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Research Status of Monitoring and Application of Machine Learning in Powder Metal Additive Manufacturing

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Abstract

Freedom of design, mass customisation, waste minimisation and the ability to manufacture complex structures are the main benefits of additive manufacturing. In the increasingly severe global economic environment, powder directed energy depostion, known as powder DED, as one of the most applied methods in metal additive manufacturing, relies on these unique efficiency advantages to attract more and more attention from the manufacturing industry. Meanwhile, the lack of reliable and uniform qualities is a key problem in DED applications. With the development of sensing devices and control systems, as well as the development and application of machine learning, in-situ monitoring technology is an effective method to enhance the reliability and repeatability of DED, while machine learning method could accomplish different tasks to help optimize the manufacturing process. In this article, we review current in-situ monitoring technologies for powder metal DED, and latest applications of machine learning in powder metal manufacturing field. Finally, several future research directions are suggested.

Keywords

Additive Manufacturing; Directed Energy Deposition; Powder; Machine Learning.

1. Introduction

Additive Manufacturing (AM) is a form of technology which uses three-dementional computer model data to connect materials jointly through repeatedly layer-by-layer deposition process to generate target parts in certain forms or functions [1]. By using this technology, workpieces with complex geometric shapes can not only be manufactured, but also various mechanical surfaces can be flexibly repaired [2, 3]. In 2019 industry analysis report Wohlers Report pointed out that the profit created in the field of additive manufacturing would be expected to reach 15.8 billion U.S. dollars [4]. As one of the most important technical branches of additive manufacturing, metal additive manufacturing technology has been widely used in various fields, such as aerospace, transportation, medical implants, and metal reprocessing. The income created by the metal additive manufacturing field has maintained a growth rate of more than 40% every year for 5 consecutive years, and will continue to receive increasing attention from society for a long time.

In metal additive manufacturing field, directed energy deposition (DED) and power bed fusion (PBF) are two manufacturing processes mainly used for metal additive manufacturing [5]. The PBF system is composed of a closed energy beam, a powder bed, a mobile base, a powder conveying system and a roller (Fig. 1a). During manufacturing the powder is selectively melted by laser and electron beams according to the target layer section. As soon as one layer is processed, the mobile base will be moved down for next layer manufacturing process. The DED system is composed of a laser, a material delivery nozzle, a fixed substrate, a hopper, and an adjustable deposition head (Fig. 1b, Fig. 2). The powdered metal material will be transported into the feeding tube by stepping motor after being placed in the hopper, and mixed with the protective gas from the nozzle port. Then the powdered

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metal material mixed with protective inert gas will be blown out and melted on the processing surface after being irradiated by the laser. After the process of the target section of a layer is completed, the nozzle moves with the deposition head to proceed to the next layer [6].

Compared with PBF, the material deposition and energy transmission of DED are more concentrated in the processing area, where the material transportation can be better controlled. The workbench is kept fixed and has a larger working range and degree of freedom. Moreover, it can be used in combination with subtractive manufacturing technology, for example, surface finishing technology and milling technology, to produce higher quality metal parts combined with the advantages of its rapid heating and cooling [7]. According to the filling type of raw material, the DED process can be divided into wire filling process and powder filling process [8]. Compared with the former one, powder filling process has less flexibility limitation, smaller projection area in the molten pool, and requires less laser energy for melting and deposition when dealing with the same manufacturing scenario [9]. Therefore, the DED process with metal powder as raw material is widely used in the field of metal additive manufacturing.

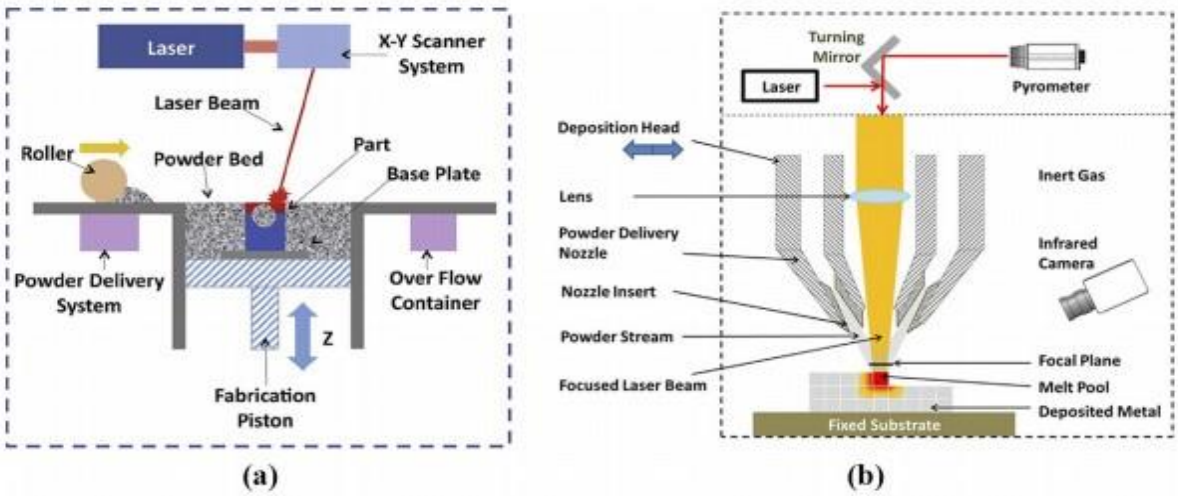

Figure 1. (a) Schematic diagram of powder bed fusion (PBF) and (b) schematic diagram of directed energy deposition (DED)

In powder DED, the coaxial powder feeding mechanism plays a vital role. It is responsible for transporting the metal material from the hopper to the coaxial nozzle through the conveying pipe, so that the metal powder and the protective gas manage to be mixed and sprayed onto the processing surface. Blockage of the feeding pipe, uneven powder delivery and nozzle sticking are the three common failures of the coaxial powder feeding mechanism. Blockage of the feeding pipe could be caused by excessive powder particle size, impurities in the metal powder, dampness of the powder and other factors. Uneven powder delivery could be caused by uneven changes in powder concentration and unregular changes in the flow rate of the protective air flow. Nozzle sticking could be caused by newly ejected powder which is melt by extreme high temperature at the nozzle. These three types of failures can cause defects such as internal voids, cracks, excessive deformation and unexpected and oversized surface roughness in the final processed parts, which will affect the practical application of parts and limit the expansion of DED technology in the field of additive manufacturing. Therefore, it is necessary to monitor the coaxial powder feeding mechanism in real time.

2. Research status of in-situ monitoring methods for powder DED

The main additive manufacturing monitoring methods at present are temperature monitoring, thermal imaging monitoring and image processing monitoring methods for the state of the molten pool. By

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using pyrometry and a vision based system, Wang et al. investigated the thermal behaviour of No. 410 stainless steel during powder-DED manufacturing, both numerically and experimentally [10]. Thermo-image data was captured by a two wavelength pyrometer, positioned outside a DED machine and directed through the thin film in the viewpoint, as shown in Fig. 2. Si-based digital CCD camera captured a field of view 22mm × 25mm, recording an image every 2s, and temperature range of pyrometer is set between 1450℃ and 1860℃. The outcome showned that a near-infrared filter was required to minimize the noise factors which could contaminate acquired images, mainly caused by metallic vapour, the heated zone above the molten pool and airborne metallic powder. Laser radiation was also found to be one of the factors that could disort the images. Regardless of image contamination, results of predicting of size of melt pool and temperature distribution were shown to be of good capability. This research was geared towards developing an improved understanding of the powder DED process and thermo-image predicting, rather than for the purpose of implementating a closed-loop control system. Hua et al. had shown that pyrometry data, basically thermo-images of melt pool, could be used to correlate melt pool size and layer thickness during powder DED processing, then she proved that this type of data could be used for closed-loop control [11]. Based on fruits gained above, Nassar et al. used pyrometry data to aid in development of a closed-loop build strategy controller [12]. The system collects temperature data which is used to select a location size for the next deposition path, avoiding to exceed areas above a pre-set temperature threshold. The outcome of the system showed more uniform material characteristics and properties, but as well increase build time by a third. Griffiths et al. were amongst the first to research the use of infrared ray (IR) imaging for in-situ measurement of powder-DED [13]. IR camera, CCD array recording element and high speed camera were all used to access the relative temperature images during the process of stainless steel 316, and manage to acquire plotted thermal profile which was relative to the maximum temperatue seen at the weld pool. Barua et al. employed a high resolution camera for melt pool monitoring and discontinuity detection [14]. Once the optical system was calibrated, the obtained images were analysed and the intensity of light rediating from the melt pool was used to determine the temperatures. It was found that the discontinuities could be observed with the camera setup and their distribution could be identified, however, no sizing information from real-time processing of images could be delivered due to the mismatch in the photograph capture frame rate and the interrogation software processing time per image.

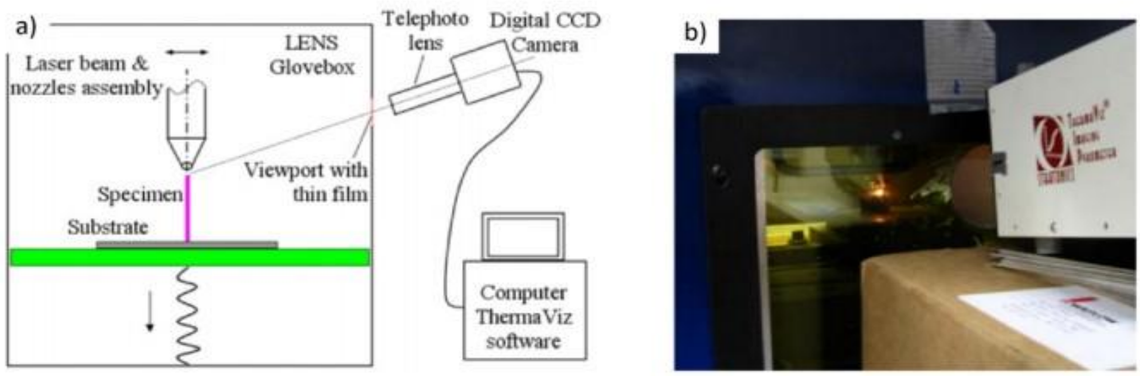

Figure 2. (a) schematic of digital CCD camera focussed through viewpoint for thermal behaviour analysis and (b) photograph of set-up selected by Wang et al. [10]

The above studies have shown that the use of thermo-image, pyrometry data and IR data allows for in-situ monitoring of powder-DED processing, and in some scenarios, monitoring methods have been linked with process inputs to allow for closed-loop control of the process, but the contamination of images caused by vapour, lack of precision due to the restriction of light wavelength, and mismatch situation where images acquaired and images being processed could not fit, allow this application to acquire a more compete way.

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3. Research status of machine learning in metal additive manufacturing and monitoring applications

Machine learning is widely used in metal additive manufacturing. It is mainly used for data analysis, performance prediction, fault identification classification, quality prediction, etc. By substituting data such as spectra, images, computer tomography, thermal imaging and other data into the machine learning model, defect data could be marked, trained within the supervised model in real time and used to predict the defect and quality.

3.1 Machine learning on data analysis and parameter optimization for manufacturing

In terms of data analysis and parameter optimization, machine learning can generate analysis process diagrams through regression models to facilitate finding the best combination of parameters. Meng et al. adopted the approach to develop the process design maps of two metals, 316L and 17-4 PH stainless steels [15]. Their studies showed that the keyhole mode criteria need to be revised based on the specific metal composition and powder layer thickness. The process map enables designers to achieve property prediction and process optimization efficiently. Tapia et al. applied Gaussian Process model, one of the basic regression model in machine learning, to make predictions of porosity and melt pool depth in L-PBF process [16, 17]. The process map of melt pool depth in terms of laser power and scan speed with the corresponding uncentainty are plotted in Figure 3. The figure as well as the results show that the joint Gaussian distribution processing has excellent regression performance and evaluation capabilities.

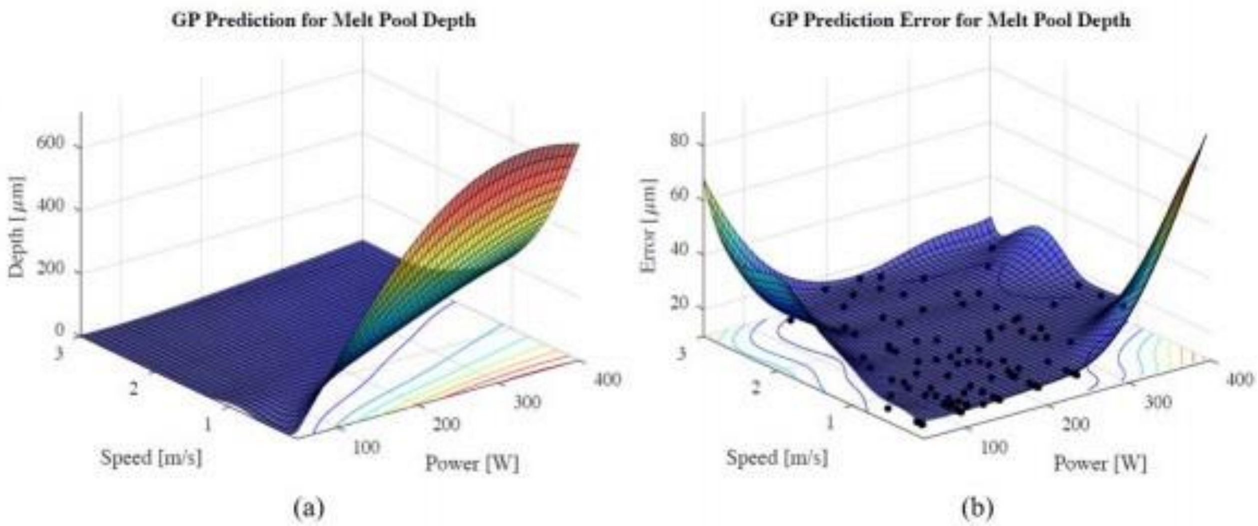

Figure 3. (a) The process map of melt pool depth in terms of laser power and scan spped of 316 stainless steel in L-PBF process, and (b) the corresponding uncertainty

3.2 Machine learning on feature extraction and defect detection for in-situ monitoring

In addition to the above applications, machine learning can also be combined with monitoring methods based on thermal imaging, infrared monitoring and image monitoring, for feature extraction especially when original data are abundant and hard to extract features that fit the model, and defect detection by data trained and generated by processed model [18]. Khanzadeh et al. applied Principal Component Analysis method to simplify the features from melt pool characteristics, and finally obtained nine principal components that account for almost 99.52% of variation in the data [19]. Scime et al. applied Same Isoscale Feature Transformation method to process the image data recorded by the camera, and use methods such as directional gradient histogram and cluster analysis to extract the image features of the molten pool [20]. These features were then brought into the support vector machine model based on classification processing to learn and distinguish the incomplete melting of

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powder, breakdown defects such as surface cracks and surface spheroidization of the workpiece. Ye et al. used a deep belief algorithm based on multi-layered Restricted Boltzman Machine, to identify and classify molten powder splash images in the molten pool with minimal data preprocessing workload and feature-free extraction [21]. This algorithm could reach 83.4% accuracy, while they found that convolutional neural network combined with support vector machine and support vector machine combined with principle component analysis could reach higher precision score. Zhang et al. studied the network combination between convolutional neural network, support vector machine and principal component analysis [22]. They extracted and classified the image data of molten powder splash in the molten pool and the surface area of the molten pool, and compared the effects of the network combination.

4. Summary

From the literature mentioned above in this paper, current in-situ monitoring technologies for powder metal DED, and latest applications of machine learning in powder metal manufacturing field are reviewed. However there are still issues remained to be solved. Firstly, the current additive manufacturing monitoring methods are mainly based on thermal imaging, temperature detection and image processing to monitor the molten pool and processed workpieces. There is a lack of monitoring methods that directly target the entire system, especially coaxial powder feeding mechanism, and it is not direct in terms of monitoring objects. Secondly, the existing detection technology system based on infrared detection and image processing has a relatively large time difference in data acquisition and software processing, and can hardly afford to achieve fast, accurate and efficient processing of the thermal imaging and image data obtained. Thirdly, the current machine learning is based on the application of thermal imaging and image processing technology for the monitoring of the state of the molten pool. It has not been directly used for the monitoring of the whole mechanism, and it has not been able to identify different types of faults. Further development of in-situ monitoring and machine learning application for metal powder DED could be processed in ways mentioned above.

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