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Acoustic emission for *in situ* quality monitoring in additive manufacturing using spectral convolutional neural networks

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Graphical Abstract

Highlights

- An *In situ* quality monitoring for AM is presented
- Our approach combines acoustic emission with machine learning
- Fiber Bragg grating is used as acoustic sensors
- spectral convolutional neural networks is used for classification in terms of quality level
- The classification accuracy of the events ranged between 83 – 89%.

Abstract:

Additive manufacturing, also known as 3D printing, is a new technology that obliterates the geometrical limits of the produced workpieces and promises low running costs as compared to traditional manufacturing methods. Although it has high expectations in industry, the absence of

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a proper *in situ* quality monitoring and control prohibits the penetration of this technology into an extensive practice. This work investigates the feasibility of using acoustic emission for *in situ* quality monitoring and combines a sensitive acoustic emission sensor with machine learning. The acoustic signals were recorded using a fiber Bragg grating sensor during the powder-bed additive manufacturing process using a commercially available selective laser melting machine. The process parameters were intentionally tuned to invoke different concentration of pores inside the workpiece medium. According to this, poor, medium and high qualities were defined and were characterized by pore concentrations of 1.42 ± 0.85 , 0.3 ± 0.18 and $0.07 \pm 0.02\%$, respectively. The collected acoustic signals were grouped accordingly and divided into two separate datasets; one for the training and one for the testing. The acoustic features were extracted from all the signals as the relative energies of the narrow frequency bands of the wavelet packet transform. The classifier, based on spectral convolutional neural network, was trained to differentiate the acoustic features of dissimilar quality. The confidence in classifications varies between 83 and 89%. Considering these are the first experiments with no optimization, the results can be considered as promising and they showed the feasibility of the *in situ* quality monitoring using acoustic emission with the sub-layer spatial resolution.

Keywords: *in situ* quality control; acoustic emission; spectral neural networks; wavelet transform; additive manufacturing; fiber Bragg gratings

1) Introduction

Selective laser melting (SLM) is a powder-bed AM technology which allows building intricate components from an alloy powder with complex 3D geometries layer by layer. Other terms that describe the same technology are Laser Cusing, Direct Metal Laser Melting, or Laser Metal Fusing. The technology has been successfully applied for fast prototyping of unique workpieces with highly complicated geometries that are impossible to produce using traditional forming methods [1]. It has also clear advantages in small series and individualized products for medical- [2,3,4], turbine- [5,6], aerospace- and space- [7,8], robotics [9], automotive and machine tool industries [10].

Even though a lot of progress has been made on behalf of the machine manufacturers to improve the process efficiency, the number of materials that can be reliably processed is currently still very limited (e.g. austenitic stainless steel, eutectic Al-Si alloys). This is the result of the extremely complex physical phenomena during the SLM process. It implies a very rapid consolidation of the

base material powder in a small material volume ($\sim 0.001 \text{ mm}^3$) using a focused laser followed by cyclic heating and cooling at high rates (10^3 - 10^7 K/s) [11]. The processing parameters such as laser energy, laser scanning velocity, hatch distance, powder layer thickness, scanning strategy, etc. have to be carefully adjusted to the alloy of interest. An improper set of parameters can lead to pronounced porosity, cracking and/or accumulation of residual stress inside the workpiece [12], resulting finally in poor mechanical properties [13,14]. The process repeatability is thus still limited, preventing the technology from being used in a much wider range. A possible solution to overcome this situation is the development of *in-situ* and real-time monitoring of the workpiece quality and to better control the machine operation [12, 15].

At present, the industrial standard for monitoring the workpiece quality with regard to porosity or cracking is X-ray tomography [16]. The tests are carried out *post mortem*, when the machine time and materials are already spent. This method is also known for being very expensive and time-consuming. Consequently, online control is of great demands and several approaches are seen to solve this problem. Temperature measurements of the processed zone with 1D or 2D pyrometers are used in multiple works [12,17,18]. The main objective is to keep the temperature parameters within a certain range that guarantees the mechanical properties of the workpiece to stay in an acceptable range. This approach uses built-in models for data analysis and provides a high spatial resolution quality control. Unfortunately, in real-life conditions, the multiple non-uniformities of the laser-matter interactions are responsible for a divergence between the models and the real-life situation resulting in performance inaccuracies. Image processing is another approach that is already introduced in a number of the available AM machines [12,19,20]. The quality monitoring is carried out with the visual inspection of each layer and an image processing routine searches for the defects. The technical realization of such system is performed using matrix photodetectors in the visible spectral range. Again, one major weakness of this system is that the quality is

monitored after an entire layer is produced. Besides, this method has certain limitations with regards to the spatial resolution and requires expensive optical systems to detect small defects.

The present study focuses on an alternative approach, in which acoustic emission (AE) is taken for *in situ* quality monitoring of the AM process. The attractiveness of AE as compared to other methods results from the high sensitivity of existing AE sensors and the relatively cheap hardware. The processing is fast in the case of AE as it is a 1D sequence as compared to imaging (2D data) or tomography (3D data). Finally, AE sensors provide a high temporal resolution allowing to precisely localizing the defects. The applicability of AE to detect defects during AM was already shown by Wu *et al.* [21] for polymer materials, although no *in situ* and real-time monitoring was proposed. At present, Fiber Bragg gratings (FBG) are often used for detecting AE signals because of its high sensitivity in a wide acoustic spectral range [22]. The combination of high sensitive AE sensors and machine learning (ML) has been already successfully applied to a number of applications. It includes the fields of tribology [23,24] and fracture mechanics [25]. All these fields have in common the complexity in the acquired data structure and noisy environments. Thus, it makes this combination promising for AM, as well.

In the recent years, convolution neural networks (CNN) has become a popular technique for acoustic tasks [26] showing high efficiency and possibilities to suppress the stationary noises. Nevertheless, conventional CNNs have certain limits when analyzing non-regular data. Spectral convolutional neural networks (SCNN) are a recent extent of conventional CNN with improved efficiency in classification/regression tasks [27,28,29]. This is achieved due to the combination of advantages of deep learning, derived from the conventional CNNs, with the spectral signal processing theory [27]. In the latter case, the local spatial structure of the input data is described by a weighted graph G . The learning of the local irregularities in the SCNN is carried out using the convolution operator, which is realized by applying G upon the input signals f . In conventional CNN, the spatial convolution using regular kernels fails when operating on the same type of data

[27,28,29]. Currently, the SCNN methods are mainly reported for images processing [27,28,29]. However, the representation of acoustic signals in the time-frequency domains using wavelets allows applying already developed 2D data processing that makes the SCNN a ready “on-shelf” solution for acoustic analysis.

The modelling of the data irregularities in the SCNN is possible using the spatial and spectral approaches and both exhibit the same classification efficiency [30]. The spectral approach was chosen in this work as the spatial one does not provide the ordering [30], which is a valuable information for the localization of the individual defects in the future. More information about the SCNN can be found in the two comprehensive reviews [30,31].

In this study, the AE signals were collected during the SLM process of a stainless steel using a fiber Bragg grating. The classification was tested using both, conventional CNNs and SCNNs. The advantages of the latter applicably to SLM are also discussed.

2) Experimental setup and acoustic datasets

2.1) Data acquisition setup

The SLM process of a CL20ES stainless steel (1.4404 / 316L) powder (particle size: 10 - 45 μm) was performed on an industrial machine Concept M2 (Concept Laser GmbH, Germany). The machine is equipped with a fiber laser operating in continuous mode at a wavelength of 1071 nm with a beam quality $M^2 = 1.02$ and a spot size of 90 μm . The Concept M2 was additionally equipped with one fiber Bragg grating (FBG) sensor to detect the airborne AE, generated during the consolidation process.

The FBG sensor is an interferometric structure, imprinted inside the core of the optical fiber with unique spectral characteristics of reflectivity. The acoustic waves created during the AM process result in periodical extensions/compressions of the optical fiber core and, consequently, the FBG

structure. These momentary deformations affect the reflectivity properties of the FBG that follow the behavior of the upcoming pressure waves. The high sensitivity and time resolution of those sensors make them very versatile for acoustic applications and were therefore chosen in this work. More details about FBGs can be found in [32,33].

The FBG was placed inside the process chamber at a distance of 20 cm away from the processed zone. This simple setup was selected in order to demonstrate the basic feasibility of using AE signals for *in situ* process monitoring under realistic manufacturing conditions and without modifying the conception of the machine. The FBG sensor was pre-strained in a special plastic holder and installed on the lateral wall inside the working chamber of the machine as shown in Fig. 1,a. Its connection to the read out system was provided via an optical feedthrough mounted on a plate that hermetically closed the working chamber. The employed FBG sensor possessed a 50% reflectivity at 1547 nm wavelength with a reflectivity band of ± 1 nm. The read out system included a tunable laser source with an output light power of 4 mW and a band of single mode of ± 0.05 nm (Yenista Inc., USA). The FBG read out was carried out by pumping the fiber with a continuous narrow band irradiation at a wavelength of 1546.8 nm and the reflected signals were digitized by a high speed photodiode. The general scheme of the FBG system is shown in Fig.1,b. The received signals were recorded through an acoustic data acquisition system connected to a personal computer with a dedicated software from Vallen (Vallen GmbH., Germany). The sampling rate of the originally digitized signals was set to 10 MHz. However, to fit the dynamic range and reduce the computational load further, those signals were down-sampled to 1 MHz. The data acquisition system was synchronized with the laser of the Concept M2 machine, providing a precise registration of the AE signals from each manufactured layer. This procedure allowed neglecting the noises from the intermediate manufacturing processes such as the deposition of a new layer of powder by the moving blade. Simultaneously, several recordings were made with a higher resolution at a sampling rate of 1 GHz using an oscilloscope Lecroy

HDO4104 (Teledyne Lecroy, USA). Those signals were used to evaluate the existence of changes in the AE content and noise parameters but they were not included into the training and tests data sets.

Figure 1: a) (left) view of the FBG location inside the AM chamber with the optical feedthrough on the chamber panel and (right) the FBG read out system and (b) scheme of the FBG read out system.

2.2) Data collection and quality categorization

The acoustic data collection was carried out throughout the manufacturing process of the entire workpiece. Its geometry was defined by a 10x10x20 mm³ cuboid. The processing parameters were adapted to create a workpiece consisting of sections with various quality levels. The parameters of the laser power P , the hatch distance h and the powder layer thickness t were kept constant at 125 W, 0.105 mm and 0.03 mm, respectively. Three scanning speeds v were used to create insufficient bonding at low energy density (50 J/mm³, 800 mm/s), optimal process condition at medium energy density (79 J/mm³, 500 mm/s) and increased porosity at high energy input (132 J/mm³, 300 mm/s). The energy density was determined according to Eq. (1) [34]:

$$E = \frac{P}{v \cdot h \cdot t} \quad (1)$$

A meander scanning strategy oriented parallel to the part edges was used. Every layer was scanned in a 5x5 mm chessboard pattern with a 1x1 mm shift between the subsequent layers. The experiment was performed in a N₂ atmosphere with an O₂ content controlled to be below 1 % throughout the process.

The produced workpiece is shown in Fig.2,a. The different laser regimes can be observed as the differences in color are related to the energy input and ultimately to the porosity concentrations. The local porosity was controlled and confirmed by visual inspection of the workpiece cross-sections and the images from the light microscopy investigations are presented in Fig. 2,b-d. They were obtained with a Zeiss Axioinvert 100 microscope at a magnification of 20x on polished cross-sections in the x-z plane (with z being the build direction) using image thresholding and area determination with Fiji (ZITAT FIJI) [35]. Fig. 2,b-d are representative cross-section images obtained from the regions processed with different scanning speeds. The largest energy input (132 J/mm³) leads to tubular defects with a diameter of around 30 µm (Fig. 2,b). With a decreased energy input to 79 J/mm³, these defects disappear and small lack-of-fusion and remaining gas porosity defects are observed (Fig. 2,c). At the lowest energy input (50 J/mm³), the lack-of-fusion becomes the predominant defect type in the form of large cavernous voids ranging in size from 10 to 100 µm (Fig. 2,d). The optically measured porosities were 1.42 ± 0.85 % (poor quality, 50 J/mm³, 800 mm/s), 0.07 ± 0.02 % (high quality, 79 J/mm³, 500 mm/s), and 0.3 ± 0.18 % (medium quality, 132 J/mm³, 300 mm/s). From the presented cases, the intermediate energy input of 79 J/mm³ (500 mm/s) creates the lowest porosity and smallest amount and size of defects. The lowest energy input (50 J/mm³, 800 mm/s) leads to defects associated with insufficient bonding, whereas the highest energy input 132 J/mm³, 300 mm/s) creates porosity typically associated with the formation of deep keyhole channels.

To summarize, the changes in the laser scanning regimes affected the shape and size of the defects. The selected laser scanning speeds were chosen to recreate specific and undesirable defects during an industrial AM manufacturing process.

Figure 2. a) SLM test workpiece produced with three energy densities where 50 J/mm³ are bright regions, 79 J/mm³ are dark regions and 132 J/mm³ are blueish regions; b) – d) Typical light microscope cross-section images of the regions produced with a) 132 J/mm³, b) 79 J/mm³ and c) 50 J/mm³. The insets show typical defects observed such as a) tubular, b) small lack-of-fusion and c) large lack-of-fusion defects. The z- and y-directions correspond to a)

3) Data processing

3.1) Features extraction

In the present work, the relative energies of the narrow frequency bands were taken as the input features for the SCNN classifier. The frequency bands were extracted using a standard wavelet packet transform (WPT) [36]. The WPT is an extension of the traditional wavelet transform that can be represented as a pass of the signal f through the set of filters [36]:

$$\varphi_j(n) = \sum_n h_0(k) \sqrt{M} \varphi(Mn - k), \quad k \in Z \quad (2)$$

$$\psi_{ji}(n) = \sum_n h_{m-1}(k) \sqrt{M} \psi(Mn - k), \quad k \in Z \quad (3)$$

where h_o is a low pass and h_m a high pass filters, $\varphi()$ and $\psi()$ are the scale and wavelet functions, respectively, j is a scale, and n is the current sampling point of the digitized signal f . The parameter m is the total number of filter channels and in traditional WPT $m = 2$, while the maximum number of scales, in this case, is equal to $\log_2 m$. The application of Eqs. (2) and (3) result in the extraction of low and high frequency bands of the digitized signal f , where each frequency band is represented by the coefficients d and is localized in both, time and frequency domains. The multiscale analysis using WPT is carried out by applying Eqs. (2) and (3) at different scales j to both, the low and high frequency bands, extracted at the previous scale $j-1$. The energies of the narrow frequency bands were employed and computed as:

$$E_{j,m} = \int |d_{j,m}(t)|^2 dt = \sum_k |d_{j,m}|^2 \quad (4)$$

Following Eq. (4), the relative energies are a normalized version of the sub-band energies so that Eq. (4) becomes:

$$\rho_{norm\ j,m} = \frac{E_{j,m}}{E_j} \quad (5)$$

where $E_j = \sum_{k=0}^{M^j} |E_{j,m}|^2$ is the total energy accumulated in all frequency bands at all scales. The result of Eqs (2) - (5) is a sparse wavelet spectrogram. An example is presented in Fig. 3, where Fig. 3,a is a collected signal and Fig. 3,b the corresponding spectrogram, built from the relative energies. Such spectrograms were the input for the SCNN and the details are discussed in Section 3.2. Several wavelet families of Daubechies, Symlets and Coiflets were investigated with regards to their applicability to the acquired AE data. The best choice was provided by the Daubechies wavelet with ten vanishing moments. It showed the minimum approximation errors on the given AE signals and so we used it for features extraction.

Figure 3: a) An example of a fragment of an AE signal that corresponds to a high quality layer produced with the optimal process condition that is with an energy density (79 J/mm^3 , 500 mm/s) and b) a spectrogram corresponding to the relative energies of the narrow frequency bands, localized in time-frequency domain. The red marker in a) shows the running window (RW).

The analysis of the acquired AE signals was performed using a running window (RW) that scan the signal and this is schematically marked by a red box in Fig.3,a. The choice of the time span for the RW is a compromise between the spatial resolution in the defects detection and the classification accuracy. On the one hand, a short running window increases the spatial resolution in the detection of possible defect areas within each layer. On the other hand, very short time spans are more affected by noises and thus decreasing the classification efficiency. Several time spans for RW were investigated and the corresponding details are discussed in the results and discussion section.

3.2) Spectral convolutional neural networks (SCNN)

In the SCNN, the convolution operation is carried out on a graph and, as already mentioned, we used the spectral approach developed by Mathieu *et al.* [27]. This approach investigates the data structure with the Laplacian L of the graph G . The weighted graph G for the set of elements $E = \{e_i, i = 1, \dots, n\}$ is defined as $G = \{E, W\}$, where $W = \{w_{ij}, i, j = 1, \dots, n\}$ is a symmetric, positively defined matrix, in which each element w_{ij} characterizes the similarities between a pair of elements $\{e_i, e_j\}$.

In the present work, the similarity was computed using a heat kernel: $w_{ij} = \exp\{\|e_i - e_j\|^2/t\}$ [30]. The un-normalized Laplacian of G was employed and defined as $L = D - W$, whereas the

elements of the diagonal matrix $D = \{d_{ii}\}$ are the sums of the raw elements of W : $d_{ii} = \sum_k w_{iy}$, $y, i = 1, \dots, n$. In the SCNN, the features from the input dataset are considered as elements collection E and the Laplacian graph can be computed for the entire input space as described above. In our setup, the dimensionality of the input space n in E is defined by the number of the narrow frequency bands, extracted as described in Section 3.1. The frequency domain for E is defined by a singular value decomposition of L , the product of which is a matrix U that includes a set of eigenvectors [37]. For this case, the direct Fourier transform for G is defined as: $E^{fft} = UE$, while its invers is $E = U^T E^{fft}$ [37]. The product of the convolution operation in the SCNN is a set of feature maps, which are computed using the Fourier Fast Transform (FFT) representation of the input dataset E^{fft} as $C = U E^{fft} k$, where k are the spectral multipliers [27]. The spectral multipliers in the SCNN are analogues to the weights in the kernel receptive fields in the conventional CNNs that provide the spatial localization of the elements E in the spectral domain. The training of the SCNNs aims to tune the multipliers k to fit the output response of the SCNN to a target function. To do so, the gradients for the back propagation for a given set E are defined by: $\Delta E = U U^T \Delta C k$, and the gradients for the updated spectral coefficients k are defined as: $\Delta k = U^T \Delta C U E$ [27,38].

The architecture of the SCNN is inherent from the one of the conventional CNNs that combines the convolution layers with the pooling ones. As mentioned before, the product of the data pass through the spectral convolution layer is a set of features maps. The following pooling layer aggregates the information resulting in the sparse representation of the data from the input feature maps.

The set of the pooling and the convolution layers provide a self-feature extraction. The output of this structure is further forwarded to the fully connected layers, where the classification of the features takes place and the results are observed in the output layer. More details on the SCNN through FFT can be found in [27].

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.

4 Results and discussions

4.1) The collected datasets

The collected AE signals were divided into three categories according to the manufacturing quality of the workpiece layers described in Section 2.2 and shown in Fig. 2,a. A number of patterns, bounded by the RW, 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 RW between both datasets. This approach simulated real-life conditions where the trained system has to operate with the new input data. The features from all RW were extracted using the maximum possible number of scales (See Section 3.1 for the explanation of the maximum scale). Then, these features were fed to the SCNN classifier. The time span of RW was selected after an exhaustive search in which the classification accuracy of SCNN was evaluated after each retraining with RWs having different time spans. The goal was to find the shortest time span that did not affect the classification accuracy and this was reached at 160 ms. Any additional decrease of the RW time span significantly increased the classification errors. Each RW was decomposed by WPT at ten decomposition levels, resulting in the extraction of 2,046 narrow frequency bands with their corresponding values of the relative energies (See Section 3.1). Taking into consideration the laser scanning speed (See Section 2.1) and the time span of 160 ms for the RW, the spatial resolution for the defect detection can be estimated. The setup presented is able to provide a quality monitoring for each 4,4, 7,2 and 11,6% of the surface area of a layer, produced with 300

mm/s (132 J/mm³, medium quality), 500 mm/s (79 J/mm³, high quality) and 800 mm/s (50 J/mm³, poor quality), respectively.

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. A decrease of the number of the convolutional layers revealed a slight diminution of the classification accuracy. In contrast, an increase of the layers number did not affect the classification performance but raised the computational time during the SCNN training.

The non-regularities in the structure of the input acoustic features can be depicted by observing the collected features in the feature space [40]. In the present work, the coordinates of each feature are defined by the values of the relative energy of the frequency band (as described in section 3.1). In Fig. 4, the sparse dataset with thirty features of each quality category is shown and each point represents a position of the individual RW in the feature space. The dimensions of the feature space are reduced via the principle component analysis (PCA) projection [41] into a lower 3D dimensional space. The data irregularity can be observed as a mixture of the features from all categories.

The classification results from the SCNN and the conventional CNN (in brackets) are shown in Table 1. In this table, the test accuracies (in rows) versus ground truth (in columns) are given. The classification accuracies in the table are defined as the number of true positives divided by the total number of tests for each category. These values are given in the diagonal cells of the table (red cells). The classification errors are computed as the number of the true negatives divided by the total number of the tests for each category. These corresponding values are filled in non-diagonal row cells.

Figure 4: Projection of the acoustic features into a 3D feature space using principle component analysis (PCA). The visualized dataset includes thirty features from each quality level. In brackets the corresponding porosity concentration is given.

Test category \ Ground truth	Poor quality	Medium quality	High quality
Poor quality (1.42 ± 0.85 %, 800 mm/s)	89 (62)	7 (19)	4 (19)
Medium quality (0.3 ± 0.18 %, 300 mm/s)	5 (25)	85 (53)	12 (22)
High quality (0.07 ± 0.02 %, 500 mm/s)	8 (20)	9 (17)	83 (63)

Table 1: Classification tests accuracy for the SCNN. In brackets the results for conventional CNN are given.

Based on the results in Table 1, the classification confidence for the different quality regimes varies in the range of 83 – 89%. These results clearly show the potential of the proposed approach, in particular when taking into account that (a) the position of the FBG is by far not ideal, (b) the acoustic emission (AE) signals detected were airborne, and (c) the narrow range of porosity investigated. Hence, we can conclude that the acoustic signal recorded by the FBG and its processing with the SCNN could be a solution for *in situ* and real-time quality monitoring in AM.

The analysis of the errors structure can be evaluated from the non-diagonal elements in Table 1 (the rows). For example, the AE test data from the high quality was classified with an accuracy rate of 83% and so it has the highest error rate. The classification error is more or less equal between the medium and poor quality. In contrast, for the medium quality, the classification

error is the highest (12%) for the high quality and the lowest (5%) for the poor quality. The situation is completely invers for the poor quality.

It is important to remind here that the medium quality is made with the lowest speed (300 mm/s), followed by the high quality (500 mm/s) and finally the poor quality (800 mm/s).

Consequently, we notice that, for the medium and poor qualities, the error rates decrease as the differences in the laser scanning speed increase. Regarding the high quality, although the error rates between the two other quality levels are very close, it is found that the lowest error rate corresponds to the medium quality (9%, 300 mm/s), which has the smallest differences in the laser scanning speed with the high quality (500 mm/s). In the opposite, the poor quality, which has the largest difference in laser scanning speed with the high quality, has the lowest error rate (8%, 800 mm/s). Hence, we can conclude that the laser scanning velocity has an impact on the self-extraction of the distinct features in the SCNN. For this reason, the AE signals may include acoustic elements that are peculiar to the other two neighbored categories. The evaluation of the mutual classification errors between medium and poor quality discovers the minimum overlap probably due to the significant difference in the laser scanning speed, thus initiating different sintering scenarios in both cases.

The results for conventional CNN are shown in brackets in Table 1. The classification accuracies observed are much lower than for SCNN confirming the efficiency of the non-regular convolution in this particular application.

Although the feasibility of the proposed approach has been demonstrated, it has some inherited privations as compared to the other monitoring methods described in the introduction. One problem is in the relatively weak acoustic emission signatures from the additive manufacturing process which is mixed with the strong noisy background. It was known that the high frequency of the corresponding acoustic content is rather difficult to detect in gas environment, putting the

physical limits on the method. However, the authors decided to use airborne AE detection in order to determine the limits of the high sensible FBG as SE sensor. Nevertheless, this difficulty can be solved by taking three actions. First, we could employ more sensitive acoustic sensors with a selective filtering on the hardware level. Second, we could modify the Concept M2 machine to have a physical contact between the FBG and the processed zone. Finally, two possible improvements are visible for the signal processing part. To start with, the involvement of deep SCNN with a greater number of layers gives additional advantages that were not exploited in the present study. The representation of data through graphs allows realizing multiple mathematical operators, including wavelet and Fourier that can be additionally involved for noise reduction within the SCNN structure. Additionally, the multiscale analysis of the input acoustic emission data can give some benefits in detection of smaller size defects. All these actions are the objectives for further developments of an efficient and cost effective *in situ* and real-time quality control monitoring for additive manufacturing.

5 CONCLUSIONS AND FUTURE WORK

This work presents the results of a feasibility study for *in situ* and real-time quality monitoring using acoustic emission (AE) and machine learning (ML). A fiber Bragg grating (FBG) sensor provided a high sensitivity in signal detection and was mounted directly inside the process chamber, 20 cm away from the processed zone. The airborne acoustic emission (AE) signals were detected and further grouped in terms of AM manufacturing quality. 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. A spectral convolutional neural network (SCNN) was involved to classify the features from different additive manufacturing quality.

The classification accuracies using SCNN are as high as 83, 85 and 89% for high, medium and poor quality, respectively. It was found that the lowest classification confidence is in recognizing the

high quality. This is certainly due to the fact that the process parameter for this category is in between with the two others providing the overlap of the features. The use of SCNN showed higher classification accuracy as compared to conventional CNN.

Finally, at present, additive manufacturing processes incorporate several independently developing techniques, such as stereo-lithography, laser sintering, multi-jet printing, powder-bed fusion and others. All those methods propose different technical solutions for AM realization, however, exploiting the same physical principles. This promises the applicability of our approach, although it was tested only on powder-bed SLM. The possible transfer of the results presented to other technologies is the subject of the future investigations.

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Captions of the figures:

Figure 1: a) (left) view of the FBG location inside the AM chamber with the optical feedthrough on the chamber panel and (right) the FBG read out system and (b) scheme of the FBG read out system.

Figure 2. a) SLM test workpiece produced with three energy densities where 50 J/mm³ are bright regions, 79 J/mm³ are dark regions and 132 J/mm³ are blueish regions; b) – d) Typical light microscope cross-section images of the regions produced with a) 132 J/mm³, b) 79 J/mm³ and c) 50 J/mm³. The insets show typical defects observed such as a) tubular, b) small lack-of-fusion and c) large lack-of-fusion defects. The z- and y-directions correspond to a)

Figure 3: a) An example of a fragment of an AE signal that corresponds to a high quality layer produced with the optimal process condition that is with an energy density (79 J/mm³, 500 mm/s) and b) a spectrogram corresponding to the relative energies of the narrow frequency bands, localized in time-frequency domain. The red marker in a) shows the running window (RW).

Figure 4: Projection of the acoustic features into a 3D feature space using principle component analysis (PCA). The visualized dataset includes thirty features from each quality level. In brackets the corresponding porosity concentration is given

Figr-1

a)

FBG sensor

FBG read-out system

Figr-2

Fig-3

Fig-4

Figr-5

Test category \ Ground truth	Poor quality	Medium quality	High quality
Poor quality (1.42 ± 0.85 %, 800 mm/s)	89 (62)	7 (19)	4 (19)
Medium quality (0.3 ± 0.18 %, 300 mm/s)	5 (25)	85 (53)	12 (22)
High quality (0.07 ± 0.02 %, 500 mm/s)	8 (20)	9 (17)	83 (63)

Table 1: Classification tests accuracy for the SCNN. In brackets the results for conventional CNN are given.