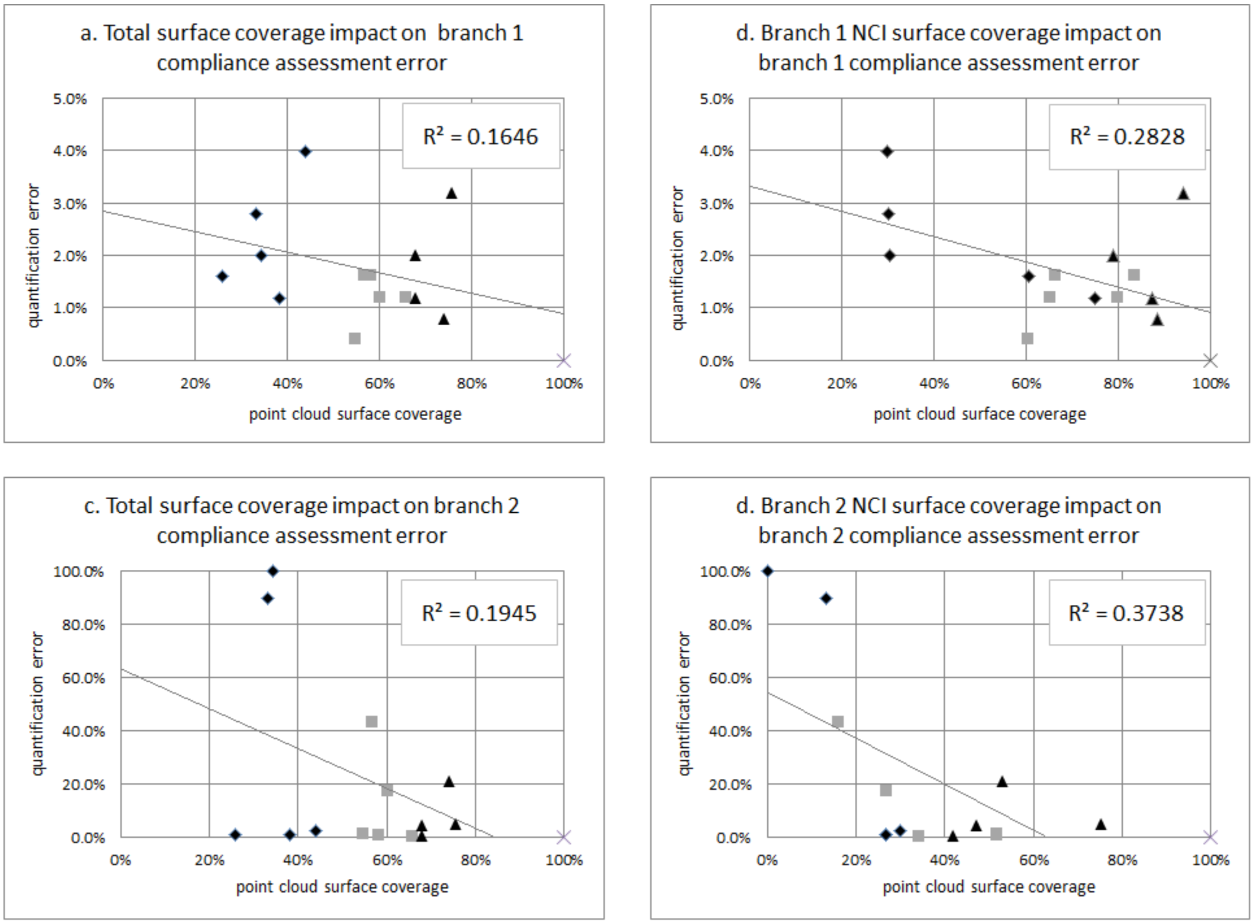

Figure 5: Input point cloud surface coverage impact on non-compliance assessment

conclusions and recommendations

Prefabrication errors are a significant source of costly rework on heavy industrial projects. Researchers have developed and validated dimensional compliance control algorithms that have the potential to improve quality control in prefabrication environments by using data from LADAR and concepts from computer vision. However, these tools need to be subjected to additional rigorous testing for robustness to non-ideal data inputs before successful deployment in the field can be achieved. Several scans were collected of an experimental pipe spool, and a surface area of assembly coverage metric was used to gauge the quality of input point clouds. Processing the data using the methodology described in section 2.3, a relationship between input data quality and the accuracy of detection and quantification of dimensional non-compliance was explored.

The result was a 100% dimensional non-compliance detection rate in the experimental study, with the exception of the case in which the NCI (pipe spool feature distinguishing non-compliant state from design state) was fully occluded. Thus, reliable detection of non-compliance is possible from a single scan, but the output is susceptible to false negatives resulting from assembly occlusion. In order to mitigate this risk and improve the methodology's robustness, at least two scan perspectives should be used to ensure dimensional non-compliance detection.

The accuracy of quantifying the detected dimensional non-compliance improved as the input as-built point cloud's coverage of the assembly's surface area increased. The error of quantification for the rotation in B2 (branch 2 of the experimental pipe spool) was greater than the error for B1 (branch 1 of the experimental pipe spool), which could be attributable to the smaller surface area of the NCI. However, the error in B2 was substantially reduced as point cloud surface coverage increased. Thus if accurate quantification is desired, it can be achieved by using additional scans in the analysis. Quantification in B1 was consistently accurate.

Future work should build on our present understanding of other pertinent variables in the methodology, particularly those involved in the manual portions of the process, in order to better determine the source of error and variability in output accuracy.

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