Research article

In-process gap detection in friction stir welding

Paul Fleming, David Lammlein and D. Wilkes
Welding Automation Laboratory, Vanderbilt University, Nashville, Tennessee, USA

Katherine Fleming
Center for Intelligent Systems, Vanderbilt University, Nashville, Tennessee, USA

Thomas Bloodworth, George Cook, Al Strauss and David DeLapp
Welding Automation Laboratory, Vanderbilt University, Nashville, Tennessee, USA

Thomas Lienert and Matthew Bement
Los Alamos National Laboratory, Los Alamos, California, USA, and

Tracie Prater
Welding Automation Laboratory, Vanderbilt University, Nashville, Tennessee, USA

Abstract
Purpose – This paper aims to investigate methods of implementing in-process fault avoidance in robotic friction stir welding (FSW).
Design/methodology/approach – Investigations into the possibilities for automatically detecting gap-faults in a friction stir lap weld were conducted. Force signals were collected from a number of lap welds containing differing degrees of gap faults. Statistical analysis was carried out to determine whether these signals could be used to develop an automatic fault detector/classifier.
Findings – The results demonstrate that the frequency spectra of collected force signals can be mapped to a lower dimension through discovered discriminant functions where the faulty welds and control welds are linearly separable. This implies that a robust and precise classifier is very plausible, given force signals.
Research limitations/implications – Future research should focus on a complete controller using the information reported in this paper. This should allow for a robotic friction stir welder to detect and avoid faults in real time. This would improve manufacturing safety and yield.
Practical implications – This paper is applicable to the rapidly expanding robotic FSW industry. A great advantage of heavy machine tool versus robotic FSW is that the robot cannot supply the same amount of rigidity. Future work must strive to overcome this lack of mechanical rigidity with intelligent control, as has been examined in this paper.
Originality/value – This paper investigates fault detection in robotic FSW. Fault detection and avoidance are essential for the increased robustness of robotic FSW. The paper's results describe very promising directions for such implementation.

Keywords Friction welding, Robotics, Feedback, Spectra

Paper type Research paper

1. Introduction

1.1 Friction stir welding

Friction stir welding (FSW) is a relatively new welding technique where the samples are joined through mechanical stirring. Figure 1 shows the basic workings of FSW.

The tool pin in the figure is rotating while traversing the material to be welded. The shoulder of the tool generates heat which allows the material to be plasticized but not melted. FSW has a number of advantages over fusion methods including (Cook *et al.*, 2004):

- excellent mechanical properties;
- no filler material, non-consumable tool;
- no fumes, porosity or spatter; and
- ability to weld alloys difficult for fusion methods.

Because of its advantages, FSW is currently employed in a number of industries including: aerospace, maritime, railroad and automobile. However, improved control and fault detection/avoidance are an important component for the continued expansion of FSW.

1.2 Automation of FSW

In this research, we examine a paradigm for monitoring the FSW process. We are interested in this in order to improve the robustness and reliability of automated FSW.

One of the challenges in fault avoidance in FSW is fault detection. Some of the faults associated with FSW are difficult to observe non-destructively. A "worm-hole" fault, which is a void in the weld line, may exist completely below the weld

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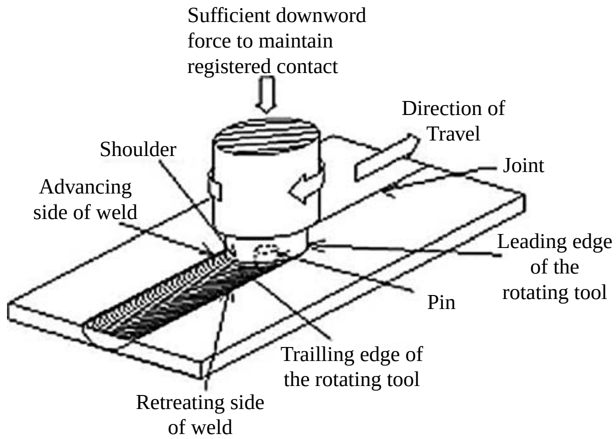
www.emeraldinsight.com/0260-2288.htm

Sensor Review
28/1 (2008) 62–67
© Emerald Group Publishing Limited [ISSN 0260-2288]
[DOI 10.1108/02602280810850044]

Figure 1 Outline of friction stir welding



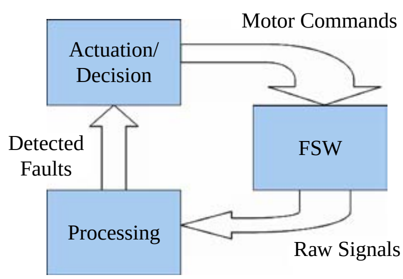
Source: Cook *et al.* (2004)

surface and therefore be unobservable to a human inspector. These faults can severely weaken the integrity of the weld. For this reason, the development of an in-process monitoring system is essential for both quality control and process yield.

In-process detection of faults in FSW is not trivial. A number of techniques for detecting weld quality and faults have been published, and many involve high-quality sensors and advanced machine learning techniques (Boldsaikhan *et al.*, 2006, Chen *et al.*, 2003). "First-order" sensing, the observation of the weld visually or direct observation of process signals, often does not provide evidence of fault occurrence. However, if the signals are first processed using modern signal processing and machine learning techniques, fault detection can be achieved. This means that feedback control for FSW is a two-step process. The raw signal data obtained from either dynamometers, acoustic emission sensors or accelerometers must first be applied to a computational unit which can quickly detect faults, or rank fault likelihood, and this information can in turn be accounted for by a process controller. In FSW, the controller can attempt to affect change by adjusting the tool rotation speed, sample traversal speed or plunge depth if it is possible to correct the for the detected fault, or else alert the operator of fault occurrence. This scheme is represented in the control loop shown in Figure 2.

In order for a successful feedback loop, fault detection schemes must be developed for all faults, and for all weld processes. In this paper, an investigation into the possibility of using force readings as a signal for the detection of gaps is presented. Gaps, caused by poor fit-up between samples to be welded, are spaces in the weld joint prior to welding. The

Figure 2 Control loop in FSW



presence of poor fit-up, like poor weld parameter selection, is not a fault in and of itself, but rather a fault causing condition. In Leonard and Lockyer (2003), gaps are listed as a potential cause of void (worm-hole) formation.

2. Experiment setup

2.1 Friction stir lap welding

As an experimental test bed, friction stir lap welding (FSLW), which is the joining of two metal sheets placed one on the other by FSW is used. Current applications of FSLW include hermetically closed boxes, wheel rims and car back supports (Ericsson *et al.*, 2007). A problem-causing condition could be the existence of a gap between the weld samples. Kawasaki *et al.* (2004) discuss the difficulties of FSW overlap welds with gaps. In this work, this sample problem is used to investigate the previously discussed control system. Specifically, the application of signal processing and machine learning techniques provides the ability to detect these faults.

2.2 Material and equipment

The samples used were 1/8 in thick 6061 Aluminum. Two samples were mounted and clamped directly one on the other as shown in Figure 3. All welds were run with a spindle speed of 2,000 rpm, and a traversal speed of 16 ipm. These values were shown to be effective FSLW parameters in the paper "Lap Joints produced by FSW on flat aluminum EN AW-6082 profiles" and worked well for this research (Mishina and Norlin, 2003). The tool used was a 01 steel tool, with a 5/8 in. shoulder and threaded cylindrical 0.16 in. long pin.

Gaps were created in the samples using a milling machine. The gap depths used are: no gap, 0.0004 in. 0.0008in. 0.0012 in., 0.0016 in., 0.0020 in., 0.0030 in., 0.0040 in. and 0.0050 in. The gaps were applied to one plate and a normal plate was placed and clamped on top for experimental welds. The plates are shown in Figure 4.

Force signals were collected with a Kistler Dynamometer at 1,000 Hz.

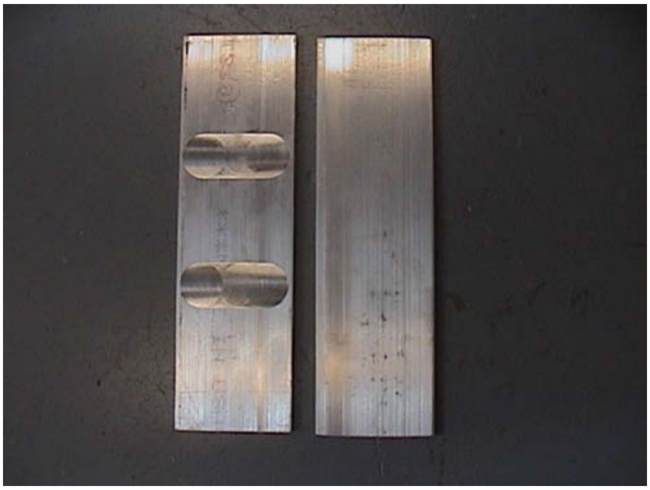
3. Results

3.1 Initial results

After welds were completed, a visual inspection of the weld surface was carried out to determine if there were clear visual

Figure 3 Samples clamped in position

Figure 4 Inserted gap of 0.0008 in



cues of the inserted gaps. In Figure 5, the surface of the weld with 0.0050 in. gaps inserted is shown to look normal, with no obvious trenches, flash or other surface features. The close up in Figure 5(b) is looking at the surface over the gap at close range to illustrate the lack of any clear signs of defects on the surface.

3.2 Collected force signals

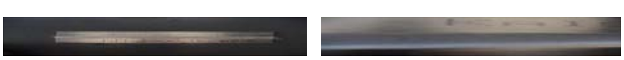
A graph showing typical axial forces for the different gap depths is shown in Figure 6(a).

One can see that for gaps of depth 0.002 in. or greater a large noticeable drop in axial force can be expected, while the drop is negligible for 0.001 in. and below. This can be further emphasized by examining the gap section in greater detail in Figure 6(b). From this we observe that the gap produces a 1,000 N reduction in force when the gap is larger than 0.002 in. There are smaller but still noticeable reductions up until 0.0012 in. These sudden drops in force are a good cue for an automated welding system that it is welding over a gap in the material, with the amount of force proportional to the severity of the gap. However, it is also possible that this information, left unprocessed, may be insufficient for accurate detection of gaps. Forces can vary from other causes. Also, when the gaps are smaller, the change in force appears insufficient for discrimination.

3.3 Feature extraction

In order for an automatic robotic welding system to detect faults given these force signals, the processing block in the control loop must extract meaningful information from the data. Simply providing the force signals may not give a robotic controller an indication of how to proceed. Feature extraction, which means representing the larger data set by a smaller representation which more effectively and purposefully describes the data helps a classifier develop a

Figure 5 Surface of weld with 0.0050 in. gap



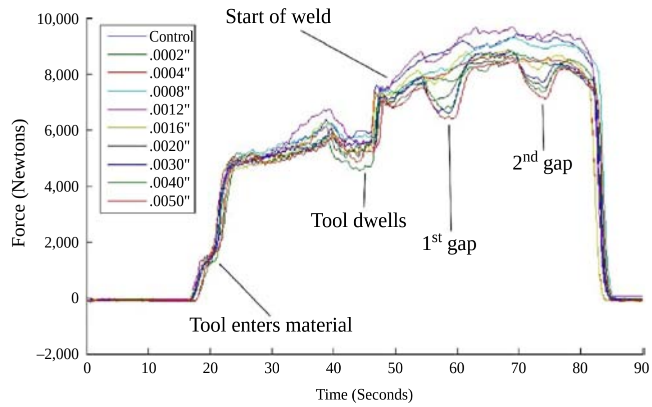
Weld surface

(a)

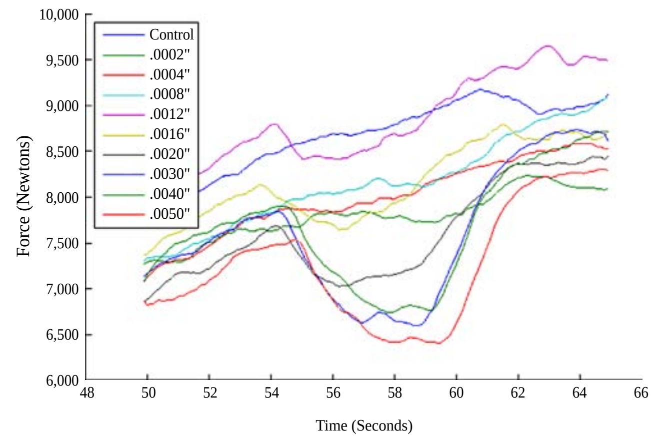
Zoomed in

(b)

Figure 6 (a) Axial forces; (b) Axial forces (zoomed)



(a)



(b)

decision-making process (Fukunaga, 1972). In the case of this experiment, by converting the data into the frequency domain and then applying techniques such as principal component analysis (PCA) and linear discriminant analysis, low-dimensional subspaces are found in which the data were nearly linearly separable, making categorization straightforward.

3.4 Frequency analysis

The frequency domain provides a rich source of information for analysis. It is quite possible that gaps will create "chatter" or amplify existing frequencies with increased oscillation. The Fourier transform can be used to determine the spectral density of the force signals. This allows for comparison of the frequency components of the collected force signals. Since, the forces are sampled, a good method for the computation of the Fourier transform is the Fast Fourier Transform, a computational method, which is implemented in Matlab (Lathi, 1998). One issue with the Fourier Transform is that either the frequency spectra for the entire signal must be computed, or else the signal must be windowed. Windowing involves selecting portions of the time signal in order to get a perspective of what the frequency spectra is at a given moment in time. For this experiment, the force signals are each windowed over the gap regions, to examine differences in spectra over gaps, rather than over the whole weld. The only exceptions are the control welds, which have no gaps, so more of the weld is used. However, the window size is constant in all cases, approximately 2 s long.

3.5 Principal component analysis

As stated earlier, it is important to find a compact, or low-dimensional representation of the data. In this experiment, the collected data were represented by frequency spectra of welds run with and without varying gaps inserted. If we consider spectra with 100 frequency bins which implies that each sample is described by a point in a 100-dimensional space. PCA attempts to project these points on to a lower dimensional space, chosen according to which dimensions maintain the highest variance (Figure 7). This is accomplished by diagonalizing the covariance matrix of the data. This operation reduces the redundancy found in data, resulting in a new, and more meaningful low-dimensional data-set (Shlens, 2005). Although it is not necessarily the best representation from a statistical perspective, PCA is used to project all the samples on to a 2D space. The results of this are informative.

Shown in Figure 8(a)-(c), are the resulting 2D representations of the weld samples after PCA with the projections of the control welds represented by red x's and the gap welds by black circles The figures are split to show the results when the principal components are computed with a varying amount of gap sizes included. Notice that after 0.004 in. gaps the representations become linearly separable. This is actually a very good result considering the fact that PCA is an unsupervised technique, meaning that no information about the classes of the data were provided to the algorithm to encourage this separation. It occurred naturally due to the fundamental differences of the data being analyzed by PCA.

3.6 Linear discriminant analysis

Linear discriminant analysis, or Fisher's linear discriminant, is also a dimensionality reduction technique. However, unlike PCA, it is given a priori knowledge of the classes of the samples and then finds a lower-dimensional projection that maximizes the class separability. This is accomplished by solving equations which maximize between-class scatter and minimize within class scatter (Welling, 2007). The results of applying this are shown in Figure 8.

From Figure 8, it can be seen that even if the gap is 0.0002 in., LDA provides a 2D representation of the data where control welds and gap welds are linearly separable.

4. Conclusions and future work

This research demonstrates two methods which could be used in designing an automatic fault detection/avoidance system for FSW. Statistical methods can be used as a pre-step to derive representations of force data which provide good insight into the state of the current weld. Deriving these representations may take some time off-line, but the projections can be then done quickly online. This can in turn be used to devise a complete real time fault avoidance control which would allow reliable and robust robotic FSW.

Figure 7 (a) PCA with only gaps greater than 0.001 in.; (b) PCA with only gaps greater than 0.002 in.; (c) PCA with only gaps greater that 0.004 in

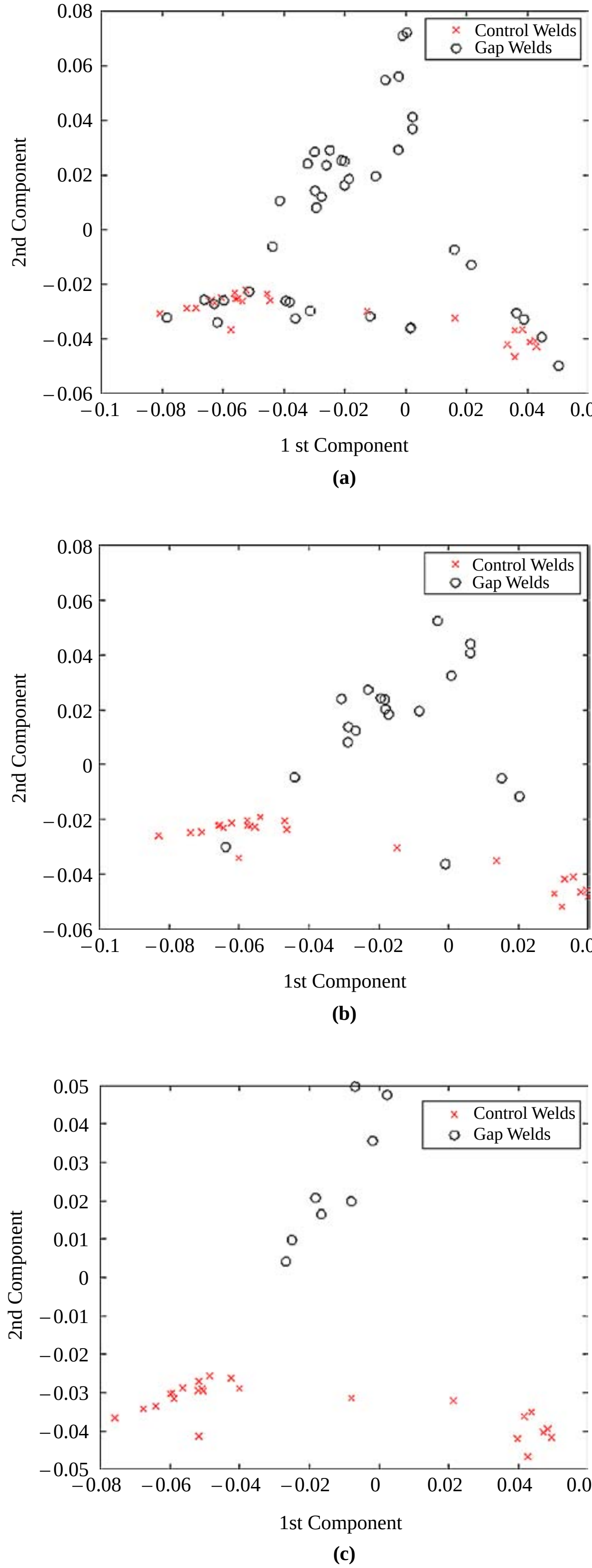
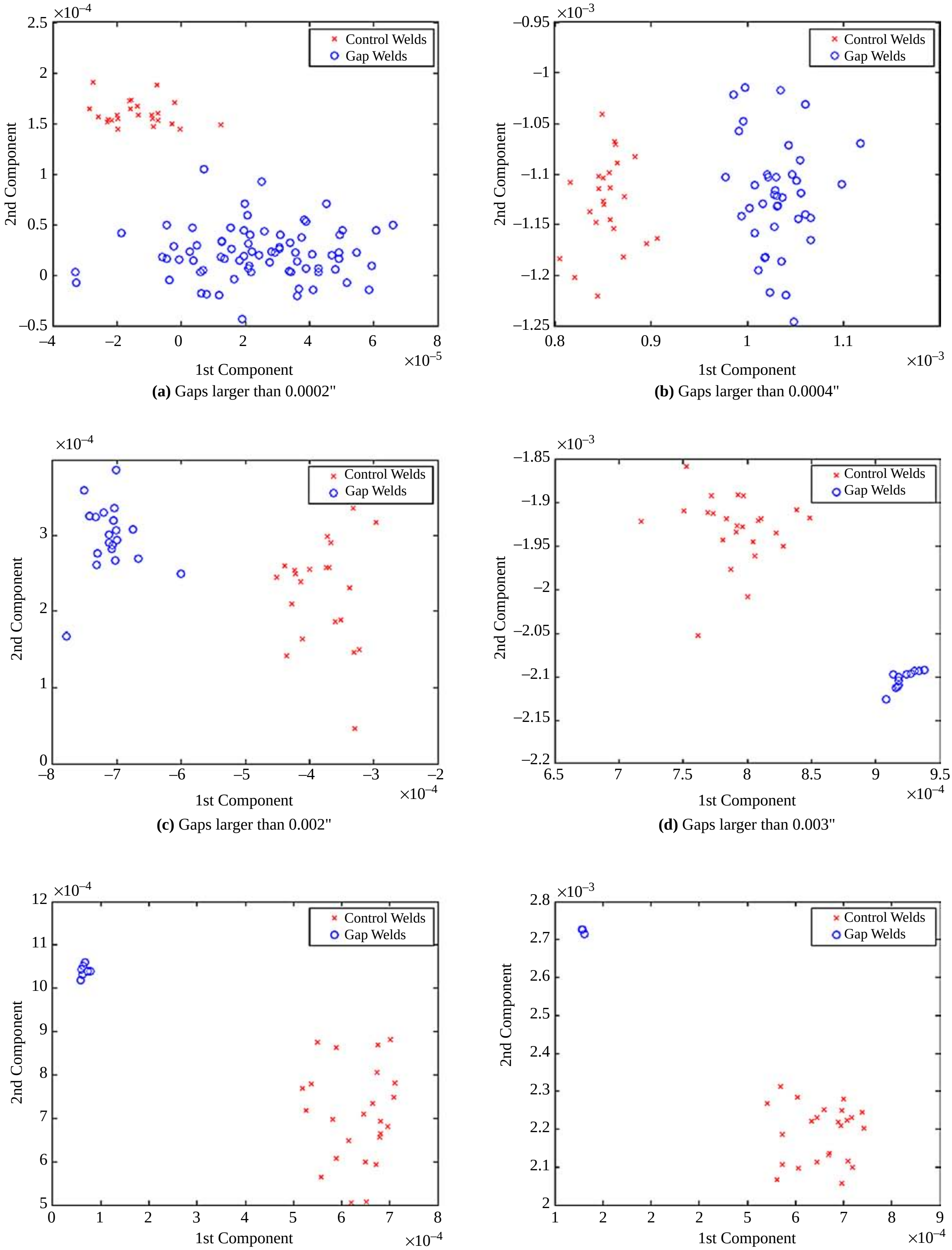


Figure 8 Linear discriminant analysis



(a) Gaps larger than 0.0002"
(b) Gaps larger than 0.0004"
(c) Gaps larger than 0.002"
(d) Gaps larger than 0.003"
(e) Gaps larger than 0.004"
(f) Gaps larger than 0.005"

Sensor Review
Volume 28 · Number 1 · 2008 · 62–67

References

Boldsaikhan, E., Corwin, E., Logar, A. and Arbegast, W. (2006), "Neural network evaluation of weld quality using FSW feedback data", paper presented at 6th International Symposium on Friction Stir Welding.

Chen, C., Kovacevic, R. and Jandgric, D. (2003), "Wavelet transform analysis of acoustic emission in monitoring friction stir welding of 6061 aluminum", *International Journal of Machine Tools & Manufacture*, Vol. 43, pp. 1383-90.

Cook, G.E., Crawford, R., Clark, D.E. and Strauss, A.M. (2004), "Robotic friction stir welding", *Industrial Robot*, Vol. 31 No. 1, pp. 55-63.

Ericsson, M., Jin, L-Z. and Sandstrom, R. (2007), "Fatigue properties of friction stir overlap welds", *International Journal of Fatigue*, Vol. 29, pp. 57-68.

Fukunaga, K. (1972), *Introduction to Statistical Pattern Recognition*, Academic, New York, NY.

Kawasaki, T., Makino, T., Masai, K., Ohba, H., Ina, Y. and Ezumi, M. (2004), "Application of friction stir welding to construction of railway vehicles", *JSME International Journal*, Vol. 47, pp. 502-11.

Lathi, B.P. (1998), *Signal Processing & Linear Systems*, Cambridge Press, Berkeley.

Leonard, A.J. and Lockyer, S.A. (2003), "Flaws in friction stir welds", paper presented at 4th International Symposium on Friction Stir Welding.

Mishina, O.K. and Norlin, A. (2003), "Lap joints produced by FSW on flat aluminum EN AW-6082 profiles", paper presented at 4th International Symposium on Friction Stir Welding.

Shlens, J. (2005), "A tutorial on principal component analysis", Technical Report, Systems Neurobiology Laboratory, University of California, San Diego, CA.

Welling, M. (2007), *Fisher Linear Discriminant Analysis*, Department of Computer Science, University of Toronto, Toronto, available at: www.cs.huji.ac.il/ ~ csip/Fisher-LDA.pdf

Corresponding author

Paul Fleming can be contacted at: paul.a.fleming@vanderbilt.edu