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Prediction of Laser Process Parameters using Bead Image Data

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비드 이미지 데이터를 활용한 레이저 공정변수 예측

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ABSTRACT

In this study reports experiments were conducted to determine the quality of weld beads of different materials, Al and Cu. Among the lasers used to make battery cells for electric vehicles, non-destructive testing was performed using deep learning to determine the quality of beads welded with the ARM laser. Deep learning was performed using AlexNet algorithm with a convolutional neural network structure. The results of quality identification were divided into good and bad, and the result value was derived that all the results were in agreement with 94% or more. Overall, the best welding quality was obtained in the experiment for the fixed ring beam output/variable center beam output, in the case of the fixed beam (ring beam) 500W and variable beam (center beam) 1,050W; weld bead failure was seldom observed. The tensile force test to confirm the reliability of welding reported an average tensile force of 2.5kgf/mm or more in all sections.

Keywords : Laser Welding(레이저용접), Deep Learning(딥러닝), Quality Determination(품질 판별)

1. Introduction

An electric motor is a typical driving device for eco-friendly vehicles and the development of batteries with excellent performance and high storage density is being actively conducted[1]. Aluminum and copper are used as key materials in battery production, and both materials have superior electrical and thermal conductivity compared to ferrous metals. However, aluminum has a lightweight of about 1/3 compared to copper, so it is advantageous for battery and vehicle weight reduction[2].

Aluminum and copper materials are used in direct or indirect combinations as they are used as core parts of secondary batteries. Various methods are used for welding or joining materials. Representative welding methods include ultrasonic welding, electric resistance welding, arc welding, friction stir welding, and laser welding[3].

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Ultrasonic welding and friction stir welding are well-known methods for joining two materials in a solid state which joins two materials below the melting point using frictional heat. In particular, the ultrasonic welding has the advantage of relatively low investment in equipment and minimal formation of inter-metallic compounds between dissimilar materials, but the material deformation and joint thickness of the joint are limited[4].

On the other hand, friction stir welding is advantageous in making good use of the intrinsic properties of metals, but the equipment is complicated and the productivity is relatively low. On the other hand, electrical resistance welding, arc or laser welding is a welding method in which a metal is heated above its melting point to fusion. It has relatively high productivity compared to the solid-state welding method, but forms a brittle weld in an unstable state in the process such as an inter-metallic compound[5].

The laser has the advantages of not only a non-contact process but also the ability to minimize the influence of the surrounding area by rapidly quenching high-density energy into a local area. For this reason, lasers have been widely applied to the production of automobile parts. High-power laser technology has been developed and utilized in various ways, starting with CO_2 laser, Nd:YAG laser, diode laser, and now fiber laser and disk laser[6].

Recently, not only these various types of lasers, but also the laser beam wavelength and beam modulation technology, etc. are actively utilized to present new solutions for difficult-to-weld materials.

Near-infrared(NIR) laser oscillation was used to improve the absorption of laser beam on the material, but visible light (VIS) green laser and blue laser are used to increase the absorption rate of difficult-to-weld materials. In particular, the green laser has the advantage that both heat conduction welding and keyhole welding are possible because the laser absorption rate for copper is about 40% at room temperature[7].

In addition to the high productivity of laser welding and the ease of automation, the technology for automatic quality inspection has also developed a lot. Quality inspection is mainly performed in the form of using vision, sound, temperature, and plasma radiation data, but a quality inspection method using artificial intelligence(AI) technology has recently been reported(8).

Real-time quality inspection is a method to take full advantage of the advantages of laser welding technology. It is a principle of evaluating the soundness of the welded part by comparing the width or uniformity of the surface bead with a predetermined standard using an image acquisition device following the welding process. If a sound weld is not produced, the data is fed back to the controller to adjust various parameters such as laser power, focus position, and welding speed.

Recently, there have been many reports of cases in which deep learning algorithms using artificial intelligence technology have been effective in high productivity and quality control. According to previous research, the quality evaluation is improved by additionally combining various signals as well as the vision data of the laser welding part[7-8].

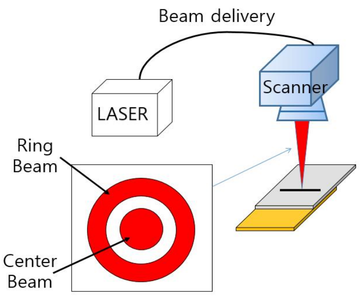
This paper reports the research results of predicting welding process variables using deep learning technology to learn by imaging welded weld beads under various conditions and using actual weld bead data as input variables.

2. Experiments

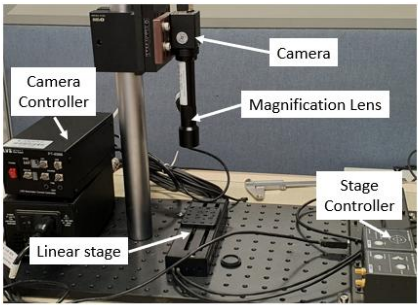
2.1 Experimental setup

Welding was performed with various process parameters using a high-power laser for manufacturing battery cells for electric vehicles. In order to determine the quality of the welded bead, the soundness of the weld was judged by comparing the cross section of the weld and the appearance of the bead.

The experimental apparatus prepared for welding is



(a) Schematic of experiment



(b) Image acquisition system

Fig. 1 Experimental system setup

shown in Fig. 1a. The laser oscillated from the laser oscillator (FL8000 ARM, Coherent Inc.) is transmitted to the laser scanner through an optical fiber transmission device, and then is irradiated onto 0.4mm aluminum and copper thin plates to form a weld.

The wavelength of the oscillated laser beam is 1,070nm and the transmitted laser beam is composed of a double core, so the diameter of the center beam is 70㎛ with the maximum output of 4 kW. On the other hand, the outer ring beam has a diameter of 180㎛ and has a maximum output of 4kW. The laser beam can be transported through a robot for long distances, and the beam can be transported with a laser scanner in the 300mm × 200mm area.

Copper and aluminum materials used for welding specimens were cut to a thickness of 0.4mm with 50mm wide and 110mm long. Two materials were welded to a length of 40mm.

As the aluminum material, Al6061-O, an Al-Si-Mg-based alloy containing 0.4 to 0.8% silicon (Si) and 0.8 to 1.2% magnesium (Mg) in aluminum was used. In addition, the copper material was oxygen-free copper, C1020P-1/2H, and the thickness of the test piece was 0.4 mm, respectively. Table 1 shows the chemical composition of the materials used.

Table 1 Specification of material

	Cu	Si	Mg	Zn	Mn	Cr	Fe	Ti	Al
Al6061	0.4	0.8	< 1.2	< 0.25	< 0.10	< 0.35	< 0.70	< 0.15	Bal.
C1020P	Cu					O_2			
	> 99.56					< 10 ppm			

(a) Material

Property	Value	Unit
Density	2700	kg/m^3
Heat capacity	900	J/(kg • K)
Thermal conductivity	238	W/(m • K)
Electrical conductivity	3.774e7	S/m
Relative permittivity	1	1
Young's modulus	70e9	Pa

(b) Aluminium

Property	Value	Unit
Density	8960	kg/m^3
Heat capacity	385	J/(kg • K)
Thermal conductivity	400	W/(m • K)
Electrical conductivity	5.998e7	S/m
Relative permittivity	1	1
Young's modulus	110e9	Pa

(c) Copper

The samples that were initially welded were divided by lot, and samples having a maximum allowable tensile force of 2.5 kgf/mm or more were classified. The welded samples that passed the tensile test were largely divided into the following three conditions to collect data.

The first condition was straight welding, and the output of the center beam was fixed at P_C=800W, v=200mm/s, and the specimen was manufactured while the output of the ring beam was incremented by 200W from P_R=1600W to 3,000W.

In the second condition, welding was performed in a straight line using a laser beam, and the output of the ring beam was fixed at P_R=500W, and the specimen was manufactured while incrementing every 50W from the output of the center beam P_C=950W to 1,250W, and the welding speed was v =200mm/s remained the same.

In the third case, the output of the center beam and the output of the ring beam were fixed at P_C=1,100W and P_R=600W, respectively, and the laser beam was transferred at a welding speed of v=200mm/s. However, while rotating the output laser beam at a frequency of 500 Hz, the specimen was manufactured while increasing the amplitude from 0.1mm to 0.5mm in units of 0.1mm.

In order to acquire image data of the bead surface, the DAQ system was used as shown in Fig. 1(b). The welding specimen moves in a straight line through a linear stage, and the CCD camera is configured to capture the image in the form of a moving picture at high speed.

Then, using eBusplay, the specimens were taken out one by one at a speed of 0.3 mm/s, and about 2,000 pieces of data were collected per sample. After storing the collected data in the workstation, deep learning was performed using the Alexnet algorithm in MATLAB-based Deep Learning Toolbox and self-developed program.

2.2 Data acquisition and Deep Learning Process

Alexnet was used as a classification model algorithm for the deep learning. Deep learning using Alexnet performed image learning by additionally inputting the code needed to determine the quality of the welded part. Prior to quality determination, data were collected by photographing specimens with a tensile force of 2.5kg$_f$/mm or higher as the result of the tensile test of welded specimens.

The collected data was observed with the optical microscope, and the learning was carried out by classifying it as Pass or Fail according to spatter or porosity on the surface of the welded part. The performance of the algorithm has been proven in previous studies. As a result of preliminary application to this study, a result value that matches at least 94% in all areas was derived.

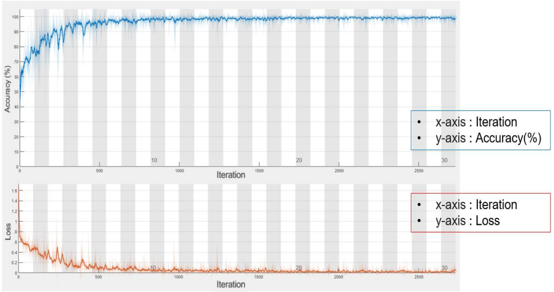


Fig. 2 Deep learning process

In deep learning, the more learning data, the better the image selection ability or discrimination ability can achieve. 360 degree rotation data were applied to the input image by using the imageDataAugmenter function to compensate for the random position of the welding specimen.

The Alexnet function is a convolutional neural network composed of 8 layers excluding inputs, consisting of 5 convolutional layers and 3 fully connected layers. By modifying Alexnet's basic classification, it was classified into Pass and Fail according to the presence or absence of porosity or spatter in the weld section.

The initial learning rate was set to 0.001, and the SGDM (Stochastic Gradient Descent with Momentum) function was used as the input argument. Fig. 2 shows the accuracy and loss graphs by plotting the training progress as training-progress. The verification data included 20% of the total data, and the total number of data in Case 1 was 14,806, in Case 2, 20,365, and in Case 3, 8,053 image data. The accuracy of the algorithm is 99.22%.

3. Results

As presented in the previous section, the results of the experiment according to the conditions are shown in Fig. 3 ~ Fig. 5. In case 1 shown in Fig. 3, center beam output is fixed/ring beam output is variable, In

Fig. 3 Center 800W – Ring Varied

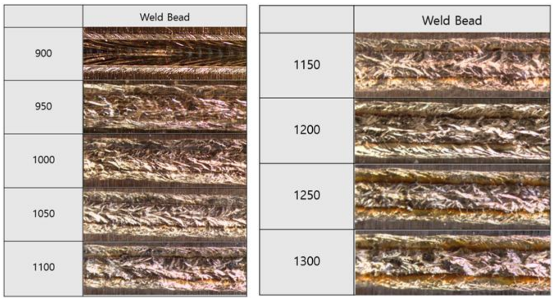


Fig. 4 Ring 500W – Center Varied

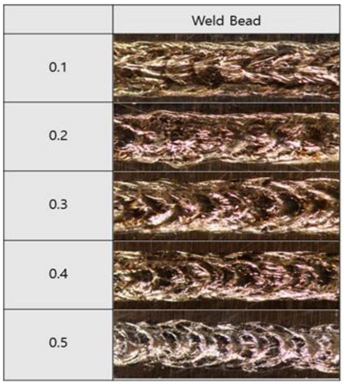


Fig. 5 Wobble mode

case 2 shown in Fig. 4, center beam output is variable/ring beam output is fixed, and Fig. 5 shows the case of fixed center beam output/fixed ring beam output and beam modulation.

For the welded sample, the shape of the bead surface was photographed from the top through the configured experimental device, and the sections were divided into ① welding start section (Start), ② welding center section (Middle), and ③ welding end section (End), respectively.

In order to secure welding reliability, experiments were carried out using the same method and conditions used in previous studies. Several specimens were manufactured under the same conditions and used for cross-sectional photography and bead photography. The appearance of the weld bead was recognized as different data depending on the lighting and the location (angle) of the specimen.

The same sample was taken under various conditions to increase the reliability of the data. In addition, by recognizing untrained image data for each experiment, deep learning was performed four or more times with different data to obtain the result value, thereby increasing the reliability of deep learning training.

Fig. 6 is the experimental result corresponding to the Case 1. As shown in Fig. 6(left), as a result of testing the pass/fail probability by presenting the test image, the passing probability was found to be more than 99.7%.

The failure probability was found to be more than 98.7% as shown in Fig. 6(right). As a result of the actual visual inspection, in the case of the passed product, the shape of the weld bead showing excellent welding quality came out. However, in the case of the failed product, spatters and cracks (scratches) were found.

Fig. 7 is the experimental result value corresponding to Case 2 (variable center beam output - fixed ring beam output). As shown in 7(left), the pass/fail probability was tested by presenting the test image and the pass probability was found to be 99.9%. Also, as shown in 7(right), when the pass/fail probability was tested by presenting the test image, the failure probability was also found to be 99.7%. As a result of the actual visual inspection, in the case of the passed product, the shape of the weld bead showing excellent welding quality came out. However, spatter and unevenness of the welding section were found in failed parts.

Finally, as presented in Fig. 8, the experimental result value for the amplitude variable under the third condition(center beam, ring beam output fixed). As shown, the pass probability was found to be 94.2%. However, the pass/fail probability was tested by presenting the test image, and as a result, the failure probability was also found to be 99.5%. As a result of the actual visual inspection, the passed product showed the shape of a weld bead showing excellent welding quality, while the failed product showed a lot of spatter.

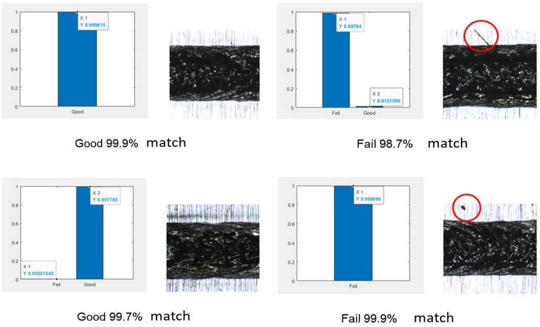


Fig. 6 Case #1

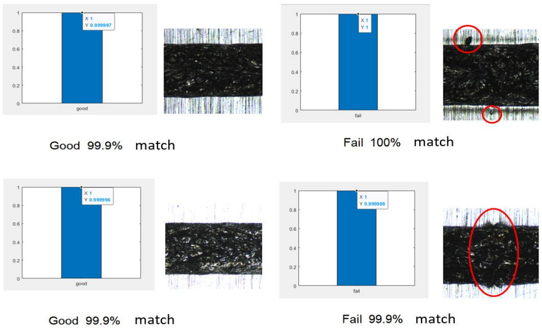


Fig. 7 Case #2

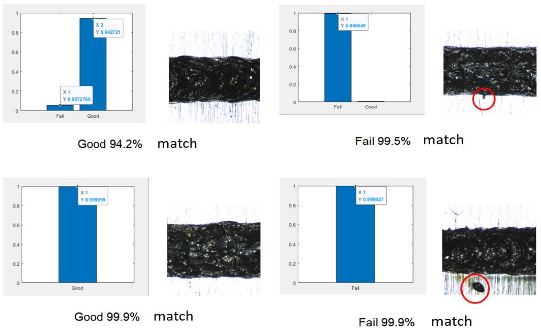


Fig. 8 Case #3

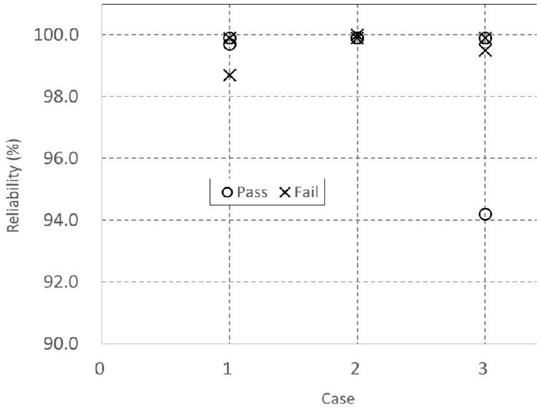


Fig. 9 Comparison of DL results

4. Discussion and Conclusion

Welding specimens were manufactured by modulating various types of laser beams using a laser beam, and welding quality and process variables were predicted using artificial intelligence techniques. As a result of dividing the average length of the welded part 50mm into 2,000 areas and determining the quality by the shape of the surface bead, defective products were selected with an average reliability of 98% or higher, and the welding specimens of good quality were selected with a reliability of 94% or higher (Fig. 9).

It showed high reliability (over 98%) regardless of whether the output of the center beam or ring beam was fixed or varied. However, results showed relatively low reliability (over 94%) when the laser beam was modulated (wobble). It is judged that the discriminability is somewhat lowered due to the non-uniformity of the bead surface caused by the wobbles rather than the reliability of the laser welding sample.

Welding sections were divided into ① welding start section (Start), ② welding center section (Middle) and ③ welding end section (End), respectively, but there was no difference in reliability between sections, and the more influenced by lighting. However, noise and image distortion appearing depending on the light and shade irradiated to the test piece were utilized as other types of data in deep learning.

Recognizing different data depending on the location (angle) of the specimen was helpful in securing various data using the same sample. By recognizing untrained image data for each experiment, deep learning was performed four or more times with different data to obtain the result value, thereby increasing the reliability of deep learning training.

Overall, the best welding quality was obtained in the experiment of fixed ring beam output/variable center beam output, particularly, in the case of fixed beam (ring beam) 500W and variable beam (center beam) 1,050W, weld bead failure was seldomly found. In the tensile force test to confirm the reliability of welding, the average tensile force of 2.5kg_f/mm or more was shown in all sections.

This study confirmed that, when imaging welded beads under various conditions using deep learning technology, the actual welding process variables can be predicted although limited, and the welding quality can be predicted.

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