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A Study of the Overhang Effects of Additively Manufactured Parts and Prediction of Geometric Deviation using Conditional Generative Adversarial Networks

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ABSTRACT

In the growing field of metal additive manufacturing (AM), the precise fabrication of parts with complex overhang geometries remains a significant challenge, directly impacting the structural integrity of the final products. This research explores the use of a Conditional Generative Adversarial Network (cGAN), specifically the pix2pix model, for predicting geometric deviations in metal 3D printed parts with overhang geometry. This method utilizes images of 2D slices obtained from 3D CAD models and X-ray Computed Tomography (CT) scanned images. The study also proposes an approach of using color-coded 2D CAD model slices as input, so the method enhances the pix2pix model's ability to distinguish between different geometric features and predict deviations more accurately. The predicted images demonstrate the potential of integrating cGANs into the AM workflow for early detection and correction of geometric deviations. This suggests a new direction for future research in applying deep learning to enhance quality control in additive manufacturing.

Keywords: metal additive manufacturing, geometric deviation, X-ray CT, deep learning, conditional generative adversarial networks

INTRODUCTION

Metal additive manufacturing has become a crucial and innovative technology for fabricating parts, assemblies, and tools in various industries, such as automotive, aerospace, and biomedical, due to its ability to offer both internal and external complex geometries [1]. However, the inherent intricacies of AM processes, particularly the difficulty of printing overhang geometries without compromising structural integrity, pose a significant obstacle to realizing the full potential of this technology. Overhang geometries in AM parts are usually inevitable and prone to geometric deviations due to the lack of material support during the printing process [2, 3]. As defects and geometric deviations are common in metal additive manufacturing [4], there is a high demand for solutions for predicting geometric deviations is in high demand [5].

Several deep-learning models have been utilized to predict geometric deviations. Ding et al. [5] presented a semi-analytical model that use a sigmoid function to predict wall thickness deviations. The pix2pix model, a type of conditional generative adversarial networks (cGAN) proposed by Isola et al. [6], is highly effective in predicting and visualizing geometric deviations in additive manufacturing. Li et al. [7] demonstrated the ability to predict geometric deviations of freeform shapes printed via material extrusion with ABS filament using conditional adversarial networks. Ramlatchan et al. [8] conducted research on predicting new data for various laser process parameter combinations using cGAN. Motivated by the need to improve precision and quality in metal additive manufacturing and to bridge the gap between design and manufacturing, this research presents a deviation prediction approach using color-coded 2D slices as input images, with colors representing geometric features. The objective of adding color to the input images is to investigate whether this addition improves the accuracy of the predicted images, making them look like the ground truth (X-ray CT scanned images). The model is trained with the number of pair image pairs of a color-code 2D slice extracted from a 3D model and the corresponding X-ray CT scan images of the actual 3D printed part. X-ray CT scanning is a promising technique for three-dimensional non-destructive testing of the internal composition and structure of various materials [9, 10]. This approach to visualizing and addressing potential deviations not only helps optimize designs for additive manufacturing (DfAM), but also has the potential to provide customizable manufacturing solutions.

METHODOLOGY

Data Collection and Processing

In this study, we have utilized a publicly available dataset of XCT images of the Overhang part from the NIST Public Data Repositor provided by Praniewicz et al.[11] . The data consists of CT scanned images of a 9mm × 5mm × 5mm rectangular prism with a 45° overhang feature and a horizontal cylindrical cutout. Figure 1 shows the three different views of the CAD part geometry.

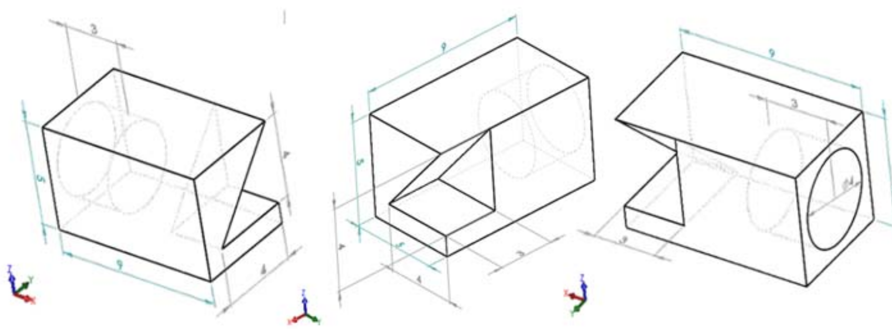

Figure 1: Three different views of the external part geometry [11]

The dataset for training, testing, and validation is prepared using several image processing techniques, such as image formatting, data augmentation, normalization, and concatenation. The color-coded input images are essential for visually distinguishing between different types of geometric deviations and features (e.g., overhangs with angles). For simplicity and to match the training data with the intended output, the format consistency of images is maintained. The grayscale CT scanned images are first converted into binary format to accentuate the contrast between the material and void spaces. They are then converted into RGB by replicating the single channel across all three RGB channels.

The generation of 2D slices from the 3D CAD model is accomplished through MATLAB. Initially, the CAD model is divided into discrete triangles. The slicing operation is performed iteratively, starting from the base of the model and advancing in the Z-axis. At each iteration, the "triPlanintersect" function computes the intersection of active triangles with the current slicing plane, delineating the perimeter of the slice which is later rendered in the figure as a 2D slice.

After generating the slices, color is applied to the the 2D slice images to correspond with specific overhang angles. Skin angles are highlighted in RGB colors layer by layer, with each color representing a specific overhang angle. The slicer code has been improved to apply this mapping and calculate the overhang angle for each segment of the intersection line in the "triPlanintersect" function. This generates 2D slices with crucial geometric features information shown by color. With the help of color-coded 2D slices, the model can effectively learn the correlation between color-coded features and actual geometric deviations. The color-coded geometric features in the slice are more salient for the model during training. In Figure 2, the surface indicates the reference plane from which the overhang angles (denoted as δ) are measured and the gradient ranging from blue to red represents surface angles from 180° to 0°. For example, green means that the part surface is perpendicular to the build plate, while yellow indicates that the angle between the downskin and the build plate is 45 degrees as shown in Figure 2.

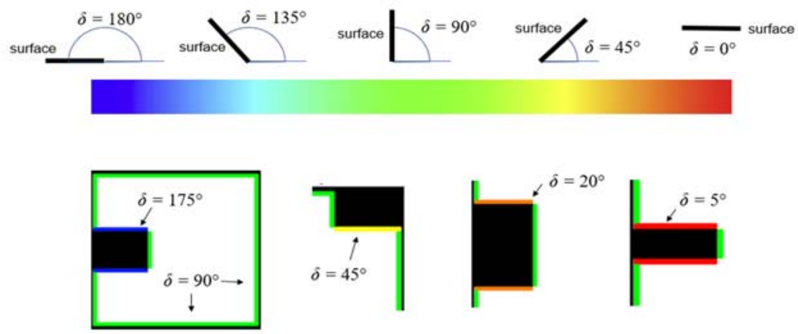

Figure 2: Generating input image for pix2pix model. Color gradient representing a range of overhang angles with blue 180° to red 0°.

MODEL SETUP AND EVALUATION

The implementation of the pix2pix model is based on the cGAN framework. The objective is to learn a mapping from an input image to an output image. The model is trained using pairs of color-coded 2D slices from the 3D geometry and its corresponding CT-scanned images. The pix2pix model consists of two main components: a generator with U-Net architecture [12] and a discriminator with a convolutional "PatchGAN" classifier to classify whether 70×70 overlapping patches are real or fake. The generator is trained to generate fake 2D slices with deviation whereas the discriminator is trained to detect those fake images (i.e., produced by the generator).

The dataset for training the pix2pix model is prepared by concatenating each pair of input and target images to facilitate the model's learning of the appropriate mappings from inputs to outputs. All images are 256 pixels by 256 pixels and 3 channels. Resizing to 286×286 pixels, random jittering, cropping, and flipping are performed to introduce variability in the dataset. Figure 3 shows the pair of images as an input to the pix2pix model.

The training dataset consists of 354 pairs of images equivalent to the number of 2D slices from a 3D CAD model. We trained the model using the Adam optimizer with a learning rate of 2e-4 and a batch size of 1, as suggested by Isola et al. [6] in the original paper. Training was conducted for 40,000 steps, with checkpoints saved every 5000 steps and the model was run through 113 epochs. The generator's loss is determined by a combination of a GAN loss and an L1 loss whereas the discriminator's loss is a binary cross-entropy loss. For regularization, dropout is incorporated in the generator's decoder and batch normalization is used to prevent overfitting.

In this study, a pix2pix model was used to generate images of a CAD model with possible defects. To obtain the best prediction results, a random search was conducted. The value of λ controls the amount of L1 loss added to the model. After being trained and tuned with different hyperparameters, the model showed favorable results with λ=125 and a learning rate of 0.001. Figure 4 shows the predicted images for different layers of the 3D CAD model. The input image is color-coded to highlight specific areas of a geometric shape. The model performs reasonably well in predicting geometric deviations, as shown by the similarity between the ground truth and the predicted images. The blue and red colored areas indicate a change in overhang angles due to the geometric features. Yellow colored areas indicate a 45° overhang feature in the 3D CAD model.

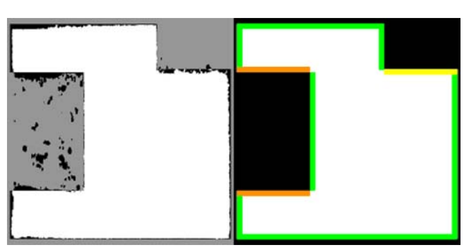

Figure 3: Pair of images as an input to the pix2pix model. (target) CT-scanned image of the part. (input) 2D slice from the 3D model with orange and yellow colors indicating geometric features.

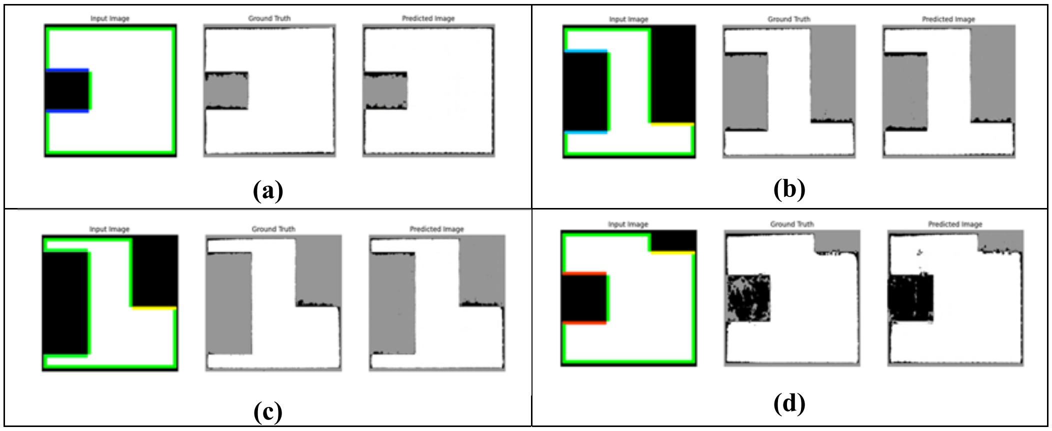

Figure 4: Predicted images from the sample with λ=125: (a) layer 15, (b) layer 80, (c) layer 153, (d) layer 302

CONCLUSION

The use of color-coded input images in the proposed approach enhances the model's sensitivity to critical geometric features, such as a 45° overhang and a horizontal cylindrical cutout. This sensitivity is crucial in AM, where geometric features can significantly impact the structural integrity and print quality. This work also establishes a foundation for future research to optimize color-coding techniques and achieve more precise deviation predictions.

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