Acoustic process monitoring in laser beam welding

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Abstract

Structure-borne acoustic emission (AE) measurement shows major advantages regarding quality assurance and process control in industrial applications. In this paper, laser beam welding of steel and aluminum was carried out under varying process parameters (welding speed, focal position) in order to provide data by means of structure-borne AE and simultaneously high-speed video recordings. The analysis is based on conventionally (e.g. filtering, autocorrelation, spectrograms) as well as machine learning methods (convolutional neural nets) and showed promising results with respect to the use of structure-borne AE for process monitoring using the example of spatter formation.

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Peer review statement: Peer-review under responsibility of the Bayerisches Laserzentrum GmbH

Keywords: structure-borne acoustic emissions; process monitoring; machine learning; laser beam welding; melt pool dynamics; seam imperfections

1. Introduction

The formation of seam imperfections (e.g. spatters and pores) is a major issue in deep penetration welding with solid-state lasers at high welding speeds above 8 m/min. The phenomena can be attributed to the gas- and fluid-sided interaction of melt and metal vapor inside the keyhole [1]. Depending on welding speed and absorbed laser power, the melt pool dynamics and the associated formation of spatters and pores differ significantly [2]. While process regimes of welding speeds below 8 m/min are characterized by a more stable keyhole formation and less seam imperfections, an increase in welding speed results in a rise of melt pool dynamics. Due to the increase in keyhole inclination at high welding speeds, the absorption at the keyhole front changes and incudes an increased metal vapor flow, which interacts with the keyhole rear-sided melt [3]. Based on the transferred momentum from the vapor flow to the melt, the keyhole starts to fluctuate. This contributes to a temporary bulging of the keyhole and can result in pore formation by a local collapse of the keyhole ground [4]. The induced melt pool fluctuations can also cause a constriction of the keyhole aperture. By affecting the outgassing conditions, the transferred momentum from the metal vapor flow to the melt is changing. If the transferred momentum exceeds a critical threshold, spatter formation occurs. The extraction of a single spatter requires the kinetic energy of the fluid element in the melt $E_{kin,ft}$ to be greater than the sum of the kinetic energy of the droplet $E_{kin,dr}$ and the surface energy of the melt $E_{surf}$ (eq. 1) [5]. This is represented by the droplet volume $V_{dr}$, velocity of the fluid element $\mathbf{v}_{ft}$, velocity of the droplet $\mathbf{v}_{dr}$, surface tension $\sigma$ and droplet surface area $\mathcal{O}_{dr}$. The flow velocities inside the melt pool are scaling exponentially with welding speed, which is why the formation of spatters increases significantly at high welding speeds [6].

$$\frac{\rho \mathbf{v}_{dr} |\mathbf{v}_{ft}|^2}{E_{kin,ft}} > \frac{\rho \mathbf{v}_{dr} |\mathbf{v}_{dr}|^2}{E_{kin,dr}} + \frac{2 \sigma}{E_{surf}}$$  (1)
The handling of the raised spatter and pore formation at high welding speeds is a key challenge in terms of quality assurance and process control. Therefore, the use of in-process monitoring is of major relevance in order to characterize the highly dynamic welding process. In this context, various approaches have been examined, which are based on different physical principles. Li et al. describe a method for detecting the electrical charge in the space between the laser welding optics and the workpiece for CO₂ lasers [7]. The electrical charge is an indicator for the formation of the keyhole. Vänskä et al. describe a setup for high-speed X-ray diagnostics, which allows the observation of the cross-sectional keyhole formation [8]. In the field of spectral monitoring, De Bono et al. used photodiodes for in-process detection of seam imperfections [9]. In addition, Kogel-Hollacher used optical coherence tomography for detecting the depth of the keyhole [10].

However, the methods described are limited due to cost-intensive additional equipment, restricted temporal resolution and restricted system robustness. In order to overcome these limitations, the use of acoustic process monitoring can be suitable. In this field, various approaches are known for in-process monitoring by recording airborne sound using microphones, predominantly in the audible range (< 20 kHz). For laser beam welding, airborne sound is mostly used to determine penetration depth [11,12]. In order to increase the content of information, the use of structure-borne acoustic emission (AE) measurements provides the possibility to detect internal macroscopic seam defects such as cracks and pores [13,14]. Furthermore, spatter formation can be detected by the induced AE due to fluctuations of the keyhole [14]. In this context, frequency ranges from 50 kHz up to 900 kHz are mostly considered. For the recording of the acoustic emission, sensors or sound conductors can be attached to the component surface. Using this method, Bordatchev et al. investigated the effect of the focus position during laser ablation on the structure-borne acoustic emissions. The statistical evaluation of the signals has shown that a reconstruction of the focal position of the laser beam is possible [15]. By using a Short-time Fourier transform (STFT) and analyzing the recorded frequency bands, it was also possible to detect the weld depth, respectively, seam imperfections during the welding process [13]. Besides the recordings based on the contact of component and sensor, there are first investigations for the detection of AE by analyzing the noise level in the experimental setup. In this context, [14] characterized the AE in the mirror adjustment of the laser welding optics, which was triggered by the backscatter of the laser beam. However, there are no investigations in the state of the art yet, which correlate AE measurements of the process induced AE including environmental noise to seam imperfections for in-process monitoring of laser beam welding at high welding speeds.

Therefore, this paper focuses on the correlation of structure-borne acoustic emission by measurements of the process induced AE to the highly dynamic process characteristics of laser beam welding at high welding speeds. In contrast to the work shown, the AE sensors were not placed directly on the sample but mounted on the clamping device. This setup allows the prevention of unmanageable measuring deviations due to mounting errors of the sensors, which occurred in previous investigations. Due to an increased system robustness and the possibility for reducing the setup time, this method ensures an increased technical feasibility for an industrial application. By correlating high-speed videography and AE measurements, this investigation allows the development of error detection algorithms based on the frequency pattern detection of typical welding imperfections in laser beam welding.

2. Experimental

The experimental procedure (see Fig. 1) was followed for partial and full penetration laser beam welding of stainless austenitic steel 1.4301 (AISI 304, X5CrNi18-10) and full penetration welding of aluminium EN AW 5083 at welding speeds of 8 m/min, 10 m/min and 12 m/min. The used specimens had dimensions of 150 mm x 40 mm and were clamped at the front of a six-axis robot (Kuka KR 60HA). A sheet thickness of 2 mm was predominantly used, whereby tests of welding 1 mm thick specimens, respectively, of welding the overlap of 2 x 1 mm thick specimens were also carried out. The bead-on-plate welds were operated by using a stationary disk laser (Trumpf TruDisk 5000.75, λ = 1,030 nm) in an orthogonal arrangement. The laser power was set for a constant welding depth of 1.7 mm for partial penetration welds as well as for a full keyhole penetration welding process. The spot diameter was 500 µm and focused on the surface of the specimens. To characterize the influence of the focal position, the focus was shifted by 1.5 mm into and above the surface in additional investigations. A Photon SA-X2 high-speed camera (10,000 frames per second) equipped with a Navitar zoom lens was used for the process recording. The camera was positioned in an angle of incidence of 60° to the surface of the metal sheet. A narrow-band filter with a center wavelength of 808 nm was used to mask out process emissions. The process was illuminated by a Cavitar Cavilux laser system (λ = 808 nm). To quantify the effect of spatter formation, the resulting loss of material was weighed by using a high-precision balance (Kern PLJ 2000-3A). The specimens were weighed before and after the welding process.

![Fig 1. Schematic of the used experimental setup](image-url)
A PXIe-8880 industrial PC with a PXIe-5172 oscilloscope card was used to record the structure-borne acoustic emissions. The maximum bandwidth of the oscilloscope card was 100 MHz with a maximum sampling rate of 250 MS/s and a signal resolution of 14 bits. Two QASS QWT-MICRO structure-borne acoustic sensors with a bandwidth between 100 kHz and 10 MHz were connected to this card, the signals of which were amplified by 40 dB using a MISTRAS 2/4/6 preamplifier. The welding process and measurement data acquisition were started automatically by a trigger signal. The raw signals were recorded at a sampling rate of 1 MHz for each channel. For a first analysis of the raw data, these were transformed using a STFT by a step size of 1,000, a frequency resolution of 2,048 frequency bins and a Hann function with a length of 64. Based on this, energy curves could be extracted. The bandwidths of the energy graphs ranged between 0 kHz and 50 kHz, between 50 kHz and 200 kHz, and between 250 kHz and 500 kHz. Taking into account the start and end time of the measurement, these graphs were used to compare the different process parameter sets. The number of samples was three for all experiments. The error bars depicted in all graphs represent the standard deviation.

3. Results

3.1. Loss of mass and melt pool dynamics

In order to determine the process characteristics by a conventional method, the resulting loss of mass was measured depending on varying penetration mode, specimen material, sheet thickness, focal position and welding speed (see Fig 2).

By partial penetration welding of 2 mm thick specimens of 1.4301, no effect of a varying focal position (± 1.5 mm) could be determined (see Fig 2a). The loss of mass was increasing starting with approx. 0.39 mg/mm to approx. 0.7 mg/mm by raising the welding speed from 8 m/min to 10 m/min. This was followed by a constant level at 12 m/min. Changing the penetration mode to full penetration welding by using same specimen material and thickness, the loss increased significantly (see Fig 2b). The values raised by 41 % at a welding speed of 8 m/min. An increase in welding speed resulted in an increase in loss of mass, reaching a maximum of 1.03 ± 0.06 mg/mm at 12 m/min. By changing the joint configuration from a single sheet (t = 2 mm) to an overlap of two 1 mm thick sheets (2x1 mm), no significant influence could be noticed, except for a 36 % reduction of loss of mass at 8 m/min. Using a sheet thickness of 1 mm, the loss of mass was noticeable falling to a constant level below 0.2 mg/mm, which can be attributed to the changed aspect ratio of the keyhole. By welding 2 mm thick specimens of aluminum EN AW 5083, the curve shows a degressive trend by increasing welding speed. Starting at a loss of mass of 0.42 ± 0.01 mg/mm at 8 m/min, the values drops to 0.06 ± 0.01 mg/mm at 12 m/min. Summarizing the results, the loss of mass significantly depends on the welding speed, penetration mode and material. In order to analyze AE measurements based on a distinction of process-driven events, the following investigation took place by a narrowed range of process parameters, which differs in maximum of loss of mass (see Table 1).

Table 1. Selected process parameters based on a sheet thickness of 2 mm

<table>
<thead>
<tr>
<th>Mode</th>
<th>Partial penetration</th>
<th>Full penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter set</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Material</td>
<td>1.4301</td>
<td>1.4301</td>
</tr>
<tr>
<td>Laser power</td>
<td>3.25 kW</td>
<td>4.45 kW</td>
</tr>
<tr>
<td>Welding speed</td>
<td>8 m/min</td>
<td>12 m/min</td>
</tr>
</tbody>
</table>

In order to specify the process sets of Table 1 in more detail, the following discussion is based on a phenomenological description of the associated high-speed recordings.

By welding 1.4301 with a thickness of 2 mm at a welding speed of 8 m/min (Fig. 3a), the keyhole was characterized by a rear-sided melt pool swelling. Due to the fluctuation of the melt pool swelling, the circular formed keyhole aperture was temporarily constricted. This was followed by a lateral-sided detachment of large spatters, which were dominated by a spatter trajectory against the welding direction. This process regime is known as Rosenthal regime [2]. By increasing the welding speed to 12 m/min, a significantly elongated keyhole was observed (Fig. 3b). The spatter detachment was initiated by fluctuations of a melt pool swelling, which was also formed at the keyhole rear side. In contrast to the process at 8 m/min, the spatters were detached in a central position and characterized by smaller dimensions. According to the process description, these characteristics can be referred to the elongated keyhole regime [2]. By changing the material and the penetration mode, the melt pool dynamics were noticeably affected. This is exemplarily shown by the full penetration weld of 2 mm thick aluminum EN AW 5083 at a welding speed...
of 12 m/min (Fig. 3c). The keyhole showed pronounced fluctuations, whereby the undirected detachment of spatters surrounding the keyhole aperture was initiated. In contrast to the process regimes of parameter set 1 and 2, the formed spatters had much smaller dimensions. Based on the adsorption of atmospheric oxygen, the melt pool surface was characterized by the formation of an oxide layer. Furthermore, an increased melt pool width could be observed, which can be attributed to the high thermal conductivity of the specimen material.

![Image](https://example.com/image.png)

Fig 3. High-speed recordings of parameters sets: (a) 1; (b) 2; and (c) 3

By correlating the given phenomenological description of process characteristics and associated loss of mass, it is possible to identify a distinctive difference in melt pool dynamics and weld seam formation. Based on these observations, the acoustic signals are examined to prove if conclusions on the process behavior can be derived. Therefore, the following section focusses on the development of error detection algorithms based on a structure-borne AE-frequency pattern detection, in order to lay the foundation for a high-speed in-process monitoring.

### 3.2. Acoustic analysis and process-driven events

The structure-borne AE measurements were transformed by applying a STFT in order to identify acoustic-driven laser beam welding events. The acoustic emissions of the robot motion (Fig. 4a) and the cross-jet (Fig. 4b) were analyzed separately from the welding process (Fig. 4c) to determine the influence of the experimental setup. The x-axis in the graphs represents the time in milliseconds and the y-axis the frequency bins. A frequency bin had a width of 487.805 Hz each. The colors represent the intensity of the pixel in arbitrary units. The maximum intensity of the pixel was set to 0.4 (yellow) and the minimum value was set to 0.02 (blue).

Analyzing the emissions that are generated solely by the movement of the robot at a speed of 8 m/min (Fig. 4a), it is possible to observe only audible signals in the low frequency range up to 50 kHz (bin 0-103). By the additional use of the cross-jet at the same robot speed (Fig. 4b), the frequency range is significantly widened up to 450 kHz (bin 0-900). By using this setup and the welding process based on parameter set 1, the graph (Fig. 4c) is almost identical to the graph caused by the emissions of robot motion and cross-jet (Fig. 4b). This indicates a majority of the cross-jet generated acoustic emissions.

![Image](https://example.com/image.png)

Fig 4. AE-STFT of different experimental settings: (a) 1; (b) 2; (c) 3

The predominant effect of the cross-jet can be also seen by comparing the mean values of the energy graphs for different welding parameter sets. This is exemplarily shown in Table 2 for the band from 250 kHz to 500 kHz.

<table>
<thead>
<tr>
<th>Penetration Mode</th>
<th>Partial Penetration</th>
<th>Full Penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Param. Set 1</td>
<td>0.4751</td>
<td>0.5940</td>
</tr>
<tr>
<td>Param. Set 2</td>
<td>0.4477</td>
<td>0.4652</td>
</tr>
<tr>
<td>Param. Set 3</td>
<td>0.4712</td>
<td>0.8552</td>
</tr>
</tbody>
</table>

Table 2. Mean values of energy diagram in band from 250 kHz to 500 kHz
No significant difference in energy could be determined due to the noticeable deviation of the values, although the melt pool dynamics and loss of mass differs significantly as shown in 3.1. The data analysis methods used included time-frequency methods, time-varying autocorrelation functions and their Fourier transforms, as well as statistics like histograms. Unfortunately, no conventional analysis method could provide a conclusive statement. Besides the conventional data analysis, a further examination was carried out by machine learning methods, in order to identify the informative value of the data and its potential for detecting correlations with the welding process.

3.3. Data analysis by means of machine learning

Since a direct processing of the raw audio signals with classical methods has proven to be quite challenging due to the strong noise influence from the cross-jet, machine learning techniques were applied to the data. The idea was to check, whether the signal contains relevant information about the experimental conditions at all, such as the speed/power settings of the laser or the thickness/material of the specimens being processed. To this end, a neural network was trained to classify the recorded signals according to the experimental conditions, using two of the three trials for training (where 70 % of the data is training data and 30 % is used for cross validating). Unused data from the third trial was used for the validation. The signals were divided into 10 ms windows (10,000 samples each) leading to 210/175/145 training samples for 8/10/12 m/min welding speeds, respectively. The neural network architecture follows [16] and consists of four 1-D convolutional layers with max pooling, an additional dropout layer and two dense layers at the end.

In the first experiment, the network was trained to classify the laser welding speed from all experiments shown in 3.1. Figure 5 shows the accuracy of the detected versus the true welding speed. It can be observed that the slowest and the fastest welding speed can be reliably detected while the medium speed is sometimes confused for the faster one. Nevertheless, the high prediction rate of over 95 % shows that the welding speed is identified systematically and not randomly.

In the second experiment, the network was trained to identify experimental conditions of four different classes at welding speeds of 8 m/min, 10 m/min and 12 m/min (see Table 3). Again, a quite good reproducibility is observed (see Fig. 6). These results suggest that the data contains a considerable amount of information about the experimental conditions.

<table>
<thead>
<tr>
<th>Table 3. Welding parameters used for machine learning-based classifying</th>
<th>Mode</th>
<th>Full penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Material</td>
<td>1.4301</td>
<td>1.4301</td>
</tr>
<tr>
<td>Thickness</td>
<td>2.0 mm</td>
<td>2 x 1.0 mm</td>
</tr>
</tbody>
</table>

3.4. Application of error detection algorithms

Based on the information contained in the data, a targeted attempt is made to establish a correlation to seam imperfections. This is carried out for spatter formation by means of the loss of mass as shown in 3.1 for the experiment. The neural net was trained with two sets and predicted to a third set from the defined parameters in Table 1. The results can therefore only be seen as sample based on 3 experiments.

In order to provide a sufficient number of training and test data sets, the acoustic data of each experiment were divided into 10 ms long sections (see 3.3). This procedure leads to a large number of test vectors from each experiment. It should be noted that the number of vectors is not constant for each of the three experiments considered, since different welding speeds lead to a different length of the acoustic signals per experiment (see Table 4).

The predicted result of the neural network is compared to the measured mass loss of the respective experiment as ground truth. The ground truth is an integral value over the entire weld seam, since no temporal resolution of the real mass loss can be determined.

| Table 4. Number of test vectors resulting from parameter sets |
|---|---|---|
| Parameter set | 1 | 2 | 3 |
| Welding speed / m/min | 8 | 12 | 12 |
| Resulting welding time / s | ≈ 1.1 | ≈ 0.75 | ≈ 0.75 |
| Number of test vectors / 1 | 109 | 75 | 75 |
Fig. 7 shows the results of the neural network on the prediction of the loss of mass over the test vectors for the three experiments. The ground truth remains constant for a single experiment, whereas the prediction is calculated for each test vector. The predicted value fluctuates around or follows the ground truth but reflects it well in the cases considered.

Further investigations will address a larger number of data sets in order to achieve a finer resolution of spatter formation and to generalize the findings. On the other hand, further conventional evaluations can be made based on the available investigations, e.g. spectral relevance analysis in order to analyze which parts of the audio signals were particularly relevant for differentiating the different classes. This procedure would provide a suitable path to extract information more direct. This then paves the way towards a real-time analysis of the acoustic signals, which is crucial for the goal of inline control mechanisms.

4. Conclusion

The occurrence of seam imperfections during the laser beam welding of high-alloy steels and aluminum represents a major challenge in terms of process monitoring. In this article, the possibility of process monitoring by structure-borne acoustic emission was implemented. The sensors were integrated into the clamping device to minimize the possible set-up effort in industrial applications. Using conventional evaluation of the signals, distinctions between process, robot and cross-jet emissions could not be resolved with a high degree of detail. In contrast, machine learning methods enabled significantly more information to be extracted from the data. In addition to the declaration of the welding speed, further considerations were made regarding spatter formation. A prediction of spatter formation was reached based on the loss of mass, even for a sample duration of 10 ms.

The investigation shows that already 10 ms short samples from the acoustic signals lead to a meaningful result, which illustrates the potential of real-time capable process monitoring.

It should be noted that the differences in the loss of mass are relatively large for the samples considered. This requires further investigations on an increased number of data sets to prove that finer differences can be resolved too. In comparison to conventional analyses, it can be shown that process-relevant information can be obtained from the data and is therefore basically suitable for in-process monitoring.

Acknowledgments

This work was partially supported by Fraunhofer Internal Programs under Grant No. Attract 025-601128.

References