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Monitoring of laser welding/AM processes combining high speed X-ray imaging, acoustic sensors and artificial intelligence

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Abstract

Laser processing (welding / additive manufacturing) is known for its complexity and high dynamics, thus challenging for in situ and real-time quality monitoring and control.
To tackle this challenge, we collected the signals from acoustic sensors. We then analyzed these signals by state-of-the-art artificial intelligence technics to classify the laser process in terms of quality.
Despite promising results, many questions remain open relating the hidden mechanisms that makes such classification approach feasible. Hence, to get a fundamental understanding of the laser process and background physical origins of the acoustic emission, in situ and real-time high-speed X-ray imaging of real laser processing was carried out at European Synchrotron Radiation Facility (ESRF-Grenoble).
The presentation makes an overview of this approach and results from ESRF.

Keywords: Additive manufacturing; laser welding; quality control; acoustic emission; high-speed X-ray imaging; artificial intelligence;

1. Introduction

In recent years, lasers are intensively integrated in more and more industrial applications, also increasing their market share in critical technologies. The on-growing consumption of lasers is stimulated by the constantly decreasing costs of this technology. Additionally, there is a significant increase in laser products line (relating wavelength, pulse length, power etc.). Both factors promise an intensive increasing in demand

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of lasers in more industrial applications. Unfortunately, laser processing is known for being complex and highly dynamics. Thus, it stochastically affects the process quality and makes the monitoring and control of the laser processing a problematic task. Particular examples are laser welding (Stavridis et al., 2014: You et al., 2018) and additive manufacturing (Everton et al., 2016; Tapia et al., 2014). Therefore, any solutions for in situ and real-time monitoring and control of those laser processes are highly demanded. The main approaches have been developed based on optical methods, which are greatly influenced by the plume formed above the processed zone. Others have used acoustic emission (AE) and state-of-the-art signal processing (Shevchik et al., 2018 and 2019). In these contributions, the process parameters were intentionally modified to get three grades of quality, which were related to the porosity content inside the workpiece. Machine learning was used to differentiate the signals from different quality. The quality grades were defined as high, medium and poor, with porosity content of 0.07, 0.30 and 1.42 %, respectively. The quality ground truth was based on post-mortem analysis of cross-sections. This approach is sufficient for cases where porosity is homogeneously distributed in the material. In contrast, it cannot be used for categories that takes places during the lase pulse such as stable and unstable keyhole. To overcome this difficulty and to be certain of the correlation between the AE signals and the real events, several series of laser experiments were performed at the European Synchrotron Radiation Facility (ESRF, Grenoble, France) using high-speed X-ray radiography combined with AE measurements. This contribution presents the main results of these experiments.

2. Experiment, material, data acquisition and processing

The complete description of the experiment setup, data acquisition and data processing can be found in (Quang-Le et al. 2018; Wasmer et al., 2018). Thus, only a very short summary are presented in this work.

An aluminum-magnesium alloy was chosen for its relative low *Z*-number. The samples had dimensions 50x20x2 mm^3.

The AE signals were acquired with a PICO sensor from PAC. The AE data were recorded by a system from Vallen. The sampling rate during data collection was 10 MHz. The AE sensor was attached to the sample holder.

The high-speed X-ray imaging was made at the beamline ID19 of the ESRF using the synchrotron X-ray source in polychromatic mode. The frame rates during the experiments were between 28 kfps and 36 kfps. The effective pixel size of the X-ray image detector was 11 µm.

Some details relating signal processing can be found in (Wasmer et al., 2018). In this study, wavelet packet transform (WPT) was applied to the acquired AE signals, where WPT is a specialization in analyzing non-stationary signals. The relative energies of the extracted frequency bands were computed using WPT and taken for further analysis. The analysis of the acquired AE data is performed with artificial intelligence (AI) for classification tasks. The method chosen in this contribution was XG-Boost (Extreme gradient boost), which is a state-of-the-art in classification/regression tasks and is a branch of AI based on decision trees (Chen and Guestrin, 2016). This algorithm is a modification of a standard gradient boost (BG). In this framework, the data input passes through a sequence of the weak classifiers, each of which extracts features. The training procedure of this approach estimates the number of the classifiers needed for an efficient features extraction and then adds new classifiers to the old one to improve the performance. The add-on of new classifiers was carried out until no further improvement in classification was possible and this task was performed via an optimization routine. In this work, the algorithmic framework was developed in Microsoft Visual Studio 2017, programming language - C# and original XG boost library (www.github.com\gmls\xgboost). The experiments were conducted using PC with i5 processor and 8 GB RAM. The time needed for each individual classification was more or less 30 msec.

3. Results and discussion

The e : 300 for conduction welding, 150 for stable keyhole, 300 for unstable keyhole, and 100 for spatter. The length of each pattern was 5 µs leading to a spatial resolution of a few µm with the given sample velocity. The dataset was divided into two different sub-sets: training and testing. The two sub-sets had no common signals, reproducing exactly real-time conditions.

The classification results are presented in Table I. In this table, the accuracy for each quality category is given in rows and can be compared to the ground truth, given in columns. The match of classification with ground truth is in the diagonal cells (grey cells), while the error structure can be seen from non-diagonal ones. The accuracy was defined as the number of true positives divided by the total number of the tests for the individual categories. For example, the category spatter was classified with an accuracy rate of 60 %. The classification errors are shared between the unstable and stable keyhole with error rates of 25 and 15%, respectively. It is observed that the overall classification confidence ranges between 60 to 99 %. It is interesting to see that the error increase with the penetration depth of the welds that is characterized by different dynamics of the overheated mater inside the process zone. The lowest accuracy was for spatter that is overlapped with stable and unstable keyholes. The spatter is at most is overlapped with the unstable keyhole. The reason in greater errors for this category is the absence of the distinct differences between both as spatter is an extreme case of unstable keyhole. The same can be concluded about stable and unstable keyholes. The errors in this case can be due to the smoothed transition of one to another. The most important result in this study is that we were able classify with confidence the category unstable and stable keyhole. Taking into account that porosity generally occurs during unstable keyhole, being able to detect the transient between both categories indicates that there is possibility to develop a control loop. But this is future work.

Table 1. Classification results for the categories conduction welding, stable keyhole, unstable keyhole and spatter.

Ground truth / Test categories	Conduction welding	Stable keyhole	Unstable keyhole	Spatter
Conduction welding	99	1	0	0
Stable keyhole	3	65	32	4
Unstable keyhole	3	15	85	4
Spatter	0	15	25	60

4. Conclusion

This work shows the possibilities to apply artificial intelligence for classification of the momentary events of the laser processing. Nevertheless, the results presented show the high sensitivity of this method to the databases and definitions of the categories. The results of this work give the main directions for further developments of artificial intelligence applicably to the real laser matter interaction processes. Namely, the application of the semi-supervised or even unsupervised learning may give better estimation of categories. The second directions may be the more precise investigation of the laser processes and development of the specialized artificial intelligence techniques that take into account the process particularities. Finally, as it is possible to detect the transition of stable and unstable keyhole and that the latter is responsible for porosity, we demonstrated the possibility to develop a control loop. All this work is in the plans for future investigation.

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