Lasers in Manufacturing Conference 2023

Al/Cu Interfacial gap prediction using multi-sensor signals and deep learning

Hyeonhee Kim[a,b], Sanghoon Kang[a,b], Yong Hoon Jang[b] ,Minjung Kang[a,*]

[a] *Korea institute of industrial technology, 21999, Republic of (South Korea)*

Abstract

In secondary batteries and fuel cells for electric vehicles, connection between electrodes is inevitable. Achieving consistent weld quality and weld joint properties is critical for reliable battery assembly and electric vehicle performance. Laser welding is sensitive to joint preparation, which secures the electrodes with a jig system, but can create unexpected gaps between the layers. The spacing between the layers provides a path for laser beam dispersion and creates a loose interface. Typically, these electrodes are connected by full-overlap joints, making it difficult to find interfacial gaps during the process. In this study, laser welding was performed the on specimen with overlap joint for Al (top, 0.4 mm)/Cu (bottom, 1.0 mm) with an artificial gap. We proposed two types of convolution neural network (CNN) models to detect gap presence using single-sensor and multi-sensor data. To develop the deep learning model (a fully connected neural network model and a convolutional neural network model), CCD camera, OCT, and photodiode sensor were selected to monitor the weld pool feature, keyhole depth and plasma wavelength, respectively. Test results showed quite good classification performance with over 98% accuracy using a multiple sensor. Multi-sensor CNNs by consolidated image data have improved accuracy compared to those using only image data.

Keywords: convolution neural network; classification; interfacial gap

1. Introduction

Aluminum and copper are the key materials as the electrode, and these are connected electrically to enlarge the battery capacity and manage the battery system [1]. Recently laser welding process are preferred to acquire the electrical joint [1-3] due to it utilizes the high-density energy via the focused laser beam. I

* Corresponding author.

allowed high welding speed with a reliable joint quality. Brand et al. [4] compared the joint performance fabricated with resistance spot welding, ultrasonic welding, and laser welding. They concluded that laser welding has the lowest electrical contact resistance and the highest joint strength compared with other joining processes [4].

The sheets used for electrodes and tabs are very thin, the gap preparation is affected to the joint quality. Especially, the gap between the layers can cause the defects such as underfill, pores, humping, and weak interface. With the recent advance of machine learning technology, the application of deep learning technology is abruptly increasing in sensing and monitoring of welding phenomena [5]. Especially, CNN (convolution neural network)-based models have been extensively developed in welding research [6,7]. The recent CNN model has strength in modelling based on continuous signals or images, whereas the MLP (multilayer perceptron) neural network model has been widely adopted for parameter-based modelling [8].

In this experiment, OCT, spectrometer and CCD camera have been employed to analyze the keyhole depth, wavelength variation of plasma plume, and molten pool feature, respectively. A deep learning mode was developed to classify the gap presence in laser welded Al-Cu overlap joints. Convolution neural networks were chosen as the deep learning models, and CNN models using single or multi sensor signals were trained and tested.

2. Experiment and methodologies

2.1. Experimental setup

A fiber laser (IPG, YLS-6000) was used for laser welding, the beam was delivered through an optic (IPF, D30) with a focal length of 200 mm. The beam was irradiated with a declined angle of 10° to avoid reflection error. At the focal point, the laser beam had a diameter of 270 µm. The base materials were selected as Al 1050 (Thickness: 0.4 mm) and C1100 (thickness: 1.0 mm) to imitate tab and bus bar welding. An artificial interfacial gap between the layers were varied from 0 to 0.1 mm, which was managed using feeler gauges. During the welding, shielding gases were not provided. Table 1 and Table 2 show the chemical composition of the base materials and parameters used in this study.

To enable real-time monitoring of the welding phenomenon, sensors were installed coaxially to the laser head, as shown in Fig. 1. A CCD camera (IDS, UI-6140CP-M-GL) was used to collect image data with a size of 472 × 202 pixels at 500 frames per second. To minimize the effect of laser-induced plasma and plume, the welding area was directly illuminated with an illumination laser beam with a wavelength of 980 nm. A spectrometer (Ocean Insight, HR4000) was used to collect 3648 wavelength signals in the 194 – 1127 nm wavelength band at 100 Hz. Optical coherence tomography, named as OCT (IPG, LDD-700), was used to collect keyhole depth measurement data at about 135 kHz by irradiating a near-infrared laser with a wavelength of 808 nm.

Table 1. Chemical composition of base materials (wt.%)

	Al	Si	Fe	Cu	Mn	Mg	Zn	Ti	V
Al 1050	99.59	0.068	0.286	0.003	0.001	0.001	0.002	0.023	0.016
C1100	-	-	-	99.959	-	-	-	-	-

Table 2. Experimental conditions for laser welding.

Parameter (unit)	Value (Level)
Laser power (kW)	1.5, 1.25, 1.0 (3)
Welding speed (m/min)	5 (1)
Gap (mm)	0, 0.02, 0.04, 0.06, 0.08, 0.1 (6)
Number of replicates	2

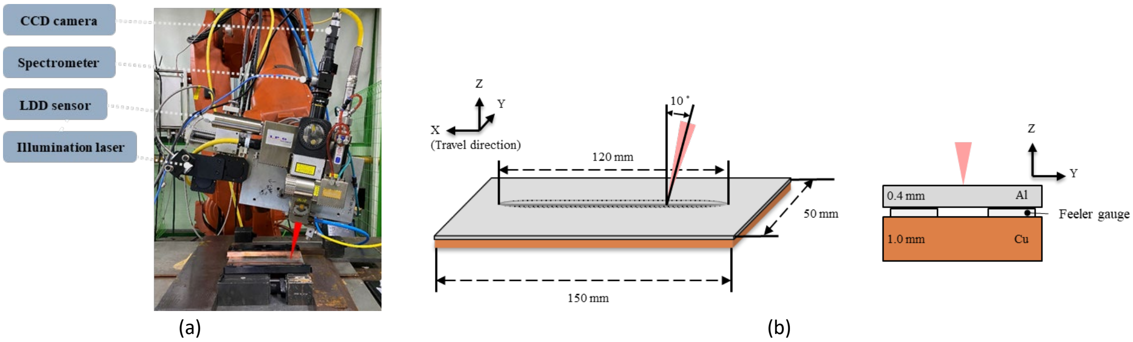

Fig. 1. (a) coaxially arranged sensors image and (b) joint configuration

2.2. Gap measurement

To demonstrate the interfacial gap, which is the target parameter for prediction, average gap distance at interface were measured from the laser welded samples. The measuring points were chosen within a 60 mm where a 50 mm away from the welding start position. The interfacial gap was defined as the average value measured from cross-sectional images at 20 mm intervals. When the average Gap was over 0.04 mm, which is 10% of the top sheet, it was treated as a gap condition.

2.3. Data preprocessing

A model was developed to estimate in real time using image data as the original data at a frequency of 500 Hz. For the spectrometer and OCT data, pre-processing was carried out using up-sampling and down-sampling methods in the time domain, respectively. Following the pre-processing steps, the frequency of the input data from all three sensors was unified to 500 Hz.

2.4. Convolutional neural network

The deep learning models used to detect the interfacial gap in the Al/Cu overlap welding are developed. The CNN layer for the CCD images was designed to extract the features through the molten pool images, and the spectrometer data within 3648 wavelengths also driven through the CNN model. In the case of OCT data, one-dimensional time domain data, it was used as a single value without performing a convolution. Optimized structure of the CNN model used in experiment were given in Table 3. Batch normalization was used between convolutional layers to improve stability and performance, and feature maps were down-sampled using max pooling. The activation function used in all the nodes except the output nodes was the rectified linear unit (ReLU) function. After the extracting the features from the CCD images, spectrometer signals, and OCT data through the CNN layers, two of fully-connected layers were added. In order to prevent overfitting, a kernel regularizer was applied to each dense layer. For the classification, the activation function used in all the nodes was the Sigmoid function, and the Adam optimizer [9] was employed with the following parameters: a learning rate of 10^{-3}, β_1=0.9, β_2=0.999, and $\varepsilon=10^{-8}$. The data points were randomly split into training, validation, and test datasets in a ratio of 70%:15%:15%.

Table 3. Architecture of the convolutional neural network.

Layer	Filter Size	Number of filters	Max Pooling	Filter Size	Number of filters	Max Pooling	
Input	Grayscale images			3648 wavelength spectrum			Keyhole depth
Convolution	3 × 3	32	3 × 3	3	32	3	
Convolution	3 × 3	64	3 × 3	3	64	3	
concatenate	3 input flatten and concatenate						
Fully connected	512 output channels						
Fully connected	256 output channels						
Fully connected	1 output for classification						

3. Results and discussion

The trained model achieved a classification accuracy of 99.98% on the training dataset, and 99.12% on the validation dataset, it indicated that the CNN model is capable of classifying samples with high accuracy. The accuracy of the test dataset was 98.88% (Fig. 2). This high accuracy on the test dataset means that the trained model is reliable and can be applied effectively to predict the interfacial gap in real welding situation.

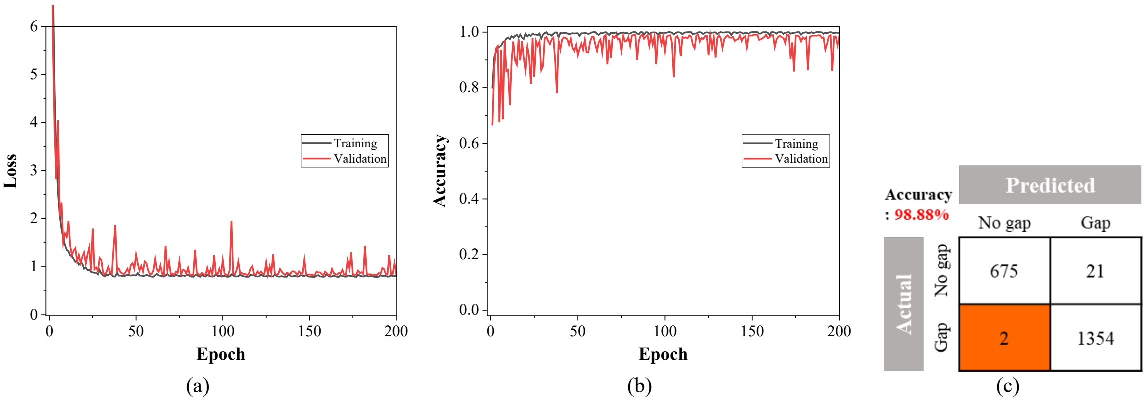

Fig. 2. Training and validation (a) loss and (b) accuracy, and (c) test results for the multi-sensor (CCD + spectrometer + LDD) model.

The accuracy, number of false positive, and precision were presented to compare the deep learning models according to the combination of sensors, as shown in Fig. 3. In the deep learning model using a single sensor, the CNN models using the spectrometer signals and CCD images accomplished a high accuracy of over 98%, while the OCT sensor model showed an accuracy of 66.08%. Under multi-sensor integration conditions, the accuracy and precision were slightly increased and numbers of false positive precision was decreased. The multi-sensor model achieved a high precision rate of 99.7%. In the dual-sensor combinations, the CCD and spectrometer combination was reliable and performed well alone. FP determined the feasibility of the model for predicting gaps. The multi-sensor model (CCD + SP + OCT) has the lowest number of FPs. It means that multi-sensor model is excellent for predicting a gap.

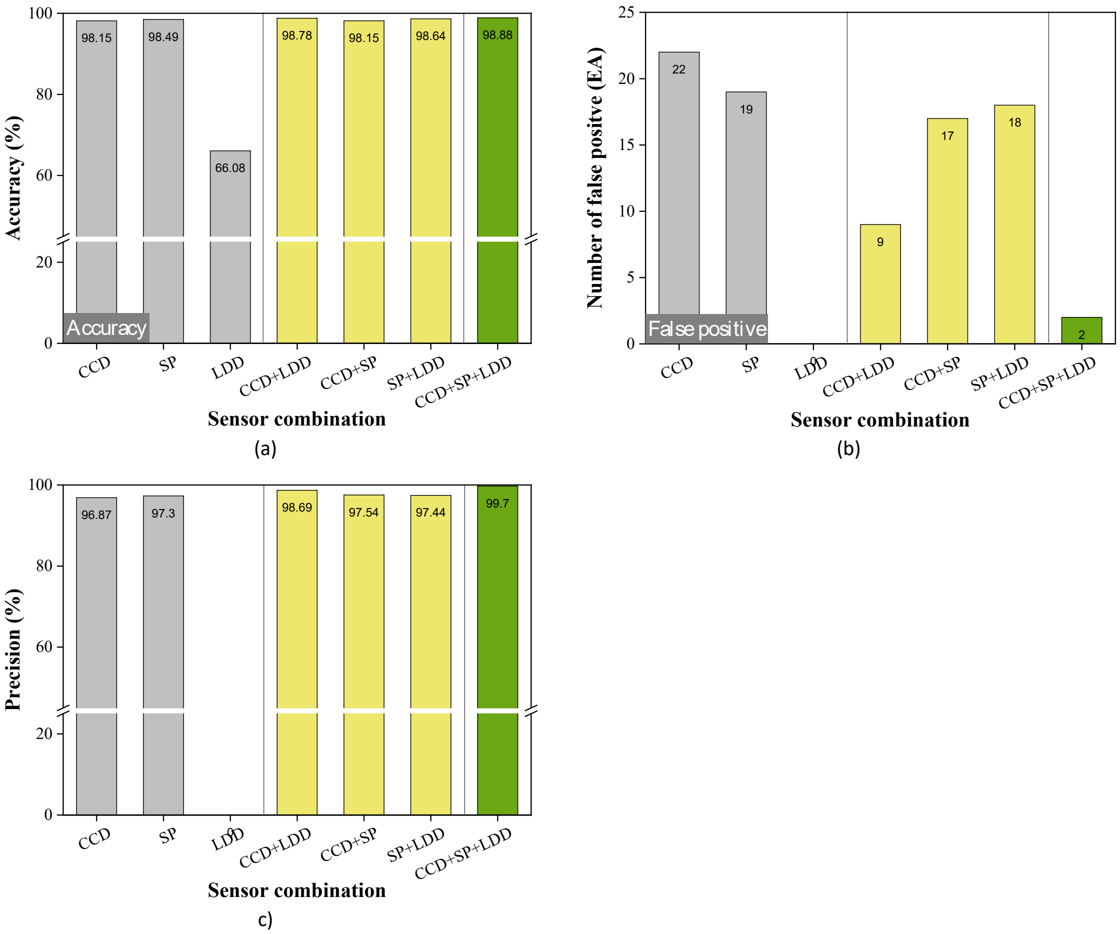

Fig. 3. Confusion matrix plot according to the sensor combination (a) Accuracy; (b) precision; (c) number of false positive

4. Conclusions

This study proposes the possibility of machine learning application for real-time monitoring and detection of interfacial gap using various sensors. The CCD images, spectrometer signal, and OCT data collected during the Al/Cu overlap laser welding were used to establish a CNN-based algorithm. The accuracy and precision of the algorithms were compared and presented according to the combinations of sensors. As a result of the single sensor learning model, the CCD and the spectrometer play a major role among the three sensors with over 97% accuracy. When sensing data is merged into the deep learning model, the accuracy and precision were increased by synergistic effect.

Acknowledgements

We acknowledge financial and technical support provided by the Korea Institute of Industrial Technology (EH-23-070).

References

1. Lee, S.S., Kim, T.H., Hu, S.J., Cai, W.W. & Abell, J.A., 2010. Joining technologies for automotive lithium-ion battery manufacturing: A review, in Proceedings of ASME 2010 international manufacturing science and engineering conference, Erie, PA, USA, 541-549.
2. Cai, W.W. 2017., Ultrasonic welding of lithium-ion batteries, in ASME Press
3. Das, A., Li, D., Williams, D. & Greenwood, D. 2018., Joining technologies for automotive battery systems manufacturing, *World Electric Vehicle Journal* 9, 22.
4. Brand, M.J., Schmidt, P.A., Zaeh, M.F. & Jossen, A., 2015, Welding techniques for battery cells and resulting electrical contact resistances, *Journal of Energy Storage* 1, 7-14
5. Cai, W., Wang, J., Jiang, P., Cao, L., Mi, G. & Zhou, Q., 2020, Application of sensing techniques and artificial intelligence-based methods to laser welding real-time monitoring: A critical review of recent literature, *Journal of Manufacturing Systems* 57, 1-18.
6. Lee, K.,Yi, S.,Hyun, S. & Kim, C., 2021, Review on the recent welding research with application of CNN-based deep learning - Part 1: models and applications, *Journal of Welding and Joining* 39, 27-35.
7. Lee, K.,Yi, S.,Hyun, S. & Kim, C., 2021, Review on the recent welding research with application of CNN-based deep learning - Part II: model evaluation and visualizations, *Journal of Welding and Joining* 39, 36-44.
8. Andersen, K., Cook, G.E., Karsai, G. & Ramaswamy, K., 1990, Artificial neural networks applied to arc welding process modeling and control, *IEEE Transactions on Industry Applications* 26, 824-830.
9. Schmalen P., Plapper, P., 2018, Spectroscopic studies of dissimilar Al-Cu laser welding, *International Manufacturing Science and Engineering Conference, American Society of Mechanical Engineers*, p. V002T04A033.