AUTONOMOUS SENSING AND LOCALIZATION OF A MOBILE ROBOT FOR MULTI-STEP ADDITIVE MANUFACTURING IN CONSTRUCTION

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ABSTRACT:

In contrast to stationary systems, mobile robots have an arbitrarily expandable workspace. As a result, the spatial dimensioning of the task to be mastered plays only a subordinate role and can be scaled as desired. For the construction industry in particular, which requires the handling and production of substantial components, mobile robots mean an unlimited expansion of the workspace based on their mobility levels and thus increased flexibility. The greatest challenge in mobile robotics lies with the discrepancy between the precision required for the task and the achievable positioning accuracy. External localization systems show significant potential for improvement in this respect but, in many cases, require a line of sight between the measurement system and the robot or a time-consuming calibration of markers. Therefore, this article presents an approach for an onboard localization system for use in a multi-step additive manufacturing processes for building construction. While a SLAM algorithm is used for the initial estimation of the robot's base at the work site, in a refined estimation step, the positioning accuracy is enhanced using a 2D-laser-scanner. This 2D-scanner is used to create a 3D point cloud of the 3D-printed component each time after a print job of one segment has been carried out and before continuing a print job from a new location, to enable printing of layers on top of each other with sufficient accuracy over many repositioning manouvres. When the robot returns to a position for print continuation, the initial and the new point clouds are compared using an ICP-algorithm, and the resulting transformation is used to refine the robot's pose estimation relative to the 3D-printed building component. While initial experiments demonstrate the approach's potential, transferring it to large-scale 3D-printed components presents additional challenges, highlighted in this paper.

1. INTRODUCTION

In situ Additive Manufacturing (AM) of concrete building components using robotic technologies provides new possibilities in design and function (Wangler et al., 2016). Current solutions for in situ AM are often static gantry systems. They benefit from a contious chain of mechanical links for precise end effector positioning, but they have to be increased in size with the constructed object (Khoshnevis, 2004). While the scale of the system can be adapted to the work volume required, the extrusion system remains unchanged, increasing manufacturing time cubically. Mobile robotic systems applied for AM could address these current limitations, as mobile systems benefit from the use of both a static and dynamic workspace, and can thus can produce structures that are larger than themselves (Sandy et al., 2016). To maintain indepencence and flexibility, however, mobile AM systems are required to gain end effector positioning precision solely through onboard sensing (Buchli et al., 2018).

This paper thus presents an autonomous sensing and localization strategy that, using purely onboard sensing, allows a mobile robot to maintain a high degree of end effector positioning accuracy while changing fabrication positions multiple times during a building task. The strategy is applied to a multi-step AM process of a column formwork, in which the mobile robot is navigated around the column to manufacture the formwork in segments around a rebar core from multiple locations. To increase the positioning accuracy, we give a detailed description of the two-stage localization approach. By conducting preliminary and large-scale testing, we validate that the implemen-

ted two-stage localization can increase the robot's positioning capabilities to enable additively manufacturing of a component. However, it has been observed that the transfer of this approach to large-scale applications to achieve sufficient accuracy from multiple consecutive robot locations will highly depend on the quality of the recorded point clouds and small material deformations.

2. CONTEXT

Localization is a core component in the autonomous navigation of mobile robots and in many applications and has therefore received much attention in the last decades (Panigrahi and Bisoy, 2021). Despite the numerous solutions to localization, there are only a few feasible solutions in AM due to the special requirements in the construction industry. Many approaches, such as Simultaneous Localization and Mapping (SLAM) or GPS, are not applicable due to environmental conditions such as obstructions or contamination, or the required accuracy, in the proposed case to be below $\pm 3.5 \, \text{mm}$. Even when combining several sensor systems like LiDAR, odometry, cameras, and IMUs, the achievable accuracy of about $\pm 5.0 \, \text{cm}$ is far below the requirements of an AM process (Blum et al., 2020). The primary approach to realise the required accuracy in a construction environment is external localization. External measuring systems such as laser trackers or camera systems in combination with markers provide a very high positioning accuracy sufficient for AM (Tiryaki et al., 2019). However, the disadvantages of these external localization methods are the additional hardware and the requirement of a continuous line of sight to the tracking system. Furthermore, camera-based localization also requires sufficient lighting conditions. Considering these

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disadvantages, localizing the robot relative to the produced object offers a way to increase the accuracy of other localization approaches in specific applications. Especially in AM, where the high positioning accuracy is only necessary to position the next layer on top of the previous one, a high localization accuracy regarding the world is not required. Thus, instead of localizing the entire robot precisely in the world map, as is the case with external localization, with relative localization only the print nozzle is aligned with the previously printed segment. To detect the robot position relative to the object, the object detection and localization problem is reversed. With a known object position, the transformation between robot and object is determined to reconstruct the robot position. The object localization can be done in many different ways (Du et al., 2019), whereby especially point cloud based methods are very promising with regard to the requirements in the building industry, including but not limited to lighting fluctuations, dust, or low color contrasts. The point clouds are, for example, recorded with a 3D scanner and then matched using an iterative closest points algorithm (ICP) (Nuchter et al., 2005). Typical 3D laser range finders, especially custom made ones like in (Nuchter et al., 2005), will have an error of at least $\pm 10\,\text{mm}$, which is too high for our proposed application. Instead, we propose to use and evaluate a Keyence LJ-V7200 2D laser profile scanner with an accuracy of about $20\,\mu\text{m}$, which is moved by the robot to get a 3D scan. Our system setup is described in Sec. 3.

3. MOBILE ROBOT SYSTEM SETUP

The mobile robot system we use to validate the proposed two-stage localization is shown in Figure 1 and was previously described in (Dielemans and Dörfler, n.d.).
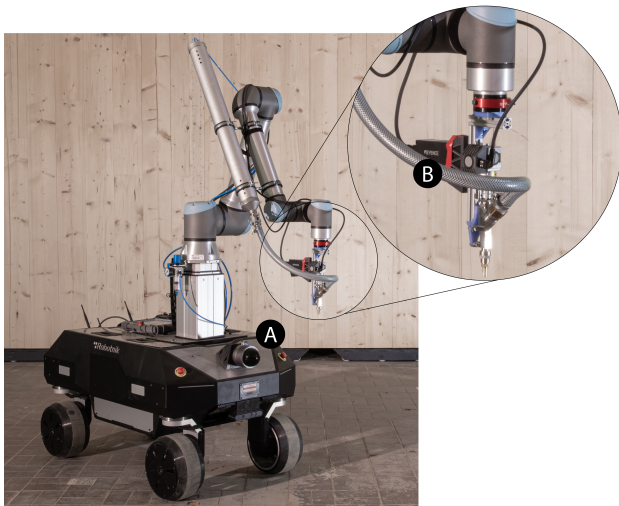

Figure 1. A 9-axis mobile construction platform for clay formwork extrusion equipped with a two-stage localization system comprising a) a Laser Range Finder on the base for rough localization via 2D SLAM in a world map, and b), a 2D Profile Laser Scanner on the end-effector for refined localization relative to the 3D-printed object.

It consists of a Robotnik RB-VOGUI+ omnidirectional mobile platform, carrying a lift axis for an extended workspace in height. A UR 10e robotic arm is mounted to the end of the lift axis for manipulation and printing tasks. The UR end-effector is equipped with a clay extrusion nozzle to enable layer-wise strand application for our research. For experimental printing,

we use a $7\,\text{mm}$ clay extrusion nozzle. The material is supplied by a pressurized cartridge mounted to the second segment of the UR. For the refined robot's base pose estimation, as well as the further control of the manufacturing process, an additional 2D-laser sensor is attached to the printing nozzle. The detailed control algorithm is provided by (Lachmayer et al., 2022).

As shown in Figure 2, the mobile system is supposed to produce a column formwork around a steel rebar cage for lightweight concrete casting, with $2.5\,\text{m}$ in height and $0.4\,\text{m}$ in diameter. As the formwork is stepwise printed, the formwork is also progressively filled with concrete.. While the whole column would fit into the robot's workspace, and thus, no robot repositioning would be necessary, the integration of the rebar cage as the core of the column requires the formwork to be produced around to prevent collisions. Since printing while moving will require significantly higher accuracy during the motion and advanced control solutions, the whole printing process is discretized into segments. Printing will only be done with the platform staying in place. An additional wait time while repositioning the robot is implemented to ensure sufficient material curing.
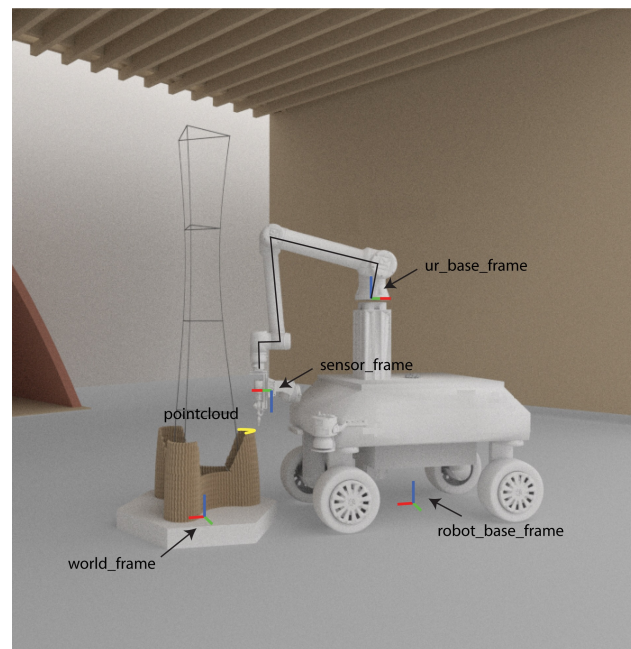

Figure 2. The 2D laser scanner at the robot's end effector is used to estimate the robot's base frame by aligning the two 3D point clouds captured from the 3D-printed object each time after a print job of one segment has been carried out, and before continuing a print job from a new location.

The robot's base navigation system assumes a 2D world for platform localization, expressed in reference to a world frame with the origin defined in an initial map. The base motion planning is based on a planar, wheeled omnidirectional model and an adaptive Monte Carlo localization approach (AMCL). The robot's poses, given as robot_base_frame in figure 2, are estimated by fusing scans from a laser range finder mounted rigidly to the base of the robot with the robot's wheel odometry. The position accuracy of the robot platform using AMCL is approximately

While the onboard localization ensures $\pm 5\,\text{cm}$ position accuracy for the platform, the TCP-positioning accuracy is even

worse due to orientation errors of the platform. In order to ensure the exact placement of the material on the previous and hardened layers, we aim to increase the positioning accuracy significantly. In our proposed case, the TCP-deviation must be below $3.5\,\mathrm{mm}$ to ensure stable printing with the $7\,\mathrm{mm}$ clay strand width. This deviation is mostly acceptable since the centre of gravity of the deposited clay strands will be above the previously printed material. Using the LJ-V7200 2D laser profile scanner mounted to the robot (see Figure 1 and 5) we can create high resolution 3D point clouds, which are later used for the refined localization.

4. METHODS AND DATA

Within the proposed system setup, we are investigating a two-stage localization system, with a) an initial localization through a 2D SLAM for global localization and positioning of the robot's base in the range of $\pm 5\,\mathrm{cm}$, and b) a second refined localization of the robot's end effector relative to the workpiece in the range of $\pm 3.5\,\mathrm{mm}$ through registering the captured point clouds against each other.

As shown in Figure 3, the robot is moved in a circular pattern around the base of the column at previously defined positions P1 to Pn. The mobile robot platform is stopped at each of these predefined positions in order to manufacture a segment of the formwork in a stationary manner. After manufacturing each segment, the robot captures a 3D point cloud from its top layer. When the system returns to that same position to continue the print job with a consecutive segment, localization errors with respect to the world map will shift the robot-base-coordinate system. These inaccuracies are indicated with numbers 3 and 4. Given the typical estimation accuracy of about $\pm 5\,\mathrm{cm}$ of the mobile platform in the world, we can state that continuing printing without additional localization is impossible. To continue printing without manually adapting the print path for the extruder or adjusting the platform position, we are in need of estimating the transformation enumerated as 5 in figure 3. By adapting the robot pose estimation about the inverse of this transformation between the initial printing position and the actual position, automatic realignment of the robot position becomes possible.
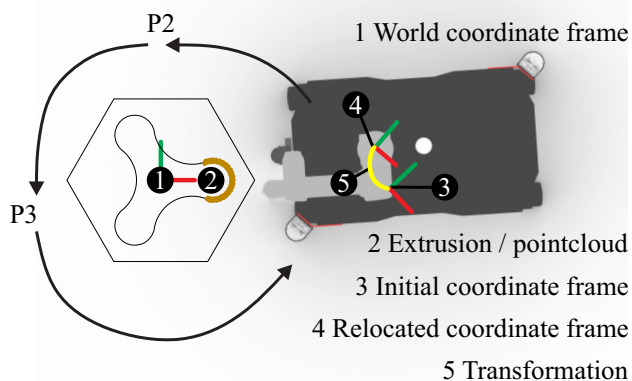

Figure 3. Mobile robot printing workflow with circular positioning around the column and the robot's coordinate frames before and after repositioning at the same location.

The required transformation enumerated as 5 in figure 3 is identified by registering two point clouds of the same printed segment, taken from the initial and relocated robot pose. The data

points are captured with the aforementioned 2D profile laser scanner mounted on the robot arm's end effector. For this purpose, each time after finishing a column formwork segment, the scanner is swept over the last layer of the printed segment in a zig-zag pattern. Sweeping is required since the scanner's high accuracy is correlated with a limited range. While scanning the printed object, the data points are transformed into the robot base frame and stored as a point cloud. After returning to the same position to continue printing, the robot scans the same segment and generates a new point cloud. As Figure 4 shows, the relocated robot pose, enumerated as 4, will deviate from the initial pose. Thus, when combining the initial and the second scan within the initial coordinate frame, they will show severe differences, only caused by the stage 1 localization error of the robot base.
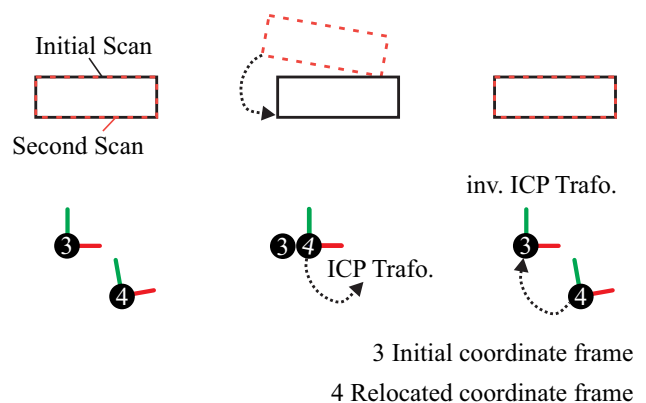

Figure 4. Utilized approach for ICP-based robot position correction

To perform point cloud registration, we use the standard Matlab ICP function pcregistericp, which calculates a rigid ICP transformation between both scans, as shown in Figure 4. Applying the inverse transformation to the estimated stage 1 robot localization will reduce the position error and estimate the robot's base with the required accuracy for contuation of printing. According to our precision requirements, this refined localization must be in the sub-centimetre range, to ensure that the extrusion paths of the segments match up.

We conducted two experiments to validate the proposed 2-stage localization approach's accuracy and repeatability. During the first experiment, we 3D-printed a small scale rectangular column and simulated the robot motion by moving the printed component. The goal was to prove that the proposed approach can achieve the required accuracy. For validation of the resulting positioning correction transformation, we were tracking the movement of the printed object utilizing an external measuring system. In a second experiment, we applied the approach to real manufacturing conditions. In this second case, the robot manufactured various segments of the large-scale vertical column as shown in Figure **??**. Subsequent to extruding one of the discretized segments, the robot is navigated to a new location according to the predefined sequence and manufactures another segment from that location. Afterwards, the robot returns to the initial position using the AMCL. Rescanning the printed segment and comparing the ICP results with the external measurement will show the applicability and challenges when scaling the approach.

It has to be mentioned that within our second experiment, the integration of the rebar cage as the reinforcement core of the

column requires the robot to produce each column segment with moving around the core. Including this movement was particularly chosen to examine the algorithm's capabilities and to assess its manufacturing applicability over several navigation and localization manoeuvres as required in large-scale processes.

5. RESULTS

5.1 Experiment 1

The first experiment was conducted at small scale to validate the actual functionality of the two-stage localization approach. For this purpose, a downsized column section was printed and a 3D point cloud was captured by moving the laser scanner above the object. As a sensor, we used the above described Keyence LJ-V7080 2D laser scanner, which is attached to the end effector as shown in 5. The scanner has a resolution in height of $20\,\mu m$ and records 800 data points over a width of $80\,mm$ with a frequency of up to $1\,kHz$. The recorded points were transformed online into the robot base frame as depicted in Figure 2.
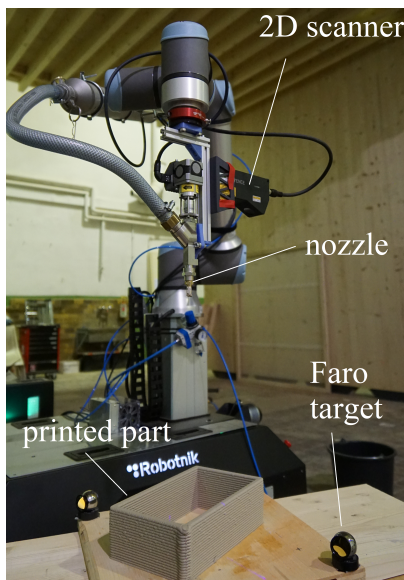

Figure 5. 3D-printing setup for the first experiment of preliminary localization validation.

After having finished the capturing of the first point cloud, we manually moved the print plate with the printed component to emulate the robot's movement. We then rescanned the printed object and received the second point cloud. Both point clouds are shown in Figure 6. The transformation matrix was calculated using the Matlab internal pcregistericp function. To compare the ICP result to more accurate object translation and rotation values, we equipped the printing plate with three Faro Vantage Lasertracker targets, and their positions were measured before and after moving the object. Merging each three measured data points allowed us to determine the pose of the printing plate.

Furthermore, we used two points to construct an x-axis. Giving the printing plane and one axis is enough to determine the definition of the y- and z-axis. Comparing the resulting two coordinate systems, one before and one after the movement, enables calculating precise shifting and rotation values between the two printing poses.
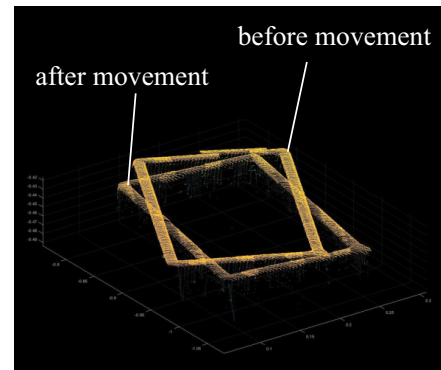

Figure 6. Recorded point clouds from small-scale experiment before and after moving the print plate.

Besides the position correction values from the ICP algorithm, Table 1 shows the resulting Faro Vantage transformation from the two externally measured coordinate systems providing ground truth. Since the external measurement and the approach used via the ICP provide a comparable translation and a similar rotation, we assumed our two-stage approach to be sufficient for localizing the robot in the subsequent printing process of large-scale components.

Trans., Rot.-XYZ	Transformation ICP [cm, °]	Transformation Faro Vantage [cm, °]
X	2.898	3.000
Y	0.374	0.000
Z	0.021	0.010
Distance	2.920	3.000
X	-0.084	-0.070
Y	-0.080	-0.072
Z	17.282	17.73

Table 1. Transformation value results from small scale testing, comparison between ICP and external measurement.

5.2 Experiment 2

We adapted the setup during the large-scale tests and added additional positioning markers to the printing plate. In combination with the robot's onboard measurement tip, we were able to compare the robot pose estimation from the ICP alignment with the measured pose via the markers at each of the printing poses for each of the segments. The initially printed segment is shown in Figure 7.

Figure 7. First printed segment.

Its corresponding point cloud of the printed column segment is shown in Figure 8. For orientation, the printed segment matches the extruded part enumerated as 2 in Figure 3.
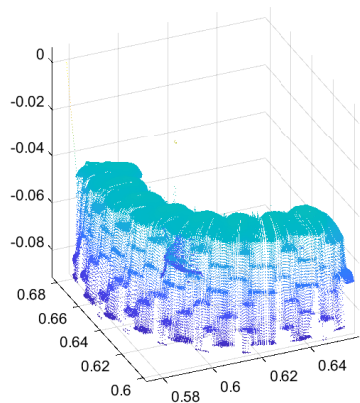

Figure 8. Initial point cloud of the first printed segment transformed to the robot base frame.

As shown in Figure 9, the simple application of the pcregister-icp to the first set of raw point clouds results in a slight tilt about the x- and y-axes. While this does not significantly affect the RMSE of the registration, it leads to a severe tilt and shift in the correlated base coordinate system. In particular, translation values in the z-direction in the range of cm appear. However, neither rotations about the x- and y-axis nor translation in the z-direction are sensible when handling a ground-based mobile platform on a flat ground. Therefore, the ICP was adapted so that only the displacement in the X- and Y-direction and a rotation about the Z-axis are available for point cloud registration. While this reduces the registration to a 2D shifting, we maintain 3D information for error calculation.
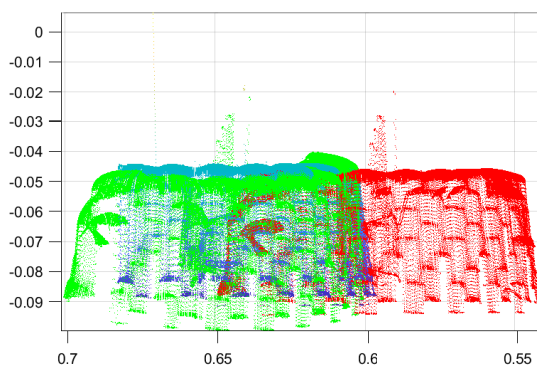
adjustment in comparison to the measured displacement of the robot base using the positioning markers and the robot's measurement tip. While the ICP alignment itself is highly precise and the correction values indicate the right direction, the accuracy has not yet proven to be sufficient to correct the robot pose within one movement. This behaviour does not fully correlate with the results of our initial small-scale experiment, in which not the robot but the printed part was moved. The main other difference between the two experiments are the scale of the scanned objects and more differences in the correlating point clouds.

Trans., Rot.-XYZ	Transformation ICP [cm, °]	Transformation Markers [cm, °]
X	-2.690	-1.000
Y	6.160	4.700
Z	0.000	-1.200
Distance	7.330	4.952
X	0.000	0.125
Y	0.000	1.006
Z	-8.430	6.305

Table 2. Transformation matrix results from the scaled testing of experiment 2, comparison between ICP and marker measurement.

Furthermore, the printed clay slightly shrinks and deforms due to the drying, and thereby, additional translational and rotational influences are added to the ICP-Transformation. The robot positioning does not induce this point cloud variation, and thus, it must not be compensated to ensure correct robot positioning. The effect can also be seen in figure 10 by the decreased radius of the primary point cloud (blue) and the missing part on the lower front of the secondary point cloud (red). The part in front is not covered by being captured from a slightly different robot pose, as induced by the localization error of stage 1.

Figure 9. Initial point cloud (blue), point cloud after repositioning (red) and transformed by ICP (green)
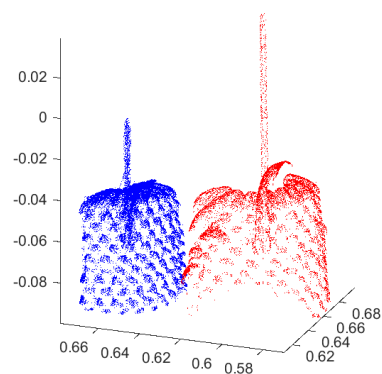

Figure 10. Initial point cloud (blue), point cloud after repositioning (red) with additional material and rebar in the back ground as well as increased radius due to drying deformations of the material.

To additionally constrain the alignment space, the X and Y translations are limited to a maximum of $10\,\mathrm{cm}$ and the rotation about the Z-axis is only valid in a range of $\pm 20°$. With this adaptation, we used the ICP to calculate an improved transformation for the blue and the red point cloud, depicted in Figure 9.

Table 2 shows the resulting translations and rotations using the

6. CONCLUSION

The first small scale experiment results prove the functionality of the proposed two-stage localization in principle. The transformation values from the ICP and the external Faro system determine the same translation and rotation of the robot, and

a position correction with the inverse transformation matrix is possible. Thus, we propose a sensible approach to improving mobile robot localization with a two-stage approach and object oriented positioning. Regarding the printed small-scale object, two main characteristics support our approach. At first, the component, and thus the scanned point clouds, have a flat surface. Thereby, any rotation about the x- and the y-axis will impair the registration quality, and the ICP will automatically avoid those unusable rotations. Furthermore, the rectangular shape provides four explicit corners, which determine the rotation of the z-axis and simplify the identification of the correct angle.

When up-scaling the printed component, as in our second experiment, the point clouds only covered sub-parts of the planned object. As shown in figure 8, this results in a partial representation of a cylinder for the first printing position when manufacturing a column causing multiple additional challenges for the ICP registration.

At first, this cylindrical shape does not allow a clear orientation of the z-axis. Even with a sufficiently large scan of the circular geometry, determining the angle is nearly impossible. Furthermore, the produced component has only a few significant features within the scanned area. While the wall structure is visible within the scans, the repetitive pattern allows for shifting without affecting the resulting registration quality, increasing the difficulty to identify the correct z-angle.

Besides the challenging rotation identification, the applicability of the presented approach is influenced by the drying deformations of the material. Significant shrinkage and deformation of the initially produced component during the curing process cause a translation in the z-axis. This prevents an exact match of the primary and secondary scans, which effects the determination of the correct transformation matrix. We assume this to happen not only for the clay printing process but also for other shrinking materials such as concrete.

At last, when the robot is relocated at a defined position, the AMCL localization of the presented platform can be too inaccurate to produce a useful point cloud with sufficient component coverage. If the data recorded after the relocating only shows a small section of the original scan with low feature density, this results in high agreement at various points and correspondingly many shallow local minima in the ICP algorithm. However, the high accuracy of the utilized scanner is required to achieve the overall required positioning accuracy based solely on onboard sensing.

7. OUTLOOK

As the initial results from the small-scale experiments demonstrate the applicability of the two-step localization approach, future work will address the scaling challenges encountered. While the high precision of our scanner ensures the point cloud quality, the use of larger point clouds by digitizing larger sections of the components seems promising to capture more features. By additionally implementing more practical limitations to the ICP, stabilization in determining and refining the transformation matrix is also aimed.

On the other hand, integrating an additional sensor system to improve the AMCL can refine the relocated positioning. Resulting in a three-step positing approach, the initial deviation

between the recorded point clouds could be reduced further and help to ensure correct translation and rotation values for components with low feature density. In particular, the weighting of the high precision scanner data with a lower-resolution system such as a camera image is a significant challenge to be investigated for the use-case of mobile robot AM.

8. ACKNOWLEDGEMENTS

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