

Automatic fault detection in Friction Stir Welding

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Abstract

Friction Stir Welding (FSW) is a relatively new welding technique where metals are joined through mechanical stirring. Due to its numerous advantages over older welding methods, it has been implemented in an increasing number of industries. However, there are remaining challenges to be overcome in FSW. One of the most serious is its reliance on accurate weld parameters. Additionally, faults or poor quality welds can develop from problems not easily detectable by an operator or robotic welder. In our work, we pursue automatic means of detecting fault occurrences and other quality problems. Force signals are collected from control welds run in aluminum as well as welds containing gap faults. Signal processing techniques, specifically Support Vector Machines (SVMs), are then used to correctly detect fault occurrences. Results demonstrate the ability for in-process fault detection of FSW.

Introduction

Friction Stir Welding (FSW), a welding technique that joins metals through mechanical stirring, is finding applications in an increasing number of industries. A diagram showing the essential workings of FSW is shown in figure 1. A cylindrical tool is rotated while traversing along the weld line. The material is plasticized—but not melted—and stirred together. The advantage of this type of welding over traditional fusion techniques include excellent mechanical properties, no filler material, a non-consumable tool, and no fumes, porosity or spatter. [2]

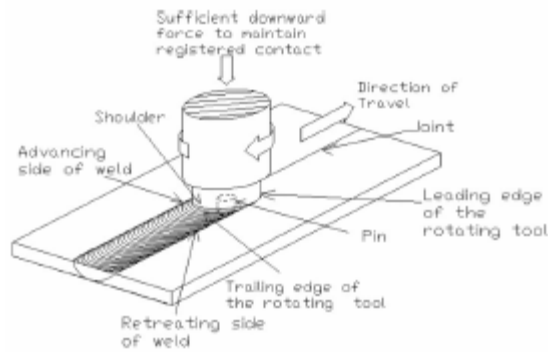


Figure 1 Friction Stir Welding Basic Diagram [2]

Robotic control and automatic fault detection

One of the challenges involved with FSW is fault detection. Faults such as tool misalignment and excessive flash can reduce the quality of the weld. If these faults are observed on a weld, the piece will be defective unless the fault is detected in-process early enough to allow for correction.

A complete robotic FSW system must include a means for detecting faults and a feedback loop for correcting them. In this work, we present one method for fault detection using the frequency spectra of collected force signals. For our experimental test bed we use Friction Stir Lap Welding.

Friction Stir Lap Welding

In Friction Stir Lap Welding, the materials to be welded together are laid one on top of the other and the FSW tool is plunged through the top material into the second. Current uses of this type of FSW include hermetically closed boxes, wheel rims, and car back supports [4]. Our set-up for Friction Stir Lap Welding is shown in figure 2.

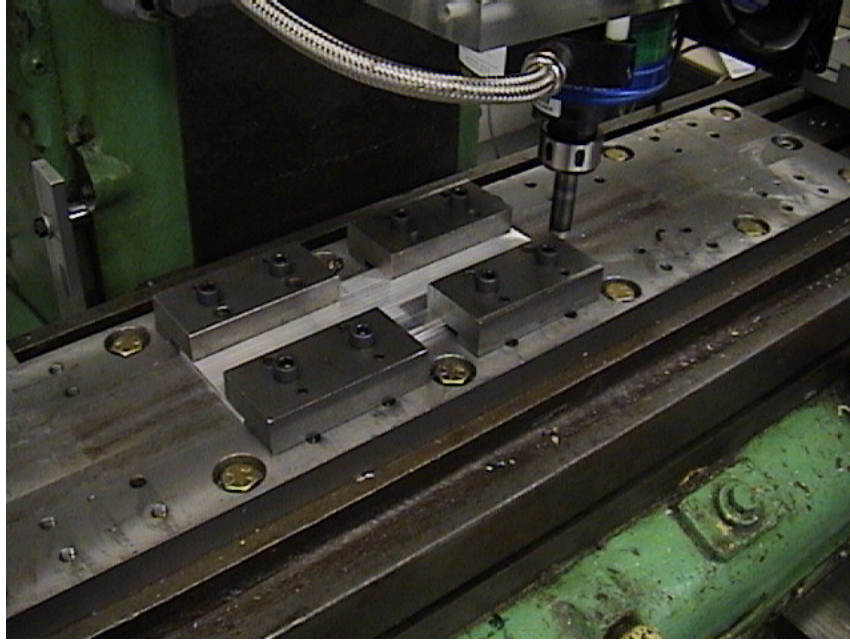


Figure 2 Friction Stir Lap Welding Setup

Gap Detection and Ranking

In order to demonstrate the possibilities for fault detection in FSW using force signals, we used the specific problems of gap occurrence in lap welding. A gap can occur between the two samples welded together and can lessen the integrity of the weld. The paper “Application of friction stir welding to construction of railway vehicles” gives examples of the difficulties of gaps in lap welding [5].

In the experiments performed for this paper, some samples that contain no gaps are run while other samples have 0.0002” to 0.005” gaps milled into portions of the lower sample. Force signals are collected using a Kistler Dynamometer during the weld. The frequency spectra of these signals are then determined using the Fast Fourier Transform. Finally, SVMs are used to determine whether the gap faults can be detected and classified given the frequency spectra of the collected force signals.

Support Vector Machines

A Support Vector Machine (SVM) is a machine learning algorithm which traditionally works by mapping input feature vectors into a feature space and then determining a decision plane in that feature space. One of the key benefits of this technique is its good generalization [3]. Additionally, SVMs can be considered more transparent than a neural network and therefore may provide more physiological insight. This may help correlate the work presented here with related research in modeling of FSW and FSW fault development.

For this work, an implementation of SVMs written for MATLAB was used [1].

Experimental Setup

In the experiments, force signals were collected from samples containing no gaps and those with gap depths measuring 0.0002", 0.0004", 0.0008", 0.0012", 0.0016", 0.002", 0.003", 0.004", and 0.005".

The first experiment (Gap Fault Detection) was performed in order to determine whether or not a SVM classifier could be built from the collected frequency spectra of the axial forces which could differentiate between welds that contained gaps and those that did not. Additionally, the performance of the classifier with respect to the depth of the gaps was calculated.

The second experiment (Gap Fault Ranking) involved determining whether a classifier could be built which could rate the severity of the detected gaps using the same signal data. A variation of SVM called Support Vector Regression was used in this case.

Results

Gap Fault Detection

In the case of gap fault detection, the frequency spectra of the various runs were computed and used as input vectors for a SVM. It was discovered that because the spectra contained a large number of frequencies, good performance was only achieved if the results were "binned" (placing the averages of regions of frequencies into bins to reduce the dimension of the spectra). Classifiers were built using different-sized subsets of the data. Specifically, some classifiers were built and tested using all of the collected data, while others were built and tested using only the control and larger gaps in order to compare the effectiveness of the classifier given very small gaps (0.0002").

For this first experiment, ten-fold cross validation was used to determine the effectiveness of the classifier. The data was randomly divided into ten groups; the classifier was then trained on nine of the groups and tested on the tenth. This was done for each of the ten groups and the average accuracy is computed. Training a SVM involves presenting the input vectors (the binned frequency spectra) and the labels (either gap or no gap) for each run and finding the decision plane in the feature space. This decision plane is then used for classification. Testing then means using the SVM to classify a given input vector (frequency spectra) and comparing it to a known label. The ten-fold cross validation process was performed five times and the overall accuracy was then computed.

Accuracy results for different bin sizes are shown in figure 3. As can be seen from this figure, over and under-binning resulted in the worst performance. The partitioning of the data into 200 bins yielded the best overall results. Figure 4 shows the detection accuracy for a 200-bin partition.

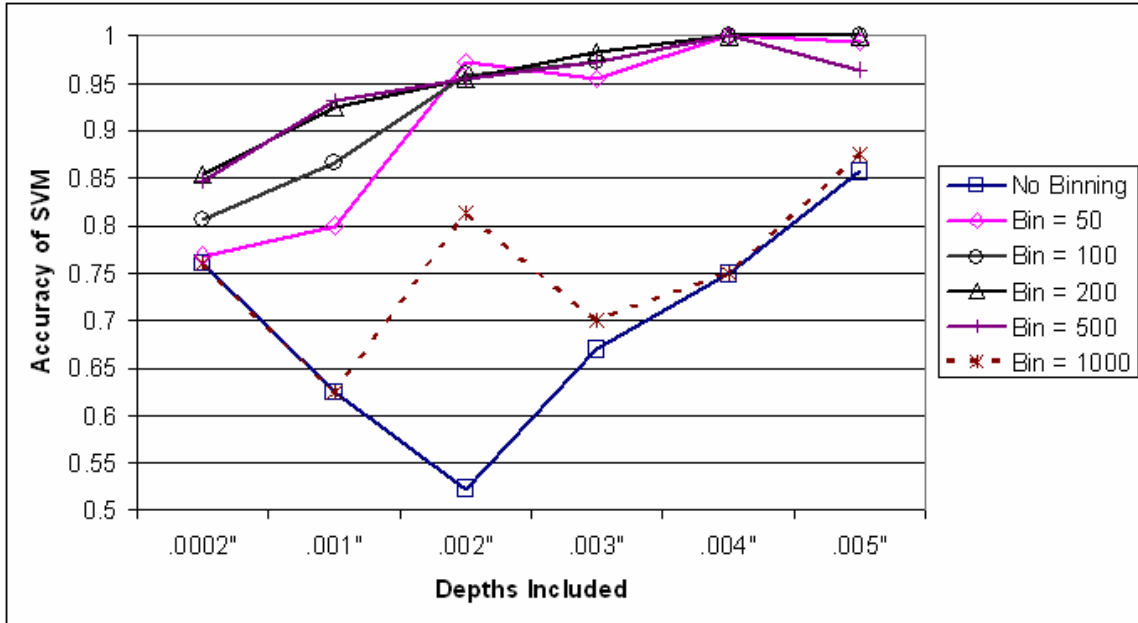


Figure 3 Accuracy Results of SVM given varying bin counts

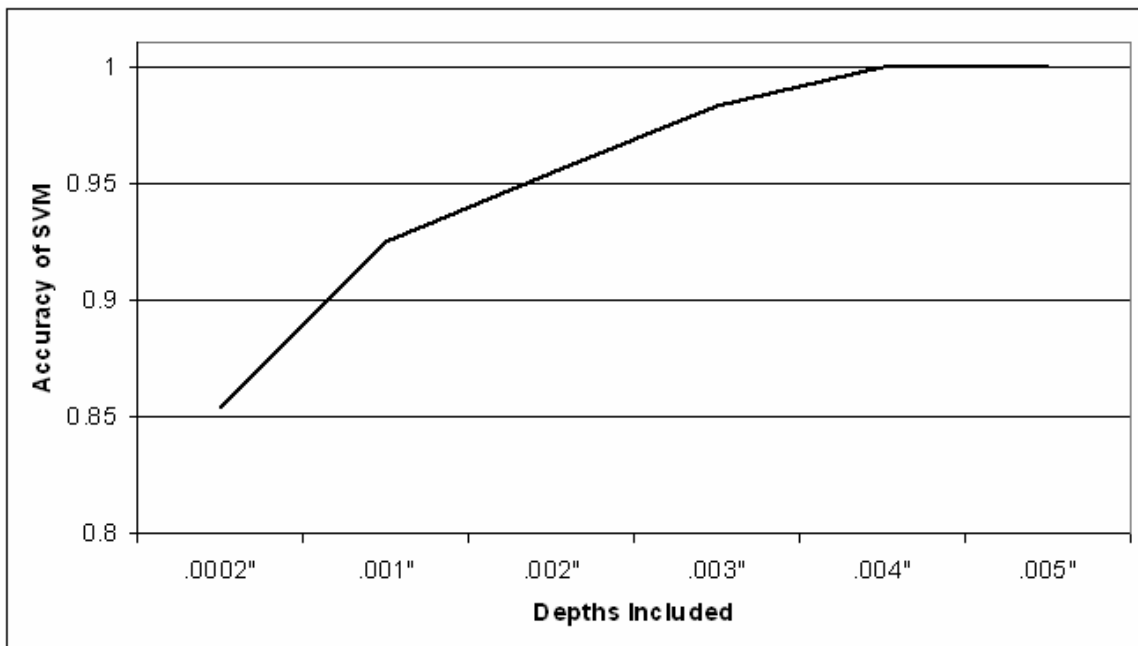


Figure 4 Accuracy of SVM with 200 Bins

These results indicate that high degrees of accuracy in detecting the presence of gaps between the weld samples are obtainable using the method presented above. More specifically, perfect detection accuracy was achieved when gap size was 0.004" and above. Although the training of an SVM might consume some amount of time, its implementation amounts to a simple algebraic computation and can be done quickly.

This would indicate that using SVMs to interpret collected force frequency spectra data can reliably detect even small gap faults. Furthermore, this can be done in real time.

Gap Fault Ranking

In the second experiment, Support Vector Regression is used. This is a technique based on Support Vector Classification where the distance from the decision plane is returned rather than a simple classification. The data from experiment 1, transformed into the frequency domain and binned, was then applied to Support Vector Regression in this experiment. This process returned an arbitrary number which was hypothesized to be related to the depth of the gap. A leave-one-out validation method was used, which means that the SVM was trained on all samples except one and then tested on the remaining sample. This process was repeated for all samples. The results of this experiment are shown in figure 5.

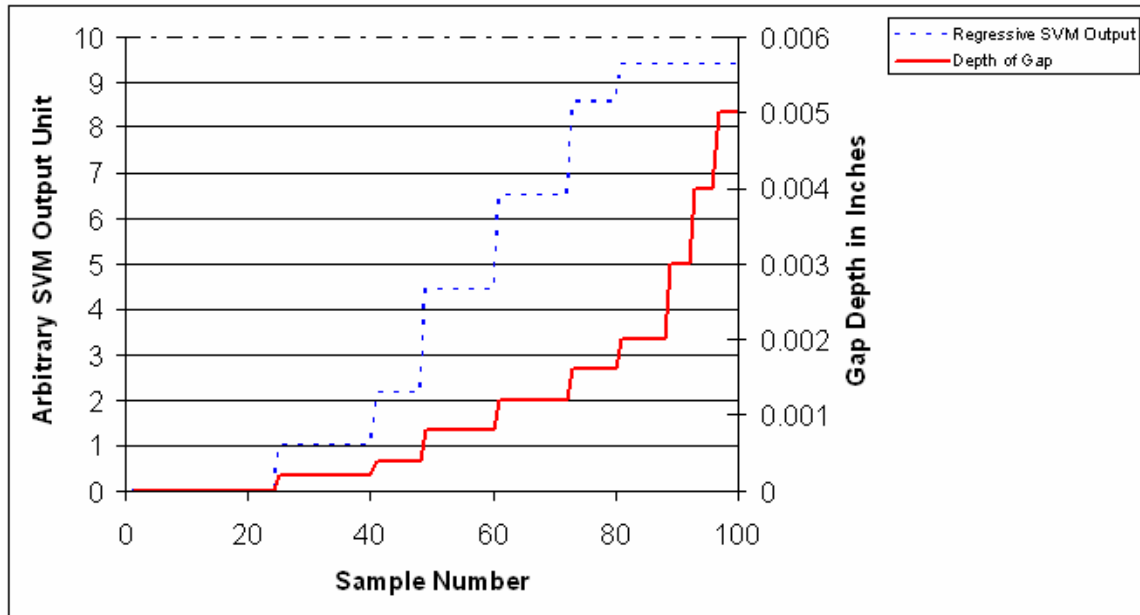


Figure 5 Result of Support Vector Regression

As can be observed in figure 5, a strong correlation exists between the depth of the gap and the output of the SVM. A mapping between the arbitrary output and the actual gap depth could be devised in order to predict the unobservable gap depth. This suggests that this method can be used not only to determine whether a gap exists, but also to characterize the severity of that gap.

Conclusion

A method for the detection of gap faults in friction stir lap welding was presented. This SVM-based method both identifies the presence of gaps and indicates the gap depths. The results presented in this paper show the effectiveness and accuracy of this technique, which can be used in a variety of other FSW fault detection scenarios. Future research will aim to apply this SVM classification technique to such scenarios.

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