

Leonardo Nicolosi

Visual Control of Laser Welding Processes by Cellular Neural
Networks

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Leonardo Nicolosi

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Visual Control of Laser Welding Processes by Cellular Neural Networks

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„The authors‘ work almost has nothing to do with CNN except using it“

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Introduction

Welding processes are the most used manufacturing methods for many production queues, for example in automotive industries. In laser beam welding (LBW), the material melt is generated by a focused laser beam, which is nowadays one of the highest available power density sources (up to 10^{10} - 10^{12} Wm^{-2}) [1]. At these high power densities it is possible to weld at higher processing speeds, to reduce the heat affected zone, and to obtain narrow weld seams.

The rapid improvement in laser welding equipment has been challenging engineers to develop advanced automatic control strategies of the process. Indeed, laser beam welding is not free of problems. First of all, it is characterized by particular fume and irradiation, which are spread into the working environment. Despite the fact that risks for human operators can be reduced by adopting particular safety procedures, errors of any type and extent expose the users to hazards. Therefore, methods of process automation could reduce or even avoid any of these dangers. Additionally, typical uncontrolled laser welding processes are performed by setting a fixed laser power measured experimentally and adding a safety surpass of about 10% to compensate for process drifts and other external influences.

As shown in Figure 1.1, the results of such processes can be characterized by significant imperfections, like smoke residue, spatters and craters, which do not only influence the aesthetics of the material stack, i.e. the *workpiece*, but most of all drastically reduce its strength and corrosion resistance. Furthermore, this strategy does not allow easily changing welding conditions during the process, such as feeding rate

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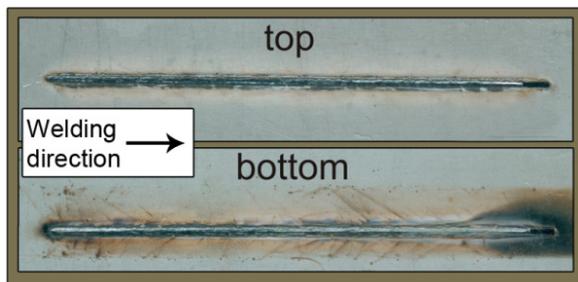


Figure 1.1: Uncontrolled full-penetration weld of two 0.7 mm thick zinc-coated steel sheets in an overlap joint with 0.1 mm gap. The process was performed at 9 m/min by using a constant laser power of 5.5 kW with 10% power as factor of safety [21].

or material thickness, which should be followed by proportionate changes of the laser power.

Despite the existence of several reasons to integrate an automation system in laser beam welding equipment, almost nothing has been done to fulfil this request. The main causes lie in the physical complexity of the process, which makes difficult the development

of exhaustive models for the characterization of its dynamics. Moreover, robust and adaptive closed-loop systems require appropriate and real-time measurement working with specific control algorithms.

In the overview given by Schmidt et al. [2], titled “*Process control in laser manufacturing – dream or reality?*”, the state of the art of monitoring and controlling techniques in laser manufacturing processes is discussed. Concerning welding of metals, the authors conclude by stating that “*although nowadays process monitoring systems are suitable for various laser applications, a process control system to prevent weld seam defects on-line is still to come and a desire of likely all users*”. In fact, in the last years, several on-line monitoring systems have been proposed and some of them have already been developed, i.e. “Laser Welding Monitor” from Precitec, “Welding monitor PD 2000” from Prometec, “processobserver advanced” from Plasmio Industrietechnik GmbH, “Weldwatcher” from 4D, and “Plasmio” from ARC Seibersdorf research GmbH. Most of them are mainly based on the analysis of the optical emissions, due to the interaction between the laser beam and the metal, by either photodiodes or video cameras, or a combination of both.

Photodiodes are relatively inexpensive and present a high temporal resolution. They allow sensing optical emissions which can be compared with previously recorded reference signals. The analysis of signal deviations from this reference leads to the detection of the occurrence of specific phenomena. Several sensors of this type have

been developed to reveal weld imperfections [4-10]. The main bottleneck of photodiodes is due to their reduced spatial resolution, which usually complicates the simultaneous detection of several defects. Furthermore, photodiodes often require destructive tests of random samples in order to establish the quality of imperfection recognition – highly dependent on the completeness of the reference data – which is both time and cost consuming.

The photodiode drawback regarding the reduced spatial information can be overcome by using spatially resolved detectors, such as CCD, CMOS, or thermal cameras. The detection of failures can be performed by extracting process image features [11, 16]. Some conventional CCD/CMOS cameras can reach high frame rates which are fully suitable for monitoring purposes. An example of a CCD camera system is the “FastCamera 34” from FastVision, based on a high-speed interline CCD which allows acquiring up to 210 *fps* at a resolution of 640x480 pixels. Another example is the CMOS “MotionBlitz[®] Cube3” from Mikrotron, which mounts a high sensitive 512x512 image sensor able to reach frame rates up to 2500 *fps* at full resolution and up to 120000 *fps* at reduced resolutions. As shown in [17], camera based systems also allow the simultaneous observation of several areas of the weld seam. Nevertheless, the capabilities of such cameras are limited if the image features must also serve as feedback information for the real-time control of process parameters. In fact, in this case it is necessary to consider, in addition to the CCD/CMOS camera frame rates, the computational cost depending on the software for image feature evaluation. As we will see in the following paragraphs, controlling rates – including image sensing, image evaluation, and subsequent actuation tasks – must be within the multi *kHz* range to guarantee a sufficient robustness of the control against external influences.

Thermal cameras have the advantage of being able to better visualize the melt pool and the keyhole opening at the same time at long wavelengths. However, the use of thermal cameras in industrial applications is limited because of their overall size and high investment costs. Another technique which makes use of both photodiodes and a CMOS camera is described in [18].

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The scope of this work is to demonstrate that a real-time control of LBW processes becomes “*reality*” by adopting cellular architectures based on Cellular Neural Network (CNN) theory [3]. The approach proposed here is focused on the use of a development platform produced by AnaFocus – the Eye-RIS vision system (VS) [19] – which includes a focal plane processor (FPP) called Q-Eye. The latter is a cellular chip where each cell consists of a programmable processor merged with an optical sensor and additional circuitry to be connected in several ways with cells in its neighbourhood. Therefore, each cell can both sense the corresponding spatial sample of the image and process this data in close interaction and cooperation with other cells. This concept allows benefiting from the advantages of both video camera systems and photodiodes, providing high spatial and temporal resolutions. In fact, the Eye-RIS VS enables capturing grey-scale images at a resolution of 176x144 pixels and reaching over 10000 *fps* for image acquisition and processing¹. In this work, it was adopted for the implementation of algorithms for image feature extraction in coaxial images of LBW processes. Concerning the latter, a number of feedback parameters can be determined or chosen from the literature in order to monitor and influence controlled variables representing the state of the system within suitable time scales. Here, two image features are taken into account, i.e. the so called full penetration hole (FPH) and spatters, which are depicted in the examples of Figure 1.2.

The FPH is an important characteristic which appears in the process images, depending on the penetration depth into the workpiece, and indirectly represents the strength of the weld seam. Thus, it is used for an instant control of the laser power in order to maintain the desired penetration depth into the material stack.

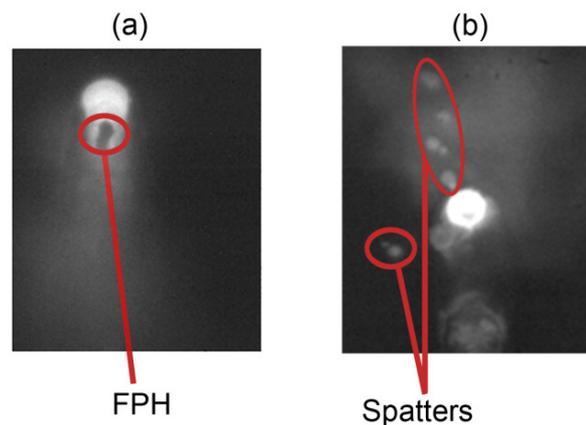


Figure 1.2: Two typical LBW coaxial process images. (a) shows an example of FPH, while spatters are visible in (b).

¹ The application of very simple procedures of image processing could lead up to around 50000 *fps*.

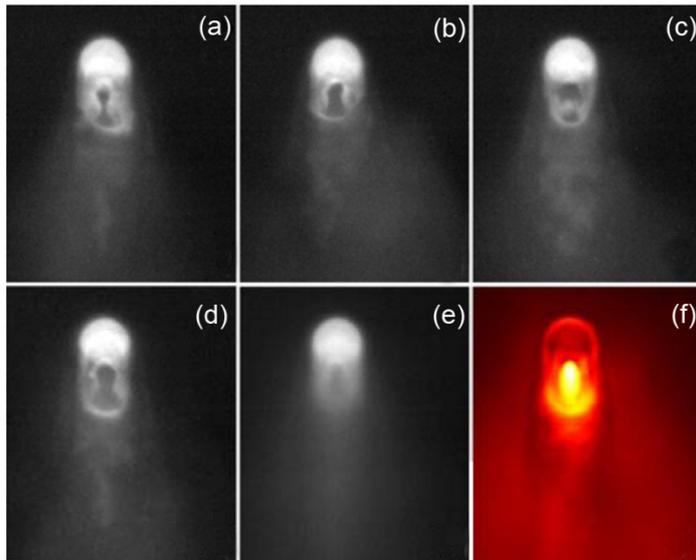


Figure 1.3: From (a) to (d), sample images of a sequence acquired at a frame rate of 3 *kHz* are shown. Pictures (e) and (f) represent respectively the mean grey value calculated over 100 images and the corresponding standard deviation [20]. Picture (f) was rescaled from 0 to 255 digits and a different colormap was used to enhance the contrast of the FPH area.

Spatters, instead, indicate that liquid steel and a large amount of rear melt pool are blowing away, leaving evident cavities and imperfections in the workpiece. They can occur because of several physical phenomena. The most common cause of spatters in industrial applications is the adoption of zinc-coated steel sheets in an overlap joint configuration, which are separated by a small gap. Therefore, the on-line detection of spatters is considered as a quality factor for the process and can be used, for instance, to detect a low gap size which is a difficult parameter to establish in production.

As afore-mentioned, a robust visual feedback system for LBW requires controlling rates in the multi *kHz* range and, consequently, image acquisition and evaluation must be performed at very high speeds. Figure 1.3 illustrates this concept for a visual control system based on the FPH detection [20]. Here, a sequence of 100 images with FPH is considered. It was acquired by the Eye-RIS VS at an exposure time of 40 μs and a frame rate of approximately 3 *kHz*. Pictures from (a) to (d) show some samples of this sequence. Picture (f) shows the standard deviation of the pixel intensity calculated over all the images with respect to the mean grey value shown in picture (e). It is evident that the contrast in the FPH area is much lower in picture (e) than in the single images (a-d). On the other hand, the standard deviation in picture (f), which was rescaled within 0-255 to enhance the image contrast, shows very strong fluctuations in the FPH area, where the intensity of the pixel varies over the whole scale. Therefore,

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due to the dynamics of the melt, the position and the shape of the FPH fluctuate rapidly within a narrow area. Thus, a fast contour detection in single images of a large series is more suitable than an evaluation of the absolute intensities.

This thesis starts with a short introduction to LBW and CNN, followed by the description of the adopted visual closed-loop control system and the control strategy. The subsequent chapters regard the heart of this work, namely the description of the CNN algorithms for the detection of FPH and spatters, which were implemented on the Eye-RIS VS. The high-speed characteristic of these algorithms has suggested the development of another strategy based on the combined detection of FPH and spatters. By the adoption of these methods, controlling rates (including image sensing and evaluation, as well as control of the laser power) within 6 and 14 *kHz* can be reached. Their feasibility in real-life applications was demonstrated by several experimental results, some of which will be largely described in the last chapters of this thesis.

The field of other possible FPH-based strategies was further explored by the execution of CNN learning procedures. CNN learning is formulated as an optimization problem, where the coefficients of the CNN template matrices must be optimized to obtain a desired output image, having specified the correspondent input image. Among several CNN structures, the continuous-time polynomial-type CNN model (PT-CNN) was chosen, since it is particularly suitable to represent complex problems and because it has a direct, very-large-scale integration (VLSI) realization, which will not be treated in this work [44, 45]. The research of a global solution was carried out by the simulated annealing which provided a good compromise between evaluation speed and extent of the search space. The strict relation of this solution to a specific VLSI realization, however, does not allow its implementation on the Q-Eye. Nevertheless, it presents noteworthy aspects, such as the full independence of a threshold value for image binarization. As we will see, the choice of this threshold value represents one of the most critical points of the strategies implemented on the Eye-RIS VS and requires a preliminary accurate analysis of process images.