Project Proposal: Predicting Deposit Morphology in Direct Ink Writing using cGAN

Problem Selection and Justification

Direct ink writing (DIW) processes, including inkjet printing, plasma jet printing, and aerosol jet printing (AJP), are widely used in printed electronics. A critical challenge in these processes is deposit morphology control, which consists of a main line (the primary printed feature) and overspray (unintended satellite droplets around the deposit). While the main line width must be precisely controlled to ensure functionality, excessive overspray can degrade circuit performance, increase parasitic effects, and reduce device sensitivity.

Currently, deposit morphology cannot be accurately predicted before printing, requiring extensive trial-and-error experimentation to determine optimal process parameters. This leads to increased lead time and production costs, as each experiment consumes expensive resources such as specialized inks, silicon wafers, and flexible substrates. Additionally, process parameter interactions are highly complex, making it difficult to derive a deterministic relationship between printing conditions and deposit characteristics. If a deep-learning-based Generative Adversarial Network (GAN) model can provide early visualization of the deposit morphology based on printing parameters, manufacturers could significantly reduce experimental costs and time, enabling more efficient process optimization.

Dataset Description

The dataset consists of high-resolution optical microscopy images of deposits produced via aerosol jet printing, a specific DIW process. The dataset captures deposit morphology variations under different atomization voltages (ATM), carrier gas flow rates (CGFR), focusing ratios (FR), and stage speeds (SS). Each image is labeled with the corresponding process parameters to enable conditional image generation. Although the dataset size is moderate, data augmentation techniques such as geometric transformations and contrast adjustments will be applied to enhance training dataset.

Deep Network Selection and Customization

A Conditional Generative Adversarial Network (cGAN) will be used as the base model due to its ability to generate realistic images conditioned on structured inputs. However, rather than adopting a standard architecture, we will develop a customized cGAN to better capture the complex process-structure relationships in direct ink writing. The model will be implemented using PyTorch, given its flexibility, extensive deep learning libraries, and optimized GPU acceleration, which will facilitate efficient training and high-resolution image generation.

Reference materials

Research Paper:

Liu, W., Wang, Z., Tian, L., Lauria, S., & Liu, X. (2021). Melt pool segmentation for additive manufacturing: A generative adversarial network approach. *Computers & Electrical Engineering*, *92*, 107183.

Mirza, M., & Osindero, S. (2014). Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*.

Narikawa, R., Fukatsu, Y., Wang, Z. L., Ogawa, T., Adachi, Y., Tanaka, Y., & Ishikawa, S. (2022). Generative Adversarial Networks-Based Synthetic Microstructures for Data-Driven Materials Design. *Advanced Theory and Simulations*, *5*(5), 2100470.

Petrik, J., Kavas, B., & Bambach, M. (2023). MeltPoolGAN: Auxiliary Classifier Generative Adversarial Network for melt pool classification and generation of laser power, scan speed and scan direction in Laser Powder Bed Fusion. *Additive Manufacturing*, *78*, 103868.

GitHub:

https://github.com/Lornatang/conditional_gan

https://github.com/qbxlvnf11/conditional-GAN

https://github.com/kmualim/CGAN-Pytorch

https://github.com/eriklindernoren/Keras-GAN/blob/master/cgan/cgan.py

Performance Evaluation and Metrics

The model’s performance will be evaluated using both image quality and statistical metrics:

- Jaccard Index (IoU): Measures the overlap between predicted and experimental deposits, evaluating structural similarity.
- F1 Score and Precision: Assess the model’s accuracy in replicating edge roughness and deposit shape, particularly in distinguishing the main line from overspray regions.
- Two sample T-tests

Schedule

Week	Tasks
1	Data preprocessing and augmentation
2	Baseline cGAN implementation and initial training
3	Model architecture refinement (loss function tuning, network modifications)
4	Model architecture refinement (loss function tuning, network modifications)
5	Performance evaluation and metric comparisons
6	Documentation and final report preparation