Automated defect detection in clay printing

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Abstract

Additive manufacturing (AM) of eco-friendly materials has the potential to decarbonize the construction industry by enabling the creation of complex structures with minimal waste. Clay has been integrated into AM processes as a building material, giving rise to an emerging research field referred to as "clay printing". Defects, such as tearing and sagging, are common in clay printing and could affect the structural integrity, load-bearing capacity, and overall durability of the structures. However, limited research on defect detection in clay printing and lack of datasets restrict the development of defect detection models. This paper presents a tool – the automated defect detection (ADD) preprocessor – developed to generate a dataset for defect detection models in clay printing. The tool uses images and videos as input for preprocessing and labeling images required to build the dataset, meeting the requirements of defect detection models based on convolutional neural networks. The ADD preprocessor is implemented and validated as a proof of concept for clay printing processes. The results demonstrate the capability of the ADD preprocessor to successfully build a dataset for the deployment of defect detection models in clay printing.

Keywords –

Clay printing; additive manufacturing; defect detection; dataset; convolutional neural networks

1 Introduction

Additive Manufacturing (AM) has become a significant innovation in the construction industry due to its numerous advantages that surpass "traditional" construction methods [1]. One key aspect, compared to traditional construction methods is the ability to create complex and customized structures without additional cost or material waste [2]. The layer-by-layer construction process enables the realization of geometrically intricate designs and freeform structures that are challenging or impossible to achieve with conventional formwork or machining methods [3]. Furthermore, additive manufacturing of eco-friendly materials has the potential to decarbonize the construction industry [4].

Clay, a traditional building material, has been adapted for AM processes and has emerged as a new research field, referred to as "clay printing" [5]. Clay printing often encounters defects during printing, such as tearing and sagging, that could affect the structural integrity, load-bearing capacity, and overall durability of the structures. By exploring synergies with concrete printing, defects in clay printing may be investigated. Defects in concrete printing, including tearing (breakpoints due to low workability of the material) [6], sagging/buckling (due to deformation under self-weight) [6] and shrinkage cracking [7], can also be observed in clay printing. However, research on defect detection in clay printing remains limited, which hinders the development of defect detection models due to insufficient data.

Efforts towards automated defect detection approaches for AM processes have been reported, where most research has been focusing on fused filament fabrication (FFF) and, more recently and to a lesser extent, on concrete printing. For FFF processes, recent defect detection approaches for offline and real-time detection have been developed based on computer vision techniques, including comparing point clouds [8] and images [9] as well as on convolutional neural network (CNN) architectures [10, 11]. Similarly, approaches based on computer vision, supplemented by machine learning and deep learning, have been developed for concrete printing to detect layer deformations [12] and to assess geometries of additively manufactured structures [13]. Further approaches devised for real time defect detection in concrete printing have been developed based on detection transformers to detect and measure tearing with high accuracy [14]. Yet current defect detection approaches present several limitations. On the one hand, vision-based systems are used in real-time defect detection to monitor printing processes and detect defects, but are limited to the view point of the vision-based systems. On the other hand, defect detection models based on deep learning, such as CNN classification models, may be trained to detect and classify specific defects, where the scope and accuracy of the defect detection models are dependent of the datasets available for training [11]. Consequently, the need for datasets arises, due to the limited availability of data regarding defects in clay printing.

In this paper, the development of a tool for automated defect detection (ADD) is presented. The tool, named "ADD preprocessor", is designed to build a dataset aiming to support defect detection models in clay printing using images and videos as input data. The image data is preprocessed and labeled to build the dataset, which meets the requirements of defect detection models based on convolutional neural networks. The ADD preprocessor is implemented and validated as a proof of concept for clay printing processes. The remainder of the paper is structured as follows. First, the methodology for deep-learning-based defect detection and the implementation of the ADD preprocessor is presented. Next, the proof of concept is described, followed by a discussion of the conclusions and potential future research.

2 Deep-learning-based defect detection model

In this section, the methodology for generating deep-learning-based defect detection models is described. The methodology is based on a previous study of the authors (described in [15]), and it is adapted for clay printing. Considering the lack of available data for clay printing, the ADD preprocessor is designed and implemented as a tool for generating datasets for defect detection models. Below, a short description of the research methodology and the implementation for the ADD preprocessor is presented.

2.1 Research methodology

The research methodology is proposed to generate a deep-learning-based defect detection model using a CNN architecture. As described in Figure 1, the creation of deep-learning-based defect detection models usually comprises two phases, the (i) data preparation phase and (ii) classification model development phase. The ADD preprocessor focuses on the data preparation phase (highlighted in orange in Figure 1) and generates a dataset D_n as an output using images and videos as input data.

In the **data preparation phase**, data is collected, preprocessed, labeled, augmented, and split. During *data collection*, *n* images of additively manufactured clay structures with and without defects are part of the dataset D_n. The images included in the dataset D_n may be collected from different sources, where the images may vary in size, color, and viewing angle. Next, during *data preprocessing*, the images are cropped, resized to a predefined size, transformed into a gray scale, and corrected for orientation to a consistent horizontal view. The gray-scale images are then *labeled* with the corresponding defect class: Tearing, sagging, buckling, and shrinkage cracking. Finally, for *data augmentation*, augmentation techniques, such as mirroring, noise, light exposure ("brightness"), rotating and random image cutouts, are applied to increase the size of the dataset D_n. Mirroring and rotating are used to improve robustness to random camera angles, while noise, cutouts, and variable exposure increase resilience to varying lighting conditions. For the next phase, dataset D_n is *split* into three sub sets, a training dataset ($D_{training}$), a validation dataset ($D_{validation}$), and a testing dataset ($D_{testing}$).

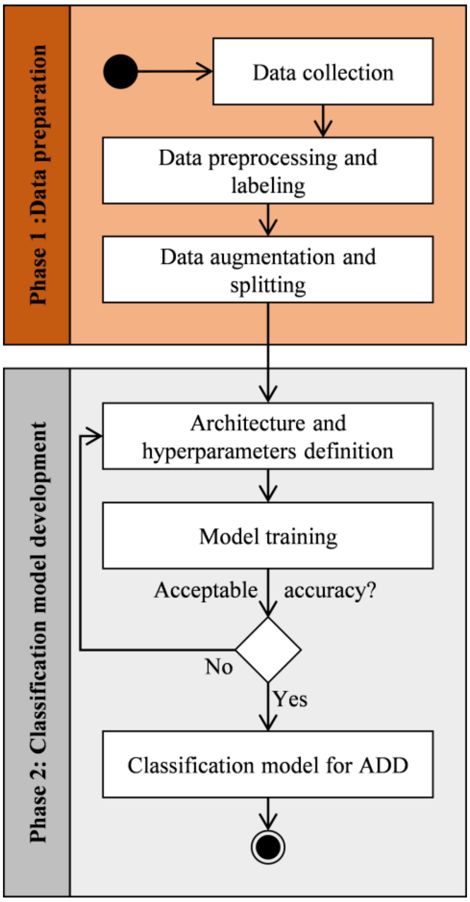

Figure 1. Methodology for generating deep-learning-based defect detection models [15]

In the **classification model development phase**, the classification model is developed in three steps, architecture definition, model training, and model testing. For *architecture definition*, the architecture of the classification model is selected and hyperparameters are defined. An architecture commonly used is the "You Only Look Once" (YOLO) architecture, which prioritizes speed, accuracy, and user-friendliness while preserving computational efficiency [14]. Upon defining the CNN architecture, the training dataset $D_{training}$ is deployed to train the CNN classification model. During *model training*, the model "learns" from existing relationships between known inputs (images) and known outputs (defect classes, e.g. "sagging"). Furthermore, loss metrics are used to guide the optimization of the CNN classification model and to evaluate the error between the predictions of the model and the actual target outcomes. In general, a decreasing loss value trending toward zero indicates that the model is effectively "learning" from the training dataset. Meanwhile, and to prevent overfitting during training process, the validation dataset $D_{validation}$ is applied to fine-tune and evaluate the performance of the models during training. Upon completing training, the testing dataset $D_{testing}$ is used to test the performance of the classification model until achieving an acceptable accuracy. During *model testing*, evaluation metrics are used, including precision, recall and the mean average precision at a single intersection-over-union threshold, to test the capacity of the model aiming to avoid false positive and false negative classifications and to expresses the prediction accuracy of the model.

2.2 Implementation

Acquiring large datasets for clay printing is challenging because of to the lack of research on defects in clay printing in the context of the construction industry. Existing labeling tools are limited to only annotate images, requiring already standardized images as inputs and additional tools for data augmentation. Therefore, the ADD preprocessor aids in collecting and standardizing images stemming from various sources, as well as to labeling and augmenting the image data to generate a dataset. To satisfy the requirements for deep-learning-based defect detection models in the context of clay printing, the following requirements are considered:

- *Image size*: CNN classification models require standardized image sizes to improve accuracy and reduce complexity [12]. Images are resized, either by downscaling or upscaling, to an optimal image size that minimizes computational cost while maximizing feature resolution. To ensure efficient batch training and adequate feature resolution, an image size of 640x640 pixels is predefined as the optimal image size for this study.
- *Colorblind model*: Variations in the material color may affect the accuracy of the defect detection models [12, 14]. By using gray-scaled images, it is possible to prevent correlating material color with defect classes, as well as to increase the computational speed of the CNN model. In gray-scale images, each pixel represents a specific light intensity, ranging from black to white, with no color information.
- *Defect labeling*: Inconsistent rheological and mechanical properties of the material, dimensions of the extruded layers, and the number of stacked layers dictate the characteristics of defects, as discussed in [14]. However, details that might resemble defects may have been intentionally designed for esthetics and function, such as water protection, shading, and ventilation. Therefore, design intentions of additively manufactured structures are considered when identifying defects during the labeling process. The labeled images are accompanied by annotation files with the same name, containing the coordinates of bounding boxes that describe the location of defects and labels of the corresponding defect types.
- *Data augmentation*: Augmentation techniques are employed to increase the size of the dataset and to improve the robustness of the CNN classification models. Random camera angles are introduced to the dataset by mirroring and rotating images in the range of [-20°, 20°]. Varying lighting conditions are introduced to the dataset by adding noise to 4% of the gray-scale pixel intensity values and by adjusting brightness in the range of [-35%, 35%].

A labeling strategy is defined for the ADD preprocessor. For each defect type, a corresponding label and index number is assigned (Table 1). Defects are manually annotated with a bounding box and labeled with the corresponding index number. The annotation is then saved in a CSV file.

Table 1. Defect labeling for clay printing

Label	Index number
No defect	0
Tearing	1
Sagging	2
Buckling	3
Shrinkage cracking	4

The ADD preprocessor is implemented using Python programming language, together with a graphical user interface (GUI) for manual user inputs and processing algorithms for resizing input images, adjusting view angles, converting the images to gray scale, and augmenting the data. The GUI, as shown in Figure 2, facilitates generating datasets by importing and saving images into user-defined file directory ("source folder" and "save folder"), as well as automating the preprocessing steps with three main trigger buttons ("crop", "process", and "save").

When importing an image into the ADD preprocessor, areas of interest of the additively manufactured structures can be manually selected using the GUI and cropped with the crop button. When importing videos, a previous step is performed to capture a frame every half a second. With the process button, processing algorithms are triggered.

First, the areas of interest are centered and resized to the predefined optimal image size. Next, the viewing angle of the printed product is adjusted to ensure horizontal orientation, and the image is converted to gray-scale. Then, the generated gray-scale images are labeled with the corresponding defect class (tearing, sagging, buckling, and shrinkage cracking). Finally, the generated gray-scale images are augmented by mirroring, adding noise (randomizing 4% of the gray-scale pixel intensity values), adjusting brightness (± 35%), and rotating (± 20°) the images. With the save button, the output images and corresponding labels and annotation files are saved for the classification model development phase.

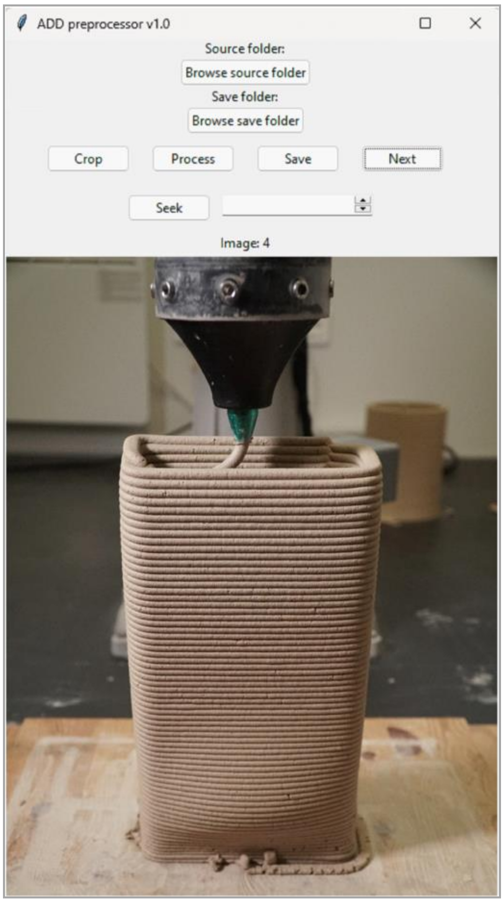

Figure 2. ADD preprocessor interface

3 Proof of concept

In this section, the ADD preprocessor functionality for generating datasets for clay printing is validated through a proof of concept. The proof of concept involves generating a dataset based on images collected from experimental tests conducted under laboratory conditions with a constant temperature of 20 °C and consistent lighting. The robotic system used for clay printing is a Potterbot SCARA v4 with a linear ram extruder and 3.5-liter extrusion tubes capable of printing highly plastic clays (Figure 3). Experimental tests for evaluating the extrudability and buildability of six clay mixtures are used to collect image data for defect detection. The clay mixtures are designed with clay contents varying between 20% and 30%, and various defects that might affect extrudability and buildability are expected during the printing process.

The images are captured with a camera with a maximum resolution of 6000x4000 pixels (Sony Alpha 6000) that is equipped with a lens with a focal length of 24-105 mm (Sony FE 24-105mm F4 G OSS) and fixed to a tripod. The focus and lens aperture are manually adjusted to ensure stable and clear image quality. Images are taken from various viewpoints, specifically highlighting defects observed during the printing process. From the images collected for validation, a total of 16 images are selected as input for the ADD preprocessor as proof of concept, from which 5 images display buckling defects, 3 images display sagging defects, 1 image displays tearing defects, and 7 images present no defects on the additively manufactured structures.

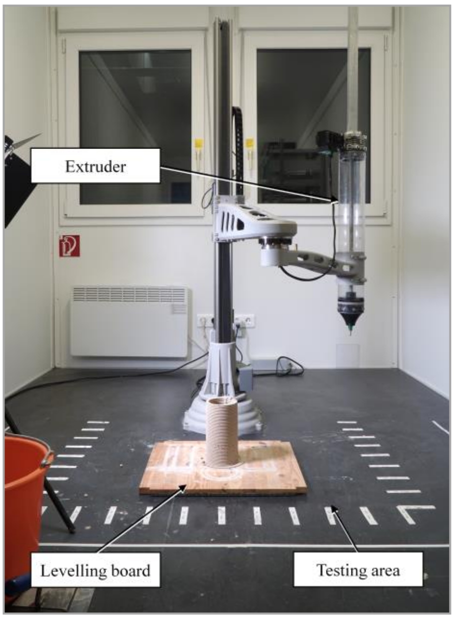

Figure 3. Robotic system for clay printing

As a result, the ADD preprocessor allows selecting areas of interest from the input images and label defects (Figure 4). The area of interests, marked exemplarily with a yellow box in Figure 4, are selected manually for cropping, focusing on the defects. Upon cropping, the defects are labeled and annotated with the corresponding defect types. As shown in Figure 4, a red bounding box annotates a sagging defect. The predefined image size of 640x640 pixels ensures adequate feature resolution to identify defects by using the context given by the pixels in the neighborhood.

The output of the data augmentation has increased the dataset size from 16 images to 64 images, providing variability in the dataset, including various viewing angles, lighting conditions, and noise. An example of the output of data augmentation for a sagging defect is shown in Figure 5. By preprocessing the images for generating the dataset, including cropping, resizing, gray-scaling and data augmentation, the ADD preprocessor not only standardizes the dataset but also prepares it for efficient training of the CNN classification model. Owing to the data augmentation techniques employed in the ADD preprocessor, the CNN classification model can be trained to have a suitable performance under random camera angles and varying lighting conditions, while avoiding overfitting.

The dataset presents positive instances that are classifiable according to defect type (i.e. images with defects) and negative instances with no detectable defects (i.e. images without defects). By including negative instances into the dataset, the defect detection model is enabled to learn patterns to not lead to false positive predictions. Even though the proof of concept has resulted in a dataset with a relatively small size, the dataset can be enlarged by collecting more images, e.g. obtained from open-access sources and from further experimental test and printings conducted in research.

By addressing the current lack of datasets for clay printing, the ADD preprocessor enables the development of advanced defect detection models that can improve the structural quality and reliability of additively manufactured clay structures. Furthermore, the ADD preprocessor can be easily employed for concrete printing due to the synergies detected among defects in clay printing and defects in concrete printing.

4 Summary and conclusions

Automated defect detection in clay printing has been hindered due to insufficient data on defects in clay printing, driving the development and validation of the ADD preprocessor, a tool designed to generate datasets to support defect detection models in clay printing. By leveraging images and videos, the ADD preprocessor processes and labels image data to create standardized

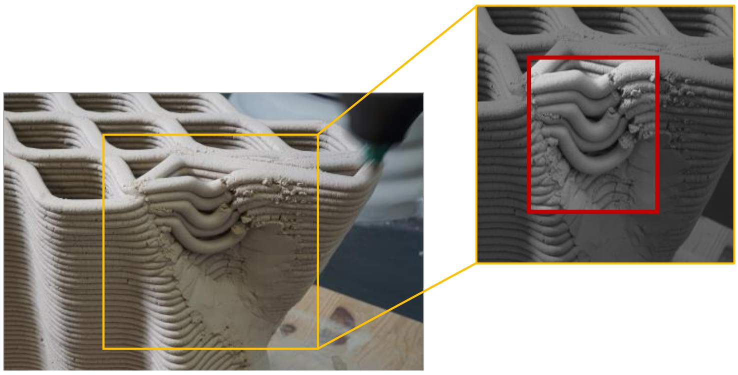

Figure 4. Identification of the area of interest (yellow box) for a “sagging” defect (red box)

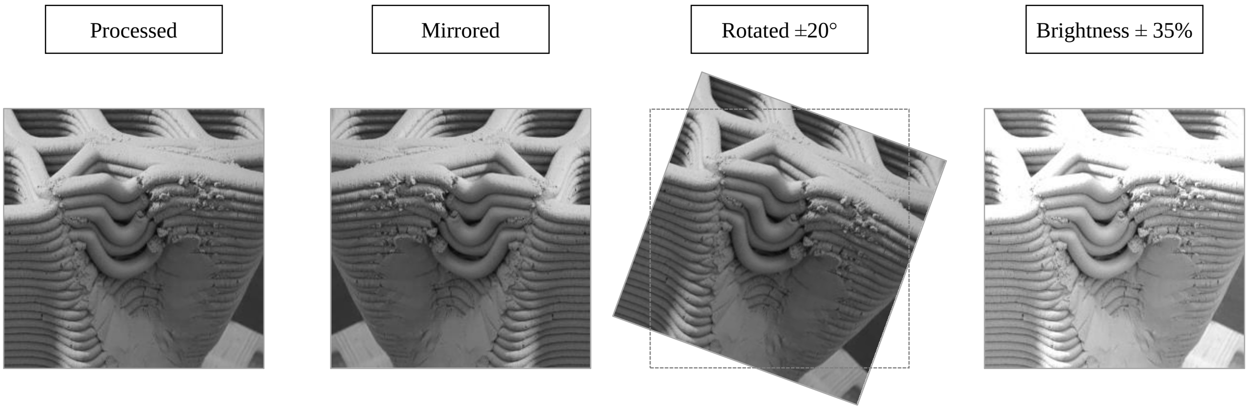

Figure 5. Outcome of the data augmentation for a “sagging” defect

datasets that meet the requirements of deep-learning-based defect detection models. The proof of concept has demonstrated the effectiveness of the ADD preprocessor in preparing positive instances that facilitate the identification and the categorization of defects (i.e., sagging, tearing, and buckling) as well as the inclusion of negative instances for more robust model training.

The ADD preprocessor possesses the ability to generate a structured dataset for defect detection in clay printing. The results showcase the potential of the ADD preprocessor to address the lack of datasets for defect detection, which has hindered the development of autonomous defect detection in clay printing. By providing a streamlined workflow for data preparation (i.e. *data preprocessing* and *data augmentation*), the ADD preprocessor supports the creation of defect detection models that are better equipped to ensure the structural integrity and quality of additively manufactured clay structures. Compared to existing labeling tools, the ADD preprocessor provides control over image standardization and data augmentation while implementing a similar labeling strategy to existing labeling tools. Yet, the manual inputs required by the ADD preprocessor, such as selecting areas of interest, could introduce subjectivity into the dataset.

To further drive the research towards automated defect detection in clay printing, future efforts could be directed towards real-time defect monitoring and towards testing the compatibility of the datasets generated by the ADD preprocessor with advanced neural network architectures, such as transformer-based models. Automated defect detection has the potential to advance the broader adoption of clay printing as a sustainable and reliable construction method.

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