Fusion of Novel Sensing Methods and Machine Learning to Solve Critical Challenges in Laser Additive Manufacturing

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ABSTRACT

The metal additive manufacturing (AM) process uses high-power lasers to rapidly melt and solidify metal powder into complex 3-D shapes, but unfortunately the rapid solidification process often results in stochastic defect formation and nonequilibrium microstructures. To fully understand the AM process and ensure a high-quality, defect-free manufacturing process, novel high-speed sensing methods that can capture key physical phenomena associated with the AM process at high resolution are needed. A team at the Johns Hopkins University Applied Physics Laboratory (APL) is developing novel spectrometry techniques capable of measurement speed exceeding 50 kHz along the laser path to aid in understanding how materials are formed under different laser inputs. The team is also developing machine learning tools to interpret these signals, thus revealing features and trends that are not apparent to human analysts in the sensor data or physical postmortem inspection results of the printed components.

INTRODUCTION

Additive manufacturing (AM) is a disruptive manufacturing technology with potential to significantly impact supply chain and engineering capability. The ability to synthesize materials directly into complex parts has shifted the paradigm for how components are designed today, from complex heat sinks to jet fuel nozzles. In addition, because of its rapid solidification rates of ~10^4–10^7 K/s, AM has enabled manufacturing of new alloys with unique microstructures and properties.

These assets do not come without challenges: most paramount is the formation of thousands of tiny defects per cubic inch of material, roughly 10–250 μm in diameter with seemingly random occurrence inherent to AM. APL has extensively researched[1–3] the generation and effects of microstructure and defects during laser powder bed fusion to build an understanding of process–structure–property–performance relationships for various AM material systems. This research includes the development of novel processing methods to tailor microstructure and evaluate the sensitivity of defect formation to changing laser processing parameters. Figure 1a shows the impact of variations in laser energy and the associated defects: lack-of-fusion and keyhole. Lack-of-fusion defects form as a result of insufficient energy to induce full melting, whereas keyhole defects form as a result of excess energy and gas entrapment. As the energy input and solidification processes change, so does the microstructure (Figure 1b), as shown in a recent study by APL and Naval Air Systems Command (NAVAIR).[1] Large defect volume fractions or gross changes in microstructure can significantly affect the mechanical properties and reliability of AM components.

Current-generation AM systems lack closed-loop control systems to ensure process stability, which means that processing conditions can drift away from notional set points and result in deleterious microstructures and defect populations. An opportunity exists to generate sensors and techniques to detect formation of process faults and mitigation strategies in real-time and in three dimensions as a geometry is being formed. It is critical that new in situ monitoring tools are developed to enable understanding of how and when defects form. At the same time, these tools will offer insight into the fundamental solidification mechanisms that result in unique microstructures. For instance, a material's microstructure reflects its thermal history during solidification and repeated heating and cooling cycles, such that an in situ thermal sensor could be incredibly useful to understand why similar processing conditions can result in different microstructures.

The variability in material performance caused by these defects gives the Department of Defense pause in applying AM to its most critical applications, which often could benefit the most from this new manufacturing technique.[4,5] Critical applications often require high process stability, repeatability, and reliability. Because there are significant consequences if these applications

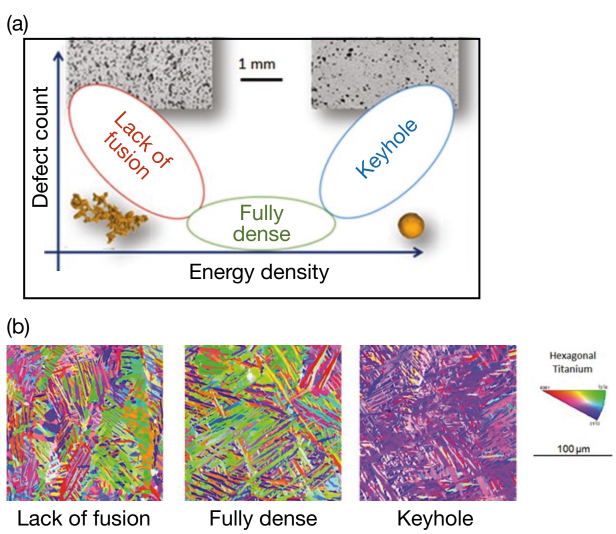

Figure 1. Impact of variations in laser energy and the associated defects. (a) Schematic showing the impact of laser processing energy on defect formation in the selective laser melting process. (Reprinted from Montalbano et al.,[1] with permission from Elsevier.) (b) Electron backscattered diffraction images showing the impact of laser energy on microstructure: as the energy is increased, the microstructural texture changes.

fail, they require engineering certainty in structural performance in order to be implemented. The conventional AM qualification and certification approaches require burdensome post-manufacturing inspection to achieve engineering confidence in AM parts. To accelerate adoption of AM and revolutionize its use in critical applications, an in situ technique is needed to monitor the manufacturing process and validate the fabricated component. Such an advance would minimize or even eliminate the need for costly, time-consuming post-manufacturing inspection steps and enable extension of AM to components that cannot be inspected because of their size or composition.

The community has recognized this challenge, and significant progress has been made in the field of in situ monitoring over the last 10 years.[6–9] Bartlett et al.[10] showed the ability to use conventional infrared (IR) cameras to detect defects on the order of 1–3 mm. Mitchell et al.[11] showed the ability to detect defects down to 70 mm but only on a small area of ~1.5 mm^2. Even with these advancements, trade-offs between speed and resolution of monitoring systems still limit functional advancement of process monitoring.[12] In practice, current in situ monitoring techniques either have insufficient temporal sampling to detect process anomalies or insufficient spatial resolution to resolve fine thermal details over large areas.

For process modeling to be relevant to the size of AM defects, detection down to 50 mm is needed, especially if clusters of small defects are present in critically stressed areas of parts.[13] It is challenging or impossible to achieve this resolution with conventional or emerging nondestructive evaluation techniques, such as x-ray computed tomography (XRCT), as growing part sizes and high-density materials limit x-ray imaging methods. In addition to issues with in situ data acquisition speed and precision, the incredible amount of data collected during a build can make the analysis of parts intractable. In recent years, advances in machine learning have helped compress data sets and find correlations where conventional mathematical closed-form solutions do not exist. Effective implementation of in situ thermal sensing combined with machine learning will enable real-time detection of defects and microstructural anomalies to reduce the burden of qualification, which will enhance quality and trust of AM parts for critical applications.

NOVEL SENSING DEVELOPMENT

The optical resolution and speed limitations associated with conventional IR cameras prevent realization of information required to detect AM physics, making it a challenge to monitor the AM process with conventional sensors. In addition, the rapid change from solid powder to molten metal to solidified part results in rapid changes in emissivity with temperature, which

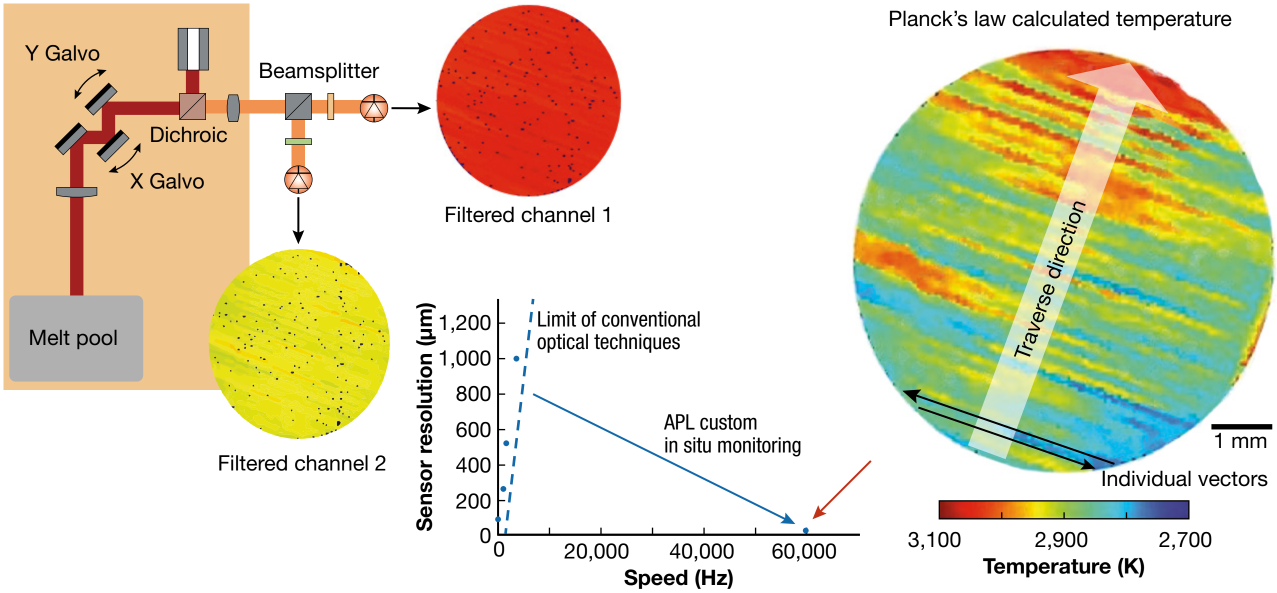

Figure 2. Custom on-axis thermal sensor compared with the sensing rate of competitive IR camera systems. This configuration allows both high spatial resolution and high speed. The sample shown is a 5-mm cylindrical screening sample with a single reconstructed thermal layer shown. The thermal data is collected layer by layer and can be reconstructed into the 3-D part geometry.

can result in spurious temperature measurements if the sensor is not properly designed or calibrated. To resolve the optical limitations, the APL team developed a unique sensor that is coaxially aligned with the laser optics, enabling the sensor to focus on the melt pool. Through the use of high-speed sensors, this approach enables high-spatial-resolution data on the melt pool and high-temporal-resolution data on the melt pool dynamics. Figure 2 shows the configuration of the sensor, which includes several photodiodes, dichroics, a beam-splitter, and bandpass filters. This configuration permits true temperature to be resolved using two-color pyrometry fitting to Planck's law. Experiments with the sensor have demonstrated increased signal-to-noise ratio and a high frame rate exceeding 60 kHz.

This proof-of-principle system enables us to resolve significant variation in the thermal response of the material. In the color contour map on the right side of Figure 2, the laser path starts in the 7 o'clock position on the sample and finishes between the 12 and 1 o'clock positions as represented by the traverse direction. Two smaller arrows show the individual laser scan paths, marked "Individual vectors." Thermal saturation is shown at the end of the laser tool path, and cool pockets are shown near the start of the tool path. The system records thermal data point by point as the laser traverses the material cross section, giving a representation of the peak thermal energy achieved at each voxel. In an ideal process, the melt pool would be the same temperature across the entire sample.

In addition to resolving pure variation in the thermal profile, the APL team is developing machine learning methods to correlate measured signals with internal defect formation, which was previously only quantifiable in XRCT in post-manufacturing nondestructive evaluation. To identify defects using machine learning, it will be necessary to index the thermal data to a ground-truth sample with independently verified defects. Figure 3 shows a preliminary index of thermal data with four processing conditions in a single sample. These zones consist of both keyhole and lack-of-fusion laser conditions in a single sample, allowing training of ground-truth defect populations (from XRCT data) for both defect class and size/volume in a single high-throughput sample.

The goal of the initial research is to find thermal fingerprints associated with defect formation in the AM process. Figure 4 shows a representative statistical sample for the thermal voxels around defects in both

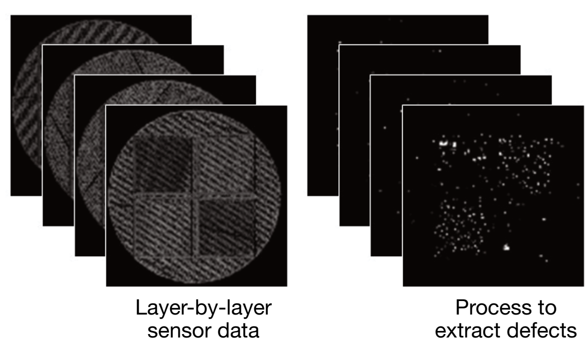

Figure 3. A composite image of thermal data extracted layer by layer compared with XRCT data showing defect location. The composite consists of both keyhole and lack-of-fusion laser conditions in a single sample, allowing training of ground-truth defect populations (from XRCT data) for both defect class and size/volume in a single high-throughput sample.

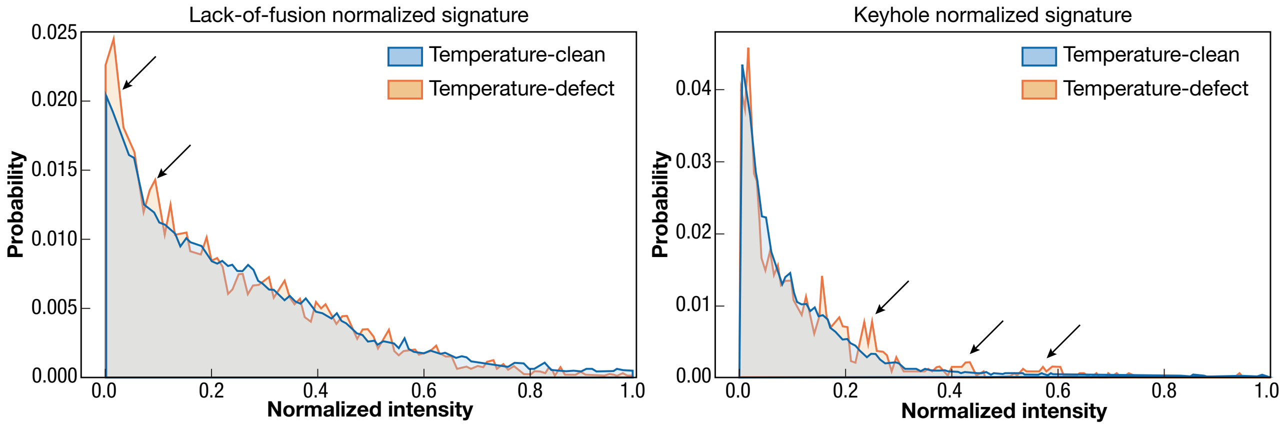

Figure 4. The distribution of thermal image voxel intensities for a lack-of-fusion sample and a keyhole sample plotted for clean and defect voxels. In the lack-of-fusion sample (left), the thermal signature amplitudes of low thermal energy appear in greater magnitude when compared with the control, while in the keyhole sample (right), thermal signatures in the high-intensity region are more prominent when compared with defect-free signatures. Plots were generated from 200 slices of each sample totaling ~820,000 voxels.

a lack-of-fusion sample and a keyhole sample. These thermal signatures show characteristics unique to each defect class and provide insight that can be used to predict different categories of spatial defects by applying machine learning to high-speed thermal data.

The ability to identify and record defects as they form in 3-D space would provide significant insight into final part performance. This is especially important in preventing potential failures in critical defect-dominated applications such as fatigue for biomedical and aerospace applications. While quantifying defects in situ would reduce post-manufacturing part qualification costs by eliminating the need to proof-test parts for critical flaws, any parts with critical defects would still have to be scrapped. However, early detection could provide further savings in manufacturing time as the process could be stopped and restarted upon detection of a critical defect potentially in the first few hours of a multiple-day print. Under the current paradigm, the weeklong print would need to be completed and then inspected after manufacturing to discover that the part contains a critical defect and is therefore insufficient to meet the application's needs.

Figure 5 shows a representative build where simulated laser faults are induced in varying layers by manipulating processing conditions. This allows visualization of defect formation and recognition where the defect-laden layers are bright spots in the processed melt pool thermal data and can be correlated to the formation as identified by XRCT. The next frontier beyond identifying

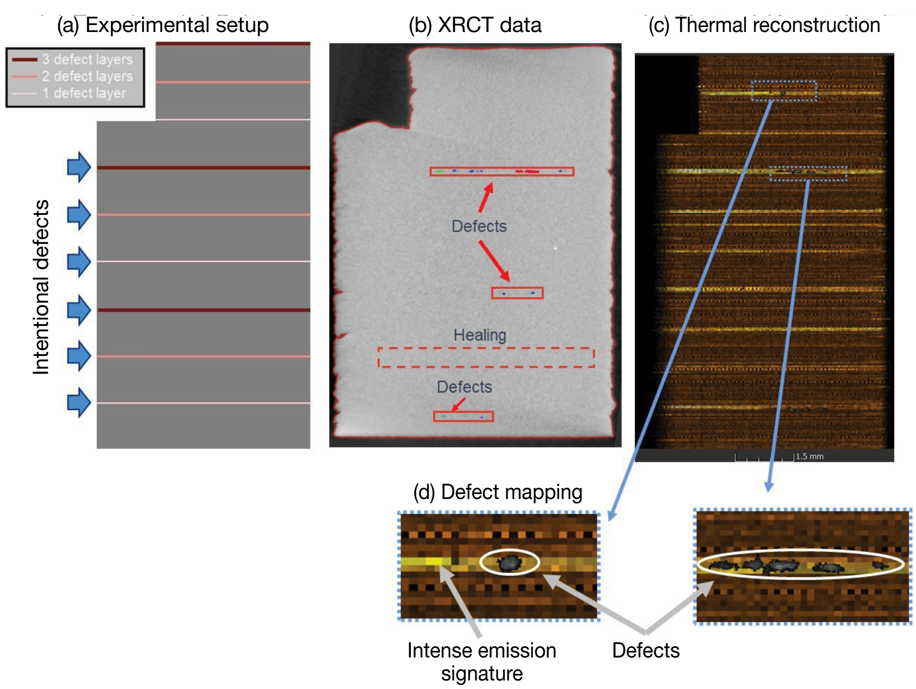

Figure 5. A representative build where simulated laser faults are induced in varying layers by manipulating processing conditions. (a) Experimental design showing simulated faults in varying layer increments (i.e., a single bad layer, two bad layers, or three bad layers). (b) XRCT of the post-manufactured sample showing defects and also an indication of healing from the secondary melting of the nominal parameter set. (c) A 2-D cross section of the 3-D thermal reconstruction with anomalous layers identified via high-intensity signals from melt pool sensing. (d) An enlarged image showing defect overlay with the XRCT and thermal data fused into a single data file.

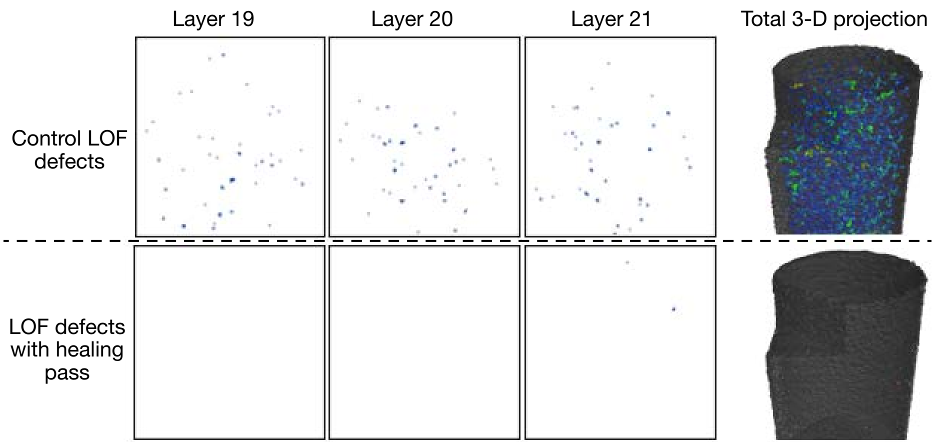

Figure 6. XRCT data for three layers in a build where contrived lack-of-fusion (LOF) porosity was selectively healed with a secondary pass. In layers 19 and 20, all defects greater than 100 mm have been healed. In layer 21, two defects are present even after the healing pass. The global sample also indicates the significant reduction in porosity between the two conditions (lack-of-fusion [control] vs. lack-of-fusion + healing pass).

defects would be real-time control preventing the formation or initiating healing of defects. This would prevent parts from being scrapped and maximize production efficiency. As a proof of principle, the APL team printed parts with known lack-of-fusion flaws and then interrupted the build process to prove that a secondary laser healing pass could recover parts with defects if they could be identified in real time (Figure 6).

The sensor has since been upgraded to better capture increased spectral channels by adding photodiodes at extended wavelengths and enhancing temporal and spatial resolution by increasing sample frequency. Figure 7 shows the new configuration. Known as SATURN (Spectrally Augmented Thermal Understanding Reducing Nonconformance), it has potential to measure four channels at 11 MHz, an increase in speed of more than 180 times, with improved accuracy. This will open the possibility of healing defects in real time, maximizing the acceptance of parts and reducing the burden on part qualification.

CONCLUSIONS AND FUTURE WORK

Metal AM has promise to revolutionize the way we develop and form materials for critical applications. A major limitation in this vision is the absence of process sensing to detect anomalies such as manufacturing flaws due to the rapid solidification of the material. This article presents a novel sensing technique capable of establishing true temperature at 60 kHz combined with a spatial resolution of ~50 mm. With each new iteration of in situ monitoring sensors, the data density and accuracy increases, allowing further coupling with machine learning to address deeper fundamental synthesis of materials via AM, such as developing new alloys specific to AM or tailoring microstructure within a part to further optimize performance. Machine learning with high data density, combined with feedback loop control, will potentially enable the process to be adjusted even before defects form, resulting in a near-perfect part. A prescribed temperature could be set and feedback loop control could enable tailored melting for any material in any geometry. This would result in microstructure control in three dimensions that has never before been possible. With gradient materials, the system could be used to look at how

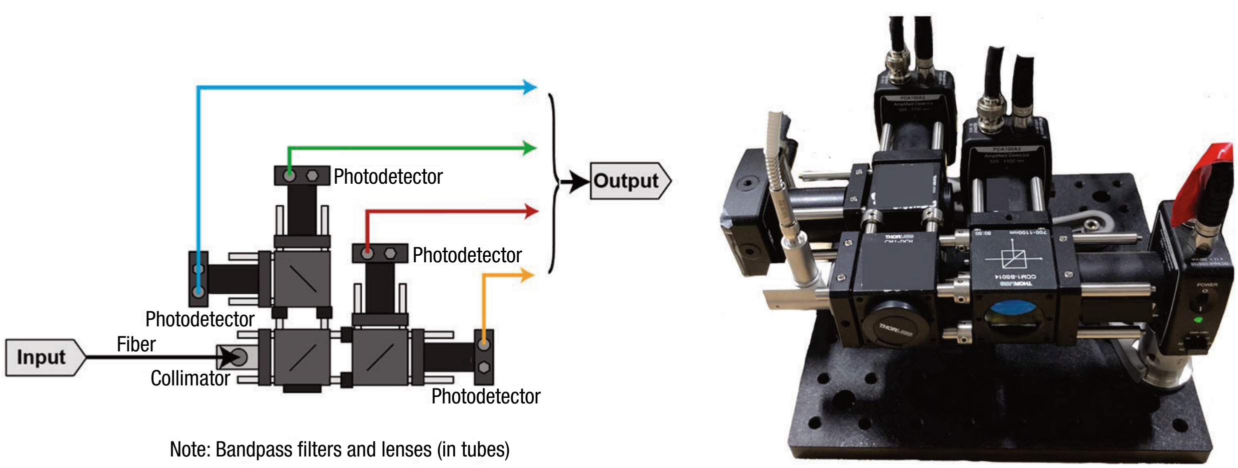

Figure 7. APL's SATURN system. This system can measure up to 11 MHz across four tailored spectral bands configured to maximize transmission and minimize noise driven by artifacts in the laser powder bed fusion optics optimized for 1070 nm.

well dissimilar material interfaces are forming.[14–16] If it is possible to realize this vision, the application of critical AM-fabricated parts will grow tremendously, enabling significant advances in a diverse array of industrial sectors, including aerospace, biomedicine, transportation, and energy.

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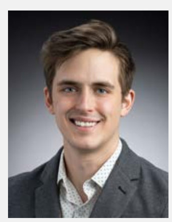

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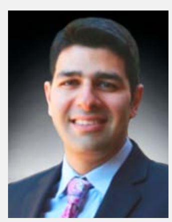

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