Abstract

This report proposes a learning algorithm to predict current in ultrasonic weld scans using a convolutional neural network (CNN). Physical current sensors are hard to embed, costly, and inefficient. In this software-based approach, we trained CNN models on weld scans to replace physical sensors with CNN models and compare their accuracy inference time. Spot weld scan is derived from ultrasonic waves captured during the welding process, ultrasonic waves are obtained using an ultrasonic sensor, each scan usually captures 2000 milliseconds of the welding process and therefore, it is 2000 pixel wide.

1 Introduction:

We used ultrasound imaging to capture spot weld scans during welding. A transducer sends out a beam of sound waves into metal sheets and captures its reflections. Weld images are derived a series of horizontally stacked 1D scan (A-scan), each which contains two or three metal sheets and the area between them. Weld nuggets potentially form between metal sheets and can only form during a short time when the welding machine is applying pressure and electric current to the spot-weld area. The area where electric current is applied is the area of interest for quality assurance applications to inspect weld nuggets. This area is only a small portion of A-scans within a 2D B-scan image, where the electric current starts to flow (current-on) and when stops flowing (current-off). The area outside of this zone is discarded during weld inspection. Obtaining accurate information about the position of current-on and current-off is challenging yet crucial to inspect weld nugget and assess the quality of welds.

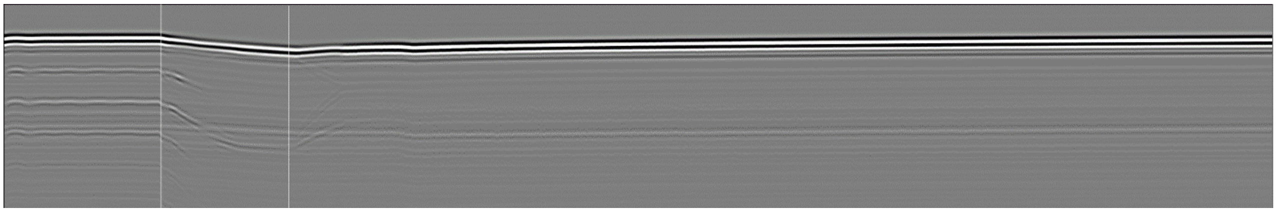


Figure 1 current-on and current-off marked in this A-scan, the area of interest is between the lines where the nugget is formed.

Traditionally, current-on and current-off information are obtained using an electric current sensor, a sensor embedded into a welding machine to send signals. Embedding current sensors in a welding robot has several disadvantages:

- Time-consuming installation
- resource-intensive
- introduce defect rate
- third party modification

We have proposed a software-based approach using a convolutional neural network replacing the physical current sensor with CNN models. We are also detecting expulsion in spot welds; expulsion is an ejection of molten metal from the weld nugget which usually occurs due to applying a high current. Detecting expulsions facilitates current-off detection and allow us to identify such welds.

2 METHODS

2.1 data collection

We acquired 18000 samples taken during real welds with a with a wide variety of geometrical and process configurations from lab and industry, with an additional 400 lab-generated samples taken during welds without application of current (no-current) to increase the variety of training data to make models more resistant to noise and improve the model's performance when there is no current during welding. The exact position of expulsion(s) is labeled (if any) and current-on and current-off positions are obtained from a current sensor during welding. A collection of sequential A-scans is used for input variables while current-on, current-off, and expulsion positions are used to create output variables. During data inspection, nearly 4000 scans with inaccurate current information due to defective current sensors were excluded from our dataset.

2.2 data processing

We generated fixed-length slices of B-scans (collections of sequential A-scans) with the same height as A-scans, 128 pixels, and an arbitrary length, set to 25. The first slice is captured by selecting all rows and the first 25 columns; the next slice is captured by shifting one row to the right and selecting the next 25 columns and continuing this process until we capture the last slice of the B-scan. The number of slices in the B-scan depends on its width, i.e., width - 25 + 1 slices. A three-dimensional array represents each slice's value for each event (i.e., current-on, current-off, and expulsion). Each slice event score is calculated based on the event's distance from the event and center of the slice in the range of 0 and 1.

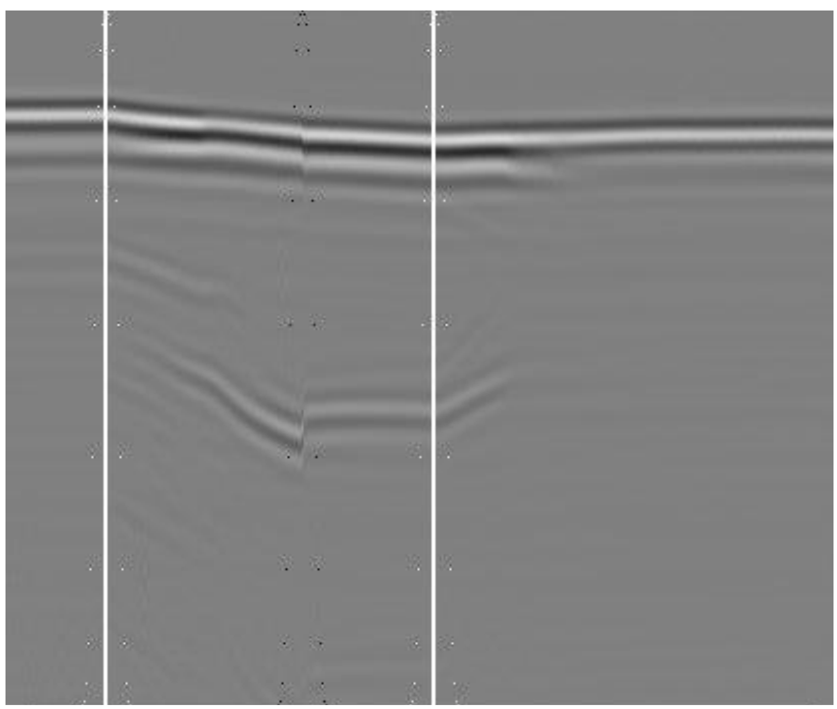


Figure 2 The position of current-on and off is marked with a vertical line

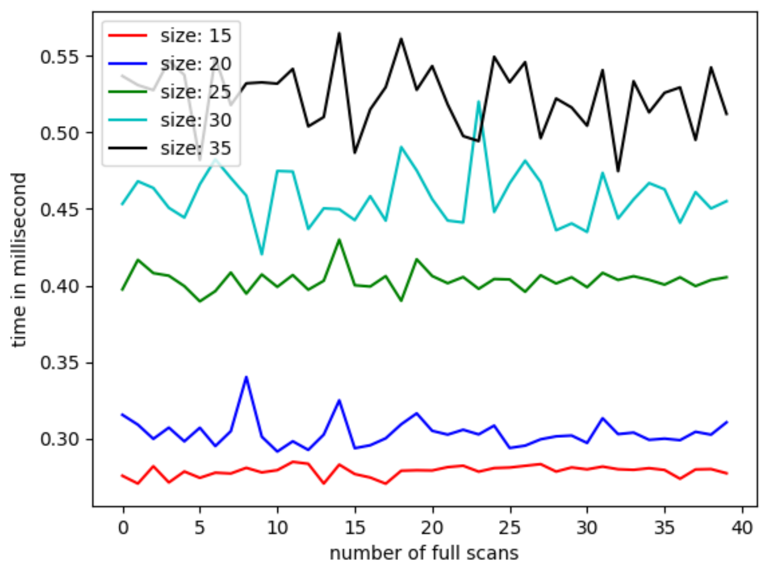
Each with/black dot represents an event score for the slice in which they are at the center, the slice with an event in its center has the highest score for that particular event (i.e., ≈ 1).

We used 90% of data for training and validation, and 10% for model testing, we also used Monte-Carlo cross-validation to train and test three folds for each model.

2.3 Slice width

Slice width is an important factor in time and performance; we aim to minimize inference time and maximize performance by optimizing slice width. Models trained on wider slices have higher inference time as slice-width changes the input array size.

Figure 3



The time for each full scan in figure 3 is calculated by averaging the delta time of each slice in the scan. The number of slices can slightly vary based on slice width, there are approximately 1500 slices in each full scan used for this figure.

2.4 Performance evaluation

Metrics we used to evaluate models are F1, recall, precision scores, accuracy and mean absolute error (MAE) of the model's output time of each event. Accuracy is decided based on the distance of the final event position compared to the actual value; we define event prediction as being accurate if it's within 5 pixels of the actual event.

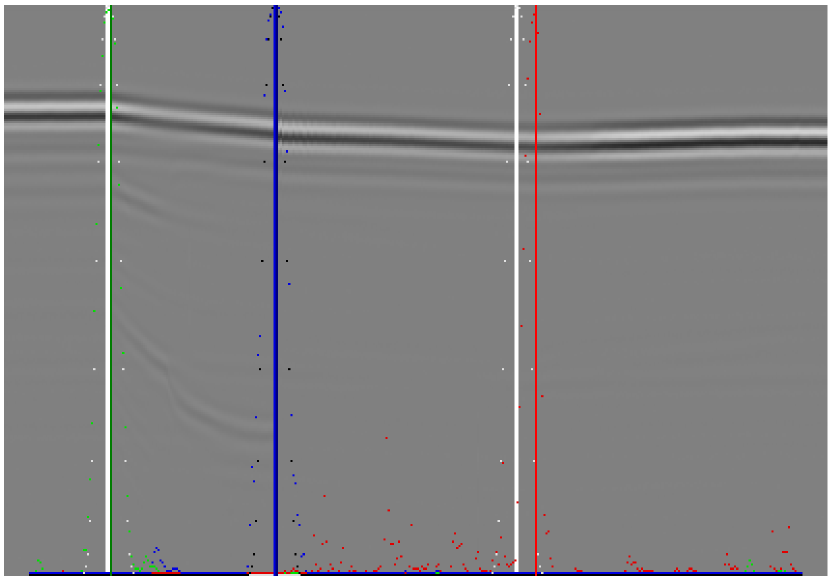


Figure 4 - Prediction calls on an A-scan. The prediction is a false positive for current-off event

We set the final position for each event in the center of the slice with the highest event score in full scans where its score is above a threshold, we used 0.5 as the threshold, scores lower than the threshold won't be considered as predicted position of the event. Predicted and actual positions of events are used to calculate MSE and identify false positives and false negatives. MSE for each event is the distance between the predicted and actual position of the event. Event position predictions where MSE is more than 5 are considered false positives for the event. False negative occurs when there is no event prediction call within 5 pixels of the actual event.

3 Results

Throughout our experiment, we tested different architectures with different networks. We used 25 as slice-width and the following CNN network to obtain the best result.

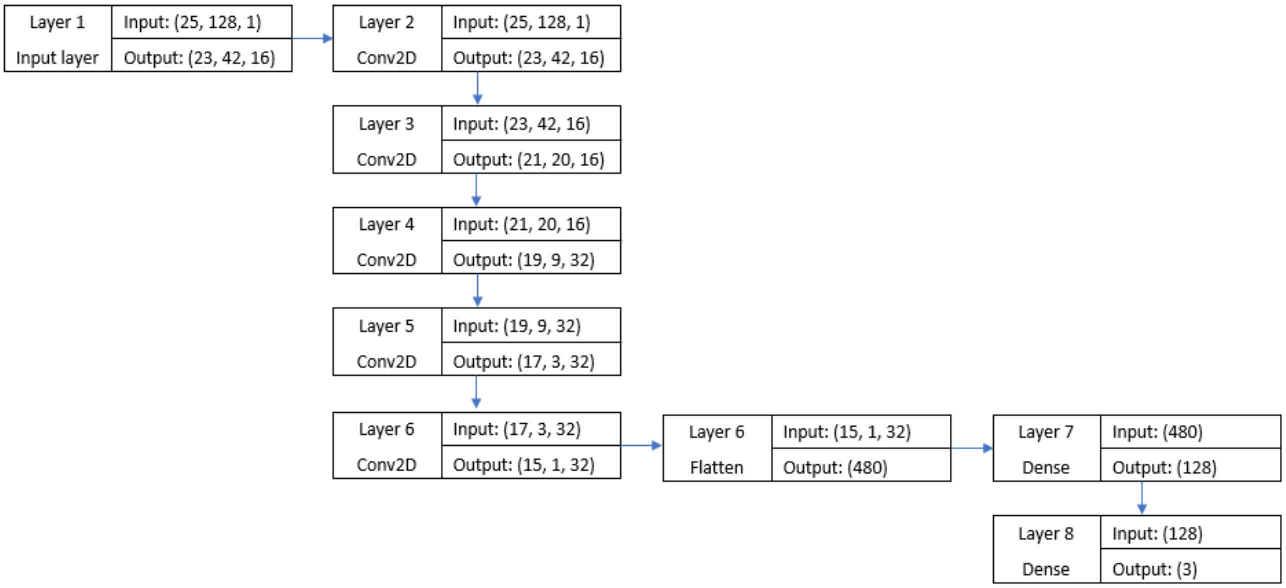


Figure 5

This model performs well on both datasets (i.e., production and industrial weld scans). Slice scores in no current scans are almost always close to zero, where a strong Gaussian distribution of event alignment score is observed in industrial B-scans (where current was applied).

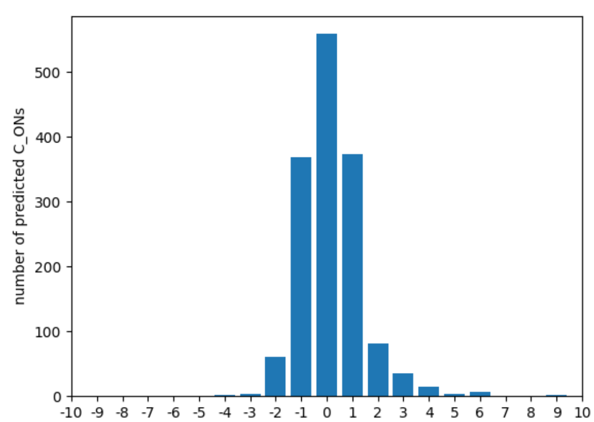


Figure 6 - position of predicted current-on with respect to actual position

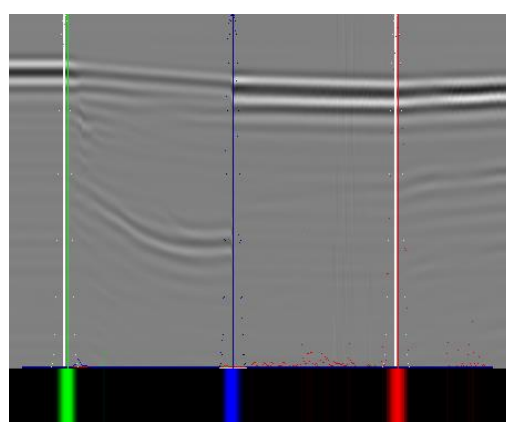


Figure 7

In figure 7, the green, blue and red line represent predicted current-on, current-off and expulsion where the color bar visualizes predicted slice alignment with each event, the more intense color-bar is, the higher alignment score is for slices in that area.

Figure 8

	Current-on	Current-off	Expulsion
Mean absolute error	1.068	1.18	
F1 score	0.994	0.989	0.993
Precision score	0.994	0.991	0.991
Recall score	0.994	0.988	0.995
accuracy	0.991	0.986	0.995

Figure 9 - Average performance metrics of a model with 3 cross-validations

4 Conclusion

We presented a CNN model achieving a current detection task with high accuracy and low inference time compared to a physical current sensor. We used the same error threshold (i.e., 5 milliseconds) and achieved 99+ accuracy. Software-based is cost and time-efficient, easier to integrate with the main system, and low maintenance, therefore, it has significant advantages over the physical current sensor. The next step for this project is to develop and optimize a higher-level algorithm to use events' alignment score to improve decision-making for the final position of current-on and current-off. We can study algorithms taking advantage of ground truths (e.g., current-on always occurs before current-off) and expulsion alignment information to eliminate false detections and improve accuracy and better techniques to minimize detection time.