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In situ and real-time monitoring of powder-bed AM by combining acoustic emission and machine learning

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Abstract

Until recently, additive manufacturing quality control has been diligently based on temperature measurements of the process zone or layer-by-layer high resolution imaging. For this, various sensors such as pyrometers, photo-diodes and matrix CCD detectors were involved. However, temperature measurements do not provide information about the heat transfer in depth thus reducing the reliability of this method. High resolution imaging controls the quality *post factum*, after a layer or even an entire part is already manufactured. No methods are known so far to monitor the quality of additive manufacturing *in situ* and in real-time with high confidence. Our approach is to monitor the quality of the additive manufacturing process *in situ* and in real-time by means of acoustic emission, detected by fiber optical sensors.
It is shown that the melting and sintering process have a number of unique acoustic signatures that can be detected and interpreted in terms of quality. The combination of such acoustic signatures is related to heat distribution and process dynamics inside the processing zone. The interpretation of AE in terms of process quality is made by machine learning. This includes the extraction and recognition of unique acoustic signatures from the different sintering or melting events and further classification of those.
The processing parameters for selective laser melting of a 316L stainless steel were tuned to create a cube with separate sections of three quality levels. The corresponding AE data was acquired; the acoustic features were extracted and classified according to the different qualities. The confidence level achieved in the classification was as high as 83-89% showing that this methodology has a big potential for *in situ* and real-time monitoring in additive manufacturing process. The technical realization of the methodology presented is flexible and it can be easily integrated in any existing commercial additive manufacturing machine (as a hardware and/or software) as an additional module.

Keywords: Additive manufacturing; quality control; acoustic emission; fibre optical sensors; machine learning;

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1. Introduction

In recent years, additive manufacturing (AM) has attracted considerable attention from the engineering and scientific communities and it is seen by many as the next industrial revolution (Zhai et al., 2014). The main reasons are twofold. First, the geometrical limitations met in the traditional subtractive and formative methods are overcome (Khairallah et al., 2016). Second, it has outstanding economic benefits (Guessasma et al., 2015; Moylan et al., 2014). These are also valid for Selective Laser Melting (SLM) (Frazier, 2014). SLM is a powder-bed AM technology that builds 3D components, layer by layer, from an alloy powder. This technology has been often used for fast prototyping of complex shapes components with good mechanical properties (Frazier, 2014).

Despite the significant progress in the AM machines, process and materials, there is a consensus among scientists and industries that there is a lack in the quality repeatability in mass production (Everton et al., 2016; Gu et al., 2016; Guo and Leu; 2013; Tapia and Elwany, 2014). This is due to the high sensitivity of the AM process to multiple unrelated factors, such as laser parameters, laser optics, mechanical and local optical material properties, particles configuration of the powder in the melt zone, etc. (King et al., 2016; Tammas-Williams et al., 2015; Shifeng at al., 2014) .

Today, the standard in industries for controlling the quality of AM produced workpieces in terms of porosity or cracking is X-ray tomography (Thompson et al., 2016). Such controls are made *post mortem*, after the machine time and materials have been already spent. This method is recognized as being very onerous and time-consuming. Attempts to incorporate quasi real-time visual quality control exist in the literature (Everton et al., 2016; Sharratt, 2015) but few of those are rarely implemented in real industrial machines (Everton et al., 2016). Two main approaches are mostly reported and they are: i) high resolution cameras and ii) temperature measurements in the melt zone (Everton et al., 2016). The major drawbacks of these techniques are that they are limited to surface measurements while no information is accessible in depth.

This contribution attempts to address the problem of *in situ* and real-time monitoring of SLM by combining acoustic emission (AE) and machine learning (ML). AE is known for decades to be very efficient, highly sensitive, cost effective and non-destructive method for tracking crack and/or defect initiation and propagation in non-transparent environments. The main obstacles of using AE technics in AM process is in the weak signals with a strong noise background. To operate under these conditions, highly sensitive AE sensors based on optical fibres were involved in this work. The simultaneous use of ML allows extracting the informative AE patterns even in presence of strong stationary noises. This approach has been already successfully applied to a number of applications, including tribology (Saeidi et al. 2016; Shevchik et al., 2016) and fracture mechanics (Shevchik et al., 2017a).

In this work, the investigations were carried out on a real SLM process using a stainless steel powder. The AE signals were recorded using a fibre Bragg grating (FBG). The classification was performed using spectral convolutional neural networks (SCNN).

2. Experimental setup

Although the approach presented in this work can be easily extended to many AM processes, the focus was kept on the selective laser melting (SLM) process. Hence, the experiments were carried out using an industrial commercially available Concept M2 machine (Concept Laser GmbH, Germany) with a fiber laser operating in a continuous mode at a wavelength of 1071 nm, the focused laser spot diameter was 90 µm and the beam quality was $M^2 = 1.02$.

The powder material was a CL20ES stainless steel (1.4404 / 316L) with a particle size distribution ranging from 10 to 45 µm.

The geometry of the experimental specimen was a cube with dimensions 10x10x20 mm^3. The sample was produced in a N_2 atmosphere so that the O_2 content stayed below 1 % during the entire process. Most of the process parameters were kept constant so that the laser power *P* was set to 125 W, the hatching distance *h* was 0.105 mm and the layer thickness *t* was 0.03 mm. Three levels of quality were produced which were characterized by different pores concentrations. They were obtained by varying the laser scanning velocity. Each velocity was chosen to achieve a specific light input providing a known concentration of pores. The energy was calculated based on the work of Thijs et al. (2010). The laser scanning velocities, their corresponding energy densities, quality levels and pores concentrations are given in Table 1. Figure 1 shows typical pictures of pores/defects taken by light microscope for the three quality levels.

The poor quality with the highest pores concentration was achieved with the highest scanning velocity. The cause of pores is the lack of energy input to sinter all particles within the laser beam. The pores in medium quality are caused by material overheating due to the lowest velocity of the laser scan and consequently a higher energy dose input locally. The highest quality is intermediate in terms of scanning velocity that provides, on the one hand, enough energy to sinter all particles inside the laser beam but, on the other hand, avoids material overheating. More details on these mechanisms can be found in (Bland and Aboulkhair, 2014).

Table 1. Process parameters: laser scanning velocity, their corresponding energy density and quality level in terms of pores

Quality level	Pores concentration [%]	Laser scanning velocity (mm/s)	Energy density (J/mm^3)
High quality	0.07 ± 0.02 %	500	79
Medium quality	0.3 ± 0.18 %	300	132
Poor quality	1.42 ± 0.85 %	800	50

Fig. 1. Representative microstructures with pores for the quality levels: (a) poor quality; (b) medium quality and (c) high quality

In this work, the AE of the entire SLM process was recorded with a FBG. This sensor was selected due to its high sensitivity and high time resolution. The FBG was simply placed inside the machine chamber, at a distance of 20 cm from the process zone. More details about FBGs can be found in (Kashyap, 2010; Ramakrishnan et al., 2016). The reflected signal was additional digitized using a high speed photo-diode, connected to data acquisition unit and data recording software. Both were from Vallen (Vallen Gmbh., Germany). All signals were digitized with a sampling rate of 1 MHz.

3. Data processing

3.1. Features extraction

In this contribution, the relative energies of the narrow frequency bands were taken as the input features for the spectral convolutional neural networks (SCNN) classifier. The frequency bands were extracted using a standard wavelet packet transform (WPT) (Tazebay and Akansu, 1995). The WPT is an extension of the traditional wavelet transform that can be represented as a pass of the signal f through a set of filters (Tazebay and Akansu, 1995).

The application of set of filters results in the extraction of low and high frequency bands of the digitized signal f, where each frequency band is localized in both, time and frequency domains. The result of WPT is a sparse signal representation with a wavelet spectrogram.

Several wavelet families of Daubechies (1992), Symlets and Coiflets were investigated with regards to their applicably to the acquired AE data. The best choice was provided by the Daubechies wavelet (1992) with ten vanishing moments. It showed the minimum approximation errors on the given AE signals and so was used for analysis.

3.2. Spectral convolutional neural networks (SCNN)

SCNN are an extension of traditional convolutional neural networks that inherits all advantages of the latter, and they are capable to process data of a more complex configuration as compared to traditional convolutional networks. Such advantages are achieved using irregular convolutional operations on given datasets. The irregularity of the given data in the SCNN is captured using graphs. This extern tool guides the network during a training procedure to optimize its structure. As a result, it gives the possibility to process strongly irregular data where the application of traditional convolutional neural networks fails completely. Several methods of the SCNN are reported in literature and, in our contribution, a spectral approach developed by Mathieu et al. (2014) was used.

The experiments in the training and testing of the SCNN were carried out in Microsoft Visual Studio C# environment, for which the original code was designed. The computer used was a single CPU one with i5 processor.

All details on the methods used can be found in (Shevchik et al., 2017b) and more details on the SCNN through FFT can be found in Mathieu et al. (2014).

4. Results and discussion

The collected AE signals were divided into three categories according to the manufacturing quality of the workpiece layers described in Table 1 and shown in Fig. 1. A number of patterns were collected from the recorded signals to form two datasets; one for training and one for the test. Each category (that corresponded to poor, medium and high quality) in each dataset was equally represented by 300 patterns and no common data existed between both datasets. This approach simulated real-life conditions where the trained system has to operate with the new input data. Then, these extracted features were fed to the SCNN classifier.

The SCNN for classification counted four convolutional layers that alternated with four pooling. The layers number was experimentally estimated as the best compromise between the computational complexity and performance efficiency (Shevchik et al., 2017b).

The classification results from the SCNN are shown in Table 2. In this table, the ground truths are given in columns whereas the results of the classification are given in rows. The accuracy is calculated from the number of the true positives divided by the total number of the tests for the individual categories. These values are given in the diagonal cells of the table (grey cells).

The total accuracies achieved using the aforementioned method ranges from 83 and 89%. These results clearly show the potential of the proposed approach, in particular when taking into account that it is only the first feasibility study. In other words, we can conclude that the acoustic signal recorded by an FBG and its processing with the SCNN has high potential to be a solution for *in situ* and real-time quality monitoring in AM.

Analysis of the classification errors can be performed by considering the non-diagonal elements in Table 2 (the rows). For example, the AE test data from the poor quality was classified with an accuracy rate of 89% and so it has the lowest error rate. The classification error is the highest (7%) for the medium quality and the lowest (4%) for the highest quality. The situation is completely invers for the high quality even though the classification errors for the medium and poor qualities are almost identical.

It is interesting to note in Table 2 that for the medium quality, the classifications errors decrease as the differences in the laser scanning speed increase. For the high quality, despite having almost identical classification errors, this still holds true. However, this is not true for the poor quality (800 mm/s) where the classification errors are the highest (7%) with the medium quality (300 mm/s) and lowest (4%) with the high quality (500 mm/s). Hence, we can conclude that the laser scanning velocity does not have an impact on the self-extraction of the distinct features in the SCNN.

When considering the porosity level, it is obvious from Table 2 that the classifications errors decrease as the differences in porosity increase. This was expected since our approach was based on the fact the defects, and in particularly, the amount of defects, in this case porosity, has an impact on the self-extraction of the distinct features in the SCNN.

Table 2. Classification tests accuracy for the SCNN

Ground truth / Test category	High quality	Medium quality	Poor quality
High quality (0.07 ± 0.02 %, 500 mm/s, 79 J/mm^3)	83	9	8
Medium quality (0.3 ± 0.18 %, 300 mm/s, 132 J/mm^3)	12	85	5
Poor quality (1.42 ± 0.85 %, 800 mm/s, 50 J/mm^3)	4	7	89

5. Conclusions

This contribution investigated the feasibility of a very innovative approach which combines acoustic emission (AE) with machine learning (ML) for *in situ* and real-time monitoring of additive manufacturing (AM) processes. For this feasibility study, an industrial commercially available Concept M2 equipped with a fiber laser (1071 nm) operating in continuous mode was used. The acoustic sensor selected was a fiber Bragg grating (FBG) due to its high sensitivity and it was installed directly inside the process chamber, 20 cm away from the processed zone. The material was a CL20ES stainless steel (1.4404 / 316L) with a particle size distribution ranging from 10 to 45 µm.

A cube with dimensions 10x10x20 mm^3 was produced in a N_2 atmosphere. During the experiment, the laser power P was 125 W, the hatching distance h was 0.105 mm and the layer thickness t was 0.03 mm were kept constant.

Three laser scanning velocities were selected to give three levels of quality levels in terms of porosity. The porosity concentrations were 0.07 ± 0.02 % (high quality; 500 mm/s; 79 J/mm^3), 0.3 ± 0.18 % (medium quality; 300 mm/s; 132 J/mm^3), and 1.42 ± 0.85 % (poor quality; 800 mm/s; 50 J/mm^3). The recorded AE signals were grouped accordingly.

A spectral convolutional neural networks (SCNN) was trained and tested on two different datasets. The Daubechies wavelet with ten vanishing moments was used to decompose all signals and the energies of the narrow frequency bands were taken as acoustic features.

The classification accuracy was in the range of 83-89%. These results show that there are distinct AE features for each manufacturing quality. The extracted features can be differentiated with machine learning technique. Taking into account that it is only the first feasibility study, the classification results can be considered as very promising and this demonstrated that our very innovative approach, which combines acoustic emission and machine learning, has high potential to be used for *in situ* and real-time monitoring of AM process.

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