32ND RESEARCH SYMPOSIUM ASNT | EVENTS.

Presented At: ASNT Research Symposium:
25 – 28 June 2024
Pittsburgh, Pennsylvania, USA

In-Situ Monitoring and Prediction of Geometric Deviation in Laser Powder Bed Fusion Process Using Conditional Generative Adversarial Networks

Prateek Neupane[1], Himal Sapkota[1], and Sangjin Jung[1]

[1]School of Mechanical, Aerospace and Materials Engineering, Southern Illinois University Carbondale
1230 Lincoln Drive, Carbondale, IL 62918
{prateek.neupane, himal.sapkota, sangjin.jung}@siu.edu

ABSTRACT

Metal additive manufacturing is a widely used advanced manufacturing technique in various industries and research fields for rapid prototyping and testing. However, it can cause inherent defects related to geometric inaccuracy and surface quality due to the layer-by-layer printing approach of 3D printers. This paper presents a methodology that combines an in-situ monitoring approach with a machine learning model to predict geometric defects in nature-inspired complex lattice structures. The machine learning model used in this study is Conditional Generative Adversarial Networks (cGANs), which can generate new images from the existing dataset of images. The methodology proposed employs an image pair consisting of CAD slices and real-time images obtained during the printing process to train the cGAN model. The similarity between the generated and actual images was analyzed using PSNR and SSIM metrics. The results indicate that the cGAN model produces precise images that closely resemble the actual images of the lattice structure.

Keywords: powder bed fusion, lattice structure, geometric deviation, machine learning, cGAN

INTRODUCTION

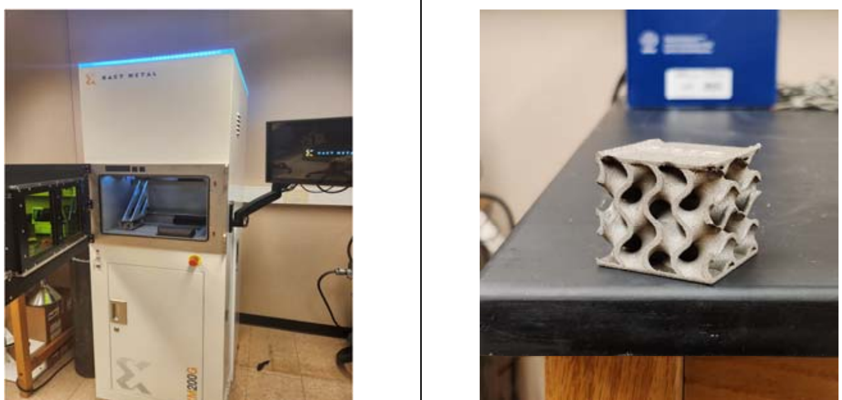
Additive manufacturing (AM) is a recent technological advancement in manufacturing, made possible by advances in computer technology and the transition from analog to digital processes. AM uses information from CAD software to direct a hardware component to create a 3D object with a layer-by-layer building strategy. Additive manufacturing differs from traditional manufacturing methods, which typically involve removing materials to create a finished part, resulting in significant material waste [1].

Defect detection using machine learning in AM is not a new concept, and several studies have employed machine learning models and methods [2-4]. Zhu et al. [2] established a mathematical relationship between the designed and final shape by using multiple transformation matrices as a parametric function to capture the deviations in FDM printed parts. In reference [3], Convolutional Neural Networks (CNNs) were utilized to predict the geometric deviation in the Selective Laser Melting (SLM) process. The multi-channel image input contained information on printing parameters and cross-sections of CAD geometry. Similarly, Ling et al. [4] used in-situ monitoring with Conditional Adversarial Networks [5] to predict the geometric deviations of FDM freeform shapes. The results showed that 99.2% of the data were within ± 0.15 mm. Previous research on geometric deviation has primarily focused on polymer-based AM processes with simple CAD models. However, there has been limited research on predicting deviations of complex lattice structures during metal AM. This paper proposes a methodology that utilizes real-time images of printed layers and the CAD cross-sectional images to train a cGAN model for predicting geometric deviations. The cGAN model consists of a generator and a discriminator that compete as adversaries. The research focuses on predicting geometric deviations in the Gyroid TPMS lattice. The layer images of the printed part require additional processing, including filtering, denoising, and binarization. For binarization, the Robust Automatic Threshold Selection (RATS) algorithm [6] was utilized in this work. The image dataset was used to train the cGAN model, and at the end of the training, the generator can produce images by taking the CAD cross-section as input and predicting the deviations on the part.

METHODOLOGY

Printing Process

The study aimed to predict the geometric deviations of a Gyroid lattice structure [7] printed using a laser powder bed fusion (PBF) technique. The XM200G metal 3D printer was used to print the lattice structure with SS316L metal powder as the printing material. The layer thickness was set to 30 µm, and the printing process took over 8 hours. Upon initial inspection, the imperfections and defects were observed on the surfaces.



(a) (b)

Figure 1: (a) XM200G metal 3D printer used for printing the parts. (b) Printed gyroid lattice structure

Dataset

The dataset utilized in this research consisted of real-time layer images of a Gyroid lattice structure obtained from the metal 3D printer. To train the cGAN model, an image pair was required, consisting of a CAD cross-section image as input and the layer image of the printed part as the ground truth. The CAD cross-section images were obtained from MATLAB code that takes an STL file of the part and returns the cross-section image at a specific height. The image was resized to 256 × 256 pixels to be compatible with our machine learning model. Similarly, the layer images of the printed part were obtained from the printer's build log. Before the image could be used for training purposes, it required further preprocessing. The images were cropped, denoised, resized, and binarized using the RATS algorithm. This enabled us to extract useful information from the image regarding geometric deviations. The two images are combined to create a training set of 512 × 256 images that were suitable for training. A total of 600 images were created and split into training, validation, and testing sets in a 60-20-20 ratio.

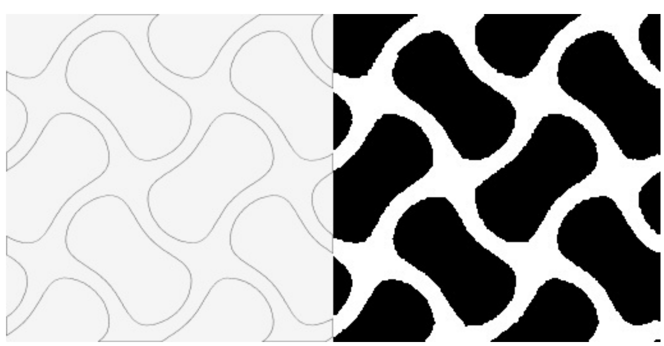


Figure 2: Dataset image including CAD cross-section (left) and binarized layer image (right)

Machine Learning Model

This study utilized a cGAN model called pix2pix [5] which can be employed for image-to-image translation. The pix2pix model is trained on an image pair and learns a mapping from input images to output. The model was implemented in the study to predict the characteristics of the printed layer based on the CAD cross-section.

A total of 600 images were obtained and split into training, testing and validation sets. The original paper on pix2pix [5] provides hyperparameter values, but they were not suitable for our task so we tuned the parameters to obtain optimal values. The model was trained for 30,000 steps using lambda (λ) = 100, batch size = 2, and learning rate (α) = 0.001. The encoder and decoder parts of the generator included skip connections to preserve information and improve image quality. The discriminator loss was defined as a combination of a GAN loss and a traditional loss metric, specifically the L1 loss, which is found to prevent image blurring. We also applied random jittering through resizing, cropping, and optional mirroring to increase dataset variety. The generator and discriminator were trained separately. The generator was trained to produce realistic images, while the discriminator was trained to accurately distinguish between real and fake images.

RESULTS

After training the model, the generator was used to produce images for testing the model's capabilities. Five CAD cross-section images from the test set were provided to the generator, and the corresponding layer image predictions were obtained. Figure 3 shows some of the predicted images, which were then compared to the ground truth of that layer. The evaluation of GAN models' performance is still an active area of research, and there are no standard evaluation criteria in place as of today [8]. Therefore, to assess the performance of the pix2pix model, we analyzed the image quality of the predicted images. We adopted the two most commonly used image quality metrics: Peak signal-to-noise ratio (PSNR) and Structural Similarity Index (SSIM) [9]. SSIM evaluates luminance, structure, and contrast to provide a similarity index between 0 and 1, where 1 indicates exact similarity between two images. On the other hand, PSNR measures the quality of the reconstructed image compared to the original. A PSNR value higher than 20 dB is considered good image quality [10]. Table 1 presents the results of the image quality metrics.

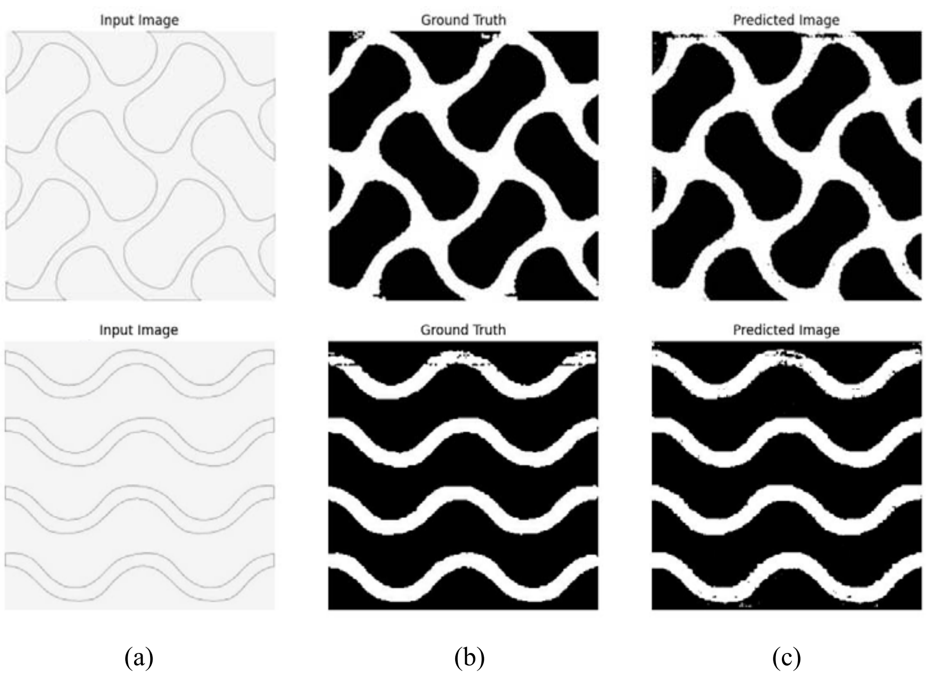


Figure 3: (a) CAD cross-section image provided to the generator. (b) The ground truth of that layer. (c) The predicted layer image obtained from the generator

Table 1: PSNR and SSIM metrics for five images generated by the generator

Images	PSNR (dB)	SSIM
Image 1	16.46	0.8237
Image 2	18.33	0.8652
Image 3	17.50	0.8369
Image 4	15.27	0.7879
Image 5	17.14	0.8265

The results show that the pix2pix model accurately predicts geometric deviations in 3D printed lattice structures, as shown by the high SSIM values in Table 1. The relatively low PSNR values means distortion or noise in the generated images (e.g., Images 1 and 4), which can be addressed through hyperparameter tuning and model regularization.

CONCLUSION

The proposed methodology was able to obtain layer images from the printer to train a pix2pix cGAN model for predicting deviations during the printing process. The performance of the machine learning model was also evaluated by using two image quality metrics. It was observed that the cGAN model can generate accurate images that closely resemble the actual images of the Gyroid lattice structure. This study paves the way for establishing a method that can identify deviations in metal AM parts prior to printing and compensate for inaccuracies to ensure more accurate printing.

REFERENCES

(1) Javaid, M., Haleem, A., Singh, R. P., Suman, R., and Rab, S., 2021, "Role of additive manufacturing applications towards environmental sustainability," *Advanced Industrial and Engineering Polymer Research*, **4**(4), pp. 312-322.
(2) Zhu, Z., Anwer, N., Huang, Q., and Mathieu, L., 2018, "Machine learning in tolerancing for additive manufacturing," *CIRP Annals*, **67**(1), pp. 157-160.
(3) Zhu, Z., Ferreira, K., Anwer, N., Mathieu, L., Guo, K., and Qiao, L., 2020, "Convolutional neural network for geometric deviation prediction in additive manufacturing," *Procedia CIRP*, **91**, pp. 534-539.
(4) Li, L., McGuan, R., Isaac, R., Kavehpour, P., and Candler, R., 2021, "Improving precision of material extrusion 3D printing by in-situ monitoring & predicting 3D geometric deviation using conditional adversarial networks," *Additive Manufacturing*, **38**, p. 101695.
(5) Isola, P., Zhu, J.-Y., Zhou, T., and Efros, A. A., 2017, "Image-to-image translation with conditional adversarial networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1125-1134.
(6) Lozanovski, B., Downing, D., Tino, R., Tran, P., Shidid, D., Emmelmann, C., Qian, M., Choong, P., Brandt, M., and Leary, M., 2021, "Image-based geometrical characterization of nodes in additively manufactured lattice structures," *3D Printing and Additive Manufacturing*, **8**(1), pp. 51-68.
(7) Schoen, A. H., 1970, *Infinite Periodic Minimal Surfaces without Self-intersections*, NASA, TN D-5541.
(8) Borji, A., 2022, "Pros and cons of GAN evaluation measures: New developments," *Computer Vision and Image Understanding*, **215**, p. 103329.
(9) Zhou, W., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P., 2004, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, **13**(4), pp. 600-612.
(10) Bull, D. R., 2014, "Digital picture formats and representations," *Communicating Pictures*, pp. 99-132.