Sensor fusion model for defect identification in friction stir welding process

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Abstract. Defect identification in friction stir welding process is a challenging task as most of the defects formed at subsurface level. The available non destructive approaches are limited only to offline assessment of the defects. In automated environment defect identification methodologies with online monitoring possibilities are gaining significant attention. In this research work sensor fusion based model has been developed for identification of tunnel defect in friction stir welding samples. Real time signal information acquired from tool main spindle motor current signal, rotational speed and vertical force signal have been fused to estimate a quantitative indicator for defect detection within the welded samples. Real time signals are acquired using a force measurement system and a speed sensor with a sampling frequency of 10 kHz. Feature level fusion modeling is incorporated to develop a methodology for defect detection in friction stir welding process. The estimate can be used for identifying defective samples from defect free samples which is advantageous in automated production environment.

1. Introduction

Automation in manufacturing is one of the greatest advancements for better productivity with high reliability over product specifications. The automated welding processes have revolutionized the manufacturing domain with its noteworthy contribution. Friction stir welding (FSW) being an emerging technique for joining both metallic [1–2] and non metallic materials [3–4] is lacking in adopting automation in terms of product quality assessment. One of the causes for the same is realized as lack in effort for monitoring the process and its outcome in a convenient way for integration with automated systems. High complexity in physics of the process leads to compensated and compromised numerical and mathematical models for reliable process modelling that meets the actual environment. Thus, the research in the line of developing methodologies for incorporating possibilities of integration of automated system might be useful.

Attempts has been made in the past years by various research groups for developing monitoring methodologies with real time signal information in FSW process. Das et al. [5] has developed methodologies based on signal information and machine learning techniques for modeling ultimate tensile strength of the joints as well as identification of defects in friction stir welded samples. The methodologies developed utilize signal features extracted only from one sensor and sensor fusion was not tested. Boldsaikhan et al. [6] developed force signal based monitoring scheme for correlating defect formation phenomenon in FSW process. In this work also sensor fusion was not considered. Kumar et al. [7] implemented various signal processing tools for extracting signal information and
predicted quality of the friction stir welded joints without sensor fusion framework. Similar research
works can also be found in the literature where various methodologies for monitoring of FSW process
were attempted without sensor fusion [8-10].

2. Experimental work

Welding experiments are carried out in a vertical milling machine modified to perform FSW
operations. The milling machine has twelve steps in tool rotational speed (50, 65, 90,125, 175, 240,
325, 440, 600, 815, 1100, 1500 rev/min) and eight steps in welding speed (22, 36, 63, 98, 132, 200,
360, 550 mm/min). The main spindle motor has a power rating of 5.5 kW with maximum current
rating of 19 A and feed motor has a power rating of 0.75 kW with maximum current rating of 5 A. The
weld configurations obtained are butt joints in aluminum alloy (Table 1) plates with dimension
110×60×6 mm. Tool rotational speed, welding speed and shoulder diameter are considered as the
process parameters and the welding experiments are performed as per the experimental conditions
reflected in Table 2. The fixed parameters considered in this investigation are shown in Table 3. After
the completion of the experiments, mechanical testing of the joints is performed for estimation of
ultimate tensile strength (UTS) of the joints. The strength values against each experiment are reflected
in Table 2. During the experiments, three different sensors are integrated with the process for signal
acquisition. The vertical force signals are acquired using a force measurement system developed by
Das et al. [11]. Main spindle motor responsible for tool rotational speed is connected with Hall Effect
current sensor for acquisition of current signal and a non contact type tachometer is used for acquiring
rotational speed signal against each experiment. All the signals are acquired at a sampling frequency
of 10 kHz with a data acquisition system (make National Instrument, model: 6259) connected with the
FSW system and sensors. Schematic of the experimental setup with sensor integration is shown in Fig.
1. In this investigation three different signals are acquired namely current signal, tool rotational speed
signal and vertical force signal. A contact type hall effect current transducer is connected to the main
phase of the motor responsible for tool rotational speed (refer Fig. 1). The acquisition of tool rotational
speed signal is done through a non contact type laser tachometer and the data is recorded using a data
acquisition system. The force signal is acquired with a force and torque measurement device
developed by Das et al. [11].

![Fig. 1. Schematic representation of the experimental setup with sensors](image)

| Mechanical Properties | Chemical Composition |
|-----------------------|----------------------|
| Ultimate tensile strength: 119.8 MPa | Al: 99.3 |
| Yield strength: 106 MPa | Si: 0.2 |
| Percentage elongation: 17.1 | Zn: 0.2 |
|                       | Fe: 0.2 |
|                       | Cu: 0.1 |
Table 2  Experimental results with UTS, YS and percentage elongation

| Exp. No. | Tool rotational speed (rev/min) | Welding speed (mm/min) | Shoulder diameter (mm) | Ultimate tensile strength (MPa) | Yield strength (MPa) | Percentage elongation (%) |
|----------|-------------------------------|------------------------|------------------------|-------------------------------|--------------------|-------------------------|
| 1        | 600                           | 36                     | 16                     | 94.05                         | 54.32              | 18.46                   |
| 2        | 600                           | 36                     | 20                     | 85.87                         | 46.45              | 21.68                   |
| 3        | 600                           | 36                     | 24                     | 78.56                         | 43.47              | 11.28                   |
| 4        | 600                           | 36                     | 28                     | 65.69                         | 43.10              | 10.54                   |
| 5        | 815                           | 36                     | 16                     | 92.00                         | 50.93              | 15.8                    |
| 6        | 815                           | 36                     | 20                     | 77.34                         | 48.11              | 12.66                   |
| 7        | 815                           | 36                     | 24                     | 85.48                         | 48.18              | 12.67                   |
| 8        | 815                           | 36                     | 28                     | 80.33                         | 46.36              | 27.78                   |
| 9        | 1100                          | 36                     | 16                     | 74.54                         | 55.11              | 5.72                    |
| 10       | 1100                          | 36                     | 20                     | 83.45                         | 44.86              | 22.28                   |
| 11       | 1100                          | 36                     | 24                     | 76.30                         | 49.87              | 12.06                   |
| **12**   | **1100**                      | **36**                 | **28**                 | **51.15**                     | **36.79**          | **7.06**                |
| 13       | 1500                          | 36                     | 16                     | 88.42                         | 47.95              | 16.86                   |
| 14       | 1500                          | 36                     | 20                     | 64.95                         | 49.77              | 4.66                    |
| 15       | 1500                          | 36                     | 24                     | 92.22                         | 54.46              | 11.4                    |
| 16       | 1500                          | 36                     | 28                     | 81.08                         | 36.91              | 27.32                   |

Exp. No. 12 sample results in defective weld with tunnel defect.

Table 3  Parameters with fixed level

| Parameters    | Value  |
|---------------|--------|
| Pin length    | 5.7 mm |
| Pin diameter  | 6 mm   |
| Plunge depth  | 0.06 mm|
| Tool tilt angle| 0°     |

3. Sensor fusion model

Brooks and Iyengar [12] presented that sensor fusion is the possible combination of sensory data or data derived from sensory data that would behave in more informative manner than the data presented or used from individual source. Real time signal processing for monitoring of process condition is not new in manufacturing domain. However, in most of the cases it is been observed that researchers and practitioners often relied on information extracted from single sensor. FSW process is complex in nature and is guided by various process parameters. Effective monitoring of the process demands efficient monitoring schemes relating to each crucial parameter. FSW process is found to be governed by three main process parameters namely tool rotational speed, welding speed and shoulder diameter [13]. Sensor fusion is often realized to be more effective if the fusion process is carried out with information extracted from sensors of different kind. In the current study these three parameters are decided to monitor with three different sensors integration with the process. For the same force sensor developed by Das et al. [11] was used to acquire vertical or plunge force signal during the process. Along with this signal, tool rotational speed signal and main spindle motor current signal correlating tool rotational speed are also acquired during the process. After the acquisition of the signals, these are processed with pre-processing steps like noise elimination and band determination over which sensor fusion is actually carried out. For signal filtration, Butterworth fifth order filter is designed in
MATLAB platform and all the acquired signals are pre-processed. The sensor fusion strategy is implemented to the signal band only related to the welding period data as the initial and ending time frame results in transient data behaviour. Figure 2 represents a schematic representation of the data fusion model presented in the present work where, S1, S2 and S3 are representing force sensor, tool rotational speed sensor and current sensor respectively.

In practice, fusion of sensor information or signal can be achieved in two broad domains. One is fusion at signal level and other one is fusion at feature level. The present work implemented the second strategy for data fusion. All the information collected from the signals is fused at the feature level. Statistical parameters viz. root mean square (RMS), kurtosis (K) and variance (V) from each signal are computed and fused for monitoring the welding process for defect estimation.

4. Defect identification with sensor fusion
In the current study statistical features namely RMS, K and V are computed over the welding period data for the vertical force signal, tool rotational speed signal and main spindle motor current signal. The features are fused in the feature space to obtain an indicator for identification of defect in the welded samples. The strategy adopted for identification is presented in the Fig. 3. During the experimental investigation it is observed that the experiments 12 leads to a defective welded sample with tunnel defect. The mechanical cross sectioning method was used for confirmation of the defect within the weld. The formation of defect in FSW process is complex to correlate to individual process parameters. The reason for formation of tunnel defect is high heat input over the material processing zone that can result from high tool rotational speed with low welding speed. High heat input leads to formation of excessive plasticized material and the material results in formation of excessive flash. This leads to less availability of material for filling the cavity formed by the rotating advancing tool in the weld zone resulting in void or empty space through the welding length. Thus, the defect is the output of combination of more than one parameter. In order to monitor the phenomena of defect formation, it is advantageous to observe these parameters in one space rather than analyzing in individual space. In this regard, sensor fusion is advantageous as information extracted from real time signal depicts the information combining all the factors influencing during the process both controllable and uncontrollable. In this work, strategy developed to produce an indicator for defect detection as reflected in Fig. 3 is comprised of three basic steps. The first step is to compute the statistical features from the signals. This creates the feature space of the process and represents the process in a feature domain from process parameter domain. The second step is to create a random variable space that will be combined with the statistical features for the development of the mathematical model for identification of the defect. The third step is to obtain a mathematical model for computing the indicator that will reflect the occurrence of defect in the welded sample classifying it from the rest of the defect free welded samples.
Fig. 3. Proposed strategy for the defect identification

The statistical features computed from the signals are combined with the random variable space variables for obtaining a single valued indicator for identification of defect. The mathematical model is presented in Eq. 1.

\[
I_D = \alpha F_i + \beta F_j + \gamma F_k
\]  

(1)

where, \( F \) represents the features computed from the signals, \( i, j, k \) represents feature type (RMS, K and V), \( \alpha, \beta, \gamma \) represents random variables from random space and \( I_D \) represents the defect indicator for identification of defect. The values of \( \alpha, \beta, \gamma \) are collected from the random variable space and the model is iterated for the computation of the defect indicator as per the proposed mathematical modeling. The iteration is terminated once the model meets the criteria of termination to produce the value differentiable for the one computed against the defect free welding cases. The defect indicator computed using the proposed methodology is presented in Fig. 4. From the figure it is evidential that the \( I_D \) computed against the defective case is far higher than that for the defect free welding cases. The investigation can provide a threshold for the users of FSW process to set a boundary for classifying defective welds from defect free welds.

In the following the various combinations of the signal features are presented that are tested for the development of the mathematical model as shown in Eq. 1. These combinations are tested with the features extracted from current signal, tool rotational speed signal and force signal using RMS, kurtosis and variance for each experimental condition.

Case 1
\[
F_{RMS} = \frac{CS}{TRS} \times FS \quad F_{KURTOSIS} = \frac{CS}{TRS} \times FS \quad F_{VARIANCE} = \frac{CS}{TRS} \times FS
\]

Case 2
\[
F_{RMS} = \frac{CS}{FS} \times TRS \quad F_{KURTOSIS} = \frac{CS}{FS} \times TRS \quad F_{VARIANCE} = \frac{CS}{FS} \times TRS
\]

Case 3
\[
F_{RMS} = \frac{TRS}{CS} \times FS \quad F_{KURTOSIS} = \frac{TRS}{CS} \times FS \quad F_{VARIANCE} = \frac{TRS}{CS} \times FS
\]
5. Conclusions
The result and discussion section shows the variation of the developed defect indicator with the experimental conditions. The developed indicator is successful in classifying defective weld from the defect free welds. This shows that the mathematical model has the potential to be developed as the machine learning system for training and testing machine intelligence for identification and classification of defects in FSW process. The following conclusions can be drawn from the current work.

- Selection of current sensor, tool rotational speed sensor and vertical force measurement sensor is found to be effective in defect detection in FSW process.
- The statistical signal features RMS, kurtosis and variance are found to be effective in delivering suitable information for sensor fusion using signal feature based sensor fusion framework.
- The developed mathematical model for estimation of the proposed defect indicator \( I_D \) is found to be effective in identification as well as classification of defective weld from the defect free welds.

The feature fusion combinations tried gives satisfactory results for all the possibilities but case 3 results in maximum variation among the defective and defect free welds.

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