





Towards Adaptive Additive Manufacturing with Semi-autonomous Robotic Binder Jet 3D Printing of Concrete

Linxiaoyi Wan¹ (✉) , Jingyang Liu¹ , Dana Cupkova^{1,2} , and Joshua Bard²

¹ Carnegie Mellon University, Pittsburgh, PA 15213, USA
linxiaow@andrew.cmu.edu

² EPIPHYTE Lab, Pittsburgh, PA 15217, USA

Abstract. This research proposes an integration of image-based feedback monitoring into a process of additive manufacturing with the aim of expanding 3D concrete printing (3DCP) capabilities toward more diverse material feedstock. Building upon our ongoing research focused on current binder-jetting techniques in 3D concrete printing, we address sequential quality control of printing with coarse powders that advance the adaptation of this technology for sustainable construction with a focus on material reuse. By incorporating an image-based monitoring system into binder jetting, we aim to enhance the adaptability and robustness of 3DCP towards using more variable and irregular powder feedstock from waste streams. A comprehensive dataset, collected over a year and comprising approximately 400 samples, was leveraged to formulate an image-based flaw-detection algorithm. Deep learning training was employed to ensure precise segmentation of printed patterns. The adoption of a dual-resolution imaging strategy further accentuated the quality of data collection and interpretation. Central to our flaw-detection mechanism is a feedback loop framework, designed to discern discrepancies between desired and printed binder deposition pathways. This study proposes an integrated approach of binder jetting with flaw-detection feedback and error rectification within 3DCP, holding a transformative potential for the broader construction technology landscape and material reuse.

Keywords: Construction robotics · Image-based monitoring · Additive manufacturing

1 Introduction

Traditional approaches in binder jetting mostly use fine and highly processed powders, paying less regard to the enormous potential offered by coarse powders, waste derivatives, and composite aggregates. This is primarily due to the difficulty inherent in coarse powder characterization, including their uneven distribution and flow during the automation process. Our study proposes a novel approach toward the automation of binder jetting while integrating an image-based monitoring system.

Our recent study on adaptive manufacturing with coarse powders [1] shared a comprehensive study of material compositions, focused on different ratios of cement, sand, and aggregate within the water-based binder jetting process for 3D concrete printing. It highlighted that the mixing ratio has a great influence on parameters such as binder expansion, penetration depth, and the resultant porosity of the mix. From this finding, we were able to determine optimal layer thicknesses corresponding to distinct mix ratios. This in-depth study of the binder-jetted printing patterns helped us to establish a printing layer structure and the binder-to-material saturation rate to validate the digital slicing model to the physical accuracy of printing with coarse aggregate. Optimization of this process helped us reduce the usage of a binder by 6–17%, as well as the wall thickness of the final product by 28%, and reduce its weight by 28.5%. This approach enabled more accurate printing with different mixing ratios of various powders without any change in the printing parameters of different layers. From our previous analysis, which was limited to a single droplet saturation test and short-line printing test for 3 different materials’ mixing ratios, we established a more precise understanding of binder behavior.

For higher proportions of aggregates in the concrete composite, there is a higher unpredictability in the horizontal expansion of the binder —a phenomenon supported by large variations in standard deviation, documented from our image analysis of droplet expansion in Table 1. The interaction of penetration depth with specific mixing ratios of concrete composite further explains the complexities in the vertical movement of the binder. The observed pattern was a clear indication that a wider spacing of the binder reduced the bleeding pattern and limitations on penetration depth. For example, in all compositions, the concrete mix with the compact aggregate ratio combined with expansive binder spacing showed less bleeding and superficial penetration. The mix with the increased aggregate ratio and narrowed binder spacing showed pronounced bleeding of the binder (see Table 2 for details). This prior work sets the stage for the current research’s trajectory and objectives focused on flaw detection in the printing process of course powders.

Table 1 Single droplet printing test results analysis.

	Material Mixing Ratio (Cement: Sand: Aggregate)		
	1:1:1	1:1:2	1:1:3
Horizontal Expansion Length (cm)	0.663	0.720	0.790
Horizontal Expansion Width (cm)	0.570	0.600	0.670
Horizontal Expansion Area (cm)	0.205	0.225	0.300
Standard Deviation	0.062	0.087	0.103

The flaw detection is addressed by incorporating the image-based monitoring feedback loop. The image-based monitoring in diverse material mixing ratios achieves a dual purpose: it opens up the use of coarse concrete composite powders in 3D concrete binder printing while also introducing a feedback mechanism through computer vision. This

Table 2. Shortline Printing Test Result Analysis.

		Penetration Depth (cm) at Mixing Ratio		
		1:1:1	1:1:2	1:1:3
Saturation Rate	14%	0.3	0.3	0.5
	18%	0.4	0.6	0.8
	22%	0.7	1.0	>1.0

system enhances the flexibility of the printing process which realizes feedback adjustments in binder placements and accentuates the potential for precision in surveilling the expansion of the binder during the printing process.

While the focus of this paper remains on concrete mix applications, these approaches offer insights that show a potential to alleviate the material characterization workload when integrating unconventional powders into the binder-jetting process. Most importantly, our digital image correction pipeline overcomes precision and quality problems that are invariably entailed in heterogeneous mixing materials.

Our study brings out the potential within 3DCP for image-based monitoring, shedding light on an indispensable role in the furtherance of the next generation of adaptive additive manufacturing [1].

2 Situating Research Background

2.1 Robotic Arm in Concrete Digital Fabrication

The technology of binder jetting was first introduced and patented by Emanuel Sachs at MIT in 1993, mixing powders with a water-based binder for printing purposes [2]. Since that time, the application realm of this technology has significantly changed. Many of the advances in binder jetting include contributions from ExOne Co. [3]. Other important advancements are the revolutionary methods like the D-shaped methodology [4] and Voxeljet Company’s take on binder jetting [5] that made it possible to print the details of a much more detailed design with increased print fidelity.

Lloret et al. [6] provide a detailed insight into how traditional casting methods integrate with new digital manufacturing processes to improve and develop difficult concrete structures. Another study shows that through robotic and automatic concrete spraying, the technology has been efficiently contributing to the construction of concrete shells, providing versatility and accuracy in building through the adoption of robotic arms [7]. Central to the use of real-time image-driven monitoring in the procedure of binder jetting is the incorporation of sensory apparatus, including optical, acoustic, and thermal sensors. Inclusion among the important steps is digital image correlation (DIC). In addition, several review works were done in connection with in-situ monitoring of Additive Manufacturing (AM) [8]. Moreover, Reiter and Agustí-Juan put forth guidelines and insights regarding the full range of structural and environmental design considerations in digital fabrication with concrete [9].

2.2 Learning Techniques in Flaw Detection Applications

Detection of flaws through Deep Learning promises to equip the construction industry with more adaptive and innovative solutions that enhance its ability to respond to issues of sustainability. Ozegenel et al. offered a comparative analysis of pre-trained convolutional neural network models in the detection of building crack flaws, an insight into the efficacy of various neural networks and their models for flaw detection [10]. Thier work is comparable to Yukang et al.'s deep-learning-based method for photovoltaic defect detection [11]. Kalfarisi et al. dealt with deep learning for crack detection and segmentation to extract accurate positional coordinates from the 3D reality mesh model, providing a quantitative assessment integrated with visualization to better detect the flaws in construction [12].

Further, an externally automated vision-based structure inspection and defect detection system, using the deep learning technique for UAVs, is an overarching approach to defect detection in such structures [13]. In the construction context, the benefits of security can be realized by employing vision and sensing techniques. For example, some authors have developed a hybrid machine-learning framework for the automation of equipment activity identification and earlier-stage fault detection in its occurrence [14]. Another predictive maintenance framework, with a focus on automatic fault detection and diagnostics, is the role of digital twins in predictive maintenance in construction [15]. Zhang also discusses an automatic method of surface crack detection and segmentation in bridges using a computer vision-based deep learning model, in support of a comprehensive solution to the flaw detection problem in bridge construction [16].

3 Methodology

Our workflow is initiated by establishing a predefined geometric pathway for layer-by-layer 3D binder jetting tasks. A pathway provides a location that gives the exact point coordinates for the robot arm to follow, and ensures that binder displacement is laid out. Meanwhile, a built-in image-based assessment is introduced using the RealSense camera after the robot arm has executed one layer of the binder placements. The camera captures a printed layer result and processes an integrated image-based post-print evaluation.

Central to our methodology is the capability to find and quantify differences from the digital model pathway to the printed output. Our framework evaluates the area of the missing portion against the predefined pathway. The ratio of the missing part area to the area of the current layer should not exceed a determined threshold and needs to be corrected before the framework allows the start of the subsequent printing layer (Fig. 1).

When the ratio of a missing pathway exceeds the limit of the determined threshold, the framework turns into a structured correction phase. First, there is an alignment of the printing pattern that visualizes the output and overlays it with the desired outcome, thus constructing a visual comparison. From this comparison, the differences between planned and actual printing could be extracted for the region of actual printing and its internal features. Subsequently, the detection of the missing areas and the computation of their centroids is executed. The robot arm, armed with this data, realigns its position and provides the binder displacement for targeted corrections. This is an iterative quality assurance process, assuring that every single layer that has been laid down in printing

meets the desired precision and accuracy. With the help of the Robot Operation System (ROS), we were able to seamlessly incorporate the whole process.

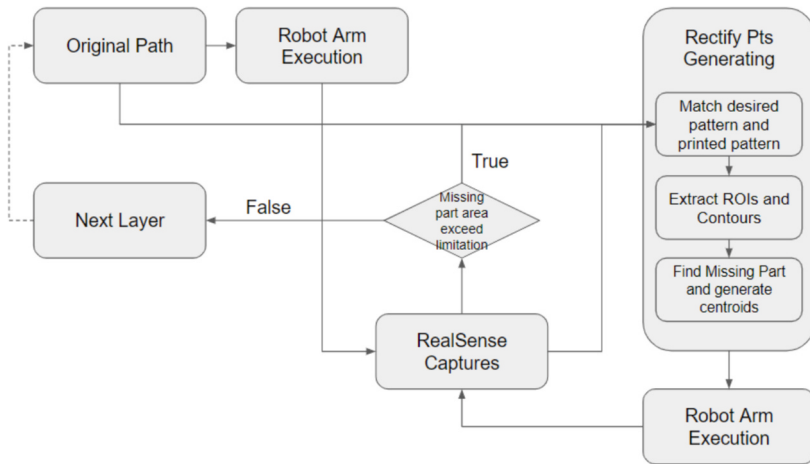


Fig. 1 Pipeline and framework of the whole system.

3.1 Robotic Operation System (ROS) based Simulation Environment Set-Up

ROS Communication System. The Robot Operating System (ROS) [17] has established itself as a powerful middleware for developing complex robotic applications. Our proposed adaptive additive manufacturing system exploits the capability of ROS to lead to seamless integration of the processes of manufacturing, monitoring, decision-making, and flaw rectification (Fig. 2). In this section, we illustrate how the ROS simulator manages communication among disparate nodes.

In this system, the node */amm_node* shall act as the epicenter node, informing the additive manufacturing process by receiving the pathway from geometric files and the rectified pathway from */print_status*. It assures that the result status of the print communicates through the */print_status* topic, and thus ensures all other associate nodes are informed about the current printing result status.

Simultaneously, the */fdm_node* supports dual service. It orders the camera sensors to take images of the printed paths and transmit them to the */layer_image* topic. Concurrently, the */fdm_node* develops an image analysis process with the corresponding pathway to detect any possible missing parts. The information on detected flaws, such as the attributes of contours and their spatial coordinates, is then relayed through the topic */flaw_data*, subscribed to by the node */flaw_detec*. This information is then further processed and rectified before printing centroids with coordinates are generated.

As the decision-making center, the */decision_node* subscribes to the topic */print_status* and */flaw_detecnode*, along with their data streams, to cull out informed decisions regarding the necessary rectification measures. It then propels these actions,

encapsulated as actionable commands, over the `/rectification_command` topic. Finally, the `/rm_node` subscribing to the `/rectification_command` topic will ensure the rectification measures, whether to execute the re-dispensing binder or jump to the next layer printing task.

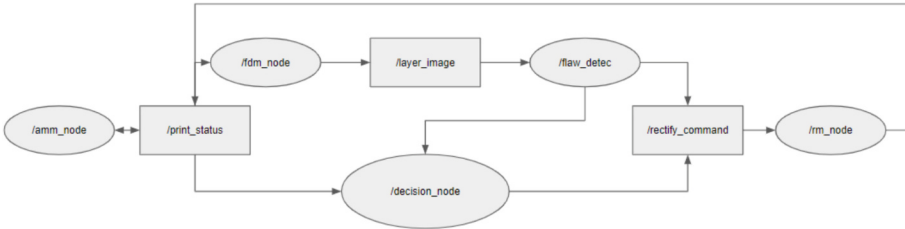


Fig. 2 Rqt graph of ROS nodes and ROS topics workflow integration

ROS Communicates with ABB RobotStudio. Since ABB’s RobotStudio software is not available for Linux, the *abb_driver* [18] enabled communication between RobotStudio and ROS.

3.2 Hardware Development and Set-Up

Our primary contribution lies in interfacing the Arduino-based binder extrusion system with signals from an ABB robot controller to dispense the binder meticulously to each predefined point (Fig. 3). A custom print head accommodates the stack for the RealSense camera placement and a rubber tube is used for passing the binding material into the syringe needle. The needle is located within a 3D printed holder attached to the tool plate of the robotic arm. This setup ensures precision and steadiness during printing operations. The system is also supported by a step motor for controlling the position of the plunger in the syringe, which is the repository for the binder.

For careful orchestration of the motor’s actions, we have set up a system based on Arduino, which interprets the signals from the robot and transmits digital signals to actuate the rotations of step motors, manipulating the plunger. Special framing was devised to limit the range of movement of the rod connected to the plunger. It was set up inline with the step motor so that the force translation from the step motor to the plunger is directionally focused. The system has an extrusion capacity of not less than 0.027 ml/droplet; hence, not less than 0.027 ml of the binding material is ejected from the nozzle. This forces the step motor to rotate for a duration calibrated to the required amount. Other concepts are also included, such as a leveling bed that includes a control system using Arduino. The bed houses a pair of electric actuators interfacing through the button-controlled signals to form a well-interfaced and friendly front for control.

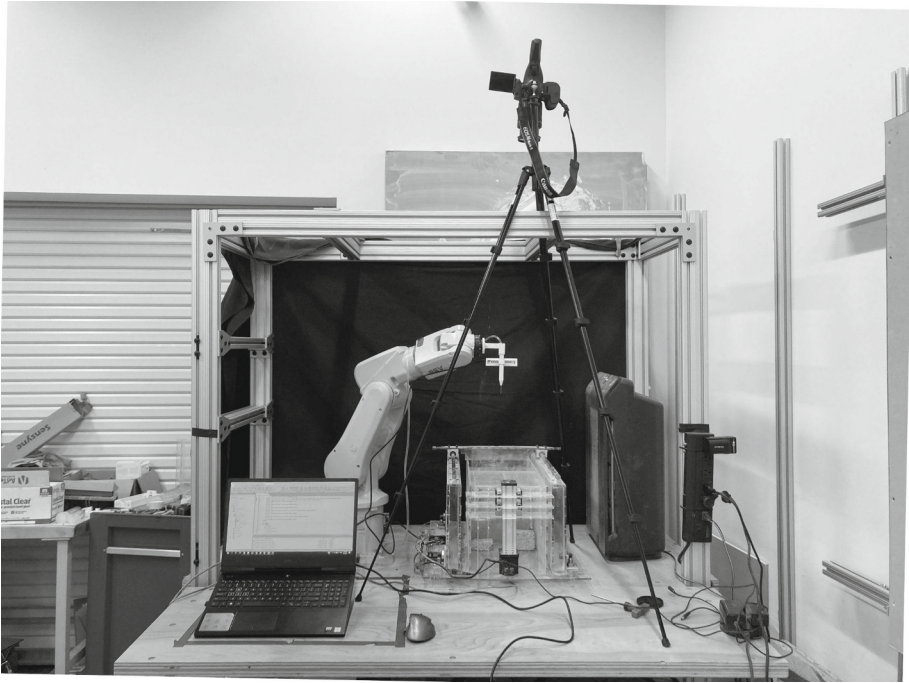


Fig. 3 Lab printing setup [1]

3.3 Flaw Detection Algorithm Development

Data Collection. The concrete mix printing patterns dataset was systematically accrued during a research development that spans one year. During this period, about 30 complex 3D printing tests were carried out so that our water-based binder jetting system could be advanced and further developed. Each of these tests bore a range of layers, minimally 10 to a maximum of 25, aggregating sample size close to 500, representing printed components for every individual layer.

Most of the images were captured using both high and low-resolution output using a dual-resolution technique. In the images, the regions of error were marked to ensure data interpretation exactness. We used custom image masks to identify the visual separation of printed and dry areas. This was the delicate and cumbersome effort of identifying the printed sections manually, where some attributes of the image, such as brightness, contrast, and threshold, were adjusted with great care. Further, we applied morphological operations, particularly dilation and erosion, to improve contour detection with each of the images available in the collection. After this first segmentation, any inaccuracy or abnormality in the masks was corrected by hand to ensure precision (Fig. 4).

During data collection, a slight distortion in photos was also noted. To address this discrepancy, we used low-resolution (1280x720) images, taken through a RealSense camera, as a baseline calibration source for ground truth. This allowed for easy detection of the matching features between the ground truth and the distorted images by



Fig. 4 left: original photo of printed layer; middle: contour detection image; right: manually corrected labeling image.

algorithms such as ORB [19] and SIFT [20]. Eventually, this process was successful, with comparison deriving the transformation matrices. This test showed that the transformation matrices could be used to warp the perspective of distorted images, thereby rectifying the orientation to be congruent with the ground truth.

Deep Learning Model Training for Printed Pattern Segmentation. The difference between the desired and the actual printed path in this research signified that the contour detection phase is crucial to better recognize the different layers of printing patterns. This resulted in an accuracy influenced—for example, by the brightness and contrast—attributes of each captured image. To have this system streamlined towards being able to consistently process such images, we adopted a learning-based approach. The main improvement was made by integrating a deep learning model so that the system was capable of segmenting the contour of the printed part. After some careful consideration, we opted to use the U-Net architecture as it has a proven track record in various segmentation tasks.

The U-Net [21] is a convolutional neural network architecture developed for semantic segmentation with biomedical image analysis. The two major parts of the architecture include the encoder and the decoder. The encoder extracts features of the image from the input. The encoder comprises a convolutional stack followed by max-pooling layers to reduce spatial dimensions. The convolutional encoder, therefore, is designed with the idea of capturing the hierarchical features present in input images at different resolutions. At every resolution of the encoder, the feature maps are upsampled and merged with the corresponding features of the encoder for spatial localization of the segmentation and simultaneously for refining them.

The architecture is built of up-convolutional blocks, which increase the spatial dimensions of the feature maps. The decoder layer is a 1×1 convolutional layer that maps the representational features to the required number of classes and then applies the sigmoid activation to retrieve the segmentation mask. The goal is to train U-Net to minimize the difference between the prediction and ground truth segmentation mask by using, typically, a binary cross-entropy loss (Fig. 5).

Rectify Point Generation. The first stage of flaw detection is related to a careful and detailed assessment of the printed pathway within our image samples. The key focus is a process identification towards successfully printed patterns. The preliminary analysis starts with the comparison of the desired and printed pathways. It is a very important step for which an attempt is made to establish the desired pathway, and results are acquired after detecting and segmenting the pathway in the feedback loop framework so that it helps in finding deviations and anomalies.

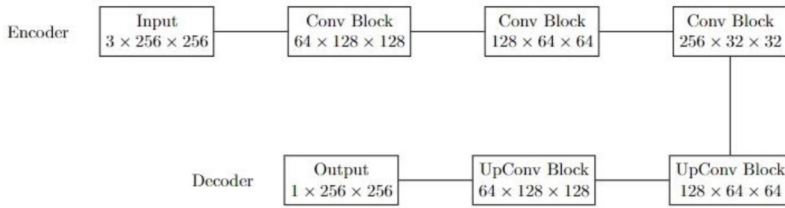


Fig. 5 U-Net Architecture for training.

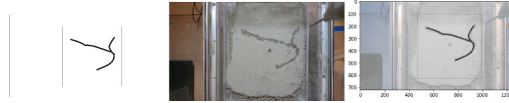


Fig. 6 left: predefined pathway and printing boundary; middle: original picture; right: overlaid picture of desired printing pathway and capture photo. This image registration process enables matching the locations of the desired pathway and the printed pathway in the pictures. Registering the images allows us to match the locations of the desired pathway in the pictures with the printed pathway.

Alignment of features in images further enables feature matching between the digital model and physical print. This alignment of the desired pathway with the printed pathway in the images provides a comparison analysis of the pathways and commences a correction phase. It is important to align the correct lines of pathways with the actual captured lines of the camera. This process was introduced to simplify the previously used complex procedure using a single droplet spreading radius calculation at every layer. The visual approach is instrumental in offsetting the pathway line in line with the spreading radius of the binder with each mixing ratio of materials. Figure 6 illustrates the process of designation for both print areas inside an inner square form and image dimensions in general inside the outer rectangle form. Building on this foundational step, we extracted the range of prints from both: the images of the desired and printed pathways (Fig. 7). This extraction helps in reducing the environmental noise and fosters accuracy in the later process of contour segmentation. The careful alignment and feature extraction bring a more precise result and strengthen the reliability of the segmentation.

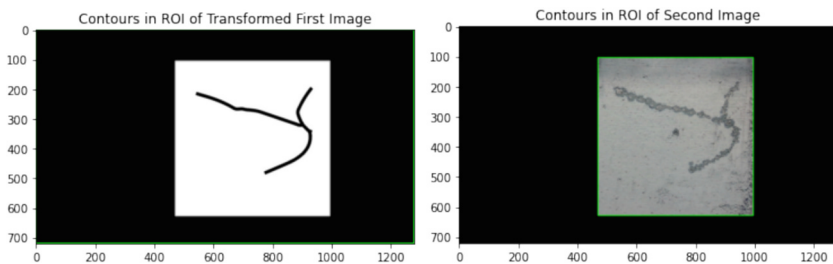


Fig. 7 left: extracted ROI of the predefined pathway; right: extracted ROI of capture photo. This image extraction process helps the system to find contours with less noise.

The trained model is used in printed pathway detections to compare the desired pathway with the one in use. The depiction is translated into a binary form, as the comparison is executed using white color values of the detected pathway pixels (1), while the remaining pixels are represented in black (0) (Fig. 8).



Fig. 8 Detected contours of the printed pathway. Left: Detected contours of the printed pathway. Right: The pixels of the printed part are labeled in white.

The similarity between the expected pattern and the printed pattern is quantitatively determined with the aid of the Structural Similarity Index (SSIM) [22]. This allows rigid and systematic comparison; and allows to location of regions that are deviating from the pathway, while more accurately identifying the regions deviating from the pathway.

The differences obtained by this comparison are those of the deficient pathway contours, while the centroids of these geometric areas are computed directly from the contours. This method produces a precise and detailed representation of the deficient areas that need rectification of the pathway and offers a higher standard for precision than the previous experiment. Analysis of the single droplet binder spreading pattern (Table 1) offers, among others, the radii averages at the different mixing ratios. Thus, by a careful comparison of the differences between the ideal pattern centroids and the pattern used with the radius of the ratio of mixing, judgments can be made as to whether rectification is required. The centroids are obtained relative to the location in the 3D model, using a reference of the outer rectangle to the four corner points (Fig. 9). The relative positions are then passed to a controller for processing by the robot arm through a ROS publisher for a precise correction of the print.

Experiment. The next stage of the flaw detection process necessitated an intensive examination of the printed pathway using image sampling.

This is an essential part required for achieving precision. This phase is significant to ensure a higher level of printing correction accuracy while using a feedback loop between the desired pathway and the actual pathway. The results obtained from the detection and segmentation of the pathway aid in the identification of deviations and anomalies.

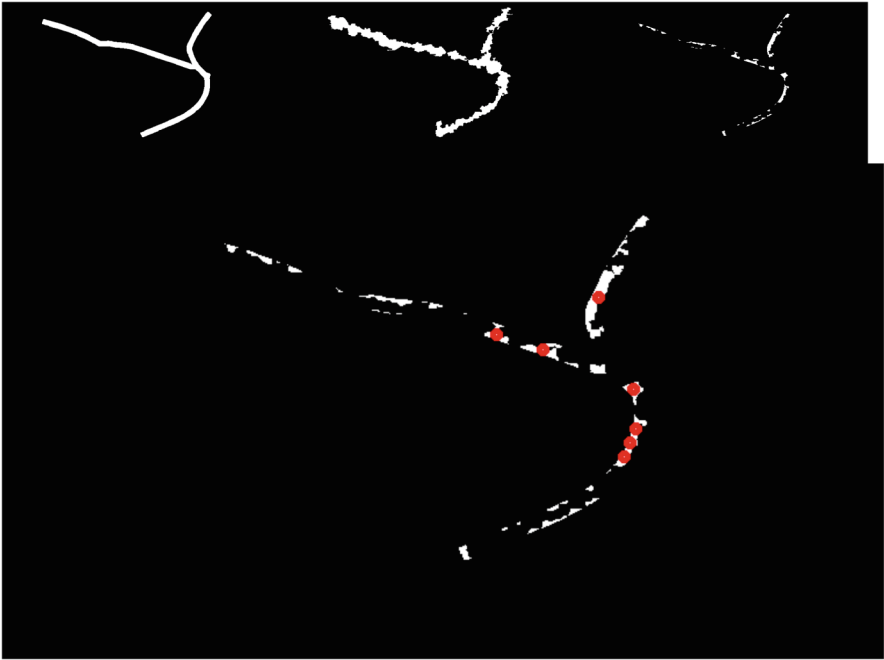


Fig. 9 Generation of rectification points. Up Left: Detected contours of the desired pathway. Up Middle: Detected contours of the printed pathway. Right: Missing part of the printed pathway. Below: Generated points to rectify on printed pathways.

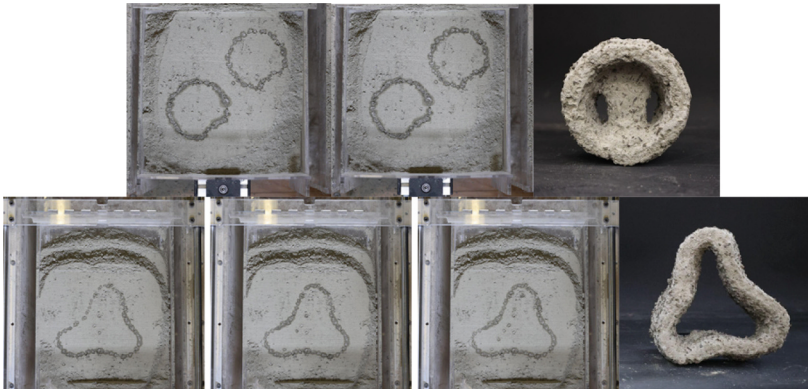


Fig. 10 Comparison of printing pathway and printed object using an image-based feedback loop. Above: One correction feedback loop needed Below: Two correction feedback loops needed.

4 Results

4.1 Test Print

The purpose of this experiment is to strengthen the adaptability of a semi-autonomous binder jetting system over non-uniform tilted surface conditions with coarse powders. Traditional binder-jetting printing processes require precise deposition by using a heterogeneous and highly processed powder and flat substrate. The precision of the print is assured by using evenly processed feedstock and heterogeneous conditions within the print bed. Any powder inconsistency or deviation from the flat print surface results in a print error. This presents a challenge to the usability of coarser powders within printing conditions, as when the print surface deviates it causes uneven integration and absorption of the binder and produces subsequent print errors.

We have designed a new printing bed to test the image feedback monitoring on a tilted print surface to allow for a more adaptive printing framework. The print bed has eight flat sections along its length and a 10° tilt across the shorter axis (Fig. 10). It is designed to simulate the complexities and difficulties involved in printing on uneven terrains and to test the limitations of our semi-autonomous system.

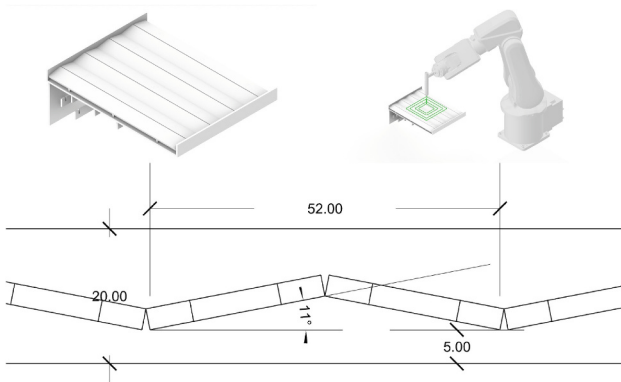


Fig. 10 Tilt printing bed and printing pathway.

The tilted orientation changes the path of printing from orthogonal to the path along the axis of the bed. The test print was produced on an angled printing bed. This experiment resulted in many observations. In particular, the droplets of the binder collect in peaks and valleys of the printing mix. During the print test, the deposition of the binder was broken in the middle sections of each tilted plate, which resulted in gaps in the print. With our image monitoring feedback system method in place, these irregularities have been studied with care. Our system analysis showed areas of discrepancy from the print pathway. Rectifying these discrepancies involved targeting the correction by depositing more binder droplets in the identified areas. Our flaw-correction image-based system is semi-autonomous and thus able to adapt to tilted surface printing (Fig. 11). We were able to increase the shape similarity of the desired pathway and the printed pathway from 93.765 to 96.237.

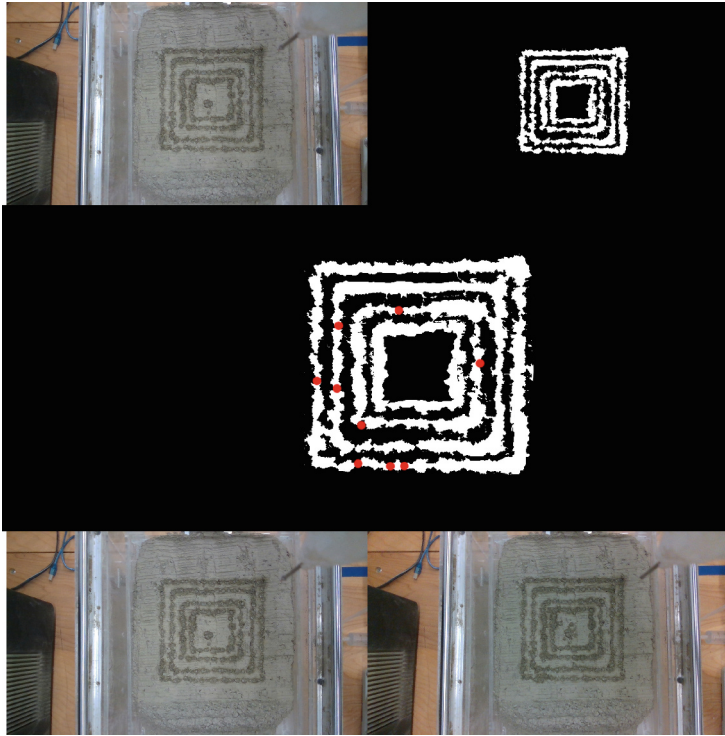


Fig. 11 Up left: actual print; Upright: recognition of printed parts; Middle: Printed pathway on tilt bed and generate rectify points; Bottom left: first round actual print; Bottom right: Rectify points actual print.

4.2 Design Print

Using the above image monitoring integrated printing methodology we designed a proof-of-concept print. It consists of printing a minimal-surface geometry object, thus validating the previously established pipeline, coupled with the lab setup as discussed above. This showcases the system's adaptability for complex shape fabrication across diverse conditions using an image monitoring feedback loop for flaw correction.

The geometry of the object was designed using the SphereCollide and SolidPoint-Collide components from the Kangaroo plugin and was later fine-tuned through the use of custom shape optimization algorithms (Fig. 12).

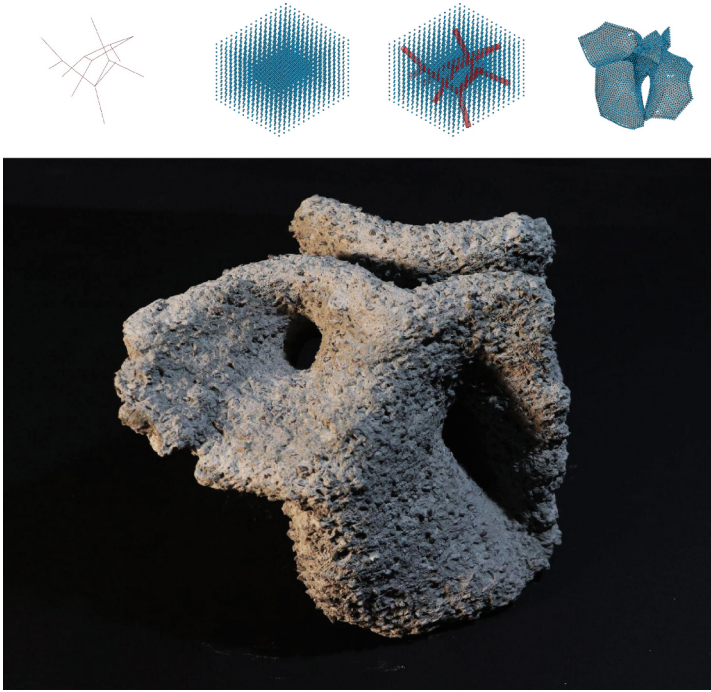


Fig. 12 Minimal surface shape generating process and printing product [1].

5 Conclusion

Our research contributes to current binder jetting techniques in 3D concrete printing while addressing a sequential quality control of printing with coarse powders. This area of focus advances the adaptation of binder jetting for sustainable construction with a focus on possibly using coarse powders from waste streams to support the future of material reuse. By incorporating an image-based monitoring system into binder jetting, we achieved higher adaptability and robustness of binder jetting and opened new pathways towards using more variable and irregular powder feedstock while assuring print cohesiveness. Our main contribution is in integrating additive manufacturing with the image-based monitoring system while focusing on variable material properties and more complex printing setups. Parameters such as the thickness of the print layers, fine-tuning the binder spacing, and absorption were studied to increase the precision of printing patterns and optimal green strength of the green bodies during printing. The flaw detection and correction framework was achieved by developing the image-based monitoring system feedback. The core innovation of this system is in training and integrating the deep learning architecture of U-Net. This process is central for the detection, real-time feedback comparison, and rectification of printing discrepancies, and ensures adaptability of printing with more diverse powder composites, as well as variability of layer parameters.

The primary benefits of the system, such as economization of the consumption of binder, yielding lightweight structures, and refining shape precision, were empirically

validated through a series of experimental trials. By advanced binder jetting techniques, combined with image-based monitoring we succeeded in improving the accuracy of printing by 2.6% while decreasing the amount of material usage by 28.5%.

Projecting into the future, this methodology supports two primary directions of AM impact: firstly, more effective integration and automation of flaw detection in manufacturing, and secondly, enabling a wider use of more diverse materials for binder jetting, such as waste streams, in uneven printing conditions.

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