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DISCRETE WAVELET TRANSFORMATION APPROACH FOR SURFACE DEFECTS DETECTION IN FRICTION STIR WELDED JOINTS

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ABSTRACT

Friction Stir Welding joint quality depends on input parameters such as tool rotational speed, tool traverse speed, tool tilt angle and an axial force. Surface defects formation occurs when these input parameters are not selected properly. The main objective of the recent paper is to develop Discrete Wavelet Transform algorithm by using Python programming and further subject it to the Friction Stir Welded samples for the identification of various external surface defects present.

Keywords: Machine Vision; Surface Defects; Friction Stir Welding; Python programming
Article Category: Research Article

INTRODUCTION

Friction Stir Welding is a solid-state joining process that generally finds application in the joining of alloys which are difficult to weld by a conventional welding process. The important input parameters which govern the quality of weld obtained from the Friction Stir Welding process are tool rotational speed (rpm), tool traverse speed (mm/min), axial force (KN), and tool tilt angle. Improper selection of these input parameters during the Friction Stir Welding process results in the formation of intermetallic compounds which are responsible for the initiation of crack nucleation and also there is the formation of various external and internal defects such as surface grooves, tunnel formation, flash formation and void formation which are responsible for stress concentration [1-4].

Nowadays, Machine Learning is being radically used in various materials and manufacturing sectors for the optimization of mechanical and microstructure properties like Ultimate Tensile Strength, Fracture Strength, Elongation percentage, Grain size, etc. Unsupervised machine learning classifiers were used by Kolokas et al. [5] for fault prognosis and forecasting in industrial equipment related to plastic and aluminium production. The results concluded that the used machine learning models were capable of predicting the faults before their occurrence. Aimiyeakagbon et al. [6] used machine learning time series forecasting approach for prediction of crack length in the riveted aluminium plates. Mongan et al. [7] combined genetic algorithm (GA) with Artificial Neural Network (ANN) for predicting the strength of ultrasonically welded joints. The model resulted high accuracy with 0.9827 as a correlation coefficient. Likely these applications machine learning is also being used in Friction Stir Welding process. Dutt et al. [8] developed artificial neural network model for studying about the correlation between the Friction Stir Welding input parameters such as a rotation rate and traverse rate with the mechanical property of friction stir welded precipitation strengthened AA7050 aluminum alloys. Hartl et al. [9] used Bayesian optimization and reinforcement learning method to improve the surface quality of friction stir welded joints. The present research focuses on the implementation of Discrete Wavelet Transformation for the detection of surface defects present on Friction Stir Welded joints. Selim et al. [10] applied a wavelet transformation algorithm for the detection of internal defects in a given aluminum component. Figure 1 shows the wavelet contour map of the three scan points on the metallic component.

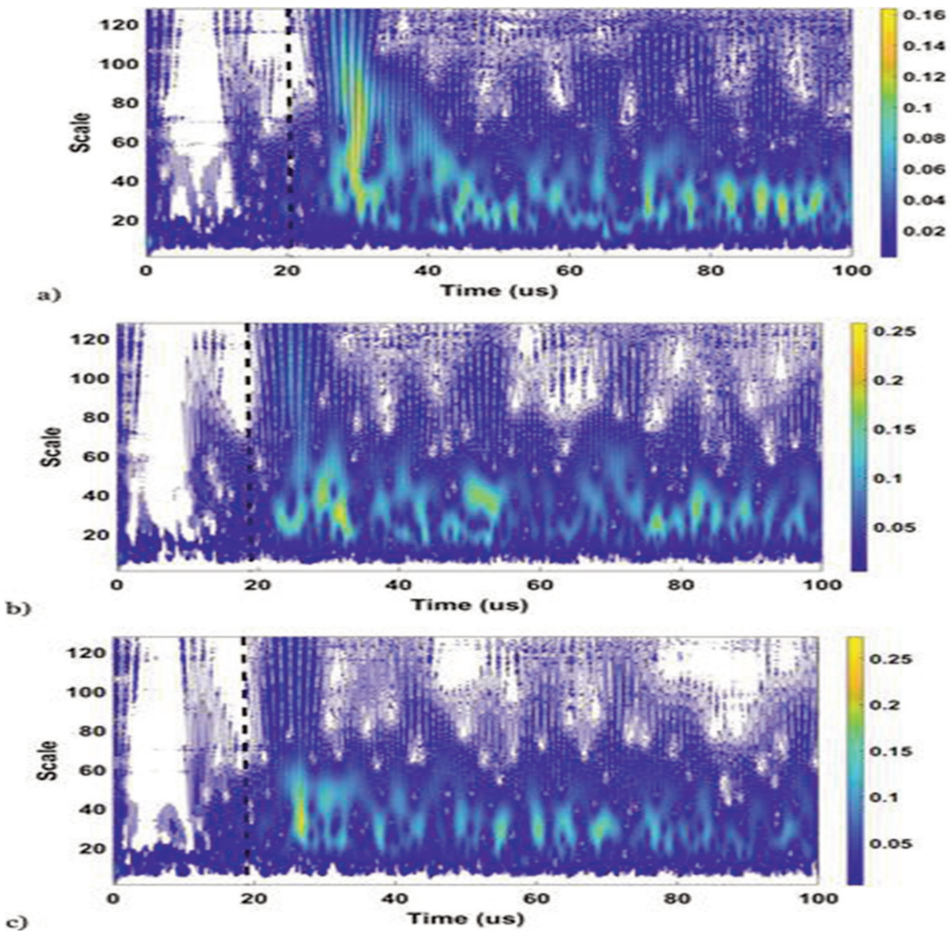

Fig. 1. Contour maps of wavelet transform at
a) Scan point 1, b) Scan point 2, c) Scan Point 3 [10].

Vermaak et al. [11] used the Dual-Tree Complex Wavelet Transform algorithm for improving fabric defect detection. Guminiak et al. [12] applied a discrete wavelet transform in the truss structures with rigidly connected bars for detecting the defects.

MATERIAL AND METHODS

In the present work, Aluminium alloy 6060 T5 plates were joined. The chemical composition of the base alloy plate is shown in Table 1. 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 a fixture. The main purpose of the fixture is to help both workpieces in a proper grip so that they do not dislocate from their original position while carrying out the Friction Stir Welding Process. The tool material for joining the plates is H13.

Table 1. Chemical Composition of 6060-T5 Al alloy in wt %.

Alloy	Si	Fe	Cu	Mg	Mn	Cr	Zn	Ti
6060-T5	0.42	0.17	0.002	0.02	0.45	0.0006	0.0002	0.01

Five Friction Stir Welded samples were prepared at particular input parameters shown in Table 2. The digital images captured of the welded samples are shown in Figure 2-6.

Table 2. Parameters selected for Friction Stir Welding process.

Sample Number	Tool Rotational Speed (rpm)	Tool Traverse Speed (mm/min)	Axial Force (KN)
1	2000	400	2.5
2	1000	200	1.5
3	1500	400	1.5
4	1500	400	2.5
5	2000	400	1.5

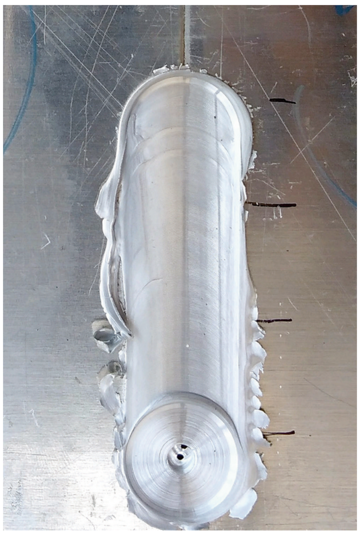

Fig. 2. Digital Cropped image of Sample 1.

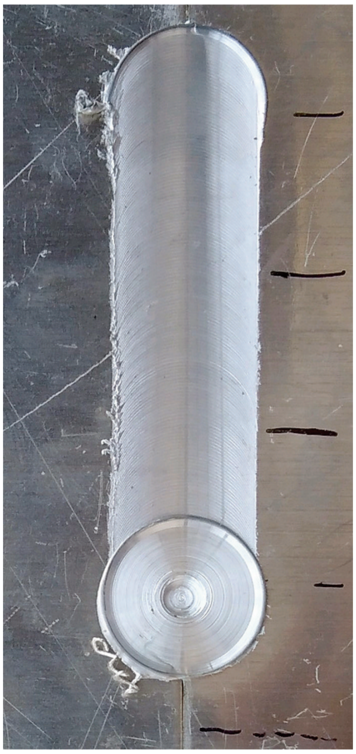

Fig. 3. Digital cropped image of Sample 2.

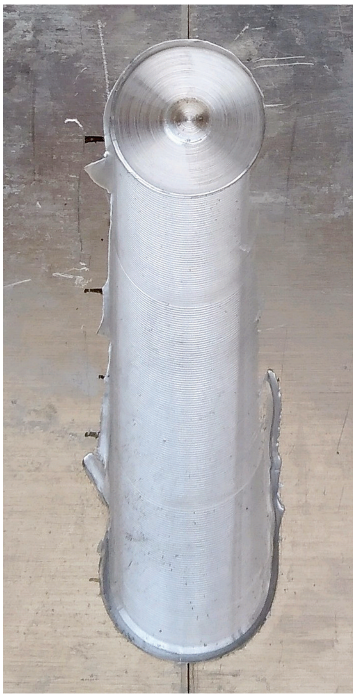

Fig. 4. Digital cropped image of Sample 3.

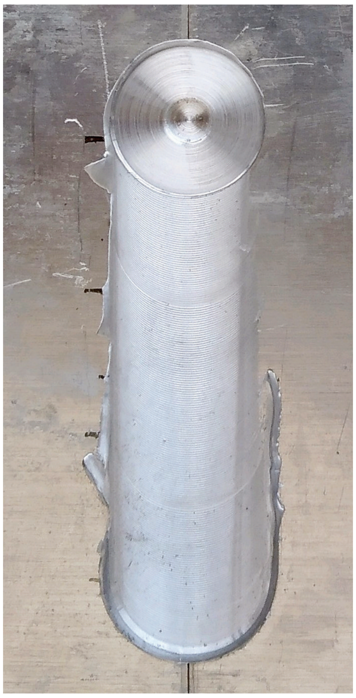

Fig. 5. Digital cropped image of Sample 4.

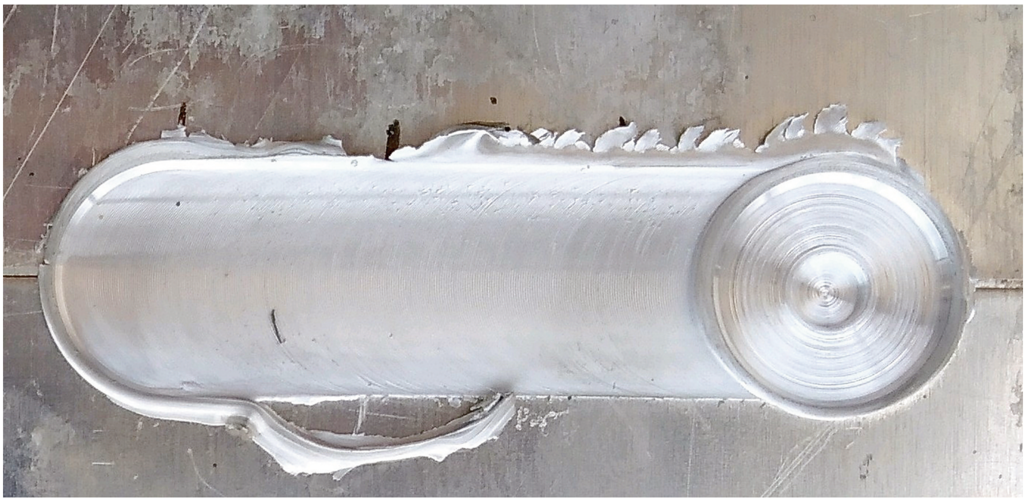

Fig. 6. Digital Cropped image of Sample 5.

These digitally captured cropped images were imported to Google Colaboratory platform for the implementation of Discrete Wavelet Transform algorithm developed by using Python programming language.

RESULTS AND DISCUSSION

The digital captured cropped image can be considered as a two-dimensional signal $s(n)$ where n is the samples of a given signal and $n = 0,1,2,\ldots$ M-1. Discrete time signal is obtained by summing up scaling function term represented by Equation 1 and wavelet function term represented by Equation 2.

$$W_{\varnothing}(j_0,k) = \frac{1}{\sqrt{M}} \sum_n s(n).\varnothing_{j_0k}(n) \tag{1}$$

$$W_{\Psi}(j,k) = \frac{1}{\sqrt{M}} \sum_n s(n).\Psi_{j,k}(n) \tag{2}$$

In Equation 1, $W_{\varnothing}$ is a scaling function, j_0 is a scaling parameter and $\frac{1}{\sqrt{M}}$ is a normalizing term used for converting a spacial domain s(n) to $W_{\varnothing}(j_0, k)$. In Equation 2 it should be noted that $j \geq j_0$. Equation 1 and 2 constitutes Forward discrete wavelet transformation while Equation 3 represents an expression for an inverse discrete wavelet transformation.

$$s(n) = \frac{1}{\sqrt{M}} \sum_k W_{\varnothing}(j_0k).\varnothing_{j_0k}(n) + \sum_{j=j_0}^{\infty} \sum_k W_{\Psi}(j,k).\Psi_{j,k}(n) \tag{3}$$

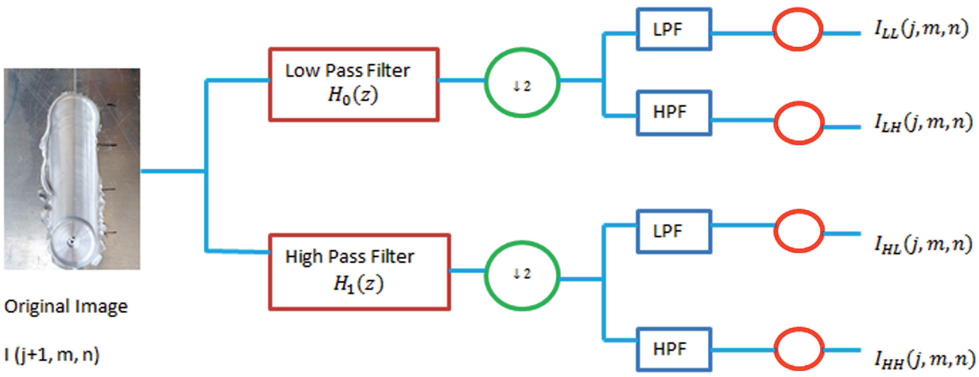

Fig. 7. Friction Stir Welded image subjected to Discrete Wavelet Transform algorithm.

It is a common fact that filters are one-dimensional in nature while images are two-dimensional in nature. So, in order to apply one-dimensional filter to the two-dimensional images, we have to apply one-dimensional filter along rows of images and then along column of images as shown in Figure 7. High pass filter extract the edges and low pass filter does the approximation. I_{LH} extracts the information from the input image and has passed through the high pass filter which acts on the row of an input image and finally results horizontal edges. I_{LL} has passed through two low pass filters and results an approximation image. I_{HL} results vertical edges while I_{HH} extracts the vertical feature of the image and has passed through high pass filter along the column of the image. The high pass filter operating along the row of the input image, so, I_{HH} emphasizes the edges along the diagonal of the image. The results obtained as depicted in Figure 8-12.

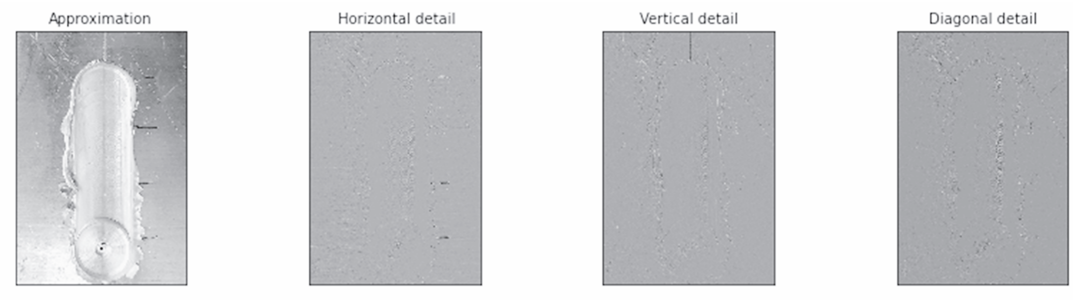

Fig. 8. Result for Sample 1.

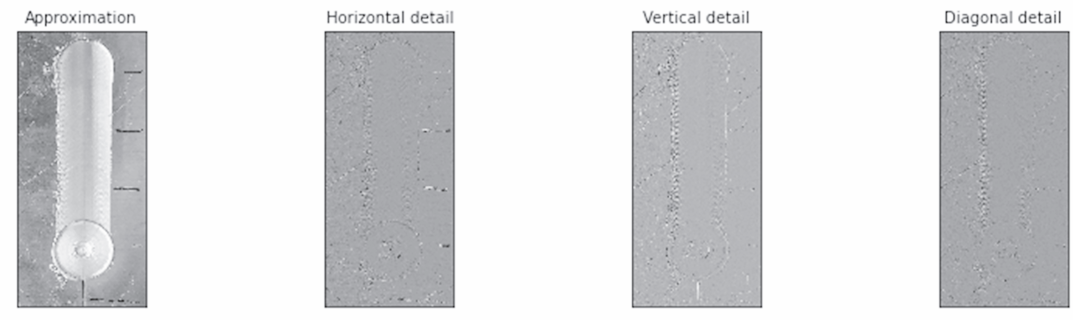

Fig. 9. Result for Sample 2.

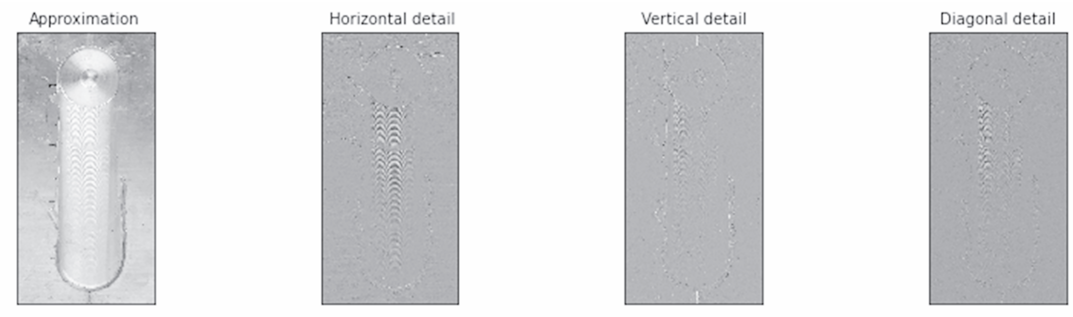

Fig. 10. Result for Sample 3.

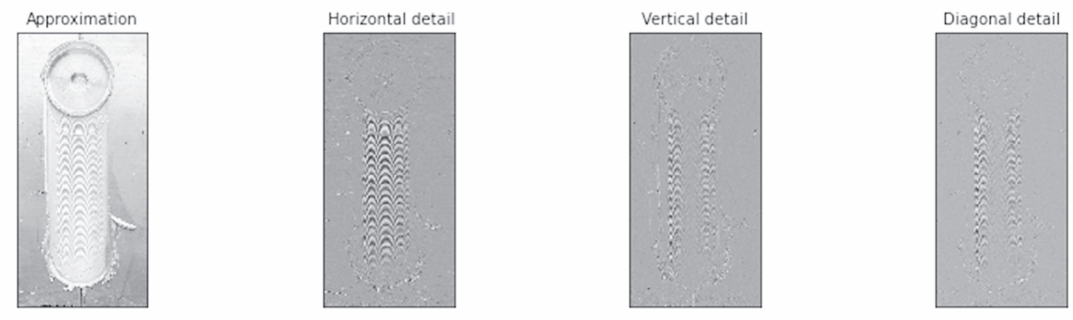

Fig. 11. Result for Sample 4.

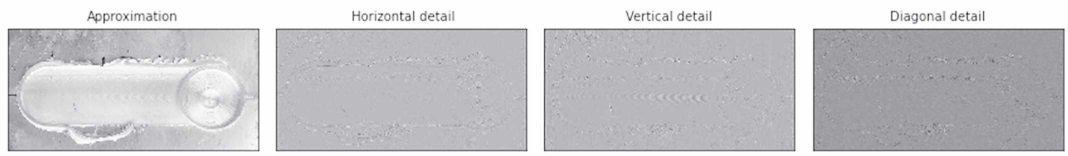

Fig. 12. Result for Sample 5.

It is observed from the results that inhomogeneous pixel present in the obtained transforms depicts external surface defects like flash formation and groovy edges.

CONCLUSION

The present study implemented the Discrete Wavelet Transform algorithm to the five friction stir welded samples for detecting the presence of surface defects such as flash formation, groovy edges etc. as a main objective. The results showed that the Discrete Wavelet Transform is able to capture and extract the minute details present on the surface of the weld and further can be used for defects detection purpose. The future study which be further carried out on this work is to implement it on real-time monitoring of defects formation.

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