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Porosity Detection of Laser Based Additive Manufacturing Using Melt Pool Morphology Clustering

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Abstract

The microstructural and mechanical properties of Laser Based Additive Manufacturing (LBAM) are still inconsistent and unreliable, which is a major barrier that prevents Additive Manufacturing (AM) from entering main stream production. The key challenge is the lack of understanding for the underlying process-properties relationship. We monitor Laser Engineered Net Shaped (LENS) process using a state-of-art thermal image system, and the resulting high-speed Melt Pool (MP) data stream is used to characterize the complex thermo-physical process. We propose a novel method based on Self-Organizing Map to cluster the MPs based on their morphology and link MPs clusters' characteristics to the porosity of fabricated parts, which is crucial to mechanical properties of parts. The results are validated using X-Ray tomography of Ti-64 thin-wall. Our approach identifies various patterns of MP morphology, which corresponds to different types of porosities. The proposed method can potentially be used to certify the part quality in a real-time and non-destructive manner.

1. Introduction

Laser Based Additive Manufacturing (LBAM) provides a unique capability for creating customized/complex shapes that cannot be produced using traditional manufacturing methods [1]. However, mechanical and microstructural properties of additively manufactured parts are still not as reliable as the traditional manufacturing methods. The time-varying the melt pool, the region of molten metal at proximity to the laser/material interface, during the build of LBAM processes is an important indicator for the underlying thermo-physical process, and is significantly correlated to the microstructural and mechanical properties of the fabricated parts, for instance, porosity and compression respectively . Since the melt pool is the initiation of the solidified part, the morphology of the melt pool is of paramount interest in enhancing the geometric integrity, microstructural and mechanical properties of the finished part.

Recent advances in the sensor technology has enabled the real-time, in-process monitoring of the melt pool employed via infrared thermography, generating huge-size, complex-structure thermal imaging data streams. The resulting enormous data sets provide tremendous opportunities for understanding and characterizing the underlying thermo-physical process, and the integrity of the finished parts. Nevertheless, characterizing and modeling the melt pool morphology is indeed very difficult because the melt pool can elongate, shrink, splash, and thus become excessive unstable during the build.

Most of the existing methods for quantifying and characterizing the time-varying melt pool are developed based on physics-based differential equations that govern the underlying thermo-physical process. Examples of this category of methods include the process mapping method developed based on Rothensal's analytical solutions[2], cladding/welding models that are used to approximate the LBAM process[3], etc. However, most of these methods that deterministic models that do not have the capability to leverage the in-process thermal imaging data, and thus cannot account the process uncertainty during the build.

A number of recent studies began to utilize the monitored thermal data streams for the purpose of closed-loop control according to the review papers by [4] . Birnbaum et al concentrated on the issues related to control of melt pool size in LBAM, and they presented process map approach to control the melt pool size in LBAM, and that approach falls down results from large amount of simulations over quite a few number of parameters in plots [5].Also, Qi et al studied physical phenomena related to melt pool, and they proposed a model for motion of melt pool's free surface in uninterrupted cladding, then they benchmarked their findings against practical results according to melt pool's width, length, and the height of solidified cladding track which corresponded to their results[6]. Pinkerton and Li applied energy and mass balance to analyze the geometry of laser melt pool. The proposed method was capable of modelling the melt pool cross-section in horizontal plane[7]. These methods mainly use simple metrics of the melt pool, such as, the peak temperature, total area, length along a certain axis, etc., as the process signature. However, such simple metrics may be not good indicators, since the overall melt pool depth and volume may be significantly different [3].

There is an urgent need for developing a formal methodology that can be used to quantify and characterize the time-varying melt pool morphology by leveraging thermal imaging data streams[8],[4].Continued existence of this need is an imperative problem because the microstructural properties and thus "trustworthiness" of LBAM parts cannot be optimized/detected due to the lack of understanding of the process-property relationship.

In this study, we propose/develop a data-driven modeling scheme to quantify and characterize the morphology of melt pool, and identify the anomalies in melt pool morphology and evaluate the geometric integrity of fabricated parts based on the X-Ray tomography validation. To begin with, we extract melt pool characteristic data based on the thermography image streams. Note that monitored thermal images of thermal monitoring system are complex-structured due to various features such as area, width, length, etc., and huge sized (e.g., 10 GB for the thermal images of a Ti-64 Thin-Wall).

We propose a method to reduce the noise level and extract features based on the thermal imaging dataset. Since contours can illustrate elongation, shrinkage, and splash on melt pool obviously; specifically, we extract the contours of melt pool morphology via selection the boundary of the melt pool based on the melting temperature of fabricated materials. At the melting temperature, solid switches to liquid phase and both are in equilibrium, and melting temperature differs from material to material, thus it is important to consider melting point to extract the boundary of melt pool in each building process. Forasmuch as the thin-wall is built up from Ti-64, the cut-off temperature of melt pools' boundary is 1636 ºC.

Secondly, we quantify and model the melt pool morphology via non-parametric curve fitting, because non-parameterization types of fittings causing well-featured representation of melt pool shape compare to parametric methods like Gaussian curve fitting. Note that previous appearance of melt pool was contour and now instead of many points, melt pool can be characterized with a few features. The results are melt pool models. To enable the implementation of functional data analysis tools, we apply the Cartesian-polar transformation to the resulting melt pool morphology and represent the melt pool morphology in the forms of angle-radius functions. Non-parametric curve fitting by cubic spline models, which are commonly used for image processing, are used to fit and interpolate the melt pool morphology functions. Thirdly, these models allow for comparing different melt pool morphology patterns, and identifying the changes in melt pool morphology. Unlike what is seen in the literature, we will compare the information of each melt pool in every layer with others. To understand the differences of melt pool characteristics and anomaly extraction during the build, we use a SOM clustering method to understand how the melt pool characteristics varies for different layers and during the build to extract the anomalies in part and also melt pools morphology patterns. These changes in patterns and anomalies may indicate the changes in the mechanical and microstructural properties of the fabricate part. Fourthly, we relate the anomalies of melt pool morphology to pores and geometric inaccuracy of parts via experimentation (X-ray).

To proof the concept of the proposed methodology, we focus on the AM of Ti-64 thin-wall parts using blown-powder DLD. We use X-Ray tomography to scan the fabricated part from multiple views and extract the porosities/ anomalies. We found strong correlation between SOM findings and X-Ray validation. At last, this provides an efficient and effective non-destructive evaluation method to inspect the anomalies and pores of additively manufactured parts.

The remaining sections are organized as follows: melt pool characteristics selection based one morphology-extracted features, using Non-Parametric feature selection method and clustering technique for anomaly detection, and validation of clustering techniques by X-Ray Tomography.

2.Melt pool Feature Selection

The morphology of melt pool shape is analogous to figure (1.a), but that demonstration is not as a function. Hence, polar transformation figure (1.b) had been applied to illustrate melt pool as a function. Note that parametric fitting methods are not capable of extracting all features of melt pool and bring about some inaccuracy due to approximation. For instance, Gaussian fitting presents melt pool with 3n parameters, and they only account for peaks and amplitude of peaks in curve, and they do not cover whole information of it. So, non-parametric methods (Figure 1.c) are appropriate solution to capture characteristics of different shapes because they include all of the points and do implement exact method. Regarding the feature extraction of various melt pools, polar coordination of melt pool shapes are variant in number of point, as shown in figure(1.b,2.b). So, an integrated method is needed to represent melt pools in similar way and one-dimension. Cubic spline interpolation is a proposed method, which uses given interpolates to find values of the underlying curve. In this case as presented in figure (1.d and 2.d), interpolate is angle of polar coordination, and radius should be interpolated according to equally divided angles for different curves. Therefore, every curve has specified number of features in one dimension because the set of angles are same for all of them, and also the value of interpolated cubic spline in the given set determines the features.

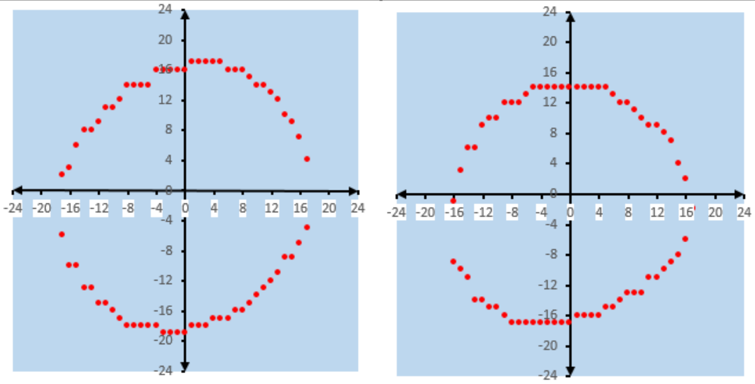

Figure 1.a : Melt Pool Extraction According to Cuttoff Temperature

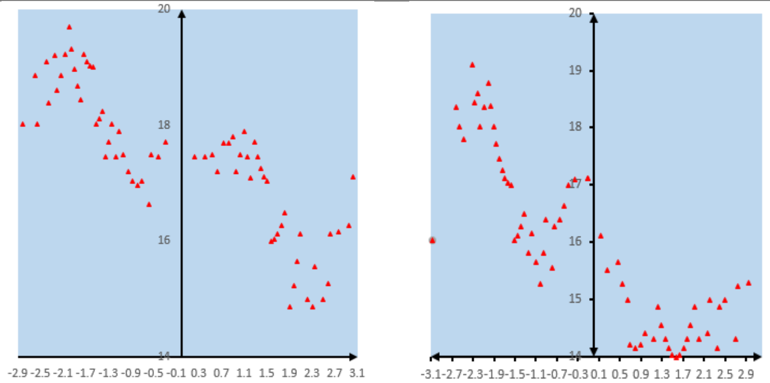

Figure 1.b : Transformation from Cartesian to Polar System

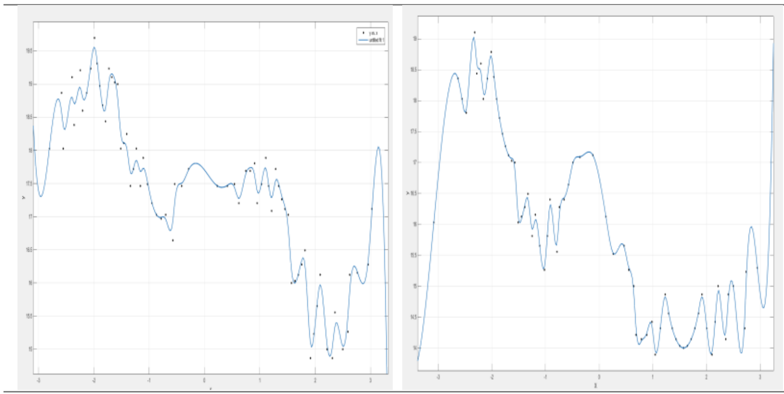

Figure 1.c :Non-Parametric Curve Fitting (Cubic Spline)

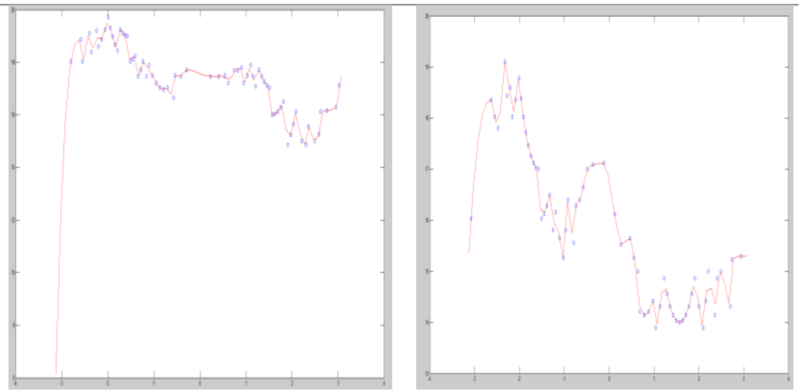

Figure 1.d : Interpolation for Feature Selection (Number of Features for Each MP = 63)

3.Anomaly Detection Method (Self Organizing Map (SOM))

After feature extraction step, SOM clustering technique is carried out to organize the melt pool shapes in apprehensible way. The most important advantage of this technique is mapping data from high-dimensionality space to two-dimensional space. In this case every melt pool has 63 features as discussed later, shown in figure (1.d and 2.d), so SOM uses this amount of features to cluster 1552 number of melt pool shape with different characteristics. According to distintiction among non-parameteric extracted features, and applying of SOM clustering method, which is capable of recognizing hidden-structures in datasets, 2-Dimensional map had illustrated the different melt pools clusters and their similarity, shown in figure 3. Another ability of SOM is indicating the correlation between clusters. Figure 3.b shows that some of clusters are not strongly correlated with others (black and red colors), and it is plausible to be interpreted as anomalies. After looking at the morphology of each cluster and capturing the centriod of them, figure 4, it can result in strong evidence for porosity characterization because obviously there is a difference among anomaly-assumed melt pools cenroids and the major clusters'. A considerable point is that the number of melt pool in clusters that they do not have strong correlation with others are so small in comparison with main clusters, so it is another reason that they can be interpreted as anomalies.

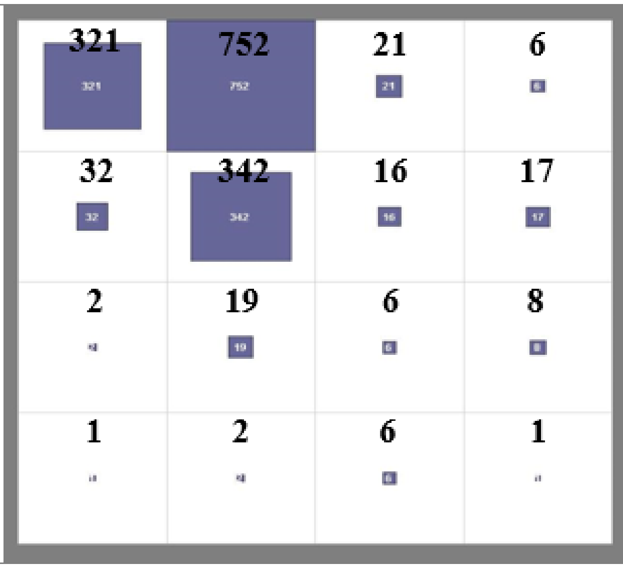

Figure 3.a : Number of Each Melt Pool in Each Cluster

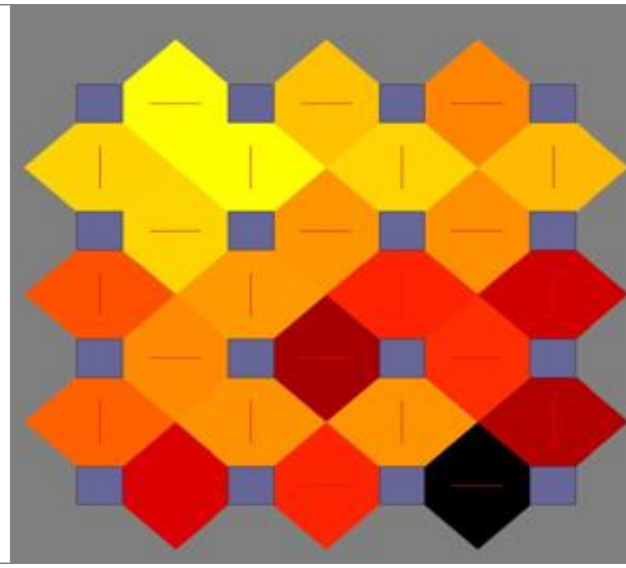

Figure 3.b :Correlation Between Clusters

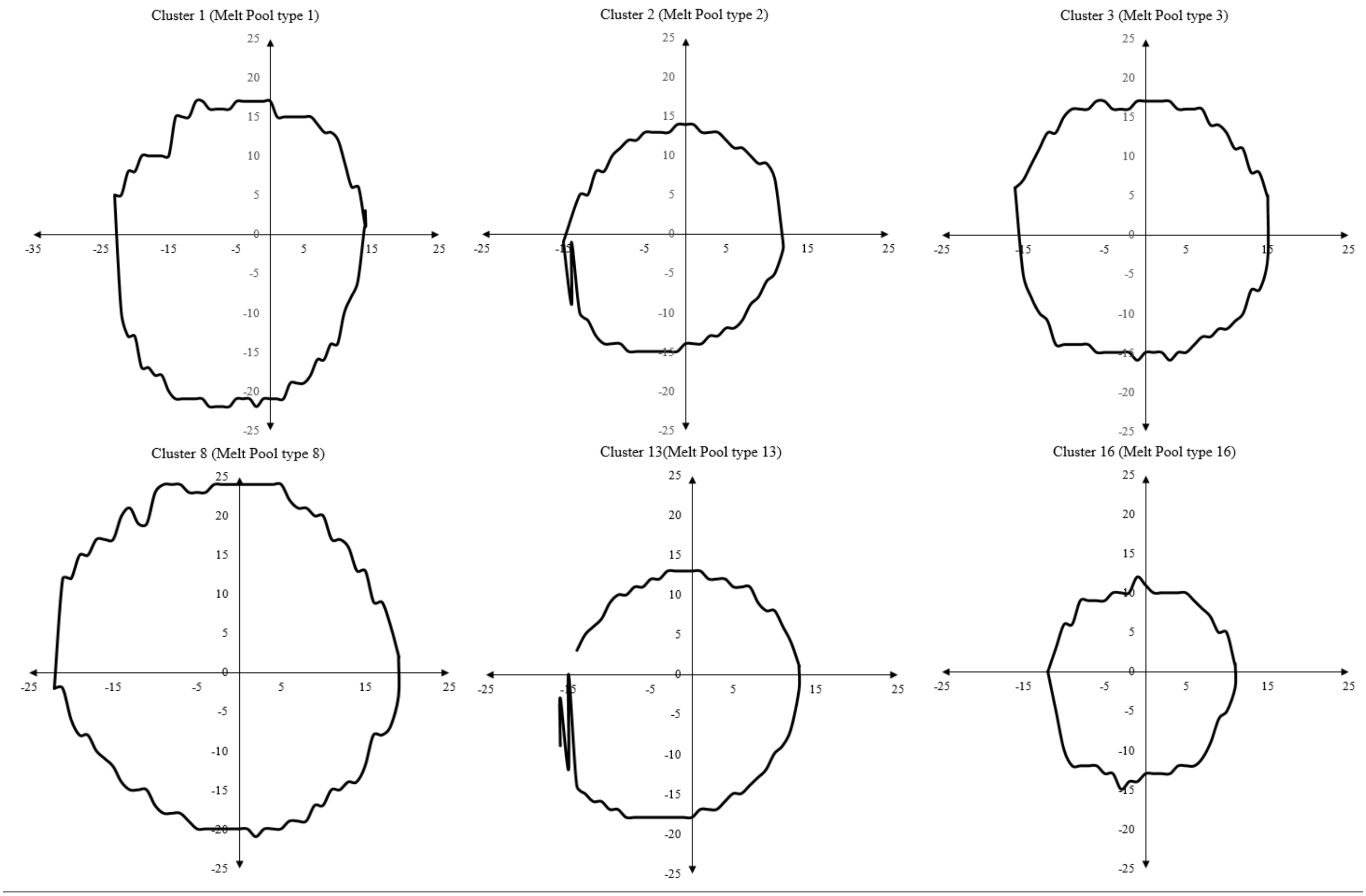

Figure 4: Centroid of Each Cluster [(Prototyping) Each Melt Pool]

Using the coordination of mentioned melt pools in Ti-64 Thin-wall and profiling equippments enable us to link each melt pool to its location on thin-wall, its features,peak tempratures, and so on.

4.Porosity location identification and applying X-Ray tomography validation method

According to corerelation anlysis in clustering section (figure 3.b), few numbers of melt pool shapes are not correlated to others. By taking into consideration of centroid of each cluster, it could be understood that the distinguished melt pools are totally different in size and shape;thus, the guessestimation of this clustering-based defect characterization method is that the distinctive morphologies are prone to be anomalies,shrinkage,splashes, unmelted area and material dissemination. Note that the different types of defects have been determined on baasis of similarity to others, and also they can be classified according to average peak temprature. The location of each anomaly has been extracted by SOM clustering method and illustrated in thin-wall in figure 5, and experimental methods called X-Ray tomography has been performed to evaluate the accuracy of mentioned approach. The captured pores, geometeric inaccuracies, lack of fusions, and also umelted areas based on X-Ray Tomography has been shown in figure 6.

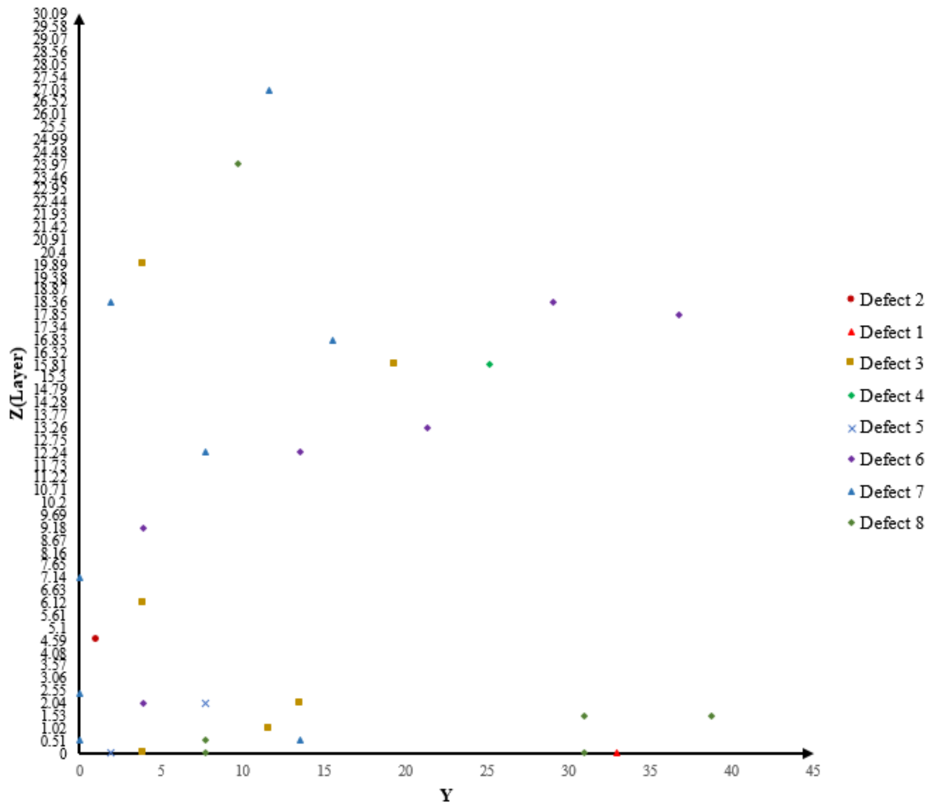

Figure 5: Thin-Wall Ti-64 Porosity Detection with SOM

$$number\ of\ anomalies\ with\ SOM = 32$$

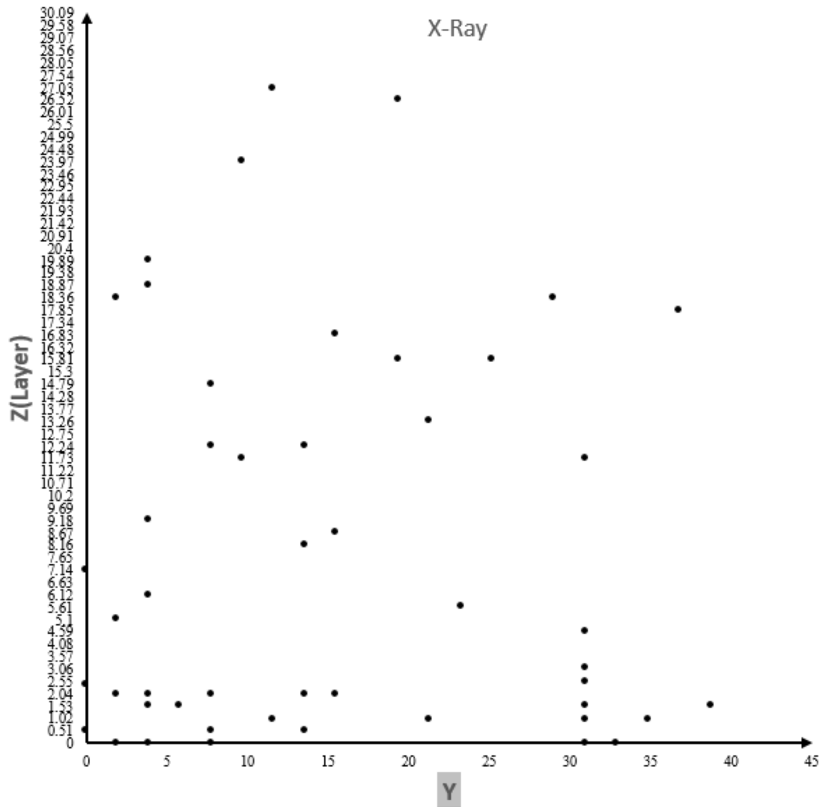

Figure 6: Thin-Wall Ti-64 Porosity Detection with X-Ray Tomography

$$\begin{gathered} number\ of\ pores, geometeric\ inaccuracies, lack\ of\ fusions, and\ also\ umelted\ areas \\ with\ X-Ray\ Tomography\ = 51 \end{gathered}$$

$$number\ of\ pores\ and\ geometric\ inaccuracy\ in\ common\ with\ both\ methods\ = 32$$

$$\begin{aligned} &SOM\ Anomaly\ detection\ method's\ precision \\ &= \frac{number\ of\ anomalies\ with\ SOM}{number\ of\ pores\ and\ geometric\ inaccuracy\ extracted\ with\ X-Ray\ Tomography} \\ &= \frac{32}{51} = 62.75\% \end{aligned}$$

Conclusion

The preliminary data of melt pool was in form of image that was captured via thermal monitoring system, and we proposed a method to characterize the melt pool morphology and extract the features in melt pool shape.Based on captured features the clustering method had been applied to distinguish between different types of melt pools and detect the dissimiliar types to others. Afterwards, X-Ray tomography used to extract the anomalies in the thin-wall. Comparing the cooordination of detected anom anomalies in these two methods indicates about 63% accuracy of clustering method. As a result, our approach identifies various patterns of MP morphology, which corresponds to different types of porosities. The proposed method can potentially be used to certify the part quality in a real-time and non-destructive manner.

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