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On the detection of defects and of incorrect actuator settings in laser machining

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Abstract

The detection of "unknown objects" is commonplace in several technical fields including sonar, radar and ultrasonic inspection. The techniques used in these fields have one common approach, that can figuratively be abbreviated as the "send & listen" approach: the emission of known wave fields and the observation of how these fields are refracted, attenuated or retarded by the unknown object. The usability of the send & listen approach for detecting defects and their causes and for silencing inherent random signal fluctuations has been researched during remote laser welding with a 4kW disk laser. We used the processing laser as a wave emitter ("send") and observed wave reception ("listen") within a multi-sensor arrangement. Sensors included band-filtered photodiodes and sound pressure detectors, both of which varied in position or direction. Our results show that the application of send & listen to laser machining may be beneficial for detecting changes in process results and for discriminating which machine setting is responsible for the individual change. In our spectral analyses we found unique spectral footprints for common defect occurrences such as lack of fusion and full/partial penetration and for common causes such as changes in axial focus, in lateral focus, in workpiece thickness, in the gap between joined parts, in laser power and in lateral beam velocity. This paper details our send & listen approach, shows some of the found spectral footprints and outlines their usability for process monitoring and control.

Keywords: laser, machining, welding, defects, detection, causes, process monitoring, control, send & listen, multi-sensor, multi-tone, footprints, neural network, microphone, photodiode

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1. Motivation

Laser machining processes involve a plethora of parameters such as laser power, feed rate, focal spot size, focal placement, incident angle, pulse rate, pulse duration, process gas type and flow, direction of beam polarization, etc. Machining results can often be detailed in a variety of entities that are equally as complex as the underlying set of parameters. In laser welding e.g. important entities of a machining result may include penetration depth, bead width, bead surface roughness, joint strength and the occurrence of surface or sub-surface defects such as pores, cracks, spatter, incomplete fusion or other deviations from desired machining results. As both, genesis and outcome of a machining result are complex, the situation, when "something goes wrong" during or after machining a workpiece, can rarely be understood with an instant grasp, a complete overview or a thorough understanding.

It involves complicated math, to say the least, to establish a functional relationship between the set of process parameters ("input"), that quantify the configuration of the laser, the robot, clamping gear, the surrounding medium and workpiece and the chosen set of entities ("output"), that quantify machining results. To make things worse, the already complex relationship between multiple inputs and multiple outputs is influenced by the stochastic interaction between beam and matter, which introduces another pool of significant, but not easy to track molecular micro- and nanoscale influences on machining results. Among these are particle shielding, evaporation, local workpiece material, shape, surface, structure, reflectivity, heat conductivity, etc. So, the involved complexity clearly drives the need for monitoring systems, that can offer the laser user better clues to what is going on when defective results occur.

2. State of Technology

Concurrent monitoring systems for laser welding, that are available on the market, do focus on their prime task of "delivering signals" to the laser user. However, proper interpretation of such signals often remains an art in itself, especially if seemingly unrelated or stochastically blurred information is provided. Stochasticity often dominates in the signals, when applying sensing devices such as photodiodes or microphones passively, Eriksson et al., 2009, Szymanski et al., 2001, Farson et al., 1997. Their passive application tends to pick-up not much more than the static or dynamic noise and flickering of optical and acoustic emissions, which are difficult to be related to more meaningful entities. The finest algorithm will not provide many clues, if all that the algorithm has to work with, consists of white or slightly colored noise. Simply directing photodiodes or microphones at the process and then hoping for a magic "wonder-algorithm" to fix, what is not in the signals, clearly can keep researchers busy without ever creating thorough advances in process monitoring. One strategy to circumvent the dangers of focusing too much on algorithms is to build or apply "better" sensors, sensors, that deliver information on physically meaningful and less noisy entities such as geometry, for instance the depth of the capillary in keyhole welding using white light interferometry, Kogel-Hollacher et al., 2014 or the camera-based supervision systems as reported by Beersiek J., 2001.

Having retrieved geometric information however provides the user not necessarily with a bag of clues on what caused the deviation that was detected by the device. Detection is necessary, but not sufficient in providing machines that are easy and effective to work with. In the scientific literature there is a tremendous focus on the detection of defects. But hardly anything is written on how to automatically retrieve the causes of detected defects, which would provide the user with a much clearer solution to avoid, prevent, cure and not just detect deviations in machining results. Detection is diagnosis. However, it falls short of the remedy.

Additionally, geometric information only covers a fraction of measurands of a machining result that are desirable to know or that are vital to product functionality. Joint strength or hardening in laser welding, subsurface cracks and porosity, subsurface fusion of welded objects may certainly be of more concern to the user than "just the looks" on the surface or in the vapor capillary, that can be recorded via camera

3. Aim

In this paper an approach is outlined on how to precisely quantify both, defects and their causes in laser machining using simple and affordable sensing devices (photodiodes and microphones) together with some instructed and not very fancy computing device (standard personal computer). The optical and acoustic emissions, that the utilized sensors pick up, are commonly known for their excessive stochasticity, which has lead researchers to the false belief, that expensive and sophisticated sensing devices are the only hope for better monitoring systems. So, answers need to be detailed as to how to suppress the noise that commonly disaffirms the use of such sensing devices and as to how to make sure that the sensor signals carry enough solid, reproducible and significant information for the intended quantification of defects and causes (which henceforth will be referred to by the term *measurands*). Furthermore, the final quantification process needs to be explained, i.e. how to map sensor signals onto measurands, and the overall performance of the approach, it's astounding precision will be deduced from experimental data recorded during deep penetration laser welding.

4. Approach

The detection and study of unknown, remote, blurred or otherwise inaccessible objects has a long tradition in science and engineering. Related identification techniques are commonly used in sonar, radar, ultrasonic inspection, mobile communication and exploration of natural resources to name a few. The advent of these techniques dates far back into the 20th century. However, in laser machining, not much notice has been given to these techniques even though the "object", the laser machining process itself, exhibits attributes of a "foreign" system, that the user would like to know a lot more about while its inaccessibility, complexity and irregularity obstructs better introspection, better control, higher efficiency or even full automation.

4.1. Stimulation – send & listen

The key element in system identification, which determines success or fate of the method, is proper excitation or stimulation of the object to be studied. Without proper excitation objects do not reveal much of their inner state. After all, unidentified objects are unidentified due to their silence, remoteness or their embedding and blurring in noise. So the fundamental idea is to make the object "scream" at the investigator loud enough in order to contrast the fuzzy environment around the object. The higher the contrast and the more detailed it is, the better the identification will work and the more information will be gathered. Higher contrast and more detail relate to sufficient amplitude and broadband stimulation.

In laser machining such broadband stimulation can be accomplished by multitone modulation of the fastest actuator, which usually is, but does not have to be laser beam power. The generated power waves do indeed make the machining process "scream" and "blink", since power waves transmit into pressure waves that microphones can pick-up and since optical emissions do start oscillating at the stimulated frequencies of the multitone modulation as well. Care has to be taken that the lowest modulation frequency is above the threshold of forming visual imprints in the machining result. During laser welding at speeds of around 40mm/s feed rate such threshold seems to be at around 400–500Hz which is roughly one period of the slowest of the power waves per 0.1mm feed. Fig. 3b shows a typical spectrum of sensor signals during laser welding with multitone stimulated laser power. Mean laser power was set at 2kW while multitone modulation forced the laser power into a [-1…1] kW variation around the mean. Fig. 3b shows sixteen equi-spaced frequencies on a fg=161.29Hz grid in the range [3·fg=484…18·fg=2903] Hz, which constitutes one of the more recent lower frequency multitone stimulations that were studied in this approach.

The sensor signals in Fig. 3b exhibit strong oscillations at the stimulated frequencies, which places the amplitudes in the spectrum well above the surrounding noise. The more such amplitudes are distinct from the visible noise floor in Fig. 3b, the less noisy the response of the studied object, i.e. of the laser welding process is and the more reproducible such amplitudes become. After spectral decomposition of sensor signals it is only the amplitudes at multitone frequencies, that will be further processed. Stimulated frequencies, that the process starts “screaming” and “blinking” at, are usually distributed by design similar to a comb of equispaced frequencies leaving enough room between “comb teeth” where the noise can settle and later be discarded. In this way, the send & listen approach forces deterministic information into the sensors and allows for filtering the noise floor off by simply neglecting what is in between the “teeth”. This is in drastic contrast to concurrent photodiode based monitoring systems which record and analyze all the noise, but fail to activate and separate deterministic information.

4.2. From spectral decomposition to measurands

The spectral decomposition of sensor signals in this work is obtained via a rolling Fast Fourier Transform (FFT) that analyses one sub-second time-frame of data and progresses to the next, for the sake of efficiency non-overlapping frame of data. If laser power mean settings are dynamically tuned and adjusted along the workpiece, then normalization of multitone amplitudes of sensor signals by the ones of the current laser power is advisable in order to free inspected amplitudes from the overlayed dynamics of the laser power mean settings. The normalized amplitudes then constitute what in system theory is called amplitude spectrum of transfer functions referring to the transmission of laser power waves into the applied pool of sensors.

By multitone excitation multiple amplitudes at excited frequencies are obtained per senor. In this work, between sixteen and thirty two frequencies and eight sensors were used, which dramatically increases the pool of information to the product of 8*16=128 or 8*32=256 sensed entities (in the following abbreviated by the term *frequency pixels* or *spectral footprints*).

Let us assume, that some of the frequency pixels do exhibit deterministic behavior and some do not. Before learning how to map footprints onto measurands statically, i.e. with the least amount of effort, care has to be taken that noisy frequency pixels are discarded from the footprints. Otherwise measurands may exhibit more noise than necessary. Furthermore, “dead” pixels which remain static while measurands are varied, also should be discarded in order to simplify and reduce the dimensionality of the mapping of footprints onto measurands. Removal of noisy pixels intends to increase reliability, while the removal of dead pixels intends to increase significance and tends to downsize and speedup computational efforts. So, basically pixels will enter the pool of mapped footprints based on two scales: one for reliability/reproducibility (noiselessness) and the other for significance (vividness with changing measurands). The testing for these properties is done in order to constitute a *mappable* footprint, *mappable* meaning that measurands can reliably be tracked using the mapping.

Such testing is not manual. It can be automated by the following experimental design which deploys a change & wait strategy such that measurands will plateau. If a frequency pixel also plateaus, then it can be considered low noise and be chosen for a static mapping. If a pixel exhibits drastic changes on the amplitude scale when measurands jump to the next plateau, then it can be considered significant and not dead. So during laser welding experiments that perform change & wait settings of measurands, a plateau-like expression of pixels is what we are looking for as it is key to the feasibility of a simple static mapping. Luckily, in all of the laser welding experiments, that were performed in this work, plateau-like expressions were observed, such as the ones displayed in Fig. 4-6.

Finally, once a footprint containing vivid, low-noise pixels is put together, mapping it onto measurands requires some learning algorithm that changes the mapping until its error is minimized. In this work, a multilayer perceptron was utilized in order to learn this static relationship between spectral footprints and measurands using the backpropagation algorithm for learning and error minimization. Backpropagation learning is a well established technique. There is nothing fancy about its use, so all means utilized in this approach readily extend into realtime or in-process applications. The approach can be structured into three steps.

1. Perform some change & wait experiments (e.g. welding for less than a minute); while doing so
   a. Stimulate with multitones
   b. Observe and record the intensity of emissions using multiple differing sensing devices
   c. Quantify the obtained plateaus of measurands in- or off-process
2. Perform some data analysis (usually done in a time frame of a few seconds); while doing so
   a. Extract stimulated amplitudes using a rolling FFT plus normalization
   b. Constitute footprints
   c. Learn relationship between footprints and measurands
3. Exploit the learned relationship to quantify measurands in- or off-process (usually done in milli- or sub-seconds when processing several seconds of data with a moderate PC)

Again, there is nothing fancy about this approach. Off-process implementation may initially require some seasoned scripting to process the recorded data and learn the relationships that later can be used to quantify measurands in- or off-process. However, as nothing here is fancy, the approach may well be integrated into any self-learning or adaptive laser system that is intended to supply its user with the clues on defects and causes that concurrent laser systems don't provide.

5. Experimental Setup

The utilized sensors throughout all experiments included two microphones and six silicon photodiodes, five of which were fed via PMMA- or SiO2-fibers arranged on-axis behind the beam splitter in the laser head and one SiO2-fiber arranged off-axis next to the microphones, see Table 1.

Table 1. Pool of sensors and channels used for the send & listen approach, PD: photo diode, Mic: microphone Sennheiser MKH816

	Sensor	Type	Filter	Fiber	Axis	Direction	Arrangement	Dominating Spectrum
1	powact	PD	–	–	on	coax	behind resonator	1030nm
2	micforw	Mic	–	–	off	forward	attached to laser head	50-20000Hz
3	micbackw	Mic	–	–	off	backward	attached to laser head	50-20000Hz
4	onaxL	PD	–	SiO2	on	coax	behind beam splitter	1030nm
5	SiO2d	PD	–	SiO2	off	backward	attached to laser head	1030nm
6	onaxr	PD	red	PMMA	on	coax	behind beam splitter	~650nm
7	onaxg	PD	green	PMMA	on	coax	behind beam splitter	~510nm
8	onaxb	PD	blue	PMMA	on	coax	behind beam splitter	~470nm
9	onaxw	PD	–	PMMA	on	coax	behind beam splitter	360-800nm

10	powdes	–	–	–	–	–	desired laser power	–

Opposed to SiO2 fibers, low cost PMMA fibers utilized in this approach seemed to have huge IR transmission losses as no photo diode signal was raised when experimentally subjecting the fibers off-axis at the reflection of a defocussed 1030nm 100W laser beam. Thus, PMMA fiber fed PDs picked up optical emissions, while SiO2 fiber fed PDs picked up reflected laser power which excessively dominated all other incoming optical emissions in the SiO2 fiber core. Powact and powdes designate actual and desired laser power. Powact was obtained from the laser electronics of the utilized Trumph 4kW disk laser (1V/500W). Powdes is an internally recorded variable obtained before its DA conversion into the voltage of the desired laser power (1V/400W). All DA and AD conversion was done at 80kHz using home-made 16bit ADCs and 12bit DACs hooked to a home-made PCIe based IO interface located in a Xenomai real-time Linux computer operating under Ubuntu 12.04. A photo of the experimental setup can be seen in Fig. 1.

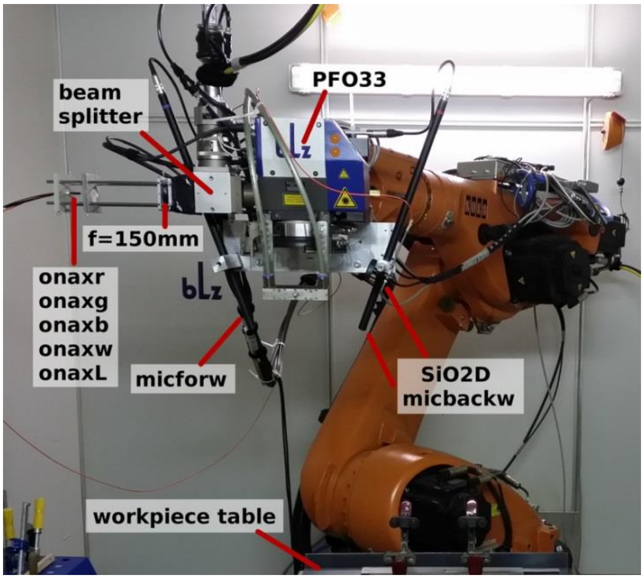

Fig. 1. Setup of utilized sensors which were attached to a remote laser head (Trumpf PFO33)

6. Measurands

In laser machining one key challenge is that even though all machine set-points are static, the results many times are not. This gives rise to personnel “scratching their heads” at the laser machine and wondering what is going on behind their delicately determined settings. In laser machining one may think everything is constant, but in reality nothing is but the settings. This problem is rooted to great extent in the fact, that laser power measured at the laser resonator does not equal the power absorbed by the workpiece, which is a multivariate function of surface reflectivity, incident angle, local heat conductivity, material homogeneity, positioning and manufacturing history to name a few. What is absorbed down at the workpiece needs to be measured there and not somewhere in the beam delivery system without ever looking at the workpiece. So, the first chosen measurand in this work is absorbed laser power estimated using emissions from the workpiece and assuming that absorbed laser power is kept constant during the initial change & wait experiments. Having an indication of what absorbed laser power may be provides an apparent remedy for all deviations from desired results that root in inappropriate fluctuation of absorbed laser power.

The list of not so constant variables in laser machining continues with the actual focal spot size, which frequently varies, even though the distance between laser head and workpiece may have been adjusted with great effort to nearly constant values when progressing along the workpiece contour. The reason for unidentified changes in focal spot size is the fact that focal spot size is a function of many other entities the user does not necessarily have control over including lens heat-up, lens contamination, incident angle, beam refraction and diffraction in generated vapours, poorly planned robot tracks, workpiece movement due to insufficient clamping, etc. As is the case with absorbed power, focal spot size cannot be measured appropriately without ever looking at the workpiece. So the second measurand chosen in this work was focal spot size estimated from process emissions under the assumption that it remained at defined plateaus during the initial change & wait experiments. Having an indication of what the spot size actually is clearly provides a remedy in case deviating machining results root in focal spot variations.

The third major cause for defective machining results, that was studied in this work, is irradiation time, which again is a function of many entities that are not under full control of the user, including all influences on focal spot velocity among which are scanner movement, poorly planned robot movements, robot inertia, surface inclination, incident angle changing with scanner motion, variations in workpiece topology, etc. Measurments need to be obtained directly from the actual workpiece and not be based on assumptions on its shape and position or on perfect accuracy of robotic placement. So the third measurand and cause for defects studied in this work was irradiation time estimated from process emissions under the assumption that it remained at defined plateaus during the initial change & wait experiments.

To complete the list of causes for defective results tracking of which would provide the user with great benefit, this work added gap detection and lateral focal placement detection to the list of interesting measurands that were studied. In lap or T-joint welding of zinc coated or zinc containing materials sufficient gap sizes are vital for the outgassing of zinc, but also dangerous for the risk of failing to join or fuse welding partners. The beam may fully penetrate both overlapping sheets without enforcing bondage, which frequently causes visual inspection of the front and rear side to fail in these cases. Additionally, a common problem in welding T-joints is placing the focal spot laterally such that the visually obstructed welding partners is perfectly hit by the laser beam. Thus detecting lateral focal placement in this configuration was studied as well.

To the five measurands that can explain defect causes as discussed above, this work added three more machining results, for which concurrent sensor systems have no simple or widely applicable quantification methods. These are partial versus full penetration status, fusion status (welding partners bonded together yes/no), which is especially difficult to detect in lap joint configurations and penetration depth.

Table 2 provides an overview of the researched measurands which were intended to be tracked synchronously from process emissions alone.

Table 2. Measurands studied during the compilation of this report; abbreviations are used in diagram legends

Abbr.	**Measurand (defect causes)**	**Abbr.**	**Measurand (machining results)**
powmean	absorbed laser power	fullpen	full penetration yes/no
z	size of focal spot (varied and expressed by axial distance from workpiece surface)	pdepth	penetration depth (estimated from visual inspection)
v, veloci	focal spot velocity	fusion	fusion yes/no
gap	gap in visually obstructed weld configurations		
x	lateral focal placement (T-joint welding)		

Table 3 lists the weld configurations that were examined on differing dates. On the final date, worst case scenarios for neural network based prediction of measurands were studied, where the neural network had to quantify combinations of measurand settings that were not used during training. Training and testing the neural network was always done with data from different welds independent from the type of the studied scenario.

7. Experiments & results

When compiling this report, data from change & wait experiments were used that were recorded during six student lab courses in the winter semester of 2014/15 and in the summer semester of 2015, see Tab. 3.

Table 3. Weld configurations, measurands that were studied and # of experiments used for analysis (each 8s of welding)

Date	Weld configuration	Measurands	# Exp.
20141124	Lap joint, 1.0/1.0mm DC04 sheet metal	powmean, z, v, fullpen, pdepth, fusion	5
20141125	Lap joint, 1.5/1.5mm DC04 sheet metal	powmean, z, v, fullpen, pdepth, fusion	5
20141201	Lap joint, 1.0/1.0mm DC04 sheet metal	powmean, z, v, fullpen, pdepth, fusion	5
20141202	T-joint, 1.5/2.0mm top/root, DC04	powmean, x, v, fullpen, pdepth, fusion	5
20150513	Lap joint, 1.5/1.5mm, DC04	powmean, gap, v, fullpen, pdepth, fusion	7
20150520	Lap joint, 1.0/1.0mm, DC04	powmean, gap, v, fullpen, pdepth, fusion	17

In each experiment 128 or 256 frequency pixels were obtained, so that the plotting of all diagrams in one day of lab course quickly rises above one thousand diagrams, which far exceeds what can be detailed here. Thus this report will show a selection of studied data. The dates and times of the respective recordings appear in the format yyyymmdd-HHMMSS on the shown diagrams. In order to learn and establish the mapping of footprints onto measurands, between four and seven weld seams were used each generated within eight seconds and each containing eight one-second sections in which measurands were allowed to plateau to known values. Once the mapping was established via training neural networks with approximately 320 to 560 footprints, the precision of measurand quantification was studied by testing the neural network with footprints as inputs that it had not "seen" before. Care was taken that training data sets and testing data sets differed. In all experiments, the footprints for testing were calculated from workpieces not used for training the neural networks. Two cases were studied, one where measurands during testing equaled those during training (best case scenario) and one where they did not (worst case scenario). The obtained neural network outputs during testing then were compared to actual values of the measurands and the difference of both was formulated as error. Error statistics were done over all footprints used in testing and the resulting mean errors, standard deviation of errors and maximum error were plotted into the legends of respective diagrams, such as Fig. 7-9. Additionally the obtained maximum error was graphically indicated in the form of a star in the time series of measurand estimations. As neural network inputs the thirty best frequency pixels were chosen using the scales detailed in Section 4.2. As outputs usually six of the measurands listed in Table 2 were chosen. Among these six outputs either gap detection or focal spot size detection or lateral focal placement detection was chosen, however not all three at the same time in order to keep weld lengths short (below 240mm) and to facilitate the ongoing lab course work using one joint type at a time. Some examples of welded workpieces are shown in Fig. 2.

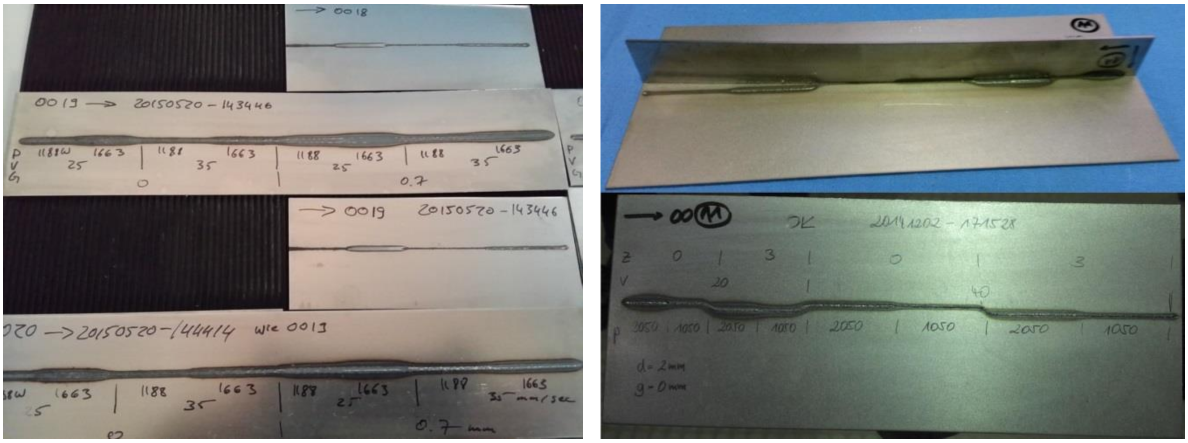

Fig. 2. (a) workpieces from overlap welding with/without gaps; (b) workpieces from T-joint welding with/without lateral offset x

The recorded time series of sensor signals were plotted into diagrams, Fig. 3, and used to tune signal amplifications well into the acceptable voltage ranges of Nyquist lowpass filters and consecutive AD converters. Spectral plots, Fig. 3b, showing the average amplitudes of stimulated oscillations per workpiece section (1s machining duration) allowed for checking whether the applied stimulation raised frequency pixels were well above the noise floor which can be observed between the “frequency teeth” in Fig 3b.

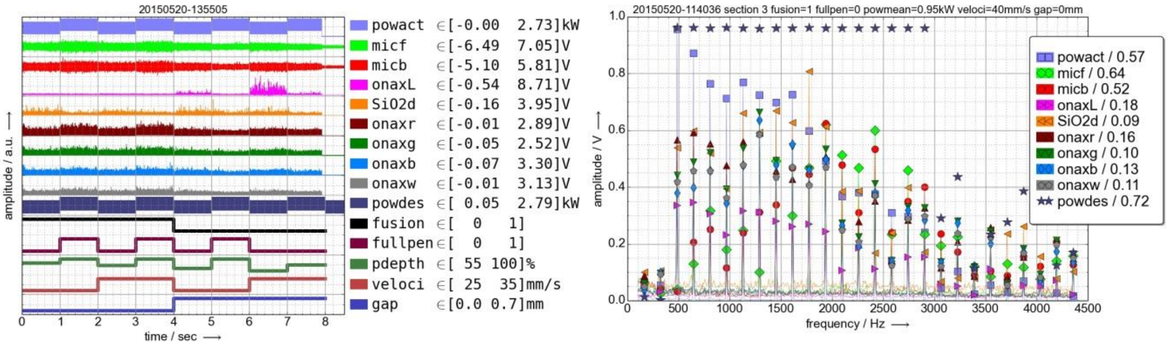

Fig. 3. (a) time series of recorded signals; (b) typical signal amplitude spectrum during stimulation with “frequency pixels” marked

Abbreviations used in the legends of displayed diagrams are listed in Tab. 1 and 2. Fig. 4-6 contain plots of the time series of amplitudes of stimulates oscillations, i.e. the timely progress of frequency pixels during laser machining. Fig. 4-6 allows for stating that pixels do plateau with apparent low-noise in several cases, that the plateaus reproduce well and that the change of plateaus is significant and in many cases drastic. This observation strongly indicates that a static mapping to measurands is likely to perform satisfactory.

Furthermore, plateau formation varies with the stimulated frequency indicating that differing frequencies do lift or do carry differing information.

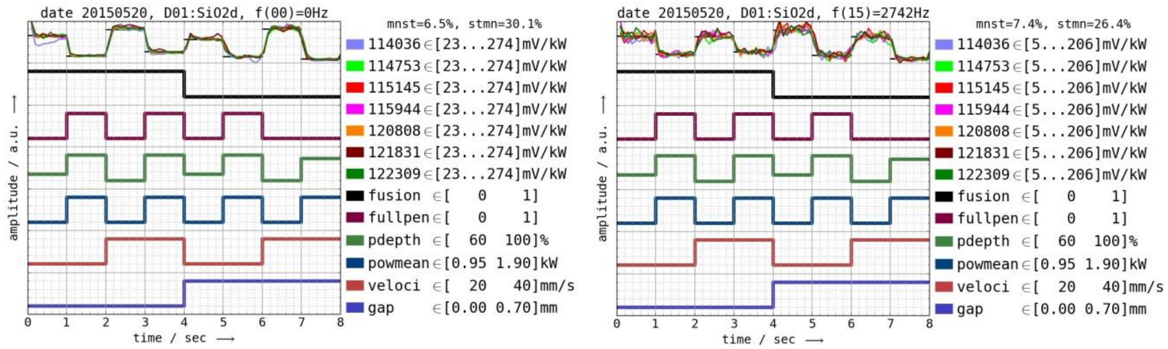

Fig. 4. time series of the amplitude of sensor SiO2d at different frequencies during the machining of seven different workpieces (20150520-114036 … 20150520-122309)

In terms of noise, frequency pixels of microphone signals, Fig. 5, do not perform significantly worse than frequency pixels of optical emissions, Fig. 6. The direction of the microphone, in Fig. 5 forward or backward to welding direction, does change pixel behavior indicating that differing microphone directions do lift or do carry differing information. Thus, multiple microphone use is likely to improve or stabilize measurand prediction and is likely to decrease error in measurand quantification.

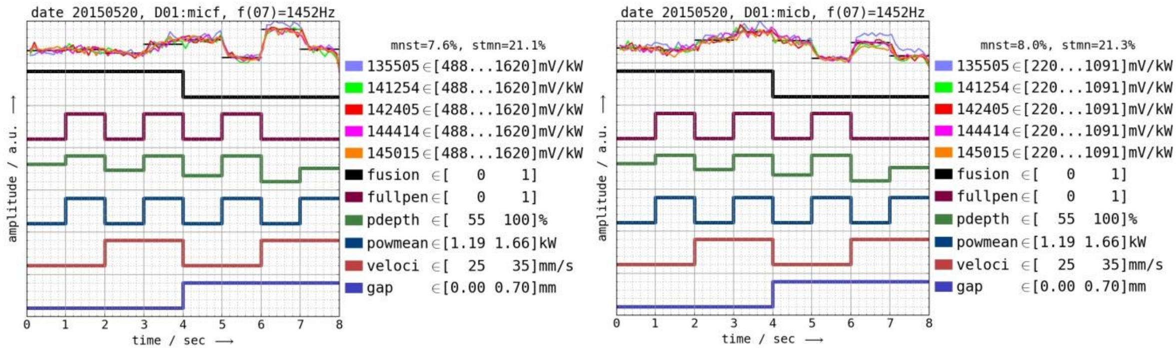

Fig. 5. time series of the amplitude of the forward and backward microphones at equal frequencies during the machining of seven different workpieces (20150520-114036 … 20150520-122309)

Frequency pixels of optical emissions, Fig. 6, do change their plateauing with optical wavelengths (here green vs. red) and with the stimulating frequency, indicating that optical filtering and spectral diversification of sensing devices does add information and thus does improve measurand quantification. Furthermore, not shown here, but recognised during analysis, frequency pixels of unfiltered emissions (onaxw) perform with respect to noise significantly worse than optically filtered versions (onaxr, onaxg, onaxb) indicating that information in onaxw gets blurred by extensive spectral noise i.e. not only by intensity fluctuation but also by color variation of optical process emissions. Thus, the use of optical filters does improve measurand prediction.

Fig. 6 also shows, that certain frequency pixels exhibit more noise than other ones indicating the necessity to be selective and to compose footprints from low-noise versions before defining neural network inputs.

For instance, onaxis red (onaxr) stimulated at 3011 Hz and onaxis green (onaxg) stimulated at 430 Hz were rejected from feeding the neural networks used in the composition of this report.

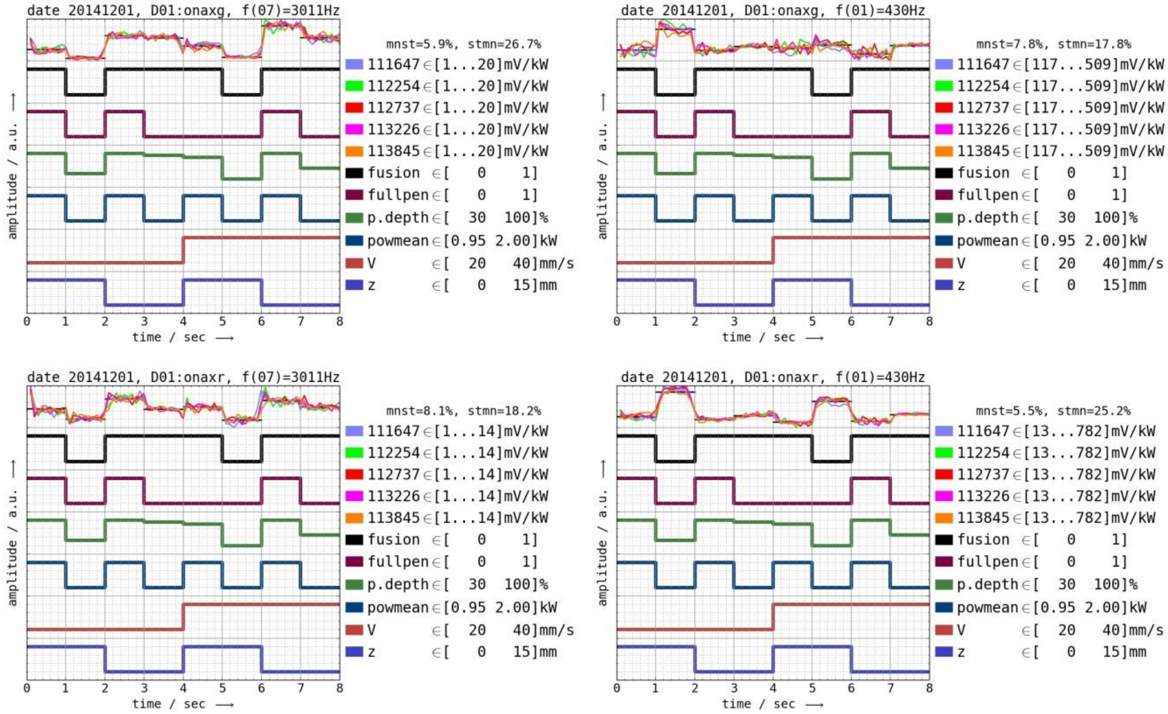

Fig. 6. time series of stimulated amplitudes of optical emissions, on-axis green and on-axis red, at differing frequencies during the machining of five different workpieces (20141201-111647 … 20141201-113845)

The time series of neural network based predictions of measurands are displayed in Fig. 7-9. Neural network outputs are printed in color, while actual measurands are plotted in black. Error statistics can be found in the legends. As mentioned before, thirty frequency pixels were computationally selected as network inputs and the hidden layer size was varied. Hidden layer sizes “x” are documented in the title of the diagrams as “NNet(x)”. Some network outputs exhibit an astonishing sub-on-percent error when subjected to the frequency pixels of a new workpiece, Fig. 7.

From the good graphical match between neural network outputs and progressing measurands and from the displayed error statistics in Fig. 7-9 it can be noted, that all measurands can be quantified with satisfactory precision. This does include gap detection (“gap” in Fig. 8 right & Fig. 9), focal spot size variation (“z” in Fig. 7), lateral focal placement (“x” in Fig. 8 left), full penetration, weld fusion, penetration depth, laser power as the workpiece “sees” it and focal spot velocity, which served to vary irradiation time.

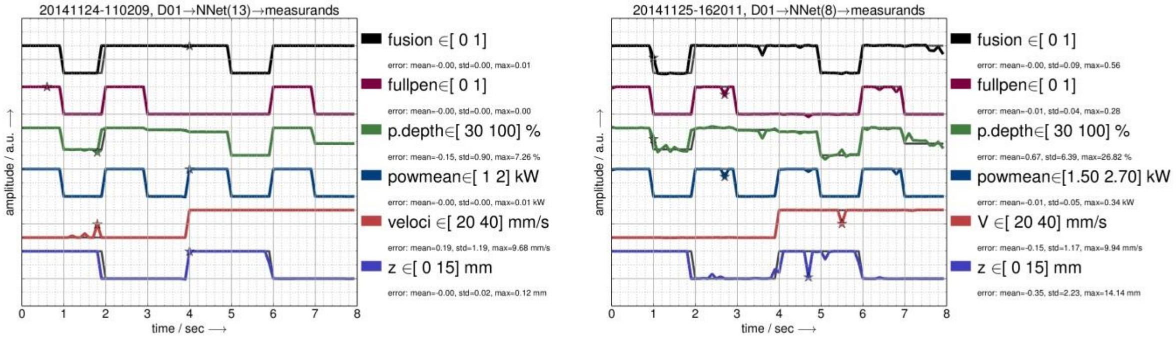

Fig. 7. time series of measurand quantities (black) vs. their estimation (color) using selected frequency pixels of stimulated process emissions and neural network based artificial learning; as specified in Tab. 3 the underlying machining process was lap welding of 1mm (left) or 1.5mm (right) steel sheets; training data comprised one weld repeated four times each 8s long

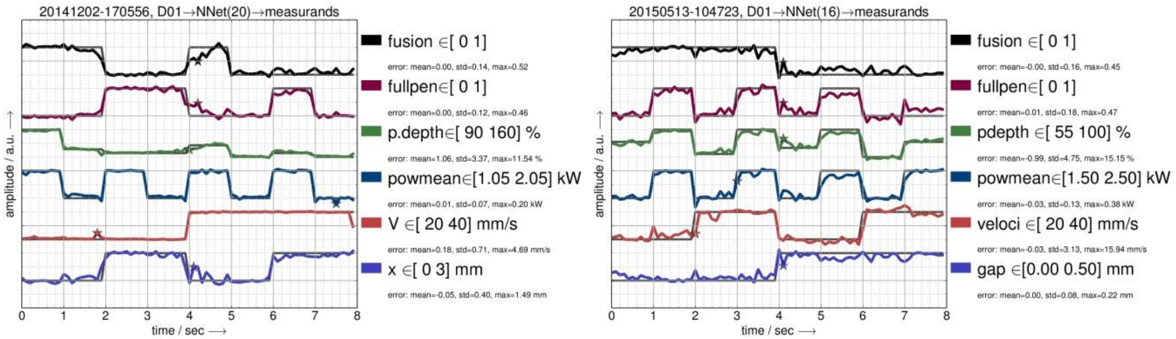

Fig. 8. time series of measurand quantities (black) vs. their estimation (color) using selected frequency pixels of stimulated process emissions and neural network based artificial learning; as specified in Tab. 3 the underlying machining process was T-joint welding (left) and lap joint welding of 1.5mm steel sheets (right); training data comprised one weld repeated four times each 8s long

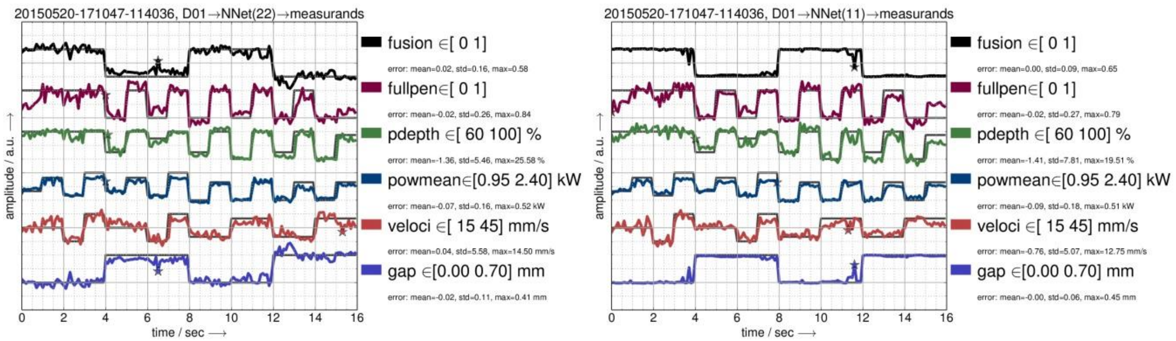

Fig. 9. time series of measurand quantities (black) vs. their estimation (color) using selected frequency pixels of stimulated process emissions and neural network based artificial learning; the machining process was lap joint welding of 1.0mm steel sheets; hidden layer sizes of 22 neurons (left) and 11 neurons (right) were used; in the first eight seconds the networks were subjected to a worst case scenario, in the subsequent eight seconds to a best case scenario; training data comprised six unrepeated welds each 8s long

8. Summary

The most essential findings from data analyses can be summarized as follows.

1. In the analysis of all experiments we never found a situation where frequency pixels were not usable to the extent that mapping them onto measurands would create inacceptable errors.
2. If measurands were forced to plateau, there were always many frequency pixels that would also plateau indicating that static mapping, i.e. mapping without time dependence, is feasible at all times.
3. Standard error deviations of estimating measurands from frequency pixels during neural network testing averaged roughly 5-10 percent.
4. In certain situations neural network output produced excellent, but “frightening” sub-one-percent errors of measurand quantification which forced us to include routines that would shut down neural network training and any further operation in case test data somehow landed in the training set. However, we never observed this case, not prior to nor during the compilation of this report.
5. We did not find pixels that would allow for even simpler univariate i.e. one-to-one mapping onto any of the measurands. This includes observations at zero frequency (mean values) of back reflected laser power. We can clearly state that back reflected laser power is not a univariate function of penetration depth. It does strongly vary with penetration depth, but the size of this variation depends on many other parameters.
6. Frequency comb design, i.e. where to place the stimulated frequencies and how far apart, seems to have an impact on the noise of frequency pixels and thus on the precision of the final mapping. However, our experiments do not allow for making clearer statements on this issue as only two variations of frequency comb design have been applied so far.
7. Increasing thickness of welded workpieces may increase pixel noise, as we generally observed more noisy pixels when welding 1.5mm steel sheets as opposed to 1.0mm steel sheets. However, it cannot be clarified yet whether this observation holds, once both sheet thicknesses are welded with the exact same senor positioning. Sensor positioning did vary with experiment days and thus with sheet thicknesses. On-axis as well as off-axis fibers were not mounted with such precision that this could not be a sensor placement issue. In our prototype we do not use fittings that would allow for exact mechanical reproduction. Especially when projecting an image of the process emissions onto on-axis fibers such precision may matter as fibers may change positions within the image with each mounting.
8. Overall our findings were surprisingly satisfactory to the point, that we think, other important measurands we were not yet concerned with, can be tracked with sufficient precision. Since computations of training and testing the neural network finished within seconds and sub-seconds respectively and since learning the measurement functions (mapping onto measurands) did require less data than what a minute of welding at different setpoints does provide, we are pleased to say that implementation of this approach requires neither excess hardware nor excess time or excess computations paving the way to implementing artificially intelligent technology for future adaptive or self-learning lasers systems on a low cost but still highly effective basis.

9. Conclusion

This work outlines a minimalistic but effective approach to lifting some of the secrets of laser welding processes with little technical overhead. Prior to this work it was not clear whether the machining process would exhibit deterministic, reliable, reproducible and significant information that could be picked up with the “simplest” forms of sensors that are available today: photodiodes and microphones. Fortunately the answer to this question turns out to be positive, at least for laser welding, the prime object of this study. This essential finding opens up a path to more sophisticated closed-loop controlled laser machines that will be easier to work with than the current generation of lasers. The price for this is not excess technical gear, but appropriately deployed knowhow. Sensing or monitoring devices, their development and cost should never eat up large percentages of the budget a user is able or willing to spend on a laser machine. Under this premise the author was researching some possibilities while rejecting others based on their bulk of gear, minimal benefits or intricate operations. Laser machining is multivariate and multivariate needs to be the sensing, if all the ever increasing information needs and demands of the user are to be met. Sensor overkill fortunately does not have to be the consequence.

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