A Study of Quality Monitoring System for Manufacturing Process Automation during Laser Tailored Blank Welding

Y. W. Park, H. Park and S. Rhee

Abstract

Welding using lasers can be mass-produced in high speed. In the laser welding, performing real-time monitoring system of the welding quality is very important in enhancing the efficiency of welding. In this study, the plasma and molten metal which are generated during laser welding were measured using the UV sensor and IR sensors. The results of laser welding were classified into five categories such as optimal heat input, little low heat input, low heat input, partial joining due to gap mismatch, and nozzle deviation. Also, a system was formulated which uses the measured signals with a fuzzy pattern recognition method which is used to perform real-time evaluation of the welding quality and the defects which can occur in laser welding.

Key Words : Laser welding, Quality monitoring, Plasma, Apatter, Photo diode, Fuzzy multi-feature pattern recognition.

1. Introduction

In comparison to other welding processes, laser welding has advantages such as high welding speed, deep weld penetration, and minimal distortion by heat. Especially in the automotive industry, the use of laser is expanding in joining sheet metals including tailored blank welding. It is necessary to estimate the weld quality in real time to maintain high productivity. Since it is very difficult to perform visual inspection during welding, however, many researchers have developed software as well as hardware to inspect weld quality.

There are many monitoring methods to estimate weld quality such as acoustic emission[1], optical signal, and image processing. Of these, the acoustic emission and optical signal measurement methods are the most popular monitoring systems. Chen et al.[2] simultaneously measured the signals of ultra-violet (UV) and infrared (IR) rays to evaluate weld quality and studied the behavior of signals according to the variations of laser power, assist gas, and welding speed. Miyamoto et al. [3] used two different photodiodes having a maximum wavelength of 950nm. Recently, Farson et al.[4] explained the relationship between the measured light signals and acoustic emission signals, using the ARMA model. Rhee et al.[5] also used the 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. [6]

In this study, laser weld quality was estimated using the relationship between the signals measured by UV and IR sensors and the weld quality according to laser welding conditions.

2. Experimental setup for laser weld monitoring system

The experimental system used in this study is as shown in Fig. 1. Welding was performed using a CO_2 laser welding machine with 6kW maximum power; two UV sensors placed at different angles and one IR sensor measure the luminosity of the plasma and spatter. The

Y. W. Park : Department of Precision Mechanical Engineering, Hanyang University, Seoul, Korea
E-mail : honeydew@ihanyang.ac.kr
H. Park : Manufacturing Engineering R & D team, Kia Motors Corp, Kyungki, Korea
E-mail : hpark21@kia.co.kr
S. Rhee : School of Mechanical Engineering, Hanyang University Seoul, Korea
E-mail : srhee@hanyang.ac.kr

measured signals were amplified through an amplifier and stored into the computer through a data acquisition board. The sampling rate of data acquisition was 1000 samples per second for each sensor.

As seen in Fig. 1, the UV sensors were placed in different angles because the object being measured differs according to the angle. The UV1 sensor that was placed at a lower angle measures the luminosity of the plasma generated above the test specimen. The UV2 sensor placed at a higher angle measures the luminosity of the plasma generated not only above the test specimen but also in the keyhole. The IR sensor measures the luminosity of the spatter.

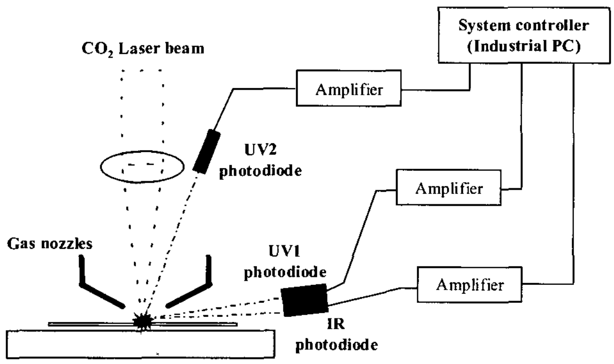


Fig. 1 Schematic diagram of experimental setup

3. Experiment

The factors that influence the weld quality in laser welding are the laser power, welding speed, amount and direction of assist gas, and the gap and the surface condition of the workpiece, etc. Of these welding variables, the laser output power, welding speed, and direction of the assist gas are used as the factors in this experiment. To investigate the relationship between the factors and the signals, two experiments were performed. One was to observe the influence of laser power and welding speed on signals, and the other was to observe the influence of the variation of the nozzle position. In the first experiment, the laser power was divided into four levels between 4.5kW and 6kW, and the welding speed was divided into 3 levels between 3m/min and 4m/min. In addition, in order to observe the influence of the assist gas direction, the position of the nozzle was adjusted so that the general welding conditions of laser output were set at 5.4kW, welding speed at 2.5m/min. The assist gas was helium. The test specimen used in the study was high tensile strength steel with dissimilar thickness of 1.6 mm and 2.0 mm which was used for tailored blank welding in car bodies.

4. Results and discussion

The laser output power, welding speed, position of the nozzle, and gap between the two workpieces influence the luminosity of the plasma and the spatter. It can be seen through the results of the experiment that the average output signal generated by the luminosity of the plasma and the spatter increased as the laser output power increased and the welding speed decreased. The standard deviation of the signals increased as the laser output power became higher and it decreased as the welding speed became slower. This was because the decreased welding speed allows enough time to form a stable keyhole. Fig. 2 and 3 show the output signal according to welding conditions.

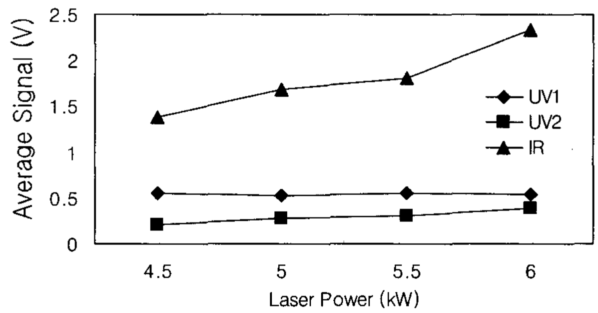


Fig. 2 Average signals according to laser power

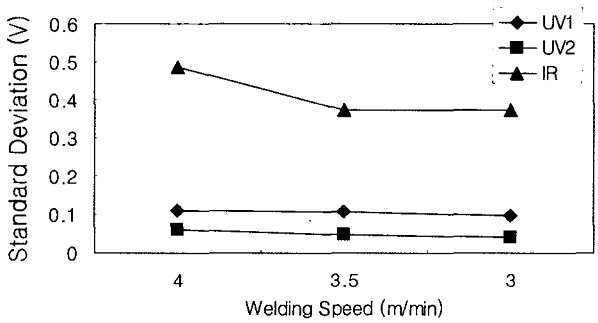


Fig. 3 Standard deviation of signals according to laser power

An examination of changes in the signal of the sensors according to the direction of the assist gas shows that the average value and standard deviation of the output signals by the UV1 and IR sensors increase as the flow of nozzle deviates farther away from the welding spot as you can see in Fig. 4 and 5. As the UV1 sensor measures the light of the plasma above the workpiece, its signal is influenced by the assist gas, which removes the plasma. When the direction of the assist gas deviates from welding point, UV1 signals become unstable because the plasma over the workpiece is not removed effectively. This greatly influences the standard deviation value, which also increases the standard deviation of the IR signal by influencing the spatter. However, in the case of the UV2 sensor, the interior of the keyhole is observed at higher angle, which makes it less susceptible to influence than the other two sensors.

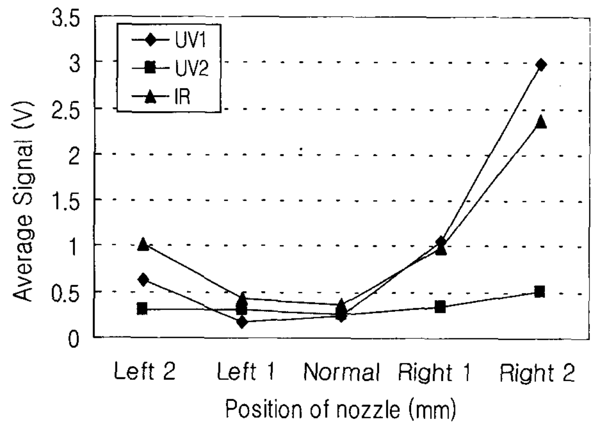


Fig. 4 Average signals according to nozzle position

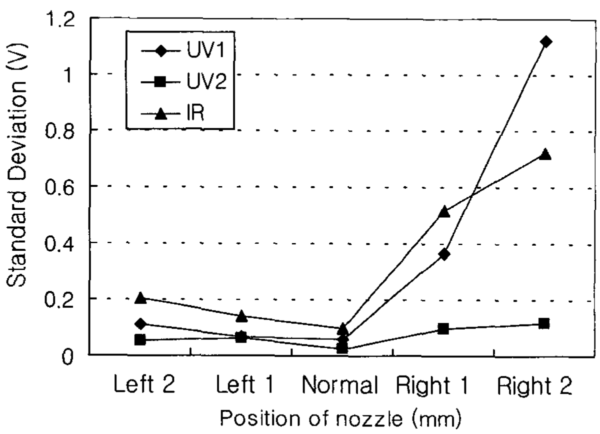


Fig. 5 Standard deviation of signals according to nozzle position

5. Fuzzy multi-feature pattern recognition algorithm

5.1 Classification of weld quality and rule base

Process of classication and determination for weld quality is shown in Fig. 6. In order to apply the fuzzy pattern recognition algorithm to laser weld quality monitoring, the defects of laser welding must be classified and a set of rules regarding the types of welding quality must be defined.

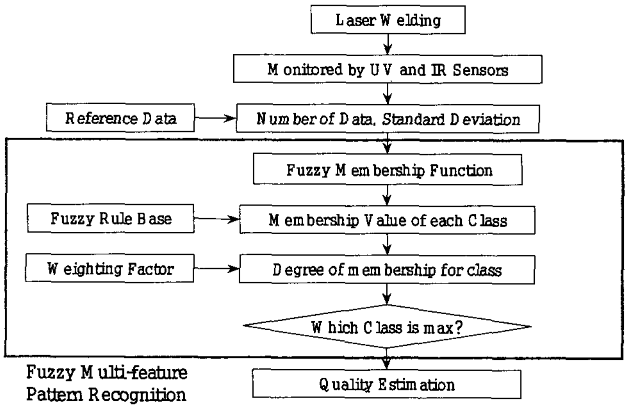


Fig. 6 Process of algorithm

Using results of experiments, the factors that influence weld quality were classified into five categories. These were divided into optimal heat input and slightly low heat input which were regarded as "good" welding and low heat input, partial joining due to gap mismatch, and nozzle deviation which were regarded as "bad" welding. To define a category, the number of signals which deviated from the limits of the reference signals and the ratio of standard deviation of actual signals to that of reference signals were used as the features of the algorithm. The reference signals were made by determining the high and low limitations using the signals from a good weld.

Table 1 shows the number of signals that deviate from the reference signal in each weld quality category, and the corresponding standard deviation value. Table 1 is used as the rules base of fuzzy multi-feature pattern recognition.

5.2 Fuzzy membership function and decision making method

In order to use the fuzzy pattern recognition algorithm

Table 1 Fuzzy rule base

Sensor	UV1	UV2	IR	UV1	UV2	IR	UV1	UV2	IR
Boundaries / Class	Upper	Lower	STD	Upper	Lower	STD	Upper	Lower	STD
Optimal heat input	Low	Low	Low	Low	Low	Low	Low	Low	Low
Slightly low heat input	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Low heat input	Low	High	Low	Low	High	Low	Low	High	Low
Partial joining	Low	High	High	Low	High	High	Low	High	High
Nozzle variation	High	Low	High	High	Low	High	High	Low	High

in weld quality estimation, the fuzzy membership function is defined. First of all, the reference signal should be determined. The signals obtained under optimal welding conditions were used to define the reference signal. In this study, the optimal welding conditions were determined at 6kW, 3m/min and 5.5kW, 3m/min. The upper reference signal was determined at a level 1.3 times the average signal, and the lower reference signal at 0.7 times the average signal. In addition, the standard deviation of the lower limit signal was determined as the reference standard deviation.

The fuzzy membership function was defined using the variation of the signals and standard deviation obtained under each welding condition. Thus, the number of signals deviated from the lower and upper limits of the reference signal, was obtained under the various welding conditions, and also a ratio of the standard deviation to the reference standard deviation was considered in this process. The criterion of weld quality is decided with the back bead width of 0.85mm. The membership function was defined based on these experimental results. The defined membership function is as shown in Fig. 7. *UMM, UMH, LMM, LMH, SL, SM, SH* in Fig. 7 are defined in equations (1)-(7).

$$UMM = Rdata \times F_{UMM} \quad (1)$$

$$UMH = Rdata \times F_{UMH} \quad (2)$$

$$LMM = Rdata \times F_{LMM} \quad (3)$$

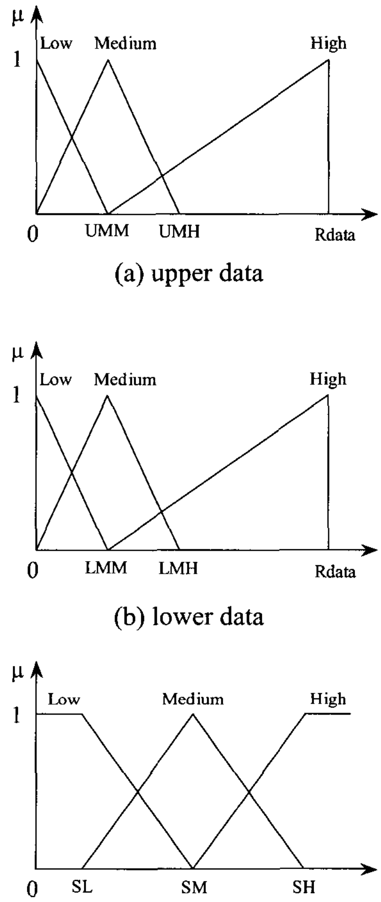
$$LMH = Rdata \times F_{UMH} \quad (4)$$

$$SL = Rstd \times F_{SL} \quad (5)$$

$$SM = Rstd \times F_{SM} \quad (6)$$

$$SH = Rstd \times F_{SH} \quad (6)$$

Where, *Rdata* is the total number of evaluated signals, and *Rstd* is the standard deviation value of the reference signal. *F* is the ratio when *Rdata* and *Rstd* are 1.



(a) upper data

(b) lower data

(c) standard deviation

Fig. 7 Fuzzy membership function

The membership function values are obtained by substituting the number of data beyond the upper boundary and below the lower boundary, and the standard deviation for the membership function defined by the previously determined rule base. The degree of membership for the five categories classified earlier can be calculated by the membership function values and weighting factors which indicate the reliability of each sensor. The equation for the degree of membership for each class of weld quality is shown in equation (8).

$$\mu_{Class} = (w_{UV1}\ w_{UV2}\ w_{IR}\ w_{UV1std}\ w_{UV2std}\ w_{IRstd}) \cdot \begin{pmatrix} \mu_{U1U} + \mu_{U1L} \\ \mu_{U2U} + \mu_{U2L} \\ \mu_{IRU} + \mu_{IRL} \\ \mu_{U1S} \\ \mu_{U2S} \\ \mu_{IRS} \end{pmatrix} \tag{8}$$

The front matrix in equation (8) is the weight matrix, w_{UV1} is the weight factor for the UV1 signal, and w_{UV2} and w_{IR}, are the weight factors for the UV2 and IR signals. w_{UV1std}, w_{UV2std}, and w_{IRstd}, are the weight factors for the standard deviation values of each signal. The first three rows in the second matrix of equation (8) are the combined values of the membership function values obtained through the number of signals that deviated from the lower and upper limit of the reference signal. The last three rows are the membership function values obtained through the standard deviation values of each sensor.

Through the above process, the 5 degrees of membership for the categories of optimal heat input, slightly low heat input, low heat input, partial joining due to gap mismatch, and nozzle deviation were calculated. The final welding quality is the category that has the highest degree of membership.

6. Quality monitoring program

Fig. 8 and 9 have shown the results, which estimate the weld qualities using the fuzzy pattern recognition algorithm. The result of welding quality evaluation under optimal heat input was shown in Fig. 8. The black line in Fig. 8 shows the signal obtained during welding, while the gray lines are the reference signals. As seen in Fig. 8, the signal hardly ever deviated from the limits of the reference signal, and the standard deviation was low. In the output data which shows the degree of membership of each welding quality, the degree of the optimal heat input is the highest, classifying the results in the category of optimal heat input and evaluating welding result as good.

Fig. 9 is an example of nozzle deviation, in which the signal deviates from the top limit of the reference signal. There is also a large difference between the standard deviation and standard deviation of the reference signals. Therefore, as seen in the output data of Fig. 9, the degree of membership for nozzle deviation is the highest among each of the weld qualities. Therefore, the weld quality is classified as nozzle deviation, and the overall welding result is evaluated as bad.

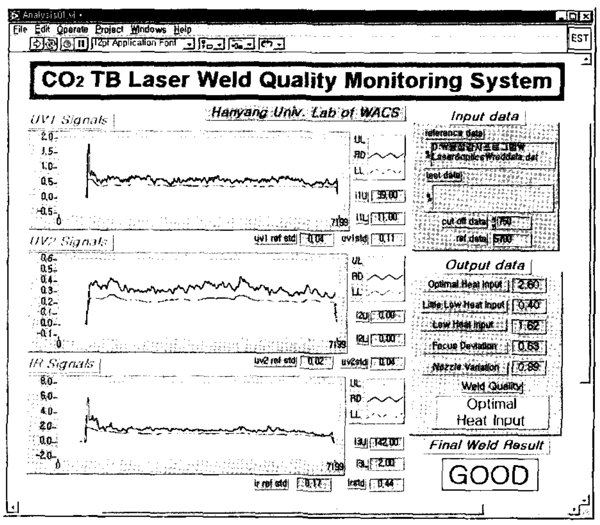


Fig. 8 Example of quality estimation program (optimal heat input)

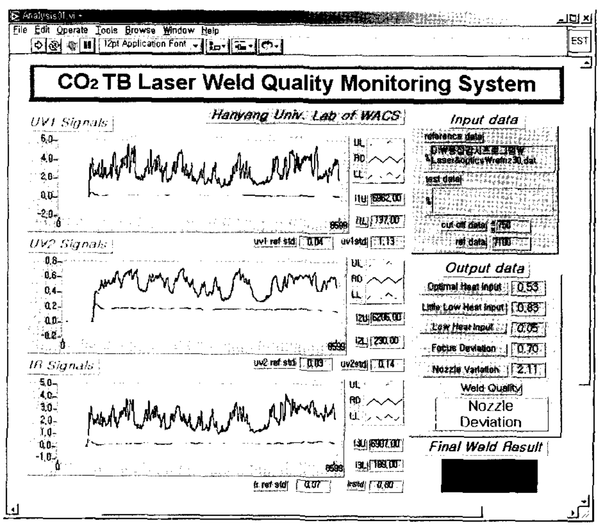


Fig. 9 Example of quality estimation program (nozzle deviation)

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.

Acknowledgements

This work was supported by the Brain Korea 21 Project and Critical Technology 21 Projects of the Ministry of Science and Technology, Korea.

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. H. B. Chen, L. Li, D. J. Brookfield, K. Williams and W. M. Steen : Laser process monitoring with dual wavelength optical sensors, *Proceedings of ICALEO '91*, (1991), pp. 113-122
3. I. Miyamoto, K. Kamimuki, H. Maruo, K. Mori and M. Sakamoto : In-process monitoring in laser welding of automotive parts, *Proceedings of ICALEO'93*, (1993), pp. 413-424
4. D. Farson, A. Ali and Y. Sang : Relation of optical and acoustic emission to laser weld penetration, *Welding Journal* , Vol. 77, No. 4 (1998), pp. 142s-148s
5. 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
6. 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. 143-150