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CIRPJ 422 No. of Pages 5

ARTICLE IN PRESS

CIRP Journal of Manufacturing Science and Technology xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

CIRP Journal of Manufacturing Science and Technology

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

Development of an adaptive, self-learning control concept for an additive manufacturing process

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ARTICLE INFO

Article history:
Available online xxx

Keywords:
Additive manufacturing
Selective laser melting
Laser beam melting
In-process monitoring
Closed-loop control
Self-learning

ABSTRACT

Error avoidance in high-precision manufacturing processes becomes more important for numerous state-of-the-art technologies. Selective laser melting is one of these technologies offering large potentials in the production of complex and flexible metal products. As the technology is relatively new, it is vulnerable for errors, given that the process parameters are not measured yet. A novel multilevel control concept, incorporating several sensors, has the potential to reduce errors significantly. For inner cascade control, the laser power will be adjusted by measurements with an intensity sensor for wavelengths in the visible range. This sensor is integrated into the optical path of the laser beam. An adapted self-learning strategy supports the stability of the process by updating the parameters of the used multidimensional model in order to attenuate environmental influences or shifts within the process. This work presents the concept of the control approach, first measurement results and the required relations between measurement, process and control parameters.

Introduction

Selective laser melting (SLM) is an additive manufacturing (AM) process that is well suited for the production of parts with complex geometries by melting powder material layer-wise. The melting process is generated by a laser beam, which is guided through a scanning unit to the build platform. After a layer is finished, the build platform with the part and powder will be lowered and a new powder layer will be coated in order to process the next layer of the product. The rising technology has several advantages: on the one hand, it does not need tools or forms for production, and on the other hand, it is able to produce complex freeform parts. The machines for selective laser melting do not exhibit a closed-loop control strategy, as yet.

In the AM process, there are some external influences that affect the process parameters, which are mainly the melt pool size and the material temperature in the melt pool. Their changes also lead to an impact on the quality parameters, which comprise the dimensional tolerances, density, tensile strength, roughness, or residual stresses [1]. Without measuring any process parameters, the external influences have a parasitic effect on the stability of the process. Therefore, implementing a closed-loop control concept offers potential to improve the product quality. Directly measuring the quality parameters is not possible. Thus, intelligent control concepts in a multidimensional input space are promising. Those quality control approaches have been successfully demonstrated for other processes in the field of turning processes [2] and the heat treatment of bearing rings [3].

In the past, several sensor concepts for the SLM process have been examined: An in-situ measurement of the process between each layer has been performed with cameras that cover the whole build platform. These cameras operated in the visible [4] and the infrared spectrum [5]. The sensors are able to detect process deviations on a global scale before or after the laser material processing takes place. Attempts of an in-process measurement of the material processing have been carried out by means of pyrometers [6], photo diodes and high speed cameras mounted coaxially to the processing beam [7]. Based on a photo diode, a PI-controller for the AM process was tested successfully [8].

Within the EU founded project MEGaFiT [9], a novel multilayer control concept was developed for the AM process, incorporating a thermal camera, a colour sensor and a topography sensor. The linking of the measured data to the quality parameters is the major challenge of the adaptive control concept. The process data can be

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http://dx.doi.org/10.1016/j.cirpj.2017.05.002
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applied within different model types and a machine learning strategy [10]. To be able to implement also complex control approaches with a number of input parameters in the AM process, a combination of intelligent self-learning methods from the field of artificial intelligence and fast process controller hardware were developed and tested.

Additive manufacturing setup

The pilot test system for the AM control is based on an SLM machine of the type EOS M250. Main components such as the laser beam source and the focus positioning system have been replaced. A Rofin 1 kW fibre laser is used for material processing. Its beam is focused and deflected by Scanlab components. To observe the behaviour of the melt pool, a colour sensor is integrated coaxially into the optical setup. Within the observed area of approximately 7 mm around the melt pool, the visible electromagnetic radiation is being detected. Besides a coating for the processing wavelength $\lambda_p = 1070$ nm, the scanner mirror possesses an additional coating for the sensor wavelengths around $\lambda_s = 880$ nm. A dichroic mirror deflects the visible content to the true colour RGB sensor. The RGB sensor of the type Sensor Instruments SPECTRO-3-FIO-ANA measures intensities within three pre-defined spectral regions, resulting in red, green and blue colour intensities. With a sampling frequency of up to 90 kHz and analogue outputs, the sensor is well suited for the high dynamic process with scan speeds in the order of 1000 mm/s. Furthermore, an in-process depth meter (IDM) based on low coherence interferometry is integrated into the optical path of the laser and an infrared (IR) camera is directed to the weld plume off-axis (Fig. 1).

Control strategy

The additive manufacturing process is divided into three control levels, which are arranged in three cascades (Fig. 2). The inner cascade 1 provides a real-time control loop of the laser power based on the melt pool properties. For that task, metamodels are used to optimise the control behaviour of a conventional single-input controller. Metamodels combine the advantages of large simulation-based models with multiple input parameters (e.g. finite element models) and simplified conventional control structures such as proportional-integral-derivative (PID) controllers. The input provided to this melt pool control consists of sensor data, a set-point value for each desired melt pool property and an estimation of the appropriate laser power that needs to be applied. The considered sensor types are assumed to deliver information on the characteristics of the melt pool. The RGB signal is expected to correlate to the melt pool size and temperature. Distances can be measured with the IDM sensor, which might reveal accidental transitions to the deep penetration welding mode [11].

The size of the melt pool, that results from an exposure, depends on the heat transfer from the laser spot to surrounding material and thus on the designed geometry of the work piece. While state-of-the-art AM technology typically distinguishes only between a few types of regions in a layer to be exposed, such as contour and core regions, a new method of geometry characterisation is introduced. Based on the geometry of the digital part model, an index will be generated for each scan vector during the data pre-processing that correlates with the expected local heat conduction. This proximity index is used as additional input of the cascade 1 controller.

The intermediate in-situ control cascade 2 determines the order of exposure during a single layer material processing. Depending on the temperature distribution captured with the thermography camera, a certain strategy is to be developed that aims at reduced temperature gradients. Temperature gradients within the production process cause residual stresses and deformations of the parts that eventually may lead to defects such as cracks and damages to the coating unit.

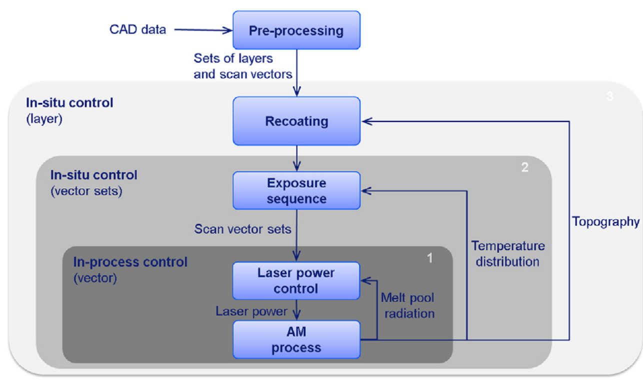

Fig. 2. Control cascades of the additive manufacturing process.

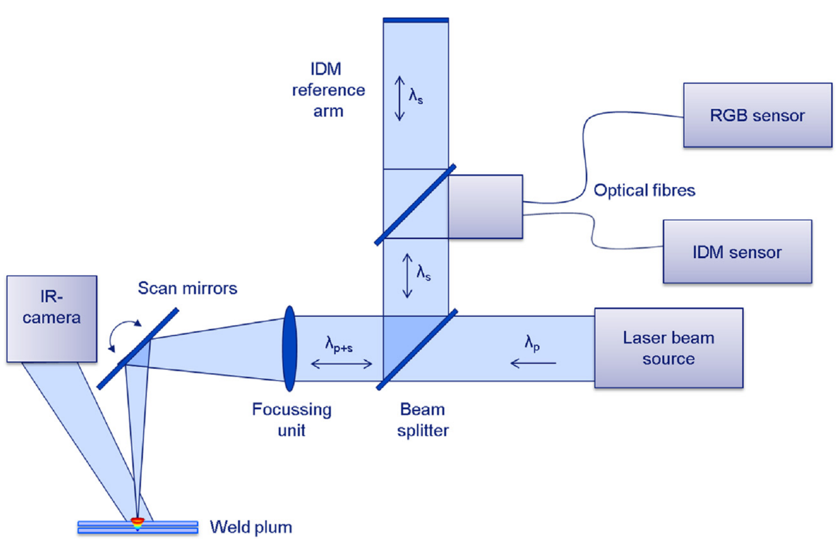

Fig. 1. Integration of the sensors into the optical setup of the AM pilot machine (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.).