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DETECTION OF SURFACE DEFECTS IN FRICTION STIR WELDED JOINTS BY USING A NOVEL MACHINE LEARNING APPROACH

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Abstract:
The Friction stir welding process is a new entrant in welding technology. The FSW joints have high strength and helps in weight saving considerably than the other joining process as no filler material is added during welding. The weld quality is affected because of various kinds of defects occurring during the FSW process. Defects like cavity, surface grooves and flash could occur due to inappropriate set of process parameters which results in excessive or insufficient heat input.
Defects analysis can be done by several non-destructive methods like immersion ultrasonic techniques, X-ray radiography, thermography, eddy current testing, synchrotron technique etc. In the present work the image processing techniques are applied over the test samples to detect the surface defects like pin holes, surface grooves etc.

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1. INTRODUCTION

Friction Stir Welding is a revolutionary energy efficient and environment friendly solid-state joining process which is used to weld the alloys which are difficult to be joined by a conventional welding process [1]. Friction Stir Welding process was invented by Wayne Thomas in 1991 basically for joining the lightweight structures [2-3]. Friction Stir Welding setup consists of base alloy plates which can be of similar and dissimilar nature, a tool which is harder than the base alloy plates to be joined, a fixture for holding the base alloy plates at the correct position and a backing plate material.

The various input parameters like tool rotational speed, tool traverse speed, tool tilt angle and applied axial force play an important role for obtaining good quality Friction Stir Welded joints. Balasubranian et al. [4] established the relationship between base material properties and Friction Stir Welding input parameters. It was observed that the tool rotational speed has a direct proportional relationship with the yield strength of the aluminium alloys. It was also observed that the traverse speed or welding speed has an inverse proportional relationship with the yield strength of aluminium alloys. The proper selection of these input parameters is very essential for obtaining sound joints. Abnormal variations in any one of these input parameters will result inappropriate rate of heating which leads to the formation of various defects. These defects can be subdivided into volumetric flaws and weld line flaws [5]. Lack of penetration, tunnel formation, formation of voids, lack of fusion, surface grooves and kissing bonds are various other defects formed during Friction Stir Welding process [6]. Huggett et al. [7] used Nondestructive evaluation (NDE) techniques of phased array ultrasonic testing (PAUT) and digital X-ray radiography for detecting the defects in Friction Stir welded Aluminum Alloy 2219-T87 specimens. Chen et al. [8] investigated about the welding defects in Friction Stir Welded Aluminum alloy 5456 joints with the help of optical microscopy (OM), energy-dispersive X-ray spectroscopy (EDS) and scanning electron microscope (SEM). It was

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observed from the microscopic examinations and fracture locations of the weld that plastic material flow can be changed by varying tool tilt angle. Kumar et al. [9] used discrete wavelet transform on force and torque signals for detecting the fault occurred during Friction Stir Welding process.

In our recent work we have used a novel Machine Learning approach for surface defect detection in Friction Stir Welded joints of an automotive grade Aluminum alloy.

2. APPLICATION OF MACHINE LEARNING IN FRICTION STIR WELDING PROCESS

Verma et al. [10] used various machine learning approaches like Gaussian Process Regression (GPR), Support Vectors Machine (SVM), and Multi Linear Regression (MLR) for performance evaluation in Friction Stir Welding process. It was observed that in comparison to SVM and MLR techniques, GPR approach works better for prediction of the Ultimate Tensile Strength (UTS) of the welded joints. Du, et al. [11] carried out study on the conditions of void formation by using Machine Learning techniques like decision trees and a Bayesian Neural Network. Schematic representation of the research is shown in the Fig.1.

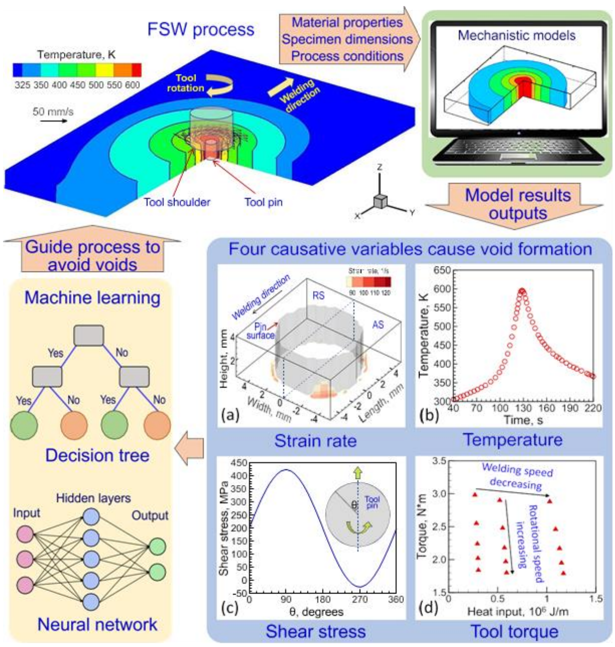


Fig.1. Schematic representation of Y. Du, et al. [11]. The components are FSW process, mechanistic models, and machine learning methods (neural network and decision tree); a) The distribution of strain rate plotted for 4-mm thickness above pin tip; b) Temperature-time curve during FSW process; c) The distribution of shear stress on tool pin with degrees; d) The distribution of torque with heat input

It was observed that both the neural network and the decision tree predicted void formation with 96.6% accuracy.

In spite of having many advantages, neural networks have two major disadvantages. Firstly, in order to get accurate results, we should have larger number of datasets. Secondly, it is easy to train the model to overfit the training data. In order to overcome these problems Mathis et al. [12] used another Machine Learning approach known as Render Forest Algorithm for predicting the hardness of Friction Stir Processed 304L stainless steel. Ersozlu et al. [13] developed an Artificial Neural Network (ANN) model for analysing the correlation between the friction welding parameters and tensile strength of both AISI 316 austenitic-stainless steel and Ck 45 steel. Between the experimental values and the ANN model prediction, a good correlation was obtained.

In FSW unlike gas arc welding the images captured have high resolution and are more clear. Thus, different image processing techniques like image pyramid, image reconstruction have been used in this work. This paper aims to identifying the defects into voids, grooves, rough texture or crack, flash and key-hole that usually occurs during the welding process using image processing techniques. The image pyramid is used to identify cracks, voids and pin holes defects whereas image reconstruction is used to analyze flash and uneven welding. Image Pyramid is an image processing technique is a type of multiscale signal representation in which a signal or an image is subjected to repeated smoothing and subsampling. Pyramid representation is a predecessor to scale-space representation and multi resolution analysis. Image Reconstruction is a pre-processing technique in which the image is reconstructed and by applying various morphological techniques like closing, opening, dilation and erosion the required features are obtained. The further experimental procedure and outcome of the research is elaborated in next section.

3. MATERIALS AND METHODS

In the present work, Aluminium alloy 6060 T5 plates were joined by using Friction Stir Welding process. The base alloy plate of the dimensions 150 mm X 100 mm X 6 mm was mounted tightly on the CNC bed with the help of fixture as shown in the Fig.2. The main purpose of the fixture is to help the both workpiece in a proper grip so that they do not dislocate from their original position while carrying out the Friction Stir Welding Process. Tool material for joining the plates is H13. The cylindrical tool design profile is shown in the Fig.3.

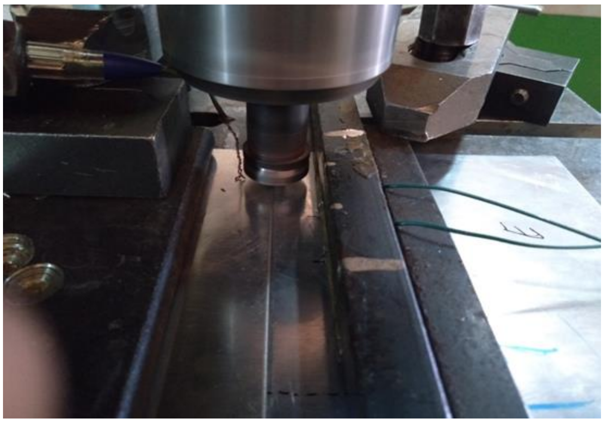


Fig.2. Experimental Setup

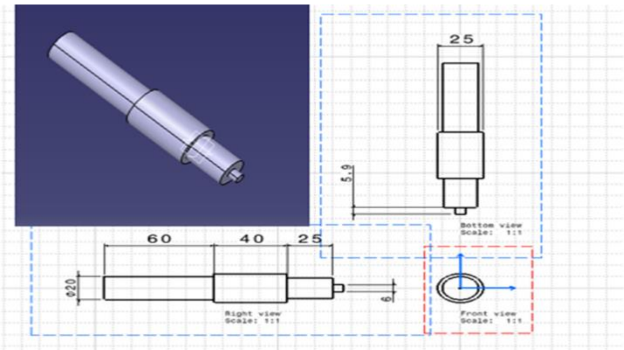


Fig.3. Design of cylindrical H13 tool

By varying the inputs i.e. Tool Rotational Speed (rpm), Tool Traverse Speed (mm/min) and Axial force (kN) as shown in the Table 1, four weld samples named Q, Z, R and L were prepared.

Table 1. Input parameters of the given sample codes

Sample Code	Tool Rotational Speed (RPM)	Tool Traverse Speed (mm/min)	Axial Force (KN)
L	2000	200	1.5
R	2000	400	1.5
Q	1500	400	1.5
Z	1500	400	2.5

The images of the welded samples is taken with a digital camera in RGB format, named as L, Q, R and Z and cropped to the size of 2706x1060, 794x 2558, 2675x 985 and 814x2559 respectively as shown in Fig.4. The entire image processing algorithm is developed in Jupyter Notebook on Python 3.0 platform using numpy, opencv and matplotlib libraries.

a) Weld Sample L

b) Weld Sample R

c) Weld Sample Q

d) Weld Sample Z

Fig.4. The various weld samples depicted in a), b), c) and d)

The further steps followed for image processing are discussed in the following sub sections.

3.1 Reading data

Initially the images are placed in a folder and are read consecutively by importing operating system and defining a path where they are stored. The images are then converted to grayscale from RGB format using cv2.cvtCOLOR command as less information needs to be provided for each pixel value.

Then to remove noise, 2D median filter is applied of kernel size (5,11) on grayscale images.

Opencv (Open source computer vision) is a library of programming functions mainly aimed at real-time computer vision. It is available freely and used widely in image processing and computer vision applications. Numpy is used for performing calculation and other mathematical, matrix and computational problems in python. Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms.

3.2 Data processing

It involves extracting required information from the images. This step is further divide into two parts as explained:

3.2.1 Image pyramid

In this technique the dimensions of image is reduced to get the most desirable features. In this project, this technique is utilized to get the cracks and pin hole defects. The images are downsized to 1.2 value which means that the width and height of the image would be divided by 1.2 in each iteration which depends upon our usage. The considered image size is 150.

The downscaled image is processed with Sobel edge detection in which horizontal and vertical edges are detected using the second order gradient. The resultant image is developed by:

$$|G| = \sqrt{Gx + Gy^2} \qquad 1$$

Where:

- G= net gradient,
- Gx= gradient in x direction,
- Gy= gradient in y direction.

For the noise removal thresholding is applied to convert it into binary with thresholding value 0.8. The various morphological operations like dilation, erosion, opening and closing are applied to get the desired results. Disc shaped kernel size of 2 is used to get output.

3.2.2 Image reconstruction

Using the python and scikit-learn library the inbuilt function, Greyconstruct is used to reconstruct the image. The image reconstruction is used to get the undesired edges which are obtained during welding. Initially the images are resized to match it in dimension with pyramid image as it is later required during image fusion.

The reconstruction function is applied on the eroded images. It is basically defined as the reconstruction of mask image by successive geodesic dilations of marker image until its contour fits under the mask image and such that the grayscale values of every pixel of the marker image is less than or equal to that of mask image.

The grayscale image of original weld sample is used as mask image while its eroded image is used as marker image. Erosion of the grayscale image has been done with the disk shaped structuring element of size 30. For further smoothening and noise reduction, 2D median filter of order 5x5 was applied on the reconstructed image. The filtered image was then used for edge detection. All the edges in the image was detected by applying Sobel approximation on to the derivative, which gives edges at the point of maximum gradient of the image. Thus, this process was helpful in detecting cracks, rough texture, edges of flash and detecting boundaries of the retreating side as well as the advancing side on the weld surface.

The morphological techniques of opening and dilation are applied to get the resultant image.

3.2.3 Image fusion

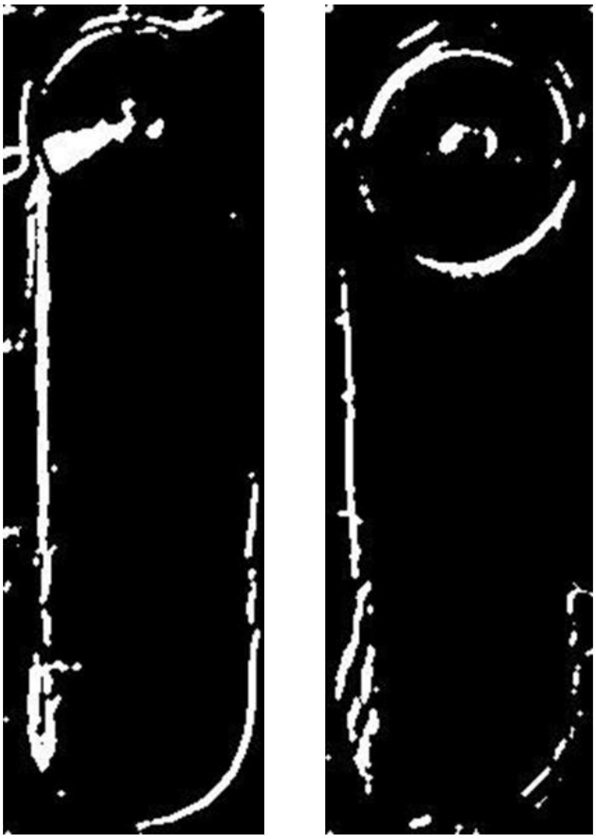
The former image processing algorithm is used to effectively detect surface grooves, voids, cavities and the key-hole on the surface of the weld, while the latter was used to effectively detect cracks and flash formations on the retreating side of the weld surface. The output binary images of the above two algorithms are merged into a single binary image which contained all kinds of surface defects.

4. RESULTS AND DISCUSSION

The resultant fused images of all the four weld samples are as shown in Fig.5.

a) Weld Sample L

b) Weld Sample R



c) Weld Sample Q d) Weld Sample Z

Fig. 5. The fused images of different samples: a) L sample b) R sample c) Q sample d) Z sample

The images in Fig.5 successfully illustrates the various defects on the weld surface like retreating edges, pin holes, cracks and rough textures.

The two algorithms applied on images are successful in implementing the results but to optimize the results more accurately more weld samples should be taken. The kernel size used in the project can be varied and different kernel shapes like diamond, square etc. can be applied to get the desired results. If further refinement of images are required then different thresholding values can be set depending upon the edges which are to be located in samples. The illumination effects during camera capturing are eliminated by setting the thresholding values thus, these effects results in low accuracy and less efficient output.

5. CONCLUSION

The image pyramid and image reconstruction algorithms are helpful in detecting various surface defects but to get more accurate results we can also use Convolutional Neural Network where we can take various defective and non- defective samples and train our data using CNN. As when the new weld sample is added the model can easily predict whether the samples has defect and if defects are present then the type of defect can be obtained using the classification technique which can be inserted along with CNN. This novel surface defect classification system for Friction Stir Welded joints that works in real-time can be implemented on the images of material running on the production line. This can be used to get better results during online as well as offline monitoring processes for various types of conventional welding processes also.

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