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Local binary pattern for the evaluation of surface quality of dissimilar Friction Stir Welded Ultrafine Grained 1050 and 6061-T6 Aluminium Alloys

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KEYWORD

Machine Learning; Friction Stir Welding; Local Binary Pattern; Machine Vision

ABSTRACT

Friction Stir Welding process is an advanced solid-state joining process which finds application in various industries like automobiles, manufacturing, aerospace and railway firms. Input parameters like tool rotational speed, welding speed, axial force and tilt angle govern the quality of Friction Stir Welded joint. Improper selection of these parameters further leads to fabrication of the joint of bad quality resulting groove edges, flash formation and various other surface defects. In the present work, a texture based analytic machine learning algorithm known as Local Binary Pattern (LBP) is used for the extraction of texture features of the Friction Stir Welded joints which are welded at a different rotational speed. It was observed that LBP algorithm can accurately detect any irregularities present on the surface of Friction Stir Welded joint.

1. Introduction

Friction Stir Welding is a solid state joining process which was developed by The Welding Institute (TWI) mainly for joining the light-weight materials like aluminium and magnesium alloys [1-3]. The Friction Stir weldability of aluminium alloys is compared to other conventional fusion welding process shown in Fig. 1. Friction Stir Welding process results high quality welds but the welding performance mainly depends on the proper selection of various input parameters like pin temperature, tool rotational speed, feed rate, welding speed, temperature distribution, rotating tool torque, applied downward forging force on tool shoulder etc.

The working mechanism of the Friction Stir Welding process is shown in the Fig. 2.

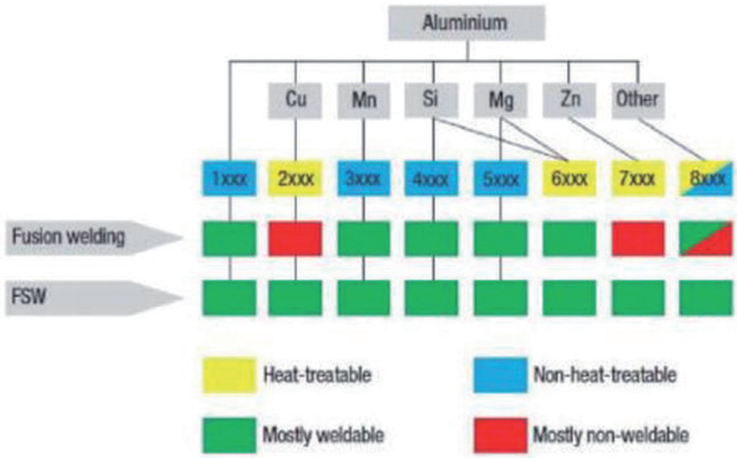

Fig. 1. Comparison of the weldability of different aluminium alloys by conventional and Friction Stir Welding process [2].

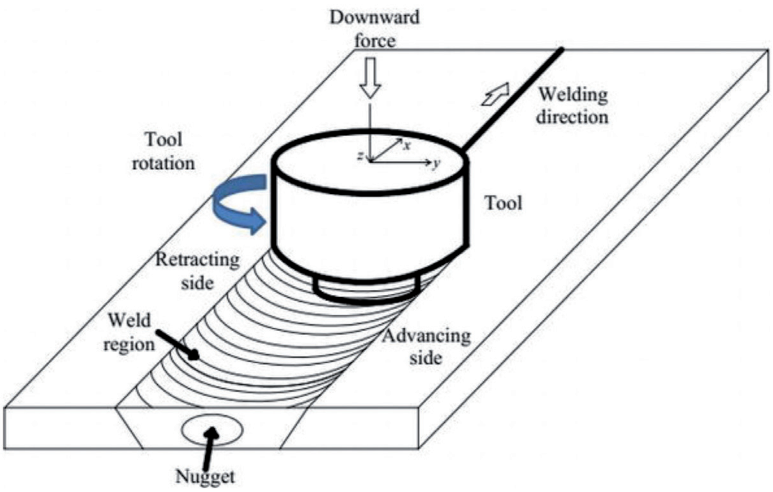

Fig. 2. Mechanism of Friction Stir Welding process [3].

The main beauty of the Friction Stir Welding process is that it uses non-consumable metallic tool which is harder than the base material to be joined [4]. The tool consists of a shoulder and pin as shown in the Fig. 3 b). The tool is plunged inside the base material by applying a downward force. The Friction Stir Welding tool possesses two types of speed i.e. Rotational speed and Traverse speed in the welding direction. Due to the rotation of the rotating tool there is a generation of friction between the work piece and the rotating tool which results in plastic deformation the work piece as shown in the Fig. 3c).

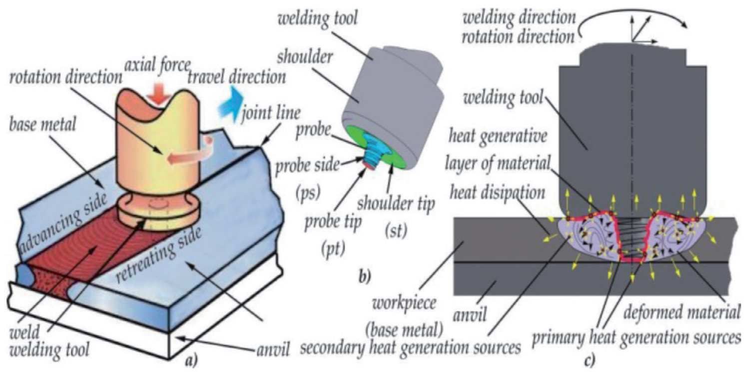

Fig. 3. a) Friction Stir Welding Setup, b) Tool Nomenclature,
c) Heat generation and plastic deformation in FSW process [5].

Due to the generated localized heat, the work piece get soften around the probe or pin region which results in the movement of soften or plasticized material from the front part of the probe to the back part of the probe. The welded joint is formed by deforming the material at temperatures below the melting point of parent material [6]. At a very cold welding conditions defects such as void formation and non-bonding can occur while at very hot welding condition issues such as degradation of the strength of the joint can occur as well as there is a formation of collapsible nugget within the stir zone occurs [7].

In the present work, a machine learning algorithm called Local Binary Pattern (LBP) has been developed for evaluating the surface defects like lack of penetration and flash formation of dissimilar Friction Stir Welded Ultrafine Grained 1050 and 6061-T6 Aluminum Alloys.

2. Working of Local Binary Pattern (LBP)

Local Binary Pattern is an important image texture analysis machine vision algorithm which is tolerant against any type of illumination changes in a real time application [8]. Local Binary Pattern creates a grey value difference between the neighbourhood pixels and the centre pixel in the sampling area. In a rectangular neighbourhood with size of 3 X 3, Local Binary Pattern is defined. Firstly, conversion of the colour image into grey scale image is done with grey scale value of 0 255. As a sampling point, pixels of the rectangular area are used. is the grey value of the centre pixel and are the grey scale values of the 8 pixels around it. The corresponding position is encoded as 1 when. The corresponding position is encoded as 0 when as shown in the Fig. 4.

Equation 1 describes the coding formula for Local Binary Pattern algorithm.

$$\text{LBP (C)} = \sum_{i=1}^{8} S\,(f_i, f_0).\,2^{i-1}$$

$$\text{S}\,(f_i, f_0) = \begin{cases} \{1, & f_i - f_0 \geq 0 \\ \{0, & f_i - f_0 < 0 \end{cases} \qquad (1)$$

Kamani et al. [9] used Local Binary Pattern for classification of car body and automatic paint defect detection. It was observed that the identification and classification of defects can be done with high accuracy. Mahram et al. [10] detected cracks and wood knots in order to classify stable and strong woods by using Local Binary Pattern algorithm. Aghdam et al. [11] worked on the defect detection using decision trees applied to LBP based features. The results showed that in comparison to other traditional schemes, the proposed classification system is faster. Luo et al. [12] for time-efficient steel surface defect classification used generalized completed Local Binary Pattern. The results showed that the method can be implemented in online monitoring system for hot-rolled steel strip.

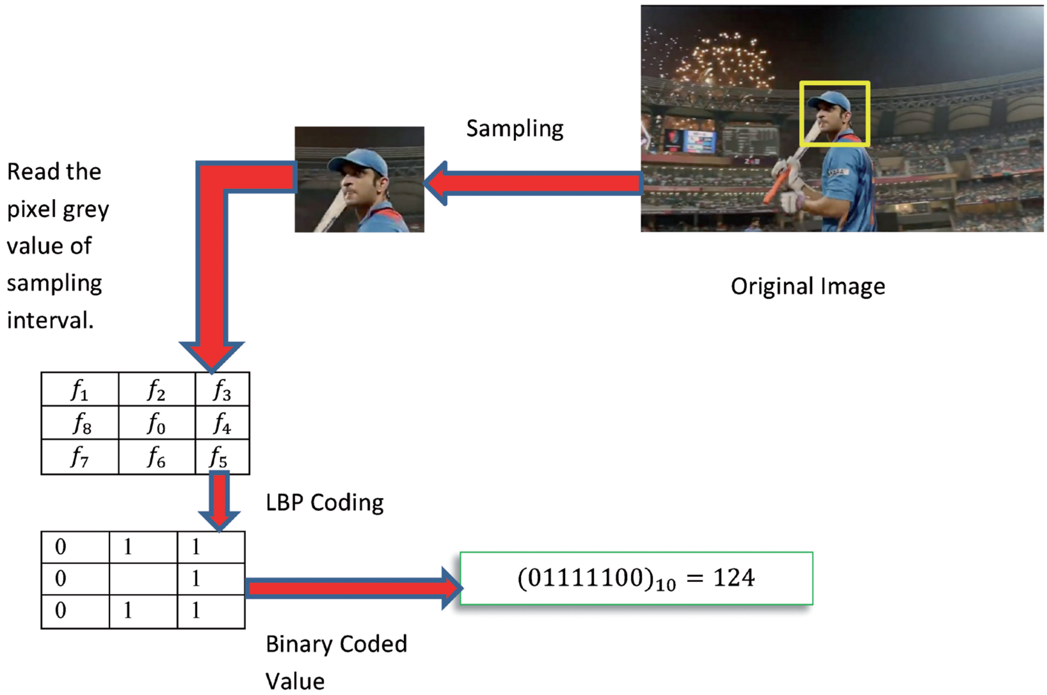

Fig. 4. Schematic diagram representing the working of Local Binary Operator.

3. Experimental procedure

Friction Stir Welding was carried out on 2 mm thick plate of commercial AA 6061-T6 and Ultrafine grained 1050 aluminium alloy plates [13]. The material used for Friction Stir Welding tool was tool steel whose shoulder geometry was concave shaped. During welding operation, constant load of 8000 KN was applied at a constant rotational speed of 800 rpm and varying traverse speed of 400, 600, 800, 1000 mm/min. Fig. 5a shows the dissimilar Friction Stir Welded joint obtained at tool rotational speed of 800 rpm and 600 mm/min while Fig. 5b shows the dissimilar Friction Stir Welded joint obtained at tool rotational speed of 800 rpm and tool traverse speed of 800 mm/min. Similarly, Fig. 6a shows the dissimilar Friction Stir Welded joint obtained at the tool rotational speed of 800 rpm and tool traverse speed of 400 mm/min, Fig. 6b shows the joint obtained at the tool rotational speed of 800 rpm and tool traverse speed of 600 mm/min, Fig. 6c shows the joint obtained at the tool rotational speed of 800 rpm and tool traverse speed of 800 mm/min, Fig. 6d shows the joint obtained at the tool rotational speed of 800 rpm and tool traverse speed of 1000 mm/min.

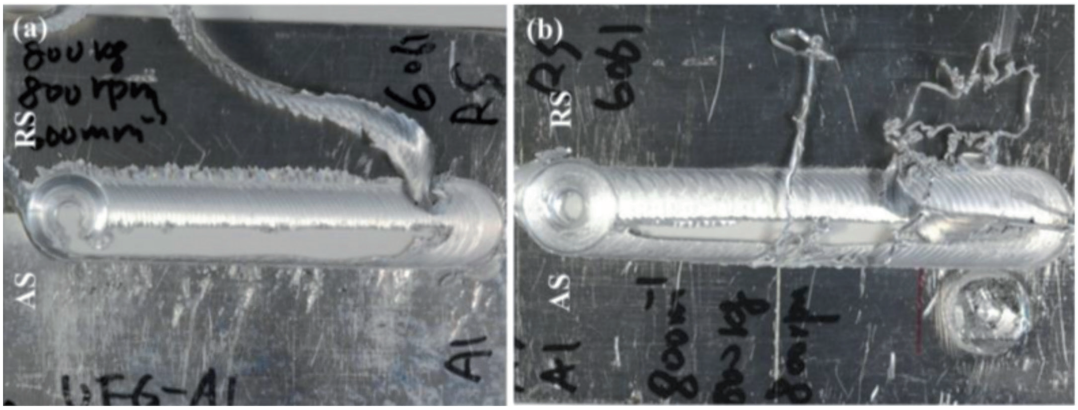

Fig. 5. Friction Stir Welded joints obtained at a constant tool rotational speed of 800 rpm and tool traverse speeds of 600 mm/min and 800 mm/min [13].

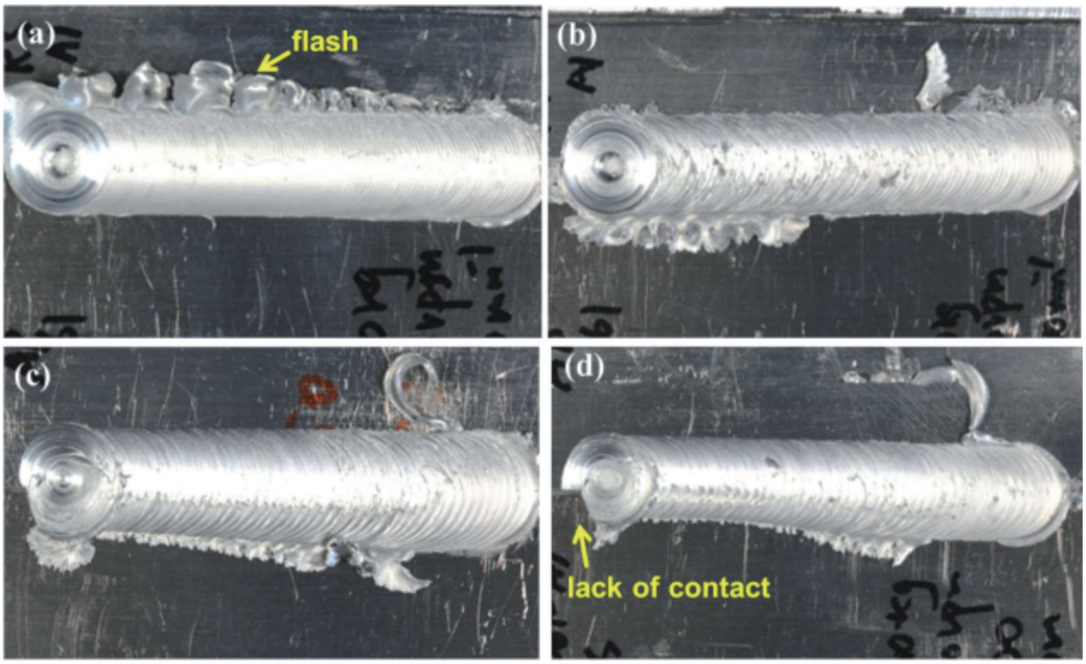

Fig. 6. Friction Stir Welded joints obtained at a constant rotational speed of 800 rpm and varying traverse speeds of 400, 600, 800, 1000 mm/min [13].

The obtained images were cropped and were subjected to various operations as shown in the Fig. 7.

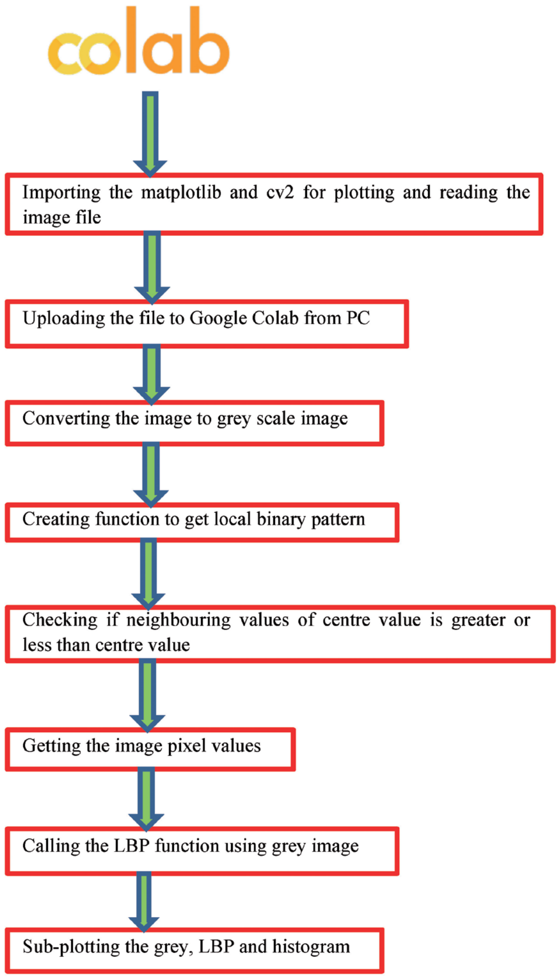

Fig. 7. Steps taken for obtaining the grey image, LBP and histogram of the Friction Stir Welded joint.

The Python programming was used for coding the algorithm and to carry out the modelling.

4. Results and discussions

The grey images, Local Binary Patterns and histograms of the Friction Stir Welded were obtained as shown in the Fig. 8-11. Local Binary Pattern can easily display the non-homogeneous nature of the image. So, various surface defects like flash formation, groovy edges and lack of contact present in Friction Stir Welded joints can be easily detected by implementing Local Binary Patterns.

From Fig. 8 and Fig. 9 it is observed that when the 6061-T6 plate is on retreating side while ultra-fine grained 1050 aluminium plate is on advancing side there is a lot of non-homogenity in the LBP converted image with few peak points in histogram. This non-homogenous nature represents improper mixing of both alloy materials.

From Fig. 10 and Fig. 11 it is observed that when the ultrafine grained 1050 aluminium plate is on retreating side and 6061-T6 plate is on advancing side the LBP converted images show more homogenous nature than Fig. 8 and Fig. 9 and also more peak values are observed in histograms comparison to the histograms of Fig. 8 and Fig. 9.

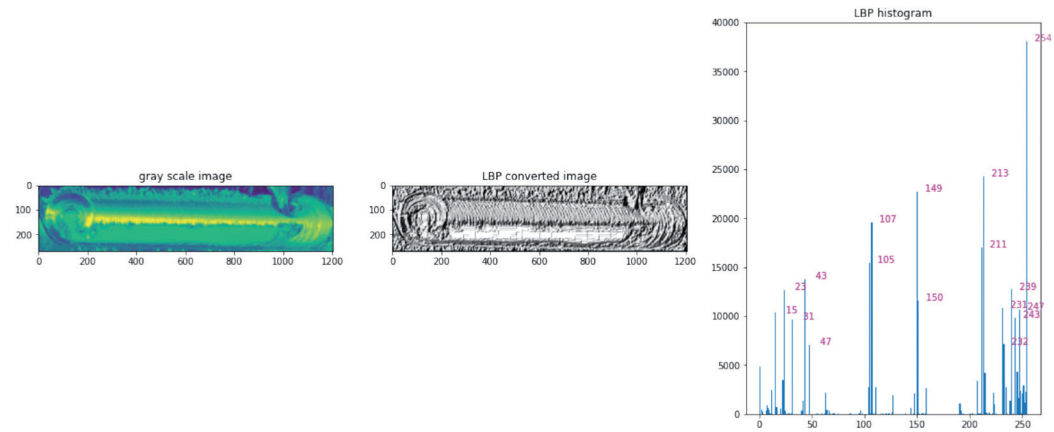

Fig. 8. Grey scale image, LBP Converted image and Histogram of Friction Stir Welded joint (6061-T6 on retreating side) obtained at the tool rotational speed of 800 rpm and tool traverse speed of 600 mm/min.

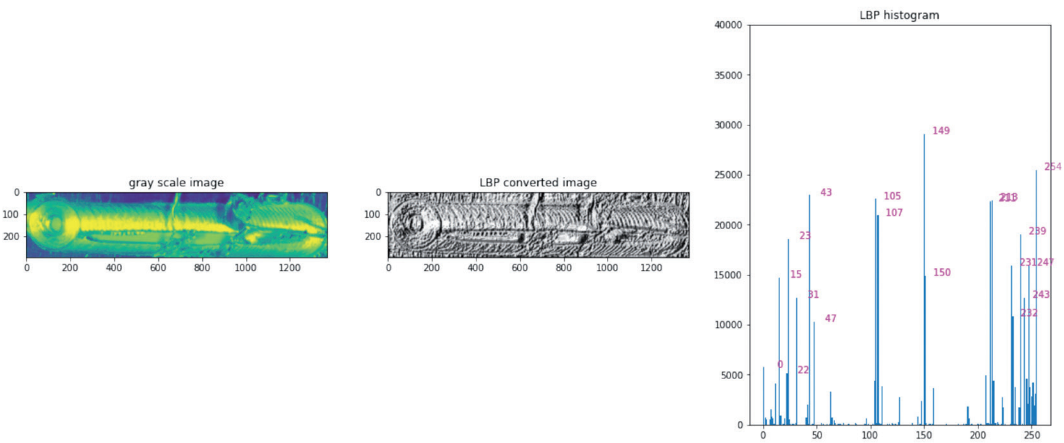

Fig. 9. Grey scale image, LBP Converted image and Histogram of Friction Stir Welded joint (6061-T6 on retreating side) obtained at the tool rotational speed of 800 rpm and tool traverse speed of 800 mm/min.

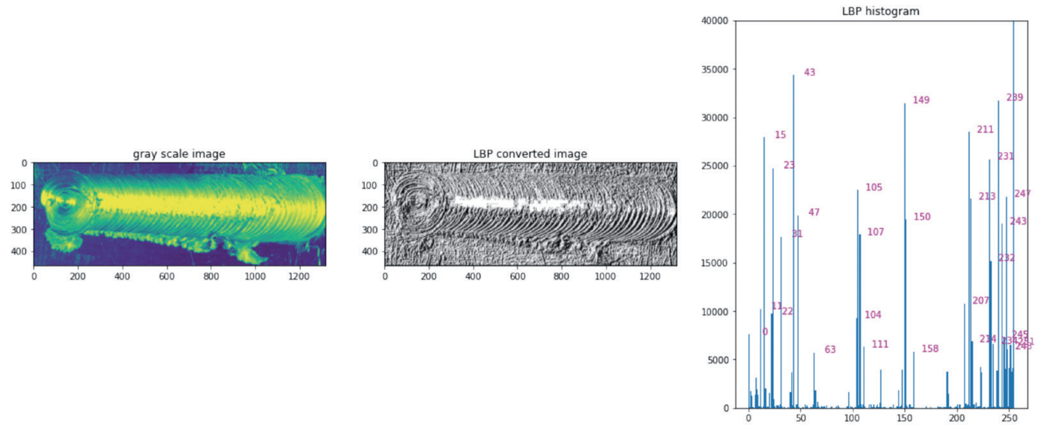

Fig. 8. Grey scale image, LBP Converted image and Histogram of Friction Stir Welded joint (6061-T6 on advancing side) obtained at the tool rotational speed of 800 rpm and tool traverse speed of 800 mm/min.

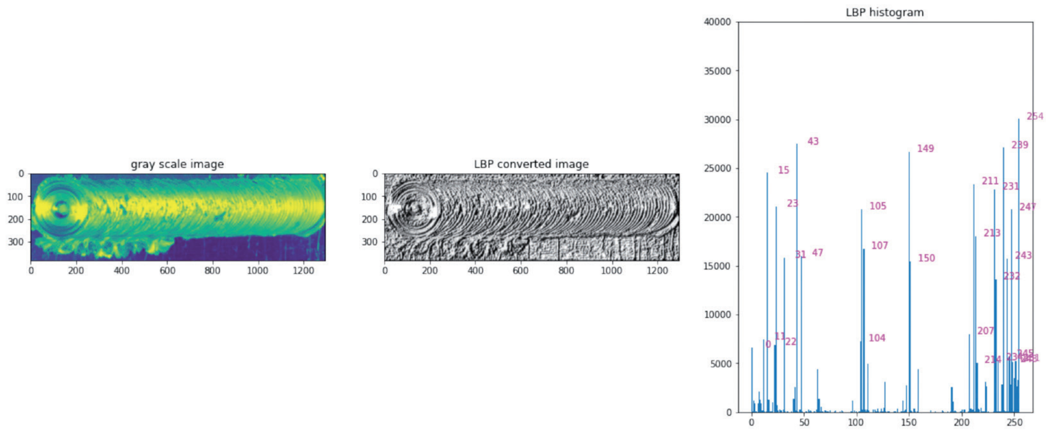

Fig. 8. Grey scale image, LBP Converted image and Histogram of Friction Stir Welded joint (6061-T6 on advancing side) obtained at the tool rotational speed of 800 rpm and tool traverse speed of 600 mm/min.

5. Conclusion

In this paper, Local Binary Pattern algorithm is proposed for evaluating the surface quality of Friction Stir Welded joints. Local Binary Pattern algorithm easily validated the detection of surface defects like lack of contact and flash formation in Friction Stir Welded joints. It is observed that when 6061-T6 is on retreating side then the LBP converted image shows more non-homogenous nature in comparison to arrangement when 6061-T6 is on advancing side also the former arrangement shows less peak values in histograms. So, it can be concluded that Local Binary Pattern (LBP) algorithm can be successfully implemented in visual inspection and in real-time monitoring.

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