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Toward Smart Monitoring of Additive Manufacturing

by Kelly T Kirk, Michael S Lee, and Samuel Edwards

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14. ABSTRACT
Additive manufacturing holds great promise for improving maintenance and sustainment operations for the military; however, concerns about part reliability persist. In this report, we discuss how smart (i.e., with machine learning) monitoring can play a role in improving confidence in 3-D-built parts. In particular, we develop and investigate a simple prototype monitoring system composed of a 3-D polymer extrusion printer and several cameras powered by real-time computer vision software and hardware. We believe that, in the future, smart monitoring will play a critical role in the certification of 3-D-printed parts.

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1. Introduction

Additive manufacturing (AM) holds promise for enhancing sustainment, reducing logistical costs, and increasing the design space of parts for Army systems. One area that could accelerate the viability of and confidence in AM is automatic or smart monitoring of the builds (NASA 2019). This process will streamline part certification, recognize defects and determine whether to continue, and potentially correct defects before the next layer is constructed. Early termination, due to the detection of catastrophic failures, would save time and reduce material usage in a resource-constrained environment such as an expeditionary mission. In situ defect correction could reduce risk and improve chances of yielding "flight-worthy" parts.

The monitoring of AM is quickly gaining traction in the literature. Methods vary depending on the type of AM and the materials used (e.g., extrusion or sintering). For example, monitoring modalities that have been applied to selective laser sintering of metal powders have included optical, thermal, acoustic, and X-ray. Monitoring for polymer extrusion, aka fused deposition modeling (FDM) has included optical, thermal (including hot plate) (Mihiretie et al. 2016), and terahertz imaging (Perraud et al. 2016).

In this work, we explore optical monitoring of the FDM-build process with in-house equipment and both third-party and in-house software. We also speculate on the future of smart AM monitoring.

2. Methods

We have connected several off-the-shelf components to develop a simple 3-D-print-monitoring system that collects data to test and train machine-learning (ML) models (Figs. 1 and 2). One of the Alienware 17 R5 laptops was installed with an Ubuntu 18.04 LTS operating system so it could easily run Docker containers and all of the NVIDIA libraries (e.g., CuDNN and CUDA drivers) for the internal GeForce GTX 1080 graphics-processing unit. The other laptop hosted Windows 10 and was used for

- monitoring the 3-D printers,
- building and slicing 3-D parts (Ultimaker Cura 4.1.0 and LulzBot Cura 3.6.3 + GCode Slicer), and
- capturing video (SpinView) with a FLIR 2K USB Grasshopper3 camera (90 fps, 2048 × 2048).

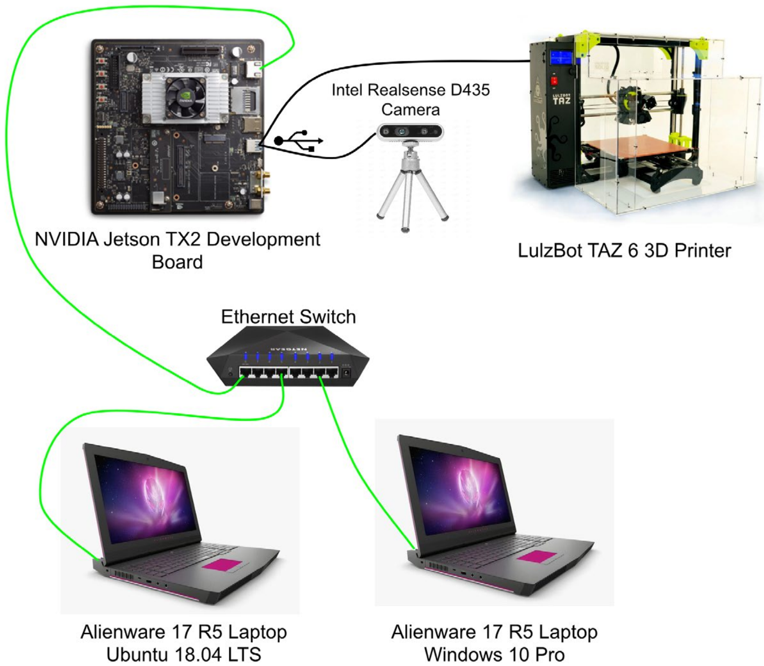

Fig. 1 Schematic of the setup used in this work

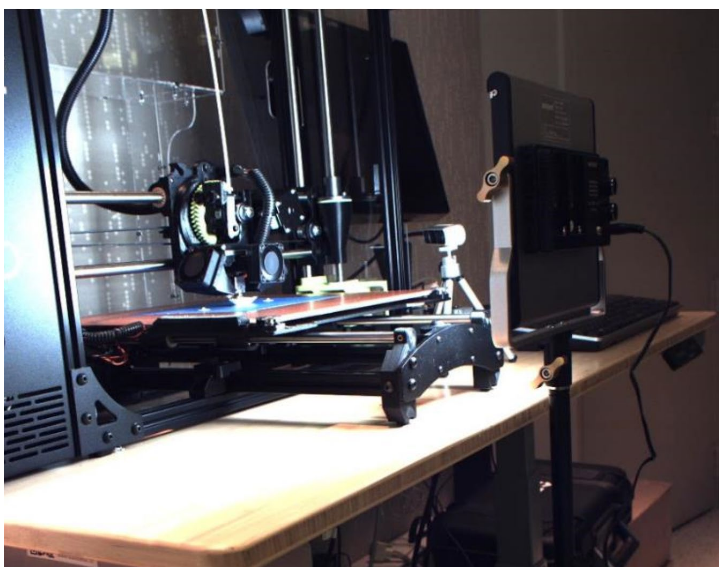

Fig. 2 Wide-angle view of the actual setup

We explored different ways to record snapshots of the printing process with different USB cameras. In the end, we had to develop our own software to record images from different USB cameras at many locations around the 3-D printers. We predict that standardization of software for these types of tasks will accelerate adoption of 3-D-print-monitoring techniques.

Early on, we had some issues with lighting and the print head blocking the view of the part. The print-head occlusion was ameliorated by only taking images while the head deposited on a designed extraneous sidepiece. The lighting issue was somewhat improved by the addition of a LED panel, shown in Fig. 2. Note the enhanced image with the use of this light panel, as seen in Fig. 3.

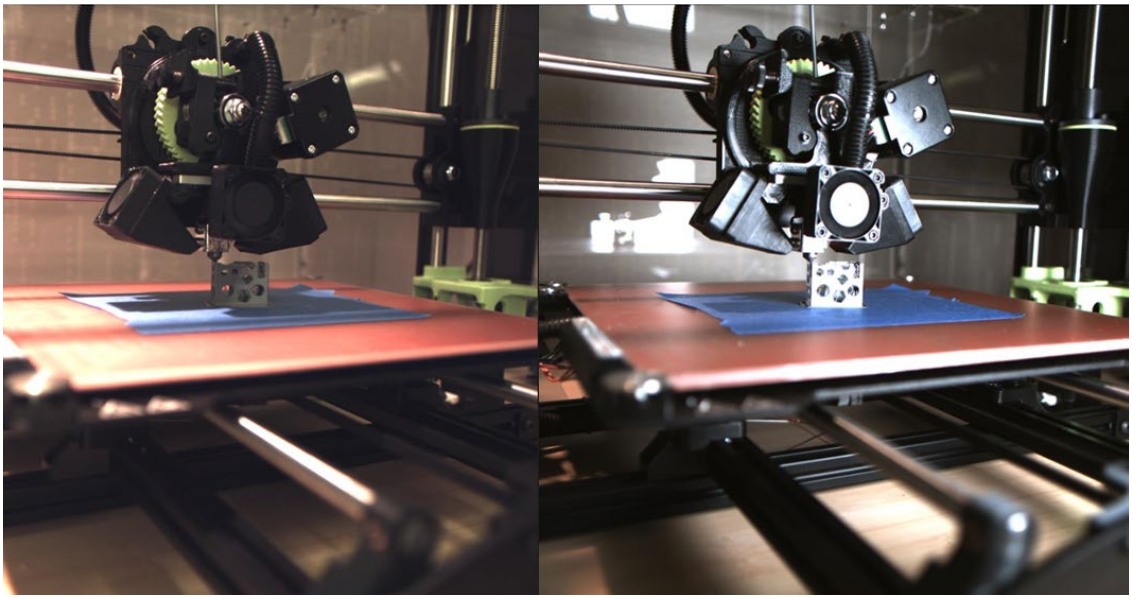

Fig. 3 Without (left) and with (right) extra lighting

On the NVIDIA Jetson TX2 Development board, OctoPrint was installed and configured to work with the LulzBot TAZ 6 3-D Printer. OctoPrint provides an open-source web interface for controlling consumer 3-D printers. Also, we installed an MJPEG Streamer to view the RealSense USB camera from the OctoPrint camera interface. The Octolapse plugin was added to create a time lapse of the 3-D prints.

One of the goals of this study was to build a collection of labeled defective-print images to train deep-learning (DL) models to detect defects. A next step would be to have the ML inference models running solely on an edge device like the NVIDIA Jetson TX2 board.

Additional software used in this project included Anaconda Python (Anaconda, Inc., Austin, Texas) and the ML-platform Keras/Tensorflow (Google, Mountain View, California) Additional hardware included the Ultimaker S5 dual-extrusion 3-D printer, which has a built-in webcam.

3. Demonstration

3.1 Structural Similarity

We first tried analyzing the image data by comparing good prints with bad prints using a structural-similarity index (Fig. 4). The bad prints were either designed or induced through parameters like print speed and nozzle temperature. The next logical step would be to process the images with a DL object detection code to 1) narrow the focus of the similarity measurement on the part alone and 2) classify the feature that appears from one frame to the next, based on a structural dissimilarity.

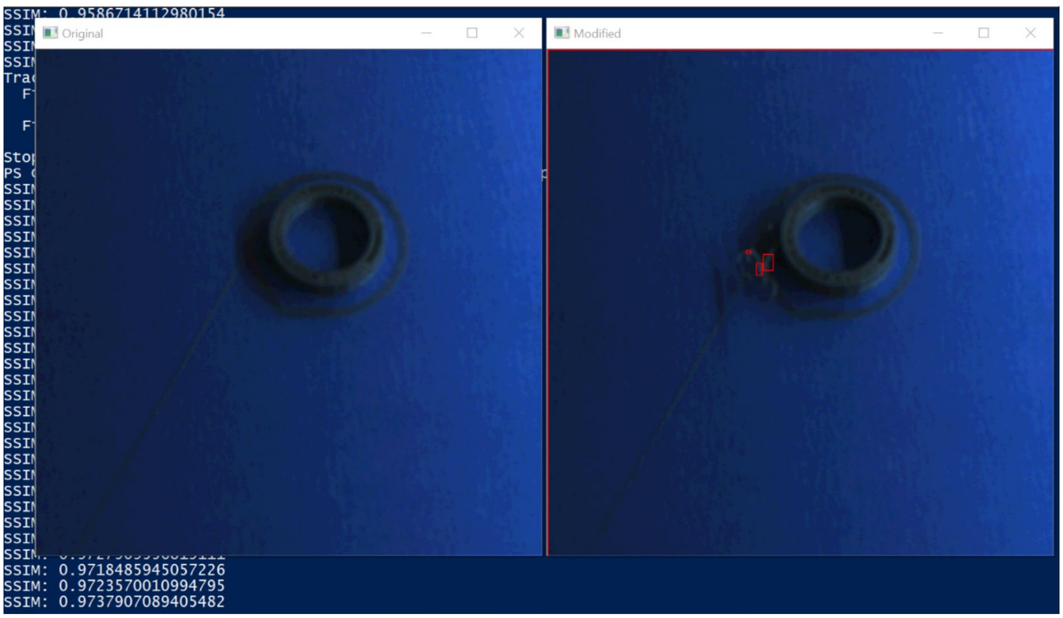

Fig. 4 Comparing images with structural-similarity index

One common AM flaw that a similarity matcher should look for is the presence of extensions between layers due to slow cooling, as shown in Fig. 5. We induced slow cooling in this part by shutting off the fan during the build process.

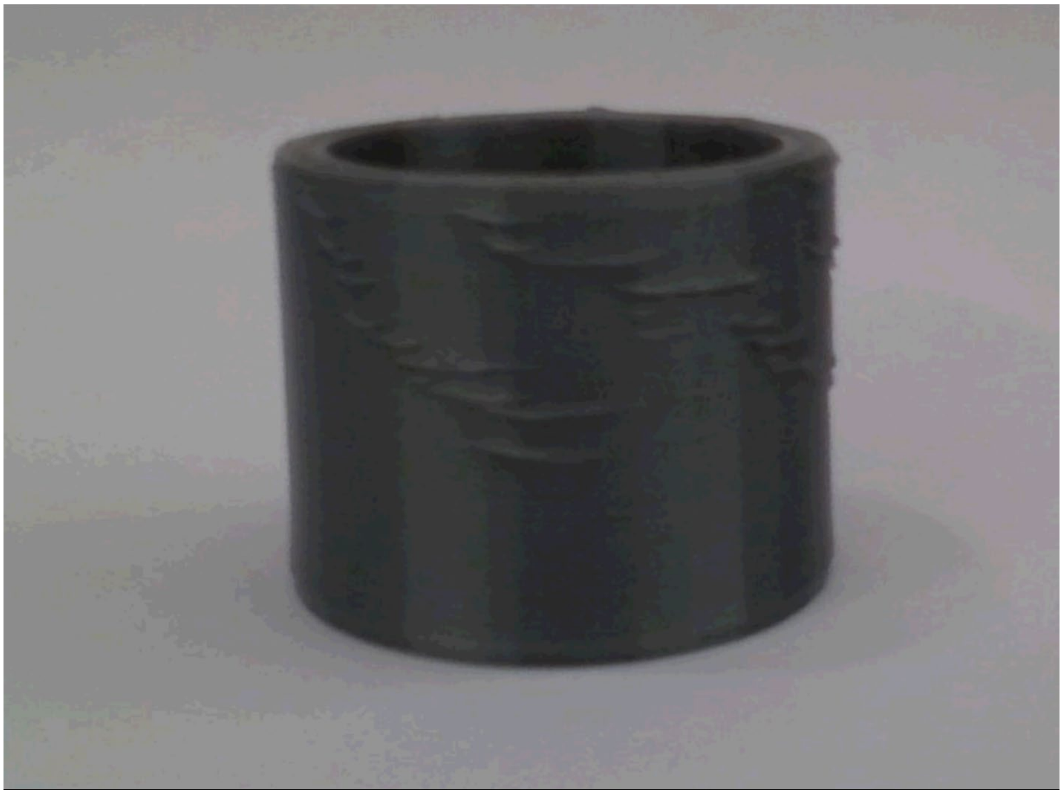

Fig. 5 **Part with significant extensions between layers caused by slow cooling with the fan off**

3.2 Spaghetti Detective

Another common AM flaw, as shown in Fig. 6, is stringing (or "spaghetti"): extruded filament that is not properly anchored to the previous build layers. The open-source tool Spaghetti Detective (Jiang and Rybnikov 2019) attempts to detect this often-catastrophic problem. Successful autonomous detection of spaghetti can be used to trigger early print termination, which can save time and money and prevent waste of materials.

Fig. 6 A stringing (or “spaghetti”) print

We added the Spaghetti Detective plugin to the Octoprint software installed on the Jetson TX2 and configured it to send a video stream to Spaghetti Detective worker modules running on Docker containers on the Ubuntu laptop. We then designed 3-D objects in Cura that were predicted to create a conduction failure, as seen in Fig. 4. To achieve library compatibility with both the TX2 and laptop, we had to build and configure the Spaghetti Detective–Docker containers from the GitHub source code. Figure 7 demonstrates how the software detected stringing/spaghetti on our 3-D printer testbed.

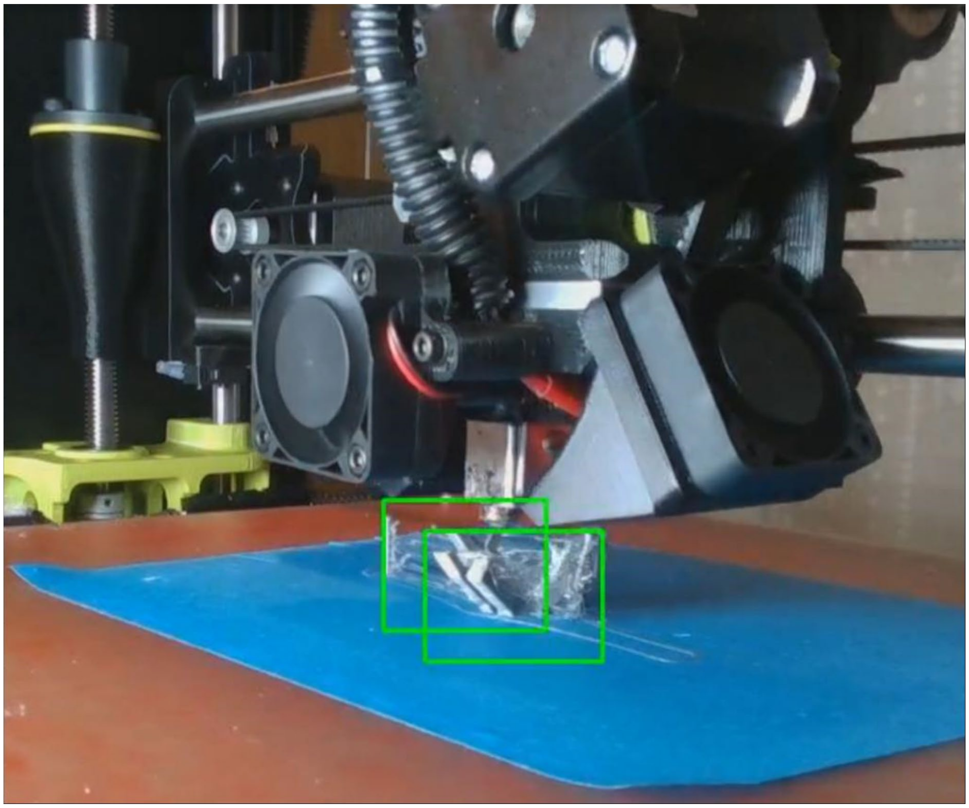

Fig. 7 Detecting stringing (or "spaghetti")

3.3 Image Segmentation

In previous work we developed an unsupervised DL technique to segment a single clean image without any prior training data (Edwards and Lee 2019). In this work, we trained our unsupervised network on a batch of images collected during the build of a part and segmented each image separately. In Fig. 8, we evaluate our unsupervised segmentation technique on some of the frames. Overall, we found the segmentation was very color-oriented and emphasized the light gradient far more than the differential texture of the blue-tape floor versus the polymer part. This implies two key points: 1) generating an even lighting of the system is crucial, and 2) unless the image is specifically zoomed in, exact focus is important to detect subtle issues in the print. On a positive note, thin features like some of the spaghetti and the intentional bottom rim are detected, which highlights the possibility a future successful segmentation algorithm will likely be pixel-based versus bounding box. On a mixed note, the sensitivity of our algorithm (and other DL-based approaches) to small gradations in light could prove useful in the detection of small deficiencies in a printed part if major light gradients and shadows can be minimized in the future through better lighting setups.

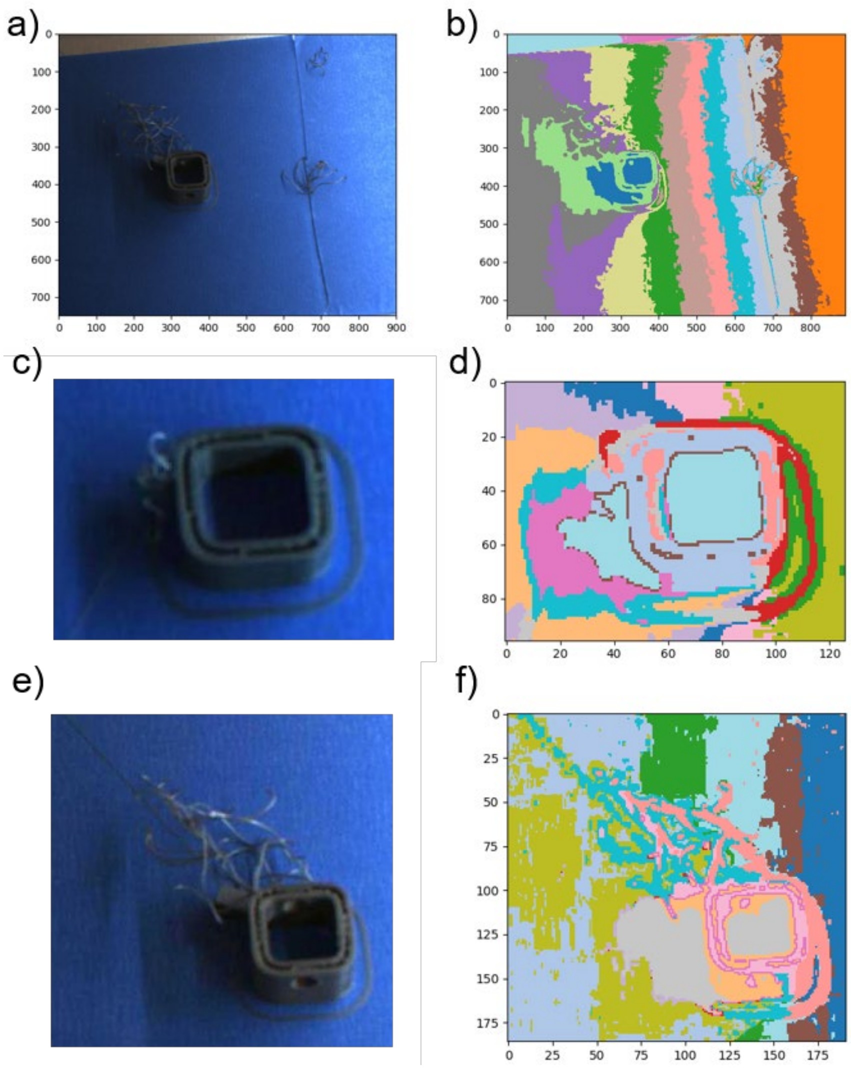

Fig. 8 Examples of unsupervised segmentation of a photo of 3-D-printed object: a) perspective view and b) segmentation of a piece riddled with spaghetti; c) close-up view and d) segmentation of a piece with a bit of spaghetti; e) close-up view and f) segmentation of a piece with a lot of spaghetti

4. Future Perspectives

While our setup and experiments only scratch the surface, they highlight some issues that need to be addressed to achieve a successful monitoring capability. As we observed, lighting is a critical factor (Fig. 4). The challenge is to minimize shadows from the part and print head with ample lighting, while not impacting the air temperature or unduly increasing power usage. Lighting can also lead to sharp reflections on a glass build plate.

Camera resolution and focus are also important. High-resolution images are desirable for detection algorithms but can add to equipment cost and will lead to heftier data-storage and bandwidth requirements. An alternative strategy is to employ a zoom lens to increase detail. The drawback, here, is a reduced field of view for larger prints.

Besides our minimal study, there is a lot of research growing in the area of print monitoring from the last few years (Rieder et al. [2014]; Everton et al. [2016]; Perraud et al. [2016]; and Brubaker et al. [2018]). One challenge for the 3-D-printing community will be the generation of a database of print mistakes. Typical defects for FDM/plastic extrusion include delamination, warping, stringing, and over- and under-extrusion. Ironically, as the quality of 3-D printing improves, it may be more difficult to induce bad prints for training data. Some defects can be corrected while printing, if they only show up in the most recent layer; others may require starting over and changing the print parameters.

4.1 Imaging and Detection

Besides enhanced lighting to mitigate shadows, we surmise that multiple camera streams will be used in the future to perform photogrammetry (Mikhail et al. 2001), which will deduce 3-D information that can be compared to the original abstract 3-D models. Alternatively, synthetic images of what the part should look like at a given build height, lighting conditions, and so on can be used to compare against the actual camera view to spot differences in ideality. This could potentially lead to defect detection. Generative ML (Huang et al. 2018) may be useful to efficiently enhance the photorealism of 3-D-rendered imagery.

4.2 Beyond Optical Imaging

A thermal camera can be used to monitor the cooling progression of the top layers. It is plausible that subtle cooling patterns could indicate whether or not the part is solid several layers underneath most recent layer. In addition, a time-varying hot plate can be used to ascertain dynamic heating/cooling properties from the bottom up (Mihiretie et al. 2016).

Among other advances for 3-D-print monitoring are these:

- Embedded nanoparticles in the polymer strand can be used as optical markers (Brubaker et al. 2018).
- Non-optical sensors: Ultrasound pitch and catch sensors can be installed on the build plate to gauge the quality of metal parts (Boström and Wirdelius 1995; Rieder et al. 2014).

In the future, sensor data will be used to create models that are more representative than the original models used to design and manufacture the part. Photogrammetry of the manufactured part could specify the actual dimensions of each part feature. Texture analysis could identify surface and even internal imperfections such as stringing, pits, and so on. Taken together, this more realistic model could be evaluated in near-real-time simulations to estimate the effects of the specific defects detected. For example, if the perceived build differed sufficiently from the desired build, the monitoring system could build a 3-D model of the perceived build, which would then be passed to a lightweight simulation program to determine whether the finished part might succumb to specific stresses in contrast to the ideal part.

4.3 Certification

Part certification is a non-trivial and often costly process. This fact is amplified when the part is mission- or life-critical (e.g., the gears of a helicopter). As a consequence, up to now most 3-D printing applications have been for noncritical parts, prototyping, and tooling (Totin et al. 2019).

We think there are at least two types of trust that can be derived about a printed part using a monitoring process:

1) The video and other sensed parameters (e.g., temperature) of the build process of Part B look identical (within a specified threshold) to the previous build's video/data of another identical Part A that was successfully tested for strength and durability.

2) The part is deemed sound, based on computational modeling of the hypothetical part derived from photogrammetric and spectroscopic observations of the build.

4.4 Monitor and Control Technology

If defects were detected in real-time, decisions could be made whether to

- alert the user by sending a text message to the operator that the part is starting to warp and/or delaminate from the build plate,
- stop the print when a certain threshold volume of spaghetti is detected, or
- correct the defect if the problem appears to be only on the most recent layer and has a chance of being repaired with tip melting and/or more extruded polymer.

Synthetic views of what the print should look like at every layer can be very helpful in a monitoring system. A real versus synthetic comparator can determine when something is wrong and may be able to outline the differing region. However, to determine what is actually wrong may require an ML algorithm. The website All3DP has done a great job in identifying and providing tips for rectification for various problems that can occur in FDM (All3DP 2019). This list could be used as a reference for the development of monitoring schemes.

5. Conclusion

Automated optical/acoustic monitoring technologies for 3-D printing are in their relative infancy compared with the print technologies themselves. If successful, however, this type of monitoring will not just improve build yields, but increase the quality of each build. It remains to be seen whether monitoring alone will lead to part certification, but it will provide ample data about the material stacking process detailing the inner composition of the built parts.

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List of Symbols, Abbreviations, and Acronyms

3-D	3-dimensional
AM	additive manufacturing
DL	deep learning
FDM	fused deposition modeling
LED	light-emitting diode
ML	machine learning
SLS	selective laser sintering
USB	Universal Serial Bus

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