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Review of In Situ Sensing for Directed Energy Deposition for Industrial Part Quality Assessment

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ABSTRACT

As the use additive manufacturing (AM) processes continues to grow in critical industries, improved quality assurance methods are becoming increasingly sought after for qualification and certification of AM components. Traditional nondestructive evaluation of printed components is often unable to supply the required confidence in print quality to justify qualification and certification, but the layer-by-layer nature of AM provides unprecedented opportunities for in situ quality inspection. This document summarizes recent developments in process monitoring research specifically related to Directed Energy Deposition (DED). Particular attention is given to three aspects of the highlighted manuscripts: (1) the type of sensors used, (2) features extracted from each sensor modality, and (3) analysis of extracted features for AM quality assessment.

Based on the review of the state-of-the-art, several observations have been made. First, none of the reviewed works have applied their trained models to real part geometries, with many of the works relying on single track experiments, thin-walled structures, and cubes. Similarly, there have not been any works demonstrating model generalizability, i.e., a model trained on data from one build allows for fruitful analysis of data from another build. Many works used machine learning techniques to distinguish different process regimes (i.e., normal, keyholing, lack-of-fusion), but very few papers have investigated stochastic variation in an already "optimized" process. Sensor fusion approaches are also limited in the DED sensing literature, but the few works that have employed such techniques have demonstrated the benefits. Finally, registration of in situ data to the build coordinate system is of paramount importance to producing industrially relevant in situ monitoring systems. Data registration allows direct correlations between process anomalies detected in the process monitoring data to localized departures in part quality, but such techniques are generally lacking in the current literature.

1. Introduction

As the use additive manufacturing (AM) processes continues to grow in critical industries, improved quality assurance methods are becoming increasingly sought after for qualification and certification of AM components. AM processes offer unparalleled design freedom, opportunities for optimized designs, and supply chain flexibility, but they are subject to stochastic fluctuations in process stability that occasionally result in process anomalies, lowering confidence in final part quality and increasing rejection rates of printed components. Due to the aforementioned geometric complexity enabled by AM, traditional nondestructive evaluation of printed components is often unable to supply the required confidence in print quality to justify qualification and certification. However, the layer-by-layer nature of AM provides unprecedented opportunities for in situ quality inspection since the construction of each layer is directly observable during the process.

This document summarizes developments in process monitoring research specifically related to Directed Energy Deposition (DED). To appropriately scope this review, works published within the last five years will be prioritized, but older, notable publications may be included where appropriate. Additionally, the term "in situ' in this review means "in the original environment," meaning that sensor setups in non-manufacturing environments (e.g., X-ray synchrotron studies of single tracks) are excluded from this document. Such studies are useful for better understanding AM process physics and their corresponding sensor signals, but the focus of this report is on useful methods for industrial quality control. Attention will be given to three aspects of the highlighted manuscripts: (1) the type of sensors used, (2) features extracted from each sensor modality, and (3) analysis of extracted features for AM quality assessment.

This report is organized as follows. First, an introduction to various types of sensors using the DED process monitoring literature are reviewed (Section 2). Next, pertinent features extracted from raw sensor data and used for data analysis are discussed for each data modality (Section 3). The methods by which these data are then used to for part quality analysis are summarized in Section 4, and conclusions are drawn in Section 5 about the current state of the art.

2. Types of Sensors

2.1 Machine Vision

Historically, vision-based sensing has received much of the attention in the in situ monitoring for DED literature and may either be on-axis or off-axis. On-axis sensing is unique to laser-based systems, while off-axis techniques are used pervasively across all DED processes due to its ease of installation and low need for system modification.

During on-axis imaging, also called coaxial imaging, emitted and/or reflected light travels along the optical path of the laser, and some optical component (e.g., a dichroic mirror) reflects a portion of the incoming light to an imaging sensor, which may or may not include additional optical filters to achieve a desired intensity level or wavelength. As the development and stability of the melt pool is critical to the successful construction of AM components, on-axis melt pool monitoring represents one of the most commonly implemented in situ monitoring techniques [1], [2], [3], [4], [5], [6], [7]. Details concerning each of these works will be presented in the following sections.

Melt pool monitoring is also frequently used for sensing during DED processes lacking an on-axis optical train, where the deposition method necessitates an off-axis sensing approach [8], [9], [10], [11], [12]. During off-axis imaging, a camera is installed inside of the build environment and used to observe the DED process. For example, Xia et al. [8] collected melt pool images from an off-axis camera and used the images to identify four different regimes of processing in a wire arc additive manufacturing (WAAM) process: (1) humping, (2) spattering, (3) robot suspend, and (4) normal. Li et al. [12] also developed an in situ monitoring method for WAAM. The authors used off-axis imaging to examine build height instabilities and process anomalies occurring in blown powder, laser DED of Al2O3. The camera, filtered to the NIR wavelengths and aided with a laser illumination source, was used to monitor the construction of a thin-walled structure. Deviations from the intended build height were measured using classical computer vision techniques, while a convolutional neural network (CNN) was trained to classify a region of interest surrounding the meltpool to belong to one of five different porosity levels, each of which corresponded to different process parameter combinations.

Finally, a number of works have also used machine vision sensors to perform in situ digital image correlation [13], [14], [15], [16]. However, these works are typically concerned with development of the imaging and analysis techniques, verification of the approach using modelling, and using the resulting data to improve understanding of thermal stress and deformation development. At present, these works appear less focused on how such approaches could be used for in situ part quality assessment.

2.2 Time Series

Vision-based sensing is still an active area of research, but time series measurements, such as acoustic emissions monitoring and ultrasonic sensing, of DED processes have become increasingly popular. Li et al. [17] performed in situ acoustic emissions sensing by mounting a piezoelectric transducer to the bottom of a laser DED substrate and used to sense acoustic wave propagation during single layer depositions under different conditions. To process the data, a sliding window approach was taken in which 15 features were extracted from the raw acoustic signals (eight from the time domain, seven from the frequency domain). The features were then fed into a support vector machine (SVM) to learn to distinguish different processing conditions, including (1) powder feeding with no laser, (2) laser melting with no powder feeding, and (3) true deposition with both powder feeding and laser melting. The trained SVM was successfully able distinguish these three processing conditions, but performance degraded when varying powder feed rate and laser power under condition three. The final SVM displayed classification accuracies ranging from 88-94%. However, it is unclear how ultrasonic monitoring using a piezoelectric sensor mounted to the bottom of the substrate can generalize to different geometries without performing real-time simulations that incorporates the build geometry at each timestep.

Similarly, Wen et al. [18] performed ultrasonic inspection during the construction of a thin-walled structure made of stainless steel 316L in a blown powder, laser DED process. The structure was printed using nominal processing parameters except in a single chosen location where the powder feed rate was dropped to intentionally induce a flaw. After fabrication of the component, a piezoelectric transducer mounted to the bottom of the substrate was used to generate guided waves that would propagate through the substrate and into the thin-walled structure. Analytical and finite element models of the setup, including a model of the component geometry, were used to simulate the expected response, while a laser vibrometer measured the out-of-plane displacement of the thin walled structure. Comparing the data vibrometer data to the simulation results enabled the successful detection of the manually induced flaw. However, it is unclear how such approaches will scale to industrial settings given the computational requirements and geometry-dependent nature of the analysis technique.

2.3 Miscellaneous Sensing Methods

Imaging and times series data represent the most common sensor types employed in the DED sensor literature. However, some recent works have investigated other sensor modalities. For example, recent works by Jeon et al. [4] and Kaji et al. [19] have made use of laser line scanners to investigate surface topologies in situ. In the work by Kaji et al. [19], a laser line profiler was mounted to the end effector of a custom, robotic laser DED system. A series of stainless steel 316L components were built, and laser line scanner data was collected on a layerwise basis. The point cloud data generated by the scanner was synced to the end effector position during the end-of-layer scans, resulting in a co-registered series of point clouds representing the deposited surface of each layer. Raw point cloud data was preprocessed to isolate the as-printed surface, remove outliers, and suppress noise. A plane was then fit to the data, and deviations from this plane were used to provide annotations for one of three classes: (1) normal, (2) concave (below the plane), and (3) convex (above the plane) regions using the DBSCAN clustering method. The annotations provided by the unsupervised annotations were then fed into a supervised machine learning model called RandLA-Net [20], which segmented the layerwise point cloud data into one of the three classes.

Uniquely, Li et al. [21] developed a method for performing full-field substrate deformation measurements during DED. Distortion of the substrate was measured during a multitrack laser DED deposition of Inconel 625 using a custom implementation of the coherent gradient sensing (CGS) method – an optical interferometry technique. The interference patterns generated by the CGS setup were then transformed into estimates of surface slope, curvature, and shape of the bottom of the substrate, and it is conceivable that such a data stream could be introduced into an industrial DED sensing system to provide substrate distortion information.

3. Engineered Feature Extraction

Once collected, data can be further processed to extract pertinent features describing the nature of the information imbedded in the sensor signatures. These features can then be used for manual analysis to inform process understanding (Section 4.1) or be fed as input to machine learning models (Section 4.2) to make assessments of part quality (Section 4.3). The following sections detail methods of engineered feature extraction wherein algorithms are manually constructed to extract features desired by the user. Discussion of machine learning methods that learn the best features to extract are left to Section 4.2.

3.1 Machine Vision

Table 1 lists engineered features extracted from machine-vision-based in situ sensing systems for DED. The most common extracted features are related to the perceived morphology of the melt pool [7], [4], [10], [5], [9], [22], [23], [1], [2]. This process typically involves some melt pool segmentation method using either a traditional computer vision or machine learning approach. Once pixels corresponding to the melt pool have been identified, morphological features, such as melt pool length and width, can readily be extracted using classic computer vision algorithms. For example, Tang et al. [5] extracted morphological melt pool features and elected to decompose the melt pool into subregions from which different features could be extracted. A laser DED process was monitored using an on-axis CMOS melt pool camera filtered to 520-710 nm, while an additional off-axis visible light and infrared camera were used to supplement the on-axis data. Sensor data was collected during the construction of single-track, multi-layer and single layer, multi-track structures printed using varying laser powers and scanning speeds. From the on-axis melt pool images, numerous morphological features were extracted from individual frames, including the melt pool width, area, texture, etc. The melt pool was decomposed into three distinct regions: (1) the melt pool head, (2) middle region, and (3) the melt pool tail, and morphological features from these three regions, as well as the melt pool as a whole, were then compared for each of the process parameter combinations. Melt pool slag formation and motion through the melt pool was also investigated. The authors noted that melt pool slag eventually form oxides, which according to Bevans et al. [24], may result in stochastic flaw formation. As such, engineered features related to slag may be important process quality indicators.

The majority of works related to monitoring of the melt pool only investigated morphological features, but other engineered features have also been explored. For example, some works have made use of the perceived temperature or image intensity values [3], [5], [7], [25] to construct more descriptive features. The best example of this approach comes from Khanzadeh et al. [3], wherein on-axis melt pool images generated by a two-color pyrometer were normalized, converted to spherical coordinates, and imputed to generate a high-dimensional feature vector containing both morphological descriptors and information related to the perceived intensity distribution from the pyrometer. The authors demonstrated that the derived morphology-temperature-topology descriptors outperform engineered features with morphological descriptors alone. Note that spatter statistics, such as spatter counts and area, have also been investigated by Ertay et al. [9] and Mi et al. [26], but, in general, such features appear to be used infrequently.

Table 1. Engineered features extracted from vision-based sensing technologies. Melt pool morphology features describe the size, shape, and location of the melt pool, and may be derived from both on- and off-axis imaging systems. Temperature and intensity features refer to measures of actual values of the imaging data.

Feature Name	Reference
Melt Pool (MP) Morphology	
Position	[7], [10]
Central Moments	[7]
Length	[4], [5], [7], [10]
Width	[4], [5], [7], [9], [10], [22]
Height	[23]
Aspect Ratio	[10]
Inclination Angle	[10]
Area	[5], [7], [9], [10]
Shape Descriptors	[1], [2]
Temperature/Intensity	
Maximum	[7], [25]
Minimum	[25]
Mean	[7]
Sum	[5]
Variability (std dev, variance, range)	[7]
Miscellaneous	
MP Morphology-Temperature-Topology Descriptors	[3]
Spatter Statistics	[9], [26]

3.2 Time Series

Table 2 lists features engineered for time series data streams produced during DED processing. Features have commonly been extracted from either the time-domain [10], [17], [27], the frequency-domain [7], [17], [27], or the time-frequency domain [7], [27]. Many of the features extracted from the time- and frequency-domains can actually be calculated in either domain, e.g., variance, skewness, kurtosis, but features related to the intensity of the signal are more commonly extracted from data in the time-domain. Whereas engineered features extracted for image-based systems typically used raw, unprocessed data as input, note that data preprocessing (e.g., denoising) appears to be a prerequisite for successful usage of time series data modalities. Video streams from a machine vision system can also be converted to time series representations by extracted pertinent features from individual frames and then treating each feature as a new time series data stream, as is done in [4], [7], [10].

As an example, Chen et al. [7], [27] performed acoustic emissions (AE) monitoring during a laser DED process under three different printing conditions representing (1) nominal print conditions, (2) crack-prone conditions, and porosity-prone conditions. Data were collected during the construction of thin-walled structures, and raw acoustic signals were first denoised before being windowed. Features were extracted for each window and included three metrics from the time domain and 12 from the frequency domain. Mel-frequency cepstrum coefficients (MFCCs) were also generated for each time window, as well as corresponding time-frequency images representing the three print conditions. A series of machine learning models were trained using either the time- and frequency metrics or the MFCC images to distinguish between different DED processing regimes. Additional details on [7] may be found in Section 4.3.

Bevans et al. [24] collected acoustic emissions data during the constructed of three thin walled geometries made of stainless steel 316L fabricated in a WAAM process. Each thin wall was exposed to one of three different contaminants at controlled locations by drilling a hole in the geometry and filling it with either chalk, oil, or sand. The process was sensed using an acoustic sensor mounted directed to the welding torch. The raw data from the acoustic sensor was first pre-processed using the discrete wavelet transform with eight octaves. The resulting signal at each octave was filtered using a manually set threshold to remove noise, and the remaining signals were reconstructed to generate a noise-filtered acoustic signal. A single engineered feature, called the Fiedler Number, was then calculated from the filtered signal and monitored in a statistical control chart. Upper and lower control limits were set using tradition control chart methods, and the in situ data collected for each of the three thin walls were then analyzed. Locations where the Fiedler Number exceeded the upper and lower control limits were identified and compared to X-ray computed tomography (XCT) data, with some out-of-control detections corresponding to regions of either high porosity or large variations in melt pool width. However, some out-of-control indications appeared to lack a corresponding indication in the characterization data.

Table 2. Types of engineered feature extracted from varies time series data streams. As opposed to categorizing the features by the type of sensor, time series features have been decomposed into those extracted from the time- and frequency- domains. Miscellaneous features are also reported.

Feature Name	Reference
Time-Domain	
Mean	[10], [17]
RMS	[17], [27]
Maximum	[10], [17]
Minimum	[10]
Variability	[10], [17], [27]
Skewness	[17]
Kurtosis	[17]
Zero Crossing Rate	[27]
Impulse	[10]
Frequency Domain	
Spectral Centroid	[7], [17], [27]
Spectral Bandwidth	[7], [27]
Spectral Roll-Off	[27]
Spectral Flatness	[7], [27]
Band Energy Ratio	[27]
Spectral Contrast	[27]
Spectral Variance	[7], [27]
Spectral Skewness	[7], [17], [27]
Spectral Kurtosis	[17], [27]
Spectral Crest	[27]
Spectral Entropy	[7], [27]
Spectral Flux	[27]
Miscellaneous	
Mel-Frequency Cepstral Coefficients	[7], [27]
Fiedler Number	[24]

4. Analysis of In Situ Data

Once pertinent features have been extracted, various analysis techniques are available for understanding process variability and/or correlating sensor data to processing conditions or part quality. The following sections highlight three common strategies for analyzing in situ data.

4.1 Exploratory Data Analysis

Exploratory data analysis refers to manual exploration of in situ monitoring data to better understand correlations process anomalies and their corresponding data signatures. These approaches may rely on machine learning or feature engineering to perform these tasks, but the final analyses are performed through manual comparisons of these results and some material quality of interest. For example, Mi et al. [26] developed an in situ monitoring system for a laser DED process to segment the melt pool and spatter particles in individual frames using a deep convolutional neural network using atrous convolutions. An off-axis, high-speed camera, bolstered by a 25 W laser illumination source, was used to monitor the melt pool and spatter particle generation during single track experiments under varying laser power and scan speed conditions. While the small field-of-view and large of amount of data generated likely limits such an experiment setup from being industrially realizable, the authors were able to successfully segment the melt pool and spatter particles from the frames of the high-speed camera. Morphological characteristics of the segmented melt pool and spatter particle counts where then compared for different process parameter combinations.

4.2 Machine Learning Approaches

Due to the complex nature of sensor signals associated with in situ sensing of AM processes, many of the reviewed works have leveraged machine learning methods to make sense of and use process monitoring data [1], [2], [3], [6], [7], [8], [10], [11], [12], [17], [26], [27], [28], [29]. The machine learning approaches employed can generally be categorized into two groups: (1) those using engineered features [1], [2], [3], [4], [7], [10], [17], [27] and (2) those using learned features [6], [8], [11], [12], [19], [26], [28], [29].

In terms of network complexity, some works have used transfer learning approaches (off of well-established networks like YOLO and ResNet) to reduce the computational burden of training [8], [11]. The work of Pandiyan et al. [6], however, represents one of the more sophisticated machine learning approaches in the literature. The authors utilized both supervised and self-supervised machine learning models, based on CNN and vision transformer (TF) architecture, to classify images from an on-axis melt pool camera (30 Hz with a 650-675 nm notch filter) as belonging to one of four possible processing regimes, each with different input laser powers. The fully supervised CNN and TF architectures both outperformed the self-supervised networks, but unfortunately no comment was made on the reduced annotation burden for the self-supervised networks – one of the key advantages of self-supervised learning methods.

Notably, Lee et al. [29] also used a melt pool monitoring setup to sense the DED process, but instead of extracting melt pool characteristics, the authors present one of the few works investigating the use of in situ sensing to detect powder feed anomalies in blown powder DED. An on-axis melt pool camera was used to collect data during DED processing of stainless steel 316L, and frames from the camera were classified as belonging to one of five classes (either normal or one of four clogged nozzles) using various machine learning models, including a CNN, knearest neighbors (KNN), decision tree, and random forest. The work of Kaji et al. [19] is also notable for its use of deep learning with point cloud data as opposed to image or time series data.

Most of the reviewed literature have made use of single data modalities for analysis. However, several recent works [4], [7], [10] endeavored to fuse multiple data streams, which has been shown to improve model performance for sensing of AM processes [7]. To this end, Shin et al. [10] used an off-axis, NIR-filtered camera and an off-axis pyrometer to sense single layer depositions from a laser DED process printed with varying laser power and speed. Melt pool morphology features were extracted from frames of the camera, and, along with the signal from the pyrometer, the corresponding feature vectors were classified as belonging to one of four states: (1) normal, (2) high pore, (3) low pore, or (4) balling. Training labels were generated via manual inspection and porosity measurements from cross-sectional images of the single layer depositions. Various machine learning techniques, including KNNs, SVMs, and fully connected neural networks, were used to perform classification, with the best performance coming from the SVM (92.7% overall accuracy).

Jeon et al. [4] also employed a data fusion approach, but it is perhaps most notable for its use of process parameters as part of the engineered feature vector. An on-axis thermal camera and a laser line scanner were used to extract meltpool morphology features during a laser DED process. Melt pool width and length were extracted from the thermal camera data, while the laser line scanner was used to estimate the total build height, melted track height, and the inclination angle of the melted track height. These features, as well as the commanded laser power and scanning velocity, were used as input to a fully connected neural network trained to predict the melt pool depth. Regression targets were generated through cross-sectional imaging at each process parameter combination. The inclusion of the process parameters represents a context-first approach to machine learning. In this way, the processing parameters may allow the model to learn the general processing regime (e.g., normal, keyholing, lack-of-fusion) while the in situ data encode the stochastic deviations from nominal behavior within a given processing regime.

4.3 Toward Industrial Solutions

Ultimately, the goal of a process monitoring system for industrial AM processes is to detect when and where various types of process anomalies occur to determine whether or not a given component is of the requisite quality for its intended application. Many of the works discussed have striven to correlate process monitoring data to differing process regimes (i.e., nominal, lack-of-fusion, keyholing), but usage of these algorithms and trained models has not been extended to real components. Some works, however, have striven to create process quality maps of printed components by applying trained models to entire components. For example, Imran et al. [23] used a stereovision system installed on a blown powder laser DED system to generate a melt pool height time series data stream, which had associated timestamps and xyz-coordinates of the deposition head, recorded at 60 Hz. Notably, the authors chose to rasterize the time series data into a voxelized representation, with missing data imputed using a convolved median filter with varying kernel sizes, instead of performing analysis in the native time domain of the raw data. Median melt pool heights were stored in the voxelized representation, and anomalous voxels were detected by comparing the measured melt pool height with the commanded layer thickness. Anomalous voxels were clustered using a connected components analysis, generating clusters of anomalous build conditions with associated sizes, which appeared to correlate well with observed build defects in thin-walled, overhanging structures.

The work of Chen et al. [7] represents one of the most complete in situ monitoring systems in terms of industrial readiness. The authors developed a ROS-based sensing and analysis system capable of distinguishing between regions lacking flaws and regions containing either high levels of porosity or high levels of cracking. A laser-based DED process was sensed using an on-axis meltpool camera filtered to the NIR wavelengths, an off-axis microphone that captured acoustic emissions, and an off-axis, long-wave infrared camera that measured thermal differences in the printed component. Key features from each sensor modalities were engineered and extracted from the data in real time, and each feature was published as a ROS topic at 30 Hz. The published features were then analyzed in real time using a variety of machine learning models, which output one of four results: (1) laser off, (2) defect free, (3) cracks, or (4) keyhole pores. Because the robot coordinates were also published and all data had associated timestamps, the ROS Approximate Time Synchronization algorithm was able to approximately map the machine learning predictions, as well as the extracted features, back into the spatial domain at 30 Hz, generating a 3D quality map of the printed component. Crucially, the authors noted that individual flaws could not be detected, but instead regions of differing flaw characteristics, high volumes of either flaws or cracks, were identified.

The majority of the reviewed works have focused on distinguishing between different processing regimes, and labels have typically been generated by varying process parameters to trip the system into process regimes known to bring about keyholing, lack-of-fusion, or balling phenomena. Despite the apparent success of these works, it is unclear how such approaches could be used in practice since most industry practitioners will not intentionally produce components with parameters known to produce low quality. It is possible that these techniques could be used to detect process drift, as proposed by Ertay et al. [9], but this has yet to be realized in the literature. Furthermore, the work of Bevans et al. [24] represents the singular work making using of statistical control chart techniques with process monitoring data that would typically be used in these situations.

Instead, the ability to detect stochastic anomalies that occur during nominal processing conditions is of most interest in industry since this most closely represents real manufacturing environments. The works of Khanzadeh et al. [1], [2], [3] represent the few publications in the DED sensing literature that have striven to correlate in situ anomalies detected in nominal processing conditions to the locations of individual material flaws, i.e., voids and pores detected in post-build XCT. The authors were successfully able to identify anomalous melt pool conditions from process monitoring data that appeared to be spatially correlated with stochastic flaws. However, the approach has only been applied to single track, thin-walled structures and more work is required to understand the success of such a technique with more complex geometries and across builds.

5. Gaps and Takeaways

Based on the review of the state-of-the-art, several observations have been made. First, none of the reviewed works have applied their trained models to real part geometries, with many of the works relying on single track experiments, thin-walled structures, and cubes. Many of these works have reported good performance, but it is unclear how models trained in these scenarios would extend into real part geometries. Similarly, there have not been any works demonstrating model generalizability, i.e., a model trained on data from one build allowing for fruitful analysis of data from another build.

Furthermore, many works have used machine learning techniques to distinguish different process regimes (i.e., normal, keyholing, lack-of-fusion), but very few papers have investigated stochastic variation in an already "optimized" process. It is unclear how such models could be used in practice since industrial practitioners would not print a component with suboptimal process parameters. Instead, there should be a push toward detection of stochastic process anomalies that can occur during printing with optimized process parameters. The statistical control chart methods presented by Bevans et al. [24] do offer an alternative approach, but put the burden of anomaly detection on the machine operator instead of the analysis software. Sensor fusion approaches are also limited in the DED sensing literature despite the few works having employed such techniques demonstrating the benefits on classification performance.

Finally, it is the opinion of the authors that a context-first approach to AM part quality assessment is of paramount importance to producing industrially relevant in situ monitoring systems. For example, data registration to a common coordinate system allows direct correlations between process anomalies detected in the process monitoring data to localized departures in part quality, but such techniques are generally lacking in the current literature. For time series and video data, the challenge of registration is more straightforward, since timestamps of the collected data can be synced with the coordinates of the machine end effector (e.g., the laser deposition head in laser DED) – a temporal data stream that is commonly available and readily readable for many commercial DED systems. For off-axis imaging modalities, however, the registration process is more challenging, and careful calibration of the camera coordinate systems to the machine and/or build coordinate system(s) must be performed. Knowledge of the real-time part geometry would be required to spatially map data from an off-axis imaging sensor to the machine coordinate system, which is why many of the works using off-axis imaging have been performed with single-track, thin-walled structures where the imaging plane is approximately aligned to the build geometry. To the knowledge of the authors, no works exist in the literature demonstrating successful registration of data collected from off-axis imaging modalities to the machine coordinate system unless it is treated as video stream, an engineered feature is extracted from the data, and the resulting feature is time-synced with the position of the end effector in a manner similar to melt pool monitoring systems.

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