ACOUSTIC EMISSION FOR IN SITU MONITORING OF LASER PROCESSING

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Abstract:
Laser processing is an important technology in industrial manufacture. Today, a standard quality monitoring of the processed workpieces mainly relies on costly X-ray or time consuming post mortem methods. The commercially available in situ and real-time monitoring units are also accessible and rely on optical measurements or high resolution imaging of the process zone. Unfortunately, their performance is greatly affected by the plume, formed during the overheating of the material. This limits the detection of defects (e.g. pores) formed inside the workpiece. To bypass the aforementioned limits, we focus on acoustic measurements that are the derivatives of the shockwaves, generated inside the workpiece directly during processing. The measurements are conducted using a high sensitive piezo sensor. The acoustic signals are analysed further by state-of-the-art signal processing. This included a compartment of wavelets and Fourier decompositions, followed by machine learning. The developed methodology is realized in a hardware unit that operates in pseudo real-time. The unit was tested on real welds with various materials. The welding experiments were performed using spot weld, Stepless High-speed Accurate and Discrete One-pulse Weld (SHADOW). The tests were carried out at different laser powers that are closely related to the weld quality. The in situ quality control unit demonstrated the capability to classify the weld quality with a confidence level ranged between 82% and 95%. Due to the similar light-matter interaction phenomena, the presented approach and apparatus can also be applied for monitoring other laser-processing technologies, namely: ablation, cutting, drilling and additive manufacturing.

1. Introduction

Laser welding is a rapidly developing technology that becomes an essential part in automobile [1,2], medical [3,4], aerospace [5,6,8] industries and heavy machinery production [8,9]. The advantages of this technology are in relatively low running costs, high processing speed and quality in terms of the mechanical properties of the welded joints [1,5,7]. The growing demand for laser welding requires the development of a reliable in situ quality monitoring and control that remains an open topic until today [1]. The challenge in developing such a system is the high complexity in laser-matter interactions [1,5,7]. This happens due to multiple physical phenomena that are present at different time scales affecting the process [5,7]. This complexity may be a reason for the deviations of the real quality from the desired one even in well controlled conditions [1,5,7]. One of the possible causes is the occurrence of pores that are a hidden threat for the mechanical properties of the processed workpieces [1,5,7]. At present, the diagnostic of pores in industrial environment is carried out with several well established methods.
Analysis of the cross-section of the workpieces is one of the most reliable techniques that allows visually inspect the processing results [1]. This method is destructive and time consuming that is obviously not applicable to every single piece in mass production. X-ray imaging is a non-destructive visualization method that allows to search the hidden pores directly inside the workpiece medium [1,10]. The drawback of this approach is the involvement of expensive and very complex equipment. In addition, rather complex image processing algorithms are needed for the search and interpretation of the obtained data. This leads to long computational time of the acquired images. These factors put technical limits on the adaption of this technology for in situ control. At present, this method is only applied for post mortem analysis of workpieces that require long manufacturing time.

The development of a real-time in situ quality control is still pushed by an industrial demand and some new approaches exist but are still at development stage. Image analysis is one of the mostly visible directions due to the availability of the cheap hardware and minimal modifications needed for already existing commercial laser welding systems. In this setup, the images of the process zone are registered in infra-red or visible spectral ranges [1]. The quality inside the workpiece medium is correlated with the surface temperature distributions and/or the geometry of the process zone [1]. The drawback of this approach is due to only surface measurements, while the inside processes remains hidden. In this situation, the aforementioned complexity of the laser-matter interactions [5,7] is, sometimes, responsible for deviations between the surface behavior and the expected behavior inside the medium, thus reducing the precision of this method.

Other methods based on spectroscopy of the evaporated materials from the process zone showed a potential but only for a limited number of applications [1]. High efficiency in detecting the plume and spatter was shown in a number of works [1]. However, those phenomena take place after overheating of the material [11], thus post-factum indicating an uncontrollable development of the process outside the acceptable quality range.

To sum up, the existing approaches for in situ monitoring have forenamed limits. Taking this into account, the present study is based on acoustic emission (AE) that has some advantages due to its nature. AE is a derivative of the elastic shockwaves deformations that take place inside the workpiece [1] and grab the information about the momentary pressure of the liquid/gas material phases inside the process zone onto the solid surrounding [1,7]. This implies direct volumetric measurements of the material behavior inside the process zone. The drawbacks of this approach are in the complexity of the AE signal interpretation. At present, AE proved itself to be a robust method for detection of the plume and spatter [1,5] that are characterized by a higher output intensity of the AE. Those events indicate extreme undesirable process behavior and the detection of the earlier quality critical events, which provide with more decision time, is an open topic. This work is a feasibility study for the detection of the momentary critical events in the AE signals and correlates those with the quality. To do so, we employ the combination of a highly sensitive AE sensor for data collection, and machine learning (ML) for data interpretation. The attraction of ML is in the possibility to create efficient correlation models to recover the links in intricate data, which is the case for laser welding processing inducing AE [1,5]. One additional motivation is given by the successful application of ML in a number of practical applications [12]. In the context of this work, ML was employed as a classification framework of the momentary quality events following the real welding process. The output of the method is a quality map of the entire welded joint with a high spatial resolution.
The hard/soft-ware realization of our approach is a full-fledged prototype of the quality monitoring system. In our setup, additional software was attached to the commercially available laser welding components. The demonstrator operates in pseudo real-time and requires no interventions inside the commercial parts. The data processing proposes a number of unique ML algorithms, the efficiency of which can be tested on the fly, adapting the algorithmic parameters to a specific application.

2. Hardware description

The hardware included a single mode fiber laser source (Fiber laser – StarFiber 150P/300P – long pulse fiber laser systems, Coherent, Switzerland) with a 1070 nm wavelength and peak output light power of 300 kW. The laser source operated in pulse mode with a repetition rate varied in the range of 0.01 – 20 Hz with a spatial Gaussian energy distribution. The output of the laser source was transmitted through a 12 µm core diameter single – mode optical fiber to a laser head. The laser head was a customized version of LASAG PH-10 Wobble (Coherent, Switzerland). Its objective had a focal length of 170 mm that focused the laser light on the sample surface into a spot of 30 µm diameter. The laser head was also equipped with a photodiode that measured the back reflected laser light from the surface of the workpiece. The photodiode was a Ge based with a spectral sensitivity ranged between (1100-1700) nm. Additionally, a narrow band optical filter was placed in front of the photodiode for selective transmittance of the back reflected laser light.

Plates from titanium (Ti) grade 5 with size 2x20x50 mm were used as workpieces. The plates were fixed in an aluminum workpiece-holder, which was placed on a U-521 PILine linear positioning Stage (Physik Instrumente GmbH, Germany). The stage provided the shifts of the workpieces in the direction perpendicular to the laser beam with a tunable velocity between 1 mm/s and 100 mm/s. In this work, the velocity was varied to achieve different welding strategies and qualities and the details are given below.

The laser welding process induced AE, which was recorded by a piezoelectric sensor Pico (Physical Acoustics, USA). The sensitivity range of the AE sensor was in the range of 50 - 1850 kHz. The AE sensor was firmly clamped to the aluminium workpiece-holder in a stationary position throughout all the experiments. The recorded AE signals were digitized by a data acquisition unit from Vallen (Vallen GmbH, Germany) with a sampling rate of 10 MHz. The redundancy in sampling rate was removed later during the signal processing. The data acquisition was triggered by the Ge photodiode of the processing head. At the same time, the acquisition duration was adjusted to the duration of the laser pulse that illuminated the workpiece.

The digitized signals were transmitted to PC where they were stored using the software from Vallen. In addition, the same computer included a specially developed software with the machine learning framework. This software processed the stored AE signals and output the results as a quality map of the weld joint. The quality map was formed as the time ordered sequence of the spatially localized momentary welding events within a single weld. Those momentary events were established before the processing. The general view of the entire setup and the interface of the software with the processing output are shown in Fig. 1.
The described system allowed realising several welding strategies that are widely used in the industry, namely: i) spot welding and ii) Stepless High-speed Accurate and Discrete One-pulse Welding (SHADOW). The settings of the power of the laser irradiation for both regimes was varied to provoke distinctive welding qualities and the corresponding settings for the power of the laser irradiation were taken from a previous work [11].

Spot welding is the exposure of separate surface areas with short laser pulses that provided deep weld but with a narrow process zone [1,5,11]. To create this regime, the laser pulse duration was fixed at 5 ms whereas the laser power was set to 20W, 40W, 80W and 120W. The sample was moved on a distance of 0.4 mm after each pulse to avoid any overlaps of the heat affected zones. Thirty five pulses for each laser power condition were applied and the corresponding AE signals were used for training of the machine learning classifier.

The welding in a SHADOW regime produces quasi continuous welds from a single pulse. It is distinguished by the lower power consumption while operating during long time periods and provides with less crystallographic changes in heat affected zone [13]. During experiments the welds of 5 mm in length were produced. The irradiated workpieces were shifted at a speed of 100 mm/s under the laser beam and were exposed with a laser pulse duration of 50 ms. The laser power was set to the discrete values of 50W, 100W, 150W, 200W and 250W to provoke different qualities. For SHADOW welding, five welds for each condition were made and used for the training of the machine learning framework. For both welding regimes, the classification tests were performed using real welds that followed after training.

3. Signal processing

All acquired AE signals were recorded in the PC and were processed with a delay of two seconds compare to each laser pulse without data loss. The saved AE signals were recovered and analyzed with our specially developed software one by one according to the time order thus following the actual welding process. For quality classification during spot welding, the entire AE signal from each individual pulse was considered as a single momentary welding event and the AE signals from those were processed entirely. For SHADOW welding regime, the recorded AE signals were evidently of a longer duration. In
In this case, those signals were scanned with a running window following the process and splitting the AE signals into a sequence of separate patterns. The processing procedure that is described below was applied to each of such patterns. The typical example of running window processing for SHADOW welding is shown in Fig. 2,a. The time span of the running window was estimated empirically during an exhaustive experimental search. On the one hand, the shorter time span provided a higher spatial resolution in the localization of the local particularities of the weld joint. On the other hand, those were more affected by the noises thus reducing the classification accuracy. It was experimentally estimated that the optimal compromise between those contradicting conditions was with the time span of 1 ms. This time span allowed classifying the weld quality for each 0.1 mm of the weld joint.

The processing of the signals was made in two steps: i) pre-processing and ii) classification. The pre-processing included the computation of two types of features that were compared with each other inside a common machine learning framework. The magnitude spectra of window fast Fourier transform (WFFT) was computed using a Hann window, decomposing the given AE signals in the frequency domain [14]. Then, the wavelet sonograms were computed decomposing the signals in the time-frequency domain [14]. The interest in wavelet application towards this problem was stipulated by wavelet advantages when operating with non-stationary data as compared to the Fourier transforms [14]. The wavelet decomposition is sensitive to the choice of the base (or mother) wavelets. In this study, the search of the suitable base wavelet was performed via an extensive search among the standard wavelets families, including: Daubechies, Symlets, Mexican hat, Coiflets, biorthogonal wavelets. The wavelet approximation errors of the collected AE signals were analyzed to make the final choice. Finally, the Daubechies wavelet with 5 vanishing moments was chosen for further analysis as it had the minimum approximation errors.

The construction of the wavelet sonograms was carried out using wavelet packets [14] and the general scheme of this transform is presented in Fig. 2,b. In wavelet transform, the signal is gated through low \( (h_0 \text{ in Fig. 2,c}) \) and high \( (h_1 \text{ in Fig. 2,c}) \) pass filters [14], resulting the extraction of the low and high frequency content. The multi-resolution analysis was achieved by including several decomposition levels, where the same operation is applied to the results of the previous split in the pyramidal way [14] according to the scheme in Fig. 2,c. The relative energies of the low and high frequency components after each such split were computed as: 

\[
\rho_{\text{norm},j,m} = \frac{E_{j,m}}{B_j}, \quad \text{where } E_{j,m} = \int |d_{j,m}(t)|^2 \, dt = \sum_k |d_{j,m}|^2 \text{ is the energy of each split and } d_{j,m} \text{ are the coefficients that are the products of each split and } m \text{ is the decomposition level. The computed relative energies of narrow frequency bands are localized in the time-frequency domain [14]. The time-frequency ordering of those was used to build the sonograms of the recorded AE signals. An example of such sonogram can be seen in Fig. 2,d.}
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Two tests were carried out in which the magnitude spectra of the Fourier transform and the wavelets sonograms were the input to the classifier.

The task of the machine learning framework in the context of the present study was to find the unique acoustic signatures of different power regimes. In our setup each power regime was closely related to the quality and the explanations are given in the next paragraph. The classification was made using random forest (RF), which is the state-of-the-art in classification / regression tasks [15,16]. The main attraction of this algorithm towards our problem is its robust operation in the presence of noises, possibilities to build hyperplanes on a data with a complex mutual configuration, insensitivity to outliers and overfitting [16]. RF is
an extension of a bigger family of machine learning algorithms based on decision trees [16] which provides the aforementioned processing advantages. The architecture of decision trees incorporates a number of nodes. Each node splits the data into smaller portions and the need for further splits is decided if the current split fulfils some pre-defined criteria. RF employs the so-called CART (classification and regression trees) [16] in which the gini impurity criteria at each next split is compared with the one of the parent node, thus deciding the needed number of splits for each particular case [15,16].

The general RF architecture includes an ensemble of decision trees, unified into a forest. The processing is carried out by forwarding the input data into a common root of the forest, where it is sub-sampled on each tree individually [15,16]. The final decision is made by voting among all the trees inside the forest after the data propagation through the forest. The outstanding performance of RF is gained due to several novelties that were introduced in its architecture as compared to other ML algorithms. This makes it efficient when operating with real life data. RF does not require any cross validation tests to estimate the tests errors. The corresponding errors are the subject of internal computations (so-called out-of-bag estimates). The algorithm operates well with big dimensions of input variables and, in this case, only important dimensions are selected and further considered for analysis. The individual splits on each tree that followed the gini impurity criteria and the same splits are inhibited for different samples of the datasets. All this preserve RF from overfitting, maximally automatizing the operation of the algorithm and still keeping all the inner parameters accessible.

4. Discussion

The relation of the welding quality to the laser power, provided in our setup, can be observed from the light microscopic images of the cross-sections in Fig. 3. The laser power was modulated during both, spot and SHADOW welds with the discrete laser power mentioned above and the corresponding quality variation, verified in earlier work [11]. The examples are given in Fig. 3,a and b. The microscopic images of the cross-sections for spot and SHADOW regimes were made post-mortem. As seen from the figures, the quality variations are in the welding penetration depth and pores presence. In the images from the figure the melt zone can be observed as a lighter color area inside the material with some textural differences. It is additionally bordered by white solid line in Fig. 3,a for better contrast. As seen for spot welding (Fig. 3,a), the powers of laser of 20W and 40 W corresponded to conduction welding with shallow penetration depths. With the powers of 80W and 120 W, the formation of vapor channel was created (so called keyhole) that resulted deeper penetration depth. The

![Figure 2](image-url)

Figure 2: a) The AE signal from the SHADOW welding regime, where the solid and dashed markers show the present and next positions of the running window during processing; b) is the magnitude spectra of the pattern, bounded by the solid marker in a); c) is the wavelet packet transform scheme, where h₀ and h₁ are low and high pass filters correspondently; d) wavelet sonogram, obtained from a pattern, bounded by a solid marker in a).
The presence of the key hole can be verified from the aspect ratio of the heat affected zone (HAZ) as is described in [11]. None of the cases in spot welding provoked the formation of pores. For SHADOW welding, the laser powers of 200 W and above were found to be the limit for the creation of pores and evidence of this is seen Fig. 3,b. The detection of pores is challenging as they are located at some depth under the surface. Those are not observable from the surface and carry a hidden threat to the mechanical properties of the workpieces. The laser powers below 200 W were characterized by different penetration depth of the melted material inside the workpiece. The experimental setup presented here provided the repeatability of the results in Fig. 3 during all experiments.

![Figure 3: Cross-sections of the workpiece after a) spot and b) SHADOW welding regimes. The markers denote the power of the laser irradiation](image)

The training of the classifier was performed using the preliminary collected dataset. The tests were done afterwards running real welding of workpieces. The results of the tests for spot and SHADOW welds are presented in Tables 1 and 2. The classification results in rows are given versus ground truth in columns. The match of the test results with the ground truth are placed in diagonal cells and highlighted in grey, while the structure of the classification errors is in the non-diagonal row cells.

The classification accuracy for the spot welds ranged from 85% to 99% for wavelets (in bold) and from 91% to 99% for WFFT [in brackets]. As seen from Table 1, the errors were mainly due to the overlap of the regimes with the neighbor laser power. It is interesting to note that the laser powers below 40 W (so called conduction welding) were classified with a high accuracy. In contrast, the welding regimes with laser power 80 W and 120 W (so called keyhole welding) showed lower accuracies. As seen from Table 1, both categories with high powers showed an overlap between each other’s. One explanation can be in the emittance of AE in a broader frequency range while material overheating at higher laser powers that brings to more complex frequency configurations, thus complicating the separation of the data.

The classification accuracy for SHADOW welds varied between 75% and 95% for wavelets and 87% and 98% for WFFT. The lower accuracy as compared to spot welding may be explained by the absorbed energies fluctuations inside a single weld caused by the local optical non-uniformities of the material that caused temperature drops. The errors structure presented in Table 2 showed an overlap between the neighbor laser power which is identical to the situation in Table 1. Also, the greater overlap between 100 W and 150 W can be explained by a smooth border between the two regimes as observed in Fig. 3,b. The overlaps between the regimes with pores formation at 200 W and 250 W in industrial applications do not make a big difference as both are dangerous for the mechanical properties of the processed workpiece. In contrast, the overlap between the laser power with pores at 200 W with the one without at 150 W is relatively low and is only 5% [-]. This relatively good separation between both regimes with a critical impact on quality demonstrates the applicability of acoustic emissions for quality monitoring. Generally this
Table 1. Classification accuracy for spot weld, where GT is the ground truth.

<table>
<thead>
<tr>
<th>GT Test</th>
<th>20 W</th>
<th>40 W</th>
<th>80 W</th>
<th>120 W</th>
<th>GT Test</th>
<th>50 W</th>
<th>100 W</th>
<th>150 W</th>
<th>200 W</th>
<th>250 W</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 W</td>
<td>99 [99]</td>
<td>1 [1]</td>
<td>-</td>
<td>-</td>
<td>50 W</td>
<td>95 [99]</td>
<td>5 [1]</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>250 W</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5 [2]</td>
<td>95 [98]</td>
</tr>
</tbody>
</table>

*the results are given in the format: wavelets [WFFT]

5. Conclusion

This work is a usage of acoustic emission (AE) and machine learning for laser welding quality monitoring. The frequency and time-frequency domains of the AE signals were exploited for signals representations and were the input of the classifier. The test results on real welds showed that this approach is technically feasible for the monitoring of the quality in commercially available laser welding machines. It was approbated on spot and SHADOW welds. The corresponding accuracy rates varied in the ranges of 85 % to 99 % and 75 % to 95 % for both welding regimes respectively. The possibilities to detect potentially dangerous welding regimes that cause the pores formations were shown. The greater error rates were observed as overlaps between the categories at higher laser powers. Mainly those regimes caused the occurrence of overheated material vapors (keyhole). Due to this, the emittance of AE is in a broader frequency range brought to more overlaps between the categories. However, it is important to underline that the regimes with and without pores are still separable with an acceptable precision.

The improvements of the classification confidence may be done with some optimizations of the processing algorithms. Those could be the usage of preliminary preprocessing to capture the training data structure. This is feasible, for example, with spectral graph methods. The extension of the classifier operation in recursive way may bring to higher efficiency as provides with better transients analysis. All this is planned as a future work.

References:


