Real-time Multimodal Sensing System for Additive Construction by Extrusion: Integrating thermal, depth and RGB data

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Abstract

Additive construction by extrusion addresses challenges such as labor shortages and inconsistent quality in traditional construction methods by offering automation, precision, and reduced waste. However, it remains challenging for large scale implementation due to dynamic printing conditions and environmental influences. Real-time control can be greatly beneficial in addressing these variations, which relies on a comprehensive and accurate real-time monitoring system. In this paper, we describe our ongoing work on developing a real-time multimodal sensing system that integrates thermal, depth and RGB data. By combining these sensors, the system can capture surface temperature and geometric data of extruded material, providing detailed feedback on its strength, extrudability and buildability. It provides new insights and information for quality monitoring systems in additive construction by extrusion, achieving a better balance between detailed detection and real-time monitoring. The methodology includes RGB-thermal image alignment, automated sample detection, and structured light-based depth sensing to refine geometric and temperature data. This system lays the groundwork for future advancements in predictive analysis and dynamic real-time printing control.

Keywords –

3D concrete printing; Multimodal sensing; Thermal; Depth; RGB; Sensor fusion;

1 Introduction

Additive construction by extrusion offers solutions that can help alleviate issues such as labor shortages and hard-to-control quality within the construction industry. [1]. It shortens construction time through continuous layer-by-layer deposition, parallel operations, and reduced reliance on curing delays[2]. Specifically, labor demand is reduced by automating processes such as material deposition and eliminating the need for formwork, which traditionally requires intensive manual effort. The precision of additive ensures consistent material distribution, minimizes human error, and enables high-quality results even for complex, customized designs. Furthermore, it optimizes material usage by precisely allocating resources, reduces waste and promotes sustainability by incorporating eco-friendly materials, making it a cost-effective and environmentally conscious solution[3].

Additive construction by extrusion faces a number of challenges when it comes to large scale implementation. First, the printing process is highly dynamic. The complex interplay of parameters such as material rheology, extrusion speed and mechanical motion can lead to unpredictable variations, making it difficult to fully rely on pre-programmed paths and prone to geometric defects. Secondly, printed structures exhibit a high degree of vulnerability to changes in material properties. Even small fluctuations in viscosity or ratios can trigger interlayer destabilization or even lead to structural collapse[4]. In addition, environmental factors such as temperature, humidity, and solar irradiance can affect early-age and final properties of concrete, including strength and durability[5, 6]. These uncertainties highlight the need for a real-time feedback and control system capable of dynamically adjusting printing parameters to efficiently maintain print quality during construction. Such a system requires accurate, fast-response, and highly automated monitoring capabilities, with the ability to capture complex variations, including geometric features and temperature differences.

In this paper, we present the development of a real-time multimodal sensing system designed to address these challenges. The proposed system aims to establish a comprehensive near real-time quality inspection framework to monitor both geometric fidelity and abnormal temperature variations. This approach enables automatic measurement of geometric deformations and concrete surface temperature shortly after deposition, with the results reported to the operator for informed decision-making. The system lays the foundation for real-time control in additive construction by extrusion. The next section provides a brief review of existing literature on reality capture and non-contact inspection methods in the field of additive construction by extrusion.

2 Related Work

Geometry Monitoring for Real-Time Control: Numerous real-time monitoring and control systems for additive construction by extrusion employ vision-based approaches, utilizing 2D RGB cameras to capture and analyze geometric features. These systems typically position cameras either directly above or at an angle overlooking the printed samples, providing continuous image acquisition of the concrete layers. For example, Kazemian[7] developed a system using a 720p camera to monitor samples with a width of 40 mm, achieving width measurements with an error margin of ±1.7 mm using the OpenCV package. Similarly, Barjuei[8] employed an industrial camera to establish a real-time vision-based control framework for layer-width monitoring demonstrating good adaptability and low error rates. Another study by Jhun[9] utilized a 2D laser and camera module to monitor thickness, width, and cross-sectional area, forming the basis of a real-time geometric quality monitoring system. Additionally, Martin[10] implemented a low-cost depth camera for real-time quality monitoring, focusing on the width and height of layers. The system improved accuracy significantly after applying a statistical filter. While these systems excel in monitoring specific geometric parameters such as width or height, providing detailed feedback on more intricate aspects of concrete, such as collapse or deformation, presents additional challenges.

To enhance the automation of geometric detail monitoring, some researchers have explored the potential of AI technologies and advanced instruments. For instance, Davtalab[11] trained a Convolutional Neural Network (CNN) to detect layer deformation, achieving an accuracy and F1 score greater than 90%. Similarly, Senthilnathan[12] utilized computer vision to analyze images containing detailed deformations by converting them into two-bin linear binary patterns. Deformations were detected using information entropy, demonstrating high sensitivity in identifying defects. Furthermore, Xu[13] employed high-precision structured light scanning to inspect 3D-printed concrete structures, achieving highly accurate geometric monitoring and introducing a novel method for evaluating printing quality. While these methods offer high-precision geometric inspection, their processing times can be relatively extended, which may make them more commonly applied to post-printing quality assessment rather than real-time monitoring.

Exploring Beyond Geometric Features: In addition to geometric features, some researchers have explored other variables as the focus of sensing and monitoring systems for quality control. For instance, Kazemian[14] compared several variables, including power consumption of the agitator motor, extrusion pressure, electrical resistivity, and computer vision, to assess their effectiveness in ensuring printing quality. The results indicated that computer vision-based methods were the most effective for controlling printing parameters and maintaining quality, while electricity consumption was the least effective. Similarly, Rehman[15] developed an integrated sensor-printer system for real-time quality control, which monitors penetration, compression, shear, and tensile tests during the printing process to provide feedback on the performance of freshly extruded concrete. Additionally, Banijamali[16] proposed a novel index combining electrical resistivity and temperature to rapidly evaluate the strength of 3D-printed concrete structures, providing an innovative method for early-age strength monitoring. While these studies provide valuable insights into strength prediction and real-time quality control, their emphasis on mechanical properties leaves opportunities to further explore the role of environmental and material temperatures in influencing extrudability and buildability during the early stages of the printing process

Temperature has been identified as a critical factor affecting the quality of extruded sample. Both environmental temperature and the heat generated during curing influence the structural integrity of the printed concrete[17]. While elevated temperatures can impact strength[18], curing times and heat-induced stresses may lead to deformation and affect bonding characteristics[19, 20]. More critically, temperature directly governs the fresh properties of concrete, including viscosity, yield strength, and flowability, which are fundamental in determining its extrudability and buildability during the 3D printing process[21].

Therefore, real-time monitoring of temperature is essential, as it directly correlates with key printing parameters such as nozzle traveling speed and interval time between layers and/or material dosing. However, the potential of temperature monitoring for real-time quality control in 3D concrete printing has yet to be fully explored.

Summary and Research Gap: Despite significant advancements in geometry monitoring and real-time control for additive construction by extrusion, existing methods, which often rely on single-sensor setups with relatively focused data sources, may benefit from further enhancements to achieve greater comprehensiveness in observed data dimensions, detail levels, and accuracy. Vision-based approaches effectively monitor parameters like width and height but may have limitations in capturing finer deformations or collapse. While advanced techniques such as AI models and structured light scanning demonstrate high precision, they are often more commonly applied to post-printing quality checks. Additionally, the potential of real-time temperature monitoring, which affects fresh material properties and plays a crucial role in early strength gain, influencing both extrudability and buildability, has yet to be fully explored. To address these shortcomings, this study proposes a multi-modal system that integrates thermal, depth, and RGB data, enabling the automated extraction of detailed, accurate geometric and temperature information to support real-time control.

3 Multimodal sensing system setup

The developed system integrates a FLIR Lepton 3.5 thermal camera and an Astra 2 RGB-depth camera to provide comprehensive monitoring of surface temperature and sample geometry during the concrete printing process. The thermal camera operates with a resolution of 160 x 120 pixels, an operational range of -10°C to 80°C, a dynamic range of -10°C to 400°C, a framerate of 8 fps, and a horizontal field of view of 57º, enabling real-time thermal data acquisition. The Astra 2 RGB-depth camera captures high-resolution RGB images at 1920 x 1080 pixels with a framerate of 30 fps and a horizontal field of view of 74.7º, while its depth function provides depth data with a resolution of 1600 x 1200 pixels at 30 fps. The depth camera employs a structured light sensor with a horizontal and vertical field of view of 58.2° and 45.2°, respectively, operating within a range of 0.6 m to 8 m and achieving a precision of ⩽ 0.16% at 1 m. Structured light technology projects a patterned field of light onto the surface, capturing deformations caused by surface geometry to reconstruct detailed 3D shapes, which is particularly effective for complex geometries [13].

Figure 1. (a)Setting of the thermal-RGB-depth camera (b)Setting of the system

The thermal camera is securely mounted on top of the RGB-depth camera using a fixed bracket, positioned 5 cm above it, as shown in Figure 1(a). This combined setup is mounted on a movable platform, located 30 cm away from the extruder and angled at 60 degrees relative to the printing platform, providing a comprehensive overview of the printing process and the sample, as illustrated in Figure 1(b). This integrated multi-modal

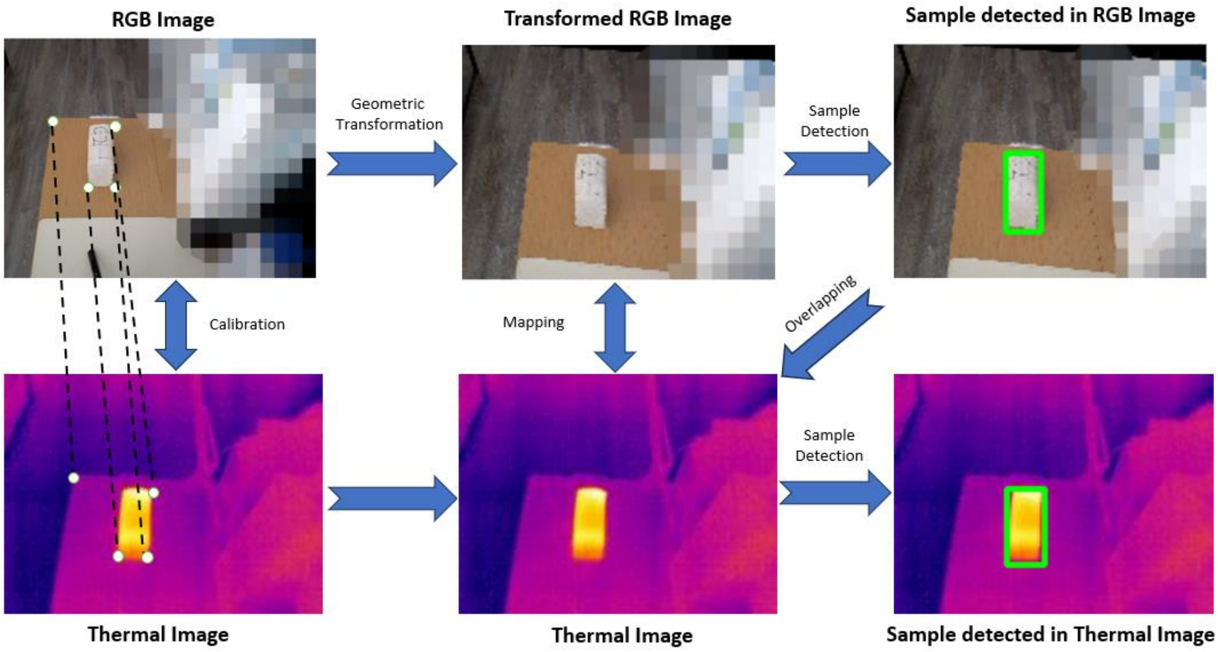


Figure 2. Thermal-RGB data alignment

sensing system enables the automated capture of detailed geometric and temperature data, supporting real-time control and enhancing the precision and effectiveness of the monitoring process during 3D concrete printing.

3.1 Surface temperature capturing

The automated process for capturing the surface temperature of a sample is as follows (shown in Figure 2): First, thermal and RGB images are captured simultaneously at a frame rate of 8 FPS, determined by the lower frame rate of the two cameras. Due to differences in the field of view (FOV) and resolution, the RGB image undergoes a geometric transformation to align its perspective and scale with that of the thermal image. This transformation is guided by a calibration process. Next, a series of image processing steps is applied to the RGB image to identify the sample's contour. The detected sample location in the transformed RGB image is then mapped onto the thermal image, enabling precise localization of the sample within the thermal image. Finally, the temperature data from the selected region in the thermal image is extracted as the sample's surface temperature. The details of each step are explained in the following paragraphs.

Geometric transformation: The RGB images undergoes a calibration process to align with the thermal images. To calibrate it more precisely, we put 4 heating points as calibration points on the printing platform so that they are obvious to identify in both RGB and thermal images. Once the calibration points are identified, the perspective transformation matrix H can be calculated by the OpenCV's package [21]. Then each pixel in the destination image to corresponding pixel in the source image can be calculated using:

$$\begin{bmatrix} x' \\ y' \\ \omega' \end{bmatrix} = H \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

Where (x, y) are the coordinates in the source image, (x', y') are the coordinates in the destination image, ω' is the scaling factor for normalization.

The main problems encountered during image transformations involve the extrapolation of non-existing pixels and the interpolation of pixel values. In cases where pixels in the destination image map to out-of-bound coordinates in the source image, extrapolation method which ensures that such pixels remain unmodified in the destination image is employed. Additionally, because the mapped coordinates are often fractional values, bilinear interpolation is used to estimate the pixel values at these fractional coordinates.

Sample detection: to automate the process of sample detection, there are 4 steps as follows: 1) Grayscale conversion, 2) Edge detection, 3) Contour detection, 4) Sample detection. First, the transformed RGB image is converted into a single-channel grayscale image, suitable for edge detection algorithms. The grayscale intensity is given by:

$$I_{gray}(x, y) = 0.2989 \cdot R(x, y) + 0.5870 \cdot G(x, y) + 0.1140 \cdot B(x, y) \tag{2}$$

Where $R(x, y)$, $G(x, y)$, $B(x, y)$ are the red, green and blue intensity values at pixel (x, y). $I_{gray}(x, y)$ is the grayscale intensity.

Then, Canny algorithm[22] is adopted to detect edges. This algorithm identifies regions of rapid intensity change, which often correspond to object boundaries. The gradient of the grayscale image is computed in the x- and y- directions using Sobel filters:

$$G_x = \frac{\partial I_{gray}}{\partial x}, \qquad G_y = \frac{\partial I_{gray}}{\partial y} \tag{3}$$

The gradient magnitude and direction are then calculated by:

$$G = \sqrt{G_x^2 + G_y^2} \tag{4}$$

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{5}$$

Then, Non-Maximum Suppression process eliminates spurious responses by retaining only the strongest gradient magnitudes along the direction of the edge. Through Double Thresholding, pixels with gradient magnitudes above the upper threshold are classified as strong edges, and those below a lower threshold are discarded. Pixels between the thresholds are treated as weak edges. Finally, Edge Tracking by Hysteresis preserves weak edges that are connected to strong edges while suppressing isolated weak edges, producing a binary edge map. Then, contours are

Figure 3. Steps to detect sample in RGB images

detected in the binary edge map. A contour is defined as a curve joining all continuous points along a boundary with the same intensity. The contour with the largest area is selected as the sample's contour. The contour detection example is shown in Figure 3.

Alignment and capturing: after detecting the sample region in the transformed RGB image, a rectangular bounding box is generated and directly applied to the thermal image. The temperature data in each pixel within the bounding box are then extracted and recorded as surface temperature.

3.2 Geometry monitoring

The system for sample geometry monitoring uses the same camera with depth mode.

Point clouds generation: The monitoring process utilizes the in-built point cloud mode, which generates a point cloud based on the depth map and the camera's intrinsic parameters. The (x, y, z) coordinate of each point are computed using the following equations:

$$x = (u - cx) \cdot \frac{z}{f_x} \tag{6}$$

$$y = (v - cy) \cdot \frac{z}{f_y} \tag{7}$$

$$z = depth(u, v) \tag{8}$$

Where u, v are the pixel coordinates in the 2D image, z is the depth value. cx, cy are the center of the optical axis. f_x, $f_x$are the focal length of the camera.

Background filtering: Once the point cloud is generated, an initial coordinate-based filter is applied to remove the background. Given the fixed relative position between the sample and the camera, the filter coordinates can be predefined as constant values. After applying the background filtering, the remaining point cloud consists solely of the platform and the monitored sample.

Plane identification and filtering: The processed point cloud undergoes a plane segmentation and filtering step to isolate the sample. The RANSAC (Random Sample Consensus)[23] algorithm is employed to identify the primary plane, which corresponds to the printing platform. Through iterative random sampling of points, potential planes are generated, and the distances between the points and these planes are calculated. Points within a predefined distance threshold are classified as inliers of a given plane. After 1000 iterations, the plane with the largest number of inliers is identified as the platform plane. To further refine the results, additional points within the threshold distance to the identified plane are included as part of the platform to remove noise. Once the platform points are filtered out, the remaining points in the point cloud are considered to represent the sample.

Outlier filtering: After the removal of the platform plane, some outliers may still remain in the point cloud. To address this, Statistical Outlier Removal (SOR) is employed to filter out these noise points. This process begins by calculating the average distance between each point and its neighboring points (e.g., the 20 nearest neighbors) to establish the global distance distribution, including the mean and standard deviation. Points with distances exceeding two standard deviations from the mean are identified as outliers and subsequently removed from the dataset. This approach, based on detecting local density variations in the point cloud, effectively eliminates noise in sparsely populated regions, resulting in a refined and clean point cloud. The process of the point clouds processing is shown in Figure 4.

4 Discussion

This system emphasizes detailed geometric and temperature inspections, delivering comprehensive and refined data to enhance real-time control in 3D concrete printing. The integration of the thermal and RGB data can extract temperature and enable continuous and automated surface temperature measurement. With its sensor refresh rate capable of handling printing speeds up to 30 cm/s, the system supports most industrial printing conditions[24-26]. Integrated with an established model of material and process parameters, the monitoring system facilitates early identification of conditions that balance the critical aspects of extrudability and buildability.

Early changes in layer geometries during the printing process can be influenced by key process parameters, such as printing speed, extrusion rate, nozzle deposition

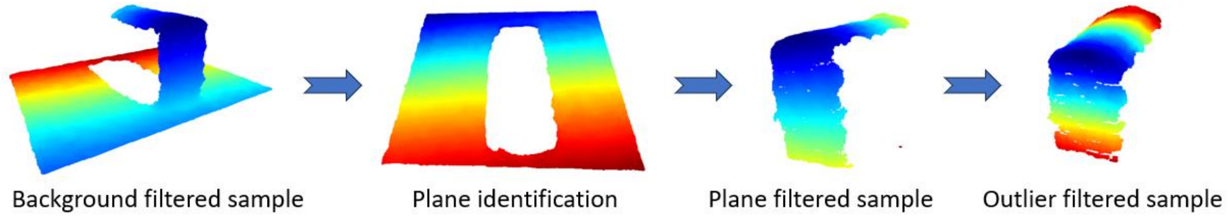
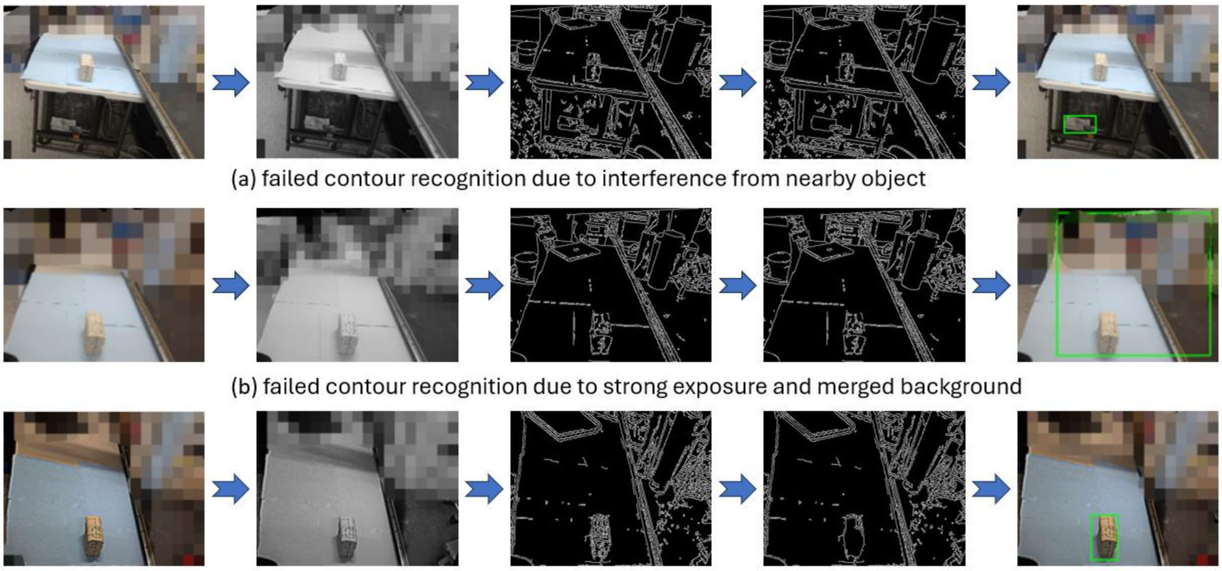


Figure 4. Point clouds processing and filtering



(a) failed contour recognition due to interference from nearby object

(b) failed contour recognition due to strong exposure and merged background

(c) Postprocessed image enhances identification ability

Figure 5. Object identification under different scenarios

height, and material properties like yield stress, stiffness, and early-age strength gain. However, geometry alone may not be sufficient to pinpoint parameters requiring adjustment. By combining object temperature - which reflects on green material properties and concrete hydration behavior - the combined data set could provide insights into which material and/or process parameters may need modification. For instance, localized temperature anomalies, such as excessive gradient or out-of-range values, combined with a slight change in layer height could indicate the potential for future excessive layer deformation or inadequate interlayer bonding, thus enabling predictive interventions on process parameters or material dosing. This comprehensive approach supports dynamic refinements to printing parameters ensuring precision, stability, and structural integrity throughout the 3D printing process.

One of the main challenges of this system lies in the automatic recognition of geometric features in images, which is sensitive to background settings and lighting conditions. When contrast is insufficient, such as under strong lighting, high exposure, or when the sample color closely matches the background, contour detection may fail. For instance, in Figure 5(b), strong exposure caused the background and sample to merge visually, resulting in failed contour recognition. Similarly, Figure 5(a) illustrates interference from other high-contrast contours in the background, which disrupted sample detection. To overcome these challenges, it is necessary to eliminate environmental interferences and enhance recognition accuracy. Techniques such as reducing brightness, increasing contrast, or applying filters can significantly improve detection performance. For example, as shown in Figure 5(c), post-processing the image to enhance contrast led to a substantial improvement in contour recognition, demonstrating the potential of post-processing in ensuring reliable image-based monitoring. These enhancements are essential for maintaining the robustness of the system in diverse operational environments.

The geometry monitoring system developed in this study provides valuable support for real-time quality control in 3D concrete printing. In terms of measurement accuracy, the system shows better performance in width measurements compared to height measurements. As shown in Table 1, the width measurement error is approximately 3.5 mm, while the height measurement error is around 5.4 mm. While these results may not surpass those of some existing systems, the approach offers distinct advantages. By using depth information to generate point clouds, the system captures more detailed geometric features than standard 2D RGB cameras. For example, at a distance of 0.7 m, it can detect deformations as small as 5 mm, which is helpful for identifying potential concrete layer deformations. Figure 6 demonstrates the system's ability to detect complex height deformations, enabling operators to monitor and adjust the printing process as needed.

Table 1 Measurement of sample width and height

Type	Captured(mm)	Actual(mm)
Width	62.4	58.9
Height	89.1	94.5

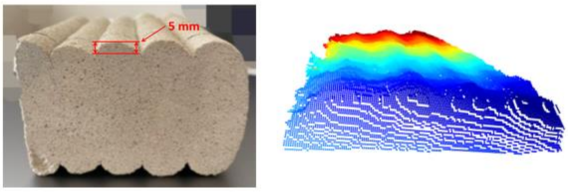


Figure 6. Sample with point clouds image

The use of a structured light-based depth sensor for geometric measurements enables high-resolution data capture but comes with several limitations in various environmental conditions. One major challenge is its sensitivity to lighting conditions, particularly in outdoor applications. In regions with strong solar radiation, the projected infrared pattern used by structured light sensors can be significantly disrupted, leading to reduced measurement accuracy or data loss. This constraint limits their effectiveness in open construction sites or large-scale outdoor 3D printing operations where environmental light fluctuations are unavoidable.

Additionally, the performance of the selected depth sensors is constrained by their frame rate, which is not particularly high. In large-scale applications, such as continuous 3D concrete printing over expansive areas, this limitation may hinder its ability to track fast-moving printing nozzles or dynamically adjust extrusion parameters in real time.

Another practical challenge arises from the presence of extraneous objects in real-world construction environments. Debris, scaffolding, and other surrounding elements can introduce noise in the captured data, making object detection more difficult. These distractions can degrade the reliability of geometric measurements and increase the risk of false detections, which is critical for autonomous or semi-automated construction processes.

From an industrial application perspective, future development should focus on selecting more advanced sensors with enhanced robustness against environmental disturbances. LIDAR-based sensors, for example, are less affected by ambient lighting and could serve as an alternative for outdoor applications, though at a higher cost [27, 28]. Additionally, improving the robustness of object detection algorithms through deep learning-based techniques could mitigate the impact of background clutter and ensure reliable detection of the printed structure. These advancements will be crucial for enabling fully autonomous and scalable 3D concrete printing systems in real-world industrial settings.

5 Conclusion

This study presents the development of a multi-modal sensing system designed to enhance real-time quality control for additive construction by extrusion by integrating thermal, depth and RGB data. As work in progress, we described the system and methodology we use to capture these data. The system aims to provide detailed feedback on geometric features and sample surface temperature. It provides new insights and information for quality monitoring, achieving a better balance between detailed geometric detection and real-time monitoring. Future work will focus on improving the system's resiliency to adapt to various outdoor scenarios and industrial environments. Additionally, future efforts will also involve developing an AI-based framework to process the captured data, enabling real-time adjustment of printing parameters and the ability to predict potential risks, ensuring improved construction quality.

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