Lasers in Manufacturing Conference 2019

3D thermal mapping during AM by LMD towards better part quality

Camilo Prieto[a*], Carlos Gonzalez[a], Sara Carracelas[a], Baltasar Lodeiro[a], Jorge Arias[a]

[a]AIMEN Technology Centre, E36418 - O Porriño – Pontevedra - Spain

Abstract

In this work we present the deployment of a novel data analytics solution on Additive manufacturing of stainless steel parts by Laser metal deposition. Several relevant parameters are monitored in a synchronized manner over time, especially the power of the laser, the thermal information by means of the high speed IR coaxial thermal images of the melt pool and the position and speed of the robot. The dataset is represented in a 3D graphic environment to facilitate its interpretation. In this environment appears the toolpath with associated information corresponding to the thermal history represented in a color scale. The significant variation of the thermal information and its distribution on the 3D map denotes areas of potential problems on metallurgical quality and suggest better design options, strategies for toolpath planning and suitable process control approaches. Part quality results are correlated with the build information of the proposed 3D mapping.

Keywords: thermal imaging: AM part quality; data analytics; toolpath planning; process control

1. Introduction

Direct Energy Deposition (DED) processes are showing a growing interest in the industry as they have strong capabilities to build large-sized components, even over non-flat surfaces and with fast building rates comparing to other AM processes. Among them, Laser metal deposition (LMD), also know as Direct Laser Deposition (DLD), processes are gaining importance and have been investigated heavily in the last several years as it provides the potential to (i) rapidly prototype metallic parts, (ii) produce complex and customized parts, (iii) clad/repair precious metallic components.

Recently, different closed-loop control systems have been implemented to improve the robustness, reliability and the geometrical accuracy of components built by powder- LMD. Specifically, researchers have monitored laser parameters, melt pool metrics, part temperature, feed material, geometry, and optical emissions during processing. A common strategy is sensing and control of melt-pool size or temperature. Other efforts have attempted to maintain a constant layer build height by directly sensing build height and

* Corresponding author. Tel.: +34-673-143-544;
E-mail address: camilo.prieto@aimen.es .

adjusting processing head position, processing speed, material feed rate or laser power. As a result, the exploitation of LMD processes continues to accelerate.

However, work remains for AM to reach the status of a full production-ready technology. Production challenges remain such as: assurance of quality, right-first-time manufacturing capability and the complexity of AM processes involving many input parameters are technological barriers preventing the widespread deployment in manufacturing sectors at industrial level.

Ensuring AM process qualification and good part quality has many different aspects, such as: part design, feedstock material, process parametrization, process planning, manufacturing strategies, inline and online monitoring and control sytems, etc. Besides geometrical accuracy of the part, microstructure is a very important characteristic of the laser deposit because it has a strong impact on the mechanical properties. The two main common defects or material discontinuities that limit final part quality are porosity and cracks. Thus, the wider adoption of AM technologies require techniques that improve the quality of parts, namely, microstructure anomalies and main process defects such as porosity and cracks.

This paper reports on the development of a prototypical implementation of 3D mapping of different relevant thermal features by LMD spatially resolved in part coordinates. As a representative case scenario for deployment of the solution, a set of stainless steel 316L coupons with T-cross geometrical shape were built with different path planning and process control conditions.

By this novel data visualization tool, throughout registered data during execution of the build up and subsequent image processing, we were able to locate potential part quality issues and evaluate the performance of different path planning alternatives and a process control system. Initial correlation of part digital information generated during build-up with as-built part testing results are presented. The proof-of-concepts shows the applicability of the approach towards process qualification for large parts manufactured by LMD, underlying sensor information analyses and relevance of the acquired process information.

2. Experimental set up, materials and methods

The robotic LMD industrial workcell and main equipment used is shown in Figure 1. It consists on a 6-AXIS industrial robot ABB4400 as positioning system that is holding and displacing LMD process head along part built. Main process equipment is a thin disk laser Trudisk coupled by 200μm optical fiber to a laser process head BEO D70 (Trumpf). A powder feeder from GTV delivers the metallic powder through a coaxial injection nozzle COAX8 from Fraunhofer IWS.

A close loop control system based on high speed coaxial MWIR imaging is installed, CLAMIR by New Infrared Technologies (www.clamir.com). The embedded system with real time processing capabilities obtains IR images of melt pool at very high frame rates (1 KHz), extract key features of this image (such as width) and based on specific algorithms, it controls the power of the laser during process by the action of an embedded PI controller

Fig. 1. Robotic laser metal deposition workstation and process and control equipment of the experimental setup

2.1. System architecture and data acquisition

Online access to different type of data originated from the laser workcell and extracted information from high speed MWIR coaxial imaging system are registered and processed via dedicated software. The architecture has been designed to be modular and fully asynchronous, based on the use of timestamps to correlate information over time.

Robot main information such as position, orientation, speed is captured along process execution. A ROS driver had been developed to integrate the cell in the OpenLMD architecture. Other main process variables as laser power, powder feed rate are registered through Analog-Digital converters.

CLAMIR imager is VPD PbSe sensor 64x64 pixels (pixel size: 50 μm), with MWIR spectral response range within 1 -5 um, frame rate 1000 images per second. Data acquisition and power actuation log at 1kHz is saved for posterior processing. MWIR coaxial image raw data may be also registered up to this frame rate.

For the purpose of the 3D mapping, datasets of the test coupons were collected at the acquisition rate of 10Hz during process execution. For data compression and easy data handling, bespoke HDF5 file format is used. Thanks to this approach, the system is capable to record all the generated process information and datasets through HDF5 and it can represent the data acquired in part coordinates in a 3D environment. Moreover, stored files can be reproduced later to recreate full process virtual visualization.

2.2. Process parametrization

Target test parts for deploying this solution are 316L stainless steel T- crosses with curved walls intersecting with ribs. CAD main dimensions are shown in figure below (height=60mm, base-t cross=30mm and 4mm thickness) The test part defined is a section of a larger component with cylindrical shape and 1m diameter.

Feedstock powder material is stainless steel 316L from Flame Spray (45-90μm particle size) and base plate of 250x125x10mm.

During process set up and parametrization, main key process parameters were investigated by standard procedure: thus, process window was defined within the following parameter set: Laser power= 1000W; Process speed=8mm/s; Powder feed rate=8g/min.

The track width after process optimization obtained is: 2.1mm. Additional process development tests as 1-layer multi tracks and several layers deposition were conducted to finally estimate other slicing/path planning configuration parameters such as overlap (55% of track width) and layer height (0.45mm).

2.3. Deposition pattern and path planning

Those parameters were used as an input in the slicing software for path planning generation. According required part dimensions, and since positive oversizing by LMD is required, different deposition strategies can be used for this complexity of the part. Patterns such as raster scanning and offset-in were generated and postprocessed for execution in robot laser workcell by in-house developed CAD-CAM for AM software. Visualization of the deposition strategies is represented by sequence of steps identified by numbers in the following figures:

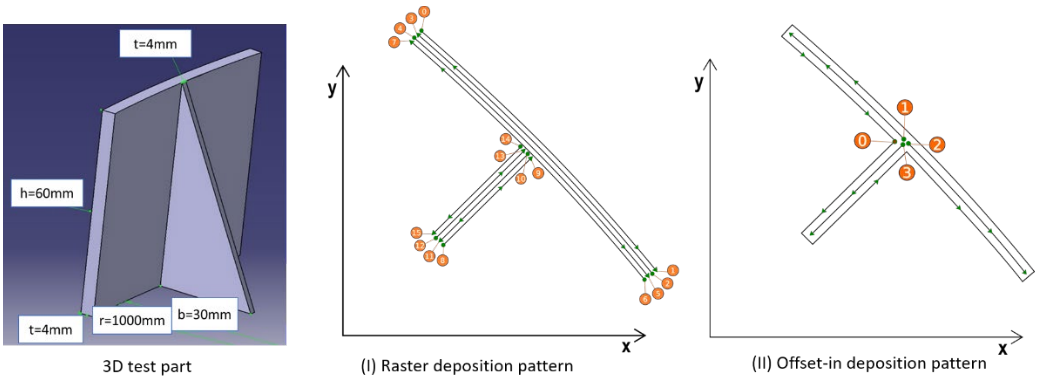


Fig. 2. 3D geometry representation of the test part (left) (I) 2D raster deposition strategy (II), laser metal deposit strategy defined as offset in. First track is the contour of the part and then several tracks identified in image as 2,3,4 are departing from central position. Generated by Slic3r open source software (https://slic3r.org/)

2.4. Image analysis features. Methodology for 3D mapping.

Coaxial thermal images are registered by a 64x64pixel 12bits MWIR Tachyon sensor (also by New Infrared Technologies) installed in CLAMIR. Besides process control capabilities based on melt pool geometrical analysis, real-time process information recorded by MWIR sensor that is analysed further offline, after process execution. The first step in the image analysis is to segment the image (using automatic thresholds based on distributions) in three regions: meltpool, tail (correspond mostly to solidification/heat affected area) and background.

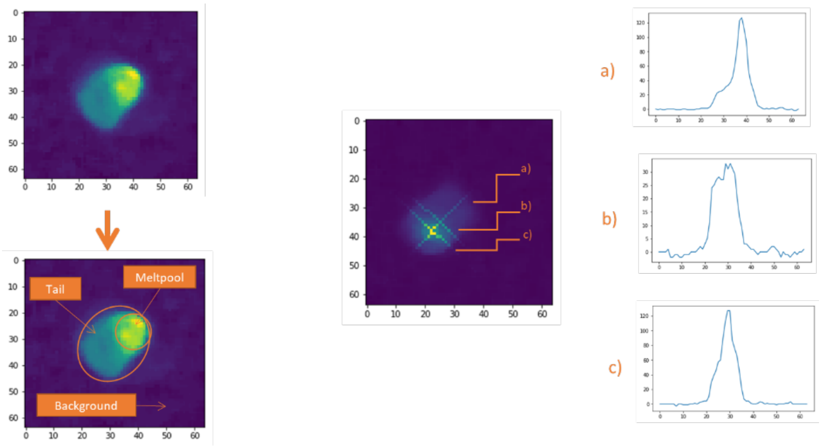


Fig. 3 left shows an in-process image data, illustrating segmentation of the meltpool and the tail area, marked by an ellipse describing the contour. On the right, it shows the longitudinal and transversal main axis (meltpool, tail) and how the gradient features are calculated (a)longitudinal, (b) tail-meltpool, (c)transversal-meltpool.

Calculation of thermal features: thermal profiles and gradients.

Thermal profiles and gradients are extracted for the two principal directions of the process, longitudinal and cross-sectional of the meltpool, and for a cross-sectional of the tail. For each image, a line is approximated following the tail direction. Using boolean operations for a parallel of this line and its perpendicular, at the center of the meltpool, the heat gradients are extracted. Using these profiles, the gradients are calculated from the highest point to the end of the tail / meltpool

Calculation of thermal features: shape descriptors.

For each zone in the segmentation, an ellipse is used as an approximation, extracting features as size and shape are calculated. The dimensionality of spatial process information can be used to determine different process conditions and faults. This shape descriptors and additional features are calculated and will be used for further machine learning methodologies.

3. Results and analyses

For the afore-mentioned hardware set up and optimized processing parameter window, a set of test componets for assessment for the data analysis were defined with the following differences:

Test part	Path planning	Control system-CLAMIR
Part A	(I)	on
Part B	(II)	on
Part C	(II)	off

Datasets of the build information collected (positioning system, laser power, powder feeder, images of CLAMIR) are registered and syncronised in hdf5 file format for posterior analysis. Full process virtual visualization in spatial coordinates is possible by representing all the recorded and processed data in a 3D environment.

List and group of data recorded

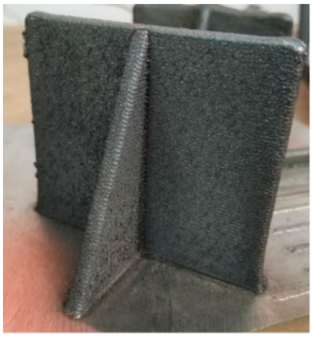
Position: x, y, z on the piece; *Orientation*: Orientation quaterns of the robot; *Speed*: Speed of the robot at that point; *Laser power*; *powder_flow*: Powder flow reading from the sensor.

Timestamp: Time & date

*CLAMIR data:*_area: area of the meltpool in pixels; clamir_power: Power output by CLAMIR; clamir_width; Clamir_ref_width: Width reference in use; clamir_temp: Internal temperature of device.

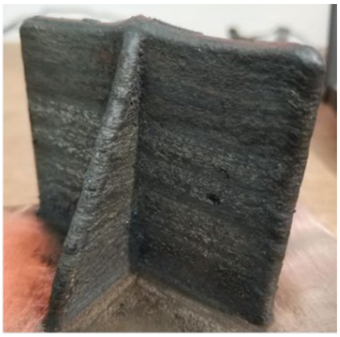
Stainless steel coupons were manufactured by LMD, visual inspection characteristics and further characterisation is correlated with the visualization of the build information by in situ monitoring system.

Visual inspection



Test part A)

Test part B)



Test part C)

Fig. 4. Photographs of the different test parts manufactured as-built stainless steel, from left to right - Part A) Part B) Part C)

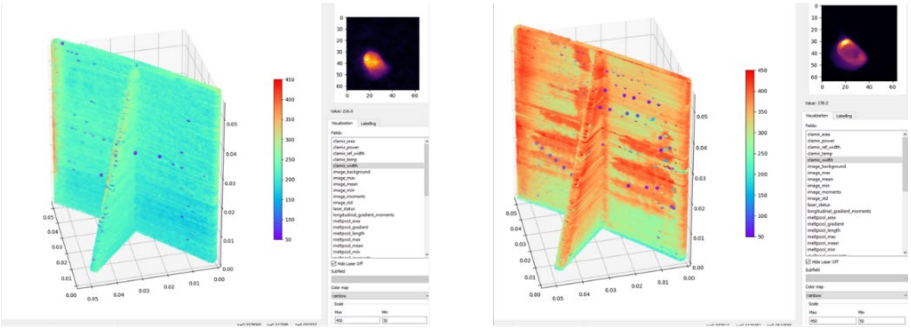
It is clearly noted by naked eye the geometrical accuracy and final finish quality is better when process control is used. Both A) and B) present quite homogenous and consistent surface quality aspect. Regarding visual differences, between part A) and part B), the first keeps better height layer consistency, and on the second, accumulation of material at start/end points of the fill in tracks and intersection of the T-cross . These observations can be correlated with the different path planning strategies. This confirms the highly influential effect of process strategy over geometrical accuracy. Besides, online control system have been implemented to improve the geometrical accuracy of components built by LMD-p to ensure geometrical accuracy of the final part

Basic part quality assessment methods as visual inspection were followed by geometrical inspection and measurement (height and wall thickness over 60mm and 4mm respectively are within initial defined tolerances in all cases)

Comparison test part B) vs test part C)

The data files contain the same design manufactured with and without laser-power control. Both files contain: robot positions, raw images from the process, measures extracted from the controller (CLAMIR) and features extracted from the images.

Actuation of laser power control on/off is investigated. In C) the melt pool width calculated by the control embedded system (clamir width) increases from the start to the end of the build as shown on the wall since deposition starts on a cool substrate and successive passes are being deposited on the previous, hot layer. Analogously, start and end of tracks suffer from overheating and several cycles. Process instabilities at the edge of the tracks lead to large geometrical deviations. In Part B) deviations in width are kept to minimum.

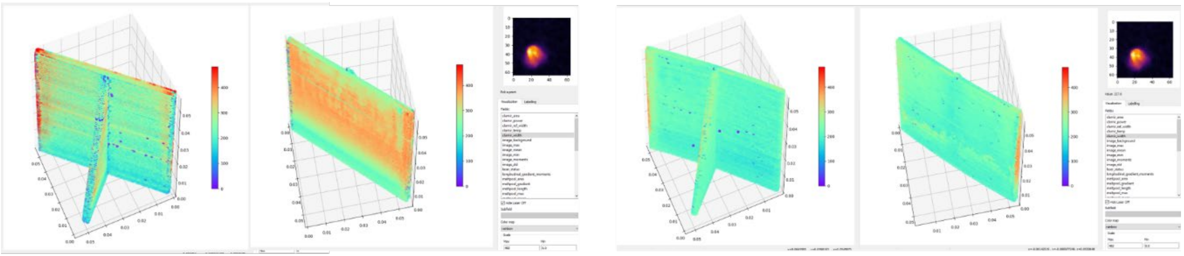


Test part B) Test part C)

Fig. 5. 3D representation of the “CLAMIR width” with and without process control (left-part B) and right-part C)

<u>Comparison test part A) vs test partB)</u>

Two different path planning strategies were investigated. Front and back 3D reconstruction of thermal feature of clamIR width is plotted for both strategies with the same colour scheme



Test part A) Test part B)

Fig. 6. 3D representation from front and rear view of the “CLAMIR width” for different pathplanning strategies (left -part A- raster deposition and right: part B-offset in

Thermal heat dissipation mechanisms depending on path planning can be better understood. For the case of raster scan, the first tracks of the layer present more instabilities that can be observed by variability of colour map. This also can be noticeable by the external surface finish roughness of the part for that face

Data correlation with information from destructive testing

A replica of part B) was manufactured and destructive testing by cross-sectional analysis and macrographs were also been carried out at z plane=30mm.

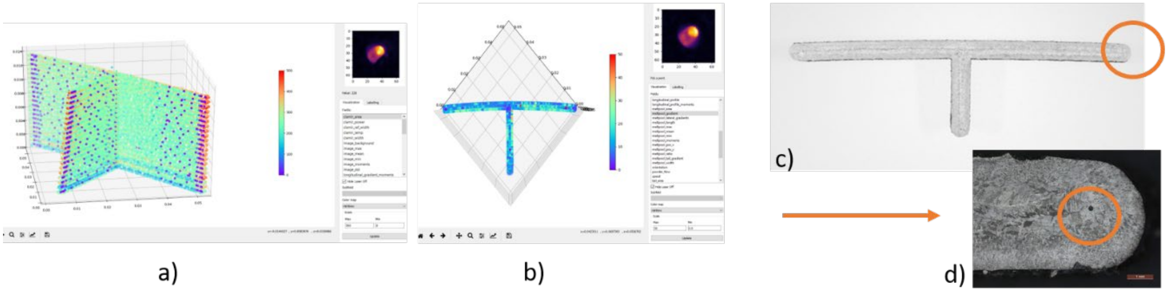


Figure 7. a) 3D representation of the "CLAMIR width" at Z=30mm with unstability of the melt pool area on the righ hand end. B) thermal gradient for the hottest part of the melt pool to heat affected zone also highlights the same area. C and d) Cross-section macrographs

Non-destructive testing by X-ray also shown identification porosity areas mostly located at those areas. 3D representation of thermal metrics can correlate to variations in material microstructure from the cross section analysis. Although these are still preliminary results, the use of thermal metrics such as meltpool and tail/heat affected gradient may allow for a non-destructive means to differ and distinct thermal histories during a build, which have an impact on microstructure.

Data correlation with NDT part quality data

Part 3D digital scanning can measure geometrical deviations and disparity map respect to target geometry. Other non-destructive tests as X-ray CT where defects such as porosity can be located positioned in XYZ part coordinates are under investigation

In-situ thermal monitoring provides a useful tool to provide information about the formation of defects or other process anomalies for additive manufacturing processes. The 3D representation colour map highlight the areas/features of major attention as the melt pool diameter/area directly relates with the heat management throughout the build process. Spatial and temporal correlation of part defects with image data will be needed to progress on the labelling of defects.

4. Conclusions and next steps

The 3D visualization of this thermal features spatially resolved during LMD build-up are effective ways to assess manufacturing strategies and the performance of a process control system. Initial experimental results validate the proposed approach.

This 3D mapping allows relating the parameters involved in the process to quality parameters measured by DT and NDT the piece. Experimental correlation between further destructive and non-destructive tests with registered data during build up are being undertaken. Ongoing work deals with the acquisition of partially labeled data with the aim of setting up detection and measurement benchmarks for defects such as porosity.

3D visualization of the build-up information allows the adoption of data-driven strategies and process/quality related decisions better and faster. By this set of image-analysis features, we set up an initial machine learning framework to establish a relationship between melt pool morphological characteristics and anomalies in the microstructure. It allows localization of potential areas of defect and constitutes first step towards digital twin (digital representation of the physical part being manufactured).

Data collected from the process can be utilized for various research and development purposes, model verifications, process characterization and process optimization. Thus, such data, collected via use of monitoring equipment can then be used to significantly reduce the time required to 'learn' about optimal process parameter set for a good quality LMD part.

In order to progress on the process qualification and consistency of high quality parts by LMD, thermal features extracted from online process shall be used to drive big data analysis tools (addressing robustness and repeatability of the process) and new data-driven solutions to detect machine malfunctions or process anomalies such as: energy source or gas flows fluctuations, clogged nozzle, stand-off deviations.

To summarize, a novel methodology and integrated solution based on data analysis of MWIR coaxial high-speed imaging features during LMD-p processes has been introduced. It provides a flexible solution capable of working with different positioning, process and monitoring equipment, thus supporting the acquisition and analysis of big amounts of process data, referred to common temporal and spatial reference systems. Hence, progress towards the implementation of in-situ monitoring for LMD process qualification has been made.

Acknowledgements

This work is carried out under FoF-04-2018 project on the topic "Pilot lines on metal additive manufacturing" http://www.integraddeproject.eu/. This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 820776.

References

Thompson, S. M., Bian, L., Shamsaei, N., & Yadollahi, A. (2015). An overview of Direct Laser Deposition for additive manufacturing; Part I: Transport phenomena, modeling and diagnostics. Additive Manufacturing, 8, 36-62.

Shamsaei, N., Yadollahi, A., Bian, L., & Thompson, S. M. (2015). An overview of Direct Laser Deposition for additive manufacturing; Part II: Mechanical behavior, process parameter optimization and control. Additive Manufacturing, 8, 12-35.

Kim, D. B., Witherell, P., Lu, Y., & Feng, S. (2017). Toward a digital thread and data package for metals-additive manufacturing. Smart and sustainable manufacturing systems, 1(1), 75.

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.

Kriczky, D. A., Irwin, J., Reutzel, E. W., Michaleris, P., Nassar, A. R., & Craig, J. (2015). 3D spatial reconstruction of thermal characteristics in directed energy deposition through optical thermal imaging. Journal of Materials Processing Technology, 221, 172-186.

García-Díaz, A., Panadeiro, V., Lodeiro, B., Rodríguez-Araújo, J., Stavridis, J., Papacharalampopoulos, A., & Stavropoulos, P. (2018). OpenLMD, an open source middleware and toolkit for laser-based additive manufacturing of large metal parts. Robotics and Computer-Integrated Manufacturing, 53, 153-161.

Knaak, C., Thombansen, U., Abels, P., & Kröger, M. (2018). Machine learning as a comparative tool to determine the relevance of signal features in laser welding. Procedia CIRP, 74, 623-627.

Khanzadeh, M., Chowdhury, S., Marufuzzaman, M., Tschopp, M. A., & Bian, L. (2018). Porosity prediction: Supervised-learning of thermal history for direct laser deposition. Journal of manufacturing systems, 47, 69-82.

Guo, P., Zou, B., Huang, C., & Gao, H. (2017). Study on microstructure, mechanical properties and machinability of efficiently additive manufactured AISI 316L stainless steel by high-power direct laser deposition. Journal of Materials Processing Technology, 240, 12-22.