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MEASURED DATA ALIGNMENTS FOR MONITORING METAL ADDITIVE MANUFACTURING PROCESSES USING LASER POWDER BED FUSION METHODS

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ABSTRACT

The number and types of measurement devices used for monitoring and controlling laser powder bed fusion (LPBF) processes and inspecting the resulting AM metal parts have increased rapidly in recent years. The variety of the data collected by such devices has increased, and the veracity of the data has decreased simultaneously. Each measurement device generates data in a unique coordinate system and in a unique data type. Data alignment, however, is required before 1) monitoring and controlling LPBF processes, 2) predicting the material properties of the final part, and 3) qualifying the resulting AM parts can be done. Aligned means all data must be transformed into a single coordinate system. In this paper, we describe a new, general data-alignment procedure and an example based on LPBF processes. The specific data objects used in this example include in-situ photogrammetry, thermography, and ex-situ X-ray computed tomography (XCT), coordinate metrology, and computer-aided design (CAD) models. We use the data-alignment procedure to align the data from melt pool images, scan paths, layer images, XCT three-dimensional (3D) model, coordinate measurements, and the 3D CAD model.

Keywords: additive manufacturing, data alignment, data fusion, manufacturing system integration

1. INTRODUCTION

For three main measurement needs, accurately qualifying complex, laser powder bed fusion (LPBF)-built, metal parts is still extremely difficult. First, there are LPBF process instabilities, which can cause significant variations in built parts. Second, there are not well-understood quantitative relationships among the CAD geometry, the raw-material properties, the fabrication process, which are needed to predict final-part properties. Third, there are the current, LPBF-system states, which are needed for control. Meeting those three needs required the extensive use of a wide range of measurement devices, including sensors and measuring machines, to understand relationships before making decisions throughout the entire additively manufactured product life cycle.

High-quality parts require 1) understanding the physical phenomena, 2) developing the correct models of the different phenomenon, 3) linking those models through data, and, finally, 4) making the best life-cycle decisions possible. Meeting those four requirements were based on the measurement, the principle of physics, and associated mathematical models.

Metal additive manufacturing (MAM), is a completely new kind of fabrication technology. The life cycle of AM parts includes designing, engineering, controlling, and inspecting. Nevertheless, the required data links needed to perform those life-cycle functions optimally do not exist. Instead, LPBF MAM process users are building new kinds of data-driven models and information links, based on new kinds of data collected by new kinds of sensors. In addition to traditional numerical types of data, many AM sensors collect a myriad of different types and quantities of in-situ and ex-situ image data. For example, there are sensors for photogrammetry and thermography and machines for X-ray computed tomography (XCT) and coordinate measurement, such as coordinate measuring machines (CMMs) [9]. Unfortunately, different sensors collect data in different, physical, local, coordinate systems. Moreover, the data from sensors in those systems must be “fused” to create the links that provide input to the models needed to make all AM-part, life-cycle decisions.

Today, aligning data is not possible because there are no procedures for both spatially and temporally aligning data from different coordinate systems. The scope of this work is on alignment of data. Data can come from scan commands, laser-spot locations, melt-pool images, layer-wise images, XCT model, CMM model, and CAD model. Our approach to aligning these different data types is to find and use the reference locations and orientations required to transform a local coordinate system into the reference coordinate system. The authors have identified the meta data needed to align related data sets, which can be used for data registration. Registered data can then be used for analyzing the quality of part.

This rest of paper has the following sections. Section 2 reviews related publications in data collected from both in-situ and ex-situ monitoring. Section 3 proposes a procedure for data alignment. Section 4 gives examples of data alignment. Section 5 discusses the proposed procedure. Section 6 concludes the paper and identify the future work.

2. REVIEW OF SENSOR DATA TYPES AND ALIGNMENT METHODS

Recently, researchers have been integrating LPBF sensors and developing techniques to apply sensor data as input to various applications, such as data analytics. The section provides a review of types of data, data fusion, and research needs.

2.1 Sensor Data Types

In-situ process monitoring is necessary for real-time control and is enabled by sensors that monitor in-process phenomena. Scime et al. [20] used a common, staring cameras with a k-Mean unsupervised classification algorithm to detect anomalies on freshly coated powder bed for laser PBF. The images are used to detect anomalies on a freshly coated powder bed surface: waviness from blade hopping, streaks, debris, voids, and incomplete spreading. Many researchers [11][12][3] have reported the use of multiple monitoring methods, including high-speed coaxial cameras, off-axis thermal detectors and/or staring cameras to collect data for monitoring melt-pool characteristics, including melt pool geometry, energy intensity, spatter, and residual heat.

Reutzel et al. [19] described measurements of melt-pool geometry and temperature with images taken by a single-color camera in the infrared (IR) range. Temperature measurements, however, were based on images taken from a dual-color camera. The authors aligned the images with built-in reference marks in addition to the part design. Everton et al. [5] described in-situ sensors and sensing techniques for monitoring part buildup, layer-by-layer, in LPBF processes. Purtonen et al. [17] applied optical sensors included photodiodes, spectrometers, Charged Coupled Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) imaging sensors, pyrometers, and infrared cameras to monitor the LPBF process.

Commonly used off-axis sensors are Digital Single Lens Reflex (DSLR) cameras. A DSLR camera can take images of the powder bed each time it is triggered. A combination of flashlights from different angles of illuminations can detect anomalies on each scanned layer [1]. Bartletta et al. [2] explored using a high-speed camera to record the laser-scanning process including melting, solidifying, and track formations. Foster et al. [6] used staring-video cameras and coaxial cameras to collect data for monitoring melt-pool characteristics with other types of sensors for data fusion to monitor the progress of melting and track formation.

2.2 Sensor Data Alignment

For the background, data alignment is part of the data registration process, as shown in Figure 1. Data registration is necessary to fuse different data correctly. Data alignment includes both temporal alignment and spatial alignment. Temporal alignment requires a synchronized clock, which usually is a prerequisite of spatial alignment. Spatial alignment is a process that converts sensor data from its original, local coordinate system to another coordinate system so that the data can be compared and fused with the data generated in the new coordinate system. AM data alignment as a research topic continues to expand. Nevertheless, the current limitations of that research are still impeding the use of advanced data analytics, which can accelerate the understanding and control of AM processes and improve decision-making across the AM part lifecycle. Specifically, data-correlation limitations include 1) a limited understanding of how to characterize the new types of sensor data and 2) there is no information to link the data correctly in space and time.

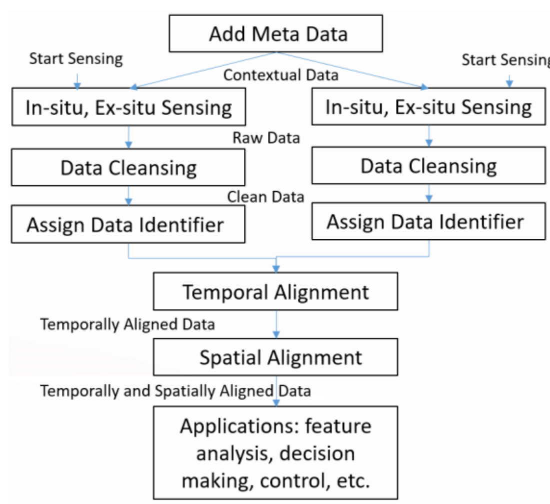

Figure 1 General Data Registration Procedure

2.3 State of Research in Sensor Data Alignment

Morgan et al. [13][14] used the direct-image-alignment approach, where no well-defined edges or corners in the build imagery can be used for alignment. This approach uses a filtered, built image and a synthetic image derived from the laser scan directions. These images are constructed so that they have high intensities where there is solidified materials and low intensities where there is unfused powder. The images must look as similar as possible so that they can be aligned by minimizing the differences. This requirement is almost impossible to be achieved due to measurement uncertainties associated with the sensor data.

Witherell [21] investigated data curation, fusion, and analytics techniques and showed an abstract data-alignment model for additive manufacturing. Bartlett et al. [2] correlated the measured surface temperature with layer-wise, scanned surface images to identify potential anomalies on the layer. The authors then correlated layer-wise measurements with the part measurements using ex-situ, scanning electron microscopy to validate the identified defects. Since the part used in the experiment is a regular shape, the data alignment is relatively simple.

Everton et al. [5] described specific sensors and sensing techniques for monitoring layer-by-layer builds in L-PBF processes. The purposes were to see 1) defects, such as pores, balling, unfused powder, and 2) cracks on a scanned surface with a correlation to the thermal images of that layer. Abdelrahman et al. [1] used a binary template created from the sliced 3D model of the part, as the reference geometry to do data alignment layer by layer. The aligned data then is used to create a 3D model to detect anomalies visually both before laser scanning and in the solidified material after laser scanning. Foster et al. [7] used angle illuminations to collect layer-wise images, which were then fused with pre-placed powder layers. Three-dimensional reconstruction of the images identifies potential flaws in the part.

Petrich et al. [16] used reference marks that were built into the part to align layer-by-layer images with an XCT model for defect location in the scanned part. Roehling et al. [18] modulated the heating and cooling profiles for visualizing the correlation between heating, cooling, and grain growth. Finally, Hirsch et al. [8] proposed a method to align 1) the design model, 2) the part slices, and 3) layer-by-layer images to create a 3D composite model for defect analysis.

2.4 Gaps and Research Needs

Clearly, there is an issue to properly relate a variety of sensors used for in-situ and ex-situ monitoring of LPBF AM processes. Those sensors provide a plethora of data, including gray-scale images and thermal data. While the data from individual sensors are important, correlations among those data can be extremely valuable. Sensor data must be aligned before the data can be applied for analysis to extract new knowledge. Data alignment is necessary to determine the state of the powder-fusion process, the material microstructure, and the fabricated part. For example, without correctly aligning measurements in the spatial domain, conflicting predictions can be made on the process performance and part quality. Lastly, there is no contextual information for data alignment. This is one of major barriers for part qualification and verification to ensure AM product quality

3. PROCEDURE FOR DATA ALIGNMENT

For in-situ monitoring, there are three sensor data types: photographic images, video clips, and time-series data. Photographic images include gray-scale images and thermographic images. Gray-scale images are commonly used to monitor melt pool shape, including its area and dimensions. Thermographic images are used to monitor temperature as well as energy intensity of a recently scanned layer. Video clips are used to monitor the dynamic behaviors in the scanning process, such as spattering and pluming. Time-series, acoustic data is collected from sonic sensors. Sonic sensor data is commonly used to monitor sparking or cracking during laser scanning.

For ex-situ monitoring, the following types of data are in the scope of this paper: XCT 3D model and points collected using CMM. CMM points should be properly associated with the corresponding features. An XCT 3D model can be used to identify pores and other defects. CMM points can be used to establish a datum reference frame and evaluate a feature’s geometry again its tolerance specifications. These two types of data are commonly used in AM and are from nondestructive evaluations of additively manufactured parts.

Another type of data is scanning paths and speed, related to in-situ monitoring data. Scan paths are series of laser spot locations that are used to guide the laser to scan the powder layer. Lastly, chamber monitoring data, such as environmental temperature, gas pressure, and CO_2 levels. Note that chamber monitoring data is out of the scope of this work.

The above-mentioned data types are related, but in different coordinate systems. Examples of different coordinate systems include 1) the CAD-modeling coordinate system, 2) an in-situ sensor coordinate system, 3) a laser coordinate system, and 4) a staring camera coordinate system. Developing a procedure to geometrically align related data types and tie them all to a common coordinate system is the main purpose of our research work. The basis of our proposed, geometric, data-alignment procedure is coordinate transformation. The same point in the space is transferred from one coordinate system to another one. In this paper, the local coordinate system is referred as the “from” coordinate system, and the new coordinate system to which the point is transferred is referred as the “to” coordinate system. For example, a melt-pool image, which is collected by a coaxial camera, can be transformed from the camera coordinate system to the laser-scanning path coordinate system.

Scanning paths can be further related to the layer images taken by a staring camera. Layer images can be related to the 3D model generated by XCT. XCT 3D model can be related to the CMM model generated by the measured points (a point cloud). The CMM model can be related to the geometric model generated by a CAD system. In that sequence of relationships, melt pool images, scan paths, layer images, XCT model, CMM model, and CAD model can be sequentially related in data alignment.

In summary, the procedure includes the following steps:

(1) Group all the related data sets for data alignment. Specifically, two related data sets must have a common reference point and known difference in orientations, see Section 4 for examples.
(2) Identify every two related data sets and pair them for coordinate transformation. Also, identify the "from" coordinate systems and the "to" coordinate system in every pair.
(3) Sequence (chain) all the pairs according to spatial and/or temporal relations. For examples of spatial relations, see Section 4.
(4) Perform coordinate transformations so that all the data sets are in one single coordinate system.
(5) The chained data sets can be assigned an identifier (ID) for indexing and searching. The chained data sets can be used, such as data analysis.

4. EXAMPLES OF DATA ALIGNMENT

This section provides some data alignment examples. The sequence of align related data sets are as follows: (1) align melt-pool images to scan path, (2) align scan paths to the layer image, (3) align layer images to the XCT 3-D model, (4) align the XCT 3-D model to the CMM model, and (5) align the CMM model to the CAD model. After alignment, melt pool images, scanning paths, layer images, the XCT 3-D model, the CMM model, and the CAD model are all in the same coordinate system. This coordinate system will be the CAD coordinate system.

4.1 Melt pool image to scan path alignment

Melt pool is generated by laser melting. As shown in Figure 2, the center of the laser spot is used as the reference point in the alignment. The point in the coaxial camera coordinate system can be estimated using the shape of the melt pool shown in the image. The center of the laser spot on the scan path is in the scanning laser coordinate system. There are at least three ways to describe a scan path: (1) the command position in the XY2-100 or G-code file [10] (Note that the command position and the true laser spot center are different), (2) the intercepted encoder position of the two galvanometers [4], and (3) using an interpretation method to predict the true laser position based on the scanning speed, laser on/off timing, and camera-triggered times. When the time that the melt pool image is taken by the camera, the true laser spot moves away from the original position. If the off-distance is very small, then it is negligible.

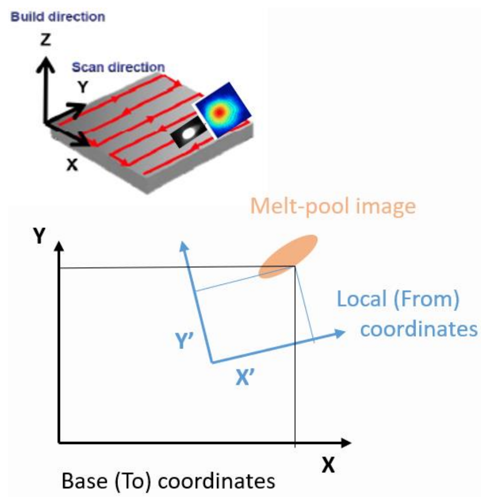

Figure 2 Melt pool images to scan path alignment

The relative orientation between the image ("from") and the layer ("To") can be computed using an appropriate image-calibration method. An image-calibration artifact with black and white grids may be used to measure the relative orientation difference between the orientation in the coaxial camera coordinate system and the orientation in the laser scanning coordinate system. The relations between the laser spot center and orientations in both coaxial camera and scanning laser coordinate systems are thus obtained for coordinate transformation. At this point, the melt-pool image is transformed to the scan path (layer) coordinate system.

4.2 Scan paths to layer image alignment

Scan paths should be aligned with the image of the layer that laser scanned. Scan paths are generated with the laser

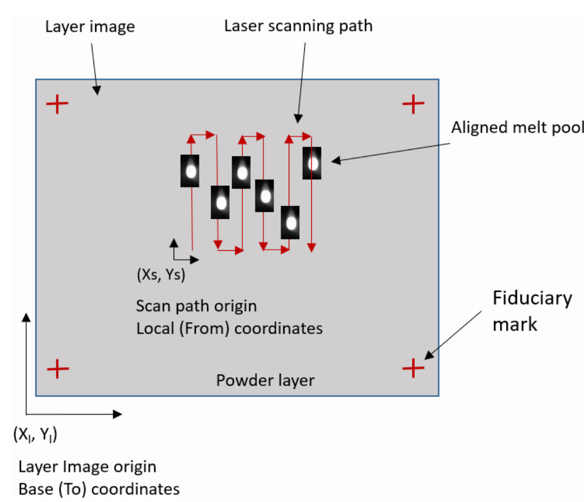

Figure 3 Scan path to layer image alignment

scanning coordinate system. Since it is not always possible to identify features on the scanned layer, fiduciary marks must be created. A fiduciary mark is created on the layer but outside the designed part during or after the laser scanning process. Four fiduciary marks can be used, minimally three. These four marks are the same artifacts in both scanning paths and the layer image. Figure 3 show an example of four fiduciary marks relative to the scan paths. With this aligning, coordinate transformation becomes possible. The "from" coordinate system is the laser scanning coordinate system. The "to" coordinate system is the layer image coordinate system. After the coordinate transformation, melt pool images, scan paths, and the layer image are all in the same coordinate system. Since there are multiple layers in an additively manufactured part, the fiduciary marks can also be used to align layers, from Layer 1 (the bottom layer) to the last Layer (the top layer), as shown in Figure 4.

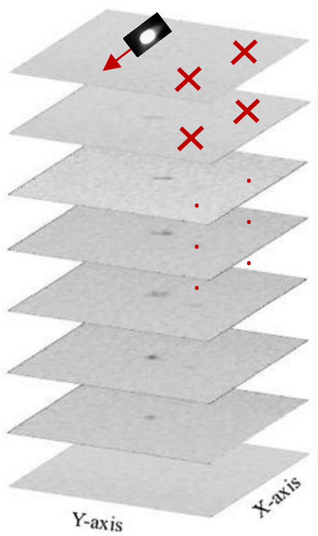

Figure 4 Layer images alignment

4.3 Layer images to the XCT model alignment

Aligned layer images should be aligned with the XCT 3-D model of the additively manufactured part. The purpose is to relate defects found in the XCT 3-D model to the defects found in the scanned layers to identify possible causes for those defects. There are some means for alignment: (1) create or specify reference datum features (e.g., plane, point, or line) in the part for alignment, (2) create fiduciary marks on last layer of the workpiece as the reference positions and align the fiduciary marks on the last layer image with the fiduciary marks shown in the XCT 3-D Model (note: the fiduciary marks has to be on the part, not outside the part so that XCT can detect them.), and (3) use mathematical algorithms to best fit layer images to the XCT 3-D model. The first method is based on geometric dimensioning and tolerancing standards, such as ANSI Y14.5. Figure 5 shows the fiduciary marks must be on the top of the part. The bottom few layers are not part of the part and are separated from the part when it is removed from the built plate.

4.4 XCT 3-D model to CMM model alignment

The XCT 3-D model should be aligned with the CMM model of the AM part. The purpose is to relate the part geometry found in the XCT model to the part geometry found in the CMM model to measure functional features, such as internal holes and thin walls, to verify if they are within the tolerances to ensure the manufactured part meets the functional requirements. The steps in the procedure includes (1) define a datum reference frame on the part for establishing a coordinate system, as defined in ANSI/ASME Y14.5, (2) align the XCT 3-D Model with the CMM model using the datum reference frame. Note that (1) a datum reference frame consists of primary, secondary, and tertiary reference planes (or equivalent geometries), (2) if datum

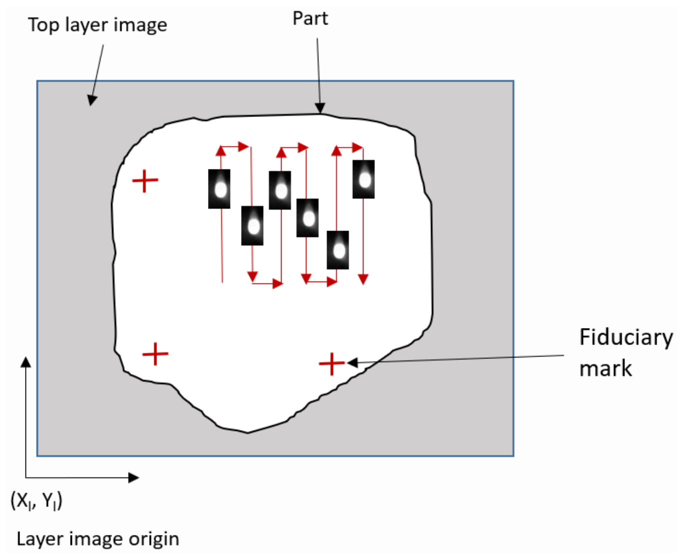

Figure 5 Layer image to XCT 3-D model alignment

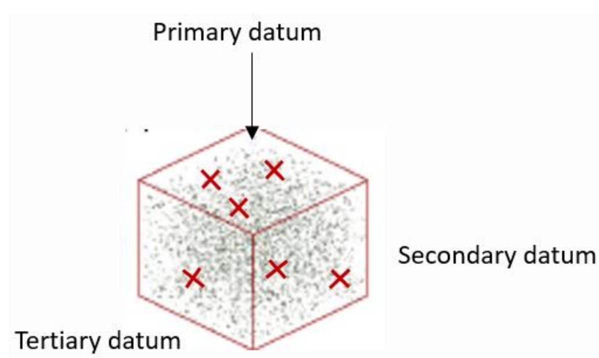

Figure 6 XCT 3-D model to CMM model alignment

reference frame is not possible to define, then other methods, such as fitting with point cloud, can be used for the alignment, and (3) CMM can be substituted with other dimensional measurement methods, such as laser scanners. Figure 6 shows an example of primary, secondary, and tertiary datums to form a datum reference frame, as specified in ANSI/ASME Y14.5.

4.5 The CMM model to the CAD model alignment

The CMM model should be aligned with the CAD model of the AM part. The purpose is to relate the part geometry found in the CMM model to the part geometry found in the CAD model to verify whether features with the specified tolerances, such as cylindricity of an internal hole, to verify if the features meet the tolerance requirements. The step in the procedure is to use the defined datum reference frame align the CMM model with the CAD model of the part for establishing a coordinate system, as defined in ANSI Y14.5. Figure 7 shows the use of primary, secondary, and tertiary datums to align CMM model to the CAD model. CMM model coordinate systems is the "from" coordinate system and the CAD coordinate system is the "to" coordinate system. With the alignment, the dimensions and tolerances of all the feature can be evaluated.

5. DISCUSSIONS

The primary challenge for AM is to control the fabrication process well enough to provide the reliability and repeatability necessary for commercial applications. For example, control is not a standalone process; control is connected to design/engineering processes upstream and inspection/qualification processes downstream. The key to the execution of all these AM processes is sensor data.

In pursuit of overcoming the challenges, methods and standards of data gathering, registration, and fusion are the critical needs [15]. First, data should be collected and curated with rich meta information, e.g., sensor meta data, installation information, and configuration information. Additionally, best practices should be developed to calibrate the measurement apparatus and document the results appropriately. In addition, the data captured should be structured and represented to support interoperability among various computer information systems owned by various stakeholders, including material suppliers, machine manufacturers, measurement devices providers as well as testing labs. Both lexicon and semantic standards are required to enable seamless integrations of data generated from AM lifecycle and value chain activities. With established common data dictionary and common data exchange format, data collected during AM processes can be aligned and fused for better process monitoring and process control. In addition, data of thousands of builds conducted distributed can be aggregated into a common data virtual repository in the form of a federated data repository which will be available for the AM community to conduct advance data analytics including data alignment and data fusion and adaptive learning to accelerate AM part development lifecycle. This research establishes a good foundation on identification of the information for data fusion and provides a initial guidance on how to align the data. The remaining challenges include 1) data alignment for unsynchronized data, 2) data alignment uncertainty qualification, and 3) geometric feature alignment.

The data alignment procedure proposed in this paper is still a conceptual exploration. Real cases of additively manufacturing part using LPBF with in-situ and ex-situ measurements using appropriate sensors should take place to validate the procedure. Furthermore, defect-detection and cause analyses should also be done using the aligned data sets.

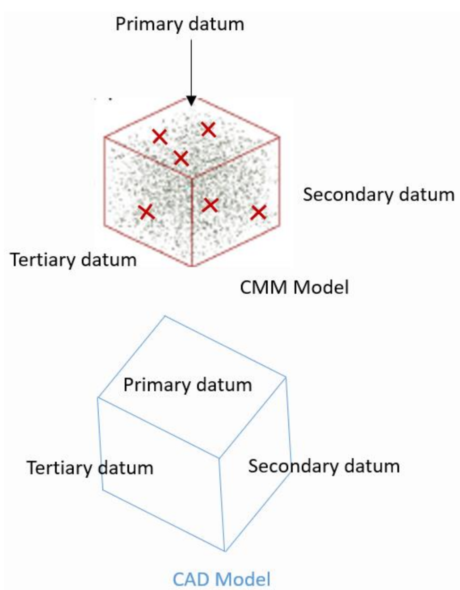

Figure 7 CMM model to CAD model alignment

6. CONCLUSIONS

The use of laser powder bed fusion, LPBF, additive manufacturing technology to fabricate complex, metal parts in aerospace and medical industries has been increasing steadily. As a result, the demands on the quality and reliability of those parts has also increased. To respond to these demands, researchers have started to implement in-situ sensors and ex-situ measurement machines to monitor LPBF processes and to detect potential anomalies in the part. Types of in-situ data include melt-pool images, movies, and acoustic signals. Types of ex-situ data include XCT 3-D models and CMM data clouds. Correlation among related datasets are critical to detect anomalies and the causes. Correlated data set can also be used to verify the quality of AM parts. Since data alignment means all data is transformed into a single coordinate system, to compute the correlation is then possible for data analytics.

The proposed data alignment procedure in this paper addresses the long standard issue of how to align images taken by a coaxial camera, laser scanning commands, and a staring camera that are related to in-situ monitoring. The proposed procedure also addresses the need of aligning in-situ monitoring data with ex-situ monitoring data from XCT, coordinate measurement, and the design model. Examples in the paper show how to relate in-situ and ex-situ data into a suite of correlated datasets that can be used for downstream applications, such as defect analysis, feature analysis, and decision making.

Future work will be in two areas. One is to provide more examples of aligning time series data, such as acoustic signals, with geometric data. Second is to develop data registration procedure to include sensor meta-data with the sensor data for AM data analytics. The procedure will lead to standardization. We expect that these standards will lead to better implementations in the L-PBF user community. Furthermore, a case study that includes design, build, measurement, test should show that data alignment can enable defect detection in AM parts.

DISCLAIMER AND ACKNOWLEDGEMENT

Certain commercial equipment, instruments, or materials identified in this paper are not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

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