Robotics and Computer–Integrated Manufacturing 49 (2018) 229–239

Contents lists available at ScienceDirect

Robotics and Computer–Integrated Manufacturing

journal homepage: www.elsevier.com/locate/rcim

In situ monitoring of selective laser melting of zinc powder via infrared imaging of the process plume

M. Grasso*, A.G. Demir, B. Previtali, B.M. Colosimo

Dipartimento di Meccanica, Politecnico di Milano, Via La Masa 1, 20156, Milan, Italy

ARTICLE INFO

Keywords:
Metal additive manufacturing
Selective laser melting
In situ monitoring
Infrared imaging
Zinc
Process plume

ABSTRACT

Despite continuous technological improvements in metal additive manufacturing (AM) systems, process stability is still affected by several possible sources of defects especially in the presence of challenging materials. Thus, both the research community and the major AM system developers have focused an increasing attention on in situ sensing and monitoring tools in the last years. However, there is still a lack of statistical methods to automatically detect the onset of a defect and signal an alarm during the part's layer-wise production. This study contributes to this framework with two levels of novelty. First, it presents an in situ monitoring method that integrates the acquisition of infrared images with a data mining approach for feature extraction and a statistical process monitoring technique to design a data-driven and automated alarm rule. Second, the method is aimed at monitoring powder bed fusion processes for difficult-to-process materials like zinc and its alloys, which impose several challenges to the process stability and quality because of their low melting and boiling points. To this aim, the proposed approach analyzes the byproducts generated by the interaction between the energy source and the material. In particular, it detects unstable behaviors by analyzing the salient properties of the process plume to detect unstable melting conditions. This case study entails an SLM process on zinc powder, where different sets of process parameters were tested leading either to in-control or out-of-control quality conditions. A comparison analysis highlights the effectiveness of plume-based stability monitoring.

1. Introduction

Selective laser melting (SLM) is an additive manufacturing (AM) process to produce metal parts via powder bed fusion. This kind of process provides great flexibility for the production of highly customized items, lightweight structures, innovative shapes, parts with complicated internal channels, etc. [1–9]. A laser is used to locally melt a thin layer of metal powder (e.g., about 40 – 50 µm) deposited on a flat substrate along a predefined scanning path. Once the SLM process of a full slice has been realized, the substrate is lowered, and a new layer of powder is deposited, and the next slice is scanned. For an overview of the process and the related technology, the interested reader may refer to the literature [1]. The accuracy of the produced parts—together with their mechanical and physical properties—make this kind of process suitable for the production of functional parts in several sectors (healthcare, aerospace, automotive, tooling and molding, etc.) [1–4]. In addition, the possibility of producing structures and free-form shapes that are difficult or even impossible to produce with other existing technologies makes SLM systems industrially attractive for a wide range of innovative applications.

However, different quality-related issues still affect the capability, stability and repeatability of the process. Local defects may occur during the layer-wise production of the part: the root causes may include improper process parameters, insufficient supports, a non-homogeneous powder deposition, improper heat exchanges, material contaminations, etc. [10–15]. A rapidly increasing literature in this framework has been devoted to the development of in-process monitoring tools [10–15]. These methods involve *indirect* measurements based on in situ sensors of quantities related to the final part quality rather than relying on direct (post-process) quality inspections. Indeed, the fast recognition of an out-of-control state is important to abort the SLM process as soon as possible saving time and preventing waste of expensive material. It is also important to implement novel feedback control strategies to mitigate the propagation of defects and, when possible, to recover from the unstable condition in a first-time-right oriented framework.

With few exceptions, in situ SLM monitoring methods proposed in the literature can be divided into two groups: (i) co-axial monitoring of the melt pool via in situ sensors by exploiting the optical path of the laser [16–28] and (ii) off-axial monitoring devoted to other categories of signatures measured by sensors placed outside the laser optical path

---

* Corresponding author.
E-mail addresses: marcoluigi.grasso@polimi.it (M. Grasso), aligokhan.demir@polimi.it (A.G. Demir), barbara.previtali@polimi.it (B. Previtali), biancamaria.colosimo@polimi.it (B.M. Colosimo).

http://dx.doi.org/10.1016/j.rcim.2017.07.001
Received 20 February 2017; Received in revised form 6 July 2017; Accepted 6 July 2017

Nomenclature

α	Type I error
A_j	Area of the ROI in the jth video frame
f_s	Sampling frequency
$f(x)$	Probability density function
h	Kernel bandwidth
IC	In-control
I	Pixel intensity
$\overline{I_j}$	Average intensity of the ROI in the jth video frame
IR	Infrared
J	Total number of acquired images
K	Number of frames included into the training phase
KDE	Kernel density estimation
$Ker\{x\}$	Kernel function
$M\times N$	Size of IR images
n_j	Number of pixels of the ROI in the jth video frame
OOC	Out-of-control
$P_1(S)$	% of frames with more than one connected component classified as ROI
$P_2(S)$	% of frames with more no connected component was classified as ROI
RGB	Red green blue
ROI	Region of interest
S	Area threshold
$\mathbf{S}$	Sample variance-covariance matrix
SLM	Selective laser melting
LHZ	Laser heated zone
T	Binarization threshold
T^2	Hotelling's statistic
$\boldsymbol{u}$	3-dimensional array representing the IR image stream
$\boldsymbol{U}_j$	jth IR video frame
UCV	Unbiased cross-validation
$\mathbf{V}$	Matrix of successive difference vectors
$\boldsymbol{x}_j$	Bi-variate monitored variable
$\mathbf{X}$	Training dataset (monitored descriptors)

[29–43]. The melt pool properties (i.e., size, shape and temperature profile) are important proxies of the SLM process quality and stability. They have attracted a wide range of research interest in recent years within the metal AM community. However, off-axis sensors offer additional information including the geometry and temperature profile over the entire track, the amount of ejected material and side-products, the powder bed homogeneity, the geometry and topography of the scanned slice, etc.

Most studies have focused on in situ sensing and data acquisition solutions, but there is still a lack of monitoring methods to automatically detect the onset of the defect and to signal an alarm during the layer-wise production of the part [12]. The first contribution of this study is an automated and data-driven tool to detect process instabilities, which inherits the signal-based process monitoring perspective adopted in the industrial statistics framework [44] and extends it to AM applications. The proposed method is based on the continuous acquisition of infrared (IR) images via an off-axis mounted thermal camera. The method integrates a data mining approach for image segmentation and extraction of relevant information within the regions of interest with a statistical process monitoring technique that allows the design of a data-driven and automated alarm rule. This approach is used for defect detection in the presence of thermally sensitive materials that produce larger amounts of metallic vapor and byproducts than other materials with a possible detrimental effect on the SLM process stability.

Zinc and its alloys belong to this category: They constitute a new family of biodegradable alloys for biomedical devices whose use in AM applications has been gaining an increasing interest [45]. However, due to their low melting and boiling points, the SLM of zinc powder produces large quantities of plume, which differs from the surrounding atmosphere in terms of chemical composition, temperature and pressure. In fact, during the SLM process, partial material vaporization may occur: King et al. [46] reported the formation of plasma due to the ionization of the metallic vapor and the surrounding gas. Further vapor formation and heating of the surrounding gas forms the process plume. The plume can induce changes in the optical properties of the beam path, which may alter the beam profile and energy density on the material's surface [47]. Moreover, heat accumulations and thermal drifts during the process can change the plume quantity and form. This yields detrimental effects on the process stability that may lead to poor part quality—especially regarding the internal and sub-surface porosity [48].

Many groups have investigated the plume properties in laser welding [49–52] and metal AM [53–54], but, to the best of our knowledge, such an information has never been used for monitoring purposes in SLM. On the contrary, this study is the first attempt to develop an in situ monitoring methodology that relies on the analysis of the process plume properties as proxies of the SLM process stability to detect unstable melting conditions since their early stage. Thermal images are segmented to extract the region of interest (ROI) that includes the plume emission. Then, a multivariate control-charting scheme is proposed to monitor the selected ROI statistical descriptors (i.e., the area and the mean intensity) to rapidly detect departures from a stable pattern in terms of plume emissions.

We compare different segmentation algorithms and propose an automated rule to isolate the ROI from the rest of the image. A case study is presented that consists of an SLM process on zinc powder where both stable and unstable melting conditions were observed. The results show that the plume descriptors can determine the stability of the process and anticipate the departure from in-control (stable) behaviors. The proposed method is compared against benchmark competitors to highlight the benefits and resulting performance.

Section 2 presents the experimental setup adopted during the SLM of zinc powder in the presence of both stable and unstable melting conditions; Section 3 describes the image pre-processing and process monitoring steps of the proposed approach; Section 4 presents a discussion of the results; and Section 5 concludes the paper.

2. Experimental setup

Zinc and its alloys are the newest family of materials in biodegradable metals. Biodegradability refers to the dissolution of the medical device inside the human body once it fulfills its duty [55]. This property is especially appealing in cardiovascular stents. The recently developed attention on zinc is due to a biodegradation rate that is slower than Mg- and Fe-based alloys [45]. The use of zinc in additive manufacturing processes has not received much attention so far due to the restricted applications of the pure metal and its alloys. Moreover, pure zinc is highly problematic within the SLM process because of its very low melting ($T_m = 693$ K) and vaporization ($T_v = 1180$ K) points [48]. These characteristics render the processability of zinc and its alloys particularly difficult due to the excessive vapor and plume generation. The process can be stabilized provided adequate solutions to eliminate the particle accumulation in the processing chamber. Within stable operating conditions, pure zinc shows a peculiar type of defect consisting of partial disintegration at high energy density levels. The defect does not manifest immediately, but occurs after a certain number of layers have been deposited with consecutive heat accumulation. As a result, a material burst is observed during the melting of a layer, which yields a disintegration of the previously built layers [56]. Such a defect can be avoided by an adequate choice of processing parameters. However, heat accumulation depends on the form and the size of the scanned geometry and prevents excessive accumulation within the entire build; this is a difficult task in practice. In particular, thinner sections are known to be more prone to