Misalignment detection and enabling of seam tracking for friction stir welding

P. A. Fleming*, D. H. Lammlein, D. M. Wilkes, G. E. Cook, A. M. Strauss, D. R. DeLapp and D. A. Hartman

This paper describes a technique for determining the position of a friction stir welding (FSW) tool with respect to the weld seam during welding. Forces are used as a feedback signal, and a general regression neural network is trained to predict offset position given weld forces. Experimental results demonstrate the accuracy of the developed position predictor. This technique is proposed for online misalignment detection or as a position estimator for in-process tracking of the weld seam for FSW and robotic FSW.

Keywords: Friction stir welding, Misalignment, Seam Tracting, Control, Automation

Introduction

Friction stir welding

Friction stir welding (FSW) is a method of welding where material is joined by a rotating tool which traverses along the joint line.[1] It was first patented in 1991 by The Welding Institute and has since found an increasing number of applications.[2] In FSW, a tool, consisting of a pin (or probe) and shoulder, rotates and traverses the joint, applies heat through friction and plastic deformation and stirs the material together.[1] The two sides of the weld are named according to whether the side of the tool is rotating with the welding direction (advancing side) or against (retreating side). This nomenclature is used throughout this paper. A number of joint types have been shown to be amenable to FSW, including single lap welds and multilap welds, two and three piece T joints, edge butts and corner fillet welds.[3]

FSW alignment and seam tracking

This paper develops techniques for misalignment detection in FSW. This technology could be useful as a means of in-process monitoring to ensure the tool is properly aligned throughout the weld. In addition, this could be incorporated as feedback to implement seam tracking for FSW.

In all FSW joint types, the alignment of the FSW tool with respect to the weld seam is important to ensure good weld quality. In butt welds, an improperly aligned tool can result in root flaws.[4] In extreme cases, a severe misalignment will result in no weld at all if the tool is entirely located in only one sample. In general, however, the effect of misalignment and its severity is dependent on weld configuration and other parameters.

T joints are particularly susceptible to misalignment, because the weld line is not observable from above. One case in which the weld is particularly sensitive to offset is the 'open air' clamp, where there is effectively open space alongside the contact plane of the horizontal and vertical members. In this case, if the probe is offset from the centre of the vertical member, material is ejected into this space leaving voids in the weld.

In this work, T joint FSW with 'open air' clamping is used as a test bed to demonstrate misalignment detection. This fixturing setup is selected because of both its sensitivity to offset and its practical implications in the industry. An 'open air' clamp simulates all clamping configurations where clamps are designed without consideration of material containment. However, it is expected that other users may prefer clamps with small fillets, as was done by Erbsloh *et al.*[5] and Fratini *et al.*[6] The approach outlined in this paper is applicable to these clamping schemes as well.

Force as process feedback mechanism

In this work, force values are used to determine offset position. Using force as a feedback signal is typical in the literature of monitoring and control of FSW.[7–11]

Although the relationship between weld force and tool alignment is not straightforward, it is possible to develop estimators which can predict offset position from the force data. This paper outlines an approach of data fusion and feature extraction to enable the monitoring and control of alignment.

Experimental setup

Experiment

To develop an offset estimator for T joints, 30 T joint welds were run with offsets ranging from 4 mm to either side in incremental steps of 0·25 mm.

The setup of the T joints is illustrated in Fig. 1. Both the horizontal and vertical members are 6061 aluminium, with the horizontal member measuring 3·175 mm in thickness and the vertical member being 9·525 mm across. The clamps were steel, with a 3×3 mm notch milled in the top to simulate 'open air'. Although not

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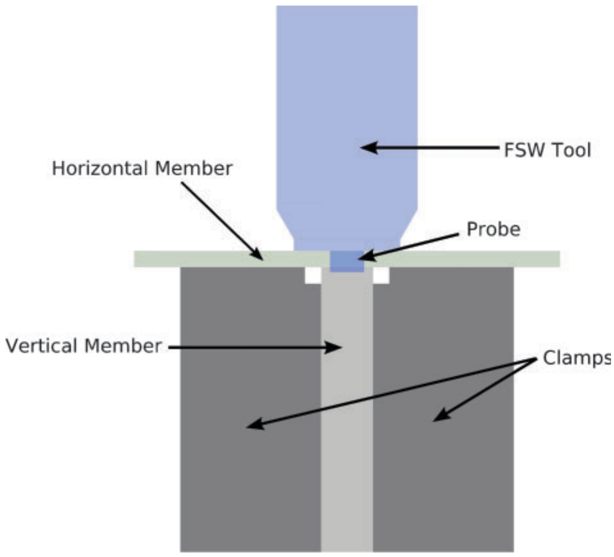


1 Schematic diagram of T joint welding configuration used in this paper

shown, the horizontal member was also clamped down. Finally, the FSW tool consisted of a 5 mm diameter by 3·81 mm long threaded probe and 19 mm diameter shoulder. The rotation speed was fixed at 1000 rev min^{-1}, and the weld speed at 100 mm min^{-1}.

Forces were recorded using a Kistler dynamometer. These forces were then inspected to determine if any exhibited a correlating relationship with the changing offset. It was discovered that indeed some forces did demonstrate this relationship.

In Fig. 2, the recorded axial forces for each run are plotted against the offset of the tool for the weld in which they were recorded. The forces are organised into a box and whisker plot. In a box and whisker plot, the border edges of each box represent the upper and lower quartiles of the data, the middle line constitutes the median, the whiskers typically extend 1·5 times the interquartile range, whereas any outliers are illustrated with a '+'.[12] This plot style is used to indicate the distribution of axial forces throughout each weld, with approximately 1000 force readings used from each weld.

Also shown are cross-sections of some of the welds corresponding to the same offset values. It can be seen that welds run with larger offsets tend to develop voids, and these voids can significantly reduce the strength of the weld. In later results, the authors group the welds into those without voids (little offset) and those with voids (greater offset) to contrast with the sensitivity of the position estimator.

A similar, but less pronounced, relationship is observed for torque. However, the x force (the force that is in line with tool travel) generally increased in magnitude as the tool moved from the advancing side of the weld to the retreating.

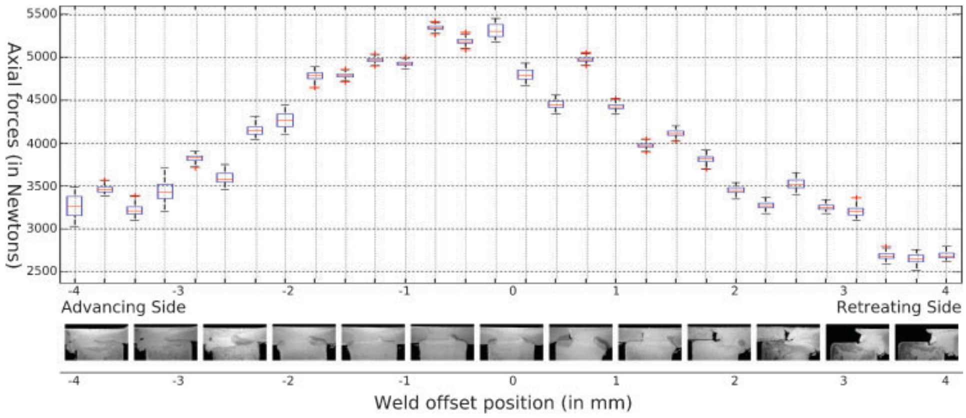
These forces allow for differentiation of the tool offset with respect to the advancing side versus the retreating side. Combining the information from the axial force with that of the planar force allows for the determination of absolute position of offset (versus merely detecting magnitude of offset without direction). Because of this, it is possible to develop a complete representation of tool position which predicts both offset direction and magnitude accurately.

Development of offset position estimator for T joints

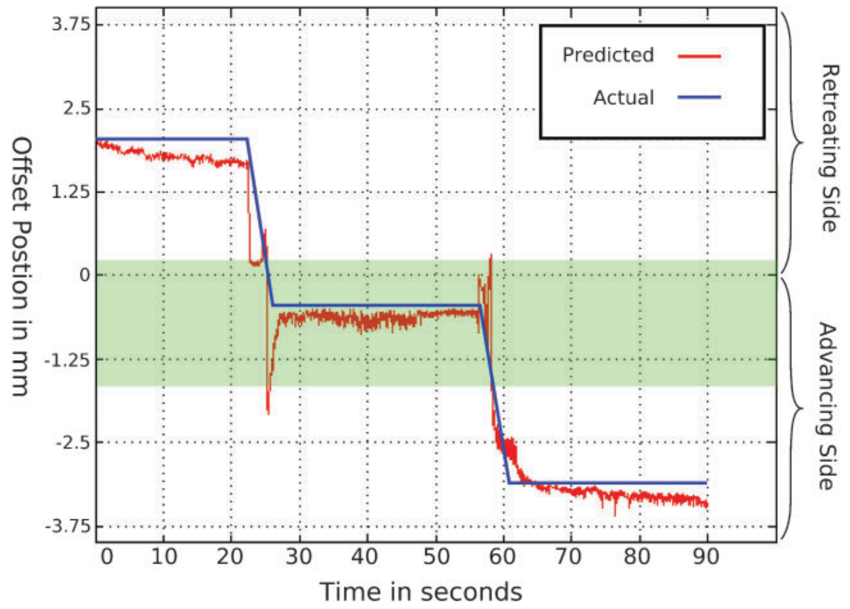
Based on these signals, an estimator was developed to predict offset given these force samples. A general regression neural network (GRNN) was selected to accomplish this. A GRNN is an artificial neural network which estimates continuous variables using non-parametric estimators of probability density functions.[13] A principle advantage of using a GRNN is that it converges to the conditional mean regression surface and can form 'very reasonable' regression surfaces with only a few samples.[13]

In this experiment, 30 welds were performed, each with a different offset. These welds were used to train the GRNN to predict offset given collected forces. The network was repeatedly trained and tested using a 'leave-one-out cross-validation'. Cross-validation estimates how well the network will perform on unseen data.[14] In this method, one run was removed from the data; the network was then trained using the remainder of runs. The trained network was then used to predict the offset of the held-out run for each force sample. The results were recorded and then the process repeated for each weld run. The estimator averaged an absolute error of 0·42 mm, and the standard deviation for all samples relative to true offset was 0·508 mm.

The accuracy of the position estimator would almost certainly improve given more training welds. However, the results will demonstrate that given the current amount of training examples, the resultant estimator does effectively track the lateral position of the weld.



2 Comparing axial forces and offset



3 Predicted and actual offsets over time

Results

Demonstration welds were run where the offset position varied during welding, which illustrate the position predicted by the GRNN estimator with the actual lateral position over time. Also illustrated for comparison is a shaded region which marks the region of offset values which did not contain a void.

In Fig. 3, the probe begins with an offset to the advancing side of the weld; it then shifts into the void free region of offset positions and, finally, shifts into the retreating side. The offset position estimates are close to the true positions. However, the lateral motion causes force disturbances which affect the prediction causing the overshoot around 25 s and the drop around 60 s. The current GRNN was trained on welds without movement perpendicular to normal travel and, therefore, errors during this motion. Anticipating this effect will need to be incorporated into any realtime control algorithm based on this method of offset prediction.

Discussion

The techniques employed in this paper for determining offset position in T joint FSW can be applied to the other joint types. The method functions by discovering the way in which offsets affect weld forces and then using a technique based on regression, pattern recognition or machine learning to develop a function or algorithm which maps from forces to estimated offset position. In the case of T joints, changing offset position affects a number of physical characteristics which in turn affects forces.

Although anecdotal, these physical manifestations exist in the other FSW joint types. In the event that changing offset positions produces only mild changes in forces, there is always the possibility of adding features such as grooves or elevations to the material or backing plate to augment the signals. Finally, in the event that offset produces equivalent changes when offset in either direction, then a weaving method could be used to gain the centre position.

Conclusions and future work

1. The forces present in T joint FSW have been shown to be able to be used as a signal for the monitoring of position of the FSW tool relative to the weld seam. Current research indicates this is true for lap joints as well.

2. An estimator, which predicts the position of the FSW tool by learning a function that maps weld forces to position, can be developed.

3. Current research focuses on the refinement of prediction techniques, application to other joint types and the implementation of a feedback control loop to maintain a desired position relative to the joint line.[15]

4. This technology could be beneficial for the implementation of automated and robotic FSW applications.

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