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REAL-TIME VISUALIZATION METHOD FOR DETECTING POROSITY IN METAL ADDICTIVE MANUFACTURING

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Abstract. *AM is a futuristic technology that can fundamentally change the basis of production technology from centralized mass production to distributed mass customization. However, as per the innovation technology adoption lifecycle, AM technology requires a process that can recognize major problems that cause a chasm in its diffusion, share them, and present practical solutions. Improving real-time tracking and visibility of AM processes is vital its optimization since it greatly impacts traditional manufacturing methods. In particular, pore errors in metal AM equipment are a major drawback that deteriorates product quality and causes monetary and time loss. AM urgently requires a methodology to track and visualize real-time pore error. In this study, we defined data and visualization methods for detecting pore errors among big data collected from metal AM equipment. Also we describe the application prototype of the proposed visualization method.*

Keywords: Big data, Addictive manufacturing, Modeling and simulation, Visualization

1. **Introduction.** Engineering constantly provides new and efficient methods of manufacturing products and services that meet the diverse needs of society. Production technology has evolved into a form of continuous innovation. It presents a new paradigm for creative destruction through disruptive innovation. Additive manufacturing (AM), better known as three-dimensional (3D) printing technology, is a production technology that manufactures products with 3D structures. It is used for producing consumer products of different sizes in various fields, including micro-products with sizes of several mm or less, foods products of unique designs, and buildings with complex shapes. Traditional manufacturing processes have changed considerably due to AM technology.

Research activities are being carried out on AM technology so that it can enter the commercial production market in multiple areas, ranging from micro parts and complex shape, to final systems (i.e., CAD to SYSTEM) [1-6], as seen in Figure 1. Efforts are being made to expand the industrial ecosystem through various business models.

In [7], Alberts et al. considered the paradigm shift in manufacturing through changes in the manufacturing methods of the automobile industry over time, as presented in Figure 2. He proposed that the paradigm of manufacturing technology is driven by the

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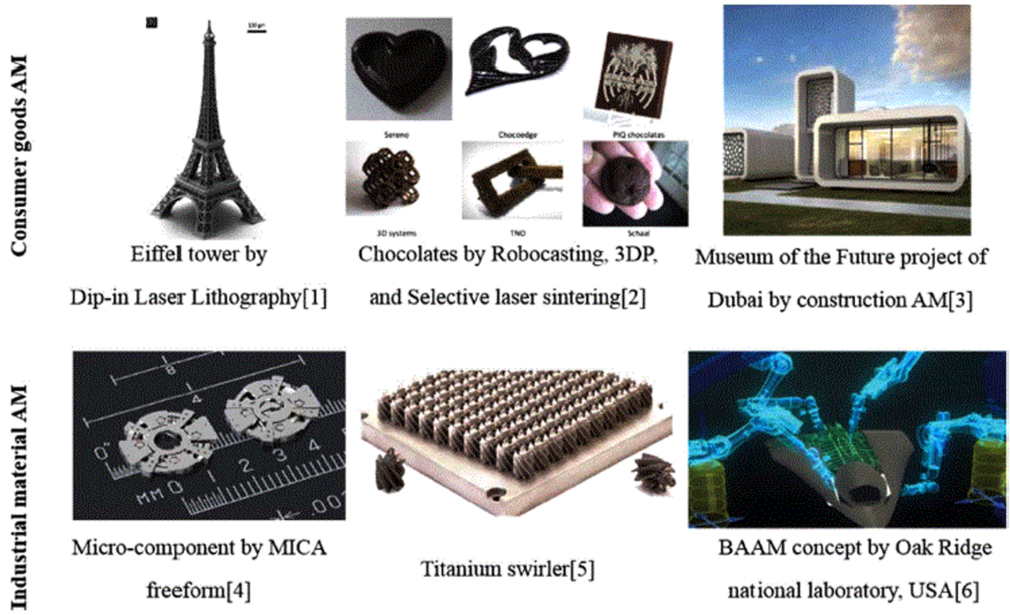

FIGURE 1. Applications of AM technology

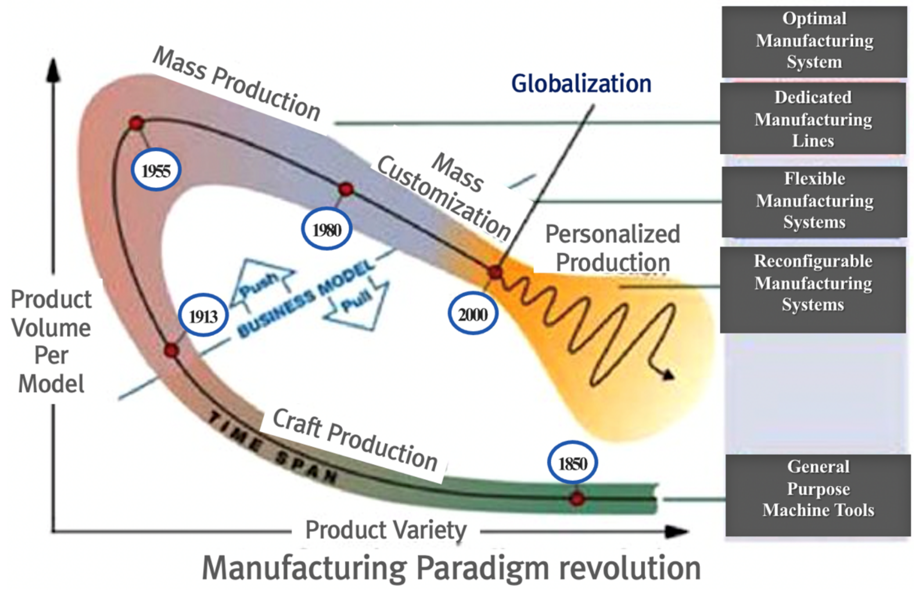

FIGURE 2. The transition of manufacturing paradigm

development manufacturing, which goes through the stages of craft production → mass production → mass customization → personalized production according to the social needs and changes in market characteristics. The production approach adopted by Ford increased the productivity and economic feasibility of mass-produced products. The combination of computer-based automation and manufacturing technologies brought a shift in production from conventional standardized mass production to partially or completely customized product production through platform-based flexible production technologies. As the market paradigm shifts from supplier-centered to consumer-centered, suppliers need new production technologies to overcome uncertainties in design, performance, price, product quantity, and after-service (AS). These drawbacks require a combination of information and communication technology, along with new manufacturing methods. AM is a futuristic technology that can fundamentally change the basis of production technology from centralized mass production to distributed mass customization. Currently, advancements in AM technology have been delayed due to insufficient technological completeness.

However, as per the innovation technology adoption lifecycle, AM technology requires a process that can recognize major problems that cause a chasm in its diffusion, share them, and present practical solutions. Shortening the industrialization cycle effectively relies on "how quickly the industrial ecosystem can be eventually solidified". In truth, the analysis results of the holders of AM patented technology indicate that the current AM technology is primarily dominated by equipment developers, main suppliers, and end consumers of industrial product supply chains. Furthermore, there is a lack of participation from producers of materials and parts that make up the majority. Therefore, if various participants take part in the AM industrial ecosystem, and participants in different areas cooperatively involve themselves in problem-solving activities, the problems posed in the current AM technology due to the so-called network effects can be solved effectively and rapidly.

Big data is typically described as collecting huge and complex volumes of datasets for effective usage. It consists of large amounts of structured data, semi-structured data and unstructured data. In recent years, a necessity has emerged for utilizing big data in AM [8,9].

Processes can be optimized through real-time tracking and visualization of AM data since it greatly impacts traditional manufacturing methods. In particular, pore errors in metal AM equipment are a major drawback that deteriorates product quality and causes monetary and time loss. AM urgently requires a methodology to track and visualize real-time pore error. In this study, we defined data and visualization methods for detecting pore errors among big data collected from metal AM equipment.

This paper is organized as follows. Section 2 introduces related works on monitoring and visualization method in metal AM. Section 3 describes the proposed method. Finally, Section 4 concludes this paper with expected effects and future research plan.

2. **Related Work.** As summarized in Table 1, the approaches for monitoring the melt pool mainly examine the appropriateness of the result value through quantification of the data measured during the formation of the melt pool, and record it by location to predict whether there is a defect in the stack. If this method is used, it may be useful to distinguish the parts that are expected to be defective among the stacked parts using the monitoring result data, but there is a limit in identifying the specific type and cause of the defect and controlling the defect in real time.

It is necessary to secure various basic data and study related to implementation in order to control in real time the defect predicted area identified through application pool monitoring data analysis. Here, the basic data means corresponding melt pool defect data for each melt pool monitoring image data, and lamination process data for removing melt pool defects from the same layer or the next side. For this, a real-time digital twin model-based monitoring technology is required. A real-time digital representation of the physical domain in addictive manufacturing is needed, to accurately monitor, predict, and control the process. The state of the physical world keeps changing as it continuously interacts with the environment and is influenced by humans [15,16].

3. **Proposed Approach.** The proposed method focuses on the real-time digital representation diverse datasets generated from the Internet of Things (IoT) during the manufacturing process. During this process, real-time tracking, analysis, and visualization are provided in the entire manufacturing process, and decision-making and knowledge discovery are supported. Figure 3 displays the real-time visualization method of pore error detection. The salient features of the proposed system are as follows.

- The environment for data accumulation of the AM process (e.g., batch type and streaming) is constructed using open-source software; it also collects AM data.

TABLE 1. Related works

Reference	Sensor	Monitoring method
Kolb et al. [3]	CMOS	Pore detection and deformation according to conditions
Gögelein et al. [4]	CMOS camera	Wall thickness value compared to actual model
Grasso et al. [5]	high speed vision	defect detection and conformance to specifications
Kelly et al. [6]	photodiode, camera	Defect analysis for shape, powder flatness, etc.
Alberts et al. [7]	photodiode	Compare the signal and noise ratios
Colosimo and Grasso [8]	photodiode, camera	Monitoring of molten pools
Clijsters et al. [9]	photodiode	Distinguish between contour scan and fill scan
Furumoto et al. [10]	pyrometer, high speed camera	Temperature measured during powder solidification by a 2-color pyrometer with optical fiber.
Islam et al. [11]	pyrometer, camera	Differences in measured values
Craeghs et al. [12]	pyrometer	Thermal deformation detection, overheat detection
Krauss et al. [13]	Infrared camera	Signal difference according to process conditions
Lott et al. [14]	high speed camera	Spot diagram value using FFT and MTF
Jani et al. [15]	pyrometer	Powder layer thickness, pyrometer signal analysis

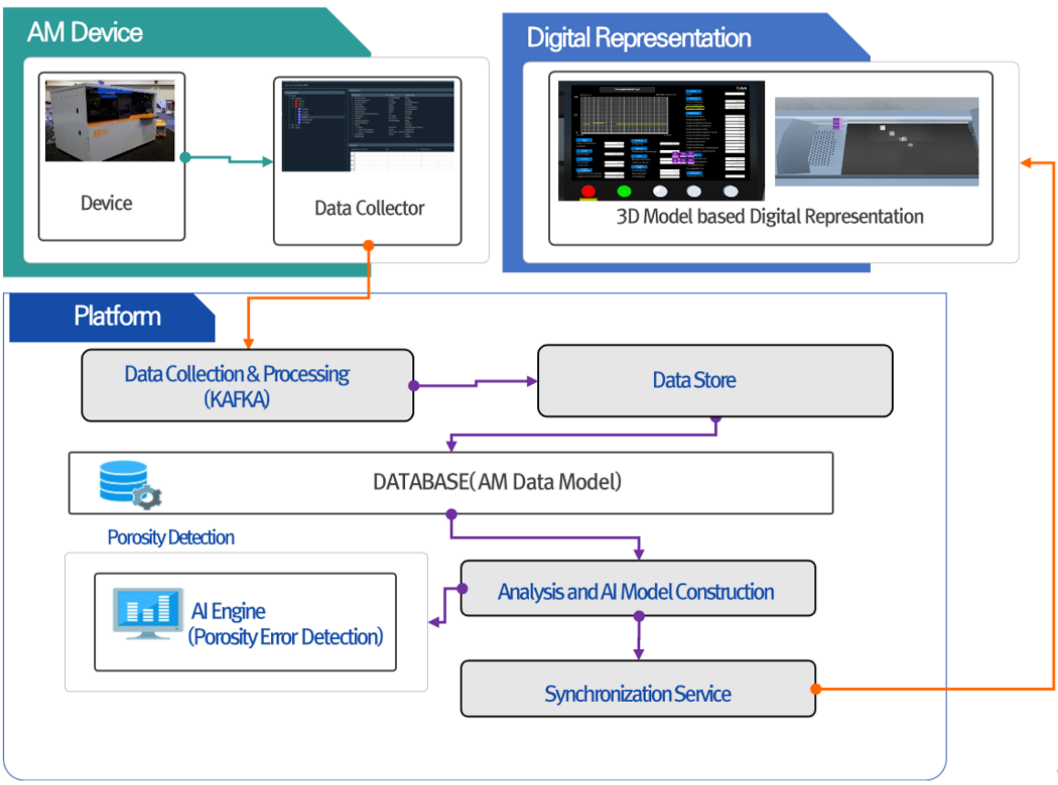

FIGURE 3. Real-time visualization process of pore error detection

- The conceptual design centered on process, data, and architecture is performed to establish an integrated system for quality control, maintenance, and efficient process support of AM.
- The developed system is constructed by applying components of the Hadoop ecosystem. Its structure can be applied universally rather than specifically according to the material and output method.
- The developed system consists of data collection, management, data applications, and infrastructure areas. Data are collected from a variety of data providers, and batch and real-time streaming data are processed on the platform.
- The developed system is developed into a structure that utilizes a database structure and a file system for storing and processing sensors and images collected from AM equipment.
- The developed system provides the ability to review real-time data via real-time digital representation of the physical domain in addictive.

3.1. **Sensor data and metadata, such as input commands, to detect pore errors.** Each part consists of a related folder labeled "X_yyy_gcode", where X represents the part number and yyy represents the description of the scan strategy. This folder contains *.gcode files (space-separated text), geometric code (G-code) generator parameter files, and G-code interpreter parameter files, all of which are tab-separated text files.

AM G-code files are provided and stored for future reference by the author. They are used for generating raw command files for XYPT (which stands for X, Y, power, and trigger) command files that contain all the details of the build scan strategy, including the event timing of the melt pool monitoring camera.

The XYPT command files are stored in the "XYPT Commands" subfolder of the "Build Command Data.zip" folder. The files are formatted with comma-separated values (.CSV) American standard code for information interchange (ASCII) text in four columns, where each file named "*layerXXXX.csv" provides a command for layer number XXXX.

The XYPT file provides basic laser positioning and control commands for AMMT. They are based on the XY2-100 command protocol for the laser system, where the X (mm) and Y (mm) columns provide the position commands for the laser. The power (W) column provides a laser power command.

A trigger column (unitless) is a decimal binary representation used for executing output trigger channels (eight labeled channels from 0 to 7). For example, to trigger channel 1 (second channel), the binary representation is 0010 and the decimal representation is "2"; therefore, the "trigger" column of the XYPT file displays "2". To trigger both channels 0 and 2 (first and third channels), the binary representation is 0101, the decimal representation is 5, and the trigger column displays "5". For this data set, only channel 1 is connected to the melt pool monitoring camera. Therefore, the "2" in the trigger column indicates the frame capture time. Several additional files related to system settings and materials are provided in the "Metadata.zip" folder.

3.2. **Process monitoring data.** Data is collected from two devices: a coaxial MPM camera and a layer camera. The coaxial MPM camera is optically aligned with the laser axis; as a result, the melt pool appears to be fixed in view regardless of the XY position. The layer camera is located in a fixed position on the build plane.

The coordinates defined to describe the orientation and position of the fixed devices, such as the coaxial MPM camera or layer camera. The spot position is defined as a $< Ax_{\text{laser}}, Ay_{\text{laser}} >$ vector. The default coordinate system $\{A\}$ and the transformation coordinate system $\{L\}$ are connected to a laser spot where the x-, y-, and z-axis aligned with the axes of $\{A\}$.

3.3. **Real-time digital representation.** This research performs the monitoring from using GE concept laser 3D printer to collect the data, to visualizing the result. Figure 4 displays the integrated data visualized in real time in a suitable form. First, data synchronization is performed to reflect the real-time nature of the equipment. Thereafter, they are graphically matched to the location, including each information. Finally, the corresponding data are visualized in the form shown in Figure 4, and the size and location of the melt pool are visualized in real time to display the state and speed of the output layer according to the laser position, which allows the user to judge pore errors in AM. In addition, exceptional situations where pore errors may occur are expressed by graphing the state changes of the melt pool according to the laser energy at the graphical inset of Figure 4. The process and salient features of the design of the dashboard-style monitoring interface for interworking real-time sensor data of AM and real-time monitoring of the corresponding data is as follows: Design the dashboard environment to read files of stored data, link them up, and recall them in a web-based dashboard environment. The real-time digital representation of the physical domain in addictive manufacturing is needed, to accurately monitor, predict, and control the process.

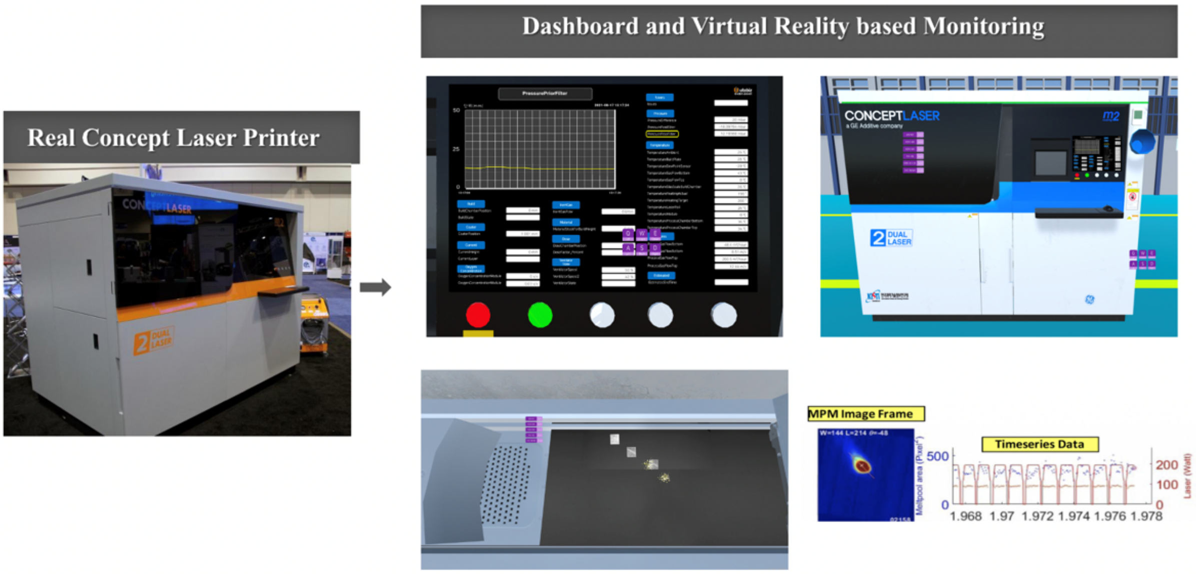

FIGURE 4. Real-time visualization for detecting porosity in metal addictive manufacturing

4. **Conclusions.** In this study, we defined data and visualization methods for detecting pore errors among big data collected from metal AM equipment. The paper focuses on the real-time digital representation diverse datasets generated from the Internet of Things (IoT) during the manufacturing process. Also we describe the application prototype of the proposed visualization method.

For future work, we are improving the platform to make it capable of analyzing a variety of AM data, and to be able to use an HPC cloud platform to share workflow among users.

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REFERENCES

[1] F. Cunha, T. Santos and J. Xavier, In situ monitoring of wire and arc additive manufacturing by digital image correlation: A case study, *Procedia Structural Integrity*, vol.37, pp.33-40, 2022.

[2] M. Piniard, B. Sorrente, G. Hug and P. Picart, Melt pool monitoring in laser beam melting with two-wavelength holographic imaging, *Light: Advanced Manufacturing*, vol.11, 2022.

[3] T. Kolb, P. Gebhardt, O. Schmidt, J. Tremel and M. Schmidt, Melt pool monitoring for laser beam melting of metals: Assistance for material qualification for the stainless steel 1.4057, *Procedia CIRP*, vol.74, pp.116-121, 2018.

[4] A. Gögelein, A. Ladewig, G. Zenzinger and J. Bamberg, Process monitoring of additive manufacturing by using optical tomography, *AIP Conf. Proc.*, vol.1650, no.1, pp.164-170, 2015.

[5] M. Grasso, G. Repossini and B. M. Colosimo, On the use of spatter signature for in-situ monitoring of laser powder bed fusion, *Spec. Interest Gr: Meet. Addit. Manuf.*, vol.1, 2017.

[6] Y.-P. Yang, S. M. Kelly, P. C. Boulware, L. Cronley, G. Firestone, M. Jamshidinia, J. Marchal, T. Stempky and C. Reichert, In-process sensing of laser powder bed fusion additive manufacturing, *Work. Predict. Theor. Comput. Approaches. Manuf.*, vol.40, 2016.

[7] D. Alberts, D. Schwarze and G. Witt, High speed melt pool & laser power monitoring for selective laser melting, *Proc. of Lane*, 2016.

[8] B. M. Colosimo and M. Grasso, Monitoring of metal additive manufacturing processes via in-situ machine sensorization, *The 14th IMEKO TC10 Work Tech Diagnostics 2016 New Perspect Meas. Tools Tech. Syst. Reliab. Maintainab Saf.*, vol.248, 2016.

[9] S. Clijsters, T. Craeghs, S. Buls, K. Kempen and J.-P. Kruth, In situ quality control of the selective laser melting process using a high-speed, real-time melt pool monitoring system, *Int. J. Adv. Manuf. Technol.*, vol.75, pp.1089-1101, 2014.

[10] T. Furumoto, T. Ueda, M. R. Alkahari and A. Hosokawa, Investigation of laser consolidation process for metal powder by two-color pyrometer and high-speed video camera, *CIRP Ann. – Manuf. Technol.*, vol.62, no.1, pp.223-226, 2013.

[11] M. Islam, T. Purtonen, H. Piili, A. Salminen and O. Nyrhilä, Temperature profile and imaging analysis of laser additive manufacturing of stainless steel, *Phys. Procedia*, vol.41, pp.835-842, 2013.

[12] T. Craeghs, S. Clijsters, J.-P. Kruth, F. Bechmann and M.-C. Ebert, Detection of process failures in layerwise laser melting with optical process monitoring, *Phys. Procedia*, vol.39, pp.753-759, 2012.

[13] H. Krauss, C. Eschey and M. F. Zaeh, Thermography for monitoring the selective laser melting process, *The 23rd Int. Solid Free Fabr. Symp.*, Austin, TX, vol.57, 2012.

[14] P. Lott, H. Schleifenbaum, W. Meiners, K. Wissenbach, C. Hinke and J. Bültmann, Design of an optical system for the in situ process monitoring of selective laser melting (SLM), *Phys. Procedia*, vol.12, pp.683-690, 2011.

[15] M. Jani, S. Chava and S. Mamilae, In-situ monitoring of additive manufacturing using digital image correlation, *AIAA SCITECH 2022 Forum*, San Diego, CA & Virtual, DOI: 10.2514/6.2022-0076, 2022.

[16] D. Seo, D. Jung, M. Kim and S. C. Jeong A workflow-based engineering data analytics platform, *ICIC Express Letters, Part B: Applications*, vol.13, no.8, pp.837-845, 2022.