Proceedings of the ASME 2021
International Design Engineering Technical Conferences & Computers and Information in Engineering Conference
IDETC/CIE 2021
August 17-20, 2021, Online, Virtual

IDETC/CIE 2021- 71813

IN-PROCESS DATA FUSION FOR PROCESS MONITORING AND CONTROL OF METAL ADDITIVE MANUFACTURING

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ABSTRACT

To accelerate the adoption of Metal Additive Manufacturing (MAM) for production, an understanding of MAM process-structure-property (PSP) relationships is indispensable for quality control. A multitude of physical phenomena involved in MAM necessitates the use of multi-modal and in-process sensing techniques to model, monitor and control the process. The data generated from these sensors and process actuators are fused in various ways to advance our understanding of the process and to estimate both process status and part-in-progress states. This paper presents a hierarchical in-process data fusion framework for MAM, consisting of pointwise, trackwise, layerwise and partwise data analytics. Data fusion can be performed at raw data, feature, decision or mixed levels. The multi-scale data fusion framework is illustrated in detail using a laser powder bed fusion process for anomaly detection, material defect isolation, and part quality prediction. The multi-scale data fusion can be generally applied and integrated with real-time MAM process control, near-real-time layerwise repairing and buildwise decision making. The framework can be utilized by the AM research and standards community to rapidly develop and deploy interoperable tools and standards to analyze, process and exploit two or more different types of AM data. Common engineering standards for AM data fusion systems will dramatically improve the ability to detect, identify and locate part flaws, and then derive optimal policies for process control.

Keywords: data fusion, metal additive manufacturing, process monitoring, process control

1. INTRODUCTION

Metal Additive Manufacturing (MAM) enables the fabrication of complex heterogeneous parts and has the potential to transform the way high-value low-quantity products are made. A significant challenge for manufacturers to adopt the technology for production is quality insurance [1]. Numerous factors—including the product design, process settings, feedstock material properties, and machine performance—contribute to the final part quality and hence need to be understood and reliably controlled [2].

To accelerate the adoption of MAM components, an understanding of AM process-structure-property (PSP) relationships and how to control part quality must be developed. Various types of sensing techniques and material characterization methods are being developed and applied to MAM for this purpose. In-situ sensors are built into the AM systems to monitor the process parameters related to energy source, motion system, build platform and build chamber atmosphere. Interest has recently been increasing regarding the development of in-situ monitoring for part quality using photogrammetry, thermometry and other non-destructive evaluation (NDE) methods such as acoustic emission [3]. Ex-situ inspection employs a wide range of NDE and destructive material characterization methods, including x-ray computed tomography (XCT), coordinate metrology and microscopy techniques.

In-situ sensing and ex-situ testing generate large quantities of data. Typically, in-situ sensing and NDE for a single build can produce terabytes of data. These data play a critical role in establishing MAM PSP relationships [4] and enabling AM process monitoring and control [5]. Many research efforts focus

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on using a specific in-situ sensing technique to detect process or part fault. Scime et al. [6] used a tower camera with a k-Mean unsupervised classification algorithm to detect anomalies on a freshly coated powder bed for laser powder bed fusion (L-PBF). Smith et al. [7] applied acoustic spectroscopy to detect near-surface defects such as pores, cracks, and voids. Yang et al. [8] use co-axial imaging system to detect melt pool anomaly for lack-of-fusion flaws. Montazeri et al. [9] compared the performance of a photodetector, (shortwave infrared) SWIR thermal camera, and high-speed video camera for overhang and non-overhang build status detection. The research result indicates that a specific type of sensor is only symptomatic of a specific type of subprocess in AM—e.g., energy-feedstock interaction, melting or solidification. However, although a multitude of physical phenomena are involved in MAM processes, little has been done to fully utilize multi-modality in-process monitoring data to estimate both process status and part-in-progress states.

On the other end, multi-sensor fusion problems have been studied intensively since the 1990s, in applications such as automatic target recognition, target tracking, automated situation assessment and smart weapons [10]. Investments in defense have resulted in immense data fusion capabilities. One seminal piece of work is the U.S. Joint Directors of Laboratories (JDL) Data Fusion Working Group process model. The JDL model and its variations provide a great foundation for characterizing hierarchical levels of collaborative data processing, reference fusion functions and applicable approaches [11].

Acknowledging the importance of data fusion for MAM part quality control and decision making, as well as the existence of data fusion theories and practices in other domains, the National Institute of Standards and Technology (NIST) is conducting a research effort to develop systematic methods for AM data fusion and standard specifications and guidance on data fusion processes, data fusion interfaces and data fusion for process control. Currently, the lack of common engineering standards for data fusion systems is a major impediment to utilizing rich data for AM process understanding and decision making. The scope of the research is shown in Figure 1. AM data sources include scanning and energy input commands, in-situ sensor measurements, ex-situ material characterizations, AM process simulations and CAD designs. The data fusion application scenarios include process monitoring, process control, AM PSP relationship identification and AM qualification, which correspond to the four levels of data fusion domains defined in the JDL model [10]. In addition, AM data fusion can be conducted at three levels—raw data, feature and decision levels—or a combination of the three, as demonstrated by [12]. At the raw data level, the fusion encompasses a simple concatenation of multiple measurements to discover information in some regions of space and time. Feature level fusion includes processing of observations into meaningful features and then conflating them to estimate the states of a system. Decision level fusion combines decisions derived from individual data sources for a final response. Raw data fusion suffers from several weaknesses including high-dimensional data challenges and data unbalance issues. Decision level data fusion is also less explored due to the difficulty in explaining a fusion result and conducting a control to influence it. The feature-level fusion has the potential to address all the challenges mentioned above but requiring witty strategies for data dimension reduction, feature extraction and conflation.

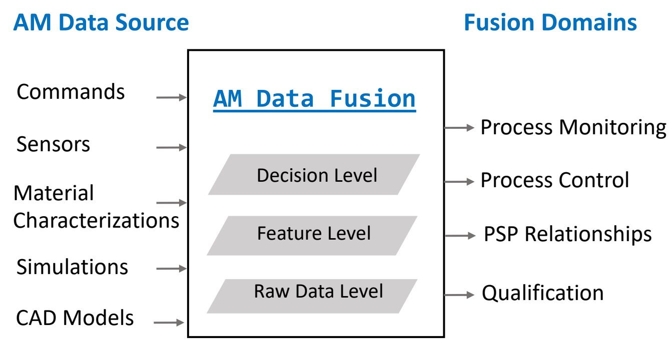

Figure 1. AM data fusion reference model

In this paper, we present a multi-scale hierarchical data fusion method for L-PBF process monitoring and control. The data include digital commands for laser scanning and laser power setting, scan position encoder measurements, images from co-axial high-speed melt pool monitoring and layerwise build surface monitoring. The in-process data can be fused at raw data, feature or decision levels, as well as at four spatial scales: point, track, layer or part. Different process control and decision-making strategies demand data fusion at different scales and levels, which will be illustrated through a case study.

The paper is organized as follows: Section two describes the multi-scale and hierarchical AM data fusion methodology. Section 3 describes a case study of applying the data fusion method to a powder bed fusion process at NIST. Section 4 presents the data fusion results and a discussion on fused data-based process control and decision making, and Section 5 summarizes the study and offers paths forward.

2. MULTI-SCALE HIERARCHICAL AM DATA FUSION

Sensor signals and small-sized images can be collected at high sampling rates during MAM build processes, resulting in hundreds to millions of data points acquired for each layer. For example, ultrasound and acoustic signals can be sampled at MHz frequencies; signals from photodetector or pyrometer can be sampled around 100 KHz. Melt pool images of small field-of-views can be acquired up to 20 KHz, while high-resolution global-view images and 3D scans are typically acquired less frequently because more measurement and processing times are needed for each sample. Digital commands are usually sent to a laser scanning system at microsecond intervals.

Trade-offs are necessary to balance the spatial and temporal requirements for in-situ sensing design. However, since part quality is the ultimate focus of MAM processes, the primary objective is to accurately detect and locate build defects for AM process monitoring and control. Hence, we propose organizing in-process data fusion in a spatial reference frame. Figure 2 shows a multi-scale hierarchical AM data fusion framework consisting of pointwise, trackwise, layerwise and partwise fusions. Macro-scale fusion functions leverage on the smaller scale fusion results. This process relies heavily on correct data registrations. Here are the details of the fusion functions.

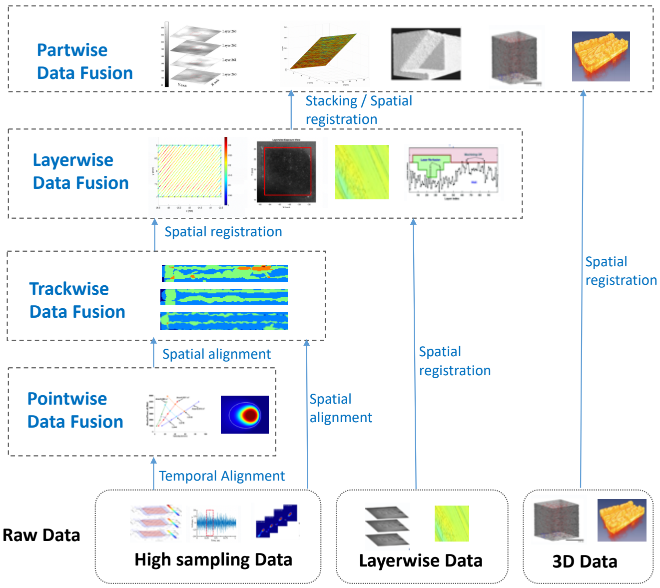

Figure 2. Multi-scale hierarchical AM data fusion

Data Registration (DR): In-process data are generated from various measurement devices or software systems and hence represented in different time and spatial reference frames. The prerequisite for data fusion is to synchronize the data and transform them into one coordinate system. This process is called data registration [13].

Pointwise Data Fusion (PDF): Pointwise fusion allows data from digital commands and high sampled in-situ sensor observations to detect process faults and apply real-time control.

Trackwise Data Fusion (TDF): Trackwise fusion integrates data collected through the current track with previous tracks to detect faults introduced between two hatchings. Functions at this scale include aggregating point data to track representation and extracting insights from multi-modality in-process data at the track scale.

Layerwise data fusion (LDF): Layerwise fusion leverages the synthesized data from both PDF and TDF, then conflates them with updated layerwise measurements from multiple modalities to estimate the quality status of the past layer. The results can be used for layer repair and scan strategy re-planning.

3D-Partwise data fusion (3DDF to avoid confusion): Partwise fusion estimates 3D build status and part-in-progress status and predicts part quality for process decision making—continue, pause or stop. The fusion may justify born-qualified parts.

Concrete examples will be presented in the next two sections to illustrate multi-scale hierarchical AM data fusion and its application domains.

3. A Use Case – PBF In-process Data Fusion

3.1 Experiment setup

This section aims to demonstrate the hierarchical AM data fusion process for a powder bed fusion build. The case study is based on the data collected from the Additive Manufacturing Metrology Testbed (AMMT) at NIST. AMMT is a fully customized metrology instrument that enables flexible control and measurement of the L-PBF process [14]. It is equipped with the capability to realize precise laser beam control. In order to advance G-code, the digital commands that AMMT uses set precise laser beam position, laser beam power and camera trigger every 100 µs [15]. A 3D build experiment was conducted on AMMT to illustrate the hierarchical data fusion functions. This experiment creates four nominally identical parts within the same build on a wrought nickel alloy 625 (IN625) substrate cut to 100 mm x 100 mm x 12.5 mm. All four parts have the same geometry: a bounding box 5 mm x 9 mm x 5 mm, a 45° overhang feature and a cylinder cavity. For demonstrative purposes, this study only uses the data from one part. The powder material is mixed recycled and virgin IN625 powder. The build consists of 250 layers at 20 µm per layer. The build employs a constant speed (800 mm/s) constant power (195 W) stripe scan pattern with skywriting. Detailed experiment description can be found in [16].

Three types of in-process data are acquired during the build: pre-loaded digital commands, laser beam position encoder measurements and in-situ monitoring data—including layerwise images (LWI) and melt pool monitoring (MPM) images. The data sets are first registered with reference to the build plate. Exemplar fusion scenarios from PDF, TDF, LDF and 3DF are presented in this section. Section 4 interprets the data fusion results.

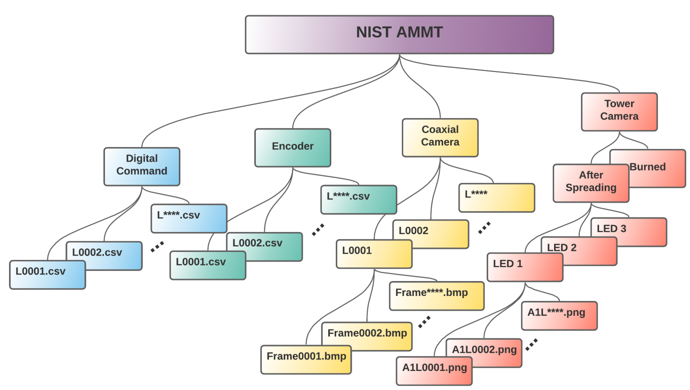

Figure 3. Structure of the NIST AMMT in-process data

Figure 3 shows four datasets collected from this experiment. The color scheme indicates the data type. Digital commands are formatted as comma-separated value (.CSV) American Standard

Code for Information Interchange (ASCII) text in four columns, representing scanner positions, laser power setting and camera trigger. Each row represents a 10-µs timestep for laser/galvo position and laser power setting. The files are organized by layer number, and each file provides the commands for all four parts. Two encoders measure the actual laser scanning positions and a laser power meter reports the actual power of the laser beam. A high-speed coaxial camera captures 10,000 in-situ melt pool images per second and is triggered by the digital command. A tower camera is responsible for a larger view that monitors the entire build plate. It captures images every layer before and after powder spreading.

3.2 Data Registration

AM data registration is a technique to fully align the data from different AM sensors and software [17]. The outcome of data registration is fully synchronized data represented in a common coordinate system [13]. This is an important preprocessing step that uses camera triggers, timestamps and file names to construct an integrated data landscape for this case study.

Digital command

Step	x_1	x_2	Power	Trigger
1	0	0	0	2
2	0	0.008	100	0
3	0.005	0.016	195	2
...	...	...	...	...

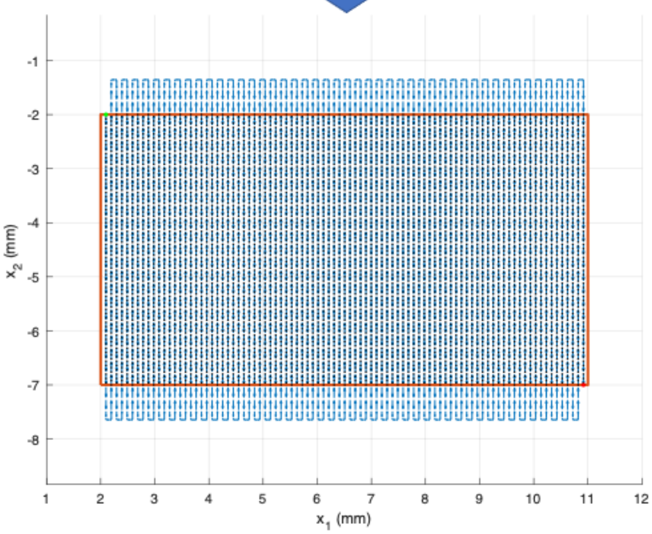

Figure 4. Digital command visualization

3.2.1 Encoder-digital command alignment

Figure 4 shows the data visualization of the digital commands. The .csv formatted command file is shown in the upper table. Parameter x_1 and x_2 are the laser positions defined in the AMMT build plate coordinate system. The Power column shows the laser power applied at that location. The Trigger column provides trigger commands to the coaxial camera. Whenever the value switches to 2, the camera takes one MPM image. The blue arrows in Figure 4 plot the scan path for the infilling and overshooting regions. The orange rectangular is the pre-contour path that employs a lower laser power of 100 W to outline the cross-sectional shape. The black dots mark the positions of coaxial camera triggers. The green and red spots mark the infilling start and end positions, respectively.

An encoder imbedded in the machine records the actual position and power of the laser beam. Figure 5 shows the fully aligned encoder data that are synchronized with the camera triggers. The next step is to register the MPM image on the build plane.

Encoder data

Step	x_1	x_1 real	x_2	x_2 real	Power	Power real	Trigger
1	0	0	0	0	0	0	2
2	0	0	0.008	0.009	100	50	0
3	0.005	0.004	0.016	0.015	195	182	2
...	...	...	...	...	...	...	...

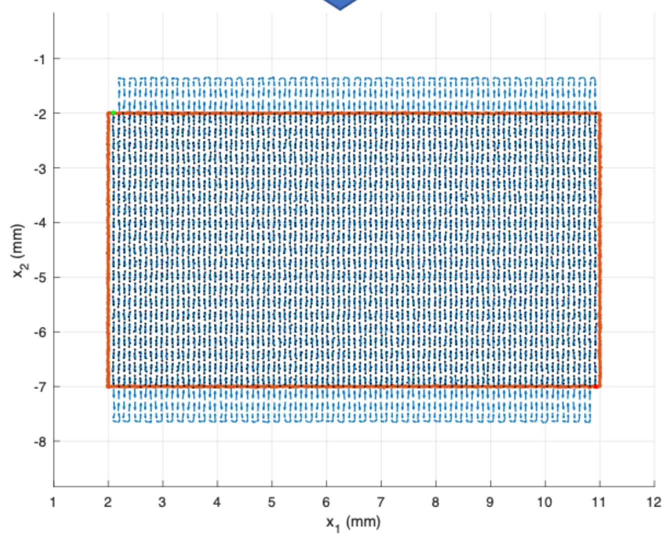

Figure 5. Registered encoder data

3.2.2 MPM data registration

The details of MPM data registration are explained in the authors' previous paper [13]. In general, the aim is to place each image at the correct position on the build plate. Figure 6 shows an MPM image registration example. Two images are registered against the actual laser beam positions at which the images were taken, based on their frame sequence numbers. This work reconstructs and presents the fundamental melting conditions spatially from the temporally organized MPM image files.

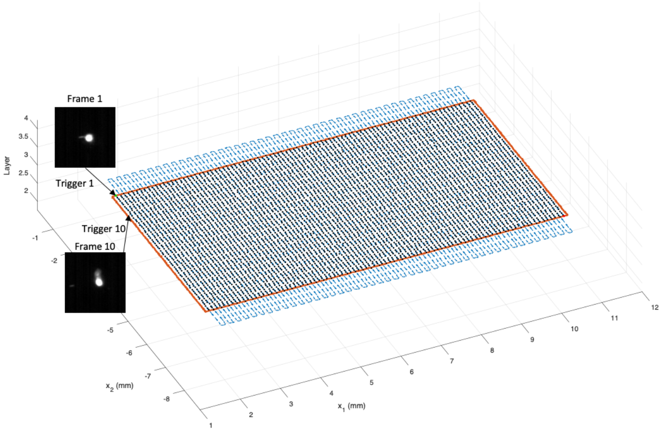

Figure 6. Registering the MPM images to fully registered encoder data

3.2.3 LWI data registration

LWI data registration has two essential purposes: aligning them to the build plate coordinates and undistorting the optical images acquired by the tower camera. Figure 7 shows the process of LWI alignment by layer number. AMMT has three LEDs in the building chamber that flash sequentially to create various optical conditions [16]. Three images are taken after a layer of powder is freshly coated. Another three images are taken after the laser finishes scanning the layer. A_i^1 , A_i^2, A_i^3, B_i^1, B_i^2, B_i^3 denote the six images collected from layer i.

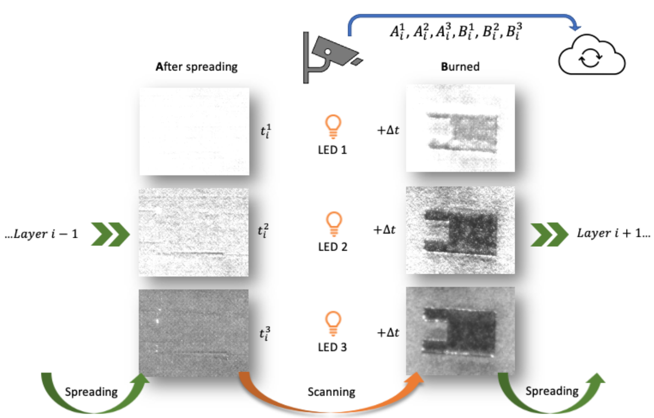

Figure 7. LWI alignment

Original LWI images show noticeable optical distortion, since the tower camera may not be an ideal pinhole camera and is not in an utterly perpendicular position to the build plate. Figure 8 shows the process of LWI image registration using 4-point homography. It picks one layer with a rectangular cross section to calculate the transformation matrix. Four corner points are hand-picked on both the LWI image and the corresponding scan command synthesized world coordinate image. Note, the manual point picking process can be replaced by image processing technique while the layerwise image resolution improved. Next, the matrix is applied to all the LWI images to correct the distortion. Note that this process assumes that the distortion is the same in all images, since the tower camera has a fixed position and the build surface remains unchanged throughout the build process.

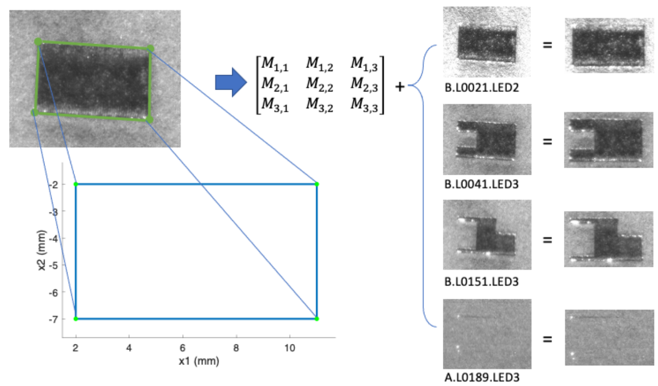

Figure 8. LWI image registration by perspective image transformation

The final step of the LWI registration is to register all the pixels into the AMMT build plate coordinate system. Figure 9 shows an example of a register individual pixel. Based on the pixel position, pixel resolution and the world coordinates of the corner points, each pixel can be registered against the corresponding coordinate on the build plate. For example, $[x_1^1, x_2^1]$ indicates the position of the bottom left corner of Pixel 2,1.

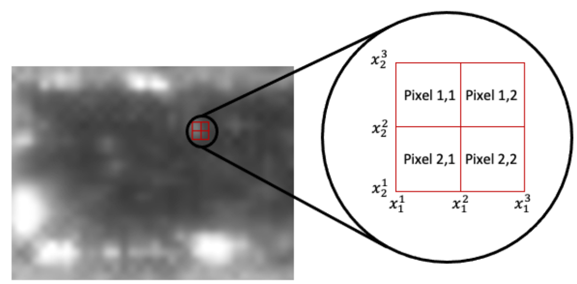

Figure 9. LWI pixel registration

3.3 Feature-based pointwise data fusion

PDF is conducted in real time to fuse high-frequency sampling data to detect process faults at the micro scale. In this case, the in-situ MPM images can be characterized by particular features. For example, to monitor melt pool size, an MPM image with 14400 pixels can be reduced to a single value—melt pool area. As a result of data registration, each point on Figure 6 has several measured numerical values—laser beam position, actual scan speed, actual laser power and melt pool size. Classical PV maps indicate certain relationships among these values. Higher laser power or lower scan velocity results in larger melt pool size when other conditions remain the same. The melt pool prediction model *S=f(P, v)* governs this relationship. If the calculated melt pool size deviates from the model, then a fault can be reported.

Figure 10 demonstrates a single-point PDF process. At location $[x_1, x_2]$, the actual laser power and scan speed is 187 W and 796 mm/s from an encoder with a measured melt pool area of 0.0268 mm^2. This value is compared to the estimated melt pool size using a melt pool prediction model derived in [18]. The error is beyond one standard deviation and assumes an irregular melt pool.

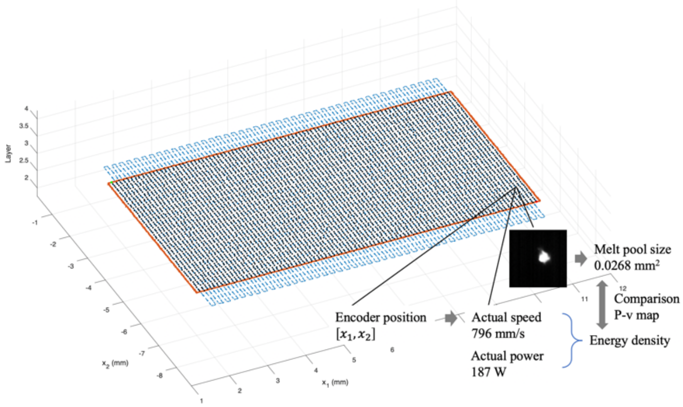

Figure 10. A PDF process

3.4 Raw-data-level trackwise data fusion

Although the PDF has the finest resolution, it does not provide direct information about a part with multiple tracks or complex scan strategies. A standalone melt pool observation only represents the transient status of a tiny region. Besides, it is isolated from the continuous melting process. An independent abnormal melt pool has less chance to result in a part defect. Hence, TDF becomes a useful technique for checking the remelting condition between two adjacent scan tracks. The fusion was realized, again, upon the fully registered MPM images aligned on two scan tracks.

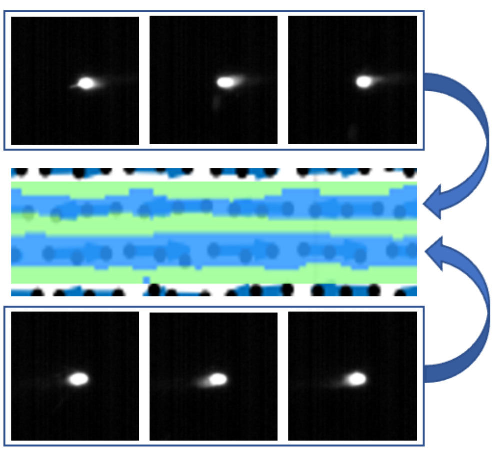

Figure 11. TDF track remelting reconstruction

Figure 11 shows an example of how the remelting status can be reconstructed simply by stitching together the melt pool images on two adjacent tracks. Two high-frequency MPM images next to each other have a time gap of 50 µs, resulting in 40 µm of spatial distance. This number is much smaller than the average melt pool length. As a result, the fusion of a series of MPM images can create a continuous melt pool track. While processing the fusion track by track, the overlapping area indicates remelting condition. In this figure, the black dots are the MPM positions, while the green and blue colors indicate the area with and without remelting, respectively.

3.5 Decision-level layerwise multimodality data fusion

LDF first fuses the high-frequency sampled data from the same layer into layerwise feature maps, where the feature selection and extraction depend on the user's interest. Figure 12, for instance, shows a layerwise melt pool size map by fusing the melt pool area feature out of each MPM image from the same layer. In the color map, warmer colors and higher elevation indicate a larger melt pool area. Note: the MPM images were taken at discrete locations. The original data points may not sufficiently create the map for the whole layer. Data interpolation techniques could be used to fill the gap. This example, for demonstration purposes, uses the Triangulation-based natural neighbor interpolation method to create the map.

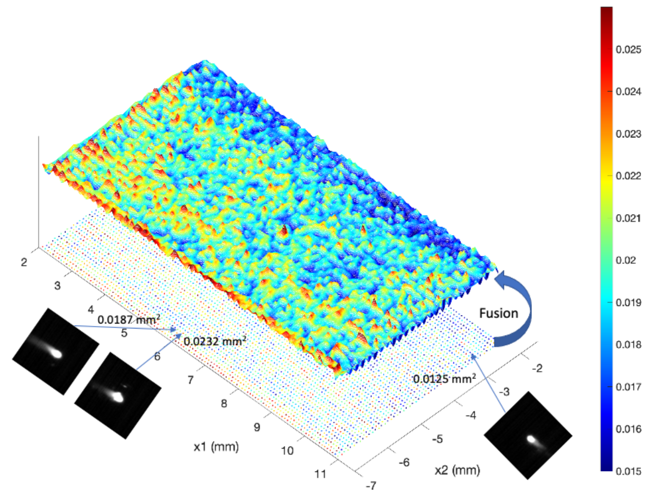

Figure 12. LDF from MPM images. The color bar scales the melt pool area from 0.015 to 0.025 mm^2.

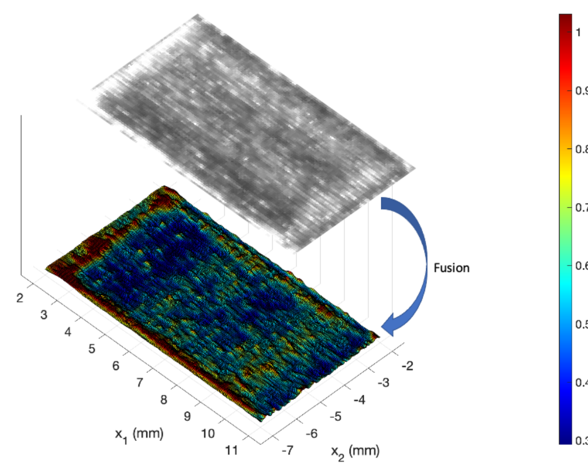

Figure 13. LDF from LWI. The color bar scales the grayscale intensity from 0 to 1, where grayscale 255 in LWI is equal to 1 in the LDF map.

Meanwhile, fully registered LWI images can also be fused based on pixel values and an appropriate scaling method, resulting in a similar map, as shown in Figure 13.

Image processing can be applied to both images. When edges are detected, geometry deviations can be measured for both modalities and indications can be derived from the layer printing quality. In the case when the indications from multi-modality data hard to agree with each other, a voting mechanism can be applied for a decision level data fusion. The weight for each measurement modality can be determined based on the uncertainty involved in the measurement. In the example above, melt pool monitoring has a higher spatial resolution, hence it was assigned a higher weight than was the layerwise imaging.

3.6 Multi-level partwise data fusion for Overhang Feature Evaluation

3DDF presents at the macro level of the fusion work (Figure 2). It focuses on part feature inspection that can provide direct insights into part quality. The general workflow is similar to a feature-level LDF. The main difference is that, instead of fusing extracted features from a single layer, 3DDF selectively picks the features at particular areas from multiple layers for fusion. The part feature could be geometric features or build features. Figure 14 shows the 3DDF result for the overhang down-skin area, which is highlighted in the CAD model on the left. This work focuses explicitly on the down-skin area with zero vertical support during the build. The top and bottom surfaces are included just for comparative purposes.

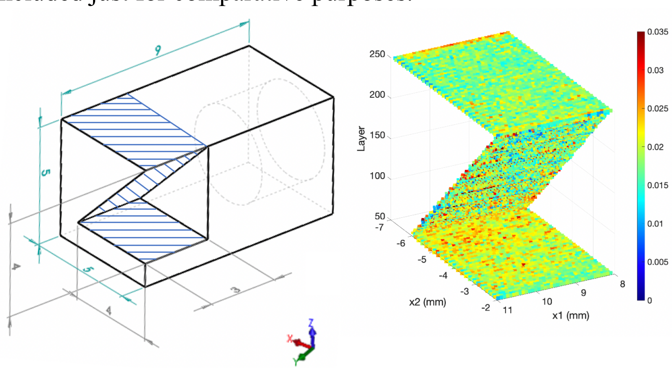

Figure 14. 3DDF for the overhanging down-skin region. The color bar scales the melt pool area from 0 to 0.035 mm^2.

4. RESULTS AND DISCUSSIONS

This section illustrates the multi-scale data fusion results for the AMMT overhang part build. It covers process monitoring to part defect identification and quality prediction. The following examples, however, should not set a limit on the potential uses of the AM data fusion framework.

4.1 Data fusion for process monitoring

Data fusion results provide a new point of view for AM process monitoring in real-time. PDF, TDF, or LDF can provide real-time process monitoring at different scales, with divergent accuracies, and for various domain interests. LDF fuses in-process data after the scan is finished for a layer and provides a plane view for that layer quality. TDF enhances the fusion scale to the track level, which may be ideal for monitoring the physical condition between tracks, such as bonding and melting conditions. PDF can be the most accurate point-to-point monitoring if the fusion can be executed timely.

In Figure 15, PDF provides measurement alignment and melt pool status inspection functions. According to our previous melt pool prediction studies [19, 20], for the same material and parts built on AMMT, PDF can be utilized to determine at each position whether the melting is normal, oversized, or undersized. In this figure, a constant laser power of 195 W and scan speed of 800 mm/s should contain the melt pool to 0.015 to 0.025 mm^2 based on the overall laser energy density input. Any melt pool outside this range would be considered an anomaly.

Figure 15 plot is for a layer with a cylinder cavity on the left and an overhang area with 45° slope on the top right. The majority of the plot is dominated by blue points that generally indicate steady melting conditions. The scattering oversized and undersized melt pools would not have a significant impact on the part. However, the melt pool size close to the cavity significantly increases where the same energy density is applied. This could be a sign that this area has geometric or other physical defects such as uneven paving powder or immense thermal residual stress.

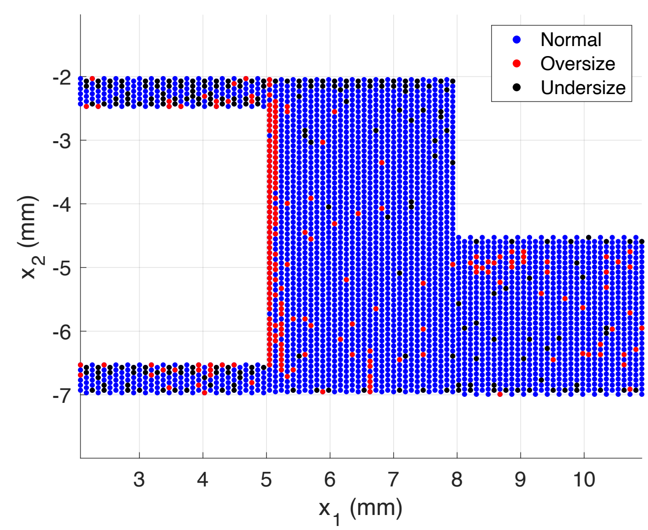

Figure 15. PDF fused result for one layer

4.2 Data fusion for part quality monitoring

Expected outcomes of AM data fusion are reliable inspection, evaluation, and improvement of the final AM part quality. Part quality, which is closely related to process quality, may not precisely equal to process quality. In other words, a few rare small process deviations such as abnormal melt pools scattered on a layer may not cause issues for the final part because the subsequent building process could compensate for them. Therefore, larger-scale fusion such as TDF and LDF may present more comprehensive pictures for part quality monitoring.

Figure 16 shows the actual measurement from XCT and LWI, and the fused results from TDF and LDF. All the figures show the top view. The cropped edge area is taken from the last layer of the build. In XCT, the edge clearly outlines the boundary of the part. The rough edge can be traced back to the same region on TDF. The TDF image shows a defect edge area not fully melted, indicating a significant lack-of-fusion. Similarly, one may observe the rough surface in the LWI image. Alternatively, this could also correlate to the large melt pool intensity region in an LDF image. The uneven surface on both the XCT and LWI images can be related to the deviated patterns in the same area as the TDF and LDF images.

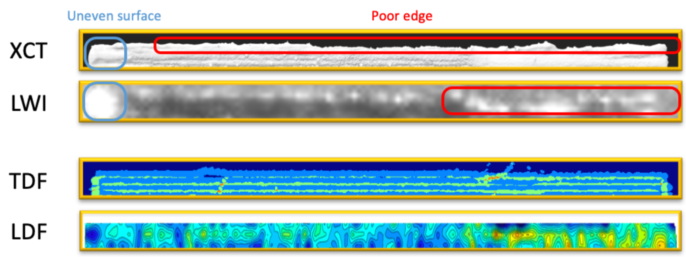

Figure 16. Comparison between raw measurements to the fused result TDF and LDF

The fusion also proves that better overlapping conditions between melting tracks can help improve the part quality in geometric accuracy.

4.3 Data fusion for process control and decision making

The LPBF process is fast and precisely controlled during the build. It is not easy to integrate human involvement into the decision-making process when the build is ongoing. For example, for our overhang part build, a laser beam quickly (800 mm/s) scans the entire layer. It can finish scanning this layer within 1.05 s. It is too short for a human to read, analyze and make a decision on.

Figure 17 shows a hypothetical PDF-based automatic decision-making process to correct the abnormal melt pool on-line. The system has detected a series of oversized melt pools at the moment (a). The laser beam continues moving along the designed path while the system makes decisions at the moment (b). The unfilled dots mark the melt pool created during the analysis period. At the beginning of the moment (c), the machine has sent a signal to the laser head to reduce the power. As a result, the following melt pool can be well controlled within the normal range. (d) shows the laser beam that has moved out of the large melting region. Thus, the decreased laser power may not produce a large enough melt pool as it fails to introduce sufficient energy to the powder. Nevertheless, the machine detects the negative results at the end of the moment (e). New observation pushes the machine to make another decision to modify the laser power to a higher value in (f). These series operations can fix most of the critical anomalies that randomly show up during the build.

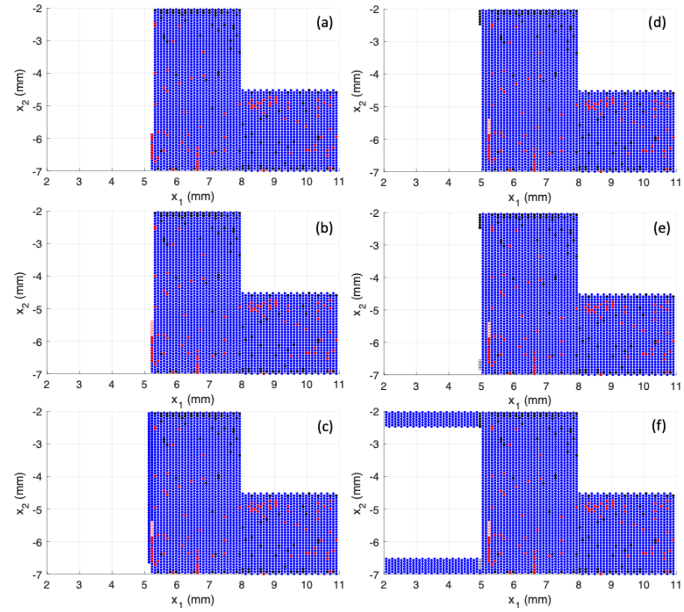

Figure 17. Hypothetical AM control strategy based on PDF. The legend is the same in Figure 15.

4.4 AM data fusion and multi-loop feedback control

AM in-process data fusion can be incorporated into closed-loop process control and real-time build decision making, as shown in Figure 18. Pointwise and trackwise fusions happen in real time and the fusion results can be part of process real-time control. For example, Shkoruta et al. [15, 21] proposed and tested laser power modulation to regulate melt pool intensity in real time and demonstrated the effectiveness of the proposed approach through experiments on the open-source SLM machine.

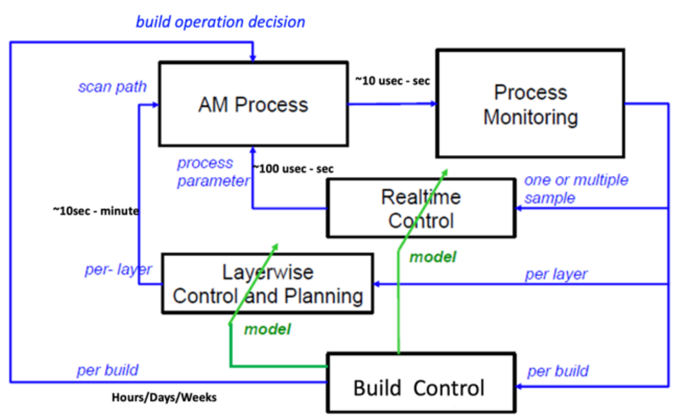

Figure 18. AM in-process data fusion for closed-loop control

The LDF is utilized for near real-time layer repair or scan strategy replanning. While the build status derived from the partwise data fusion will be used to justify if a build should continue or stop to prevent waste.

5. CONCLUSION

This paper proposes a comprehensive AM data fusion framework that captures multi-scale hierarchical in-process data melding for process monitoring and control. PDF, TDF, LDF and 3DDF can be used in various applications. Selecting data fusion at the right scale(s) leads to an enhanced build performance. Data registration as a preprocessing step yields ready-to-integrate data with preferred formats, structure and features.

AM data fusion is an essential technique for presenting meaningful information to AM end-users for decision making. Reading individual MPM images and manually aligning to the processing parameters can be difficult. With data fusion techniques, the numerical values, binary images and grayscale pixels become useful information that can be fully utilized in AM QA/QC. For example, the fused PDF presents almost the entire landscape of the layerwise part quality to the AM end-users with compatibility and originality. TDF builds upon the PDF to use raw MPM images to investigate the remelting conditions between tracks, which provides straightforward insights to the users on how strongly the material is bonded.

Along with the visualization and data processing functions, the proposed fusion work provides opportunities to realize real-time control and robust decision-making. Online layerwise rescan strategies or scan replanning can bring back the part quality after a defect layer.

Future works include developing rapidly deployable and interoperable data fusion tools to analyze, process and exploit two or more different types of data from the same or multiple sensors. The aim is to develop a automatical data fusion tool for different types of AM machines. New capabilities will be developed to better organize information from multiple sources, and further dramatically improve the real-time data fusion ability to detect, identify and locate part flaws, and apply controls to eliminate them. Such methods as the monitoring framework mentioned in Section 4 will be implemented, evaluated and validated using NIST AMMT to advance the development of AM QA/QC standards.

DISCLAIMER

Certain commercial systems are identified in this paper. Such identification does not imply recommendation or endorsement by NIST; nor does it imply that the products identified are necessarily the best available for the purpose. Further, any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NIST or any other supporting U.S. government or corporate organizations.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Institute of Standards and Technology (NIST) under Cooperative Agreement number NIST 70NANB18H258.

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