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Real-Time Process Modeling & Control of Direct Ink Write 3D Printing using Computer Vision and Machine Learning

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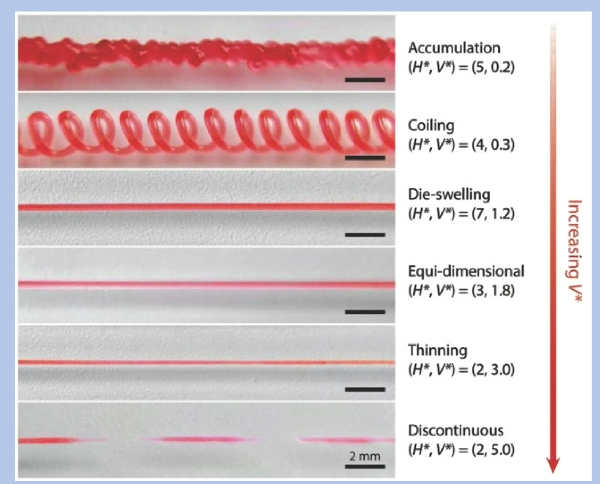
Background & Motivation

- DIW 3D printing provides large design space
- This big-data problem is well-suited for Machine Learning (ML)-based modeling and optimization approaches
- Previous methods for 3D printing control relied on convolutional neural networks (CNNs) – classified prints as “good”, “medium”, or “bad”
- Previous optimization approaches used iterative adjustments.

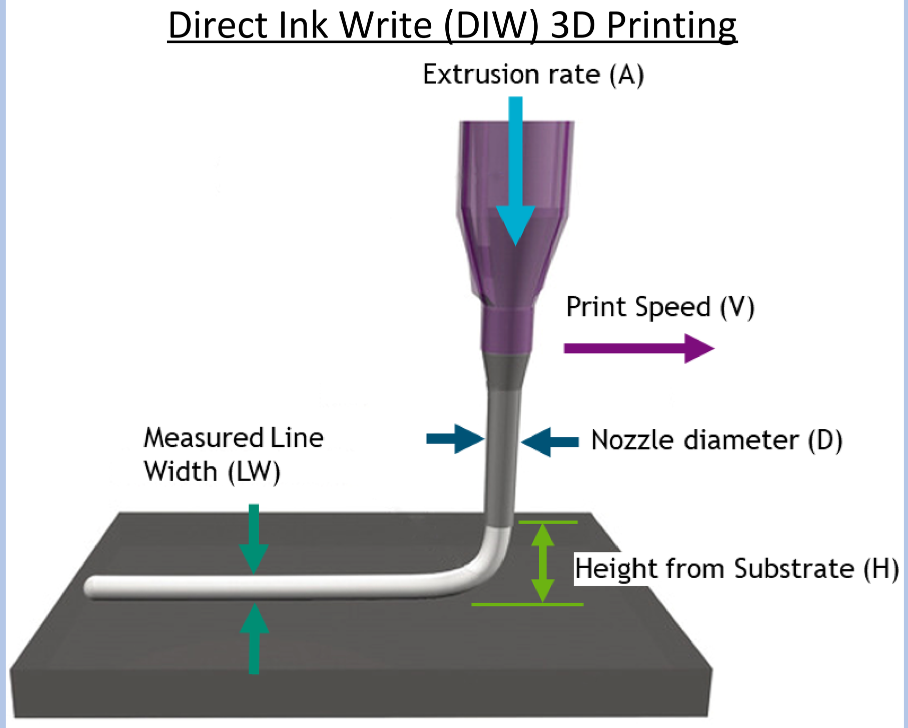
- We propose a real-time process monitoring and control approach that is both material agnostic and output-driven.

Design Space Characterization

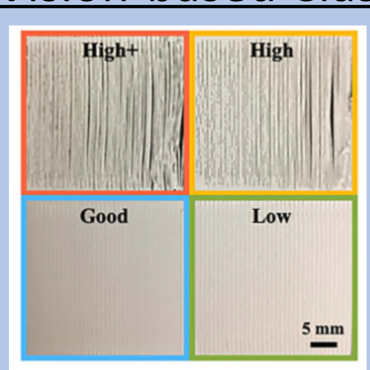


H. Yuk, et al. *Advanced Materials* 4, 579-587, 2017.

Direct Ink Write (DIW) 3D Printing

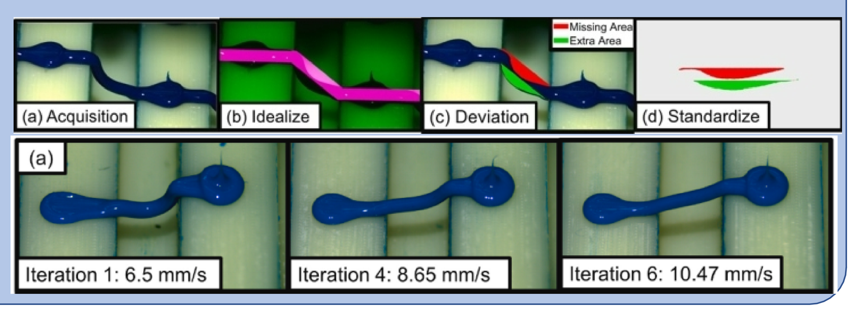


Vision-based Classification



Z. Jin, et al. *Advanced Intelligent Systems* 2, 1900130, 2020.

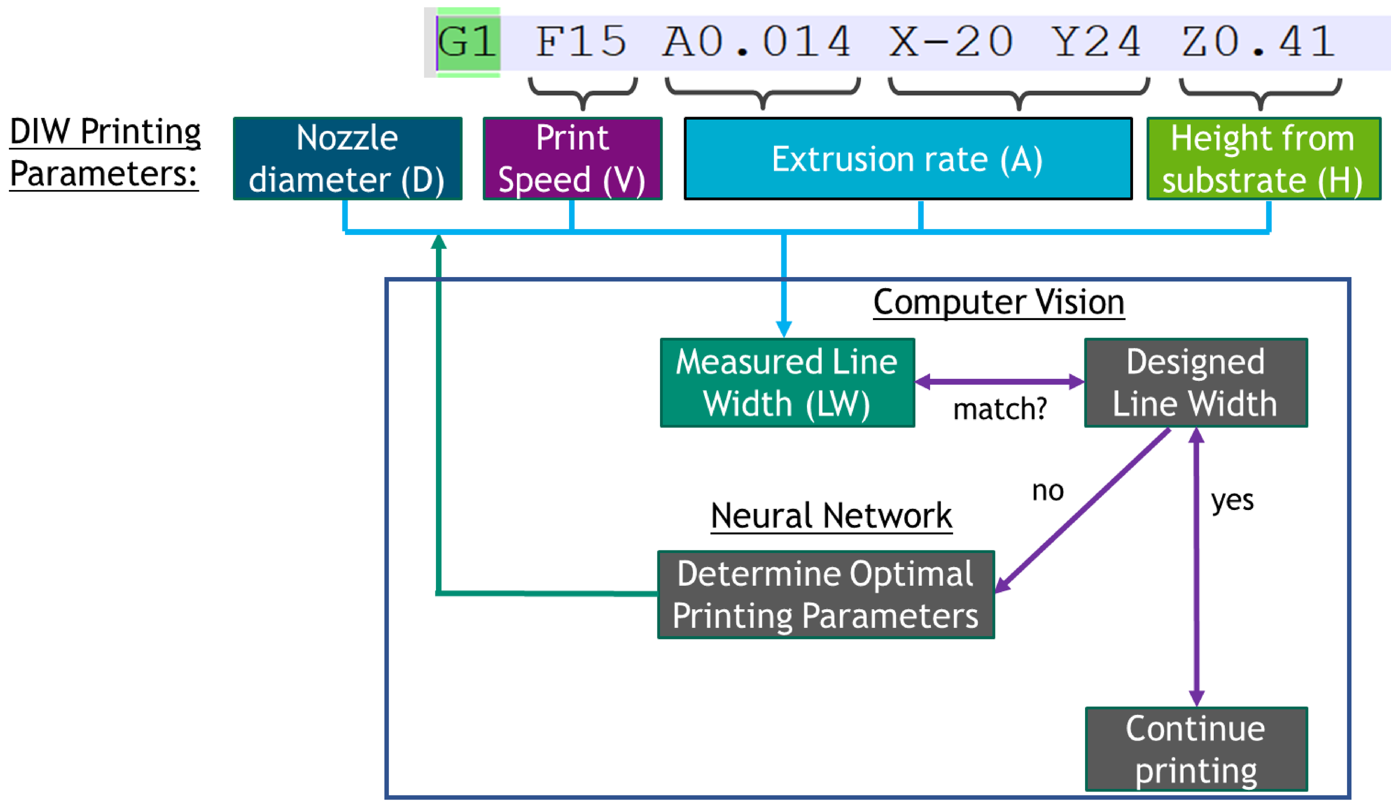
Vision-Assisted Optimization



M. Johnson, et al. *Additive Manufacturing* 46, 102191, 2021.

Experiment Design

Single G-code command to print a line:



After choosing a nozzle size, we can represent our entire DIW design space with a single line of G-code.

- G-code is the language a 3D printer uses to interpret motion and extrusion commands.

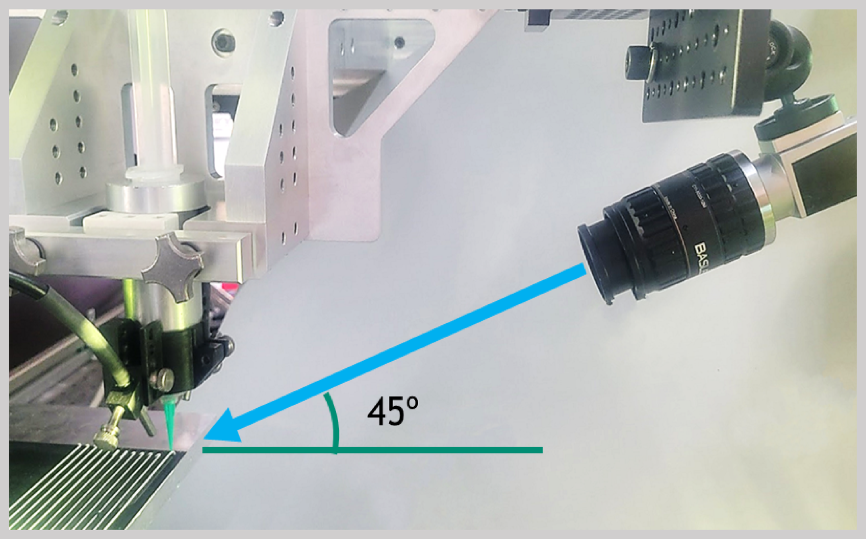
We will select:

- 3 nozzle sizes (D)
- 5 print speeds (V)
- 4 extrusion rates (A)
- 4 heights from substrate (H)

= 240 combinations of different input parameters

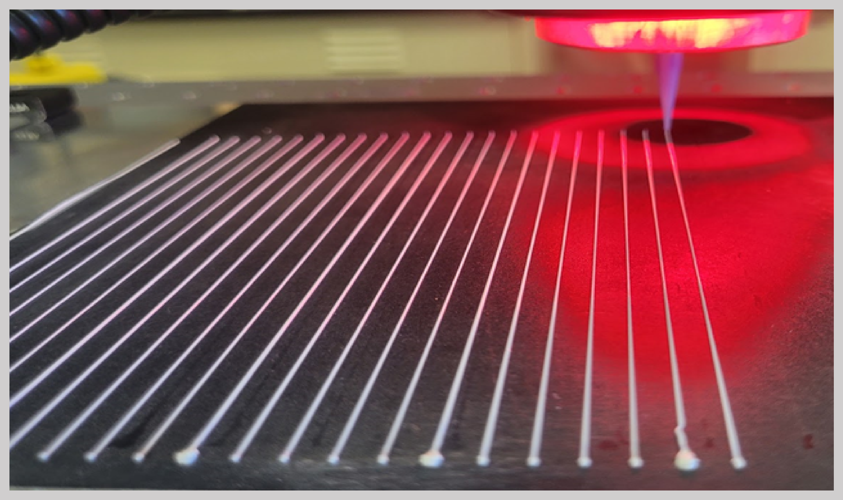
Approach (Computer Vision)

- Camera aimed at print head for in-situ measurements of printed line-width.

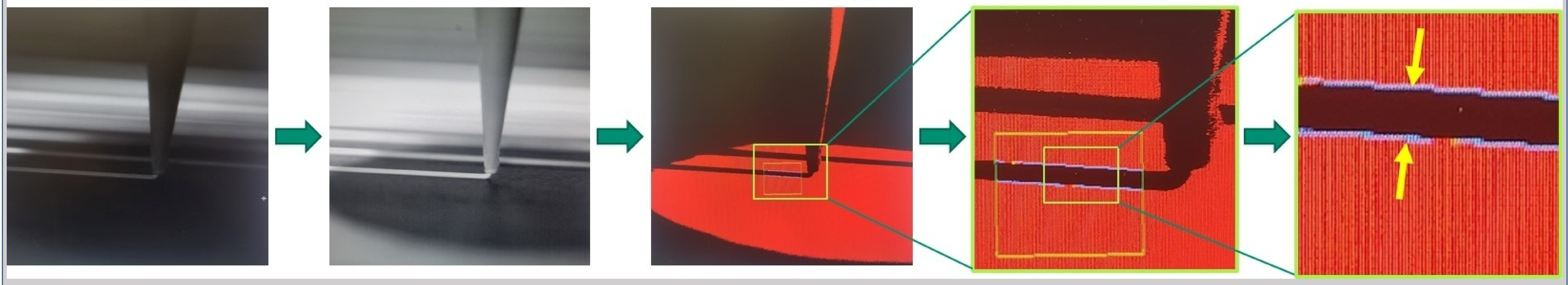


Neural network training will consist of printing all 240 combinations.

Measuring the line width as follows:



Printed Lines for Neural Network Training



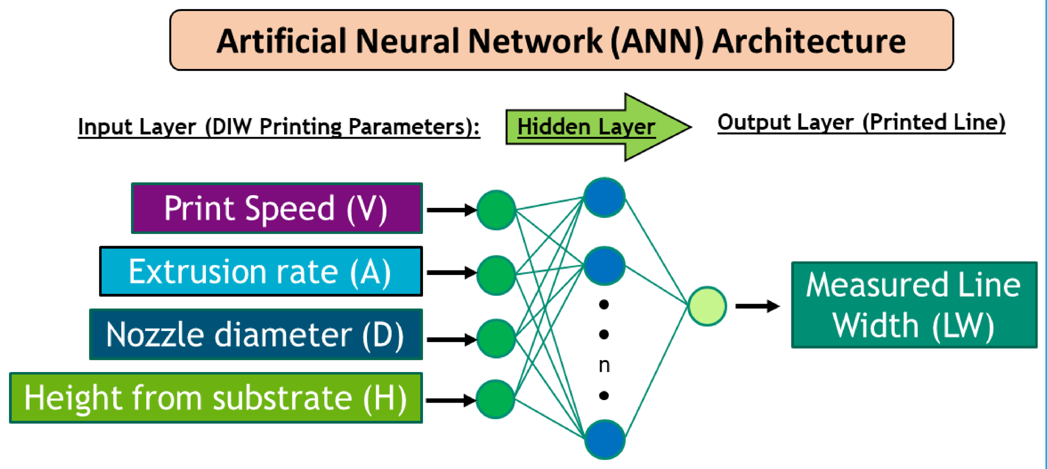
This computer vision set-up can provide sampling rates up to 200Hz.

Cameras provide 250 pixels/mm for a resolution of 2.5µm/pixel.

Results

Neural Network Modeling

The ANN used below captures the relationship between the input and output DIW printing parameters.

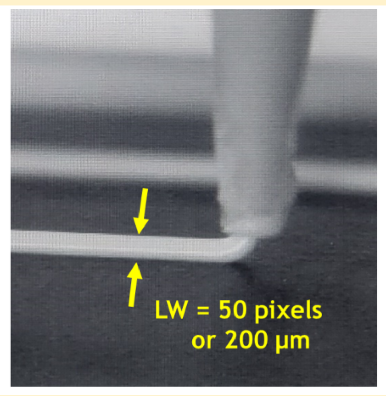


Example code used to print 200µm line:

```
>> target_line = 50/250 (50 pixels) 250 pixels)

target_line =

    0.2000  = 200 µm

>> print_parameters = network(target_line)

print_parameters =

    0.2500  → Nozzle diameter (D)
    3.1400  → Height from Substrate (H)
   58.9300  → Print Speed (V)
    0.6200  → Extrusion displacement (A)
```

Our 4 primary printing parameters

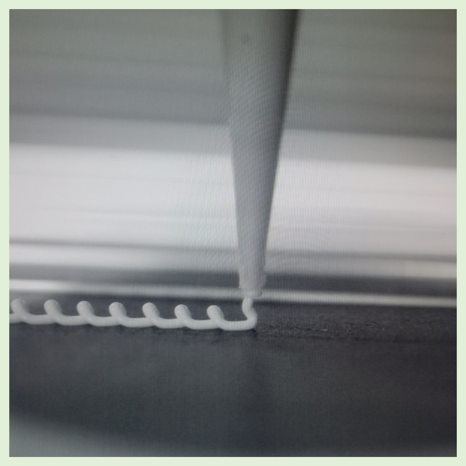
Printed line at iteration 1:



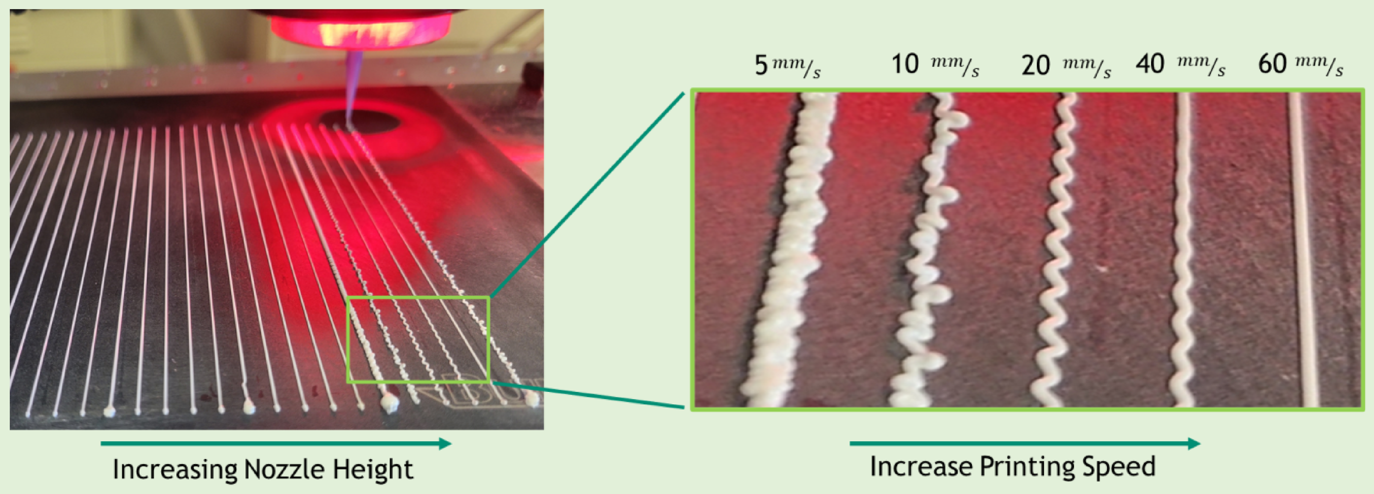
Printed sample at iteration 1:

Real-time Monitoring and Adjustment

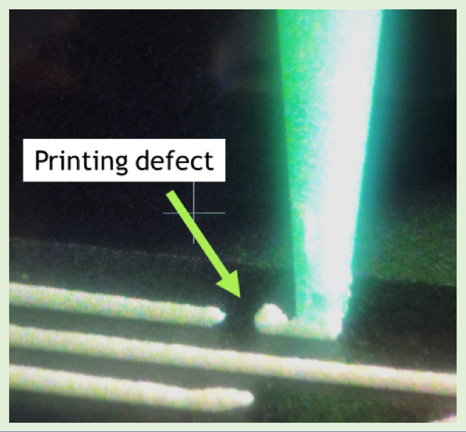
Error #1: Coiling defect



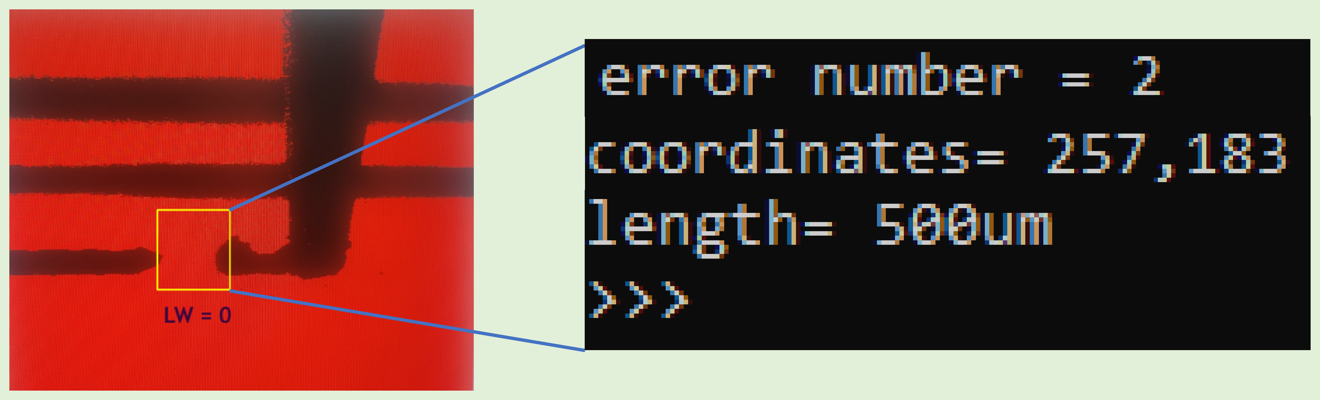
Solution: Increase printing speed to 60 mm/s



Error #2: Printing defect

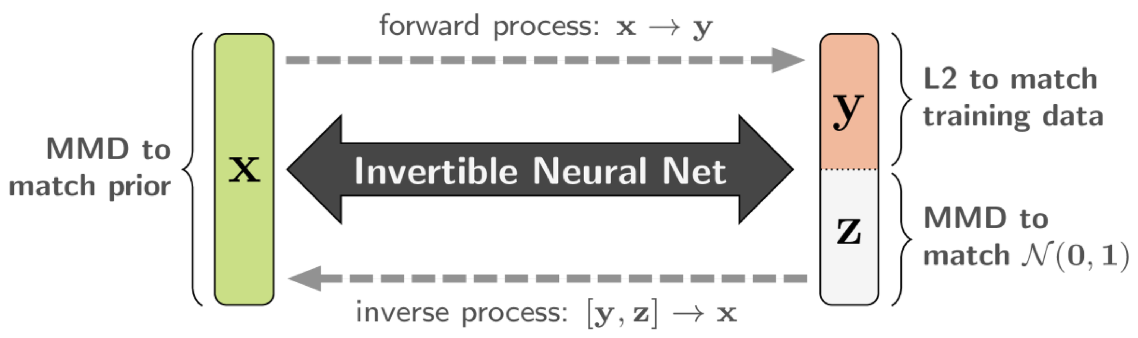


Solution: Log coordinates and location for re-print

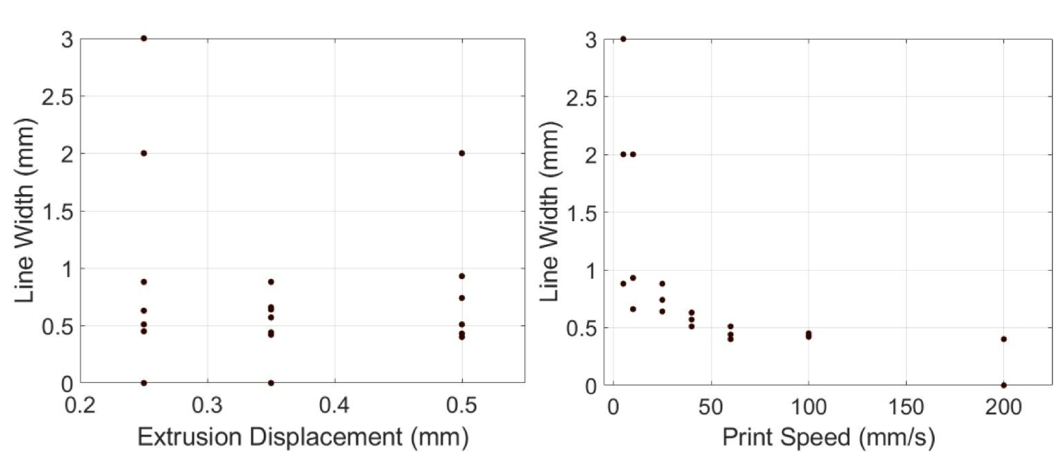


Inverse Neural Network Parameter Optimization

Generated an invertible neural network so we can begin at any measured line width and determine optimal path to target print parameters.



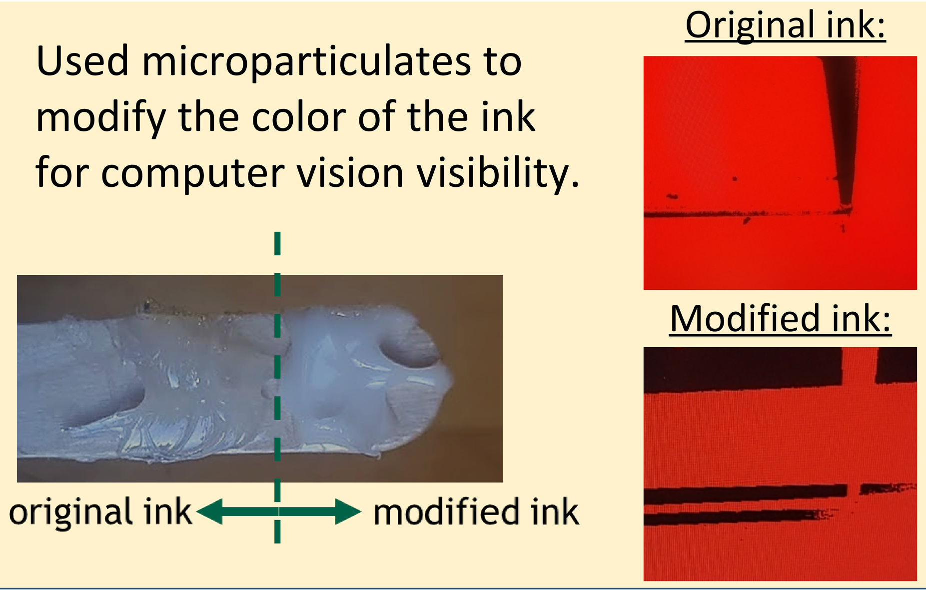
Fix 2 of 4 variables: D = 0.84mm, H = 1



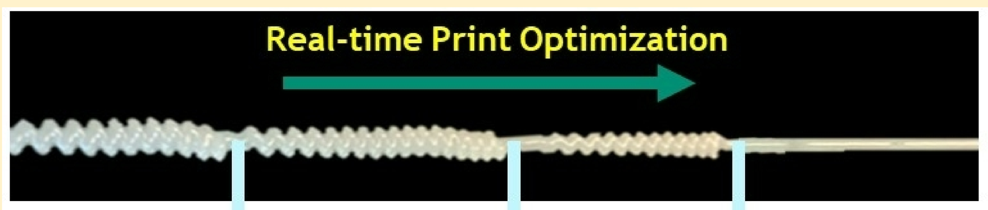
Material Agnostic, Real-time Process Control

We attempt to print an epoxy/acrylate material which was not used for the neural network training.

- Used microparticulates to modify the color of the ink for computer vision visibility.



Begin with randomized print settings & rapidly determine optimized settings.



Line Width: 419	Line Width: 294	Line Width: 235	Line Width: 178
D = 0.84	D = 0.84	D = 0.84	D = 0.84
V = 10	V = 5	V = 60	V = 10
A = 0.6	A = 0.6	A = 0.3	A = 0.3
H = 2	H = 1.5	H = 1	H = 1

Significance

The development of real-time monitoring of DIW 3D printing using computer vision and cutting-edge machine learning methods enables process control and in-situ print correction. Furthermore, a material agnostic approach was developed, eliminating the need for time-consuming trial and error approaches for the discovery of 3D printing parameters. This approach lays the ground work for the successful extrusion-based 3D printing of novel materials with minimal operator interaction.

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