Adaptive Perception and Modeling for Robotized Construction Joint Filling

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Abstract –

Construction robots must perceive and model their surroundings to compensate for uncertainties in their workpieces. This research investigates a technique to enable the autonomous sensing and modeling of construction objects and features so construction robots can adapt their work plans and perform work. To that end, the Generalized Resolution Correlative Scan Matching (GRCSM) construction component model fitting technique is presented, which registers BIM models to point cloud sensor data. The registration results enable the robot to update its workpiece models to reflect their actual condition. An experiment was conducted in which virtual sensor data was generated for a virtual construction joint, and joint profile models were registered to form a model of the joint. It was found that the GRCSM construction component model fitting technique can be used in combination with a low precision sensor to estimate the pose and geometry of a virtual construction joint with a mean norm positioning error of 1.7 mm. The GRCSM construction component model fitting technique appears promising for the geometric estimation of construction objects, especially for situations involving full automation, detailed construction work, incomplete sensor data, and complex object geometry.

Keywords –

Construction Robotics; Robot Perception; Model Fitting; Construction Joints; GRCSM

1 Introduction

The construction industry is often considered one of slow change, hazardous conditions, old technology, and stagnant productivity levels. Robotics offers the potential to change that by reducing construction project cost, shortening project lead time, improving construction quality, and improving worker safety [1]. However, the construction industry's adoption of robotics has proven slower than other industries, such as manufacturing. This is largely attributable to technological challenges arising from the unique characteristics of the industry [2].

One such challenge is the construction robot's need to perceive its workpieces and adapt its plan in order to reliably perform quality work. In contrast with construction robots, many manufacturing robots are able to perform work with little or no sensing of their workpieces. This is made possible through tight control over the manufacturing robot, its environment, and its workpiece. Such control enables the robot to neglect stochastic variation and leverage a simple a kinematic chain to estimate its pose (i.e., position and orientation) relative to the point of interest on its workpiece.

However, such control is generally much looser for the construction robot. For example, far greater uncertainty exists in the pose of the construction robot relative to the jobsite due to the robot's need for mobility and the high uncertainty inherent in mobile robot pose estimation methods. Similarly, greater uncertainty exists in the pose of the construction robot's workpieces relative to the jobsite due to loose construction tolerances and high process variation. Additionally, uncertainty exists in the actual geometry of the construction workpiece due to such factors as material variation, material deflection, and process variation. Given the high uncertainties present, the construction robot cannot reliably determine its pose relative to the workpiece through a kinematic chain like the manufacturing robot, but rather, must perceive the workpiece in place.

The objective of this research is to develop a means by which a construction robot can perceive and model the workpieces in its immediate environment so it can ultimately adapt its plan and autonomously perform detailed construction work.

2 Related Work

Past research has been conducted in the sensing and modeling of construction objects and environments. Such researchers employed various sensing and modeling techniques for the purposes of project progress monitoring, as-built documentation, material quantity estimation, material tracking, obstacle avoidance, and object manipulation.

To circumvent the challenges and computational burden associated with fitting models and extracting meaning from dense point clouds, Cho et al. [3] proposed leveraging human cognition to assist in the modeling of a construction environment. In this approach, a human selects a geometric primitive (e.g., cuboid or cylinder) or a complex model (e.g., excavator or bridge) from a database and manually aims a laser rangefinder at strategic points on the physical object to obtain individual point measurements. The selected model is then fit to the sparse point cloud. McLaughlin et al. [4] used the same approach, but developed three additional construction workspace model types: partitions, convex hulls, and tight-fitting bounding boxes. Kim et al. [5] applied the aforementioned partition and convex hull methods for such purposes as obstacle avoidance, accident prevention, and material tracking. However, all such variations of this sensing approach rely on human operation, which is not suitable for autonomous applications.

Kim et al. [6] later demonstrated that convex hull modeling could be used in combination with a more automated form of sensing, flash laser distance and ranging (flash LADAR), in which a 2D array of measurements can instantly be obtained by pointing a flash LADAR sensor in the general direction of interest. The approach was only demonstrated with large objects and coarse models for such purposes as obstacle avoidance, and did not include semantic recognition of the objects it detected. Thus, the approach is not suitable for the autonomous recognition and manipulation of detailed construction components.

Stentz et al. [7] developed an autonomous excavator for excavating soil and loading it into a parked truck. The excavator used laser rangefinders for sensing the soil terrain and a nearby truck. A 2D grid of height values was fit to the terrain data and a parametric truck model was fit to the truck data. The terrain model was used to determine where to remove soil and the truck model was used to determine where to dump soil. The approach reportedly worked well, but was only demonstrated with large objects and coarse models. The approach may not be suitable for the manipulation of detailed components.

Work has also been done in the sensing and modeling of small, targeted construction components. Kim et al. [8] scanned individual stones with a combination of projected laser beam and charged-coupled device (CCD). However, the highly irregular stones were simply modeled as cuboids of corresponding principle dimension (i.e., tight-fitting bounding boxes). Kahane and Rosenfeld [9] used a similar projected laser and CCD to measure the gap width between adjacent wall tiles to aid in the placement of tiles by an autonomous tiling robot. Although the gaps were targeted and measured accurately, they were only modeled by a single parameter: gap width. Such simple models may not be sufficient for detailed construction manipulation tasks.

Authors like Sicard and Levine [10] and Kim et al. [11] employed a method called polygonal approximation and syntactic analysis to extract 2D models from weld joint data obtained from a projected laser beam and CCD. In this approach, data points were evaluated one by one and combined into linear segments via polygonal approximation. The segments were then merged according to prescribed syntactic rules used for describing weld joints. However, the syntaxes developed in such studies were only capable of handling a handful of simple joint types because the complexity of segmentation and syntactic rules tends to increase with increasing component complexity. Furthermore, such methods are susceptible to failure under conditions of partial object occlusion and incomplete sensor data.

All of these studies suffer from limitations which inhibit their employment in the robotic perception and manipulation of detailed construction components. Such limitations include the need for human intervention, the lack of semantic object recognition, the lack of modeling detail necessary to perform detailed work, the inability to handle a variety of complex components, and the susceptibility to modeling failure under partial object occlusion and incomplete sensor data. The research described herein seeks to address such limitations by enabling a construction robot to autonomously perceive its workpieces through the fitting of geometrically complex models to sensor data with sufficient fidelity to ultimately adapt its plan and perform detailed construction work.

3 Research Contribution

This paper offers three central contributions. First, this paper introduces a modified search algorithm for such purposes as fitting a geometric model to a point cloud, fitting a point cloud to another point cloud, or fitting a point cloud to a map. Specifically, the modified algorithm is called Generalized Resolution Correlative Scan Matching (GRCSM) and is a generalization of Multi-Resolution Correlative Scan Matching (MRCSM) [12]. Second, this paper introduces a construction component model fitting technique, also referred to as GRCSM, in which the GRCSM algorithm is applied in order to fit a model of a construction component to a robot's sensor data. Lastly, this paper provides an initial investigation into the capabilities and limitations of the GRCSM construction component model fitting technique as a model fitting tool for construction robot perception via experimentation.

4 Technical Approach

This work focuses on the detailed modeling of targeted workpieces for robotic manipulation. Specifically, this work employs a model fitting technique whereby complete models of construction components are fit to point clouds so that contextual meaning can be directly applied to the data. Although the technique can be applied to either 2D or 3D models and sensor data, 2D models and sensor data are used here.

Despite the existence of numerous construction tasks to which such modeling techniques could be applied, construction joint filling is used as an example application in this work due to its commonality across a range of construction activities. Activities such as welding, caulking, drywall finishing, tile grouting, spray insulating, and pipe soldering may be classified as joint filling. In this paper, joint filling refers solely to the placement of filler or sealant material into the joint, although the full treatment of an actual construction joint might require additional tasks such as scraping, cleaning, masking, priming, backing, tooling, and cleaning.

4.1 General Setup

Many interdependent technological advancements must come together to support the successful operation of a construction robot on a real-world construction project. Rather than attempting to address all aspects of the problem at once, this research focuses on a portion of the problem, leveraging the assumption that the other supporting components are also in place. The general setup is described as follows.

First, it is assumed that the construction robot has access to a Building Information Model (BIM) containing the designed geometry of the construction project, which is reasonable considering the rapidly expanding use of BIMs in architecture, engineering, and construction [13]. Second, it is assumed that the robot has been placed, tele-operated, or autonomously navigated in such a manner that it has reached the near vicinity of the object of interest. Furthermore, it is assumed that the robot's pose estimation error is small enough that it can aim its sensor in the direction it expects to find the object, and despite pose errors, still detect the actual object within the sensor's operational window. This is a reasonable assumption considering that today's indoor mobile robots are able to localize themselves on the order of several centimeters and a single degree [14]. Lastly, it is assumed that the sensor is capable of adequately sensing the object of interest. In reality, highly reflective or transparent materials tend to degrade the data quality of many sensors, and specialized sensing modalities may be necessary for such cases. In the experiments described here, materials were intentionally chosen based on sensor compatibility.

4.2 Modeling

In order for a robot to identify or manipulate a construction feature, a feature model is first needed. Construction joints are used as an example here to demonstrate feature modeling. For most construction joints, the majority of the feature's descriptive information lies transverse to the joint. Thus, one modeling strategy would be to model the feature in thin 2D slices and assemble the slices to create a 3D model. Such an approach is employed in this work. Given that the square butt joint is arguably the simplest and most common joint type, it is used as the illustrative example.

The techniques presented in this paper tend to be best suited for situations in which modeling accuracy requirements permit the fitting of fixed models to the data. Given that a joint's primary feature of interest is the gap formed by two construction components, a model in which each of the two component models is free to translate and rotate offers considerable descriptive capability for the gap. Since each of the two individual components has three degrees of modeling freedom, and the gap is defined by a combination of those two components, the gap model has six degrees of freedom. The square butt joint model is shown in Figure 1, where it has been decomposed into an individual component model, a combined component model, a separated component model, and a gap model.

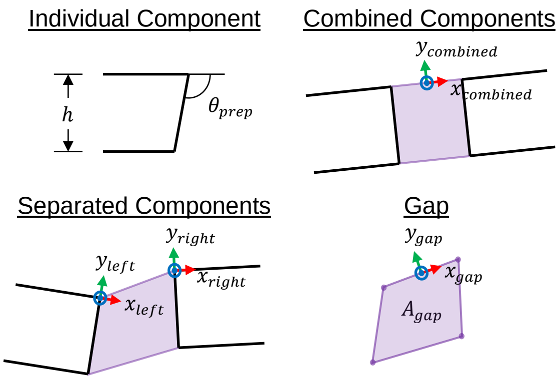

Figure 1. Square butt joint model decomposed into individual component, combined component, separated component, and gap models

4.3 Sensing

A wide range of sensors could be used for the sensing of such construction components. In addition to various modalities (e.g., optical, ultrasonic, laser, etc.), sensors can output data in a range of dimensions (e.g., 2D, 3D, etc.). Since laser data can easily or directly be converted to spatial data, and because the majority of a joint's descriptive information lies in its transverse plane, the authors chose to use a 2D laser rangefinder in this work.

4.4 Model Fitting

In this paper, the authors take the approach of fitting complete models to sensor data so that any contextual meaning associated with the model can be directly related to the data. One of the benefits of this approach is that it does not require sophisticated rules for segmenting data, regardless of the complexity of the model. Another benefit of this approach is its robustness to incomplete sensor data.

The technique presented here for fitting models of construction components to sensor data is referred to as the Generalized Resolution Correlative Scan Matching (GRCSM) construction component model fitting technique. It employs a search method called the Generalized Resolution Correlative Scan Matching (GRCSM) search method, which is a generalization of Olson's Multi-Resolution Correlative Scan Matching (MRCSM) search method [12]. Like MRCSM, GRCSM is a brute force search method that uses multiple resolution levels to quickly narrow a search. However, the two methods differ in that MRCSM performs a search over two resolution levels, while GRCSM searches over any arbitrary number of resolution levels. GRCSM automatically determines and implements the appropriate number of resolution levels based on the specified search window size and desired fit tolerance.

One particular benefit of the GRCSM search method is its immunity to local minima entrapment, which is a well-known issue for search methods like Iterative Closest Point (ICP) [15]. The GRCSM construction component model fitting technique can be generalized to 3D data and 3D models, but is presented here in the context of 2D data and 2D models.

The GRCSM construction component model fitting method is comprised of three primary stages: determining the appropriate number of resolution levels, building a component model lookup table for each resolution level, and fitting the sensor data to the component model by searching for a best fit. The first step in determining the appropriate number of resolution levels is to determine the search-range-to-tolerance ratio r for each degree of freedom (e.g., x, y, and θ), as shown in Eq. (1), where w is the search window size and t is the loosest allowable fit tolerance.

$$r = w/t \tag{1}$$

The number of resolution levels L is then determined as shown in Eq. (2), where s is the search test quantity per level for each degree of freedom and *ceil* is a function that rounds a number up to the nearest integer.

$$L = ceil\left(\frac{\ln(r)}{\ln(s)}\right) \tag{2}$$

The second step in the GRCSM method involves building a component model raster lookup table for each resolution level, starting with the highest resolution table. The table and its entries can be thought of as a uniform grid of cells. The dimensionality of the table corresponds to the dimensionality of the search (e.g., 2D, 3D). The size of the high resolution table is determined along each dimension as shown in Eq. (3), where c is the number of high resolution grid cells. Margins can be added to the high resolution table in integer multiples of s^{L-1}, but c should still refer to the expression shown in Eq. (3).

$$c = s^L \tag{3}$$

The scale q (e.g., $1\ mm/grid$) of a cell along any dimension is given by Eq. (4).

$$q = w/c \tag{4}$$

The component model is then projected onto the high resolution lookup table. If the model already exists as a bitmap representation, or can easily be converted to such form, then it can be directly inserted into the table, provided appropriate scaling. Alternatively, the model's vertices can be projected onto the lookup table and intermediate points can be interpolated between the model's vertices. After a bitmap representation of the model has been established, a probabilistic distribution is applied to the model to reflect the stochastic nature of the sensor, as suggested by Olson [12]. For simplicity, the authors employ a radial Gaussian distribution with standard deviation equivalent to that of the sensor. The bitmap representation and stochastic counterpart for an arbitrarily shaped object profile are shown in Figure 2.

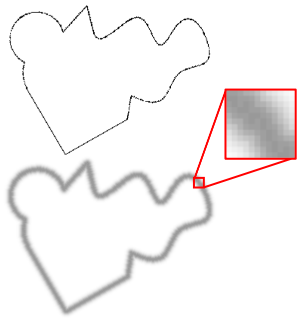

Figure 2. Bitmap (top) and stochastic (bottom) representations of an example arbitrary profile

After the high resolution lookup table is complete, lower resolution lookup tables are produced by iteratively employing Olson's [12] technique for generating a low resolution lookup table. To generate a lower resolution table, the first cell of the lower resolution table is set to the maximum value found in the first $s \times s$ block of cells in its high resolution counterpart. Similarly, the second cell of the lower resolution table is set to the maximum value found in the second $s \times s$ block of the high resolution table, and so on. As such, each new table becomes $1/s$ the size of its higher resolution counterpart. This process continues until L tables, including the high resolution table, are obtained. The lowest resolution table then becomes of size $s \times s$. An example set of lookup tables for an arbitrarily shaped object is shown in Figure 3, where dashed lines have been superimposed on the lowest two resolution levels to help illustrate the process.

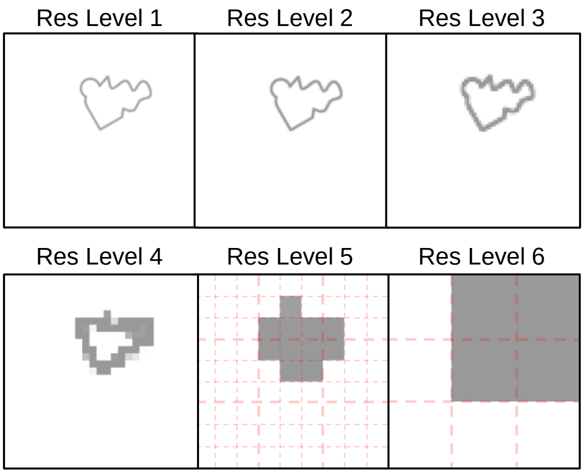

Figure 3. Model lookup tables at various resolution levels for an arbitrarily shaped object

It is expected that such lookup tables may only need to be built once for a construction feature if it possesses a uniformly designed cross section, as is the case for most construction joints.

The third step in the GRCSM method involves fitting of the sensor data to the component model by searching for a best fit between the data and the lookup tables. Using the expected sensor-to-joint pose as a reference, the data points are projected onto the lookup table and the corresponding values are summed to provide a fit score. To start, the data points are transformed and projected onto the lowest resolution table using various pose combinations. For each degree of freedom, the immediate search window i is given by Eq. (5), where v is the current resolution level.

$$i = \frac{qc}{s^{L-v}} \tag{5}$$

The immediate search window is divided into s uniform intervals, such that test points lie at the center of each interval. Similarly, s test points are also created for the other degrees of freedom. The data is then projected onto the table for each of the f^s pose combinations. The table values are summed, and the total fit score is recorded for each combination. The scores are then added to a list, and the pose of highest score is removed from the list and explored at a new resolution level. This process is repeated until the highest scoring pose found on the list coincides with the highest resolution level (Level 1). Such pose is then selected to represent the best fit between the data and the model. An example search process is shown in Figure 4.

Figure 4. Example GRCSM search process showing the best fit results at each resolution level leading to the final fit result

It should be noted that during the process, it is possible to move bi-directionally along the resolution spectrum and jump more than a single level, given that search transitions are dictated by the highest score found in the score list. Furthermore, it should be noted that the scores in the score list have both an associated pose and resolution level. That is, the same pose can be explored at more than one resolution level.

For the case of a single construction component, the GRCSM model fitting process is straightforward. However, for the case of a construction joint, which is comprised of two components, the process occurs differently. First, a combined model is built from the two component models such that their relative pose matches the BIM. The GRCSM method is applied to the combined model. The pose corresponding to the fit of smallest error is selected as the combined pose estimate. The process is then repeated for each component individually, using the combined pose estimate to initialize the search. Furthermore, the search window for the individual components is limited to a fraction of the designed gap width in order to avoid erroneously fitting a model of one component to the sensor data of other components. The resulting pose estimates are then adopted as the component pose estimates, and the joint gap is modeled directly from the transformed component models.

5 Experiment

An experiment was conducted in a virtual environment to evaluate the ability of the GRCSM model fitting approach to estimate the geometry of a square butt joint that deviates from its expected, i.e., designed, geometry. A randomized square butt joint was generated by specifying information about the gap and the two components that comprise the joint. The transverse parameters of the expected joint are listed below, where a, b, and c are counterclockwise rotations about x, y, and z, respectively.

- Gap width (top corner to top corner): 25 mm
- Workpiece thickness: 25 mm
- Workpiece width: 200 mm
- Expected pose in world frame:
  $\bar{x} = 0\ mm, \bar{z} = 50\ mm, \bar{a} = 0°, \bar{b} = 0°, \bar{c} = 0°$

The joint was extended along a third dimension by uniformly spacing two-dimensional cross sections, or slices, along the world y-axis. The joint was made continuous by interpolating between particular slices designated as transition slices. The joint was generated by randomizing various geometric joint parameters. The joint was comprised of 83 cross-sectional slices and took the form shown in Figure 5. Dashed lines denote the joint's 83 cross-sectional slices, and solid lines denote the joint's 12 transition slices.

A virtual sensor was used to generate virtual sensor data of the joint. The virtual sensor was modeled after a 2D scanning laser rangefinder that outputs range and bearing measurements. Loosely modeled after the Hokuyo URG-04LX-UG01, the sensor was assigned bearing increments of 0.352° (10 $bits$) and a range standard deviation of 3 mm. Uncertainty in the sensor's bearing measurement was neglected. The sensor's scan window was set to $\pm 30°$. The virtual sensor scanned the joint while translating along the world y-axis, 250 mm directly above the expected center of the joint. The virtual sensor data was generated by projecting a beam onto the incident joint face, finding the point of intersection, and adding a normally distributed random range error corresponding to the sensor's standard deviation. The resulting virtual sensor data is shown in Figure 5.

The GRCSM construction component modeling fitting technique was then applied to estimate the poses of the two workpieces at each slice along the length of the joint. For the GRCSM search, the fit tolerances for x, y, and θ were set to $\pm 0.5\ mm$, $\pm 0.5\ mm$, and $\pm 0.3°$, respectively. The test quantity per level was set to three, and the search windows for x, y, and θ were set to $\pm 121.5\ mm$, $\pm 121.5\ mm$, and $\pm 45°$, respectively. All computational processing was performed in MATLAB using an Intel® Core™ i7-4900MQ 2.80 GHz central processing unit.

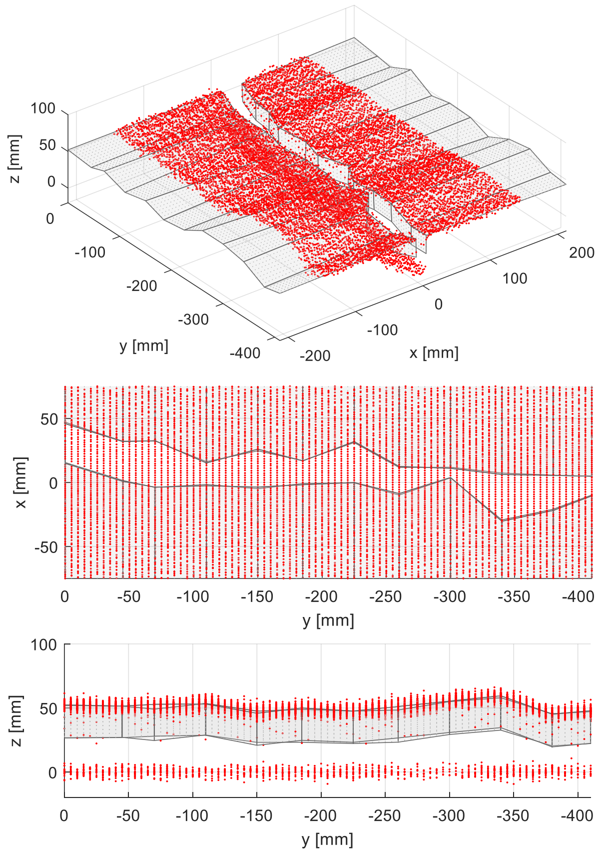

Figure 5. Virtual square butt joint and sensor data

The dataset was processed a second time to provide a comparison between the MRCSM and GRCSM search algorithms. MRCSM was simulated in the experiment by restricting the number of GRCSM resolution levels to two, with an equal number of tests for each resolution level.

Because the gap is defined by the two workpieces, the gap's pose and geometry was extracted directly from the workpiece model results. The 2D gap geometry (e.g., cross-sectional area) was converted to 3D (e.g., differential volume) by projecting the information half the distance between slices in both directions.

6 Results

The gap modeling results for the GRCSM model fitting technique are shown in Figure 6, where the results are represented as a collection of gap pose estimates and differential gap volumes estimates, and the gap origin is defined as the midpoint between upper corners of the workpiece models.

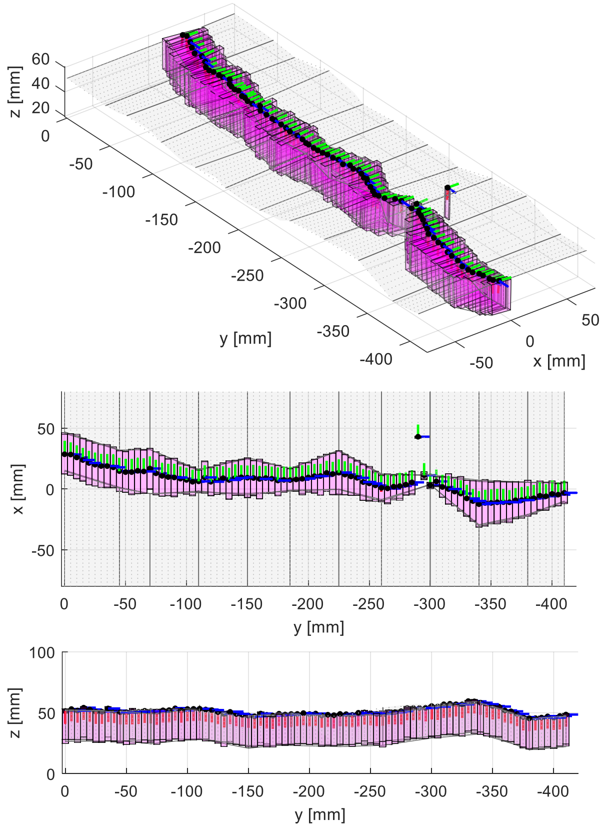

Figure 6. Model fitting results using the GRCSM construction component model fitting technique

The model fitting pose estimation error statistics for the virtual joint are shown in Table 1, and a plot of the estimated poses and differential volumes are shown in Figure 7.

Table 1. Absolute gap pose error statistics

	Min	Max	Mean	Std Dev
$\lvert err_x \rvert\ (mm)$	0.0	37	1.6	4.0
$\lvert err_z \rvert\ (mm)$	0.0	2.2	0.6	0.5
$\lVert err_{pos} \rVert\ (mm)$	0.0	37	1.7	4.0
$\lvert err_\theta \rvert\ (deg)$	0.1	10	2.3	2.0
$\lvert err_V \rvert\ (cm^3)$	0.0	1.3	0.3	0.2

The mean processing time was found to be 0.082 $s/scan$ for the GRCSM component model fitting technique. Additionally, the mean processing time was found to be 630 $s/scan$ when using MRCSM to perform the search, suggesting that the GRCSM search algorithm executed the search an average of 3100 times faster than the MRCSM implementation.

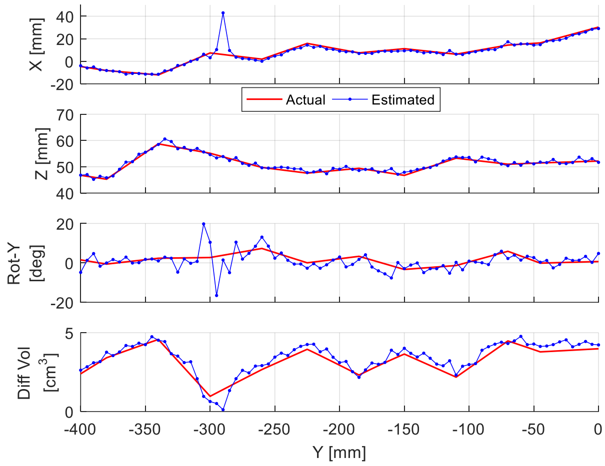

Figure 7. Gap pose estimates using GRCSM

7 Discussion

GRCSM was explored as an alternative model fitting approach to ICP that is free of local minima entrapment. Although ICP is sufficiently robust and accurate for many coarse model fitting applications, the authors anticipate that an entrapment-free approach will be critical for detailed construction tasks, such as welding.

As indicated by the experimental results, the GRCSM model fitting technique appears capable of estimating the geometry of a virtual construction joint. At a rate of 0.082 $s/scan$, the processing time for the entire joint was found to be 6.8 s. This appears reasonable for a real-time scan-and-plan procedure in a real-world construction operation. With further algorithmic and hardware improvements, it is not unreasonable to expect that processing times can continue to be reduced.

This research provides a construction component model fitting technique which enables a construction robot to perceive and model the workpieces in its immediate environment so it can ultimately adapt its plan and autonomously perform construction work. Despite the large uncertainties in robot pose, workpiece pose, and workpiece geometry, this framework enables the robot to perceive the workpiece directly and perform quality work. As opposed to past construction component modeling techniques, this technique eliminates the need for human involvement, provides a level of semantic recognition, offers sufficient modeling detail for detailed construction work, handles a variety of complex component geometries, and offers improved robustness to partial object occlusion and incomplete sensor data. The GRCSM component modeling technique appears to be a promising tool for the geometric estimation of construction components, especially for situations involving full automation, detailed construction work, incomplete sensor data, and complex object geometry.

8 Conclusion and Outlook

The objective of this research was to explore the extent to which a construction robot can perceive and model construction work components, which is a critical step in making adaptive manipulation decisions to accomplish work. This paper began by briefly describing the sources of uncertainty confronting the construction robot and driving the need for component modeling. The Generalized Resolution Correlative Scan Matching (GRCSM) construction component model fitting technique was then introduced to address such a need. An experiment involving the geometric estimation of a virtual construction joint was presented to evaluate the ability of the GRCSM construction component model fitting technique to model construction joints.

It was confirmed that the GRCSM construction component model fitting technique is capable of estimating the pose and geometry of a virtual construction joint. It was also found that the GRCSM search algorithm is significantly faster than MRCSM in executing the model fitting searches described in this paper. However, it was found that GRCSM is susceptible to modeling failure under certain conditions.

Future work is needed to compare the performance of the GRCSM construction component model fitting technique with other model fitting techniques, such as polygonal approximation and syntactic analysis, for construction feature modeling. It may also prove beneficial to explore the use of segmentation in the GRCSM construction component model fitting technique for such purposes as improving robustness to nearby objects. Additional work is also needed to evaluate how the construction component model fitting technique handles cases with multiple similar objects or unexpected objects in the scene. Lastly, additional work is needed to convert a component model into a robot plan and physically execute the plan on a real construction feature.

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