Original Research Paper

Machine Learning Approach for Defects Identification in Dissimilar Friction Stir Welded Aluminium Alloys AA 7075-AA 1100 Joints

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Abstract: Machine learning approaches are now applied in various manufacturing industries. Various machine learning algorithms can be implemented for prediction of the particular mechanical properties like Ultimate Tensile Strength (UTS), Elongation percentage and fracture strength of the given mechanical component and also image processing algorithms can be applied for defects detection in the mechanical components. In our recent work, we have used a novel machine learning approach for the detection of the surface defects in dissimilar Friction Stir Welded joints by using Local Binary Pattern (LBP) algorithm. The results obtained are satisfying and it is concluded that the LBP can be implemented in the detection of surface defects.

Keywords: Friction Stir Welding, Local Binary Pattern, Machine Learning, Surface Defects

Introduction

The Welding Institute (TWI) located in UK invented a solid-state joining process popularly known as a Friction Stir Welding process in 1991. Friction Stir Welding process overcomes the disadvantages of other conventional welding process in terms of joint quality. Friction Stir Welding process arrangement as shown in the Fig. 1 consists of some important components like a rotational tool, two or more alloy plates to be joined, a fixture arrangement for clamping the alloy work piece firmly at a particular location and a backing plate material. It should be noted that Friction Stir Welding process doesn't require any filler material for joining of the alloy plates (DebRoy and Bhadeshia, 2010; Mishra and Ma, 2005; Rhodes *et al.*, 1997). Under the influence of an axial load the tool pin generates heat which plasticize the material and further tool pin rotation causes the displacement of the plasticized material. The plasticized soft material deposits in the gap located at the trailing edge (Sun *et al.*, 2017). The formation of welding defects is governed by material flow occurring during Friction Stir Welding process (Khairuddin *et al.*, 2012). Schematic mechanism of material flow in Friction Stir Welding process is shown in Fig. 2. The effects of various input welding parameters such as a tool rotational speed, tool inclination angle, tool traverse speed and applied axial force play a vital role in the formation of defects in Friction Stir Welded joints. The two important factors which contribute to the quality of joints are proper intermixing of materials and an adequate heat generation (Schmidt and Hattel, 2008). Any slight variation of the discussed input parameters causes the formation of intermetallic compounds and an external and internal defects like flash formation, groovy edge formation and tunnel defects.

Costa *et al.* (2018) compared the weldability of heat treatable AA-6082 T6 aluminium alloy and non-heat treatable AA-5754 H22 aluminium alloy. It is observed that as compare to non-heat treatable aluminium alloy, heat treatable aluminium alloy are more prone to defects formation. Luo *et al.* (2019) gave the reason for the weakening strength of Friction Stir Welded 2219 aluminium alloy. Metal failure and plastic deformation were the reasons behind the formation of defects in the nugget zone and at the interface of nugget zone and thermo mechanically affected zone as shown in the Fig. 3.

Surface defects present on the friction stir welded joint can be classified into cracks, grooves, key-hole, voids and formation of the flash. These defects weaken the load bearing capacity of the Friction Stir Welded joints and also the mechanical properties like Ultimate Tensile Strength (UTS), fracture strength, elongation percentage starts degrading.
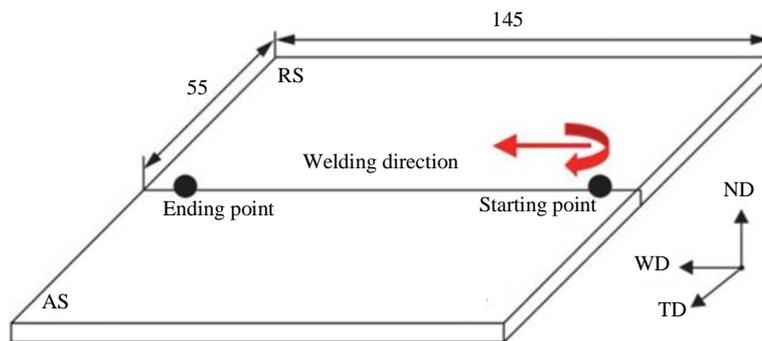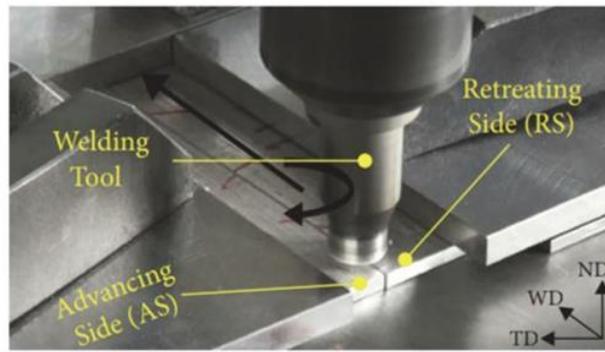
Fig. 1: Friction Stir Welding working process (Sun *et al*., 2017)
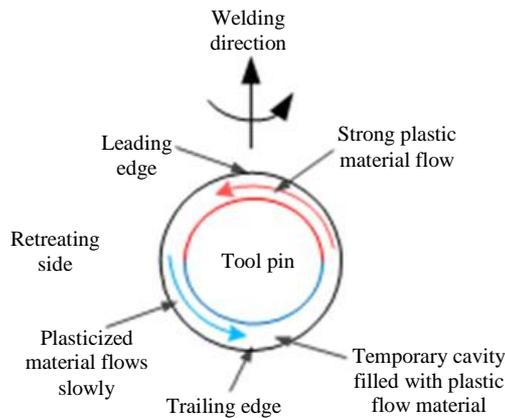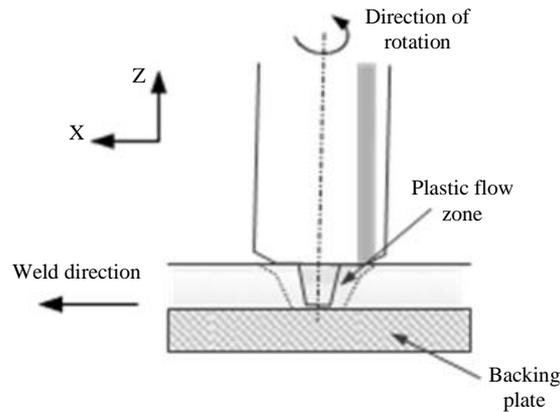
Fig. 2: Material flow mechanism in friction stir welding process (Khairuddin *et al*., 2012)

Nowadays, Artificial Intelligence techniques like Machine Learning and Deep Learning are finding various applications in a smart manufacturing process (Wang *et al.*, 2018). Machine learning parses and learns from the available dataset while Deep Learning models create the Artificial Neural Network algorithms in various layers depending upon its usage. The main advantage of Machine Learning over Deep Learning is that it takes less time to train the models in comparison to Deep Learning. Park *et al.* (2016) designed a Convolutional Neural Network (CNN) based Machine Learning model for surface defects identification. Scime and Beuth (2019) constructed a computer vision and unsupervised machine learning models for the identification of in-situ melt pool signatures for identifying the flaws in a Laser powder bed fusion additive manufacturing process. Song and Yan (2013) proposed a robust feature Local Binary Pattern (LBP) Descriptor to prevent a noise called the AECLBP while the defect recognition from the hot rolled steel strip. Ko and Rheem (2016) also used Local Binary Pattern (LBP) for defect detection in polycrystalline solar wafers. It was observed that compared to other related methods, the LBP method has an advantage for identifying various low gray level defects.
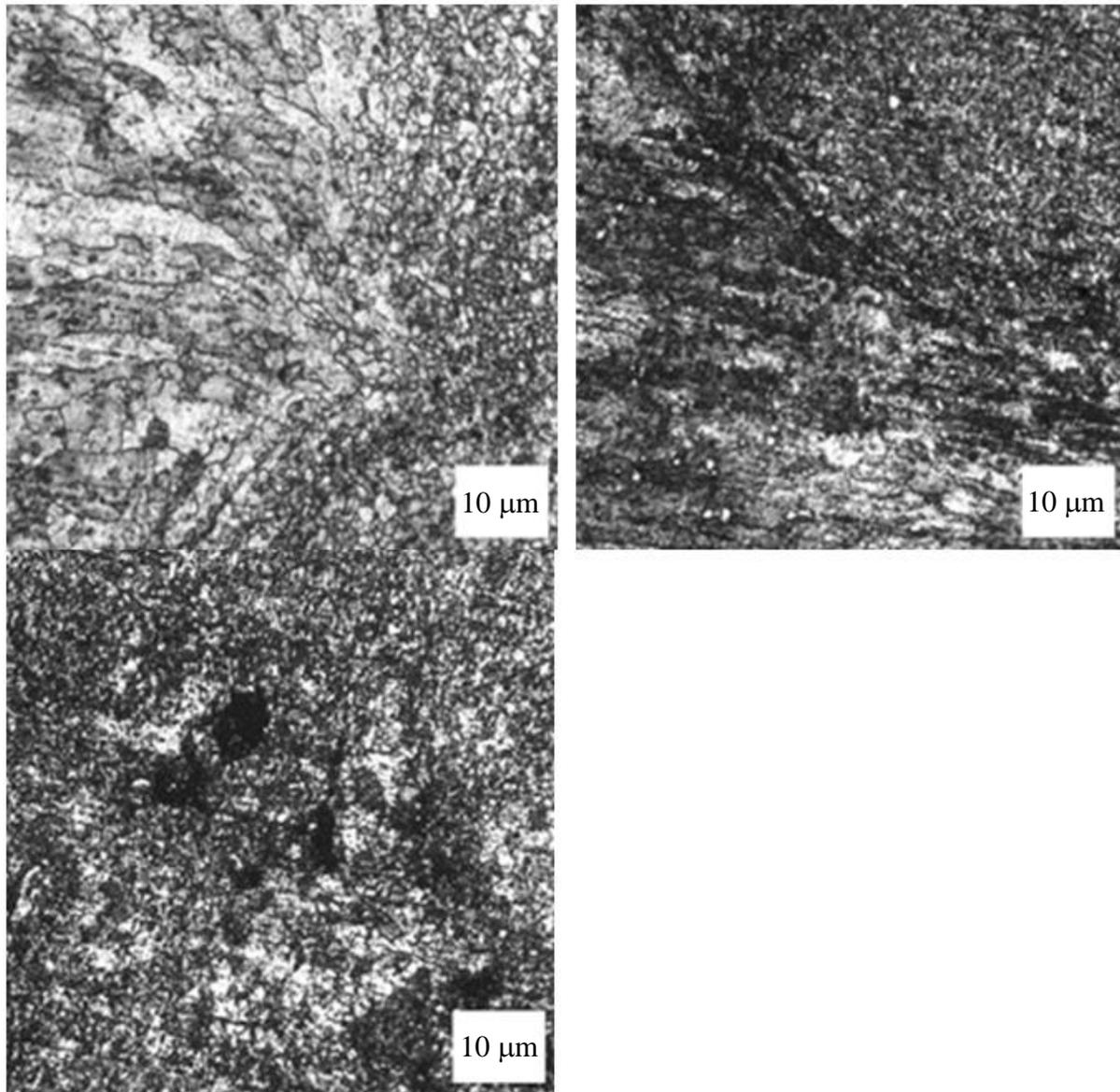
Fig. 3: Defects in nugget zone and at the interface of thermo-mechanically affected zone and nugget zone Luo *et al.* (2019)

The main objective our research is to construct an algorithm based on Local Binary Patterns (LBPs) for the identification of external surface defects such as flash formation and groovy edges in Friction Stir Welded joints. In our present work we have joined dissimilar aluminium alloy of grades AA 7075 and AA 1100 together. The next section will be focusing on the various types issues arising during the joining of aluminium alloys by Friction Stir Welding process.

Materials and Methods

In the present work, firstly alloy plates to be joined were machined at the sides to be joined in order to avoid any surface irregularities. AA 7075 and AA 1100 plates of dimensions 150×100×6 mm were clamped at the fixture mounted on CNC machine and they were joined by Friction Stir Welding process with the help of H13 tool steel. The composition of AA 7075 and AA 1100 are shown in the Table 1 and 2. The design of the tool used for Friction Stir Welding purpose is shown in the Fig. 4.

After joining process, the high resolution digital image of the Friction Stir Welded joint is captured as shown in the Fig. 5. The digital image was further cropped and divided in to two digital images as shown in the Fig. 6 and 7 representing the weld with flash formation and other the weld with good surface regularities.

In this research study algorithm for constructing the Local Binary Pattern was developed by using Python programming language executed on Google Colaboratory platform. The python libraries used for image processing in the code are numpy, matplotlib and cv2. The digital image were cropped to the resolution of 1511×2237 for obtaining the low level gray image which were further converted to Local Binary Patterns and histogram for each obtained Local Binary Patterns were plotted.

Table 1: Chemical composition of AA 7075 alloy

Component	Weight %
Al	87.1-91.4
Cr	0.18-0.28
Cu	1.2-2
Fe	Max 0.5
Mg	2.1-2.9
Mn	Max 0.3
Other, each	Max 0.05
Other, total	Max 0.15
Si	Max 0.4
Ti	Max 0.2
Zn	5.1-6.1

Table 2: Chemical composition of AA 1100 alloy

Component	Content%
Al	99.0
Cu	0.12
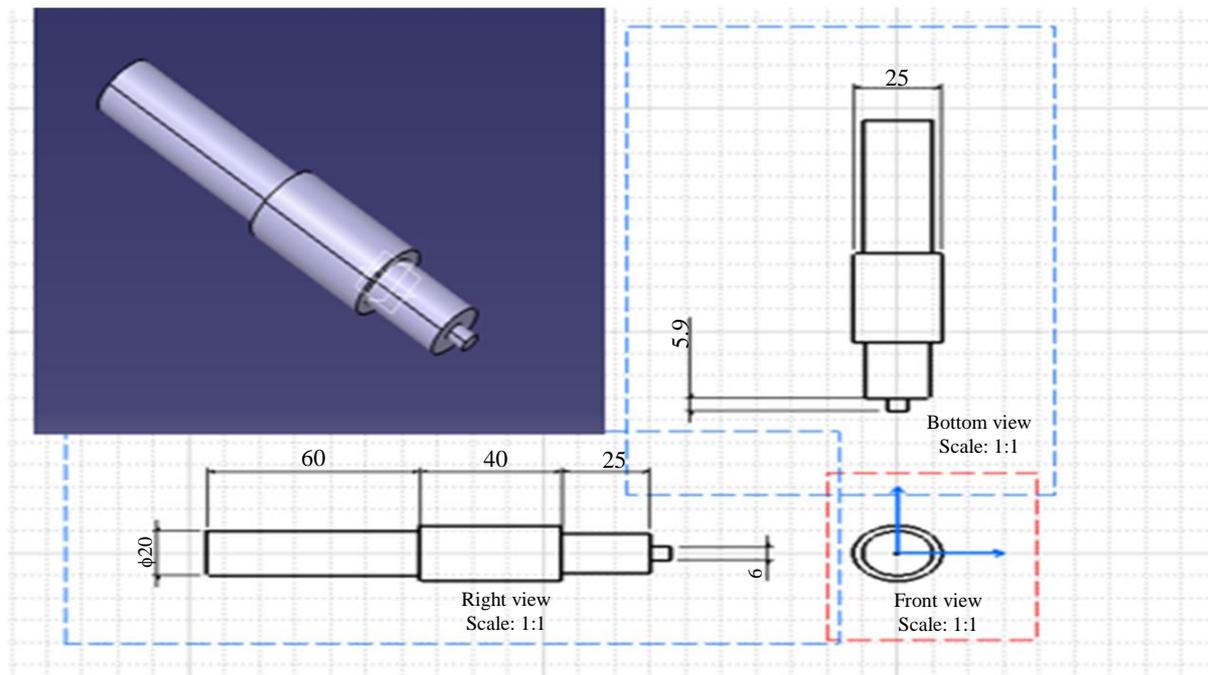
Fig. 4: Design of cylindrical H13 tool
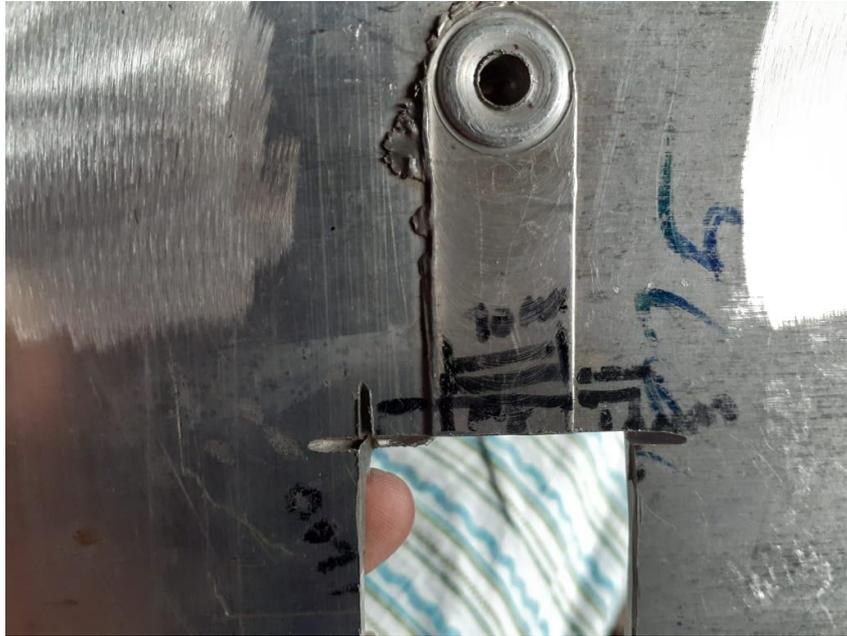
Fig. 5: Dissimilar weld of AA 7075 and AA 1100 alloy

Fig. 6: Cropped image of Friction Stir Welded joint consisting of flash formation

Fig. 7: Cropped image of friction stir welded joint with no irregularities

Results and Discussion

The texture descriptor is used to describe the coarseness, regularity and directionality of patterns in texture images (Russ, 1990). Local Binary Pattern (LBP) is one of the descriptors used for understanding the images. For obtaining the Local Binary Pattern (LBP) of a given image, the given image should be converted to a Grayscale image. Once the grayscale image is obtained, we get the texture distributor consisting of various descriptive vectors as shown in the Fig. 8.

The yellow highlighted region shown in the texture distributor matrix is the centroid of the pixel, while 10, 12, 9, 6, 7, 19, 7, 10 and 16 are the descriptive vectors:

$$b_k = \begin{cases} 1, if \ g_k \geq g(x) \\ 0, otherwise \end{cases} \qquad (1)$$

The main idea of the Local Binary Pattern (LBP) is that if the neighbour value is greater than the center value then replace it by 1 and if it is less than the center value put 0, which indicated from the Equation 1. Noise

is an uncertainity in image which is sensed by any image analysis instrument.

In the Python code, a function is created to obtain the Local Binary Pattern (LBP) of the given images. The size of the kernel taken is 3×3. The subplot of the grayscale, Local Binary Pattern (LBP) and histogram for the given cropped sample consisting of flash formation is shown in the Fig. 9. It is observed that the hetrogenity in the LBP converted image is shown by black patches which represent the surface irregularities on the Friction Stir Welded joint. On the other hand, Fig. 10 represents no such formation of dark patches in the LBP converted image which represents no such irregularities present on the portion of Friction Stir Welded sample.

The obtained results are satisfied with the LBP model used by Liu *et al.* (2019) who used an improved MB-LBP defect recognition approach for the surface of steel plates. It is observed that the LBP model used in this research is able to classify the irregularities present in the Friction Stir Welded joint with a good accuracy.
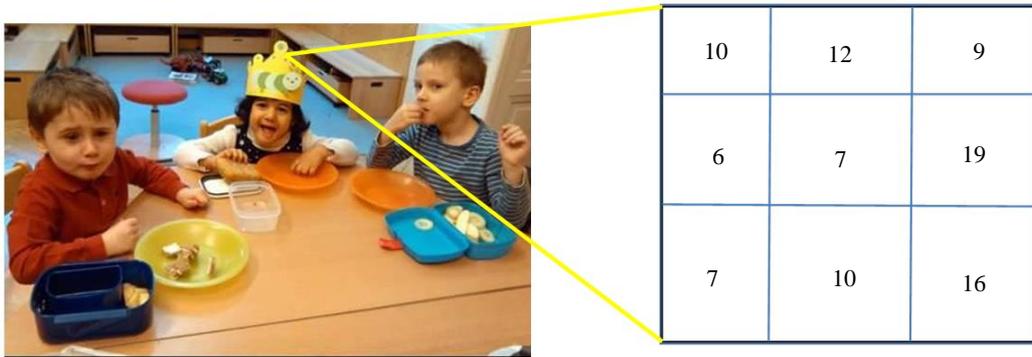
Fig. 8: Representation of LBP descriptor of an image
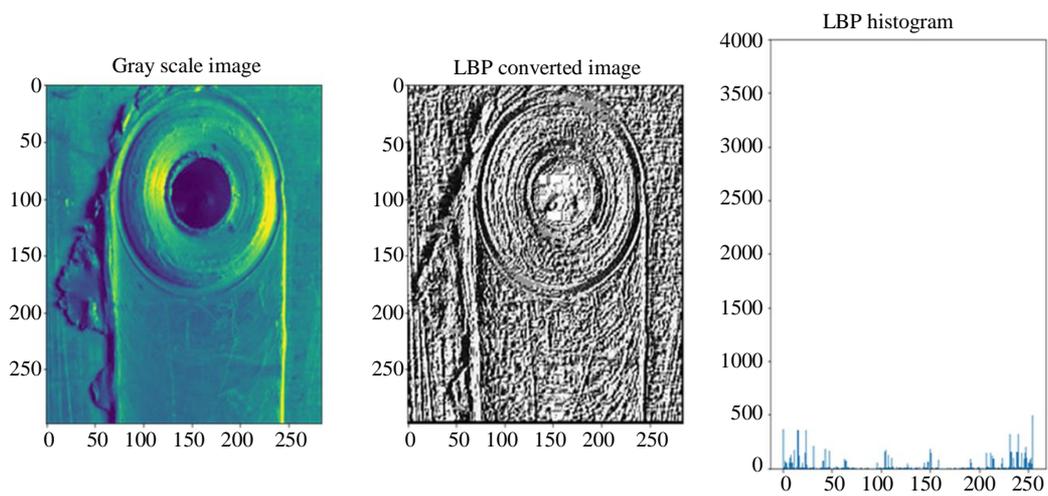
Fig. 9: Gray scale image, LBP converted image and LBP histogram of cropped portion of Friction Stir Welded joint consisting of flash formation
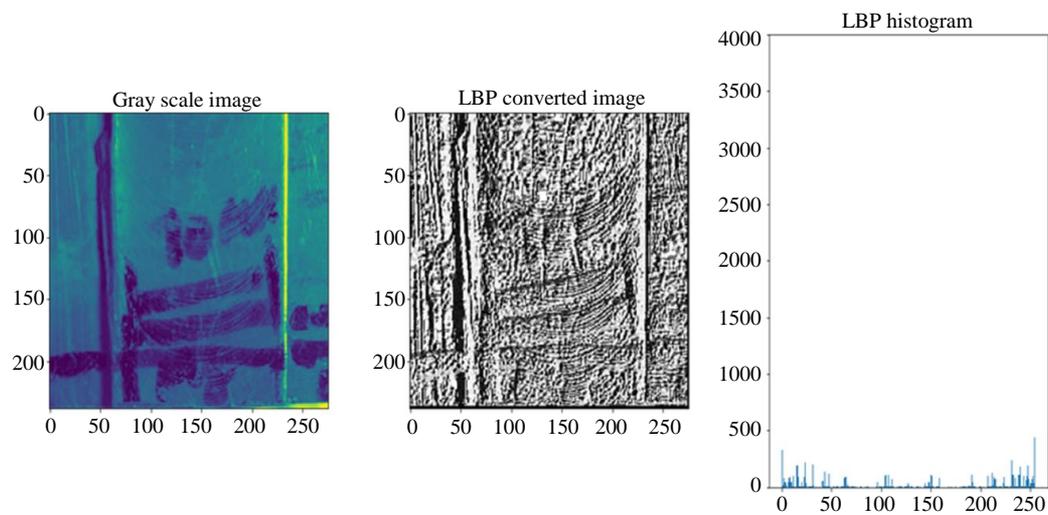
Fig. 10: Grey scale image, LBP converted image and LBP histogram of cropped portion of Friction Stir Welded joint without any irregularities

Conclusion

Local Binary Pattern (LBP) algorithm using Python programming was successfully implemented for the detection of surface irregularities present on the Friction Stir Welded joint of dissimilar alloy of aluminium. It is observed that the Local Binary Pattern histogram obtained from the cropped image consisting of surface irregularities and other cropped image without any surface irregularities vary in nature. The experimental result also shows that proposed Local Binary Pattern (LBP) algorithm has several advantages in cost and time saving and displays higher performance than traditional manpower inspection system. It can be concluded that the Local Binary Pattern (LBP) images can be used as a powerful texture descriptor. However, some further improvement is needed in enhancing the algorithm because Local Binary Pattern is unable to extract texture feature in a large size and structure.

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Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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