WHEN AE (ACOUSTIC EMISSION) MEETS AI (ARTIFICIAL INTELLIGENCE) II

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Abstract:

Acoustic emission (AE) is an effective method to monitor and control the quality in different technical processes, including tribology and fracture mechanics. However, in highly dynamic processes, the processing of AE signals is very burdensome. At the same time, artificial intelligence (AI) has been considered as a new and powerful tool to overcome both: the complexity of the large data processing with a reasonable computational time. In this contribution, we will present two examples from completely different process where AE techniques are combined with AI in order to make a significant step forward in process monitoring and quality control.

To start with, in additive manufacturing, which has been at the center of attention in recent years, we will demonstrate that the combination of AE with AI makes possible to detect several types of defects, including pores.

With the second example, we will prove that the combination of AE with AI is a very promising approach for in situ and real-time monitoring of electrical discharge inside natural rocks.

1. Introduction

Analysis of acoustic Emission (AE) takes its origin from the middle of the 20th Century and its progress has been closely related to the development of measuring devices [1]. AE based methods have numerous advantages such as high sensitivity, indifference to structural resonances and mechanical background noises, real-time capability of monitoring as well as early and robust detection of defects [2]. In addition, in recent years, the AE machine manufacturers have made a significant progress to simplify the usage of the hardware for data recording and storage. This makes AE now has become very much a mainstream. Consequently, AE techniques are considered by many as being one of the most effective monitoring methods, in particular for Nondestructive Testing (NDT), Nondestructive Inspection (NDI), and Nondestructive Evaluation (NDE) [3]. This technique has been successfully applied to a broad range of engineering applications, as well as investigations of a wide range of materials, material compositions and structures [1]. The industrial applications of AE also includes the tracking of dynamic processes, such as failure of brittle components [3] and, more recently, laser welding and/or additive manufacturing (AM) [4, 5].
Despite all the advantages of the AE, its major drawback is the interpretation of the AE signals. This is particularly true for complex and dynamic processes. The main reason is that the AE signals content is generally the result of mix of multiple background physical events, which take place inside a material at different time scales. Taking this into account, each specific application requires an exclusive understanding of the specifics of the AE generation, ideally relating those with the underlying fundamental physical phenomena. Unfortunately, in most real-life cases, the combinations of the physical phenomena that take place at the same time cannot be recovered with details. One typical example is the AE of laser-material interaction. The complexity of AE, in this case, is additionally complicated by the presence of noise that is a vital part of the real-life conditions and industrial environments. Under such circumstances, a new approach is necessary to bring a robust analysis of the AE signals into real-life applications. Artificial Intelligence (AI) may be a solution as it possesses numerous of advantages. AI allows bypassing the development of complex physical models for process understanding. It relies on statistics that can be easily collected in industrial applications. Also, AI allows using highly non-linear data transforms and automatically reduce the noises. To do so, AI builds complex empirical rules for intricate big data, thus correlating the acquired AE with the real events. The latest achievements in AI allow reducing the effect of the non-accuracies in preparations of training sets which results in reducing the preparation costs. These capabilities of AI were exploited for continuous crack propagation, laser welding and additive manufacturing [6]. The requirements for AI are sufficient AE data (input data) that corresponds to the desire outputs such as quality, quantification of defects, or some other process related phenomena of interest.

In fracture mechanics, the AE signals may have at least the five following origins (1) elastic interaction & impacts; (2) changes in stress-strain state of a local volume around the crack tip; (3) plastic deformation and damage at the crack tip; (4) generation, motion and interaction of dislocation; (5) energy liberation when two new surfaces are created due to crack initiation and propagation [2].

Additive manufacturing and laser welding are analogous in numerous aspects. Both processes have phenomena such as rapid heating, melting, solidification, and cooling. Consequently, the content of the AE signal seize comprise material phase changes, dynamics inside the melted material and solidification processes. In addition, the AE signals are altered by the material and surface characteristics (e.g. chemical composition, phase transformation, optical properties, surface roughness, and environments), machine parameters (e.g. laser type, spot size, wavelength, pulse length, optical components) as well as the process parameters (laser power, scan speed, and scan line spacing). In addition, additive manufacturing is known to be prone to various defect types such as pores, balling, unfused materials, and cracking [7-10]. Under these circumstances, AE is of main interest in process monitoring. Obviously, even with the help of a fundamental physical understanding of the laser-material interaction, to correlate the AE signals with the real events is a challenge.

This contribution is an extension of our previous work [6]. Hence, we present two examples where acoustic emission (AE) was selected as a process monitoring method and the recorded data where analyzed by artificial intelligence (AI). The first case shows how AE system can be used for quality monitoring of additive manufacturing. The second is related to the monitoring of the pre-weakening of rocks during electric discharge.
2. Signal processing - Deep learning

In recent years, deep learning (DL) is actively introduced in many practical applications becoming an essential part of speech recognition, natural language processing, internet services and tele-communications [11, 12]. Originally inspired by the biological neuronal systems [11], today, this technique outperforms other traditional processing approaches in analysis of big arrays of data even in unsupervised way [11-13]. Such a rapid introduction from theory into practice in the past decade was possible thanks to the developments in optimization techniques that allowed involving a greater number of the basic computational units (neurons, decision trees etc.) into the DL architectures [11-13]. Consequently, this has given advantages in selection of more relevant information while suppressing the non-relevant one and made it possible to analyze more intricate data arrays [14]. At present, further developments in this field turn DL into a ready “on-shelf” tool. Thus, DL also starts to be involved into more complex scientific problems, for example description of dynamic systems [15], analysis of DNA [16] and computer vision tasks [11]. Such universality, combined with the computational power, makes DL attractive for industrial applications, and the first successful trials are seen in the literature. An interpretation of the acquired data for classification of the critical states in the same way was also shown in the field of fracture mechanics, laser welding and additive manufacturing [6]. The aforementioned applications are distinguished by the extreme operating rates. The complexity of those industrial problems is in the acquired data that take into account the dynamics of the underlying physical phenomena. Usually, in real-life, the latter is known for high non-linearity thus making interpretation in terms of existing physics extremely difficult, but still possible involving DL [6].

Today, DL incorporates a number of additional tools that increase the analytical efficiency when operating with real-life data and that can be involved to solve the industrial problems. Obviously, DL has become an attractive framework also for the monitoring of processes in real-life applications [6, 17-19] thus motivating us to investigate its applicability for various industrial problems. Under such circumstances, DL has many advantages in particular in extracting the relevant information [14]. As an example, belief propagation networks collect the relevant information in analogy with the renormalization that is widely used for the analysis of complex physical systems [15]. Convolution networks (CN) reach excellent results involving the convolutions over the given data that is followed by data compression [11]. The strong side of this technique is the recent extension for the adaptive and non-regular convolutions that allow operating on more complex data-grids [11]. Some other optimizations on simple feed forward networks also bring to better performance of those when analyzing complex data [11]. All this gives a rich instrumentation for development of new architectures and methods and adapt those to specific applications.

3. Examples

3.1 Example 1: AE meets AI in the field of AM quality monitoring

The first example shows that AE is strong instrument for monitoring in situ and in real-time the quality in additive manufacturing. Today the quality monitoring in additive manufacturing (and generally in all laser based processes) is mainly carried out either with temperature measurements of the melt pool or high resolution imaging of the process zone [7, 20]. Despite all the efforts to bring these technologies to the market, there is a consensus among scientists and industries that these monitoring techniques still do not provide acceptable rates in quality reproducibility during production [7, 20].
Wasmer, Shevchik et al. [17, 18] proposed an approach which combines AE with AI for in situ and real-time monitoring of AM. The results were obtained on real process.

An industrial 3D printer Concept M2 (Concept Laser GmbH, Germany) was used. It is a powder-bed technology, also known as a selective laser melting (SLM) process. The machine was 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 powder had a particle size distribution ranging from 10 to 45 μm and was made of CL20ES stainless steel (1.4404 / 316L). In addition, an opto-acoustic, a fiber Bragg grating (FBG), operated as an acoustic sensor. The FBG was mounted in the machine 20 cm away from the process zone.

A workpiece with dimension 10x10x20 mm$^3$ was produced under N$_2$ atmosphere (See Fig. 1a). During the process, the laser power $P$ was 125 W, the hatching distance $h$ was 0.105 mm and the layer thickness $t$ was 0.03 mm. Three laser velocities were selected to achieve three porosity contents that determined three different quality grades. The three colors visible in Fig. 1a correspond to the different process parameters, where 800 mm/s are bright regions, 500 mm/s are brown regions and 300 mm/s are dark/blueish regions. Typical light microscope images of the three qualities are shown in Fig. 1b-1d. The porosity concentration was 0.3 ± 0.18 % (medium quality; 300 mm/s; 132 J/mm$^3$; Fig. 1b), 0.07 ± 0.02 % (high quality; 500 mm/s; 79 J/mm$^3$; Fig. 1c), and 1.42 ± 0.85 % (poor quality; 800 mm/s; 50 J/mm$^3$; Fig.1d). In Fig. 1, 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 is based on Fig. 1a.

In terms of signal processing, the main techniques employed are based on Deep Learning (DL), in particular Convolution Neural Networks (CNN) [17] and Spectral Convolution Neural Networks (SCNN) [18]. In both cases, the search of distinct features is carried out in the time-frequency domain using wavelet spectrograms. Also, the intensity measurement of the AE components in spectrograms was taken as the relative energies of the narrow frequency bands which were the input features for the NN classifiers. The frequency bands were extracted using several wavelet families such as Daubechies, Symlets, and Coiflets as well as adaptive $M$-band wavelets.

The analysis of the acquired AE signals was performed using one or two running windows (RW) that scanned the signal. The choice of the time span for the RW is a compromise between the spatial resolution in defects detection and 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 noise and thus are deteriorating the classification efficiency. Several time spans and using of two RW were investigated.
Obviously, to achieve the best classification accuracy, there are many decisions that have to be made. The choices included the selection of the NN (CNN or SCNN), the number of convolution layer, number of pooling layer, wavelet family, decomposition level, or type of adaptive wavelet, the number of running windows, their corresponding time spans, etc… Wasmer, Shevchik et al. [17, 18] defined that the best choice was provided by the NN and wavelet which showed the minimum approximation errors on the given AE signals. In terms of RW, the time span was selected after an exhaustive search in which the classification accuracy was evaluated after each retraining using RWs with different time spans.

A typical AE signal from one complete layer of medium quality (300 mm/s) is shown in Fig. 2a. Figure 2a contains two running windows that are delimited by the red and a green box. They represent a long (LRW – red box) and short running windows (SRW – green box) scanning the acquired signal. Figure 1b is the reconstructed spectrogram from the relative energies of the $M$-band wavelets from a pattern of the signal in Fig.2a that is bounded by the red box between 0.2 and 0.4 s [17].

In terms of NN used, Fig. 3 displays a scheme of the CNN used in Wasmer et al. [17]. In this figure, it is seen that the spectrograms build from the LRW and SRW pass through two different convolution layers from which a series of perception maps 1 are build. Then, the information is combined in the pooling layers 1 before the information from both flows is pushed into a common convolution layer 2 followed by a second pooling operation (see pooling 2 in Fig. 3). The final classification is carried out in fully connected layers. The classification result/accuracy is the output of the procedure which is often given in a table.

Figure 2: a) A typical AE signal from one complete layer of medium quality (300 mm/s). The red and green boxes are the long (LRW) and Short Running Windows (SRW) scanning the acquired signal; b) reconstructed spectrogram for the LRW time span bounded by red lines in Fig. 2a.

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The main results of these feasibility studies from Wasmer, Shevchik et al [17, 18] are summarize in Table 1. In this table, the numbers in bold and in italic are the lowest and highest classification accuracies found to date. 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. For example, the highest accuracy rate for the poor quality was 89%. The classification error is more or less equal between the medium and high qualities, 4 and 7%, respectively.

It was found that, by and large, the lowest accuracy rate was found using the Daubechies wavelet with ten vanishing moments to reconstruct the spectrogram, one running window and the conventional CNN for classification. In contrast, the best results are mainly obtained using also the Daubechies wavelet with ten vanishing moments to reconstruct the spectrogram, one running window but with the spectral CNN (SCNN) for classification [18]. However, it is important to note that using $M$-band wavelets, two running windows and the conventional CNN, the classification accuracies are only slightly lower than the highest ones presented in Table 1. Therefore, it shows that there is still some potential improvement by using $M$-band wavelets, two running windows and the SCNN as a classifier.

To conclude this example, Wasmer, Shevchik et al [17, 18] could demonstrate that their innovative approach that is combining AE with AI has some potential for in situ and real-time monitoring of additive manufacturing (AM) processes.
Table 1: Classification accuracy test results in % for three categories of events*

<table>
<thead>
<tr>
<th>Ground truth</th>
<th>Test</th>
<th>Poor quality</th>
<th>Medium quality</th>
<th>High quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poor quality (1.42 ± 0.85 %, 800 mm/s)</td>
<td>62 - 89</td>
<td>19 – 4</td>
<td>19 – 7</td>
<td></td>
</tr>
<tr>
<td>Medium quality (0.3 ± 0.18 %, 300 mm/s)</td>
<td>25 - 5</td>
<td>53 – 85</td>
<td>22 – 10</td>
<td></td>
</tr>
<tr>
<td>High quality (0.07 ± 0.02 %, 500 mm/s)</td>
<td>18 - 8</td>
<td>21 – 9</td>
<td>61 – 83</td>
<td></td>
</tr>
</tbody>
</table>

Red and light red highlight the classification accuracies and errors, respectively

3.2 Example 2: AE meets AI in the field of fracture mechanics

Pre-weakening of solid materials using electric discharge is a new technique aiming at reducing the costs and energy consumption of raw materials processing in mining and recycling industries. However, the absence of an effective pre-weakening quality control prohibits its introduction into a wide practice. In our previous work [6], we showed the potential to use AE to monitor this process with transparent materials. The aim of this work is to show that this process can be applied to real mining materials.

Stones of different sizes were selected from a copper ore. The stones were separated by successive sieving in 4 size categories; (i) 25-31mm, (ii) 31-35mm, (iii) 35-40mm and (iv) 40-45mm. Each stone was then submitted to a single pulse using the same voltage generator as previously described [6, 23]. Each stone was placed individually on the metallic conveyor belt that acts as a counter electrode and aligned with the electrode as shown in Fig. 4. The gap between the electrode and counter electrode was fixed at 50 mm for all the tests and the belt was kept motionless.

![Figure 4: Schematic representation of the setup.](image-url)
The stones were treated at 200kV and four different capacitance (10, 15, 22.5 and 37.5 nF), which correspond to energy of 200, 300, 450 and 750 J per pulse. For the two smaller sizes categories, 30 stones of each were tested at each energy level. For the two larger stone sizes, 20 stones of each were tested at each energy level. This gives a total of 400 stones tested.

For each electrical pulse, the corresponding AE signal was recorded simultaneously. The detection of the acoustic signals was made directly inside the water filled chamber using an acoustic hydrophone sensor R30UC. It was placed at a distance of 20 cm from the electrode gap (See Fig. 4). The AE signals were recorded with a 10 MHz sampling rate for 20 ms and the record was synchronized with the pulse start.

Contrary to our work with transparent samples, the categorization is not straightforward as the presence of cracks inside the sample cannot be directly observed. What can be characterized is the presence or absence of discharge and the eventual fragmentation of the stone in pieces. To quantify the fragmentation the weight of the stone before ($W_{before}$) treatment is measured and the weight of the larger remaining particle after discharge is measured ($W_{after}$). The weight loss is then calculated as $W_{loss} = (W_{before} - W_{after})/W_{before}$. Two examples of stones from the category 25-31 mm are given in Fig. 5. The two stones have a weight loss of 44 and 6%, respectively.

In this work, we defined 5 categories based on the weight loss and presence or absence of discharge. The absence of discharge is easily recognizable due to the lack of discharge sound and lack of damage on the stone. The AE signal as shown in Fig. 6a is also very characteristic. The amplitude and duration of AE is much less than for other categories as presented in Fig. 6b and 6c. The next category is a weight loss between 1 and 10% as illustrated in Fig. 5d with the corresponding AE signal shown in Fig. 6b. This category is often also considered as surface discharge as the path is mainly at the surface of the stone and entered the stone only in a small edge as shown in Fig. 5d.
Figure 6: a) AE signal for a pulse without discharge, b) AE signal from the stone shown in Figure 2b and d, corresponding to 6% weight loss, c) AE signal from the stone shown in Figure 2a and c, corresponding to a 44% weight loss. d), e) and f) are the corresponding sonogram.

The last two categories correspond to various degree of fragmentation, the first with a weight loss of 10-50% and the second with a weight loss of more than 50%. A stone with a weight loss of 44% is shown in Fig. 5c and the corresponding AE signal is in Fig. 6c.

The AE signals for the no discharge case are easily separated from the discharge case with both a lower intensity and shorter duration of the acoustic emission (see Fig. 6a and 6d). However, all the other signals where discharge occurred are showing similar characteristic and similar sonograms (see Fig. 6b, 6c, 6e and 6f). Indeed, the frequency with the highest response on the sonogram is around 300 kHz and corresponds with the highest sensitivity of the sensor. The amplitude and duration of the signals, as well as the frequencies are similar and advanced processing techniques are needed to separate the signals.

For this work, we used a similar approach to our previous work [6]. We used first wavelet decomposition in order to extract the features from the AE signals. In this work we used standard Daubechies wavelet with 10 vanishing moments to decompose the signals in time-frequency domains.

Before classification, only the most informative features are selected using the principal component analysis (PCA) [24]. The disposal of non-informative features decreases the noise and additionally reduces the computational complexity [24].

The classification was performed using support vector machine (SVM), a statistical learning technique proposed by Cortes and Vapnik [25].

The classification results are presented in Table 2. As expected the classification results of the no discharge category presents no difficulty to correctly separate. Good news is for the correct separation with a 90% accuracy of fragmentation with a weight loss of more than 50%. This category corresponds to discharge with the most damage created and means that the process is running correctly. It is important to recognize sample from this category. The category surface discharge is also relatively well separated with an accuracy of 70%. The categories in between suffer from a lower accuracy of 53 and 66%. This can come from the fact that the boundary between the category are just arbitrary selected and it is well possible that these categories have common features with neighboring categories as the process is not expected to physically vary between them. It is also well possible that a lot of invisible
cracks are created in the stones without the stone being fragmented, a process known as pre-weakening. In this case the acoustic signal is expected to be very similar to a complete fragmentation. This could explain why a lot of signals from low weight loss categories are classified in the more than 50% weight loss category.

Moreover, the process was not run in optimal conditions as the gap between the electrodes was kept constant at 50mm. This gap is good for big stones that fill most of the gap and thus limit that amount of discharge occurring in the water above the stone. For the small stones, a large portion of the discharge will occur anyway in the water which means that all the signals will have common water discharge features and not only the stone from the 0 - 1% weight loss category.

4. Conclusions

Following our first contribution “When AE (Acoustic Emission) meets AI (Artificial Intelligence)” presented at the 21. Kolloquium Schallemission – in Fulda, Germany, 2017 [6], we presented two new examples where AE meets AI. The first example is related to quality monitoring of additive manufacturing (AM) process. To do so, the approach is to use state-of-the-art opto-acoustic sensors as AE sensors and analyses the recorded AE data with Deep Learning (DL) techniques such as convolution neural networks (CNN) and spectral neural networks (SCNN). It was found that the classification accuracy between three close categories varies significantly depending on the selection of the NN (CNN or SCNN), the number of convolution layer, number of pooling layer, wavelet family, decomposition level, or type of adaptive wavelet, the number of running windows, their corresponding time spans, etc…. However, the best classification accuracies are higher than 83% even though the results are only based on two feasibilities studies. This demonstrated the potential of this approach to be industrialized as in situ and real-time quality monitoring in AM processes.

A second example related to highly dynamic fracture mechanics, in particular for mine industries. We demonstrated that by combining AE with AI, it is possible to classify with acceptable accuracy the effect of electrical discharge in rocks in terms of weight loss (WL). This is also an important result as it may allow saving a significant amount of energy in the mine industry, especially for pre-weakening of rocks. This technology was patented [26].

Finally, based on the two examples presented, it can be concluded that by combining AE signals with a state-of-the-art signal processing, it is possible to address highly complex industrial processes. We demonstrated that, even in very noisy and dirty environments, we are able to achieve reliable classification of investigated events. This makes this methodology very effective for industrial applications even though it does not explains the nature of the AE signals, but this is planned as the future work.

Table 2: Classification accuracy test results in % for three categories of events*

<table>
<thead>
<tr>
<th>Ground truth Test</th>
<th>No discharge</th>
<th>WL 0-1%</th>
<th>WL 1-10%</th>
<th>WL 10-50%</th>
<th>WL &gt;50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>No discharge</td>
<td>100</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>WL 0-1%</td>
<td>-</td>
<td>70</td>
<td>-</td>
<td>3</td>
<td>27</td>
</tr>
<tr>
<td>WL 1-10%</td>
<td>-</td>
<td>7</td>
<td>53</td>
<td>2</td>
<td>38</td>
</tr>
<tr>
<td>WL 10-50%</td>
<td>-</td>
<td>8</td>
<td>-</td>
<td>66</td>
<td>26</td>
</tr>
<tr>
<td>WL &gt;50%</td>
<td>-</td>
<td>5</td>
<td>-</td>
<td>5</td>
<td>90</td>
</tr>
</tbody>
</table>

*Red and light red highlight the classification accuracy with the ground truth and classification mistakes, respectively.
References:


