Segmentation of Workpiece Rust Based on Cross Maximum

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Abstract. Rust is an oxide produced by the reaction of metal and alloy surface with oxygen. It is a defect that greatly affects the quality of the workpiece. In order to solve the problem of rust segmentation more conveniently, a threshold segmentation algorithm based on cross extremum method is proposed, which determines the threshold of rust segmentation adaptively combining the global and local features of the image. Firstly, as the threshold is hard to determine in the small and medium area rust segmentation of a workpiece, the super red method and saturation method are combined to pre-process the image. Secondly, because the gray value of the rust spot area is the maximum value of the image neighborhood, the cross-extremum method is used to extract the characteristic points of the rust spot. Finally, the threshold of rust segmentation is determined according to the proposed feature points. Experiments show that the horizontal and vertical extremum method can complement each other to extract the feature points of rust as fully as possible. And the algorithm can extract some feature points of rust better for different workpieces in varying backgrounds. The detection accuracy of the algorithm reaches 96.3%, which has important signification of application.

1. Introduction

The image segmentation is a process of dividing an image into different regions according to a certain similarity criterion, as the key step of pre-processing in the image processing, computer vision and other fields. Its quality seriously affects the subsequent processing steps. Now there are lots of methods of image segmentation mainly including threshold-based segmentation methods, image segmentation methods based on region growth, wavelet transform-based segmentation methods, neural network-based segmentation methods and other methods.

Among all of methods mentioned before, the algorithm based on threshold segmentation has become the most widely used image segmentation algorithm because of its high computational efficiency and fast speed. The key of the threshold segmentation algorithm is to determine the appropriate threshold which is the direct basis of segmentation result. Such as the maximum between-class variance method (OTSU)[1], the threshold segmentation algorithm with the largest entropy[2], the co-occurrence matrix method[3].

The region-based growing method is mainly an algorithm for segmenting similar regions[4]. According to the principle of the smallest difference between classes and large interval differences, the pixels adjacent and similar to the seed pixels are continuously merged and grown, then the segmented area is obtained.
The image segmentation method based on wavelet transform mainly uses the mathematical principle of wavelet transform to decompose the histogram of the image into different levels of wavelet coefficients. It selects the corresponding threshold according to the wavelet coefficients, and then obtains the segmentation area[5]. The thickness of the segmentation can be controlled by the scale change.

The segmentation algorithm based on neural network mainly uses the training of neural network to obtain the decision function, and through the decision function to classify each pixel, in order to achieve the effect of segmentation[6]. This method has good scalability, has good tolerance to noise and types in the image, and has the ability for complex image segmentation problems, such as semantic segmentation[7]. For example, U-net network is used in medical image segmentation[8].

In addition, there are image segmentation algorithms based on clustering analysis[9] and segmentation algorithms based on fuzzy set theory[10]. From the above analysis, it can be seen that there are many kinds of image segmentation algorithms, and each of them has its own advantages and scope of application. The fascinating part of the segmentation algorithm is that it is necessary to continuously research and select the best segmentation algorithm according to needs, when there is no universal algorithm for all tasks.

At present, in the field of rust segmentation, detection, and recognition, the main rust feature points obtained are using deep learning and machine learning techniques according to color and saturation. The most commonly used rust segmentation is to segment according to color features. The R channel value of the image was used to characterize the rust defect detection of the high-voltage transmission line anti-vibration hammer[11]. The main method was to count the normal workpiece RGB. The average value of the R channel in the model space was set as the threshold, and the threshold was used to determine whether there was a rust defect. And the super red method was proposed for the obvious difference between rust and other background objects under natural light, emphasizing the role of gray-scale method based on R channel in rust detection[12]. Another used HSI color model and gray level co-occurrence matrix to identify the rusty area in the image[13]. According to the color feature detection, the main problem was that the color feature of the rust is relatively simple. Therefore, the effect of the algorithm is unstable, and the requirements for the imaging condition of the image, the corresponding light, the background condition and other conditions are relatively high, and both of them leads to the limited application.

At the same time, machine learning methods are also widely used in rust recognition, including the use of deep convolutional networks to extract rust features and mathematical methods to simulate the rust part. The use of deep convolutional networks such as Faster-RCNN[14] was used to identify rust and defect areas, while a combination of RPN and FPN was taken to detect the rust area to obtain its location[15]. The advantage of the deep learning algorithm is mainly the generalization effect. The effect of rust recognition about irregular size and shape is good, but the training process on network requires a large number of labeled images, and takes a long time on the two-stage target recognition algorithm. The mathematical algorithms for the simulation of rust part include the applications of Berlin nose[16] and the Bayesian classifiers, the latter is trained as the corresponding classifiers to identify the rust parts and non-corrosion parts. The RUDERM method[17] combined Fourier transform and image processing technology to extract rust features. The generalization ability based on machine learning methods is relatively strong, but it requires a large number of image annotation data sets with long data pre-processing time and lengthy training time.

In summary, the segmentation algorithms still have many problems, such as relatively simple application scenarios, high requirements for images, relatively complex algorithm principles, or a large amount of labeled data for training. This paper proposes a threshold rust segmentation algorithm which is more convenient. It does not require a large amount of annotation data to train the corresponding network or classifier. At the same time, the application scene has been expanded to a certain extent, which can be used for complex scenes or high saturation backgrounds.

In this paper, in order to obtain the better characteristic points of the rust part to determine the threshold, the saturation and color information are combined to highlight the rust part and remove the
image noise. Because the rust part is the largest gray-scale value in the neighborhood, the cross-
maximum method is proposed to extract the characteristic points of rust. The segmentation rust threshold
is determined finally. The algorithm in this paper can adaptively confirm the corresponding threshold
for each workpiece picture without tedious image processing, and only needs threshold segmentation to
get the rust area. At the same time, good generalization effect can be achieved without training.

2. Analysis of the difficulty of rust division
Because the rust is red and the saturation is high, the R-space method[11-12] or saturation (S) method[13]
in HSV color space is generally used to extract rust. However, when the rust area of workpiece is small
or the background saturation is high as shown in Figure 1, the R-channel and S-channel are shown in
(b)(c). It can be seen that the R-channel is less tolerant to noise. When there is a high saturation area in
the background or the workpiece body, the method of saturation highlighting the rust area is invalid.

![Image](image1.png)

Figure 1. R-channel and S-channel image of workpiece with rust

In this paper, the region in the image is divided into the background part, the main part and the rust
part. The main part is the object attached to the rust part, while the background part is the background
area in the figure where the main part is removed. The difficulties in the division of rust on the workpiece
includes complex background, high noise, uncertain relative saturation of each part of the image,
uncertain size of rust area.

In view of the above difficulties, an adaptive rust segmentation method is proposed in this paper. The
main work is as follows:
1. Propose a new rust highlighting method, combining the super red method and the saturation S-
space to overcome two problem. One is that the outline of the red part of the super red method is
inconspicuous. Another one is the effect of high saturation of rust segmentation in the main body and
the background area when only the saturation S-space is used.
2. Propose a new cross-extreme threshold segmentation method. The main part obtained in 1 is taken
from each \(1 \times k\) horizontal area and each \(k \times 1\) area in the vertical direction, which is respectively
 regarded as the characteristic point of rust.

3. Algorithm and process of Rust detection
This paper proposes a series of solutions for the problems of small rust area, complex background, and
complex main structure. This section includes the algorithm of this paper from the three aspects which
are the background, the main body and the rust.

3.1 Processing of the rusty part
The pre-processing of the image is to reduce noise and increase the contrast of the rust area. This part
use super red method and saturation space method.

The super red method [12] to process the image is as follows:

\[
p_1 = 2.0 \times R - 1.0 \times G - 1.0 \times B
\]  \hspace{1cm} (1)

The saturation space method is to extract the image of the S-channel in the HSV color space, and the
high saturation position will be highlighted in the S channel image.

\[
p_2 = S
\]  \hspace{1cm} (2)
The super red method are shown in Figure 2(a). Compared with the image obtained by the saturation space method shown in Figure 1(c), it can be seen that both can emphasize the rust area, but both have their own drawbacks. The super red method is based on the color characteristics to highlight, but the results obtained are relatively dim and unclear. The saturation space method is ineffective when the background or subject saturation is also high. Therefore, this paper adds the result images obtained by the two algorithms to P, and acquire their respective strengths.

\[ P = p_1 + p_2 \]  \hspace{1cm} (3)

The final result is shown in Figure 2(b). It can be seen that not only the rust area is more prominent, but the outline is also clearer.

3.2 Basic Principle of the cross-extremum method

After the image pre-processing in 3.1, the processed image P is obtained with a size of M×N. The processed image has more prominent rust parts. It can be seen that the rust part has the largest gray-scale value in the neighborhood.

In order to obtain the rust characteristics more comprehensively, we merge the maximum value feature points obtained by crossing the horizontal and vertical directions which can obtain the more representative feature points in the trace area.

For the picture P, the size is M×N, and \( p_{i,j} \) represents the pixel value at \( (i,j) \), \( t_{i,j} \) represents the maximum value in the range of \( k \times N \) in the horizontal direction.

\[ t_{i,j} = \max \left\{ p_{i,j}, \ldots, p_{i,j+N-1} \right\} \]  \hspace{1cm} (4)

\( s_{i,j} \) represents the maximum value in the range of \( M \times k \) in the vertical direction. The change step of \( (i,j) \) is k. The pixel value \( p_{i,j} \) which is beyond the image is filled with 0.

\[ s_{i,j} = \max \left\{ p_{i,j}, \ldots, p_{i,j+k-1} \right\} \]  \hspace{1cm} (5)

\[ i = 1,1+k,1+2k,\ldots; \quad j = 1,1+k,1+2k,\ldots \]  \hspace{1cm} (6)

Finally, the set of \( t_{i,j} \) and \( s_{i,j} \) is taken as the eigenvalue T of the whole image:

\[ T = \{t_{1,1}, t_{1,1+k}, t_{1,1+2k}, \ldots, t_{1+k,1}, \ldots, s_{1,1}, s_{1,1+k}, s_{1,1+2k}, \ldots\} \]  \hspace{1cm} (7)

The total number of eigenvalues \( T \) is \( z \):

\[ z = \left\lfloor \frac{M+1}{k} \right\rfloor \times \left\lfloor \frac{N+1}{k} \right\rfloor \times 2 \]  \hspace{1cm} (8)

The set T which is the feature point of the rust obtained by the cross method includes the feature value of part of the background area and the main area. Among them, the small gray value of the background area will have a greater impact on the segmentation, especially when the rust area is small,
and the feature value of the rust in the feature value set T is less, so the feature value set T is further processed.

3.3 The treatment of background and main part
In the previous papers, the functional simulation method was adopted. This method is more time-consuming, and scenarios it uses is limited. It is easily affected by the complex background in some cases. In this paper, the main part is segmented out using a general segmentation method to obtain an image $P'$. The background part of the image is 1 and the gray value of the main part is 0. The size of the original image $P$ is $n \times n$, and the size of the background image $P'$ is $n \times n$. Therefore, the characteristic points of the background part are as follows:

$$Q = P \times P'$$

(9)

$$Q = q_{i,j}$$

(10)

Let the number of feature points in Q be N, and take the mean $\bar{Q}$ as the representative of the background.

$$\bar{Q} = \frac{1}{N} \sum_{i=0,j=0}^{q_{i,j}}$$

(11)

The value of feature points smaller than background $\bar{Q}$ in set T is removed, and the influence of smaller value on threshold determination is removed from the set T:

$$T' = T[t > \bar{Q}]$$

(12)

After the processed set $T'$ is obtained, the mean threshold $t$ is finally obtained:

$$t = \text{avg}(T')$$

(13)

3.4 Rust segmentation process
Summarizing the above rust segmentation process, the part rust segmentation flowchart is as follows:

4. Experimental Analysis
The experimental analysis module mainly determines the influence of parameter k on the experimental results. It detects the effectiveness and reliability of the segmentation algorithm of this paper from the workpiece rust pictures from the Internet or self-photographed in different situations.

4.1 Determination of parameter k
The algorithm in this paper needs to determine the parameter k, which is the determination of the area size in the cross maximum algorithm.
The larger the parameter k, the more detailed information of the rust area may be ignored, and the more inaccurate the segmented area. The smaller the parameter k, the more intersecting areas and the longer processing time. The changes of the segmented area and algorithm time with the change of k value are shown in Figure 4. It can be seen that the larger the k value, the smaller the area obtained by segmentation. The reason is that the larger the k value, the larger the region where the extreme value is taken. Some small thresholds will be covered, and the final threshold obtained will be too large, so the area obtained by segmentation will show a downward trend. The larger the k value, the shorter times the extreme value needs to be obtained, so the k value is inversely proportional to the algorithm time.

![Figure 4. The relationship between the change of parameter K and the area of segmentation and the time of algorithm.](image)

In order to see the different segmentation effects brought by different k values more clearly and intuitively, as shown in the Figure 5 are the different segmentation effects when k=3(b), k=5(c), k=50(d), and k=100(f). There is no significant difference in the segmentation effect at 3 and 5, but when k=100, the segmentation area is reduced more and the difference is more obvious.

![Figure 5. The result of segmentation for different K](image)

We finally take the segmentation k=3 to take into account the time and the more comprehensive segmentation area.

4.2 Algorithm segmentation diagram

In order to detect the segmentation effect of the algorithm, select part rust figure 6(a) with simple background, part rust figure 6(c) with complex background, and figure 6(e) with higher saturation. The algorithm can segment the rust area more accurately as shown in the figure:
4.3 Rust detection experiment

In order to verify the accuracy of the rust segmentation algorithm, the accuracy of the algorithm was tested on a specific data set. The data set consists of 92 rusty parts pictures and 16 normal parts pictures. The image firstly removes a small area of connected domains through the algorithm of this paper. Then if the segmented image still has connected domains, it is considered to be a part with rust, if not, it is considered to be no rust. The final test results are as Table 1.

Table 1. Styles available in the Word template

| Sign            | Normal | Rust | Total |
|-----------------|--------|------|-------|
| Testing Normal  | 12     | 0    | 12    |
| Testing Rust    | 4      | 92   | 96    |
| Total           | 16     | 92   | 108   |

We can get that the final detection accuracy is 96.3%. It can be seen from the table that the error mainly occurs in the detection of normal parts as rusty parts. The main reason is the uneven illumination on the surface of the workpiece and the reflective noise on the surface of the part has too much influence on the detection. But in general, the algorithm can distinguish rusty parts from normal parts.

5. Conclusion

This paper mainly focuses on the segmentation of parts rust based on the original paper [18]. In order to highlight the rust, the super red method and the saturation method are combined, so that it can overcome the rust segmentation under the background of high saturation, but also retain the clearer rust area. At the same time, the cross-maximum method is proposed to keep the characteristic points of rust in the horizontal and vertical directions. The algorithm in this paper can segment the rust of the parts in the figure more clearly, and can achieve 96.3% accuracy in the rust detection experiment, and there is no error left after segmentation of the rust-free image. Compared with 94% accuracy of paper[14] based on neural networks, the accuracy in this paper has improved. However, because this paper is mainly based on the color characteristics of the rust, it is more accurate for the segmentation of the rust color distribution than the single part drawing, but for the rust color, such as the black of deep corrosion, it will affect the segmentation. The segmentation results are prone to holes. For this part of the rust segmentation, a single color criterion may not meet our requirements, so this is also the focus of future research.

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