Color Based Image Processing Techniques to Detect Oxide Film during Welding

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***Abstract*— From naval to aerospace and industry to household, everywhere the necessity of aluminum is felt. But oxide film can be formed on this metal and its alloys during casting or welding due to high affinity of aluminum for oxygen. This phenomenon can further lead to porosity which is a vital defect. Visual inspection is not sufficient due to different human constraints. So, many image processing techniques have been developed. For better welding, we propose here two useful and efficient techniques. Unlike most of the previous techniques, our proposed techniques are color based processing. In this manuscript, our main goal is to detect oxide film and we show that the task is successfully done by our methods.**

Keywords— Welding, Oxide film, Image processing

I. INTRODUCTION

Welding is a process that seams two metals or thermoplastics by melting the chunks using high temperature heat [1]. But during or after welding, several defects can be occurred due to operator, metal or environmental issue. The common defects in welding are: incomplete penetration, incomplete fusion, undercutting, slag inclusions, porosity, flux inclusions, cracks etc. [2]. In case of inclusion there can be two types of inclusion: solid or gaseous. For gaseous inclusion, oxide film is mostly responsible. When the environment oxygen comes near with the metal and then reacts with metal then oxide film is produced. This is a common instance for aluminum, silicon and chromium and their alloys [3]. This phenomenon can be occurred for both welding and casting of Aluminum (Al). The oxide film has high melting temperature than aluminum or aluminum alloys [4]. So, the weld pool needs also high temperature which can create hydrogen and carbon-dioxide and later this can be entrapped in the oxide film. So, this oxide film can boost up defects like porosity that is hydrogen-related [5]. As a result of this, different mechanical faults like static and cyclic strength reduction happen [6]. So this oxide film should be removed prior welding either in cleaning process or using laser or by chemical treatment. But to remove the film after welding or casting we first need to detect it either using eye or by image processing techniques. As industrial production and working speed is going high, intelligent techniques are more suitable for this detection purpose.

Besides doing welding, inspection of welding is also important. If machine is employed for this detection purpose, it will be more efficient and faster than human based inspection. For this purpose, we propose digital image processing techniques based on color images for assessment purpose. We mainly focus on oxide film detection on the welding surface for better welding and reducing defects. There are several methods to detect defections in welding both in material field and image processing field. In material field, radiographic inspection, magnetic particle inspection, liquid penetrant inspection, ultrasonic inspection are mainly used [7]. In image processing field, most of methods are machine learning based and works with radiographic images. In this sense, our method is different. We deploy two easy but efficient techniques to detect the oxide film upon the metal surface. As our methods are color based, so our main focus is to detect color. It is easier to detect color in hue, saturation, value (HSV) color space than red, green, blue (RGB) color space. Among our methods, one method is about defining HSV range [8] and other method is based on color histogram [9]. We will show that these two techniques are well-suited in the field of oxide film detection method.

The remainder of the paper is organized as follows: section II is about related works, in section III proposed methods are discussed, in section IV we discuss result and discussion and at last section V concludes our study.

II. RELATED WORKS

Several research works have been done and published in recent years. Some researchers worked on welding defects and others worked on steel structure defects. The recent progress and future research direction have been discussed by Sun et. al. [10]. According to [10], the defect detection method in steel industry can be several types: statistical, filtering, models and machine learning.

In [11], Yahia et. al. proposed an artificial neural network based welding defect detection method which can detect contours in radiographic images using edge detection method. Mekhalfa et. al. [12] used adaboost algorithm to classify four kinds of welding defects and claimed that their method is superior than support vector machine (SVM). Their proposed method is also based on radiographic image. Yuan et. al. [13] proposed another radiographic image based defect detection method in welding. In [13] they fused four types of data from four kinds of image processing techniques like edge extraction, analysis of wave, segmentation with dynamic threshold and weld district extraction. Recently, Tao et. al. [14] proposed a method which can detect and classify any surface defect. Their method is based on two networks: cascaded autoencoder (CASAE) and convolutional neural network (CNN). In [15], rather than image processing, optical spectrum based defect detection system for arc welding was proposed. Another ANN based method was proposed by Hasan et. al. [16]. The input image to their method is radiographic and the input features to the network are geometry based. A multi-sensor

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based defect detection method for disk laser welding was introduced in [17]. They detected three kinds of defects using CNN.

It is clear from the above research works that most of the proposed methods are based on radiographic image and machine learning methods. Their method is complex. To capture radiographic image of any object, extra equipment is necessary and machine learning methods are mostly computationally inefficient and dataset dependent. In contrast to this methods, our methods require normal RGB image which can be captured with normal camera and are fast. So, we tried our methods for color image while limiting our focus within detecting oxide film.

III. PROPOSED METHODS

We use two established methods [8,19] to extract the oxide film layer from the input welded image. Both methods are based on color.

A. Method 1

This method [8] is all about defining Hue, Saturation, Value (HSV) value range. In this method, we at first convert the input Red, Green, Blue (RGB) color space to HSV color space. Hue means a color, saturation means vibrancy or the amount of gray in a particular color, value means brightness or the intensity of that color. From Fig. 1, we can say that hue can be represented as angle on the above circle. The full circle is 360 degrees but hue can be normalized within 0-255 range where 0 means red. It is also clear from Fig. 1 that the lower the saturation value, the more gray, which means faded. In case of value, it is mainly the description of how much dark or white a certain color is. Like hue, the saturation and value have also the same range 0-255.

Table 1 describes the algorithm of our method. The first step is color space conversion. There are some reasons behind the conversion between HSV and RGB. HSV color model processes color as same as human eye can see. On other hand, RGB color spaces is the depiction of three basic or primary colors like how much red, green and blue exist [18]. So, it is easy for us to search a specific color in a certain image and create a mask for that. On second step, we detect the HSV values in the region of interest (ROI). After that, a mask has been created using the HSV value range. At last step, we bitwise AND the HSV converted image and the mask image to find the detected oxide film.

TABLE I. ALGORITHM OF METHOD 1

Step-1:	Load the image and change the color space from RGB to HSV
Step-2:	Detect the HSV values of oxide film area
Step-3:	Define the high and low HSV value range for the oxide film area
Step-4:	Create a mask image using the above range
Step-5:	Bitwise ANDing the HSV color space converted image and the mask image
Step-6:	Show the detected oxide film portion

B. Method 2

This method is based on color histogram proposed by Swain et. al. [19]. In [19], two methods were proposed called histogram intersection and histogram backprojection which are used for object identification and localization, respectively. We adopt the histogram backprojection method.

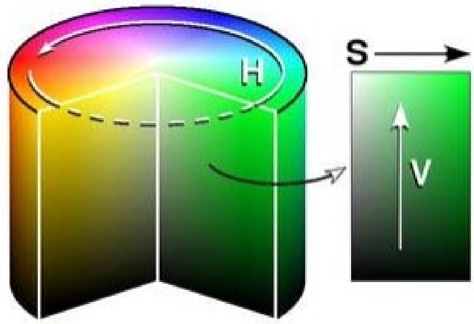


Fig. 1. Wheel of HSV color space [18].

The main concept behind this method is color histogram. The basic advantage of using color histogram is that it is mostly independent of occlusion and different view. In this method the core concept involves histogram backprojection. A ratio matrix is calculated for the target image (M) and ROI image (I) according to (1). Following this, the histogram ratio (R) is backprojected on the image as the probability of being the desired pixel. This is done by (2). After that, convolution is done with backprojected image (b) according to (3) where D^r is a disc (a mask) with radius r. Then a function called 'loc' at (4) is defined so that it can extract the peak intensity pixels from the convolved image.

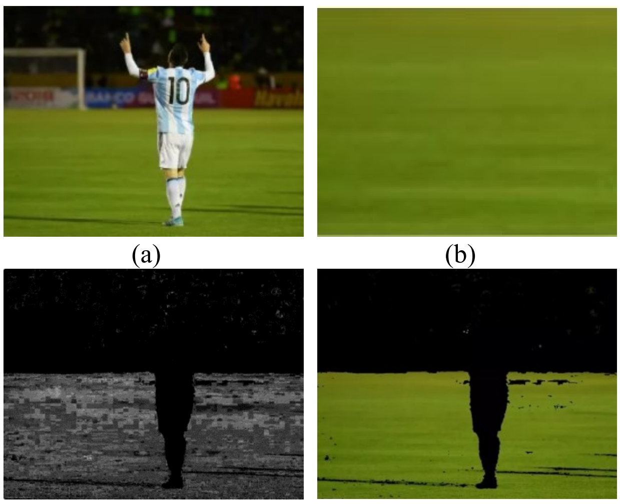
$$R_j = \frac{M_j}{I_j} \tag{1}$$

$$b_{x,y} = \min(R, 1) \tag{2}$$

$$b = D^r * b \tag{3}$$

$$(x_t, y_t) = loc(max_{x,y}\, b_{x,y}) \tag{4}$$

For example, from Fig. 2(a), we want to localize the ground from the picture with player. For this we need an ROI image that is Fig. 2 (b). When we create a histogram of backprojected image, the image will be like Fig. 2(c) where the brighter pixels are more probable to be our desired ground. After convolution and thresholding final image, Fig. 2(d) can be found.



(a) (b) (c) `(d)

Fig. 2. Example of object localization using histogram backprojection. (a) target image (b) ROI image (c) backprojected image (d) output image [19].

The algorithm of this method is described in table 2. In first step, color space conversion from RGB to HSV is done for both target image and ROI image. The reason behind this been was described earlier. In the second step, color histogram of both images is calculated. Then, ratio of these two histograms is calculated according to (2) and backproject it to the image. At step 4, we create a disc shape to convolve this with the backprojected image and the convolution is done in the following step. In steps 6, 7, and 8, convolved image is thresholded and bitwise ANDing with the target image. Thus the oxide film is detected.

TABLE II. ALGORITHM OF METHOD 2

Step–1:	Load the target and ROI image and RGB to HSV color conversion
Step-2:	Calculate the color histogram of above two image
Step-3:	Calculate the ratio of histograms ($\frac{\text{ROI image}}{\text{Target image}}$) and backproject it.
Step-4:	Create a morphological shape (Disc)
Step-5:	Convolve the backprojected image with the above defined shape
Step-6:	Thresholding the convolved image
Step-7:	Bitwise ANDing the target image and thresholded image
Step-8:	Show the detected oxide film portion

IV. RESULT AND DISCUSSION

Fig. 3 describes a welding image. The greenish color indicates an oxide film. We use this image as our input image for both methods. We use windows 10 64 bit as operating system (OS), 8 GB RAM and core-i7 processor. For simulation purpose, we use open source distribution Anaconda and Jupyter notebook integrated development environment (IDE) as our programming environment. We used openCV and numpy with python as programming language.

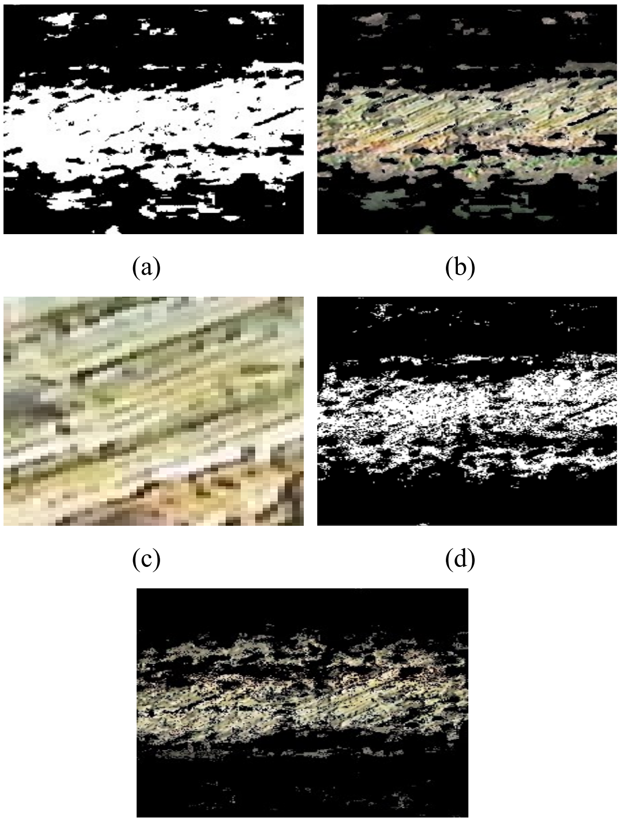
Here, our target is to detect the oxide film from the input image that is the greenish part, marked as red box in Fig. 3. For this purpose, we use two color based methods.

Fig. 3. A welded metal image with oxide film (red marked) on surface.

As we use openCV, we have to change the color space format from BGR (the default format for openCV) to HSV. For method 1, we define the HSV range. Our defined range was from (5,20,60) to (63,255,255). The mask image is created using this range which is as shown in Fig. 4(a). Then we bitwiseAND the mask with the input image and find image of Fig. 4(b) as our detected oxide film.

In our another method, called method 2 we use the same input image. This method is based on color histogram and histogram back-projection. We use the greenish part as our region of interest image as shown in Fig. 4(c). The back-projected image of ROI on the target image is shown in Fig. 4(d). In this figure, the brighter pixels are higher probable area for oxide film. Then as previous method, we bitwiseAND the convolved back-projected image and target image. To get the final oxide film detected image as shown in Fig. 4(e), a threshold limit 50 is used.

We also calculate the program execution time for both methods. From table 3, we can see that method 1 is faster than method 2.



(a) (b) (c) (d) (e)

Fig. 4. (a) Mask image created for method 1 (b) Detected oxide film part using method 1 (c) ROI image used for method 2 (d) Histogram backprojected image of ROI for method 2 (e) Detected oxide film part using method 2.

TABLE III. EXECUTION TIME COMPARISON BETWEEN TWO METHODS.

Method	Execution time (second)
Method-1	0.00299
Method-2	0.01396

From above output images, we can confirm that our methods are fit for processing color image of oxide film for better welding. Unlike any other methods, without using radiographic images we can process directly color images within short time. Though our method sometimes can fail due to brightness and color variation, it can be overcome by trained machine learning methods on diverse color datasets. But due to lack of color dataset on oxide film, we cannot use machine learning methods.

V. CONCLUSION

In this manuscript, our main target was to extract the oxide film portion from the welded metal surface. We successfully did that by deploying two color based methods. In future, we will try to develop efficient machine learning based methods that can detect other defects also besides oxide film in color images.

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