A Contrast Adjustment Thresholding Method for Surface Defect Detection based on Mesoscopy

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Abstract — Titanium coated surfaces are prone to tiny defects such as very small cracks which are not easily observable by the naked eye or optical microscopy. In this study, two new thresholding methods, namely, Contrast Adjusted Otsu’s Method and Contrast Adjusted Median-Based Otsu’s Method, are proposed for automated defect detection system for titanium-coated aluminum surfaces. The two proposed methods were compared with four existing thresholding techniques in terms of accuracy and speed of defect detections for images of 700, 900 and 1000 dpi obtained using high resolution scanning. Experimental results have shown that the contrast-adjusting methods proposed have performance similar to Minimum Error Thresholding and is generally better than Otsu’s Method.

Index Terms—Mesoscopy, High resolution scanning, Coated Surface Inspection, Defect Detection, Image processing, Image analysis

1. INTRODUCTION

INSPECTION and detection of defects on coated surfaces are essential steps in the preliminary assessment of coating processes. Defects that are identified can then be modified to satisfy pre-determined quality requirements or in cases of severe defects, the coatings would be rejected. In addition, close inspection of physical abnormalities in the coating would provide an understanding into the possible mechanism of defects formation, and the knowledge gained can then be implemented into improvements of the coating process.

Several nondestructive techniques (NDT) are available for detecting defects on coated surface. Common techniques employ the use of a fluorescent material on the coating layer. Defects can be located and measured based on the fluorescence emission [1].

Other techniques include, mapping surface potentials using electrostatic methods [2], characterization of film failures by bismuth electrodeposition [3], and interfacial defects detection using infrared thermography [1, 4]. Although these methods can be used to detect defects in coating, they require specific procedures and set up which may not be easily be integrated into the assembly lines for a production environment.

In a production environment, manufacturers usually adopt visual inspection techniques to detect product defects along the assembly or production line. These inspection methods use image processing and analysis to determine non-conformity of products based on pre-determined criteria, and have been successfully used to detect surface defects on LCD screens [5], ceramic and tiles [6], steel [7-9] and textiles [10, 11]. Visual inspection techniques were also used to evaluate non-uniformity on surfaces of bottle caps [12] and detect defects on solar modules [13].

Image acquisition is an important process in visual inspection. Traditionally, optical microscopy are used for surface inspection to capture high-resolution images, although it has limited field of view and is more suitable for small samples [8]. In contrast, conventional photography can capture the subject as a whole due to its large field of view, however the resolutions of the images obtained are much lower as compared to images from microscopy. A technique known as mesoscopy aims to combine the large field of view of traditional photography with the high-resolution capabilities of optical microscopy. Mesoscopic apparatus and techniques have been developed to capture large bulk volumes of materials. Past studies have used this technique to digitize cultural paintings [14], analyze textured patterns on Korean paper and defect detection on LCD screens [15]. Mesoscopy have also been used with spectroscopic technique to reconstruct spectral reflectance of mineral pigments on Japanese paintings [16].

In manufacturing scenario, high resolution image acquisition system have been used to detect defects on production samples, such as on steel surfaces as small as 2.75 μm per pixels [8]. These defects are usually miniscule in size, requiring a very high-resolution image of the surface for analysis. An important process in image analysis is thresholding, which reduces the color or grayscale image into binary. Thresholding is the simplest technique to segment an image into regions having common properties. It creates black and white binary images from grayscale or color images by transforming the intensity of all pixels to single values of either one or zero. Tresholding reduces the intensity of pixels.
below a certain value to zero (black) while pixels above the designated value are given one (white). Thresholding is useful for rapid evaluation on image segmentation due to its simplicity and fast processing speed.

Otsu’s Method of Thresholding [17] is a popular technique for image thresholding, and has been used as the default method for thresholding in software such as MATLAB. Kittler and Illingworth have developed a Minimum Error Thresholding (MET) method [18], which has been proved to be superior to other methods of thresholding in a survey of 40 different methods [19]. Modified approaches using these methods were also proposed, in which the median of the image histogram data are used instead of the mean. The median extension of the original Otsu’s method and MET were found to work better than their original counterpart for images with highly skewed and heavy-tailed color distribution [20].

In this paper, a Contrast-Adjusted Otsu’s Method and Contrast-Adjusted Median Based Otsu’s Method were developed to distinguish coated and uncoated regions of metal specimens by applying image-specific contrast adjustments and then utilising Otsu’s Method and Median-Based Otsu’s Method for the thresholding process. The thresholding will classify the segments in the image into coated and uncoated regions. The performance of the two proposed methods is then compared with Otsu’s Method, Median-Based Otsu’s Method, MET and the Median-Based MET.

II. METHODOLOGY AND TESTING

A. Image Acquisition and Preparation

In this study, images of titanium coated aluminum disc specimens are captured at high resolutions of 700, 900 and 1000 dpi using a line sensor camera of high spatial accuracy and color fidelity. The image size was constrained to 1000 x 1000 pixels. Thus, one pixel is approximately equivalent to 36, 28, and 25 μm for 700, 900 and 1000 dpi resolutions, respectively. Fig. 1 shows the images of the sample captured at the different resolutions and their respective grayscale image.

B. Image Thresholding and Binarization

For defect detection, the color image is first converted to grayscale and a thresholding technique is then utilized to obtain the corresponding black and white image. It is expected that the defect would be highlighted in a different color (white) as compared to the rest of the coating (black).

The grayscale image can be expressed in \(L\) gray levels \([1,2,\ldots,L]\). The number of points with gray level at \(j\) is denoted by \(m_j\) and the entire number of points can be expressed as \(M = m_1 + m_2 + \ldots + m_L\). The histogram of this gray-level is regarded as an occurrence distribution of probability, which can be expressed as:

\[
p(k) = \frac{m_k}{M}, \quad p(k) \geq 0, \sum_{k=1}^{L} p(k) = 1
\] (1)

The threshold, \(t\) is the gray level that divides the image into two classes \(C_0\) and \(C_1\), i.e. foreground and background. The class \(C_0\) represents pixels within levels \([1,2,\ldots,l]\) and \(C_1\) denotes pixels within level \([l+1,\ldots,L]\).

1) Otsu’s Method for Thresholding

The Otsu’s Method finds the optimum threshold, \(t^*\) by maximizing the between class variance [28],

\[
t^* = \arg \max_{t \in [1,L]} \sigma^2_B
\] (2)

Where the between-class variance, \(\sigma^2_B\) is given by,

\[
\sigma^2_B = \omega_0 (\mu_0 - \mu)\] + \omega_1 (\mu_1 - \mu)^2
\] (3)

Where the occurrence of probabilities of the two classes, \(\omega_0\) and \(\omega_1\), the average of the two classes, \(\mu_0\) and \(\mu_1\), the total average, \(\mu\), the foreground and the background class variance, \(\sigma^2_0\) and \(\sigma^2_1\), can be expressed respectively as:

\[
\omega_0(t) = \sum_{k=1}^{l} p(k)
\] (4)

\[
\omega_1(t) = 1 - \omega_0(t) = \sum_{k=l+1}^{L} p(k)
\] (5)

\[
\mu_0(t) = \frac{\sum_{k=1}^{l} k \cdot p(k)}{\omega_0(t)} = \frac{1}{\omega_0(t)} \sum_{k=1}^{l} k \cdot p(k)
\] (6)

\[
\mu_1(t) = \frac{\sum_{k=l+1}^{L} k \cdot p(k)}{\omega_1(t)} = \frac{1}{1-\omega_0(t)} \sum_{k=l+1}^{L} k \cdot p(k)
\] (7)

\[
\mu(t) = \frac{\sum_{k=1}^{L} k \cdot p(k)}{L}
\] (8)

\[
\sigma^2_0(t) = \sum_{k=1}^{L} (k - \mu_0(k))^2 \cdot p(k)
\] (9)

\[
\sigma^2_1(t) = \sum_{k=l+1}^{L} (k - \mu_1(k))^2 \cdot p(k)
\] (10)

\[
\sigma^2_B = \sum_{k=1}^{l} (k - \mu)^2 \cdot p(k)
\] (11)
It was found that maximizing between class variance $\sigma_b^2$ is similar to minimizing within class variance, $\sigma_w^2$ or the mean square error between the resultant binary image and the original grayscale image based on a simple relationship [20]:

$$\sigma_b^2 + \sigma_w^2 = \sigma_t^2$$  \hspace{1cm} (12)

And the within class variance, $\sigma_w^2$ is given by:

$$\sigma_w^2 = \omega_b(t)\sigma_0^2 + \omega_l(t)\sigma_1^2$$  \hspace{1cm} (13)

Therefore, the threshold $t^*$ can also be found by minimizing within the class variance:

$$t^* = \underset{t \in [0, L]}{\text{argmin}} \sigma_w^2 = \underset{t \in [0, L]}{\text{argmin}} \{\omega_b(t)\sigma_0^2 + \omega_l(t)\sigma_1^2\}$$  \hspace{1cm} (14)

A median based extension of the Otsu’s Thresholding Method has been shown to be more robust in the determination of threshold, especially when the distribution is skewed and heavy-tailed [20]. In this study, the median based Otsu’s method is applied by using median values instead of mean values of the grayscale level distribution, and finding the mean absolute deviation from the median to estimate the dispersion instead of the variance, as proposed by Xue and Titterington [20]. The mean absolute deviation is denoted as MAD.

The threshold is selected by:

$$t^* = \underset{t \in [0, L]}{\text{argmin}} \{\omega_b(MAD_0(t)) + \omega_l(MAD_1(t))\}$$  \hspace{1cm} (15)

Where MAD$_0$ and MAD$_1$, are the mean absolute deviations from the median for the foreground and background class, $C_0$ and $C_1$, giving:

$$MAD_0(t) = \sum_{k=0}^{L} \frac{p(k)}{\omega_b(t)} |k - m_0(t)|$$  \hspace{1cm} (16)

$$MAD_1(t) = \sum_{k=1}^{L} \frac{p(k)}{\omega_l(t)} |k - m_2(t)|$$  \hspace{1cm} (17)

where $m_1$ and $m_2$ are the sample median for $C_0$ and $C_1$ respectively.

3) Minimum Error Thresholding (MET) Method

Another method for determining the threshold is the Kittler and Illingworth’s Minimum Error Thresholding (MET) [18]. This method optimizes the average pixel classification error rate directly, and has been found to be the best thresholding technique for NDT images [19].

The threshold is selected by:

$$t^* = \underset{t \in [0, L]}{\text{argmin}} \{\omega_b(t)\log \frac{\sigma_0(t)}{\omega_b(t)} + \omega_l(t)\log \frac{\sigma_1(t)}{\omega_l(t)}\}$$  \hspace{1cm} (18)

4) Median-Based Extension of MET Method

Similar to Otsu’s Method, the median-based MET is regarded to be more robust in finding the optimum threshold in the presence of skew and heavy-tail in the gray level distribution [20]. Thus for this study, the median based MET as proposed by Xue and Titterington [20] was utilised. The threshold for median-based MET is selected using similar set of rule for finding the optimum threshold using MET, substituting the standard deviation of a particular class with the mean absolute deviation from the class median:

$$t^* = \underset{t \in [0, L]}{\text{argmin}} \{\omega_b(t)\log \frac{MAD_0(t)}{\omega_b(t)} + \omega_l(t)\log \frac{MAD_1(t)}{\omega_l(t)}\}$$  \hspace{1cm} (19)

C. Proposed Thresholding Methods

1) Contrast Adjusted Otsu’s Method

In this study, a thresholding method is proposed that includes a contrast adjustment routine utilising Otsu’s thresholding (Eqn. 14) to calculate the maximum cutoff value for image contrast stretching, and then to apply the same Otsu’s thresholding method to calculate the threshold of the contrast enhanced grayscale image for conversion to a black and white image.

Fig. 2(a) Original Image Histogram and 2(b) histogram of an image that has undergone contrast adjustment subroutine with the background removed

As Otsu’s method calculate the threshold to divide the image into two classes according to the grey levels, using the threshold value as the maximum cutoff value for image contrast stretching yields a unimodal histogram, as shown in Fig. 2(b), indicating that the image is uniform. The contrast change is shown.
adjustment was made by mapping the foreground class \([1, 2... r]\) to the original range of the image \([1, 2... L]\). This can be expressed in pseudocode as:

\[
\begin{align*}
\text{GrayscaleImage } I & \text{ [image.rows, image.columns]; } \\
\text{MaximumGrayLevel } L & = 255; \\
\text{Threshold } t & = \text{Otsu\_Method}(I); //from \text{Equation 14} \\
& \text{for } r = 1: \text{image.rows} \\
& \quad \text{for } c = 1: \text{image.columns} \\
& \quad \quad I[r, c] = (I[r, c] / t) * L; \\
& \quad \text{end} \\
& \text{end} \\
\end{align*}
\]

The resultant image is then converted to a binary representation, utilising the threshold value calculated by Otsu’s method (Eqn. 14). As Otsu’s method assume that the image histogram is bimodal, applying it on the contrast enhanced image will split the unimodal distribution into two [18]. This characteristics enables the contrast adjusted method to be more accurate, as the defects on the coated material are categorized along with the background of the image resulting to a simpler image for segmentation.

![Flow Diagram of the Image Processing and Analysis](Image)

Fig. 3 Flow Diagram of the Image Processing and Analysis

2) **Contrast Adjusted Median Based Otsu Method**

Similarly, for the second proposed method, the contrast adjustment is made by mapping the foreground class to the original range of the image as described in the pseudocode. Eqn. 15 is used to determine the threshold, as described in Median-Based Otsu’s Method. This approach is not applicable to the MET method and its median-based extension, as the criterion for MET will fail to find any local minima to compute the optimum threshold as the distribution has only one mode.

Utilisations of the thresholding methods are incorporated in the steps for processing and analysis of the image, as shown in Fig. 3. These 6 different methods converts the grayscale images into their respective binary representation (black and white). In a binary image, a pixel has either the value of 1 (white) or 0 (black). The pixels are converted to 1 if their gray levels are \(> t^*\) and are converted to 0 if the gray levels \(\leq t^*\). Since the coating is assumed to be uniform, binarization will completely represent coated surface to black. Defects will be highlighted since their pixels representation will be converted to 1 (white) in the binarization process.

### D. Defect Detection and Analysis

1) **Defect Filtering and Recording**

After binarization, the area containing defects are distinguishable, as the defects will have the same pixel values as the white background. A flood-fill algorithm [21] is used to find connected components with 8-connected neighborhood. The connected components are then selected according to its size, \(A_k\) based on a pre-determined minimum size, \(i_{\text{min}}\) and maximum size, \(i_{\text{max}}\) value to account for noises and effects of uneven light source.

\[
i_{\text{min}} < A_k < i_{\text{max}} \quad (20)
\]

The value of \(i_{\text{min}}\) is set at 2, while \(i_{\text{max}}\) is set at 500 for the 700 and 900 dpi images. This configuration indicates that the smallest defects detectable is 3 pixels wide, which is approximately 100 \(\mu m\) for 700 dpi and 85 \(\mu m\) for 900 dpi. For the 1000 dpi image, the \(i_{\text{min}}\) is set at 3, indicating the smallest defect detection resolution of 4 pixels, equivalent to 100 \(\mu m\).

The area of each defects are also calculated. The area of one defect is expressed as \(A_k\), where \(k = 1, 2, ..., N\) and \(N\) is the number of defects detected based on the number of connected components that agree with the set of required conditions (20). For each \(A_k\), the area is calculated based on the number of pixels, \(m\), for the corresponding area of defects, \(A_k\), such that \(A_k = a_1 + a_2 + ... + a_m\).

The centroid of the defects can be expressed as \(C_k (x, y)\), where \(k = 1, 2, ..., N\), and \(N\) is the number of the defects detected based on the number of connected components that agree with the condition set in \(A\). Each \(C_k\) is calculated based on the centroid of pixels \(m\) for the corresponding area of defects \(A_k\). The centroid of the defect can be calculated using:
Since the processed effects in the original image... 

As, an adjustment [proposed] 

Median-Based Otsu – Contrast Adjustment [proposed] 
Minimum Error Thresholding (MET) [18] 

Median-Based MET [20] 

C_{kx} = \sum c_m \cdot \delta_{m} \cdot A_k 
C_{ky} = \sum c_m \cdot \delta_{m} \cdot A_k 

Where C_{kx} is the x-coordinate and C_{ky} is the y-coordinate of the defects.

The centroid value indicates the position of the defects. In this study, we mark the location of defects in the original image by red crosses having the size of 3 pixels. Since the processed image and the original image have the same sizes, the position of the defects in the original image directly correlate with the binary image.

2) Sample Surface Area Estimation

The surface area is calculated to determine the area of defects with respect to the coated sample surface area. In this study, an image segmentation technique is used for edge determination using the Sobel operator [22]. The edge detection was applied on the grayscale image, which resulted in a binary gradient mask that exhibited a stark contrast between the sample and the background, which can then be segmented effectively. The surface area of the coated samples were computed based on the filled binary gradient mask as it represent the surface of the sample, given by $A_T$.

3) Calculation of Defect Percentage

The percentage of the sum of defect area as compared to the total size of the samples is calculated to determine the extent of defects detectable using the methods proposed. The total defect surface area, $A_D$ is represented by the summation of surface areas of $A_k$ for N number of detected defects, denoted as:

$$A_D = A_1 + A_2 + ... A_N = \sum_{k=1}^{N} A_k$$

Thus, the percentage of defect, $P_d$ for each image can be calculated by:

$$P_d = \frac{\sum_{k=1}^{N} A_k}{A_T} \times 100\%$$

<table>
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<th>Thresholding Method</th>
<th>Grey Level Threshold T*</th>
<th>Number of Defects Detected</th>
<th>Total Defect Surface Area (Pixels)</th>
<th>Percentage of Defects (%)</th>
<th>Time Taken (seconds)</th>
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In the experiments, the proposed method is implemented in MATLAB R2013a and ran on an Intel® Core™ i7-3770 CPU 3.40 GHz processor with a 16 GB RAM and a Windows 7 platform. The images obtained from the mesoscopic image capture system were processed in accordance to the steps shown in Fig. 3. Comparison were made between the 6 thresholding methods on their ability and efficiency in detecting defects in the coated sample.

Table 1 shows the threshold level obtained from the image using the six thresholding methods, the total number of defects, the percentage of defects, and the total time taken to complete the detection tasks for 700 dpi images. Similarly, Table 2 and Table 3 shows the summary of results for 900 and 1000 dpi images respectively. Generally it was observed that higher resolution images yield the largest number of defects. The median-based methods generally detected more defects than their non-median counterparts, except for the case of applying median-based Minimum Error Thresholding on the 700 dpi image. However, this high defect detection ability required more time to complete, as the data would need to be rearranged to obtain the median value. It can also be observed that for the cases of both contrast-adjusted and original Otsu’s Methods, higher resolution does not always indicate higher count of defects. Fig. 4 shows a segment of the results from the samples using 6 different algorithms for 1000 dpi resolution.

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III. EXPERIMENT AND RESULTS

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Methods, higher resolution does not always indicate higher count of defects. Fig. 4 shows a segment of the results from the samples using 6 different algorithms for 1000 dpi resolution.
Fig. 7 Region C at (i) 700 dpi, (ii) 900 dpi, (iii) 1000 dpi and (iv) optical microscope at 50X magnification

IV. DISCUSSIONS

To verify the accuracy of defect detection, the results were compared with images obtained using optical microscopy. 3 regions on the sample that contains large defects were identified using a light optical microscope and is compared alongside their corresponding images obtained at 700, 900 and 1000 dpi. These regions, denoted as A, B and C as shown in Fig.5-7, were chosen for having defects larger than 50 μm. It can be shown that as the resolution of the image is increased, the defects are increasingly visible.

The three regions were also used to compare the accuracy and speed of the 6 thresholding methods in detecting defects. Fig 8 summarized the comparison and the results are summarized in Fig. 8. The methods has been arranged to rank the methods according to its ability to detect both region in the shortest time.

Since median-based methods involved determination of the median, thresholding methods of Median Based Otsu, Contrast Adjusted Median Based Otsu and Median Based MET were found to take the longest times for defect detections. For low-resolution images, the computation time would not be apparent, however for high-resolution images, the difference in efficiency would be noticeable. The computation can be improved by pre-arrangement of the intensity values prior to calculation of the means [20]. Furthermore, median based methods had lower threshold values which may increase the rate of false detection. Such occurrence may be due to effects of lighting and shadows in the samples. As can be seen in Fig 4, the effect of shadows in the lower region of the samples are identified as defects by the median-based thresholding methods.

The contrast adjusted methods proposed in this study shows consistent defect detection performance for the three image resolutions of 700, 900 and 1000 dpi. Both contrast adjusted Otsu and Median-based Otsu detected the highest number of defects as compared to the other thresholding methods in the same category. This suggests that the contrast-adjusted method can be a useful complimentary method to threshold images with bimodal grey level distribution. The method is similar in its efficiency as compared to Minimum Error Thresholding, and is generally better than the Otsu’s Method currently employed in software packages such as MATLAB.

V. CONCLUSIONS AND FUTURE WORKS

Two thresholding methods, Contrast-Adjusted Otsu’s Method and Contrast-Adjusted Median-Based Otsu’s Method were developed for detection of defects on high resolution images of titanium coated aluminum specimens. The performance of the two methods were compared to four existing thresholding methods. It was found that the proposed methods were able to correctly detect the highest number of predetermined defects in different sets of image resolution and performed better than Minimum Error Thresholding and Otsu’s Method. However, the lighting and shadow effects were found to influence the accuracy of defect detection. Thus, it is recommended that a fuzzy clustering algorithm or wavelet analysis is incorporated into the image pre-processing to distinguish affected regions and reduce false detections.

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