
Statistical process monitoring and control methods for in-situ detection and localization of defects in laser powder bed fusion

M. Grasso, G. Repossini, B.M. Colosimo

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

marcoluigi.grasso@polimi.it, giulia.repossini@polimi.it, biancamaria.colosimo@polimi.it

Abstract

Key industrial sectors for the implementation of metal additive manufacturing (AM) systems, like aerospace and bio-medical industries, involve stringent quality and certification requirements that are difficult to meet at the current technological maturity level. One major barrier is represented by the limited stability and repeatability of the AM processes. This motivates the development of in-situ monitoring and control solutions for a zero-defect oriented production. Most efforts in the literature and in industry have been focused on gathering in-situ sensor data so far, but what is still lacking is the availability of data analytics tools able to make sense of big amounts of acquired signals and yield automated defect detection and localization capabilities. Automated alarm rules represent a first necessary step to design novel closed-loop control strategies for defect mitigation or even defect repair methods that are still not available in commercial systems. In this framework, we present statistical image-based methods for in-situ monitoring of various kinds of “process signatures” aimed at characterizing the melting state and detecting local defects during the layer-wise production of the part. The proposed methodologies are applied to real case studies in Selective Laser Melting (SLM).

Additive Manufacturing, Laser Powder Bed Fusion, in-situ monitoring, zero-defect, image analysis

1. Introduction

Different authors pointed out that the lack of process stability and repeatability still represents a major barrier for the industrial breakthrough of metal additive manufacturing (AM) systems [1-4]. Most AM system developers are currently investing R&D efforts in the development of integrated sensing equipment to gather data during the layer-by-layer production. At the same time, there is a quickly evolving literature devoted to AM process monitoring tools to extract different descriptors of the process stability and quality from in-situ sensor data. Different review studies were aimed at providing an overview of the rapidly evolving state-of-the-art in this field [1-6].

The largest portion of the literature currently focuses on sensing configurations and data pre-processing methods for feature extraction. Very few studies have proposed statistical monitoring methods able to detect the onset of defects via automated alarm rules (see for example [6] and the literature therein). As a matter of fact, the ability of making sense of large amounts of in-situ data (e.g., infrared images, high-speed video image data, etc.) to activate in-process actions still represent an open issue and currently lacks in off-the-shelf AM systems. In fact, feedback control strategies and defect removal methods have been investigated by very few authors so far (see Section 4).

This study reviews the state-of-the-art on in-situ monitoring for laser powder bed fusion processes. It presents a discussion of the needs for advanced data mining techniques for effective and reliable in-process detection of defects in the framework of zero-defect AM processes. Examples of novel image-based statistical process monitoring tools for in-situ detection and localization of defects in laser powder bed fusion are presented as well.

2. In-situ monitoring methodologies

In laser powder bed fusion, different kinds of defects may originate during the production of the part. They include internal and sub-surface porosity, which is particularly critical as it affects the fatigue performances and the crack growth characteristics [7]. The fatigue performances and the fracture behaviour are also affected by the presence of unmelted powder particles within the part or other contaminant materials. Residual stresses represent another type of defect, which may lead to cracking, delamination and part warping. Geometrical defects are also common in this kind of process as a consequence of out-of-control melting conditions, which are more likely to occur in critical features like overhang regions, thin walls, acute corners, etc. The generation of super-elevated edges, i.e., ridges of the solidified material at the edges of the successive layers, is particularly critical. Indeed, when super-elevated edges protrude from the powder layer, they may interfere with the recoating system, increasing its wear and negatively affecting the consequent powder bed uniformity. The generation mechanisms of various defects is related to the balling phenomenon, i.e., the solidification into spheres instead of solid layers [8]. This yields an impediment to interlayer connection. It also increases the surface roughness and the internal porosity [9].

In-situ process monitoring is aimed at detecting (and, in some cases, localizing) most of those defects during the process. The mainstream in-situ sensing methods can be divided into two categories, i.e., “co-axial” and “off-axial” methods. In co-axial configurations, the sensors exploit the optical path of the laser. In off-axial configurations, the sensors are placed outside the optical path, with a given angle-of-view with respect to the region of interest. Both co-axial and off-axial sensing setups mainly consists of cameras (either in the visible or infrared

range, with different spatial and temporal resolution characteristics depending on the application) and pyrometers [1-6]. Few studies considered different sensing methods. They include recoating system vibration sensors [10], ultrasound and acoustic emission sensors [11-12], and baseplate distortion sensors [13].

The quantities measured during the process can be referred to as “process signatures”, as they represent measurable proxies of the process quality and stability. The NIST report [1] defined the process signatures in AM applications as “dynamic characteristics of the powder heating, melting, and solidification

processes as they occur during the build”. Fig. 1 shows an example of different levels of process signatures in laser powder bed fusion. Table 1 summarizes the literature on in-situ monitoring classified in terms of monitored signatures. The table also reports the most relevant defects associated to each category of process signatures. However, the correlation analysis between in-situ measured quantities and post-process metrological part characterization still represents a topic where further and continuous research efforts are needed.

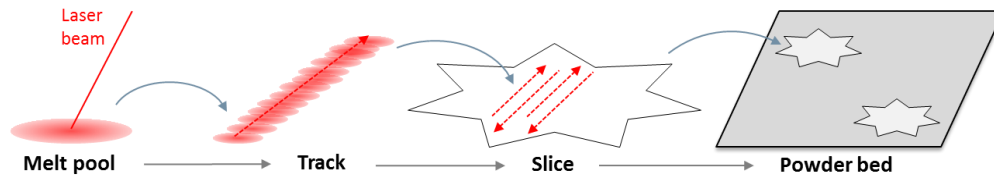


Figure 1. Different levels of in-situ monitoring for laser powder bed fusion processes

Table 1 Classification of the literature on in-situ monitoring with respect to the monitored process signatures

Monitored quantities (process signatures)		Literature on in-situ monitoring	Related defects
Melt pool	Size	[14-21]	Porosity, unmelted powder particle inclusions, residual stresses, delaminations, geometrical/dimensional defects
	Shape	[16, 18 - 20, 22 -23]	
	Temperature intensity	[16 – 18, 20, 22, 24 -26]	
	Temperature profile	[24]	
Track (scan path)	Track geometry	[23, 27]	Porosity, unmelted powder particle inclusions, residual stresses, delaminations, geometrical/dimensional defects
	Temperature / intensity profile	[28 – 33]	
	Ejected material	[30 – 31, 34 – 35]	
Slice	Surface pattern	[36 – 41]	Porosity
	Geometry	[39]	Geometrical/dimensional defects
	Thickness profile (topography)	[36 – 38, 42 – 43]	Geometrical defects, porosity
	Thermal map	[29, 32, 44]	Porosity, residual stresses, geometrical defects
Powder bed	Homogeneity	[39 – 41]	Porosity, unmelted powder particle inclusions, geometrical defects
	Thermal map	[13, 44 – 45]	Residual stresses, geometrical defects

The highest detail level can be achieved by monitoring the melt pool properties. The melt pool is a primary feature of interest in laser powder bed fusion [14 – 15, 17-18, 21, 23 – 24]. Indeed, its properties determine the geometrical accuracy of the track, the solidification behaviour and the geometrical/mechanical properties of the final part. The melt pool size, shape and temperature stability influence the internal porosity and the presence of unmelted particles within the bulk material. They also determine the development of residual stresses and following cracking and delamination problems. Melt pool monitoring can be achieved only via co-axial sensing. To this aim both co-axial cameras (visible or near infrared range) and co-axial pyrometers were proposed in the literature (see Table 1).

Further process signatures can be monitored at track level. They include: i) the geometry of the track, ii) the temperature profile over the track and iii) material ejected as a consequence of the laser-material interaction [30 – 31, 34 – 35].

The geometry and the temperature profile of the track are affected by the occurrence of the balling phenomenon, lack-of-fusion or local over-heating conditions, surface and geometric errors and porosity formation.

At slice level, the main quantities of interest include the surface pattern and topography of the slice, together with its geometry and thermal map. Process monitoring at slice level

may reveal surface irregularities, e.g., caused by balling, porosity and super-elevated edges [10, 36-37], and deviations from the nominal geometry. The thermal map over the slice is another relevant feature to determine irregularities, e.g., caused by lack-of-fusion or local over-heating [29].

Eventually, by monitoring the powder bed homogeneity it is possible to detect rippling caused by recoater bouncing effects and/or rectilinear grooves generated either by particles dragging or other recoating system damages [39]. The thermal map stability from one layer to another was proposed to assess the powder bed quality as well [45].

Process monitoring at track, slice and powder bed level usually required off-axial sensors, mainly cameras in the visible or infrared range.

3. Data mining tools for zero-defect AM processes

Despite a rapidly evolving literature on in-situ monitoring tools and considerable R&D efforts from major AM system developers, the integration of on-line methodologies to make sense of big amounts of acquired data and to automatically signal defects and out-of-control conditions is still missing in commercial systems. Indeed, the term “monitoring” in the mainstream AM literature is used to indicate data collection and feature extraction methodologies. Instead, from a statistical

monitoring perspective, the same term refers to the detection of defects and faults via automated alarm rules. This latter kind of monitoring is needed to actually enhance the intelligent capabilities of next-generation AM systems and to pave the way to zero-defect oriented AM productions.

We present some examples of novel statistical process monitoring methods based on video image data acquired during laser powder bed fusion processes. They couple image-processing and data mining tools with statistical tools for industrial quality control. All of them are based on off-axial machine vision setups, exploiting a high-speed camera in the visible range (example 1 and 2) and an infrared camera (example 3).

3.1. Example 1: hot-spot detection via high-speed vision

Good internal, mechanical and geometrical properties are achieved when a fast solidification (i.e., a fast cooling transitory) follows the laser scan of each portion of the part. In some cases, a local increase of the actual energy density (e.g., in the presence of overhanging regions, thin walls or acute corners largely surrounded by loose powder) may yield to local over-heating phenomena, followed by a slower cooling phase. This generates “hot-spots” during the laser scanning, and those hot-spots are symptoms of local out-of-control conditions. A method to automatically detect both when and where (within the slice) a hot-spot event occurs was proposed in [6]. High-speed video image data (e.g., 300 fps or higher) were acquired during the laser scan of each layer. A variant of the Principal Component Analysis (PCA) [46] known as T-mode PCA, was applied to batches of video images and iteratively updated as new frames were acquired. A multivariate statistic, i.e., the Hotelling’s T^2 , was used to synthesize the pixel intensity variability and auto-correlation patterns. The result was a statistic that exhibits local peaks in the presence of pixels with anomalous intensity patterns, i.e., hot-spots. A clustering-based alarm rule was eventually proposed to automatically detect and localize the presence of the defect. Fig. 2 shows an example of the T^2 statistic in the presence of a hot-spot and the corresponding clustering pattern.

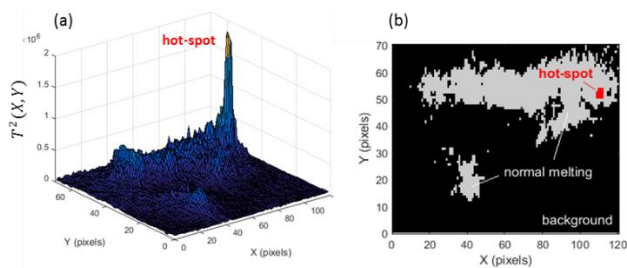


Figure 2. (a) 2D pattern of the T^2 statistic in the presence of a hot-spot; (b) corresponding clustering result, where the hot-spot is properly localized (red region)

A more recent study of ours showed that by including the spatial correlation information among the image pixels into the T-mode PCA formulation, the hot-spot detection is enhanced [47].

3.2. Example 2: spatter signature characterization

The same machine vision setup (at higher speed, i.e., 1000 fps) was used to determine whether the spatter behaviour can be used as a proxy of the process stability [34]. Rather than applying a batch-wise PCA analysis, an image segmentation was applied, frame by frame, to classify the foreground objects into spatters and laser heated zone. For both these two regions of interest, different synthetic descriptors were computed. A classification model was developed and tested on video image data acquired

during the production of specimens with either in-control and out-of-control (lack of fusion and over-melting) process parameters. Fig. 3 shows an example of the spatter signature in two different conditions: the over-melting state yields a larger spread and a larger amount of spatters than the in-control state.

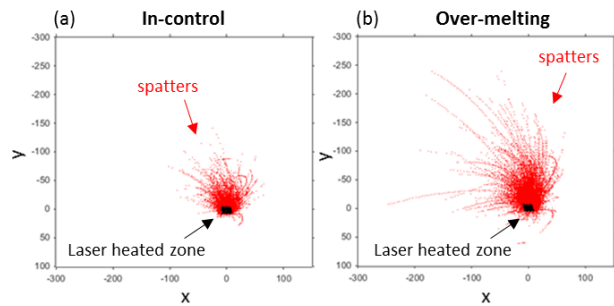


Figure 3. (a) spatial spread of spatters under in-control conditions; (b) spatial spread of spatters under over-melting conditions

The analysis confirmed that the spatter-related information allows improving the classification between different melting conditions with respect to the analysis of the laser heated zone alone (benchmark approach). This suggests that the spatter behaviour can be used to design process monitoring methodologies and to keep under control the process stability over time.

3.3. Example 3: plume signature characterization

The last example refers to the use of infrared video imaging to capture and characterize another by-product of the process, i.e., the plume, which represents a further source of information about the process quality and stability [35]. The plume differs from the surrounding atmosphere in terms of chemical composition, temperature and pressure. It can induce changes in the optical properties of the beam path, which may alter the beam profile and energy density on the material surface [48]. Moreover, heat accumulations and thermal drifts during the process can cause changes in the plume quantity and form, with detrimental effects on the process stability and part quality, especially regarding the internal and sub-surface porosity [49]. We proposed an image-based approach aimed at segmenting the infrared images acquired during the laser scanning and isolating the plume-related region of interest. The plume area and intensity were measured and a multivariate control charting scheme was proposed to quickly detect anomalous plume behaviours. Fig. 4 shows an example of process plumes resulting from infrared image segmentation under both in-control and out-of-control conditions. The out-of-control plume was observed as a consequence of a partial disintegration of the part during the laser powder bed fusion of zinc powder, which is a thermally sensitive material that produces large amounts of metallic vapour.

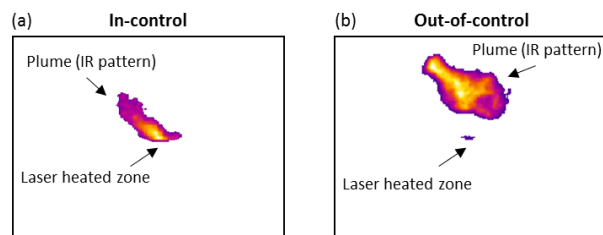


Figure 4. (a) Infrared pattern of the plume under in-control conditions; (b) infrared pattern of the plume under out-of-control conditions

The analysis showed that the multivariate control charting scheme allows one to detect unstable laser-material interactions and to anticipate the occurrence of process failures.

4. Towards feedback control in metal AM

AM system controllers available off-the-shelf do not integrate feedback control functionalities, which are needed to exploit in-situ sensor data within a closed-loop control framework.

Very few seminal studies have been devoted so far to the development and testing of feedback control techniques in laser powder bed fusion. Kruth et al. [19] and Craeghs et al. [14] proposed an adaptive correction of the laser power based on the melt pool area measured via co-axial pyrometer (acquisition frequency of 20 kHz), being the pyrometer signal proportional to the melt pool area. These authors showed that the feedback control method allows improving the geometrical accuracy of overhang regions. Craeghs et al. [14] also demonstrated an improvement of the surface roughness during the SLM of cubes with small scan spacing.

The possibility of defect repairing was proposed as well. In particular, both in-situ laser re-melting and selective laser erosion techniques were shown to be feasible to mitigate different kinds of defects and to enhance the quality of the final part. Mireles et al. [50] studied the possibility of in-situ defect correction by re-melting the affected area, and they tested the method for in-situ correction of artificial pores of size 100 – 2000 µm. The use of re-melting was investigated in [51-52] as well, to improve the surface finishing of outer surfaces and the internal density. Yasa et al. [51] also discussed the combination of laser powder bed fusion and selective laser erosion, i.e., a subtractive process based on material evaporation. The aim was to improve the surface quality and mitigate defects (e.g., super-elevated edges).

Currently, the closed nature of most AM systems and their controllers imposes a barrier to the implementation of novel controlling strategies. Nevertheless, there are efforts to develop an 'Open Communication Protocol' for open communications of real-time, position-synchronized sensor data for PBF systems [53].

5. Conclusions and future developments

In-process detection of defects and feedback control methods are expected to experience a substantial step forward in the next few years because of an increasing industrial pull for these technologies. As a matter of fact, the most relevant industrial sectors for AM process implementation, e.g., aerospace and healthcare, involve applications where defects can not be tolerated. Moreover, powder bed fusion processes are very long (a few days to produce a part) and metal powders are still quite expensive: because of this, high scrap ratios can not be sustainable. To face this issue, the development of process monitoring methodologies based on in-situ sensing as well as novel feedback control strategies was indicated as a priority research area by many recent keynote studies, European projects and national roadmaps.

The process monitoring methods here presented are aimed at implementing automated defect detection and localization rules in laser powder bed fusion. The next step consists of integrating those monitoring tools with novel feedback control strategies to mitigate or even repair the defect. Another future development consists of fusing data and information gathered from multiple sensors, including both co-axial and off-axial devices, to achieve a more complete and reliable characterization of the process quality and stability.

References

- [1] Mani, M., Lane, B., Donmez, A., Feng, S., Moylan, S., & Fesperman, R. 2015. "Measurement Science Needs for Real-time Control of Additive Manufacturing Powder Bed Fusion Processes", *NISTIR 8036*, <http://dx.doi.org/10.6028/NIST.IR.8036>
- [2] Tapia, G., Elwany, A. 2014. "A Review on Process Monitoring and Control in Metal-Based Additive Manufacturing". *Journal of Manufacturing Science and Engineering*, **136**(6), pp. 060801.
- [3] Everton, S. K., Hirsch, M., Stravroulakis, P., Leach, R. K., & Clare, A. T. 2016. Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing. *Materials & Design*, **95**, 431-445.
- [4] Spears, T. G., & Gold, S. A. 2016. In-process sensing in selective laser melting (SLM) additive manufacturing. *Integrating Materials and Manufacturing Innovation*, **5**(1), 1.
- [5] Olakanmi, E. O., Cochrane, R. F., Dalgarno, K. W. 2015. "A review on selective laser sintering/melting (SLS/SLM) of aluminium alloy powders: Processing, microstructure, and properties". *Progress in Materials Science*, **74**, pp. 401-477
- [6] Grasso, M., Colosimo, B. M., 2017. Process Defects and In-situ Monitoring Methods in Metal Powder Bed Fusion: a Review, *Measurement Science and Technology*, **28**(4), 1-25, DOI: 10.1088/1361-6501/aa5c4f
- [7] Edwards, P., O'Conner, A., & Ramulu, M. 2013. Electron beam additive manufacturing of titanium components: properties and performance. *Journal of Manufacturing Science and Engineering*, **135**(6), 061016.
- [8] Kruth, J. P., Froyen, L., Van Vaerenbergh, J., Mercelis, P., Rombouts, M., & Lauwers, B. 2004. Selective laser melting of iron-based powder. *Journal of Materials Processing Technology*, **149**(1), 616-622.
- [9] Li, R., Liu, J., Shi, Y., Wang, L., & Jiang, W. 2012. Balling behavior of stainless steel and nickel powder during selective laser melting process. *The International Journal of Advanced Manufacturing Technology*, **59**(9-12), 1025-1035
- [10] Kleszczynski, S., zur Jacobsmühlen, J., Reinartz, B., Sehrt, J. T., Witt, G., & Merhof, D. 2014. Improving process stability of laser beam melting systems. In *Proceedings of the Fraunhofer Direct Digital Manufacturing Conference*.
- [11] Rieder, H., Dillhöfer, A., Spies, M., Bamberg, J., & Hess, T. 2014. Online monitoring of additive manufacturing processes using ultrasound. In *Proceedings of the 11th European Conference on Non-Destructive Testing, October* (pp. 6-10).
- [12] <http://www.freepatentsonline.com/y2017/0146488.html>
- [13] Dunbar, A. J. 2016. Analysis of the Laser Powder Bed Fusion Additive Manufacturing Process Through Experimental Measurement and Finite Element Modeling. *Doctoral dissertation, The Pennsylvania State University*.
- [14] Craeghs, T., Bechmann, F., Berumen, S., & Kruth, J. P. 2010. Feedback control of Layerwise Laser Melting using optical sensors. *Physics Procedia*, **5**, 505-514.
- [15] Craeghs, T., Clijsters, S., Kruth, J. P., Bechmann, F., & Ebert, M. C. 2012. Detection of process failures in layerwise laser melting with optical process monitoring. *Physics Procedia*, **39**, 753-759.
- [16] Craeghs, T., Clijsters, S., Yasa, E., Bechmann, F., Berumen, S., & Kruth, J. P. 2011. Determination of geometrical factors in Layerwise Laser Melting using optical process monitoring. *Optics and Lasers in Engineering*, **49**(12), 1440-1446.
- [17] Clijsters, S., Craeghs, T., Buls, S., Kempen, K., & Kruth, J. P. 2014. In situ quality control of the selective laser melting process using a high-speed, real-time melt pool monitoring system. *The International Journal of Advanced Manufacturing Technology*, **75**(5-8), 1089-1101.
- [18] Berumen, S., Bechmann, F., Lindner, S., Kruth, J. P., & Craeghs, T. 2010. Quality control of laser-and powder bed-based Additive Manufacturing (AM) technologies. *Physics procedia*, **5**, 617-622.
- [19] Kruth, J. P., Mercelis, P., Van Vaerenbergh, J., & Craeghs, T. 2007. Feedback control of selective laser melting. In *Proceedings of the 3rd international conference on advanced research in virtual and rapid prototyping* (pp. 521-527).
- [20] Van Gestel, C. 2015. Study of physical phenomena of selective laser melting towards increased productivity. *PhD Dissertation, Ecole Polytechnique Federale De Lausanne*
- [21] Lott, P., Schleifenbaum, H., Meiners, W., Wissenbach, K., Hinke, C., & Bültmann, J. 2011. Design of an optical system for the in situ

- process monitoring of selective laser melting (SLM). *Physics Procedia*, **12**, 683-690.
- [22] Yadroitsev, I., Krakhmalev, P., & Yadroitsava, I. 2014. Selective laser melting of Ti6Al4V alloy for biomedical applications: Temperature monitoring and microstructural evolution. *Journal of Alloys and Compounds*, **583**, 404-409.
- [23] Doubenskaia, M. A., Zhirnov, I. V., Teleshevskiy, V. I., Bertrand, P., & Smurov, I. Y. 2015. Determination of true temperature in selective laser melting of metal powder using infrared camera. *In Materials Science Forum*, **834**(93-102). Trans Tech Publications.
- [24] Doubenskaia, M., Pavlov, M., Grigoriev, S., Tikhonova, E., & Smurov, I. 2012. Comprehensive optical monitoring of selective laser melting. *Journal of Laser Micro Nanoengineering*, **7**(3), 236-243.
- [25] Chivel, Y. 2013. Optical in-process temperature monitoring of selective laser melting. *Physics Procedia*, **41**, 904-910.
- [26] Pavlov, M., Doubenskaia, M., & Smurov, I. 2010. Pyrometric analysis of thermal processes in SLM technology. *Physics Procedia*, **5**, 523-531.
- [27] Kanko, J. A., Sibley, A. P., & Fraser, J. M. 2016. In situ morphology-based defect detection of selective laser melting through inline coherent imaging. *Journal of Materials Processing Technology*, **231**, 488-500.
- [28] Krauss, H., Eschey, C., & Zaeh, M. 2012. Thermography for monitoring the selective laser melting process. *In Proceedings of the Solid Freeform Fabrication Symposium*.
- [29] Krauss, H., Zeugner, T., & Zaeh, M. F. 2014. Layerwise monitoring of the selective laser melting process by thermography. *Physics Procedia*, **56**, 64-71.
- [30] Lane, B., Moylan, S., Whittenton, E. P., & Ma, L. 2015. Thermographic Measurements of the Commercial Laser Powder Bed Fusion Process at NIST. *In Proc. Solid Free. Fabr. Symp (Vol. 575)*.
- [31] Bayle, F., & Doubenskaia, M. 2008. Selective laser melting process monitoring with high speed infra-red camera and pyrometer. *In Fundamentals of Laser Assisted Micro-and Nanotechnologies* (pp. 698505-698505). International Society for Optics and Photonics.
- [32] Schilp, J., Seidel, C., Krauss, H., & Weirather, J. 2014. Investigations on temperature fields during laser beam melting by means of process monitoring and multiscale process modelling. *Advances in Mechanical Engineering*, **6**, 217584.
- [33] Grasso, M., Laguzza, V., Semeraro, Q., & Colosimo, B. M. 2016. In-process Monitoring of Selective Laser Melting: Spatial Detection of Defects via Image Data Analysis. *Journal of Manufacturing Science and Engineering*, **139**(5), 051001-1 – 051001-16.
- [34] Reposini et al. 2017. On the use of spatter signature for in-situ monitoring of Laser Powder Bed Fusion, *Additive Manufacturing*, <https://doi.org/10.1016/j.addma.2017.05.004>
- [35] Grasso, M., Demir, A.G., Previtali, B., Colosimo, B.M. (2017), In-situ Monitoring of Selective Laser Melting of Zinc Powder via Infrared Imaging of the Process Plume, *under review in Robotics and Computer-Integrated Manufacturing*
- [36] Zur Jacobsmühlen, J., Kleszczynski, S., Schneider, D., & Witt, G. 2013. High resolution imaging for inspection of laser beam melting systems. *In 2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)* (pp. 707-712). IEEE.
- [37] Kleszczynski, S., zur Jacobsmühlen, J., Sehart, J. T., & Witt, G. 2012. Error detection in laser beam melting systems by high resolution imaging. *In Proceedings of the Solid Freeform Fabrication Symposium*.
- [38] Zhang, B., Ziegert, J., Farahi, F., & Davies, A. 2016. In situ surface topography of laser powder bed fusion using fringe projection. *Additive Manufacturing*, **12**, 100-107.
- [39] Foster, B. K., Reutzel, E. W., Nassar, A. R., Hall, B. T., Brown, S. W., & Dickman, C. J. 2015 Optical, layerwise monitoring of powder bed fusion. *In Solid Free. Fabr. Symp. Proc.*, 295-307.
- [40] Neef, A., Seyda, V., Herzog, D., Emmelmann, C., Schönleber, M., & Kogel-Hollacher, M. 2014. Low coherence interferometry in selective laser melting. *Physics Procedia*, **56**, 82-89.
- [41] Erler, M., Streek, A., Schulze, C., Exner, H. 2014. Novel machine and measurement concept for micro machining by Selective Laser Sintering, *Solid Freeform Fabrication Symposium*
- [42] Zur Jacobsmühlen, J., Kleszczynski, S., Witt, G., & Merhof, D. 2013. Elevated Region Area Measurement for Quantitative Analysis Of Laser Beam Melting Process Stability. *In Instrum. Meas. Technol. Conf. I2MTC* (pp. 707-712).
- [43] Land, W. S., Zhang, B., Ziegert, J., & Davies, A. 2015. In-situ metrology system for laser powder bed fusion additive process. *Procedia Manufacturing*, **1**, 393-403.
- [44] Wegner, A., & Witt, G. 2011. Process monitoring in laser sintering using thermal imaging. *In SFF Symposium, Austin, Texas, USA* (pp. 8-10).
- [45] Islam, M., Purtonen, T., Piili, H., Salminen, A., & Nyrhilä, O. 2013. Temperature profile and imaging analysis of laser additive manufacturing of stainless steel. *Physics Procedia*, **41**, 835-842.
- [46] Jolliffe, I. 2002. Principal component analysis. *John Wiley & Sons, Ltd.*
- [47] Colosimo, B.M., Grasso, M. 2017, Spatially weighted PCA for monitoring video image data with application to additive manufacturing, *under review in the Journal of Quality Technology*
- [48] King, W.E., Barth, H.D., Castillo, V.M., Gallegos, G.F., Gibbs, J.W., Hahn, D.E., Kamath, C., Rubenchik, A.M., 2014. Observation of keyhole-mode laser melting in laser powder-bed fusion additive manufacturing. *J. Mater. Process. Technol.*, **214**(12), 2915–2925
- [49] Montani M, Demir AG, Mostaed E, 2016. Processability of pure Zn and pure Fe by SLM for biodegradable metallic implant manufacturing, *Rapid Prototyping Journal*, Accepted article, 10.1108/RPJ-08-2015-0100
- [50] Mireles, J., Ridwan, S., Morton, P. A., Hinojos, A., & Wicker, R. B. 2015. Analysis and correction of defects within parts fabricated using powder bed fusion technology. *Surface Topography: Metrology and Properties*, **3**(3), 034002.
- [51] Yasa, E., Kruth, J. P., & Deckers, J. 2011. Manufacturing by combining selective laser melting and selective laser erosion/laser re-melting. *CIRP Annals-Manufacturing Technology*, **60**(1), 263-266.
- [52] Grum, J., & Slabe, J. M. 2006. Effect of laser-remelting of surface cracks on microstructure and residual stresses in 12Ni maraging steel. *Applied Surface Science*, **252**(13), 4486-4492.
- [53] Dunbar, A.J., Nassar, A.R., Reutzel, E.W., Blecher, J.J. 2016 A real-time communication architecture for metal powder bed fusion additive manufacturing, *Proceedings of the 27th Annual Solid Freeform Fabrication Symposium*, 67-80, 8-10 Aug 2016, Austin, TX, USA