

IMPARTING MACHINE INTELLIGENCE INTO DIRECT INK WRITE MANUFACTURING

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Key Words: Direct Write, Additive Manufacturing, machine learning, image classification

While digital manufacturing methods such as computer numerical control machining and additive manufacturing have enabled the creation of small lots of components with various complex shapes and materials. Understated, is the degree of individual process engineering and expertise required to tune material behavior, processing conditions to achieve expected properties. Current robotic manufacturing control frameworks lack the sensing and autonomy to effectively perceive and decide a course of action in response to these dynamic manufacturing environments. As a result, many commercial platforms limit user control over materials to ensure repeatability at the cost of agility. This paradigm fundamentally prevents the maturation of processes like direct ink write (DIW) additive manufacturing, which has been used to 3D print tissue scaffolds, ceramics, metals, magnets, and free-form structures.^[1-5] In DIW additive manufacturing, both the materials behavior and desired structure are constantly changing, but the machine itself is rigid and never “learns” from past experiences. In general, only the user learns, thereby creating experienced “super users”. Using DIW as an example, we will present how materials and printed device development spurred the push to address the gap between robot and human experience by combining image classification, adaptive feedback, and analytical methods. A generalizable image classification method was developed to characterize the spanning behavior of a thixotropic fluid printed across 2- and 3-D gaps. The automated classification informed how to adapt the tool path and subsequently predict printing conditions for log-pile structures. By harvesting the relevant data and outcomes with user context, we seek to build an open knowledge community to enable more task-agnostic direct ink write manufacturing.

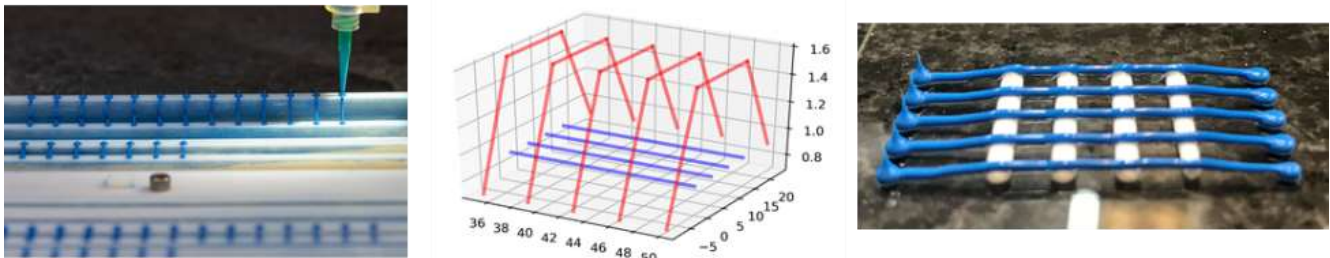


Figure 1 – The printer trains itself how to print a spanning feature on a pre-defined “obstacle course” (left), this information is used to predict tool path for a two-layer log pile structure of dimensions not included in the training set (middle). The structure is successfully printed and the image classifier verifies success (right).

- [1] Skylar-Scott, M. A., Uzel, S. G., Nam, L. L., Ahrens, J. H., Truby, R. L., Damaraju, S., & Lewis, J. A. (2019). Biomanufacturing of organ-specific tissues with high cellular density and embedded vascular channels. *Science Advances*, 5(9), eaaw2459.
- [2] Jones, Ivy Krystal, et al. "Direct ink write fabrication of transparent ceramic gain media." *Optical Materials* 75 (2018): 19-25.
- [3] Jakus, Adam E., et al. "Metallic architectures from 3D-printed powder-based liquid inks." *Advanced Functional Materials* 25.45 (2015): 6985-6995.
- [4] Compton, Brett Gibson, et al. "Direct-write 3D printing of NdFeB bonded magnets." *Materials and Manufacturing Processes* 33.1 (2018): 109-113.
- [5] Tan, Alvin TL, et al. "Direct-Write Freeform Colloidal Assembly." *Advanced Materials* 30.44 (2018): 1803620