Machine Learning-Enabled In-Process Defect Detection

PROJECT ID: B2-19

Principal Investigator:
Qian Yang (UCONN)

Co-Principal Investigator:
Anson Ma (UCONN)

Student Researchers:
Yushuo Niu, Ethan Chadwick (UCONN)

IAB Mentors:
Patrick Kinlen (Boeing)
Paul Olubummo, Jun Zeng (HP),
Baris Unal (Triton Systems)
Konstantine Fetfatsidis (Desktop Metal)
Amit Surana (Raytheon Technologies)

Automatic defect detection for 3D printing processes is critical to the quality assurance of 3D printed products and remains an active area of research. However, there are two key challenges in the current state of practice. First, the current available methods for computer vision-based process monitoring typically work well only under specific camera viewpoints and lighting situations, requiring precise calibration and making it difficult to implement on different industrial setups easily. Second, many defect detection techniques are specific to pre-defined defect patterns and/or print schematics. In this project, we have applied novel machine learning methods to tackle these challenges. Specifically, two deep learning models have been developed for automatic defect detection. Our first model solves a binary classification problem, identifying the presence or absence of defects. Our second model solves an image segmentation problem, identifying the locations of defects with respect to the reference frame. For any given print layer, two images are used as model inputs, namely, a reference schematic of the desired print, and a camera image of the actual print results. By directly identifying the differences between these two images, defects are detected efficiently without pre-specification of defect types and desired print schematics. These models are also robust to perturbations in the imaging setup such as camera angle and illumination. In training these models, data augmentation was used to reduce the number of datapoints required significantly. Only 50 pairs of experimental camera images were needed to train our preliminary models. In terms of accuracy, an F1-score of 0.94 and 0.86 were achieved for the classification and localization models, respectively. Further, these models are capable of making predictions in near real time using a standard personal computer, requiring less than 0.75 s per layer and 1.29 s per layer for classification and localization, respectively. These times are relatively short compared to the print time per layer, but will be further improved in future work.

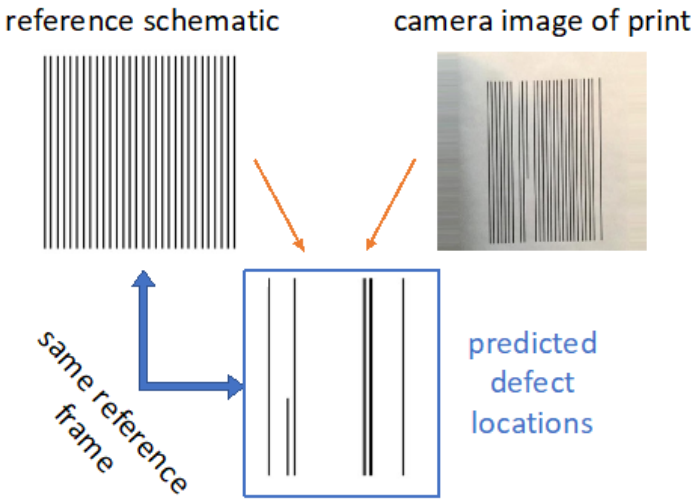

Figure 1. Our robust defect localization model takes as input a reference print schematic and a camera image of the print, and predicts the precise location of defects with respect to the frame of reference of the print schematic. This model currently requires 1.29 seconds for prediction. A lighter, faster model that simply identifies the presence or absence of defects has also been developed, which requires 0.75 second for prediction.