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Prediction of Cu-Al weld status using convolutional neural network

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Abstract

Welding copper (Cu) and aluminum (Al) result in brittle intermetallic (IMC) phases, which reduces the joint performance. The key for a strong joint is to maintain an optimum amount of Al and Cu composition in the joint. To implement this without the destruction of the sample is a challenge. For this purpose, high-resolution images of the weld zone are utilized after welding. With the image processing technique, the presence of (Al/Cu) material melted is distinguished. Therefore, the different weld type/status like insufficient melt, optimum melt, and excessive melt is detected from the images.
This paper analyses the weld images and applies the convolutional neural network technique to predict the weld type. The microstructure and Energy Dispersive X-ray Spectroscopy (EDS) analysis of the fusion zone for each weld types are correlated to the weld images.

Keywords: Aluminum-copper joints; Laser welding; weld analysis; Intermetallic phases; Energy Dispersive X-ray Spectroscopy (EDS) analysis; Image processing; Convolution neural network; weld type prediction

1. Introduction

Laser joining of copper (Cu) and aluminum (Al) sheet is difficult because of excessive brittle intermetallic phases (IMP) formed in the joint, which results in reduced performance (Solchenbach & Plapper, 2013). The traditional approach is to irradiate laser from Aluminum (Al) sheet to control the weld depth and intermixing of Cu in Al (Solchenbach & Plapper, 2013) (Fetzer et al., 2016) (S. S. Lee et al., 2010).

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Irradiation of laser beam from low meting point side of Al (660° C) allows for braze welding of Al to Cu. This approach is useful for this combination because the detrimental intermetallic phases formed can be minimized. Laser beam oscillation/trajectory is well suited for welding highly reflective metals in dissimilar combination like Al and Cu because a larger weld seam can be obtained with a high intensity in the range of 10^7 W/cm^2 in keyhole mode. Welding from Cu sheet (Cu on top) is challenging in terms of higher reflectivity, thermal conductivity and melting temperature (1080° C) in contrast to Al. Therefore, welding from copper side is more demanding to couple laser radiation into Cu and to deal with the intermetallic phases formed. Recently with the availability of high power Infrared lasers (Mathivanan & Plapper, 2021) (Kaiser et al., 2020) (Hollatz et al., 2020) (Mathivanan & Plapper, 2019b) (S. J. Lee et al., 2014) and green laser (Mathivanan & Plapper, 2020), the welding from Cu sheet to Al is gaining attention. Shaping the laser pulse influence the weld bead by providing tailored heat input to the material (Lerra et al., 2019) (Mathivanan & Plapper, 2019a).

This research investigates fusion welding of Cu-Al (Cu on top) in spiral profile with laser wavelength of 1030 nm. A spiral trajectory (circular profile resembling a spot weld) is chosen to resemble a bolted connection in contrast to welding in linear profile (Mathivanan & Plapper, 2019b). This paper exploits the higher solubility of Al in Cu (Cu on top configuration), which is about 18.5 at%. With this, a higher amount of Al can be intermixed to Cu during welding process. Therefore, a higher depth of penetration is feasible. A strong joint based on fusion welding of Cu to Al is achieved. For welding dissimilar metals, it is important to optimize the resulting intermetallic phases, at the same time increase the number of beneficial phases in the weld seam. Therefore, the key for a strong joint is to have an optimum melt of Cu and Al.

The main objective of this paper is to identify different type of weld/class based on Cu and Al mixing on the top of weld bead for weld qualification, nondestructively. Optical analysis of the top bead (Cu sheet) is selected for identification, as it is rapid, nondestructive, and relatively inexpensive in comparison to destructive cross-sectional analysis of the weld seam (Schmalen et al., 2018). Use of automatic and nondestructive identification of weld type enables implementation of quality check for all the samples which improves the product quality. In this research high-resolution images of weld zone are acquired and processed with computer vision package to apply preprocessing and then the images along with its weld class/type is fed to a convolutional neural network architecture (CNN) and predicted. The CNN architecture is selected because the network can predict the weld class by automatically learning basic features like lines and edges in the weld zone because of Cu, Al mixing. Deep learning models are able to predict the weld defects like blowout, humping, undercut (Zhang et al., 2020) and misalignments (Digital et al., 2020). With high speed camera (2.5 kHz framerates) and CNN model, can be used for predicting the laser power in powder bed fusion process (Kwon et al., 2020).

This manuscript is organized starting with the details of the materials used, welding parameters and the acquisition of the weld images are explained in experimental setup section 2. The analysis of optimum weld bead (Cu top view) and classification of weld type is discussed in section 3.1. The microanalysis and the elemental composition in the weld bead are discussed in 3.2 and 3.3 respectively. The convolution neural network architecture and the model performance is explained in section 3.4. Finally, the conclusion and future work is discussed in section 4.

2. Experimental

2.1. Materials

Copper and Aluminum sheets, each of dimension 40 mm x 50 mm x 0.4 mm is welded in overlap configuration. The Copper (Cu-OF) sheet used is oxygen free 99.95 % pure and Al (Al1050) sheet is 99.5 % pure.

2.2. Welding setup

A schematic view of the laser welding setup and trajectory is shown in Fig. 1. The Cu sheet is placed in overlap configuration on the Al sheet of thickness 0.4 mm each. Disk laser (TRUMPF) of wavelength 1030 nm and maximum power of 2000 W is used for welding. The laser parameters used for welding is shown in Table 1. The laser beam is focused by black bird scanning system and irradiated on top of Cu sheet to a spot size of 110 µm.

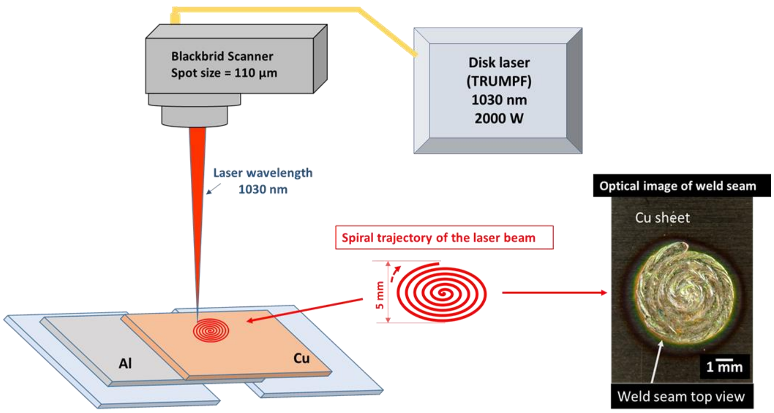

Fig. 1. Schematic of the laser welding process and the welding trajectory

Table 1. Laser parameters used for welding Cu-Al in this paper

Heat input [J/mm]	Laser Power [W]	Velocity [mm/s]
3.40	1700	500
3.60	1800	500
4.00	2000	500
4.25	1700	400
4.50	1800	400
5.00	2000	400
5.00	1500	300
5.14	1800	350
5.33	1600	300
5.67	1700	300
6.00	1800	300
6.67	2000	300
8.50	1700	200
9.00	1800	200
10.00	2000	200
17.00	1700	100

The laser beam is moved in spiral trajectory (from inside to outside the spiral) so that the weld bead is a circular profile (Top view of Cu). The diameter of the spiral profile is fixed to 5 mm and the number of turns of spiral is set as five (n=5).

2.3. Weld image acquisition

High resolution optical images of the weld seam (top view of Cu as shown in Fig. 1) is acquired by Fujifilm X-Pro20 camera for nondestructive analysis and prediction using convolution neural network (CNN) (Abadi et al., 2015) (Chollet & others, 2015). The dimension of the acquired raw image is 6000 x 3376 pixels.

For microanalysis, scanning electron microscope (Hitachi SU-70 FE-SEM) is used with energy of 20 keV and Energy Dispersive Spectrometer (EDS) analysis is performed for estimation of elemental composition of Cu/Al in the weld seam.

3. Results and discussion

3.1. Analysis of optimum weld bead on Copper sheet

The application of laser radiation melts the copper and aluminum which then intermix and solidify to form a weld joint also called as fusion zone. Depending on the laser energy applied different level of Al and Cu intermixing is obtained. With increasing amount of Al in the fusion zone, different bead pattern appears on the top of the weld seam (shown in Fig. 2) which forms the basis for classification of weld type and prediction (in section 3.4).

Fig. 2. Optical macro images of the different weld bead type from top of Copper sheet

Low laser energy of less than 3.0 J/mm result in no weld. At low laser energy, the reflection of laser radiation by Cu is very high and there is no coupling of laser energy into the material. This condition is unsuited for welding. This condition is termed as “No weld” or class 0. Increasing the laser energy to 3.4 J/mm results in penetration of Cu sheet but the amount of Al melted is very less. This condition is called as “Insufficient weld” or class 1. Further increasing the laser energy to 4.5 – 5.3 J/mm more of Al is melted in the fusion zone and is termed as “Low weld” or class 2. Laser energy of 5.3 - 6 J/mm results in further increase of Al in the fusion zone and this condition is termed as “Ok weld” or class 3. Increasing the laser energy to above 6 J/mm and higher results in excessive Al in the fusion zone. This condition is termed as “High weld” or class 4. Table 2 summarizes the weld class and the description of the weld status.

Table 2. Description of weld class/ type

Weld Class/ type	Description of weld status
0	No weld
1	Insufficient weld
2	Low weld
3	Ok weld
4	High weld

The amount of Al and Cu mixed must be optimum to have a strong joint. The condition "2" and "3" are acceptable weld beads and the weld status is "Good/Accept". The conditions "0", "1" and "4" are unacceptable as the Al and Cu melted is insufficient or excessive and weld status is termed as "Bad/Reject". These conditions are explained in detail in the section 3.2.

3.2. Scanning electron microscopy (SEM) analysis of the weld bead features

The bead structures of the "Low weld/class 2", "Ok weld/class 3" and "High weld/class 4" is analyzed using a scanning electron microscope. The weld bead is oriented in triangular or pointed in the direction of the laser beam in case of low weld as shown in Fig. *3* (a). The weld bead becomes flatter as the intermixing of Al and Cu is increasing in the case of "Ok weld" (Fig. *3* (b)), which is an optimum melt condition. Further increasing more of Al and Cu to mix, leads to excessive intermixing and there is no visible bead track in the weld zone. A large crack of about 1-2 mm is found in the middle of the weld seam as shown in Fig. *3* (c), which is detrimental for the joint strength and is an unacceptable weld.

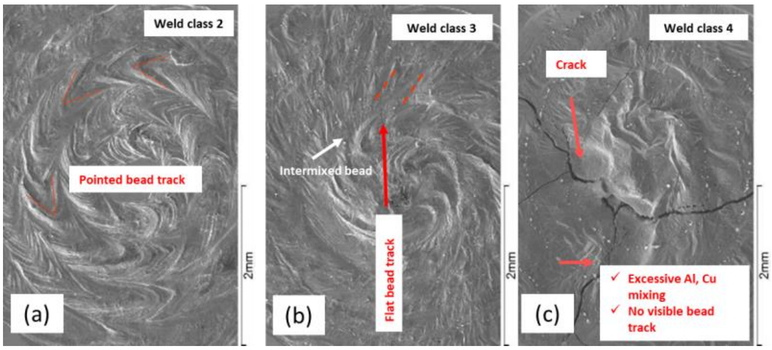

Fig. 3. SEM images of the weld class 2 (a), class 3 (b) and class 4 (c) showing bead features

3.3. Energy Dispersive X-ray Spectroscopy (EDS) analysis of the weld bead

The amount of Al/Cu diffused to the top of weld seam is a result of the laser energy input which relates to the weld bead features on the top as shown in Fig. 4. Ten equally spaced points are taken for EDS analysis in the fusion zone along the diameter of the weld zone as shown in the plot (Fig. 4). From the EDS analysis the amount of Cu present in the top of the weld seam is investigated. The amount of Al increase, and the amount of Cu decrease in the fusion zone, as the laser energy increases. The weight % (wt%) of Cu in these points are measured and plotted in the Fig. *5* For class 1 weld the amount of available copper is in the range of 90-100 wt%. The amount of copper in class 2, 3 decrease to a range of 80-100 %. In the class 4 weld seams, the amount of Cu% degrease significantly to 55-85 wt %. The key for a strong joint is to avoid decreasing the mixing percentage of Cu below 80 wt%. As the 70-80 wt% (red dashed line in Fig. 5) results in formation of detrimental phases like Cu_2Al, Cu_3Al_2, Cu_4Al_3, and CuAl.

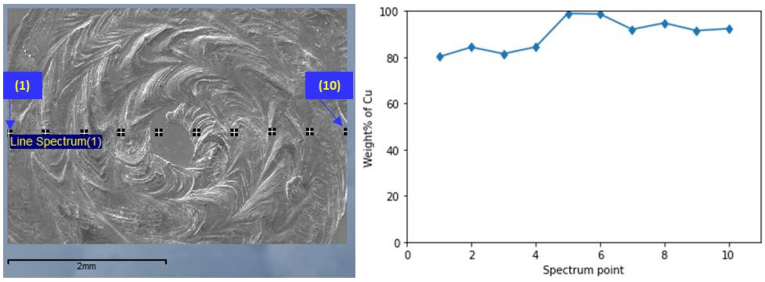

Fig. 4. SEM image of weld class 2 and corresponding Energy Dispersive X-ray Spectroscopy (EDS) spectrum points

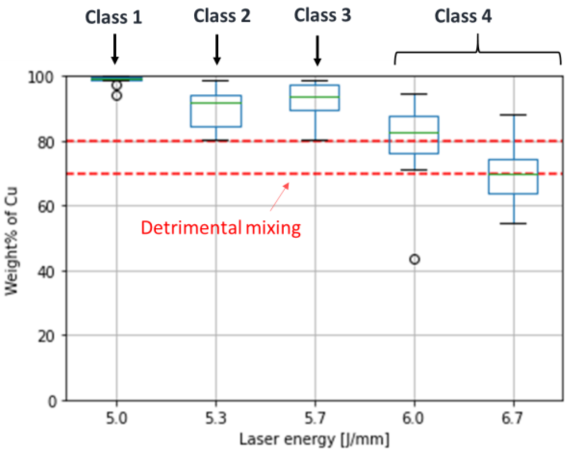

Fig. 5. Box plot of EDS line spectrum for different weld class

The amount of Cu, Al intermixed on the top weld zone and the bead features are proportional. Simple optical method relating to the bead features is enough to identify different weld class as shown in Fig. 6. Identification of the weld status from the high-resolution optical images, automatically is required to qualify an “Acceptable” (class 2, class 3) or “Unacceptable” weld (class 0, class 1, class 4). Convolution neural network (CNN) model is better suited for this purpose as it can identify the weld types based on automatic feature extraction. The CNN architecture used to predict the weld type is explained in the section 3.4. This technique is non-destructive and relatively inexpensive which can be implemented in the existing production line after the welding. Therefore, this is a good quality inspection/analysis technique.

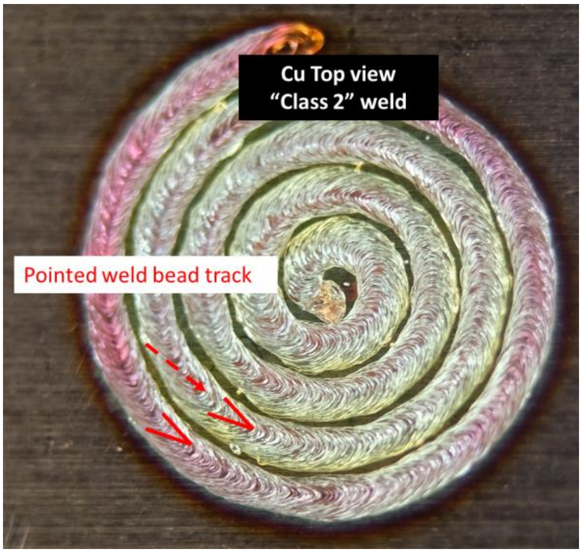

Fig. 6. Optical image of the weld seam (Class 2) showing the weld bead track

3.4. Convolution neural network (CNN) model for prediction of weld types

A convolution neural network (CNN) model is designed to predict the weld status from the high-resolution optical images. The model architecture (Fig. 7) is created with four convolution and pooling layers. The resultant of the final pooling layer is fed into a flatten layer and dense layers (Fully connected). The final output layer predicts the 5 different classes i.e., class 0, class 1, class 2, class 3, and class 4.

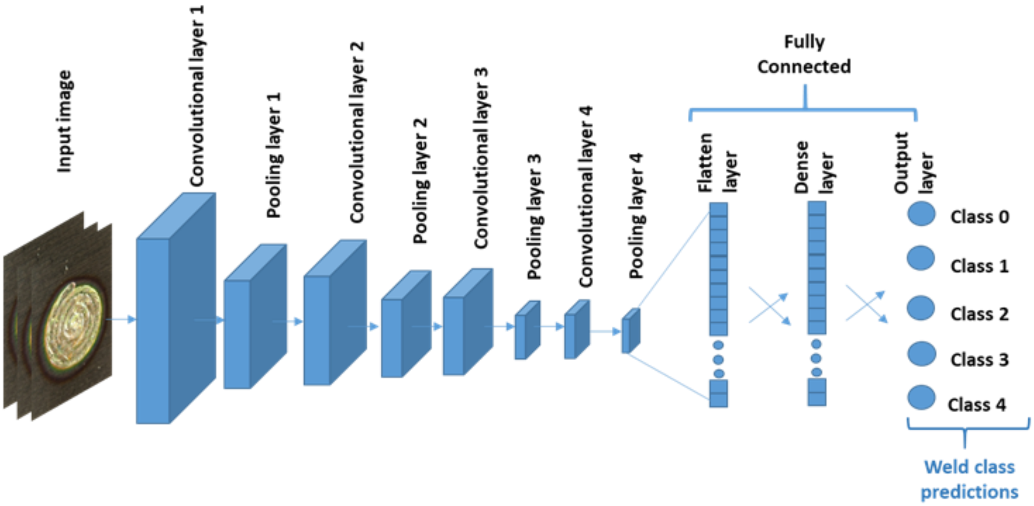

Fig. 7. Architecture of the neural network model for prediction of the weld status form optical image

The network model is compiled with "Adam" optimizer and loss function used is "sparse_categorical_crossentropy". The network is trained for 25 epochs with (total number of samples = 184) 90% data used for training and 10% for validation.

The trained model after 25 epochs predicts the weld class (class 0, class 1, class 2, class 3, and class 4) with 100% accuracy in both training and test validation data set as shown in the Fig. 8. The model does not have over fitting problem as the accuracy of both training and validation dataset converge to 100% accuracy. However, the model must be tested in future works with dataset including the orientation and noisy image for the robustness of the model prediction.

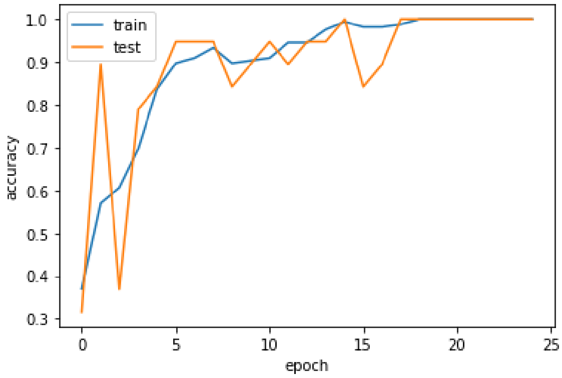

Fig. 8. Plot of model performance: accuracy vs number of epochs

The confusion matrix in Fig. 9 shows that the result of "actual" vs "model prediction" weld class. The diagonal elements show the number of correct predictions and the non-diagonal elements show the wrong prediction.

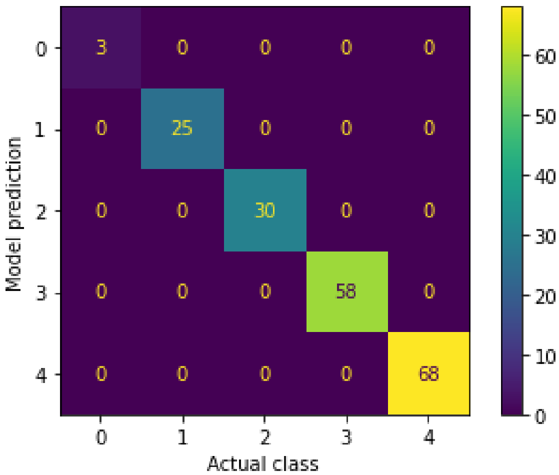

Fig. 9. Confusion matrix of the trained model: actual class vs model prediction

As the presented CNN model prediction can identify the weld status i.e., no weld (class 0), insufficient weld (class 1), low weld (class 2), ok weld (class 3) and high weld (class 4), this technique can be used as for automatic quality check or to qualify the Cu-Al weld.

4. Conclusion

Laser welding of Cu and Al was carried out by spiral trajectory of the laser beam and different weld class or types are identified. With SEM-EDS analysis, the weld bead feature, and the composition of Cu in weight % for different weld class was explained. It is desired to have sufficient melt of Al and Cu as in “class 2” or “class 3”, in the weld seam for strong joint. Identification of these weld classes from high resolution optical images is an important information to decide, whether to accept or not accept the welded sample.

For this purpose, a CNN model was designed and trained to predict the weld types on the optical images, with 100 % accuracy after 25 epochs. With high accuracy based on the CNN model prediction, desired weld seam class can be accepted. As this technique is nondestructive, fast, and inexpensive, it can be implemented as an automatic quality control procedure. In future work, the model must be trained to predict different Cu sheet thickness and the robustness of the model should be improved to predict the weld status from noisy image and different orientation.

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