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Closed-Loop Control of 3D Clay Printing Using Machine Learning

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Extended abstract

Introduction and Problem Statement

This paper presents ongoing research that aims to develop a closed-loop and real-time error detection and correction system in 3D clay printing (3DCP) using computer vision and machine learning.

3D printing (3DP) enables the fabrication of objects by depositing material layer by layer based on a digital model. Liquid Deposition Modelling (LDM) is one of the 3DP methods in which a fluid/dense material is extruded through a nozzle to construct an object by depositing layers on each other (Gentile et al., 2024). 3DCP refers to the LDM process in which clay (or earth-based materials) is extruded to fabricate objects. It requires precise parameter control to ensure printing quality (Xing et al., 2021). Similar to other LDM processes, it is sensible to mixture composition (Gentile et al., 2024). There is growing literature on the use of 3DCP in the built environment (Abedi et al., 2025; Asaf et al., 2023; Gomaa et al., 2022; Sahoo & Gupta, 2025; Yin et al., 2023).

In 3DCP, clay, a naturally occurring, malleable material, is mixed with water and additives. Its variability in water content and viscosity, which results from the non-standard mixing process, poses challenges related to extrusion defects, weak inter-layer bonding, and shape deformation. These challenges affect structural integrity and printing quality. Even within a single prototype, variations in printing quality can occur across different layers due to changes in the clay mixture. Traditional fixed-parameter methods fail to adequately accommodate these rapid and unpredictable shifts in material state, typically requiring human intervention during the printing process, which is not always possible or effective enough.

Traditional open-loop approaches operate based on pre-set parameters without real-time feedback, assuming constant material properties and environmental conditions (Zhu et al., 2021). As a result, they cannot dynamically adjust to fluctuations in extrusion consistency and inter-layer adhesion, which makes them especially prone to printing errors caused by the natural variability of the material (Figure1). Without real-time sensing and adjustment, these systems struggle to compensate for changes in material behavior and it often leads to inconsistent results and defects.

Figure 1. Samples of printing failures due to material variability.

Employing computer vision, coupled with machine learning (ML) techniques, can offer a more robust solution for monitoring the 3DCP process. It can allow to dynamically detect and respond to real-time variations in clay properties, adjusting printing parameters actively and automatically rather than relying on static presets. Recent research has explored automated solutions using computer-vision based ML for quality monitoring and improvement during various 3DP processes primarily with concrete, thermoplastics, and metals (Brion & Pattinson, 2022b; Farrokhsiar et al., 2024; Geng et al., 2023; Kazemian et al., 2019; Mehta et al., 2024; Najjartabar Bisheh et al., 2021; Shojaei Barjuei et al., 2022). These materials typically exhibit relatively stable and predictable behaviors under standardized printing conditions. Thus, they allow consistent quality control and parameter optimization. In contrast, clay's inherent variability makes it more challenging to manage. More research is needed to develop closed-loop systems integrating computer vision and ML for real-time monitoring and correction specific to 3DCP.

Objective

This research aims to develop an ML-assisted closed-loop quality monitoring and improvement system for 3DCP to mitigate printing quality problems that can result from the non-standard viscosity of extruded clay.

ML is a subset of Artificial Intelligence (AI) that has an increasing potential to develop the capabilities and efficiency of AM, and it can handle the challenges and optimize the various aspects of AM processes by extracting patterns, learning from data, and building effective predictions (Ukwaththa et al., 2024). ML can play a crucial role in real-time defect detection, process optimization, and adaptive control in 3DP and help to ensure more precise and reliable printing outcomes.

In deep learning-based image classification (a subset of ML), models such as Residual Attention Networks (ResNet) can enhance defect detection by focusing on relevant image regions while minimizing background noise. So, they can be particularly effective for identifying fine-grained defects in 3DP (Wang et al., 2017; Zhao et al., 2017).

Unlike open-loop systems, closed-loop systems can process sensory data by recognizing changes in material properties, environmental disturbances, and calibration errors in real-time. They can continuously update the printing parameters and allow real-time correction of extrusion inconsistencies and printing errors (Zhu et al., 2021).

In this project, we aim to integrate computer vision into the control loop for real-time data collection during printing, along with a ResNet to detect printing failures and adjust the printing speed to mitigate them. This method is suggested to enable automatic and dynamic adjustment of printing speed to ensure consistent material extrusion, and to enhance the quality and reliability of clay-based 3D printed structures.

Methods

The research methodology includes the following steps:

1. Printing multiple prototypes at various speeds to create a dataset, resulting in different levels of print quality due to material extrusion.
   1.1 Evaluating the prototypes' print quality to identify optimal and poor outcomes.
   1.2 Capturing images and relevant G-code data as a CSV file during the printing process.
2. Labelling the collected dataset according to print quality.
3. Training a ResNet model using the labelled data to teach correlations between the images and print quality.
4. Implementing a closed-loop system that adjusts G-code parameters (printing speed) in real-time, responding to changes in material extrusion.
5. Printing a final prototype using the closed-loop system to verify its functionality.

In this research, an LDM WASP Extruder XL 3.0 (with an 8 mm nozzle) mounted on a COMAU NJ60 2.2 industrial robot arm is used for 3DCP (Figure 2). Two Raspberry Pi Camera Module 3, each equipped with additional lighting sources aimed at the nozzle, are mounted on both sides of the extruder to monitor the extrusion continuously and capture images with a specific interval throughout the printing. Preliminary research shows that consistent lighting is crucial for computer vision-based ML accuracy, as variations such as reflections or shadows can negatively impact predictions. Thus, mobile lighting sources attached to the nozzle are used to ensure uniform conditions. This setup is used to print a series of prototypes at varying speeds, which results in different print qualities across the prototypes (Step 1).

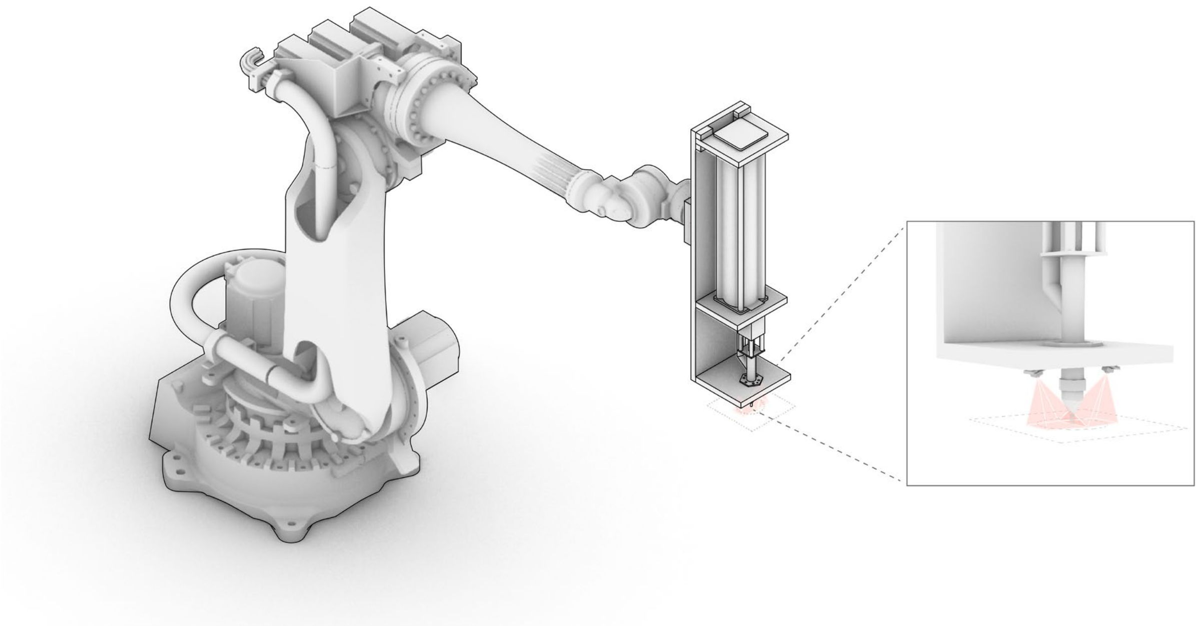

Figure 2. The 3DCP setup design with the extruder and cameras integrated into the robot arm.

The printed prototypes were assessed based on their quality, with a focus on the amount of extrusion, and sorted by their shell thickness (Step 1.1). The prototypes that matched the nozzle diameter (8 mm) were used as the standard benchmark and labeled as the optimum (good) extrusion. The remaining ones were sorted from very thin (low extrusion) to very thick (high extrusion).

The dataset includes images and G-code data (mainly printing speed) stored in a set of Comma Separated Values (CSV) collected while printing prototypes at different speeds (Step 1.2). Then, it was augmented with techniques like rotation, scaling, mirroring, brightness adjustments, and normalization. After that, the data is labeled into three categories (Step 2): low, good, and high extrusion, following the assessment in the previous step.

The defect detection system used in this research (Step 3) utilizes the ResNet Attention-56 deep learning model developed by Wang et al. (2017). It was also applied by Brion and Pattinson (2022a) to control the material flow rate in thermoplastics. This model integrates attention modules and residual blocks to improve feature extraction, reduce noise sensitivity, and enhance defect detection accuracy. It uses a deep residual attention network to process deviations from optimal printing parameters and improves feature extraction by selectively focusing on critical areas of the images. It allows the model to learn the complex relationship between extrusion amount and printing speed to predict and correct errors dynamically (Brion & Pattinson, 2022a). Additionally, Gradient-weighted Class Activation Mapping (Grad-CAM) visualizes the model's decision-making process. Grad-CAM generates heatmaps that highlight the parts of the image most influential in the model's predictions. It offers a more transparent approach that improves trust and interpretability in defect detection. Together, they enhance the system's reliability and adaptability to different 3DCP conditions.

For real-time adjustment of G-code parameters (Step 4), a closed-loop correction mechanism is being developed to dynamically adjust the robot arm's movement speed (RAMS) and optimize extrusion. This loop (Figure 3) first processes the captured images through ResNet to predict shell thickness deviations (due to low or high extrusion). The predictions are monitored within a defined time window (Pm). Corrective actions (increasing or decreasing the speed) are triggered if the shell thickness is predicted to deviate from the optimal value for more than 10 seconds. In this case, the system overwrites the remaining robot program by increasing or decreasing the RAMS parameter. A 40-second monitoring pause follows each execution of speed correction. This allows the system to stabilize before resuming real-time monitoring.

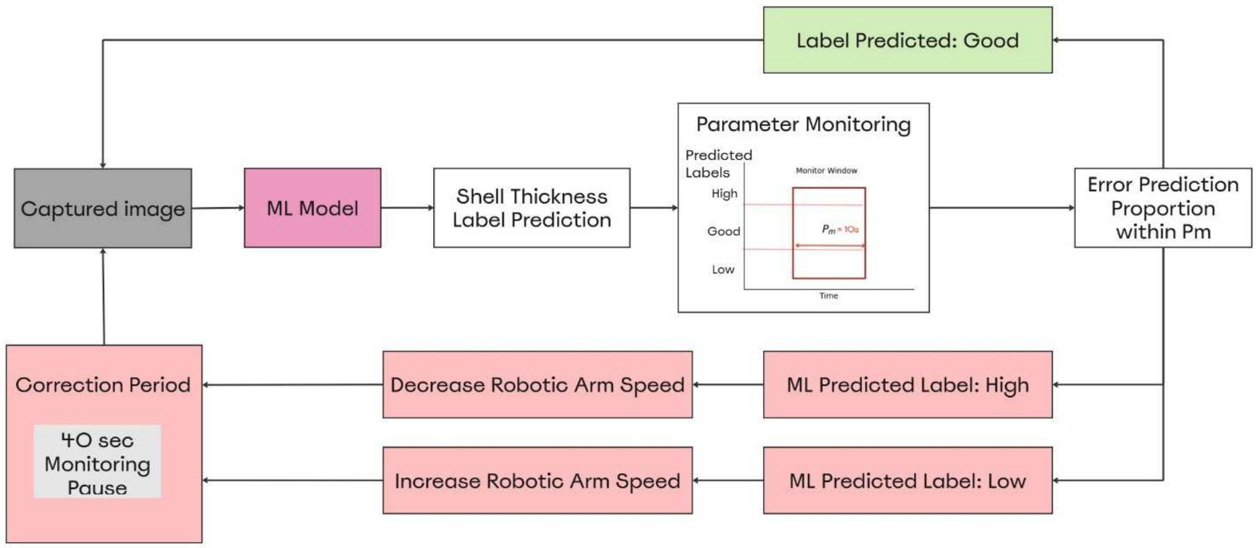

Figure 3. Closed-loop correction workflow

The key factor in determining print quality is the relationship between the nozzle diameter and the observed shell thickness in the specific printing section. By monitoring whether the deposited shell thickness matches or deviates from the nozzle diameter, the system can assess whether the extrusion amount is appropriate or needs to increase or decrease to ensure optimal print quality. Other factors, such as surface texture quality, inter-layer bounding, or structural integrity, can be included in the assessment and training of the ResNet. However, these aspects are left out of the scope of this research for now. Currently, our main challenge lies in the real-time adjustment of the robot programs to update the printing parameters dynamically. After this step is completed, the project will continue validating its results on a large-scale prototype (Step 5).

Conclusions

This ongoing research provides insights into using ML and computer vision techniques to develop a closed-loop system for real-time error detection and mitigation in 3DCP. It mainly focuses on detecting undesired changes in material extrusion due to clay mixture inconsistencies and correcting them by adjusting the printing speed in real time. Additionally, the closed-loop control system can adjust the printing speed as triggered by the trained model. Our experiments so far have shown that ResNet is effective in the real-time detection of extrusion amounts. We also conclude that two-head or multi-head ML models perform better than single-head models in this context. Future studies should involve comparisons with different ML architectures to determine the most effective method for this task.

To ensure reliable results, it is crucial to maintain consistency in dataset collection and calibration conditions. Conditions such as lighting, print base color or patterns, and background environments should remain uniform during dataset collection and calibration. If varying conditions are unavoidable, a significantly larger and more comprehensive dataset is required to ensure robust generalization by the ML model.

Images must be labeled clearly to avoid confusion and potential degradation of model performance. Clear labeling significantly reduces prediction errors arising from manual labeling inconsistencies.

Finally, aligning image sizes between the dataset collection and calibration phases enhances overall performance. Variations in image size can negatively impact model predictions by shifting the model's focus away from important regions. Ensuring that the calibration images match the size of the dataset images maintains consistency. It helps achieve more reliable predictions. This can be particularly important after reinstalling or repositioning the cameras.

The next phase of this research will evaluate different ML architectures to find the best model for the specific 3DCP application. Instead of broadening our dataset to capture varying conditions, we plan to keep our experimental conditions uniform throughout the data collection and calibration phases.

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