On the Pretreatment Process for the Object Extraction in Color Image of Wear Debris

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ABSTRACT: In this article, some pretreatment techniques used for the object extraction in color debris image were introduced, which was an important basic work in ferrographic technology to identify precisely wear debris produced by friction and wear from the relative motions between machine parts. These pretreatment techniques included image enhancement, image segmentation, filling pore, image erosion, and recognition of wear debris. The results showed that these methods were feasible and effective, which could be applied to extract object of color wear debris image successfully and precisely. It provided an important basis for the recognition technique of wear debris which was related to monitoring machine operation state and fault diagnosis.


Key words: wear debris; pretreatment; color image; identification

I. INTRODUCTION

As one of the most effective methods for machine condition monitoring and fault diagnosis, ferrographic technique has been playing an important role (Beddow et al., 1980; Bowen and Westcott, 1982; Kirk et al., 1995; Yang, 2002). However, with the fast development of modern industry, the traditional ferrography could not satisfy the real demands because of its subjectivity, low precision, and time consuming (Peng and Kirk, 1998). Therefore, the development of automatic ferrography is essential for overcoming the current technique defects (Peng and Kirk, 1999). Fortunately, with the development of image acquisition and analysis techniques in recent years, automatic analysis of the wear particles is possible and developed rapidly by studying image processing and artificial intelligence techniques (Russ, 1990; Peng et al., 1997; Podsiadlo and Stachowiak, 1997). In our previous study, it was studied the application of gray relational grade identification in the identification of black and white images of wear debris (Hu et al., 2004). However, under the conditions of actual machine operation, some wear particles were usually colored because of the color of some alloys themselves or from the high temperature induced by friction. Because there is few characteristic information of debris in grey debris image, this system based on color debris image is developed to increase reliability and veracity of debris identification in this article. A kind of system namely DAIAS (Debris automatic Identification and Analysis System) was developed to overcome some shortcomings of traditional ferrography based on image enhancement, image segmentation, filling pore, erosion, and marking of wear debris etc. In this system, object extraction is an essential step, which is a precondition and base of identification and analysis of debris. Figure 1 shows the whole process of pretreatment technique.

II. IMAGE ENHANCEMENT

During the image processing, noise often corrupts original debris images which is from the imaging equipment and exterior environment interference. In the case of noise, the uniformity and continuity of color are likely to be augmented or lessened suddenly, which can lead to the illusive debris edges or some noise dots isolated.

Under some conditions, it is difficult to understand the exact physical course and mathematics model related to decrease quality of image. However, some reasons that give rise to corrupt image can be evaluated (Sun, 2004). For the original debris image, the reasons of the decrease of image quality are from random noise and impulse noise. Image enhancement is to improve the image effect visually using a series of techniques, or to apply certain transformations to an input image in order to obtain more detailed or less noisy output image. The task of image enhancement is a difficult one considering the fact that there is no general unifying theory of image enhancement currently, because there is no general standard of image quality that can serve as a design criterion for an image enhancement processor. Thus, in order to stand out object information and attenuate noise, the appropriate method of image enhancement should be selected to treat the debris image.
In general, good result of processing can be obtained by applying several techniques altogether. Therefore, aiming at main noise of debris image, both methods of weighted mean filter and adaptive median filter are selected to control noise while preserving the integrity of edges and detailed information, and then obtain satisfactory results.

A. Weighted Mean Filter. Weighted mean filtering is a spatial image enhancement method. It can be viewed as replacing the value of every pixel in the image with a new value which comes from the convolution operation of neighborhood window in debris image and weighted mean template. In the present article, the weighted mean template with a window size $3 \times 3$ was selected. Figures 2a and 2b shows the structure and coordinate of template, respectively. As shown in Figure 2a, the central coefficient is the largest, and the other coefficients become smaller when the distance becomes larger between the central position and neighbor position. We pay more attention to the central position to reduce blur of smooth processing. The size $3 \times 3$ of neighbor window center at the pixel point $(x, y)$, that is the processing point, was shown as follows.

$$
\begin{array}{ccc}
(x-1, y-1) & (x, y+1) & (x+1, y+1) \\
(x-1, y) & (x, y) & (x+1, y) \\
(x-1, y+1) & (x, y-1) & (x+1, y-1)
\end{array}
$$

The color image of debris is true colors (32 bits) in this study. The CIE (Commission Internationale de l’Eclairage) color system specifies colors in terms of the relative saturation of three primary color, i.e., R(red), G(green), B(blue) (Hsiao and Tsai, 2004). It is noted that the saturation of each of these primary colors can be specified within the range of 0 (none) to 255 (highly saturated). According to this theory, the color “white” is composed of RGB with the saturation of each of the individual colors set to 255. Similarly, the color “black” can be obtained by specifying the saturation parameters of each of the three primary colors as 0. Therefore, the color image of debris can be fully described in terms of parameters RGB within the range of 0–255. The value of pixel $(i,j)$ in color image of debris can be defined as $R(x,y)$, $G(x,y)$, $B(x,y)$. Consider the following weighted mean filter:

$$
R(x, y) = \frac{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j) R(x+i,y+j)}{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j)} \quad (1 \leq x \leq M-1, \quad 1 \leq y \leq N-1) \quad (1)
$$

$$
G(x, y) = \frac{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j) G(x+i,y+j)}{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j)} \quad (1 \leq x \leq M-1, \quad 1 \leq y \leq N-1) \quad (2)
$$

$$
B(x, y) = \frac{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j) B(x+i,y+j)}{\sum_{i=-1}^{1} \sum_{j=-1}^{1} w(i,j)} \quad (1 \leq x \leq M-1, \quad 1 \leq y \leq N-1) \quad (3)
$$

where $R(x,y)$, $G(x,y)$, and $B(x,y)$ are the filter outputs that replace the original colors value at pixel $(x,y)$. From these formulas it was shown that the weighted mean filter intended to remove the random noise by weighted mean calculation of the processing point and
neighborhood point. However, when the operation of template arrives at image border, no pixel point is the counterpart of the weighted coefficients at convolution operation. Generally, two solutions for this problem are as follows: one is to omit the boundary pixel; another is to copy the boundary pixel point of original on the exterior of image edge, which can continue to run convolution operation. But the latter method would lead an unsatisfied effect in smoothing processing. As a result, the former method is chosen (Baxes, 1994). Figure 3a shows the original color debris of image, the result of weighted mean filtering is shown in Figure 3b.

B. Adaptive Median Filtering. Adaptive median filtering is a modified filtering method, which is based on classic median filtering. If there is little impulse noise in an image, a better result of filtering can be obtained according to the median filtering (Peng et al., 2004). However, a large of impulse noise in the image and an anamorphic image will be gained through this method. Although the weighted mean filter has processed image, some isolated noise and impulsive noise were still in the debris image. Hence, a verdict operation is joined in median filtering to improve the effect of filtering. During this verdict operation, it is judged whether the pixel point \((x,y)\) is impulse noise or not. This algorithm is introduced through an example that processed a primary color \(R\) of pixel. Now, five symbols are defined: \(S_{xy}\) is the neighborhood window of debris image; \(R_{xy}\) is the R color of central pixel point \((x,y)\) in \(S_{xy}\); \(R_{\text{min}}\) is the smallest \(R\) color of all pixel points in \(S_{xy}\); \(R_{\text{max}}\) is the largest \(R\) color of all pixel points in \(S_{xy}\); \(R_{\text{med}}\) is the median \(R\) color of all pixel points in \(S_{xy}\).

The adaptive median filter works at two layers defined as layer A and layer B, respectively.

For layer A:

\[
A_1 = R_{\text{med}} - R_{\text{min}} \\
A_2 = R_{\text{med}} - R_{\text{max}}
\]

If \(A_1 > 0\) and \(A_2 < 0\), then move to layer B. Otherwise, enlarge the size of window. If the size of window is not larger than \(S_{xy}\), then repeat layer A. Otherwise the output of filter is \(R_{xy}\).

For layer B:

\[
B_1 = R_{xy} - R_{\text{min}} \\
B_2 = R_{xy} - R_{\text{max}}
\]

If \(B_1 > 0\) and \(B_2 < 0\), then the output of filter is \(R_{xy}\). Otherwise, the output of filter is \(R_{\text{med}}\), where the \(S_{xy}\) was chosen to be \(3 \times 3, 5 \times 5, 7 \times 7,\) or \(9 \times 9\). The merit of this method is that can preserve detail and reduce the distortion of filtering processing. Figure 3c shows the result of the adaptive median filter.

III. IMAGE SEGMENTATION OF COLOR IMAGE OF DEBRIS

Since the color of object is different from background, the technique of threshold segmentation is applied in the DAIAS, which has less computation. The theory of thresholding segmentation was introduced as follows:

Supposing \(f(i,j)\) is the gray-level image, the image is divided two parts by threshold \(t\) which is obtained by certain criterion, and the segmented result is defined as:

\[
\text{Background: } B = \{ f(i,j) \leq t \} \tag{4}
\]

\[
\text{Object: } O = \{ f(i,j) > t \} \tag{5}
\]

However, this segmentation theory is aiming at grey image. The color image cannot segmented by this theory. Whereas, it can be used that the three primary colors RGB of all pixels to computer threshold of color image, which simulates fixing threshold method of grey image obtained from computing grey-level value of all pixels in grey image (Hu et al., 2006). In our DAIAS, according to different kinds of color image of debris, two methods with the new fixing threshold theory are developed to segment the color image of debris.

A. Threshold Segmentation of RGB Histogram. The diagram shows the distribution of grey level of grey image, which is named grey level histogram. The histogram is the basic statistical characteristics of grey image, in which the abscissa expresses the grey level and the ordinate frequency of grey-level of pixel. In term of the principle of grey level histogram, a color histogram that is composed of three primary colors histogram—\(R, G, B\) histogram can fully describe the color image. Figure 4 shows the RGB histogram of a color image. Its threshold segmentation based on RGB histogram is intuitionistic. Threshold can be selected by distribution of the three primary colors in RGB histogram. Supposing the colors values of pixel \((i,j)\) are \(R(i,j), G(i,j),\) and \(B(i,j)\), the histogram is

\[
H_R(k) = \sum_{i,j} \delta(R(i,j) - k) \tag{6}
\]

\[
H_G(k) = \sum_{i,j} \delta(G(i,j) - k) \tag{7}
\]

\[
H_B(k) = \sum_{i,j} \delta(B(i,j) - k) \tag{8}
\]

Where \(\delta(x)\) is the Dirac delta function.

and \(B(i,j)\), the image is divided two parts by thresholds \(t_R\), \(t_G\), and \(t_B\), and the segmented results are defined as:

\[
\text{Object: } O = \{ R(i,j) \geq t_R \text{ and } G(i,j) \geq t_G \text{ and } B(i,j) \geq t_B \}
\]

\[
\text{Background: } B = \{ R(i,j) < t_R \text{ or } G(i,j) < t_G \text{ or } B(i,j) < t_B \}
\]

The color image of debris that presents phenomena of double peaks in RGB histogram can obtain a good result of segmentation using threshold segmentation of RGB histogram. In this RGB histogram, the valley value that is between two peaks, is regarded as threshold (Wu et al., 2002). Figure 5 shows the whole process of image segmentation, in which the threshold is selected by left-key and right-key of mouse. The interface of the threshold segmentation of RGB histogram is shown in Figure 6.

**B. Adaptive Threshold Method.** A number of thresholding methods were proposed recently. In general, the familiar thresholding selection methods include histogram thresholding, maximum entropy thresholding, maximum interclass variance, fuzzy thresholding and so on. Ostu method (maximum interclass variance method) is one of the most widely used thresholding techniques in image analysis because of its simple algorithm and small amount of computation, which has shown a great success in image segmentation (Ostu, 1978). When the object takes a high proportion in the debris image, a good result of image segmentation can be obtained. However, when the proportion of object is small, using this method can not access to separate object and background. In this case we propose an adaptive threshold selection method which is based on Ostu method to improve the segmented precision.

**B.1. Ostu Method.** Suppose that \(S = \{0,1,2, \ldots, L-1\}\) is the gray degree aggregation of a piece of debris image, and the number of image pixel with \(i\) gray degree is \(n_i\). Total number of image pixel \(N\) and the probabilities of \(i\) gray degree \(p(i)\) are calculated as follows, respectively,

\[
N = n_0 + n_1 + n_2 + n_3 + \cdots + n_{L-1}
\]

\[
p(i) = \frac{n_i}{N}
\]

Supposing the selected threshold value of debris image is \(T\), the distribution probabilities of background and the object are as follows, respectively:

\[
o_0(T) = \sum_{i=0}^{T} p(i)
\]

\[
o_1(T) = \sum_{i=T+1}^{L-1} p(i)
\]
On the basis of Eqs. (8) and (9), the means and variances associated with the background and object can be further calculated as follows.

\[
\mu_0 = \sum_{i=0}^{L} \frac{ip(i)}{C_0(T)} \quad \mu_1 = \sum_{i=T+1}^{L-1} \frac{ip(i)}{C_1(T)}
\]

\[
\sigma_0^2 = \frac{1}{C_0(T)} \sum_{i=0}^{L} [i - \mu_0(T)]^2 p(i)
\]

\[
\sigma_1^2 = \frac{1}{C_1(T)} \sum_{i=T+1}^{L} [i - \mu_1(T)]^2 p(i)
\]

Then the interclass variance of object and background is defined as

\[
\sigma_{\text{between-class}}^2 = C_0(T) \sigma_0^2 + C_1(T) \sigma_1^2
\]

where \( \mu = \frac{C_0(T) \mu_0(T) + C_1(T) \mu_1(T)}{C_0(T) + C_1(T)} \) is the grey average value of whole image.

A selected threshold value \( T_{\text{ostu}} \) was developed by Ostu’s maximizing \( \sigma_{\text{between-class}}^2 \).

\[
\sigma_i^2 = \frac{1}{C_i(T)} [i - \mu_i(T)]^2 p(i)
\]
**B.2. Adaptive Threshold Segmentation of Color Image of Debris.**

Ostu method can be only applied to segment grey debris image. It is well known that the depiction of color image is different from that of grey image. Grey image can be described with grey-level of pixel, however, color image is described with three primary colors RGB. Since color image cannot be segmented using Ostu method directly. To apply segmentation method of grey image to color image, an idea of linearity combination of RGB's 3D vector is constructed.

\[
f(i,j) = 0.299 \times R(i,j) + 0.587 \times G(i,j) + 0.114 \times B(i,j)
\]

where \(f(i,j)\) is the result of linearity combination of three primary colors of pixel. In the color image, \(f(i,j)\) of pixel \((i,j)\) is equal with grey-level value of pixel of grey image. In this way, the segmentation method based on grey image can also separate the background and object of color image.

Ostu method can only segment the image of big object, which is similar with grey image. Since the proportion of object is low, the color information of the object imposes little effect on the total RGB histogram. Moreover, the between-class variance rule function would appear double or several peaks, so that the total threshold obtained from the Ostu method is not the right threshold (Hu et al., 2006). Under this circumstance, partial background of color image of debris is considered as the object incorrectly. To select the precise threshold, it is necessary to improve the scale of object information toward the segmented histogram. In this case, it is proposed an adaptive threshold selection method to process further segmentation for object region. Because the segmented region becomes less, the scale of object information becomes higher. Finally, the right threshold can be gained. Before discussing this algorithm, it is necessary to show a basic assumption, that is, the debris image whose colors of object are brighter than the background. In what follows, the algorithm of adaptive threshold selection can be expressed as follows:

1. Use Eq. (17) to calculate the total threshold \(t\).
2. Use Eqs. (12)–(15) to calculate the means and variances associated with the object and background \(\mu_1, \sigma_1, \sigma_0, \mu_0, \) and \(\sigma_1, \sigma_0\), respectively.
3. Compare \((\mu_1 - \mu_0) > 2(\sigma_0 + \sigma_1)\) to see whether \((\mu_1 - \mu_0) > 2(\sigma_0 + \sigma_1)\). If not, go to next step (4). Otherwise, go to the following step (8).
4. Suppose \(t_{\text{min}} = t\).

\[
T_{\text{Ostu}} = \text{Arg}\left\{\max_{0 \leq T \leq L-1} \sigma_{\text{between-class}}^2\right\}
\]  

Figure 7. Flow chart of adaptive threshold.

Figure 8. Image segmentation of adaptive threshold method of (a) small object of color image of debris; (b) treated image by adaptive threshold method; (c) large object of color image of debris; (d) treated image by adaptive threshold method. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]
where the verdict inequation \((\mu_1 - \mu_0) > 2(\sigma_0 + \sigma_1)\) is gained from distributions of colors information of object and background. The algorithmic flow chart was shown in Figure 7.

The less the area of object in total image, the more the times needed to segment using adaptive threshold method. As an example, debris image in Figure 8a in which object possess 3\% area is segmented three times by adaptive threshold method to gain right result. From the example of Figure 8b, it can be seen if the process of calculating threshold goes deeper, the more exact threshold can be gained, and finally it can be obtained the right threshold automatically. In case of debris image in Figure 8c in which object possesses 15\% area is segmented only one time to obtain object extraction, as shown in Figure 8d. That is, the adaptive threshold method can be used directly to separate larger object from background exactly, which is consistence with Ostu method’s results. It was demonstrated that the adaptive threshold method is flexible and adaptable.

IV. POST-PROCESSING OF SEGMENTATION IMAGE

A. Filling Pore. After segmenting image, some pores will appear in the wear debris image, because the color information on small parts of debris is different from that of whole debris, and it is not usually easy to separate them from background. For instance, Figure 9a shows this kind of segmentation image. It can lead to extraction error of characteristic information of debris and gain false identification and conclusion of debris analysis. Hence, the algorithm of filling pore must be used to modify the segmentation image. The result of filling pore is shown in Figure 9b.

B. Image Erosion. After a series of image processing, the debris image can meet the basic need. However, under some conditions, some small and inanition particles are still appeared in the wear debris image. Those small and inanition particles must be wiped off, because it is only interesting in wear debris with obvious characteristic in the ferrography study. At the same time, light fuzzy image from the image enhancement will lead to taking the illusive edge of debris as debris falsely in the process of image segmentation. Figure 10a shows the two cases mentioned above. Aiming at these adverse factors, an algorithm of image erosion is used to process debris image, which can eliminate verge of debris and wipe off small and inanition particles.

In the algorithm of image erosion of the DAIAS, two 3 \times 3 templates are applied in the debris image repeatedly, which is equal with the function of a 5 \times 5 template.

\[
\begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1
\end{bmatrix}
\quad \begin{bmatrix}
0 & 1 & 0 \\
1 & 1 & 1 \\
0 & 1 & 1
\end{bmatrix}
\quad \begin{bmatrix}
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
0 & 1 & 1 & 1
\end{bmatrix}
\]

In general, a better goal can not be obtained if only using erosion method in image one time. If applying erosion method more times, it may gain a satisfied result. In Figure 10a, debris image arrives at the demands after erosion two times. The process of erosion can be seen in Figures 10b and 10c.

C. Marking and Binarying of Debris Image. In order to not lose color and texture information of debris, one kind of method that the debris is signed directly in image is used in the DAIAS. Firstly, the center \((O)\) and radius of debris \((r)\) are confirmed. Then, the interior part within the round whose center and radius are \(O\) and \(r\), respectively, is the area of debris. Figure 11b shows the result of debris marked. It can be seen clearly that circles lie on the debris. That is, a circle symbolizes a wear particle. The color and texture

![Figure 9](image9a.png) ![Figure 9](image9b.png)

**Figure 9.** Filling pore of (a) segmentation image of emerging pore; (b) treated result by filling pore method. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

![Figure 10](image10a.png) ![Figure 10](image10b.png) ![Figure 10](image10c.png)

**Figure 10.** Image erosion of (a) segmentation image; (b) image processed one time by erosion method; (c) image processed two times by erosion method. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]
parameters of debris are extracted in the research of characteristic parameters of debris, which is based on the debris surface in this circle. Although using this method will lose small area of debris occasionally, the color and texture parameters of debris are exact, which can be gained through the average method of all pixels on the debris surface. The maximal virtue of this algorithm can decrease the computation operation of debris parameters greatly, and reduce the running time of computer.

On the other hand, it must describe the figure and contour of wear debris exactly in order to obtain the shape and size parameters of debris. The method of debris marking mentioned above cannot realize this goal. In our DAIAS, the method of image binaryen- ing is developed to resolve this problem primely. The color of background is “white” and the color of debris is “black.” That is, the color of background is composed of RGB with the saturation of each of the individual colors set to 255, and the color of debris can be obtained by specifying the saturation parameters of each of the three primary colors as 0. Both extracting the shape and size parameters of debris exactly and reducing the operation of computation are the goals to use this method. The result of the image binaryening was shown in Figure 11c.

V. CONCLUSIONS

1. Both methods of weighted mean filtering and adaptive thresholding selection can remove noise in the wear debris image effectively, and the useful detailed information was preserved simultaneously.

2. In the process of image segmentation, the method of threshold segmentation of RGB histogram and adaptive threshold method can be used in different debris images, which enlarges the applicable range of image segmentation.

3. Using filling pores and image erosion methods to treat some debris images can reduce the disturbance of useless information in the debris image.

4. Using the methods of marking in the center point of debris and image binaryening can reduce computation operation of debris parameters greatly.

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