A METHOD FOR DETECTING DEFECTS IN LASER WELDINGS FOR THE AUTOMOTIVE INDUSTRY

Sergio Saludes * **José M. Bernárdez** * **Roberto Arnanz** *
Fernando Rodríguez * **Luis J. Miguel** ** **José R. Perán** ***

* *CARTIF*
Parque Tecnológico de Boecillo, P205. 47151 Boecillo, Valladolid (Spain)
** *ITAP*
University of Valladolid. P° del Cauce s/n. 47011 Valladolid (Spain)
*** *Escuela Técnica Superior de Ingenieros Industriales. University of Valladolid. P° del Cauce s/n.47011 Valladolid (Spain)*

Abstract: During last years, car manufacturing industry has been concerned with requirements in vehicle mass reduction, impact security improvements and emission reduction. In response to this challenges, tailored blanks have been developed. Those specimens are formed by welding two different thickness metal sheets prior to be stamped. The welding method usually employed is laser welding, whose properties are particularly suitable for that purpose. In this paper, a method for detecting superficial and inner fault in laser weld is presented. The method is based on the analysis, in frequency and time domain, of the electromagnetic radiation emitted during the process. Results obtained in an industrial facility under production conditions are presented. *Copyright IFAC 2005*

Keywords: Fault detection, laser welding, manufacturing processes

1. INTRODUCTION

The automobile industry has recently incorporated a new technology in order to improve the quality of its products: the laser welding process. The goal of laser welding is multiple, and includes vehicle mass reduction, impact security improvements and emission reduction. This is achieved welding two metal sheets one of them thiner than the other so the weight of the whole element can be reduced without losing impact security in the parts where it is needed.

The defects that can appear during the laser welding process are: holes, porosity, surface appearance and partial penetration. In the car manufacturing process, the stage that follows the laser welding is stamping, where the different car body parts take their shape. If the weld has defects, it probably will break. This will introduce delays in the whole manufacturing process.

During high speed CO_2 laser welding, faults may occur due to the state of the cross section of the specimen, gap, flow rate of the assist gas, travel speed and laser power. On the production line, a slight alteration of the welding condition produces many defects and it is very difficult for operators to detect them with the naked eye. Also, the shape of the weld bead is an important factor in deciding the strength of the workpiece. Therefore, development of a monitoring system in laser welding which detects weld defects and bead shape is required. Such system should detect defects in real time, in order to prevent continuous occurrence of defects, reduce the loss of material and guarantee good quality.

There are many methods for laser monitoring systems, such as the ones using acoustic emission (Farson and Hillsley, 1996), optical signal and image processing. The method using optical signal is the main object of research in monitoring systems. (Chen *et al.*, 1991) simultaneously measured the signal of ultra-violet (UV) and infrared (IR) radiation to evaluate weld quality and studied the behavior of signal according to the variations of laser power, assist gas, and welding speed. (Gatzweiler *et al.*, 1998) measured and compared the sound signal with the plasma signal during laser welding and researched on the effect of gas. In addition, they studied the relationship between the full penetration and plasma signal at the top and bottom of the workpiece. (Miyamoto *et al.*, 1993) used two different photodiodes having a maximum wavelength of $950nm$. Recently, (Marson *et al.*, 1998) explained the relationship between the measured light signals and acoustic emission using an ARMA model. Park and Rhee (Park and Rhee, 1999*b*) also used photodiodes to explain the relationship between the plasma and spatter and bead shape according to the welding variables. Through a correlation between these signals and weld quality, a multiple regression analysis and neural network were used to estimate the penetration depth and width of the weld bead (Park and Rhee, 1999*a*).

2. PROCESS DESCRIPTION

During the laser welding process, a beam with intensity greater than $1\ MW \cdot cm^2$ is focused on the surface of the workpiece and a thin capillar (keyhole) in a moving material is created. The keyhole is filled with metallic plasma and surrounded by molten material. To keep the keyhole open, the metal vapor pressure inside the keyhole must be slightly hight than the ambient pressure. The excess pressure is necessary to balance the pressure due to surface tension which is given by $p = \gamma/r$, where γ is the surface tension coefficient and r is the radius of keyhole, see (Szymanski *et al.*, 2001). This pressure is balanced mainly by the pressure driven by the flow of the metal vapor through the keyhole and partly by the ablation pressure. Any distortion of the pressure balance generate pressure fluctuations inside the keyhole (Klein *et al.*, 1996), (Klein *et al.*, 1994). Irregular oscillations are observed in the radiation of plasma expanding from the keyhole, (Hongping and Duley, 1996). It is obvious that by suppressing the plume oscillations or making then more regular (periodic) one can obtain better welding results, (Otto *et al.*, 1994), without faults. Some researchers, (Xie, 1999), state that the keyhole has a characteristic oscillation frequency. According to them, this frequency depends solely on the material that is being welded and neither the welding speed, nor the nature of the shielding gas affects that frequency.

2.1 Experimental setup

A Trumpf Turbo 8000 CO_2 laser with output power of up to $8000\ W$ was used. It operated in a continuous-wave regime.

Two $1.5\ mm$ diameter optical fiber were used to collect and transmit the plasma-emitted and molted-emitted radiation to two different photodiodes. The first one was IR sensor intended to detect variations in the shape of the pool of molten material. The second one was a UV and visible light detector. The intensity variations of the plasma plume generated above the test specimen were registered by the second detector. A data acquisition board was used to measure and collect data using a PC with a sampling rate of 10000 samples per second.

The specimens were galvanized steel sheets of $1\ mm$ thickness which is used in car bodies. Beam-on-plate welding was carried out at power ranging from 6 to $8\ kW$. The welding speed varied between $10\ m/min$ and $5\ m/min$. The flow rate of the assist gas (helium) was $40\ l/min$.

3. FAULT DETECTION IN TIME DOMAIN

As the measured radiation is related with the melting of the welded metals, it is expected that defects in the welding process will produce changes in the signal to be analyzed. If the width and depth of the keyhole is constant, and the laser power is constant too, the quantity of melted metal at each point will be the same and the produced radiation will be constant along the process. If for example a lower penetration depth or a porosity occurs in any point of the welding, the radiation will instantaneously decrease as it can be seen in figure 1.

In (Alipi *et al.*, 2003) a method using statistical parameters and parameters based in the deviations of a cubic interpolation of the signal is proposed. Though it is based in the analysis of the time signal it does not indicate the position of the change or, what is the same, the position of the defect in the welding. The method explained later in this paper allows the detection and location where the defect occurs.

Defects detection will be based in locating radiation signal variations that can be associated with some type of fault. These issue can be included in what is called detection of abrupt changes (Basseville and Nikiforov, 1993). Many tools and different filters have been developed for detection of abrupt changes in the literature.

The algorithm used in this case is a CUSUM RLS adaptive filter that combine an adaptive LS filter with a CUSUM test for change detection (Gustafsson, 2000). The idea is to update the least squares estimate in between the alarm times and restart the LS algorithm after the alarm. The alarm indicating an abrupt change in the data is generated by the CUSUM test when the test statistic is higher than a prefixed threshold. The problems to solve are thresholds and parameters setting and determining what of the abrupt changes in the signal are associated to defects in the welding process.

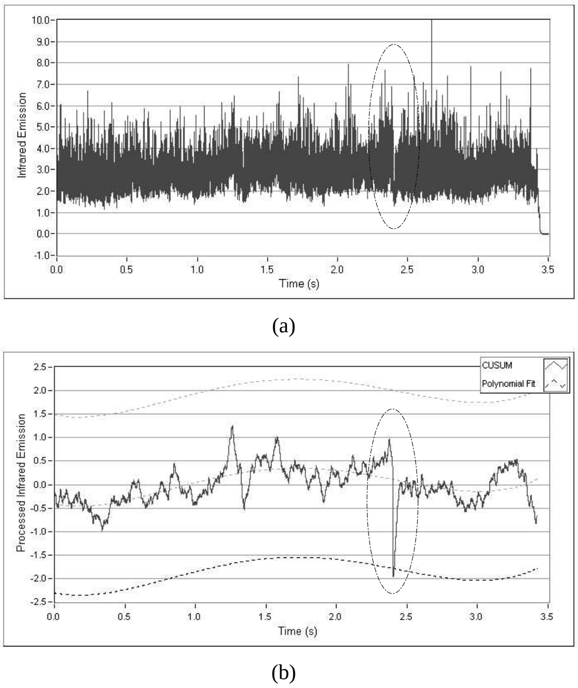
In the welding process the laser power and welding speed are set constant. However, the measured radiation is not constant as it was expected. There are several causes for this, as for example dirty lens or sensors and heating of the laser resonator. Most of these will produce a signal with changes that could generate an alarm with the CUSUM algorithm used if the thresholds are not set properly (figure 1(a)).

In this case the method for parameters setting has been based in experimentation. A set of well and bad welded pieces have been processed so the alarms would only be associated to the pieces with one or more known defects. As the algorithm fires the alarm exactly at the moment of the abrupt change and the welding speed is constant it is easy to correlate the alarms with the position of the defects and iteratively modify the parameters of the algorithm to eliminate false alarms. The variation of the laser power and measured noise level for different pieces make that most of the parameters must be adaptive.

The method proposed is as follows:

- Signal normalization
- A polynomial interpolation of the signal is obtained, and from that a polynomial limit curve that guarantees that a fixed percentage of the measured points are lower than it. (Dashed lines in figure 1(b)).
- CUSUM adaptive filter is applied, and an alarm is taken into account when the algorithm has declared a falling edge in the signal, it is a transient change and the value of the minimum of that valley overpasses the polynomial limit curve. This means that the abrupt change correspond to a 'hole' in the radiation emission with a higher value than the noise of the signal. (Continuous line in figure 1(b))
- CUSUM is applied iteratively for different values of alarm threshold of the algorithm to obtain an estimation of the severity of the change in the signal, something that give an idea of the fault size.
- The signal is divided in a fixed number of sections and it is counted the number of alarms that belongs to each of the sections.

The output of the algorithm implemented for diagnosis is an array in which each element is an estimation of the probability of having a defect in a concrete section of the signal. This allows detecting defects in the welding process and locating them along the seam.



(a)

(b)

Fig. 1. Example of hole in the seam. (a) Measured infrared emission and (b) result of signal processing

4. FAULT DETECTION IN FREQUENCY DOMAIN

Some authors, (Xie, 1999), have found that the plasma plume fluctuate in height during laser welding of steel. The plasma plume grew in size continuously to a maximum height and then became small with respect to the elapsed time. When the plasma is small enough, the plasma grew again to start another cycle of the fluctuation. The frequency of such oscillation have been found to range between $0.9\ kHz$ and $1.5\ kKz$ for steel. The frequency of plasma fluctuation in laser welding might be a material constant irrelative to welding parameters.

The authors found in previous work that in the frequency domain the signal energy decreases significantly in the case of a partial penetration fault, see (Rodríguez *et al.*, 2003). Based on this result a method for detecting lack of penetration has been developed. The method comprises two parts. In the first one, some features are extracted from the signals generated by both photodiodes. In the second one, these features are classified by means of multilayer perceptron neural network.

4.1 Feature extraction

The time-domain signal coming from both sensors is segmented from its pedestals in order to isolate the signals corresponding to the weld. A subset of background noise is also collected for further processing.

Once the complete set of samples of the whole weld is acquired and segmented, is divided into N equal-

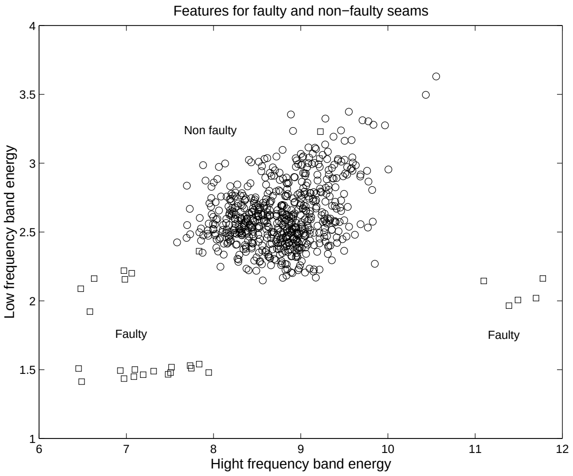


Fig. 2. Features for the visible photodiode signal

size segments.N depends on soldering speed and weld length. Also, an equal-size subset of the background noise data is extracted. In this work $N = 30$.

Then, a Fast Fourier Transform (FFT) performs a frequency domain transformation for each segment, and for the background noise. FFT allows to characterize each portion of weld in relation with its frequency components distribution. A global RMS value is calculated for each segment, and the RMS data for four frequency bands is also obtained. Two of these bands come from the visible range photodiode signal and the other two from the infrared range photodiode signal. The bands are ranging from $500\ Hz$ to $1500\ Hz$ and from $4000\ Hz$ to $5000\ Hz$. In figure 2, the values for bands from visible sensor are shown. Note the separation between faulty and non–faulty seams.

A normalization for each segment is done obtaining relative harmonic distribution for each frequency band. Also, the spectral distribution of the background noise data for each sensor is subtracted for each segment of the frequency data.

All of this calculation results in four parameters for each sensor and for each segment: normalized and noise-free data of RMS values for the four frequency bands, global weld RMS and global noise RMS. Signal to noise ratio (S/N) is then calculate in order to assure the minimum S/N which allows failure detection.

The features that are computed for the visible signal can be used also for detecting faults in the system itself. Dust in tubes, ageing of transmission optic fibers, photodetectors failure or amplifiers gain deviation are tracking by checking this minimum S/N ratio all over the weld.

4.2 Feature classification

In order to determine the quality of the seam, i.e., to determine the presence of lack of penetration, the extracted features are classified using a multilayer perceptron neural network.

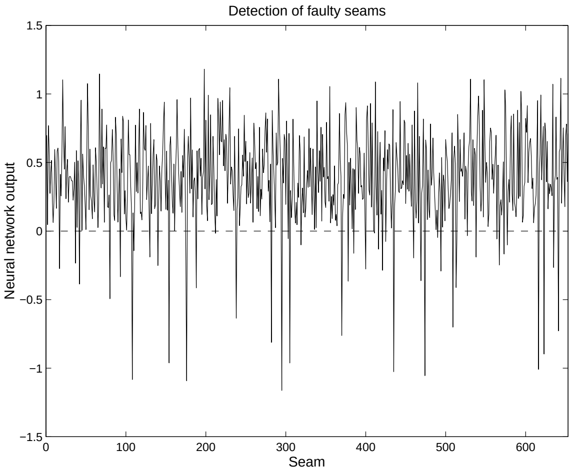


Fig. 3. Classification result for the features shown in figure 2

The training data set was formed with features coming from faulty and non faulty seams. To obtain seams affected of lack of penetration, the laser welding facility described in 2.1 was set up for welding at low power. Examples of non–faulty seams were obtained during normal operation and its quality was assured by visual inspection.

Since the output of the neural network ranges from -1 to 1, a threshold is adopted. Those seams which neural network output is greater than 0 are considered non–faulty seams and those with neural network output minor than 0 are classified as faulty seams. In figure 3 a typical neural network ouput is shown.

5. EXPERIMENTAL RESULTS

The algorithms explained in section 3 and section 4 have been tested in the industrial laser welding facility described in section 2.1. Two kind of experiments have been carried out, one of them intended to evaluate the frequencial algorithm and the other one for testing the temporal method.

5.1 Frequency domain

The experiment performed for assessing the frequency domain method has been done in an automated fashion. That means that workpieces incorporating a seam diagnosed as a faulty one were put apart by the robot in charge of removing finished workpieces. Then, every produced workpiece is processed in the stamping line, with faulty labeled ones separated from non–faulty labeled ones. Those steel panels in which a breakage was found after the stamping process were marked. Finally, the number of breakages is compared with the number of workpieces that had been labeled as faulty with the method.

Table 1. Results in frequency domain for model *A*

Classification	Ratio (%)
Faulty seams classified as faulty	100
Faulty seams classified as non–faulty	0
Non–faulty seams classified as faulty	1.601
Non–faulty seams classified as non–faulty	98.414

Table 2. Results in frequency domain for model *B*

Classification	Ratio (%)
Faulty seams classified as faulty	100
Faulty seams classified as non–faulty	0
Non–faulty seams classified as faulty	0.688
Non–faulty seams classified as non–faulty	99.332

The experiment was carried out in two parts. In the first one, the objective was the car model *A* and 19375 seams were inspected, 11 of them broke during stamping process. In the second part, that affect car model *B*, 153728 seams were diagnosed. Only 5 breakages appeared. Tables 1 and 2 show the results obtained. Posterior inspection of broken workpieces revealed that the most probable cause of that breakages was lack of penetration. The origin of this kind of fault is not simple and several bad tunned parameters are involved, like welding speed, laser power and laser–workpieces alignment. According to the obtained results, the frequency domain algorithm has proved to be an efficient method for detecting that class of fault, at the same time that keeps a low rate of false alarms. However, the number of breakages is not high enough to come to a conclusion with respect to the performance of the algorithm. So, an extension of the experiment should be done.

5.2 Time domain

The time domain fault detection method is intended for finding small defects that can be present in the seam. These faults typically are holes, both trespassing and not trespassing, with sizes ranging from $0.5\ mm$ to $2\ mm$. In figure 4 a non trespassing hole is shown.

In order to simulate such kind of defects, small scraps have been removed from the edge of the thinnest of the workpieces to be welded. These scraps have been done in such a way that they are not visible when the workpiece is look at from above, i.e., from the side the laser hits the workpiece. Then, the workpieces have been welded under normal conditions. Afterward, visual inspection has been carried out. Finally, the visual inspection findings have been compared to the ones obtained through the time–domain algorithm. Results are summarized up in table 3.

The detected holes ratio seems to be very low but can be explained if it is taking into account how the detection algorithm works. As it is based in a polynomial fit of the signal to decide if a signal change is or not a fault, the number of valleys in the signal corresponding to holes will affect the limit used. So the presence of various defects with great changes in the same signal can move the polynomial to a limit that small holes with low changes do not overpass that limit. If number of faulty seams is counted instead of detected holes, the results can be seen in table 4.

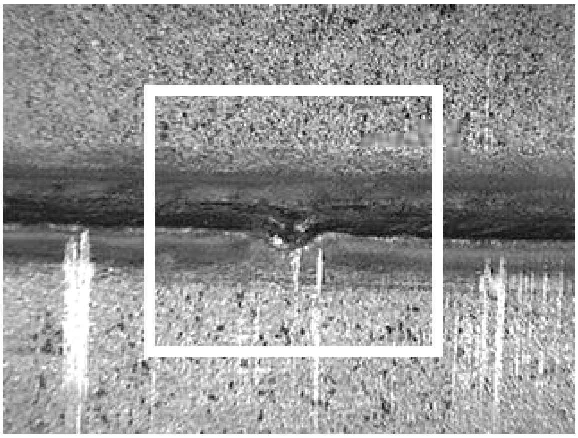


Fig. 4. A typical non–trespassing hole. The defect is $1.03\ mm$ width and $0.77\ mm$ hight

Table 3. Results in time domain for model *B*

Classification	Ratio (%)
Detected holes	55.1
False alarms	2.04

Table 4. Results in time domain for model *B*

Classification	Ratio (%)
Faulty seams detected	75
False alarms	0

6. CONCLUSION

In this paper, two different methods for detecting faults in laser welded seams have been presented. Both methods, working together, are capable of detecting the most common faults that would be present in the seams that are welded in car manufacturing processes, such are holes and lack of penetration. Both methods share the measurements devices.

The visible, infrared and ultraviolet radiation emitted during laser welding process is collected by means of two photodiodes, and the signals generated by these devices are processed in two different ways.

The first processing is performed in the time domain. The CUSUM algorithm is applied to the signal generated by the infrared detector in order to find abrupt changes in it, that are associated with local defects, such holes. The method also provides an estimation of the defect location along the seam.

The second method is carried out in the frequency domain. It is based on the computation the armonichal distortion in both photodiode signals. These values are processed by means of a neural network trained with examples of faulty and non–faulty seams. This method is intended to detect lack of penetration, although also is sensitive to other type of faults.

The frequency domain based method has been tested in an industrial facility under industrial production conditions and has been used to check 173103 seams corresponding to two different car types. The results obtained show the ability of the algorithm to detect all the faulty seams as well as a low false alarm rate. On the other hand, the time domain method exhibits a promising performance, although the required performance to be applied in an industrial facility has not been reached yet.

7. ACKNOWLEDGMENTS

The authors would like to express their gratitude to Gregorio Ortega, Juan Berrio and Julio C. Revilla of Renault España S.A., Valladolid Body Car Factory, for their skilled technical advise and for the allowance to install the developed algorithms in an industrial facility.

REFERENCES

Alipi, C, G. D'Angelo, M. Matteucci, G. Pasquettaz, V. Piuri and F. Scotti (2003). Composite techniques for quality analysis in automotive laser welding. In: *International Symposium on Computational Intelligence for Measurements Systems and Applications*. Lugano, Switzerland.

Basseville, M. and I.V. Nikiforov (1993). *Detection of abrupt changes: theory and application*. Information and system science series. Prentice Hall. Englewood Cliffs, N.J.

Chen, H. B., L. Li, D. J. Brookfield, K. Williams and W. M. Steen (1991). Laser process monitoring with dual wavelength optical sensors. In: *ICALEO*. pp. 113–122.

Farson, D. F. and D. K. Hillsley (1996). Frequency-time characteristic of air–borne signals from laser weldings. *Journal of Laser Applications*.

Gatzweiler, W., D. Maischner and E. Beyer (1998). On–line diagnostics of process–control in welding with CO_2 laser. In: *Hight Power* $C0_2$ *Laser System and Applications*. pp. 142–148.

Gustafsson, F. (2000). *Adaptive filtering and change detection*. John Wiley and Sons.

Hongping, G. and W. W. Duley (1996). Resonant acoustic emission during laser welding of metals. *Journal of Physics D: Applied Physics* **29**, 550–555.

Klein, T., M Vicaneck, J. Kross, I. Decker and G. Simon (1994). Oscillations of the keyhole in penetration laser beam welding. *Oscillations of the keyhole in penetration laser beam welding* **27**, 2023–2030.

Klein, T., M. Vicanek and G. Simon (1996). Forced oscillations of the keyhole in penetration laser beam welding. *Journal of Physics D: Applied Physics* **29**, 322–332.

Marson, D. F., A. Ali and Y. Sang (1998). Relationship of optical and acoustic emission to laser weld penetration. *Welding Journal* **4**, 142–148.

Miyamoto, I., K. Kamimuki, H. Maruo, K. Mori and M. Sakamoto (1993). In process monitoring in laser welding of automotive parts. In: *ICALEO*. pp. 412–423.

Otto, A., G. Deinzer and M. Geiger (1994). Prediction of weld data using process control based on surface temperature measurement for high–power energy flow processes. In: *SPIE*. pp. 282–288.

Park, H. and S. Rhee (1999*a*). Analysis of mechanism of plasma and spatter in CO_2 laser welding of galvanized steel. *Opics Laser Technology* **31**(2), 119–126.

Park, H. and S. Rhee (1999*b*). Estimation of weld bead size in co_2 laser welding by using multiple regression and neural network. *Journal of Laser Applications* **3**(11), 143–150.

Rodríguez, Fernando, Sergio Saludes, Luis J. Miguel, Juan A. Aparicio, Santiago Mar and José R. Perán (2003). Fault detection in laser welding. In: *Proc. of the SAFEPROCESS Symposium*. Washington.

Szymanski, Z., J. Hoffman and J. Kurzyna (2001). Plasma plume oscillations during welding of thin metal sheet with a CW CO_2. *Journal of Physics D: Applied Physics* **34**, 189–197.

Xie, J. (1999). Plasma fluctuation and keyhole instability in laser welding. In: *ICALEO*. pp. 11–20.