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Prediction of penetration depth in Al/Cu overlap laser welding with a combination of various sensors and deep learning

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Abstract

Al/Cu laser-welded overlap joints, in which weld-penetration depth significantly influences both joint strength and electrical conductivity, are widely applied in automotive battery cells. In this study, the penetration depth was predicted using coaxially photographed weld pool image data (high-speed, CCD camera), photodiode, and spectrometer as input data. Penetration depth was measured by the optical coherence tomography (OCT) system and treated as output data. Input data were preprocessed using various methods such as average, fast Fourier transform (FFT), and short-time Fourier transform (STFT). Two types of convolution neural network (CNN) models were tested. One is based on a unisensor CNN using only weld pool image data, and the other is a multi-sensor CNN using an additional photodiode or spectrometer signal. A total of 10 combinations were constructed and evaluated for comparison. The highest accuracy was obtained with an average absolute error of 0.02035 mm and a coefficient of determination of 0.98985.

Keywords: Al/Cu overlap welding; optical coherence tomography system; convolution neural network

1. Introduction

In Al/Cu overlap-welded joints, it is crucial to precisely control the depth of the weld penetration into the lower sheet. Insufficient penetration depth can lead to a reduced joint area, while excessive penetration depth can increase the formation of an intermetallic compound (IMC) [1, 2]. Therefore, the penetration depth of the Al/Cu overlap welding joint can be used as a criterion to evaluate weldability. Recently, many studies have

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used various sensors and deep learning to assess the weldability of welded joints. However, most of the previous research focused on classifying the condition of the weld, and there is a lack of studies quantitatively predicting the penetration depth. This study used images, photodiodes, and spectrometer sensors as input data and OCT signals as output data. We compared and evaluated various CNN models that predict penetration depth using sensor combinations and preprocessing methods.

2. Experiments and methodology

2.1. Experiment and setup

Used base materials of 0.4 mm thickness Al 1050 alloy and 1.0 mm thickness Cu 1100 for the welding. Completely overlapped the Al sheet onto the Cu sheet. The experiment involved a disk laser with a maximum output of 3 kW and a fiber laser with a maximum output of 6 kW. The laser head and a high-speed camera (HSC) were coaxially aligned for the disk laser, and the photodiode was positioned non-coaxially to obtain input data. Additionally, the penetration depth data, serving as the output data, were obtained using Trumpf's optical coherence tomography (OCT) system known as weld depth monitoring (WDM) (Fig. 1(a)). And for the fiber laser, we obtained the input data by configuring the laser head, CCD camera, and spectrometer coaxially. Additionally, we simultaneously used IPG's OCT system, known as laser depth dynamics (LDD), to obtain the output data, which is the penetration depth data (Fig. 1(b)). A total of 25 diverse welding conditions were determined using these two systems. Detailed information on the experimental conditions can be observed in Table 1. In addition, to validate the deep learning models used, we conducted experiments by keeping the welding speed fixed and gradually increasing the laser output.

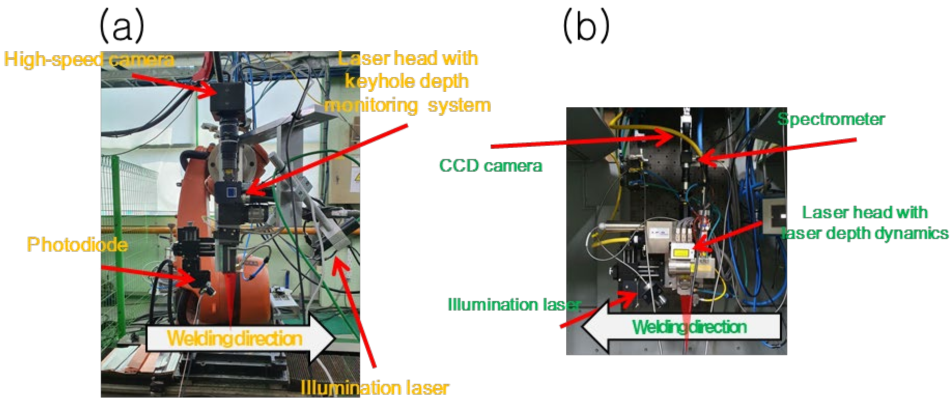

Fig. 1. Configuration of experimental system. (a) Disk laser system (b) Fiber laser system.

Table 1. An example of a table

An example of a column heading	Disk laser system	Fiber laser system
Beam size (μm)	300	270
Laser power (W)	1100 - 1600	706 - 1600
Welding speed (m/min)	3 - 7	3 - 7
Working distance (mm)	323	160

2.2. Data preprocessing

The image data was preprocessed using a method that involves averaging the intensity of each pixel every n images. The photodiode signals underwent signal preprocessing using the following techniques: (1) down-sampling in the time domain, (2) fast Fourier transform (FFT), and (3) short-term Fourier transform (STFT). The spectrometer data was preprocessed using the Fourier method. The OCT data, which represents the penetration depth, was down-sampling in the time domain.

2.3. Deep learning models

To predict the penetration depth, we constructed a uni-sensor model using only image data and a multi-sensor model that incorporates photodiode or spectrometer data as additional input data. The structure of these models is depicted in Fig. 2. As an exception, the photodiode data transformed using FFT were directly flattened and connected to the image data without passing through a convolutional layer.

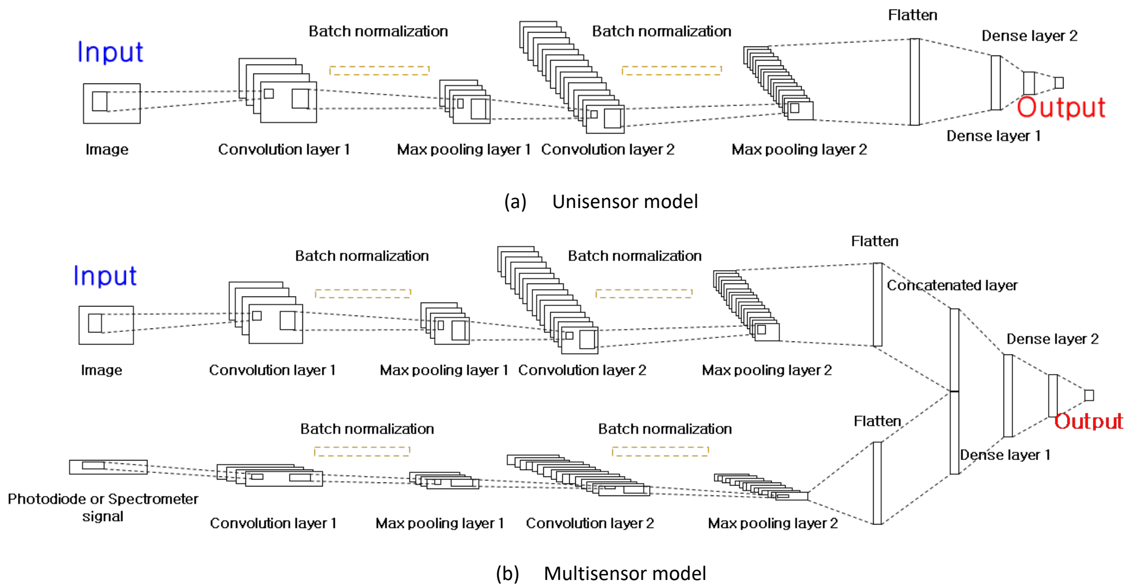

Fig. 2. Structure of deep learning models

3. Results and discussion

3.1. Training and validation.

The training errors of all models decreased rapidly initially and converged after approximately 300 epochs, indicating no signs of overfitting. As shown in Fig. 3, all models exhibited low MAE and a high coefficient of determination results during the training phase. In the validation phase, the combination of HCS and photodiode showed no significant difference in MAE and coefficient of determination values among the models (Fig. 4). However, the STFT-multi-sensor model yielded the lowest MAE of 0.02839 mm and the highest coefficient of determination of 0.98411. On the other hand, the combination of CCD and spectrometer showed more significant variations in MAE and coefficient of determination results across different models. The model utilizing the multi-sensor at 500 Hz exhibited the lowest MAE of 0.01988 mm and the highest coefficient of determination of 0.99143, indicating the best performance among all the models.

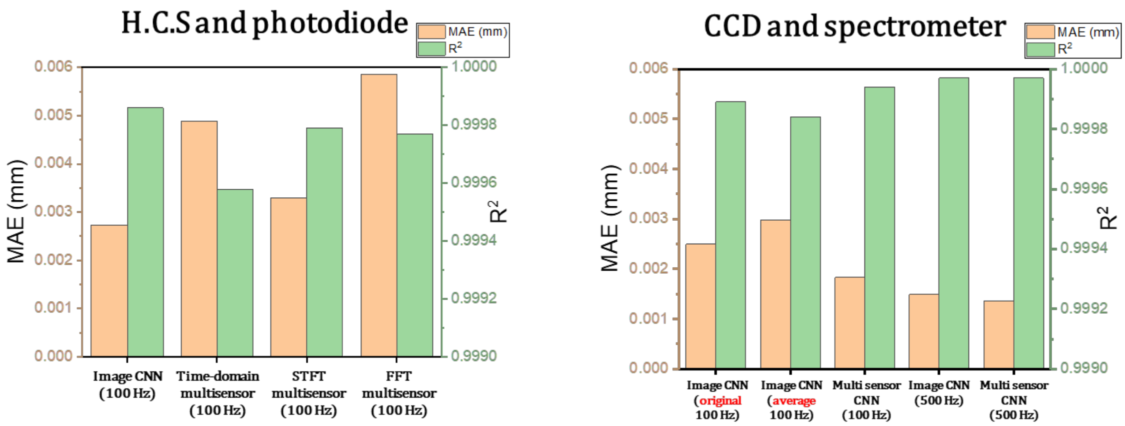

Fig. 3. Training errors by model types

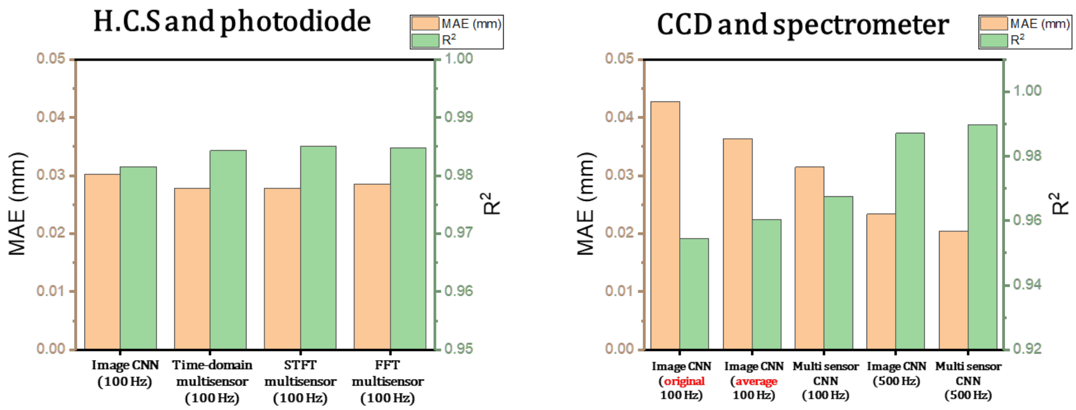

Fig. 4. Validation errors by model type

3.2. Model test

The trends and magnitudes of errors in the model's test phase were similar to those observed in the validation (Fig. 5). In the case of the combination of HCS and photodiode sensors, the STFT multi-sensor model continued to exhibit the lowest MAE and the highest coefficient of determination results. Similarly, the 500 Hz multi-sensor CNN model demonstrated the lowest MAE and the highest coefficient of determination results for the combination of CCD and spectrometer sensors, consistent with the validation outcomes.

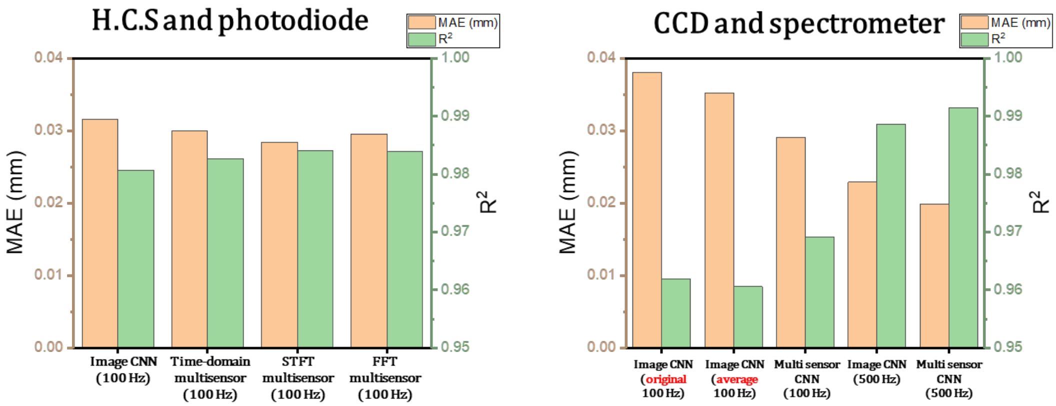

Fig. 5. Test errors by model type

4. Conclusion

We employed a CNN (Convolutional Neural Network) for predicting the penetration depth in Al/Cu overlap welding using image data, photodiode data, and spectrometer data. Notably, the accuracy improved when utilizing a multi-sensor CNN that incorporated image data along with an additional sensor, surpassing the performance of using image data alone. Comparing the two sensor combinations, the model using CCD and spectrometer demonstrated better accuracy in both MAE and R^2 analysis compared to the model using H.C.S and photodiode.

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