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LAYER-WISE IN-PROCESS MONITORING-AND-FEEDBACK SYSTEM BASED ON SURFACE CHARACTERISTICS EVALUATED BY MACHINE-LEARNING-GENERATED CRITERIA

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Abstract

In the laser powder bed fusion (PBF-LB) process, a set of parameters that are considered optimal are selected. Still, a set of parameters cannot accommodate complex model geometries, model placement in the build chamber, and unforeseen circumstances, leading to internal defects. Therefore, a new in-situ monitoring and feedback system has been developed to suppress the occurrence of lack-of-fusion (LOF) defects in the PBF-LB process. This system measures surface properties after each laser irradiation to predict whether LOF defects occur. Then, if necessary, a feedback process is performed to re-melt the same surface. Evaluation thresholds are defined by a combination of aerial surface texture parameters created in advance by machine learning of surface properties and defect occurrence. For example, a square pillar of Inconel 718 alloy built with feedback had a higher relative density than one without feedback.

Introduction

The laser powder bed fusion (PBF-LB) process is a manufacturing method that can create parts with complex shapes by irradiating laser beams to melt and solidify metal powder layers. However, in the PBF-LB process, even if a set of parameters (such as laser power, scanning speed, hatching pitch, and layer thickness) that are considered optimal are selected, the parameters may become inappropriate due to complex model geometries, model placement in the build chamber, and unforeseen circumstances. Moreover, spattering is challenging to suppress only by selecting process parameters. As a result, lack-of-fusion (LOF) defects may occur inside the built parts, reducing their strength and reliability.

The Technology Research Association for Future Additive Manufacturing (TRAFAM) was established in 2014 to spearhead a national project in Japan. The initiative was developed in two phases, each contributing significantly to the evolution of additive manufacturing. The first phase, from FY2014 to FY2018, was dedicated to developing next-generation industrial 3D printers. The second phase (FY 2019-FY 2023), which followed, was titled "Fundamental Technology Development Project for Improving Production Efficiency through Additive Manufacturing," two academic institutions were commissioned to conduct research and development. Kindai University played a central role in developing laser beam powder bed fusion (PBF-LB) technology, while Tohoku University and JEOL played a central role in the practical application of electron beam powder bed fusion (PBF-EB) technology. These institutions did not merely supervise the project but played an integral role in its execution.

The main objectives of the second stage were to gain a comprehensive understanding of complex melting and solidification phenomena to enable accurate defect prediction and to devise preventive measures against such defects. An in-process monitoring, and feedback system has been conceptualized and integrated into the PBF process. This strategic integration aims to achieve two outcomes: reproducible and stable production.

Therefore, we developed a new in-situ monitoring and feedback system in this study to suppress LOF defect occurrence in the PBF-LB process. This system measures surface properties after each laser irradiation to predict whether LOF defects occur. Then, if necessary, a feedback process is performed to re-melt the same surface. Evaluation thresholds are defined by a combination of aerial surface texture parameters created in advance by machine learning of surface properties and defect occurrence. For example, a square pillar of Inconel 718 alloy built with feedback had a higher relative density than one without feedback.

Online control of Additive Manufacturing (AM) processes is considered the inevitable function for the next generation of powder bed fusion machine[1]. To achieve the online control, the in-situ monitoring and feedback are required. The in-situ monitoring techniques and associated parameters for PBF-LB are outlined in the following Table 1. Data acquisition occurs at different timings, utilizing various monitoring approaches for comprehensive process understanding and control.

Scan-wise data acquisition means acquiring data with the progress of laser scanning. During scan-wise data acquisition with a sampling rate ranging from 100s to 20,000s Hz, a Co-Axial configuration is employed, integrating a thermoviewer and capturing visible images. Co-Axial configuration of the measuring apparatus inserts the dichroic mirror in the working laser axis, and the reflecting light from the laser spot is observed. This approach yields valuable information on factors such as melt pool (MP) stability, dimensions, input power, and spattering[2]–[4]. These parameters contribute to controlling the laser's operational parameters and enable data collection for Statistical Quality Control (SQC) and Quality Assurance (QA) purposes. However, feedback of laser power and scanning speed are practically impossible. The feedback loop process takes a certain amount of time: 10—500 ms. The scanning speed of PBF-LB is several hundred millimeters per second. Ordinarily, the scanning pattern is a checkerboard with a block size of around 10 mm and a strip with a width of around 10 mm. A scanning line length in their scanning pattern is 10 mm, which takes 10 ms when the scanning speed is 1000 mm/s. It is shorter than the feedback loop processing time.

Moving to the layer-wise level, data acquisition at 10s Hz to 100s Hz occurs out-of-axis, using a thermoviewer and capturing visible images. This monitoring strategy provides insights into temperature distribution and spattering phenomena[5]. Additionally, data collected during this stage pertains to the surface texture of the powder bed, surface texture parameters, luster of the surface, and temperature distribution. The laser parameters and recoating process are controlled using this information, contributing to surface quality and

Table 1 Styles of feedback and its parameters. Bold italic is measures hired in this system.

Timing of data acquisition	Monitoring	Parameters (Exploited info/data)	Controlling (Feedback)
Scan-wise *Sampling rate:* *100s — 20,000s Hz*	Co-Axial: • Thermoviewer • Visible image	• MP stability, dimensions • Input power • Spattering	• Laser params • Data for SQC → Layer-wise • Data for QA → not Feedback
Sampling rate: *10s Hz — 100s Hz*	Out-of-axis • Thermoviewer • Visible image	• Temp. distribution • Spattering	
Layer-wise *Each layer* *or every n-th layer*	Powder bed: • Surface texture • Visible surface image • Thermoviewer	• Surface texture params • Luster of surface • Temp. distribution	• Laser params • Recoating
	Built surface: • Surface texture • Visible surface image • Thermoviewer	• Surface texture params • Temp. distribution	• Laser params • Mending built surface (remelting, machining)

MP: Melt pool, Temp.: Temperature, Params: Parameters uniformity. Lastly, during the mending process for the built surface, which includes re-melting and machining, the focus remains on the built surface's quality. The monitoring encompasses surface texture parameters, temperature distribution, and laser parameters, all of which are vital for ensuring the integrity of the final product. Our system employed the layer-wise monitoring of the built surface and powder bed to obtain surface morphology parameters and feedback by re-melting the built surface according to a specific criterion of surface morphology parameters.

System configuration

The layer-wise in-process monitoring-and-feedback system was constructed from a laser beam powder bed fusion machine, a pattern projection profilometry equipment, and their controller (Fig. 1). The system was based on the in-situ monitoring system for the co-axial melt pool observation[3]. However, this research did not use its melt pool in-situ monitoring system.

A pattern projection profilometry equipment can measure the surface morphology. Its resolution was 69 μm/pixel in the horizontal x- and y-axis directions and 15 μm or less in the z-axis direction. A pattern with stripes of 16 pixels width and 16 pixels spacing was projected during the measuring process. One pixel was equivalent to 69 μm on the building surface. The pattern was then moved horizontally by 1 pixel, and 16 images were taken and the measurement time totaled 2.9 seconds, comprising 1.9 seconds for pattern projection and image capturing, 0.3 seconds for point cloud data calculation, and 0.7 seconds for surface morphology parameter computation.

The activity sequence of the system is shown in Fig. 2. The surface morphology was measured after the powder bed forming and the laser scanning. After measuring the scanned built surface, the defect generation in the following layers was predicted. If n defects were not predicted to be generated, the process proceeds to the next layer. On the contrary, if defect generation was predicted, the laser scanning was repeated; this re-melting is the feedback process.

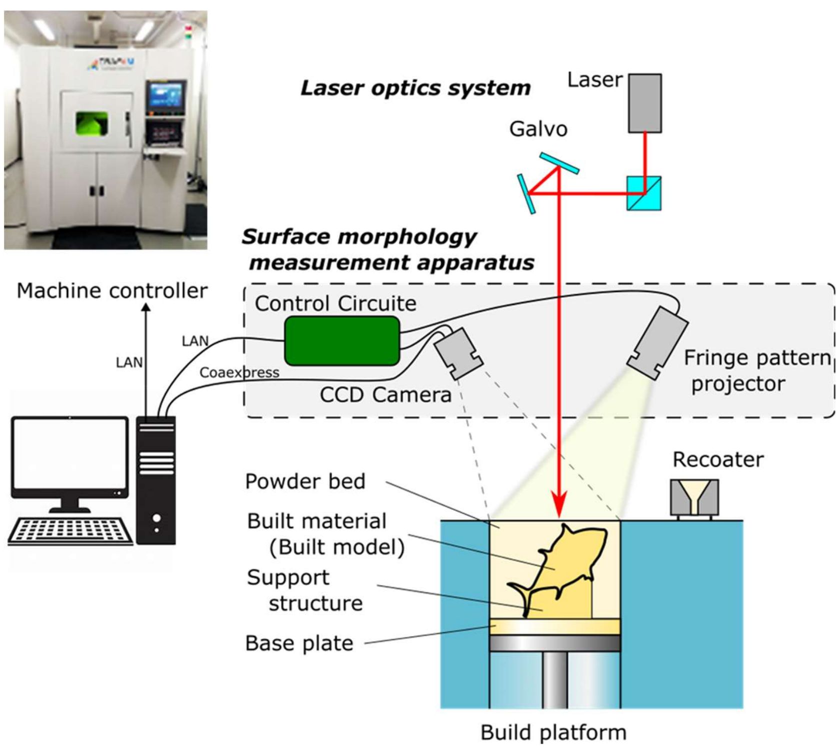

Fig. 1 Schematics of the in-situ monitoring and feedback system.

The criteria for initiating a re-melting process were determined by selecting specific surface morphology parameters denoted as S_i [6]. These parameters, including Sku, Sal, Sda, Sha, and Sdr, exhibited a higher correlation with relative density values than the 39 surface morphology parameters outlined in the ISO standard (Fig. 3). In the preliminary experiments, cuboids were built with various process parameters. Their surface morphology on their top surface was measured using the coherent scanning interferometry (CSI) technique (NewView9000, Zygo). The relative density of the cuboids was measured using the Archimedes method. On the S_i vs relative density plot, the correlation was determined. A series of preliminary experiments established the permissible range for each surface morphology parameter. When a value of S_i fell within the range $S_i^{Lower} < S_i < S_i^{Upper}$, the relative density value exceeded 99.9%. When all surface morphology parameter values fell within the fully dense range, it indicated a reduced likelihood of defects in subsequent layers. In other words, the condition $\bigcap_i \{S_i^{Lower} < S_i < S_i^{Upper}\}$ held true.

As an option, the Support Vector Machine (SVM) was also provided as a classification algorithm to assess the defect generation in the following layers. The teaching dataset comprised surface morphology parameters denoted by Si and process parameters, including the laser power, the scanning velocity, the hatching

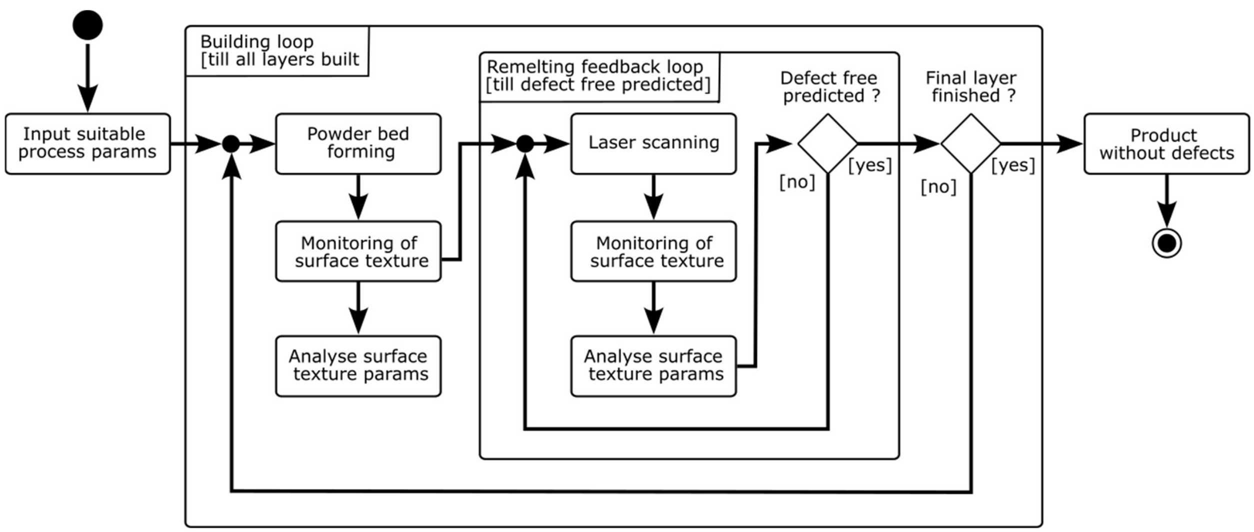

Fig. 2 Activity diagram of the in-situ monitoring and feedback system.

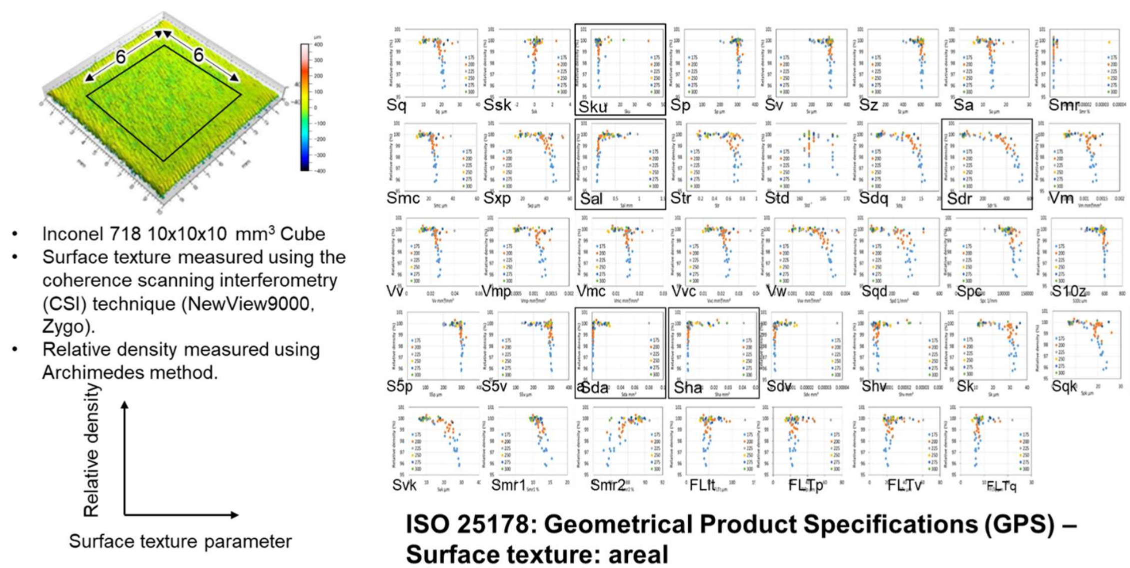

Fig. 3 An example of surface morphology and the relationship between the surface morphology parameters and the relative density.

pitch, and the layer thickness. For each entry in the teaching dataset, the outcome was classified as either "OK" or "NG" based on the value of relative density; when the relative density value exceeded 99.9%, it was "OK," otherwise, "NG." However, as a result, the predictions made by SVM have not achieved a sufficiently high accuracy. It was considered that the number of teaching data sets was not enough.

Building with re-melting for a square pillar of Inconel 718

A square pillar of Inconel 718 was fabricated, and the effect of re-melting on the surface morphology parameters was checked. Fig. 4 shows the appearance of a square pillar of Inconel 718, the change of Sku value for each layer, and examples of surface roughness images. The change of Sku value is with the layer number and before and after the re-melting. During the examination of the initial laser-scanned surface of each layer, it was observed that the Sku values occasionally exceeded the threshold of 5. However, following the application of the re-melting process to the initial laser-scanned surface, a reduction in Sku values below 5 was consistently achieved, indicating a substantial improvement in surface quality. Layers in the lower and middle sections consistently exhibited comparatively higher Sku values on their initial laser-scanned surfaces. In specific instances, Sku values for these layers surpassed the threshold of 10. This observation underscores the tangible improvement in surface morphology achieved through re-melting, contributing to the enhanced quality and uniformity of the manufactured components. These findings affirm the positive and beneficial impact of the re-melting process on overall manufacturing quality and consistency.

Conclusion

A system with layer-wise surface monitoring and feedback to re-melting the built surface is constructed, and a projection mapping unit is installed inside the PBF-LB machine. Surface characteristics analyzing

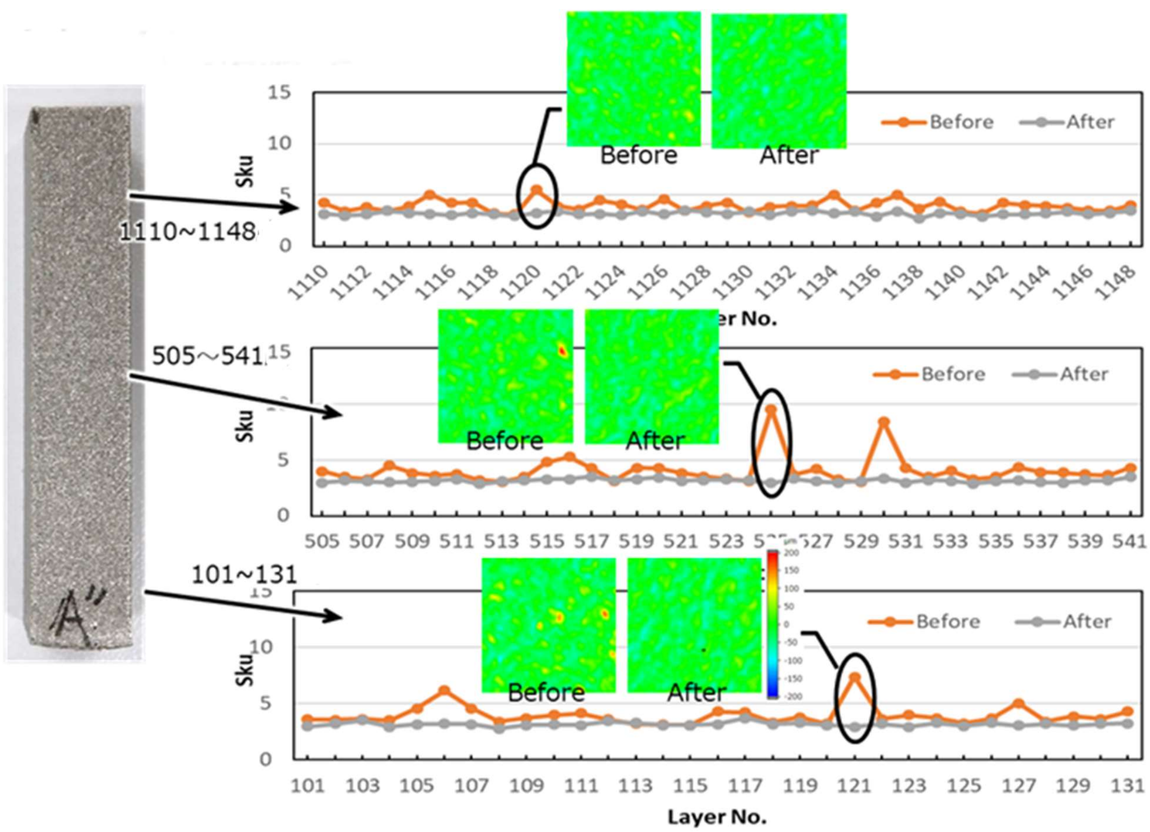

Fig. 4 Effect of re-melting for Inconel 718 pillar. For lower middle, and upper part of pillar, change in Sku value is plotted with the layer number. Surface morphology images before and after the re-melting process are depicted as examples.

software is installed in a controller of the PBF-LB machine, and re-melting is triggered when surface roughness and internal defects are predicted based on surface characteristic values. The re-melted surface exhibits a smoother texture and is expected to ensure a fully dense building.

Acknowledgment

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