Laser Weld Quality Monitoring System

H. Park, Y. Park and S. Rhee

Abstract

Real time monitoring has become critical as the use of laser welding increases. Plasma and spatter are measured and used as the signal for estimating weld quality. The estimating algorithm was made using the fuzzy pattern recognition with the area of data that is beyond the tolerance boundary. Also, an algorithm that detects the spatter and the localized defect was created in order to find the partially produced pit and the sudden loss of weld penetration. These algorithms were used in quality monitoring of the CO_2 laser tailored blank weld. Statistical program that can display the laser weld quality result and the signal transition was made for the first stage of the remote control system.

Key Words : Laser welding, Photodiode, Plasma, Spatter, Fuzzy multi-feature pattern recognition, Statistical program

1. Introduction

Laser welding process is one of the most important manufacturing processes in industries, such as automotive company. Because of advantages over arc welding, the importance of using lasers in the automobile industries is expanding. Presently, one of the important regions of laser welding studied is the real time monitoring system. In high speed CO_2 laser welding, the weld bead changes according to the variation in weld parameters such as condition of the specimen, laser power, amount of assist gas, weld speed, etc. Despite changes in the welding conditions, weld bead geometry and quality should be consistent. Therefore, a reliable laser weld quality monitoring system has been considered.

There are several methods of estimating the laser weld quality, such as using acoustic emission,[1,2] optical signal[2-7], and image processing. However, most studies have focused on the relationship between particular signals and weld defects, rather than the development of algorithms, which detect the weld defects by using the signals. Therefore, in this study, plasma and spatter, according to the change of welding parameters, during tailored blank welding, were measured. These signals were used to design a reliable laser weld quality monitoring system, which detects the defects.

H. Park is with the Manufacturing Engineering R&D Team, KIA Motors, Kwangmyung, Kyungki-Do, Korea,
Y. Park and *S. Rhee* are a Graduated Student and an Associate Professor, Department of Mechanical Engineering, Hanyang University, Seoul, Korea.
E-mail : srhee@hanyang.ac.kr, TEL : +82-2-2290-0438

2. Experiment

In laser welding it has been known that the keyhole and plasma are important in the process of transferring the laser energy to the work-piece. The spatter amount plays a significant role to determine the weld quality. By analyzing the wavelength signals, the behavior of plasma and spatter that shows the state of the weld bead was identified by each selecting photodiodes of ultraviolet and infrared range respectively.

In this study, two different types of photodiodes were used: ultraviolet range and infrared range. To measure the intensity of plasma and spatter light, the wavelength range selected for the ultraviolet photodiode (UV) was 260-400nm and the infrared photodiode (IR) was

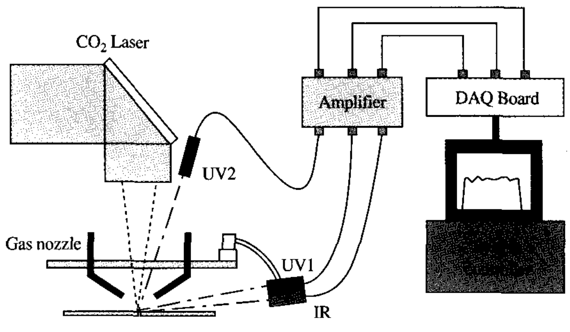

Fig. 1 Schematic illustration of measurement system

700-1700nm. The measurement system schematic diagram used in this experiment is shown in Fig. 1. The sensors were placed in different positions. There were two sensors for the plasma signal; the low aiming angle sensor (UV1) was for the plasma plume and the high aiming angle sensor (UV2) for the plasma in the keyhole. The laser used in the experiment was a continuous wave (CW) CO_2 laser with a maximum output of 6kW.

3. Laser weld quality monitoring using fuzzy pattern recognition algorithm

3.1 Classification of detects and the rules of determination

The light intensity emitted from plasma and spatter varied depending on laser power, weld speed, work-piece conditions, etc. In butt laser welding, as the laser power decreased, the signals of UV1, UV2, and IR sensors decreased. When comparing the butt welding with the bead-on-plate welding under the same conditions, it was observed that the signals obtained from UV2 and IR sensors for the bead-on-plate welding were higher than those for the butt-welding were. Therefore, by considering the signal variation, according to the heat input and focus-off, the weld quality could be determined. In order to determinate weld quality, fuzzy multi-feature pattern recognition algorithm was used. Fig. 2 shows the process of this algorithm

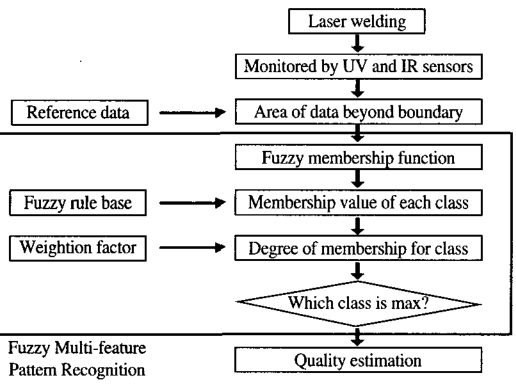

Fig. 2 Process of fuzzy multi-feature pattern recognition algorithm

The types of weld quality determined through the monitoring system were classified as optimal heat input and little low heat input which represented a good weld, and low heat input and weld seam offset which represented a bad weld. Reference signals were determined from sample signals for good welds. The relationships between each weld quality and the variation of signals obtained are as follows. In the case of the optimal heat input, the size of the keyhole must be sufficient to ensure the heat input can fully penetrate to the backside of the work-piece. The signals measured in this case were very similar to those of the reference signals. Furthermore, the numbers of data deviating beyond the upper or lower sides of the reference signals were relatively small. In the case of where the input of the laser transmitted were below the optimal level, the signals generated fluctuated greater than that at the optimal level of the reference signals. However, by carrying out the Erichsen test, which is a formability test, the results indicated a good formability and this eventually resulted in a good weld. For the case of low heat input, the heat of laser transmitted to the weld pool failed to reach a certain value thus, a perfect keyhole was not produced and the weld penetration did not reach the backside of the work piece. Compared to the reference signals, the signals deviated a little beyond the upper side, and much beyond the lower side. As the heat input of the laser was decreased considerably, a perfect weld was rare and most of the measured signals deviated far beyond the lower side. In the case of weld seam offset where the laser was not positioned accurately on the welding seam but was focused on one side of the plates, the signals generated were somewhat similar to those of bead-on-plate welding. Therefore the signals of the UV2 and IR increased due to the plasma and spatter amount that leaked out from the keyhole became zero. However, the UV1 signals showed an unexpected irregularity. It was determined that it was caused by the nozzles for the assist gas being located at the front and rear side of the welding point. These experience results were used as the rule base of the fuzzy multi-

Table 1 Relationships between weld quality and feature value

Sensor / Feature / Class	UV1		UV2		IR	
	Upper	Lower	Upper	Lower	Upper	Lower
Optimal heat input	L	L	L	L	L	L
Little low heat input	M	M	M	M	M	M
Low heat input	L	H	L	H	L	H
Weld seam offset	L	H	H	L	H	L

feature pattern recognition. Table 1 is the rule base of this algorithm. In Table 1, L means Low, and M and H stand for the Middle and High.

3.2 Fuzzy membership function

In order to determine the weld quality, fuzzy multi-feature pattern recognition was used as the quality estimation algorithm. The reference signal was determined by capturing the signals generated from good quality weld on a sample thickness. Welding was carried out on galvanized steel with a thickness of 1.5mm and 0.7mm. The optimal conditions were 6kW of laser power and 7m/min of welding speed. Under these conditions, welding was repeated 3 to 6 times and the signals from each sensor were recorded and saved. The average values of each of these saved signals were calculated and filtered to make reference signals at the optimal conditions.

The tolerance boundary was determined by defining the tolerance rate of each reference signal. The tolerance rate was determined as 30%. To estimate the defects, information from the signal difference between the reference signals and the signals upon occurrence of defects had to be fuzzed. Therefore, a membership function for the amount of data above and below the tolerance boundary was defined.

Meanwhile, when the actual signal goes beyond the reference signals the following two particular patterns may occur. First in Fig. 3, signal A only goes beyond the tolerance level at a short time, but the amount was large. Then, most signals of signal B went beyond the tolerance boundary, but the amount was small.

Therefore, if the membership function is decided only with the number of data that goes beyond the boundary,

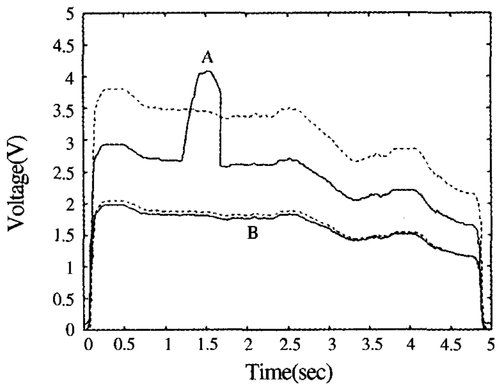

Fig. 3 Specific sensor signals

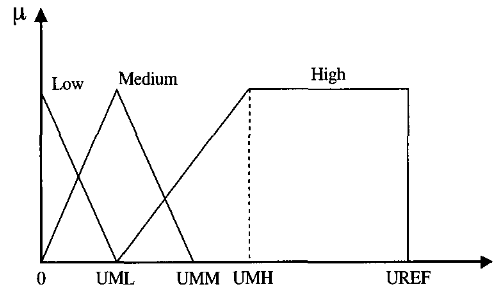

Fig. 4 Membership function for upper data

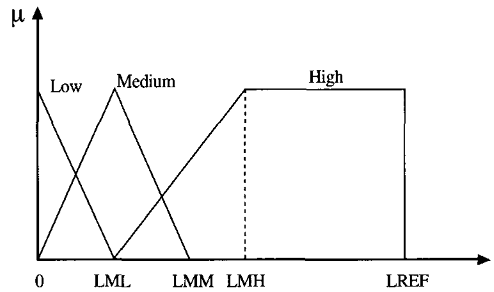

Fig. 5 Membership function for lower data

such as in the case of signal B, which does not present a problem in the weld quality, it can be estimated as bad, and in the case of signal A, which shows a defect in the results, it will be estimated as a satisfactory weld. Therefore, the area of signals that goes beyond the tolerance boundary was used as the data in deciding the membership function.

In the tailored blank process, the formability of the work piece is the most important quality index. Therefore, the membership function based on each signal and the results of the Erichsen Test, as shown in Fig. 4 and Fig. 5, was determined. The degree of membership for the weld quality, such as optimal heat input, little low heat input, low heat input and weld seam offset, was calculated using this membership function and the weights of each sensor, indicating the accuracy of the sensor. These degrees of membership are shown in equations (1), (2), (3), and (4).

$$\mu_{optimal} = W_{UV1}(\mu_{U1UL} + \mu_{U1LL}) + W_{UV2}(\mu_{U2UL} + \mu_{U2LL}) + W_{IR}(\mu_{IUL} + \mu_{ILL}) \quad (1)$$

$$\mu_{little} = W_{UV1}(\mu_{U1UM} + \mu_{U1LM}) + W_{UV2}(\mu_{U2UM} + \mu_{U2LM}) + W_{IR}(\mu_{IUM} + \mu_{ILM}) \quad (2)$$

$$\mu_{low} = W_{UV1}(\mu_{U1UL} + \mu_{U1LH}) + W_{UV2}(\mu_{U2UL} + \mu_{U2LH}) + W_{IR}(\mu_{IUL} + \mu_{ILH}) \quad (3)$$

$$\mu_{wso} = w_{UV1}(\mu_{U1UL} + \mu_{U1LH}) + w_{UV2}(\mu_{U2UH} + \mu_{U2LL}) + w_{IR}(\mu_{IUH} + \mu_{ILL}) \quad (4)$$

Here, w_{UV1} is the weight value of UV1, which was 0.15, w_{UV2} is the weight value of UV2, which was 0.55, and w_{IR} is the weight value of IR, which was 0.3.[6] μ is the degree of membership according to the rule base. The maximum value of the calculated degrees of membership for the every weld qualities was regarded as the final weld quality.

Furthermore, when determining defect of the weld, the data generated from the initial and the final range of the welding process were excluded, since the signals at these ranges become unstable due to transient. Also, the number of data that will be excluded must be determined after considering the characteristic of each hardware. In this study, 500 transient data were excluded.

4. Spatter detecting algorithm

Generally, when a lot of spatter occurs in the welding process, it is considered an unsatisfactory weld. Spatter is a part of the weld metal that bounces outside the weld pool. When the size of the spatter is large, this indicates that there is a pit in the weld. Therefore, when monitoring the weld quality, the large spatters must be detected. As shown in Fig. 6 when spatter is produced, no particular signal change can be found in UV1 or UV2, but only in the IR sensor signals, which measures in the infrared rays regions. When spatter is produced, an instantaneous pulse signal occurs. In order to detect this, a trend removal method was used. With this signal as a basis, the statistical control limit, 3σ (which are used as the general quality control) was applied. It was decided that everything beyond this limit was spatter. Small spatter, unless continued for a long time, does not actually give sufficient evidence to determine a bad weld quality. Also, with this algorithm, not only can the spatter amount be detected but the position of the spatter can also be seen.

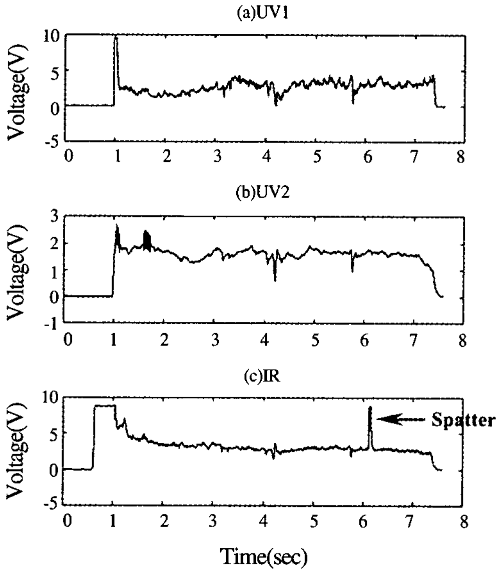

Fig. 6 Example of signals with spatter

5. Statistical program

Fig.7 shows the statistical program of the results for welding products within a certain period of time. It consists of the number of times of welding, the count of good and bad weld and the rate of good weld according to the kind of steel, parts and welding direction. Two graphs show the transition of average signals and weld result. Using this program, we can find the trend of signal transition and weld quality and recognize the problems in sensor or weld machine. As data in this program are transferred using Internet or TCP/IP, remote monitoring can be possible.

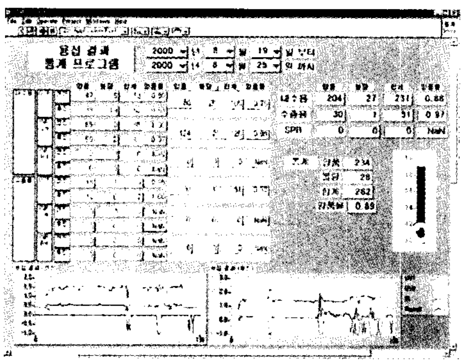

Fig. 7 Example of statistical program

6. Results and discussion

The estimation of weld quality on galvanized steel was carried out. The weld quality was determined using various conditions by adjusting the laser power. Fig. 8 shows the welding results was decided as a good weld quality under optimal conditions. The gray lines are tolerance boundaries. The black lines in the middle represent the signals of actual welding. As seen in the figure, the actual welding signals are well within the tolerance boundaries. Therefore, since most signals are within the tolerance boundaries, the degrees of membership were 1.96 for optimal heat input, 0.05 for little low heat input, 1.30 for low heat input, and 0.14 for weld seam offset. As the largest degree of membership was shown in optimal heat input, it can be concluded that the weld quality was good. The reason why the membership degree of low heat input was high due to the fact that the rules of deviating beyond the upper limit are the same as low.

The Fig. 9 shows the results of determining the weld quality when the laser power was lowered than 4kW. Back beads did not generate due to significant reduction of laser power. Therefore, as the amount of plasma and spatter significantly reduced, so did the voltage of the signals. Therefore, the degree of membership is greatest on the low heat input at 1.57. As a result, the weld quality was bad.

Fig. 10 shows the results when spatter is produced.

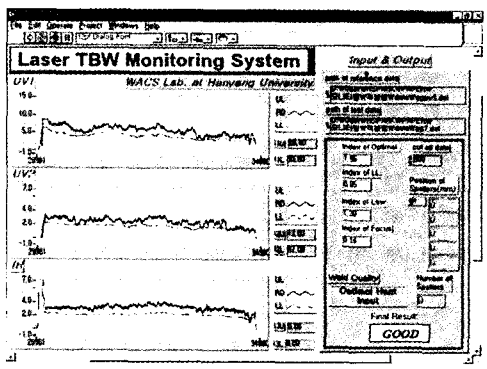

Fig. 8 Example of laser weld quality monitoring (Optimal heat input)

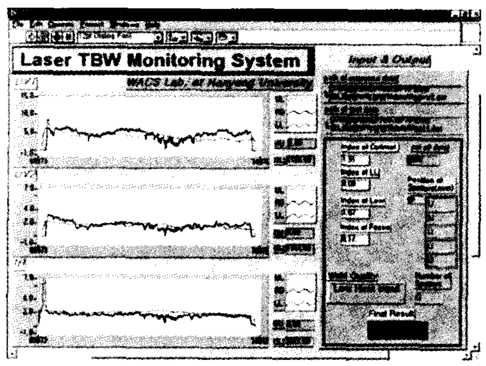

Fig. 9 Example of laser weld quality monitoring (Low heat input)

After the welding began, approximately 2.5 seconds later two quite large spatters occurred, and after approximately 4.8 seconds another spatter produced. However, the spatter detector only detected the first two spatters. As the last spatter was considered as small, gave no indication of the weld quality because it was not regarded as a spatter. The position of the produced spatter was at positioned 183mm and 194mm from the beginning of the weld.

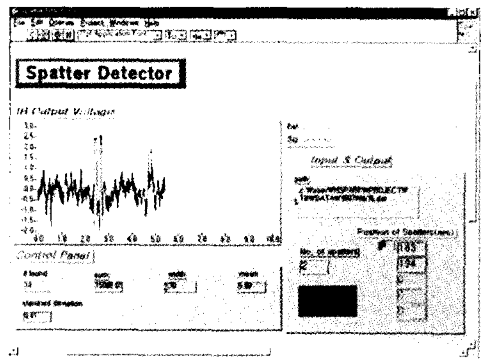

Fig. 10 Example of spatter detecting program

In the case of using galvanized steel, a fuzzy pattern recognition algorithm was used to decide the weld quality. Even if this program was applied to the welding processes on the galvanized steel with different thickness, this could also be applied to cold-rolled steel with the identical algorithms with the reference signals modified accordingly.

This software was very flexible to be used on different thickness or materials since it always determined the weld quality with relative values for optimal conditions. Integration of this monitoring system with previous algorithms[7], capable of predicting shapes and sizes of laser welding beads, will further increase the weld quality monitoring system.

7. Conclusion

In CO_2 laser welding, the plasma and spatter were measured by using photodiode to design a monitoring system. Fuzzy pattern recognition was used to design an algorithm that estimated the quality of the weld. This real time monitoring system can weld defects caused by power change and weld seam offset. Furthermore, a spatter-detecting algorithm was made to find the spatter that influences the weld quality.

These two algorithms were applied to the tailored blank weld quality monitoring system.

References

1. D. Farson, K. Hillsley, J. Sames and R. Young: Frequency-Time Characteristics of Air-Borne Signals from Laser Welds, *Journal of Laser Applications*, Vol. 8, No. 1 (1996), pp.33-42
2. D. Farson, A. Ali and Y. Sang: Relationship of Optical and Acoustic Emission to Laser Weld Penetration, *Welding Journal*, Vol. 77, No. 4 (1998), pp.142s-148s
3. H. B. Chen, L. Li, D. J. Brookfield, K. Williams and W. M. Steen: Laser Process Monitoring with Dual Wavelength Optical Sensors, *Proceeding of ICALEO '91*, (1991), pp. 113-122
4. W. Gatzweiler, D. Maischner and E. Beyer: On-line Diagnostics for Process-control in Welding with CO_2 Lasers, *High Power CO_2 Laser System & Applications,* SPIE 1020, (1988), pp.142-148
5. I. Miyamoto and K. Mori: Development of In-process Monitoring System for Laser Welding, *Proceeding of ICALEO '95*, (1995), pp.759-767
6. H. Park and S. Rhee: Analysis of Mechanism of Plasma and Spatter in CO_2 Laser Welding of Galvanized Steel, *Optics & Laser Technology*, Vol. 31, No. 2 (1999), pp.119-126
7. H. Park and S. Rhee: Estimation of Weld Bead Size in CO_2 Laser Welding by Using Multiple Regression and Neural Network, *Journal of Laser Applications*, Vol. 11, No. 3 (1999), pp.143-152