Monitoring of 3D concrete printing quality through multi-view RGB-D images

Ahmed Magdy Ahmed Zaki[1], Marco Carnevale [2], Hermes Giberti [2] and Christian Schlette[1]

[1]SDU Center for large structure production, University of Southern Denmark, Odense Denmark
[2]Dipartimento di Ingegneria Industriale e dell'Informazione, University of Pavia, Pavia, Italy

ahza@mmmi.sdu.dk,marco.carnevale@unipv.it,hermes.giberti@unipv.it,chsch@mmmi.sdu.dk

Abstract -

Large-scale 3D printing using concrete is a promising technology in the construction industry. In recent years, with the introduction of new commercial products and some real-world building projects, 3D concrete printing is moving from experimental and lab-scale applications towards regular construction operations in the field. In this paper, a solution for quality monitoring of 3D concrete printed structures after printing is shown. The solution is based on the use of multi-view RGB-D images captured using a low-cost stereo-depth camera. The objects considered in the paper are 3D printed using a gantry 3D concrete printer. The object scanning process is described. Then the 3D reconstruction of the printed structure 3D model is explained. Finally, a quality assessment technique to evaluate the accuracy of the printed structure is introduced. This technique to quantify the printing error, compares the reconstructed 3D model of the actual state of the print and the CAD model used in the printing planning.

Keywords -

3D printing, concrete additive manufacturing, 3D vision, multi-view reconstruction

1 Introduction

3D concrete printing (3DCP) is a highly growing trend in the construction field [1]. This is due to the many advantages of 3DCP in comparison to traditional techniques [2] as it increases construction speed, decreases material waste, and enhances flexibility to construct complex shapes without the need for specific and expensive formwork.

On-site, the printing quality is highly dependent on many factors. The most important of them is the operator's experience in setting up the machine and dialing the right fundamental printing parameters - i.e. the movement speed and material flow rate, which accurately match the used material mix and the current environmental conditions such as temperature and humidity. Additionally, the printing quality can be affected by basic machine accuracy and fluctuations in the quality of the extruded material and external factors.

Post-printing quality monitoring is necessary to evaluate the mechanical characteristics of the print. The presence of extra material, material leakage, first layers tearing, or layers closure pattern can affect the object's geometrical accuracy.

In literature, many research works have focused on technological aspects related to the optimization of the printing process like the construction of the printing machine itself which could be a gantry system or robotic manipulators. Other investigated problems are the optimal material mix, finding printing parameters, and evaluation of mechanical characteristics of the printed parts at their wet and hardened states. While there is a lack of systematic approaches that defines the necessary tools and methods to monitor and evaluate the 3D concrete printed objects.

The goal of this paper is to introduce a methodology for quality inspection of 3D concrete printed objects. This is achieved by quantifying the printing error of cured prints by comparing their reconstructed 3D model "as-built" from multi-view RGB-D images against its initial CAD model "as-planned" which was used for the generation of movement commands for the printing process. In figure 1, an example of the multi-view images of a polygon-shaped 3D concrete printed object are shown. These images are used to reconstruct the 3D model shown in figure 2 that could be compared with the object CAD model for error assessment.

Figure 1. Example of multi-view images

The paper is structured as follows. In Chapter 2, related work is summarized. In chapter 3, the 3D reconstruction

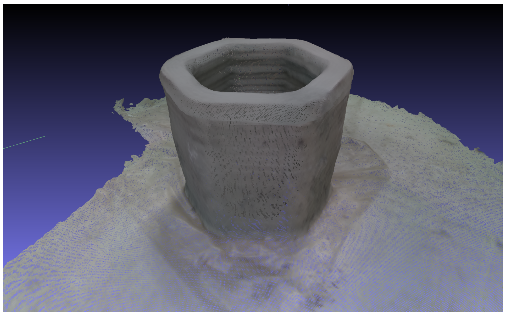


Figure 2. Output: 3D model

technique and the 3D model elaboration are described. In chapter 4, the experimental setup and test results are shown. In chapter 5 the conclusions are shown.

2 Related work

In the field of 3D concrete printing, few systematic approaches were proposed for digital quality inspection of the printed objects. While in the construction field, digital measurement tools are becoming essential for quality evaluation. Several techniques [3, 4] were introduced for quality evaluation based on the use of multi-view images and point clouds of concrete buildings and roads.

The most used form of digital information is the point cloud [5], that are used for several purposes such as 3D model reconstruction, geometry quality inspection, and construction progress tracking. These point clouds are mostly captured using laser scanners or being generated elaborating images or videos of the considered object.
Laser scanner [6] and structured light sensors [7] are the most used in application requiring accurate measurements. These sensors present some limitations like high prices and low portability due to their big size.
Recently, computer vision-based quality monitoring techniques are gaining popularity thanks to the fast development of low-cost, accurate, and small vision sensors and the development of machine learning techniques. These machine-learning techniques are mostly based on the elaboration of color images.
Techniques based on the 3D reconstruction using multi-view images are commonly used for quality monitoring in civil infrastructures, for example, roads [4, 8] and building [3, 9], having big dimensions where low accuracy margin is acceptable. While for more accurate quality inspection multi-view solutions based on laser scanners are preferred [10, 11].

In our previous paper [12], we have discussed two 3D reconstruction techniques based on the use of multi-view RGB-D images. These images are captured by a low-cost stereo depth camera (Realsense D415 camera) attached to the end-effector of a six-axis collaborative robot. One of the introduced techniques, odometry-based technique, does not require previous pose knowledge at each viewpoint. It is based on the estimation of the 3D camera pose capturing each of the RGB-D images. These poses are then used for the 3D model reconstruction of the covered workpiece visible in the captured images. In the present work, a modified version of the odometry-based technique is applied to reconstruct the 3D model of concrete printed objects. With respect to the previously introduced work, only considering workpiece to be placed within the workspace of a robotic manipulator, in the present work the algorithm has been modified to be able to deal with bigger objects (typical of 3D printed concrete structure) and a higher number of images.
In this paper we propose a quality monitoring technique based on the comparison between the reconstructed 3D model of a 3D printed object and its original CAD model.

3 Multi-view 3D reconstruction and 3d model elaboration

In this section, the approach used for the 3D construction process of an unknown object is introduced. The solution is based on matching the RGB-D multi-view images to estimate the camera pose while capturing every image. Knowing the pose, color, and depth information at every viewpoint of the object, it is possible to integrate all this information to create a 3D model of the object. This technique was initially introduced for indoor scene reconstruction as shown in [13]. A variation of the algorithm has been introduced in our previous works [12, 14]. The proposed solution, in the previous papers, is used to reconstruct the 3D model of a workpiece considered in a contact-based robotic application. In the current paper, the algorithm is modified and applied in the field of 3D concrete printing considering relatively bigger objects that are scanned in a higher number of multi-view 3D images. The summary of the proposed approach is shown in figure 3. Step 1 is to capture multi-view RGBD images of the object. Step 2 is to elaborate the images to relate them to common reference. Step 3 is to integrate the images content to reconstruct the 3D model of the object. Step 4 is to extract only the object from the 3D model. Step 5 is to compare the reconstructed 3D model with the CAD model of the object to determine the printing error. The steps are described in details as follows.

To capture several images from different perspectives that cover all the objects or at least the interested area. In this work, the Realsense D415 [15] which is a low-cost 3D stereo depth camera is used.
The D415 stereo depth camera captures the RGB-D images using different sensors. The color image is captured by an RGB sensor having a resolution of up to 1920 X 1080 pixels and is able to capture up to 30 frames per

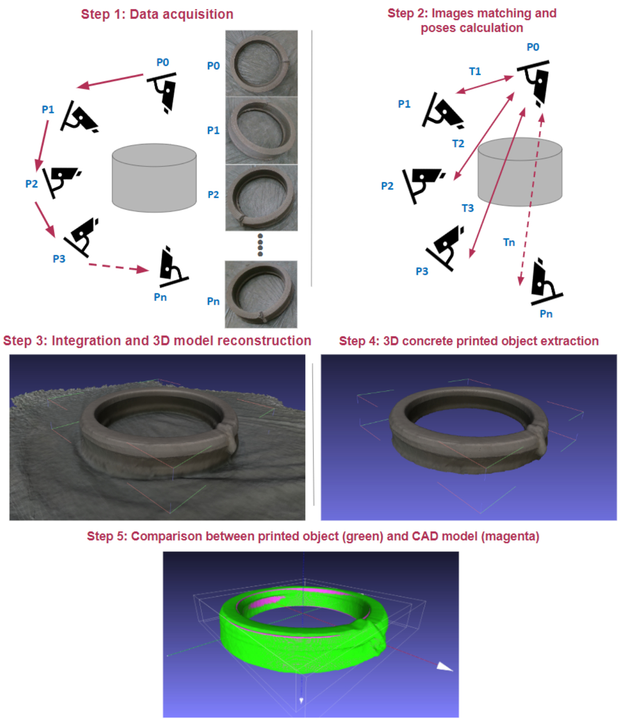


Figure 3. Proposed solution summary

second (fps).
In stereo cameras such as Realsense D415, the depth image is captured using two sensors, and the depth information is perceived by comparing the position of the pixels in the two images. The depth value of each pixel is calculated using triangulation methods considering the known physical distance between the two sensors. The depth image captured has a resolution of up to 1280 X 720 pixels at a frame rate of up to 90 fps.
Due to the fact that the RGB-D images are captured using different physical sensors, it is necessary to align the images. The alignment process consists of changing the parameters such as dimension and coordinate system origin of an image (color or depth) to match the other one. This step is necessary to have both images with the same dimension and refer to the same coordinate system. In such a way, a pixel in one image has the same exact position in the other image.
The multi-view RGB-D images are captured by a moving camera. That means that every image is referred to the camera coordinate system at that moment. The first step in the developed algorithm is the estimation of the camera pose of each image using the RGB-D odometry technique introduced in [16]. Every image is compared to the consecutive one to calculate the pose change.
The estimation of the pose change between two images, consists in the calculation of the homogeneous transformation matrix. If applied to one image, it matches it to the other one like it has been captured from the same position and same camera orientation.
The calculated camera motion matrices, are used to refer all the images to a common coordinate system. The common reference frame used is the frame of the first image. The referring process consists in the use of the camera motions found for every image to refer the content of the image to be with respect to the common reference frame.

3.1 Scanning process and 3D model reconstruction

The quality of the reconstructed 3D model is highly dependent on the input data. The color and depth sensors are set to the maximum resolution of 1920 X 1080 pixels and 1280 X 720 pixels respectively.
The depth measurement accuracy is dependent also on the distance between the observed object and the camera at the moment of capturing the image. For the resolution used, the optimal range for depth accuracy is between the minimum of 450 mm and the maximum of two meters. This range guarantees the accuracy of the readings with errors lower than 2% of the total distance between the object and the camera.

The 3D reconstruction technique used, is based on matching the images and comparing the overlapped parts in them. To guarantee that, the frame rate or the number of images that the camera can capture at every second and the camera movement have to be related to have the time necessary to capture the images covering all the parts of the object without large movement between sequential images. In this work, the camera is moved manually. Where the user moves the 3D stereo depth camera around the object to be scanned and capture RGB-D images of all the interested areas. The relationship between the camera movement speed and number of the RGB-D images captured is explained in our previous work [12].

The considered work-pieces in this paper have dimensions between one meter and two meters, in terms of length and width. The height is lower than 0.5 meters. To reconstruct the required 3D models, a dataset of 100 RGB-D images is used. In case of having a data set higher than the fragment size, the data set is partitioned in patches of 100 RGB-D images or less.

3.2 3D model elaboration and object extraction

The quality evaluation of a 3DCP object, which may not coincide perfectly with the starting CAD model used for generating the printing trajectory, could be done using the explained algorithm for the 3D model reconstruction of the object in its dry state.
The quality evaluation procedure, consists of the reconstruction of the 3D model of the observed scene containing the printed object. The 3D model is then cropped to

extract only the 3D model of the object. The extracted part is then compared to the initial CAD model of the object to evaluate its quality to find the zones having similarities and zones having printing defects. The process in detail is explained in the following.

To extract only the object that we are interested in, it is necessary to make some assumptions about the scanning and the printing processes. The first assumption is that the object is positioned, in most of the RGB-D images, in the center of the covered area. The second assumption is that the printing process happened over a flat surface.

With the first assumption, the search algorithm could consider only the center of the constructed 3D model of the scene. That means only a part of the model has to be analyzed. The second assumption allows us to consider that in the central area could be found the 3D printed object and the floor on which it was printed. Searching in the model for a plane surface (points having the same height and connected together), it is possible to find all points combining the floor. By removing these points, it is possible to obtain the points of the object.

3.3 Registration of CAD and scanned point-cloud

To evaluate the reconstructed 3D model accuracy of the 3DCP object, it is compared with the CAD model. The comparison accuracy depends on the ability to compare an exact point in the scanned point cloud to the exact relative point in the 3D model. To guarantee good comparison accuracy the two point clouds have to be aligned.

Alignment of point clouds, known as the point cloud registration process, is a well-known problem in computer vision and is widely used in construction to compare and inspect buildings, roads, and civil infrastructures using laser scanners or similar scanning techniques. The 3D registration process consists of finding the transformation matrix that if applied to the second model aligns it to the first one and also refers both of the models with respect to the same reference coordinate system.

Different registration techniques can be applied that can be categorized into coarse and fine registrations [17]. Coarse registration is a feature-based technique that matches the features in the two point-clouds. The most used strategies are classified as point-based, line-based, and surface-based. These methods are very accurate but highly dependent on the similarities level of the two point-clouds that is dependent on the sensor noise, scanning point of view, point-clouds density, and geometrical non-conformity due to fabrication process accuracy. To guarantee high accuracy, complicated feature extraction tools may be necessary to develop.

Fine registration techniques are based on approximate iterative processes to find the optimal rigid transformation matrix between the two point clouds. The most used technique is Iterative Closest Points ICP [18, 19] and its variations. These techniques are based on the minimization of positional errors of relative point sets selected from the two point clouds. This implies the necessity for a good initial guess of the rigid body transformation to avoid local minimum problems. Elaboration time is dependent on the point-cloud size.

In the case of 3DCP objects, using the above techniques leads to registration failure for the following reasons. The low geometrical conformity of the printed object due to printing accuracy tolerance. Also difficult to identify features like lines or surfaces in the noisy scanned point cloud. Finally, lack of initial transformation guesses to be used for ICP techniques as the scanning process is done manually and the camera origin is not referred to a known reference frame.

To overcome these limitations, we propose an easy and fast-to-apply registration technique to align the two point clouds based on more general features considering the overall point clouds. These features are the boundary box and the three-dimensional center of the object. Aligning these features allows an alignment of the two 3D models.

4 Experimental setup and scanning results

In this section, the introduced 3D reconstruction algorithm is applied to reconstruct the 3D model of a 3D printed concrete object. The experimental setup used is a modular gantry system 3D concrete printer. As a first step of the analysis, the model reconstruction has been tested with images gathered by manual scanning: a 3D camera is moved around the object to capture the multi-view RGB-D images. Scanning results in terms of the reconstructed 3D models are shown together with an example of accuracy measurement of the reconstructed 3D model.

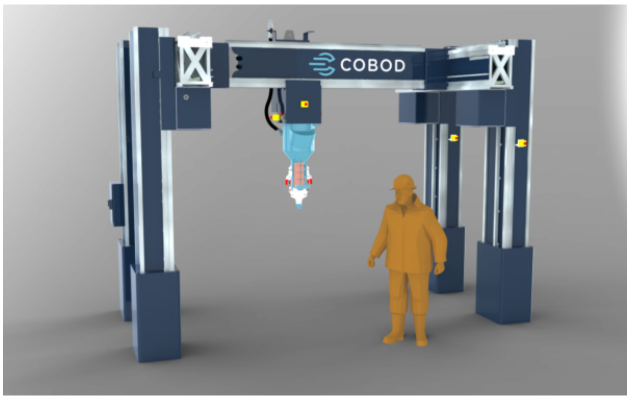
4.1 Gantry systems 3D concrete printer

Experiments done in this paper are done in collaboration with COBOD International A/S. It is a company providing innovative solutions in the construction field combining 3D printing and robotics technologies to automate the construction process. Printing solutions could be based on the use of robotic manipulators or gantry systems.

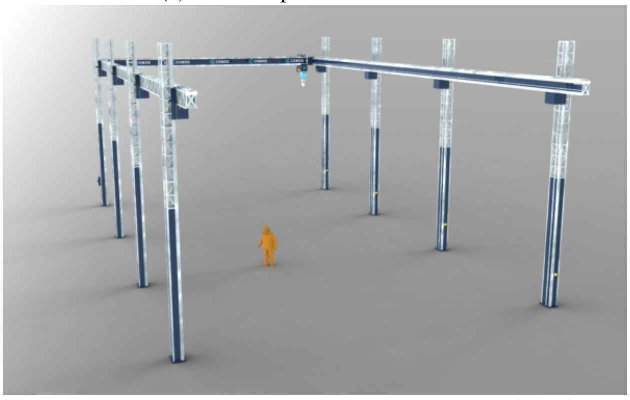
The main product is BOD2 shown in figure 4 which is a modular gantry system that can have different sizes based on the size and shape of the building needed to construct. The smallest version BOD2 2-2-2 has a print area of 4.52 x 4.55 x 3.09 m. The biggest is BOD2 5-10-4 which has a print area of about 12.10 x 24.75 x 8.14 m.

4.2 3D reconstruction results and quality assessment

The 3D concrete printed object conformity with the design ("as-planned" CAD model) is an essential crite-



(a) Smallest printer BOD2 2-2-2



(b) Biggest printer BOD2 5-10-4

Figure 4. BOD2 models `https://cobod.com/bod2/`

rion for its validation, i.e. are mechanical rigidity and the possibility of assembling the printed object to other components highly affected by accurate, conform 3DCP execution according to the planned geometry. To check the geometrical conformity, in this section a 3D printed concrete object is scanned and the proposed 3D reconstruction algorithm is used to reconstruct its 3D model that allows for error quantification.

Using RGB-D odometry technique previously described in [14], a set of 100 color and depth images, similar to those shown in figure 1 for the polygon shape object, are integrated to reconstruct the 3D model shown in figure 2. The developed 3D reconstruction pipeline is applied also to scan the ring shaped 3DCP object shown in figure 5. The ring-shaped object has an outer diameter of 0.8 meters and a height of 0.1 meters.

3D concrete printing process, similar to small dimension and traditional PLA 3D printing process, may lead to geometry deformation related to the first layers adhesion failure or to the layer closure area. The goal is to quantify the highlighted errors in correspondence to the layer closure and first-layer adhesion. The 3D reconstructed model of the object is shown in the sub-figure 6b.

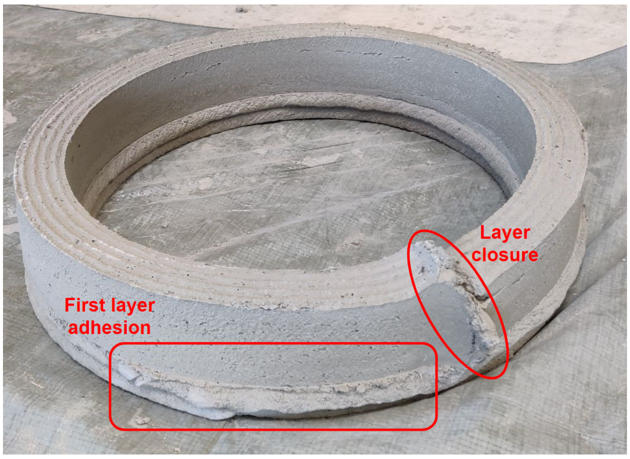
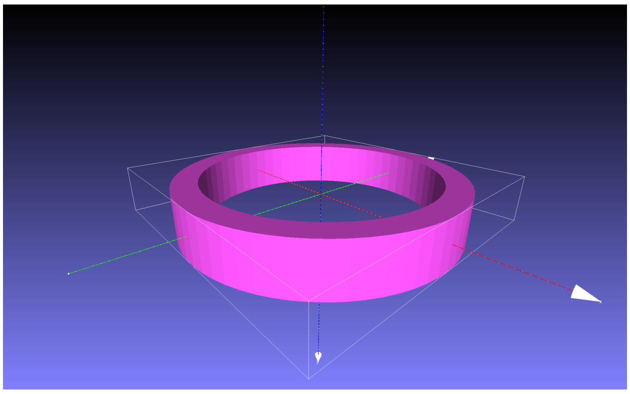


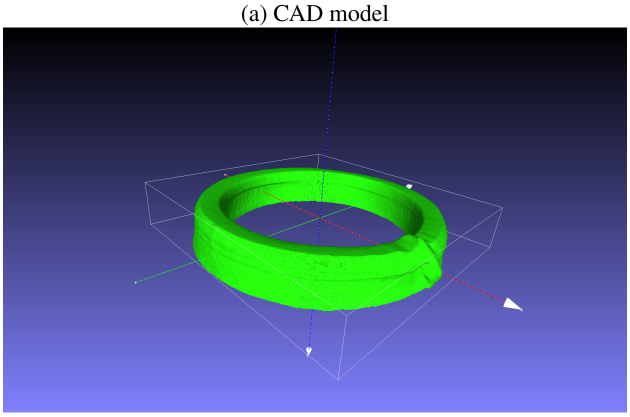
Figure 5. Ring shaped object

Hausdorff Distance is used to compare the 3D reconstructed model of the print's actual result and the ground truth or the 3D CAD model of the object used to generate the trajectory of the 3DCP.
Hausdorff distance measures the magnitude of the biggest printing defect that may cause low resemblance between the printed object and the CAD model. To calculate Hausdorff distance it is necessary to calculate all the distances between relative points in the two point-clouds and find the maximum of them.
To calculate the Hausdorff Distance Meshlab [20] is used. Meshlab is an open-source 3D model elaboration software. It allows us to calculate, between two aligned and down-sampled point clouds, maximum distance (Hausdorff distance), minimum distance, distance mean value, and Root Mean Square error.
The two 3D models of the ring shaped object are shown in figure 6. The sub-figure 6a represents the CAD model or the ground truth to which the reconstructed 3D model shown in the sub-figure 6b is compared.

Comparison results are shown in the figure 7. The Hausdorff algorithm is applied over a total of 159039 relative points. The error is represented as a color-map. Lower values of errors, distances between relative points in the two 3D models, are represented in orange color. Points where higher error occurs are represented slight green while the maximum error is represented by a blue color. For better understanding of the error measurement results, on the left side of the figure, a histogram representation is used to show the quantity of points having different error values. Most of points, especially the points that are part of the upper surface are having the lowest error values. Considering all points, error mean value of 0.0057 meters and error Root Mean Square of 0.0073 meters are obtained. The printing defect in correspondence to the layer



(a) CAD model



(b) Constructed 3D model

Figure 6. Comparison between CAD model and output 3D model of the actual print

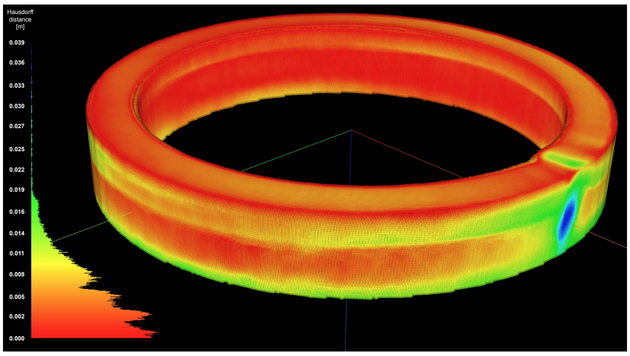


Figure 7. Hausdorff distance comparison applied to the ring case

closure is where the maximum error is obtained. Error value is 0.039 meters. A higher error values are obtained in correspondence to the first layer adhesion failure.

5 conclusion

In this paper, a vision-based approach for the quality monitoring of 3D printed concrete objects is proposed. The solution consists of the use of a low-cost stereo-depth camera to capture multi-view images to reconstruct its 3D model. To quantify the accuracy of the printed object, the 3D reconstructed model ”as-built” is compared to its ”as-planned” CAD model. The developed algorithm for the 3D reconstruction works in two configurations. In the first configuration, the 3D camera is moved manually around the object. This configuration could be used for either onsite or offsite quality monitoring since the camera is manually moved between viewpoints. The second configuration for automatic scanning is mostly used for onsite quality monitoring where the camera is attached to the printer and moved around it to scan the object without the need to move the object from its printing position. The viewpoint in this latter case is generated automatically knowing the position of the printed object. To quantify the accuracy, the reconstructed 3D model and the initial CAD model are compared using the Hausdorff Distance function. Future work is to exploit quality monitoring results to highlight the defects of the 3D printed concrete object and to generate instructions to adjust them, e.g. by controlling the printer to fix-up gaps with additional material or to direct workers to surface finishing and grinding operations where over-extrusion or extra material is present.

References

[1] Guowei Ma, Richard Buswell, Wilson Ricardo Leal da Silva, Li Wang, Jie Xu, and Scott Z. Jones. Technology readiness: A global snapshot of 3d concrete printing and the frontiers for development. *Cement and Concrete Research*, 156:106774, 2022. ISSN 0008-8846. doi:https://doi.org/10.1016/j.cemconres.2022.106774. URL `https://www.sciencedirect.com/science/article/pii/S0008884622000655`.

[2] Ayesha Siddika, Md. Abdullah Al Mamun, Wahid Ferdous, Ashish Kumer Saha, and Rayed Alyousef. 3d-printed concrete: applications, performance, and challenges. *Journal of Sustainable Cement-Based Materials*, 9(3):127–164, 2020. doi:10.1080/21650373.2019.1705199. URL `https://doi.org/10.1080/21650373.2019.1705199`.

[3] Fei Dai and Ming Lu. Assessing the accuracy of applying photogrammetry to take geometric measurements on building products. *Journal of Construction Engineering and Management*, 136(2):242–250, 2010. doi:10.1061/(ASCE)CO.1943-7862.0000114.

URL https://ascelibrary.org/doi/abs/10.1061/28ASCE29CO.1943-7862.0000114.

[4] Laura Inzerillo, Gaetano Di Mino, and Ronald Roberts. Image-based 3d reconstruction using traditional and uav datasets for analysis of road pavement distress. *Automation in Construction*, 96:457–469, 2018. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2018.10.010. URL https://www.sciencedirect.com/science/article/pii/S0926580518304047.

[5] Qian Wang and Min-Koo Kim. Applications of 3d point cloud data in the construction industry: A fifteen-year review from 2004 to 2018. *Advanced Engineering Informatics*, 39:306–319, 2019. ISSN 1474-0346. doi:https://doi.org/10.1016/j.aei.2019.02.007. URL https://www.sciencedirect.com/science/article/pii/S1474034618304683.

[6] Daniel Huber, Burcu Akinci, Pingbo Tang, Antonio Adan, Brian Okorn, and Xuehan Xiong. Using laser scanners for modeling and analysis in architecture, engineering, and construction. In *2010 44th Annual Conference on Information Sciences and Systems (CISS)*, pages 1–6, 2010. doi:10.1109/CISS.2010.5464818.

[7] Kwangwoo Wi, Vignesh Suresh, Kejin Wang, Beiwen Li, and Hantang Qin. Quantifying quality of 3d printed clay objects using a 3d structured light scanning system. *Additive Manufacturing*, 32:100987, 2020. ISSN 2214-8604. doi:https://doi.org/10.1016/j.addma.2019.100987. URL https://www.sciencedirect.com/science/article/pii/S2214860419312023.

[8] Jaeheum Yeon, Julian Kang, and Wei Yan. Spall damage repair using 3d printing technology. *Automation in Construction*, 89:266–274, 2018. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2018.02.003. URL https://www.sciencedirect.com/science/article/pii/S0926580517307392.

[9] Tarek Rakha and Alice Gorodetsky. Review of unmanned aerial system (uas) applications in the built environment: Towards automated building inspection procedures using drones. *Automation in Construction*, 93:252–264, 2018. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2018.05.002. URL https://www.sciencedirect.com/science/article/pii/S0926580518300165.

[10] Jie Xu, Richard A. Buswell, Peter Kinnell, Istvan Biro, John Hodgson, Nikolaos Konstantinidis, and Lieyun Ding. Inspecting manufacturing precision of 3d printed concrete parts based on geometric dimensioning and tolerancing. *Automation in Construction*, 117:103233, 2020. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2020.103233. URL https://www.sciencedirect.com/science/article/pii/S0926580519311070.

[11] Richard Buswell, Jie Xu, Daniel De Becker, James Dobrzanski, John Provis, John Temitope Kolawole, and Peter Kinnell. Geometric quality assurance for 3d concrete printing and hybrid construction manufacturing using a standardised test part for benchmarking capability. *Cement and Concrete Research*, 156:106773, 2022. ISSN 0008-8846. doi:https://doi.org/10.1016/j.cemconres.2022.106773. URL https://www.sciencedirect.com/science/article/pii/S0008884622000643.

[12] Ahmed Magdy Ahmed Zaki, Marco Carnevale, Christian Schlette, and Hermes Giberti. On the use of low-cost 3d stereo depth camera to drive robot trajectories in contact-based applications. *The International Journal of Advanced Manufacturing Technology*, pages 1–15, 2023.

[13] Sungjoon Choi, Qian-Yi Zhou, and Vladlen Koltun. Robust reconstruction of indoor scenes. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5556–5565, 2015. doi:10.1109/CVPR.2015.7299195.

[14] Ahmed Magdy Ahmed Zaki, Marco Carnevale, Hermes Giberti, and Christian Schlette. Digital model reconstruction through 3d stereo depth camera: a faster method exploiting robot poses. *Procedia Computer Science*, 217:1542–1549, 2023. ISSN 1877-0509. doi:https://doi.org/10.1016/j.procs.2022.12.354. URL https://www.sciencedirect.com/science/article/pii/S1877050922024395. 4th International Conference on Industry 4.0 and Smart Manufacturing.

[15] *Intel® RealSenseTM Camera 400 Series (DS5) Product Family Datasheet*. Intel Realsense, 1 2019. Revision 005.

[16] Frank Steinbrücker, Jürgen Sturm, and Daniel Cremers. Real-time visual odometry from dense rgb-d images. In *2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops)*, pages 719–722, 2011. doi:10.1109/ICCVW.2011.6130321.

[17] Liang Cheng, Song Chen, Xiaoqiang Liu, Hao Xu, Yang Wu, Manchun Li, and Yanming Chen.

Registration of laser scanning point clouds: A review. *Sensors*, 18(5), 2018. ISSN 1424-8220. doi:10.3390/s18051641. URL https://www.mdpi.com/1424-8220/18/5/1641.

[18] Jiaolong Yang, Hongdong Li, Dylan Campbell, and Yunde Jia. Go-icp: A globally optimal solution to 3d icp point-set registration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(11):2241–2254, 2016. doi:10.1109/TPAMI.2015.2513405.

[19] Hao Men, Biruk Gebre, and Kishore Pochiraju. Color point cloud registration with 4d icp algorithm. In *2011 IEEE International Conference on Robotics and Automation*, pages 1511–1516, 2011. doi:10.1109/ICRA.2011.5980407.

[20] Paolo Cignoni, Massimiliano Corsini, and Guido Ranzuglia. Meshlab: an open-source 3d mesh processing system. *ERCIM News*, 2008(73), 2008. URL http://dblp.uni-trier.de/db/journals/ercim/ercim2008.html#CignoniCR08.