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Non-destructive Oil Seal Defect Detection Based on Machine Vision

Cheng Lv, Jiaofei Huo*, Mengqi Tian

School of Mechanical Engineering, Xijing University, Xi'an, Shaanxi, China.

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***Corresponding author:** Jiaofei Huo, School of Mechanical Engineering, Xijing University, Xi'an, Shaanxi, China.

Abstract

Traditional manual oil seal defect detection methods are inefficient and prone to false negatives and false positives. In order to improve the detection efficiency and accuracy, this paper proposes a vision-based oil seal defect detection method. Firstly, an image acquisition system is built to capture oil seal defect images. The images are preprocessed by applying a Gaussian filtering algorithm to smooth the images, and the oil seal images are cropped and position-corrected to be placed at the center. Then, defect region localization and segmentation are performed. Using grayscale difference features, gap and fringe defects are located in the inner lip area of the oil seal, while cut and impact defects are located in the lip region. Finally, defect features are extracted using various algorithms including grayscale linear transformation, histogram equalization, and morphological processing to enhance image features. Defect features are manually selected and then displayed and annotated on the original images. Experimental results demonstrate that this non-destructive detection method exhibits good performance in terms of detection speed, defect detection rate, and false positive rate.

Keywords

Oil seal, machine vision, image processing, defect detection

1. Introduction

Oil seals are mechanical sealing devices that play a critical role in hydraulic and pneumatic systems. They are primarily used to prevent leakage of liquids or gases in machinery. Typically made of rubber or other elastic materials, oil seals are prone to defects that can significantly impact their sealing performance, leading to operational issues and reduced lifespan of the machinery. Currently, most oil seal manufacturers rely on traditional manual inspection methods, which are time-consuming and can result in high rates of false positives and false negatives, thereby increasing production costs.

With the development of computer vision technology, machine vision techniques have been widely employed in surface defect detection [1]. Liu, et al. [2] proposed an edge extraction method based on threshold variations and a statistical approach for oil seal defect recognition, enabling the detection of concave defects and burrs on the inner lip sealing position and outer contour of the oil seal. Shi, et al. [3] presented a defect detection method using Otsu threshold segmentation and chain code extraction of oil seal edge contours, followed by fitting of circular contours using the least squares method. Zhang, et al. [4] utilized image processing techniques and feature extraction to construct a graphical segmentation model for precise determination of defect types.

Currently, non-destructive testing techniques based on visual inspection [5-6] and image processing algorithms [7] have become mainstream in industrial product inspection. In this study, we focus on the types of oil seal defects and employ visual algorithms based on the Halcon library [8] for defect detection. Analysis is then conducted based on the detection results.

2. Classification of oil seal defects

The oil seal used in this study is a commonly used skeleton oil seal in the market, with an annual production volume in the millions. The oil seal model being tested in this study is TP-16-28-7, which has an inner diameter of 16mm, an outer diameter of 28mm, and a thickness of 7mm. In the visual non-destructive testing algorithm presented in this paper, the oil seal images captured by the camera are single-channel grayscale images. The material of the oil seal and various defect features are represented by different shades of gray in the image. The defects of the oil seal mainly consist of four types, all of which are located in the critical area of the oil seal, namely the inner lip. These types are bruise, gap, burr, and cutmark, as shown in Figure 1.

(a) bruise (b) gap (c) burr (d) cutmark

Figure 1. Types of oil seal defects.

3. Oil seal defect detection based on vision algorithm

3.1 Detection process design

As shown in Figure 2, this section presents the design of an oil seal defect detection process based on traditional visual algorithms. Firstly, the oil seal image is captured and undergoes filtering to make the image smoother. Then, the image is cropped to extract a region of interest 1 (ROI1) with the centroid (Row, Col) of the foreground image (oil seal) as the center and a length equal to the diameter D plus 10 as the side length. The image is cropped based on the generated Mask. Next, a region of interest 2 (ROI2) is segmented and extracted, which corresponds to the annular region where the defects are located, based on the radial grayscale feature differences of the image. Subsequently, the grayscale linear transformation algorithm and histogram equalization algorithm are combined to enhance image features using morphological operations such as image enhancement and opening/closing operations. Then, the defect features are analyzed, such as the area, roundness, and height of the bounding rectangle of the defect region, for manual extraction of the defects. Finally, the extracted defects are marked and displayed on the original image, completing the oil seal defect detection process.

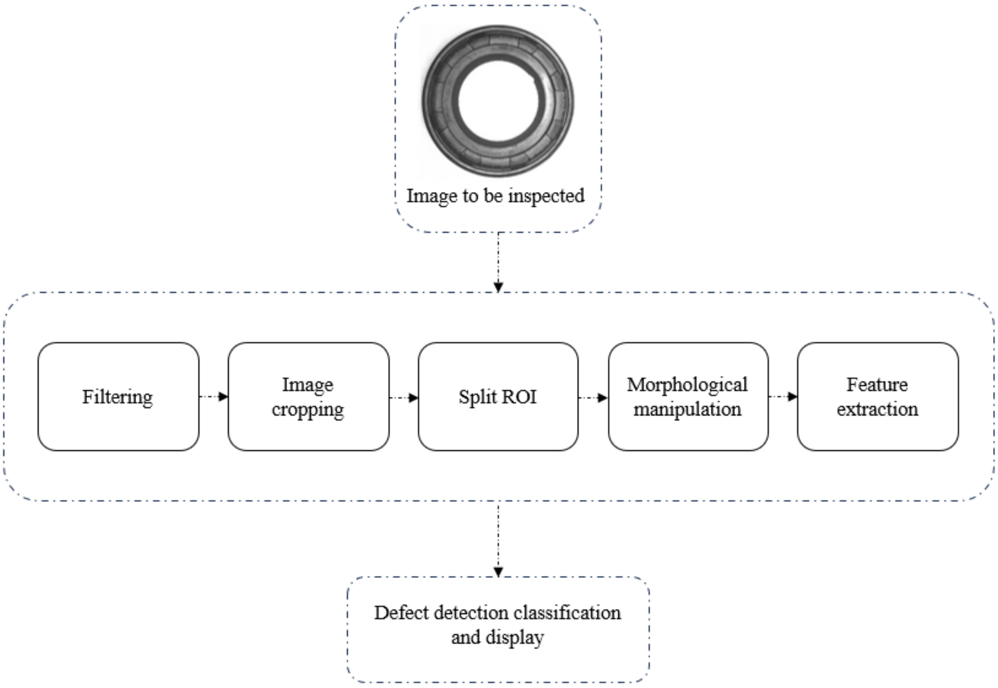


Figure 2. Defect detection flowchart.

3.2 Image preprocessing

During on-site inspection of oil seals, to ensure clear oil seal images, image preprocessing algorithms are used after image acquisition. These algorithms crop the foreground image and place it in the center of the image to avoid detection and misjudgment issues caused by positional differences. Additionally, this approach reduces the time complexity of defect detection. The image preprocessing process includes filtering, cropping, position correction, and ROI extraction.

(1) Image filtering

Filter

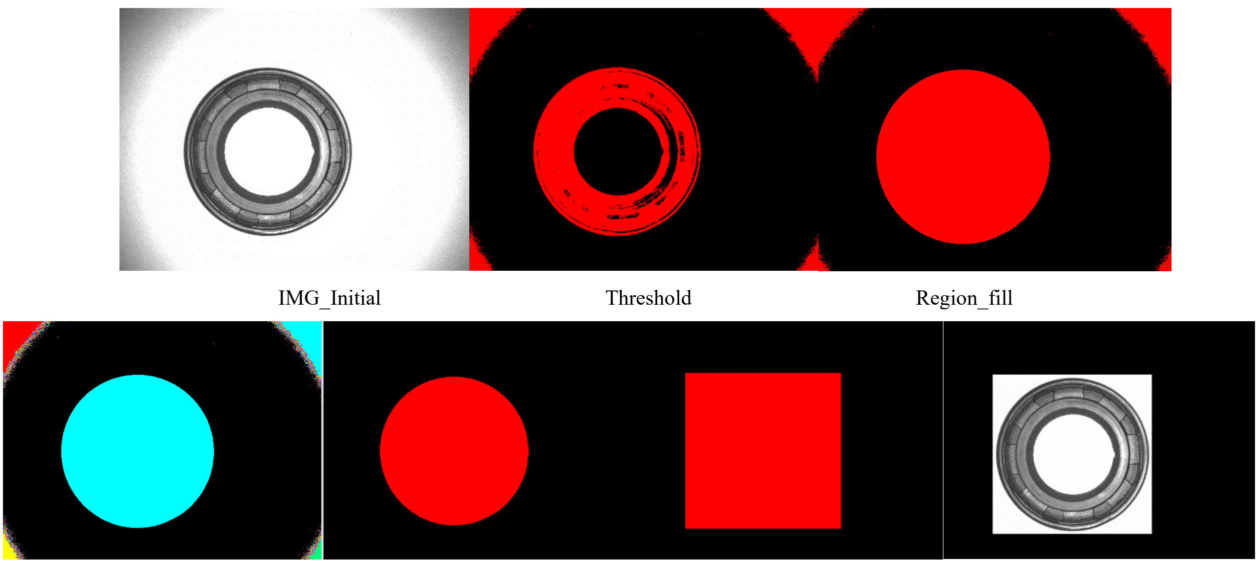
Commonly used filtering algorithms include Gaussian filtering, mean filtering and median filtering. For precision-demanding detection tasks, the Gaussian filtering algorithm is primarily adopted. As shown in Figure 3, the original image and the image after Gaussian filtering are presented. The Gaussian-filtered image suppresses image noise and makes the image smoother compared to the original image.

Original image Gaussian filtered image

Figure 3. Gaussian filter diagram.

(2) Image cropping

Image cropping is a process that involves a series of algorithms to extract the region of interest from the original image, as shown in Figure 4. Firstly, the threshold segmentation algorithm is applied to segment the areas with grayscale values within the range of [0, 150]. Then, the region-filling algorithm is used to complete the segmentation of brighter areas that cannot be separated. Next, the connected region labeling algorithm is employed to separate the corner regions of the edges into individual regions. Based on the differences in area characteristics of these individual regions, the region with the maximum area is manually selected as the region of interest. Due to potential distortions in the image center, the coordinates of the center and the radius of the minimum enclosing circle are calculated based on the region of interest, generating a mask. Finally, the cropped result is obtained by extracting the corresponding region in the original image using the mask. This processing technique enables foreground objects to be placed in the center of the image and eliminates most of the non-interesting regions, thereby improving the efficiency of defect detection.



Connection Selected_shape Mask_ROI1 IMG_ROI1

Figure 4. Image cropping.

3.3 Defect area localization and segmentation

From the previous section, it is evident that the cropped image eliminates most of the background. Since the four types of oil seal defects are distributed in specific areas, based on the radial grayscale difference characteristics of the foreground image, the gap defects and burr defects of the oil seal can be located in the darker inner lip area of the image. The cut and scratch defects are located outside the inner lip area of the image, as shown in Figure 5.

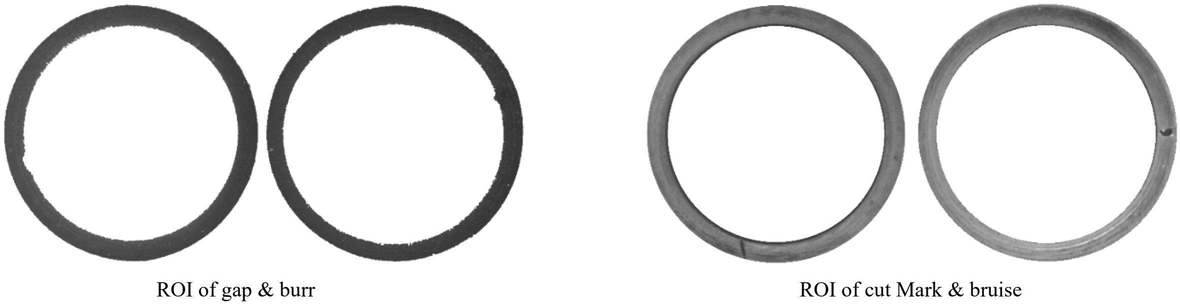


Figure 5. Positioning and segmentation of oil seal defects.

3.4 Defect feature extraction

The previous section demonstrated the region localization and segmentation of four types of defects in the oil seal: burrs, gaps, cuts, and scratches. In this section, algorithms will be designed based on the characteristics of each defect. These algorithms include Fourier transform-based frequency domain filtering and image enhancement techniques such as grayscale linear transformation and histogram equalization. Image morphological processing techniques such as dilation, erosion, opening, and closing operations will also be utilized. Other algorithms such as region subtraction and threshold segmentation will be employed. Manual selection and extraction of defects will be performed based on features such as minimum bounding rectangles or region areas. Finally, the defects will be drawn and displayed on the original image.

(1) Extraction of defective features of oil seal notches

For the feature extraction and visualization of the oil seal gap defect, the following steps are taken. Firstly, the gap region is subjected to a closing operation based on a circular kernel with a radius of 9 pixels to smooth the edges. Then, the region-filling algorithm is applied to fill the closed-edge region, and the maximum inscribed circle region of the filled area is obtained. By performing a region subtraction between the filled area and the maximum inscribed circle region, the gap defect region is obtained. Next, the region labeling algorithm is used to separate disconnected regions, and the gap defects are selected based on the thickness characteristics of the regions. In order to make the defect features have a more regular shape, an opening operation using a circular kernel with a radius of 2 pixels is applied to remove small edge protrusions. Finally, the gap defects are displayed in the image. This completes the feature extraction and visualization of the gap defect. The reference image is shown in Figure 6.

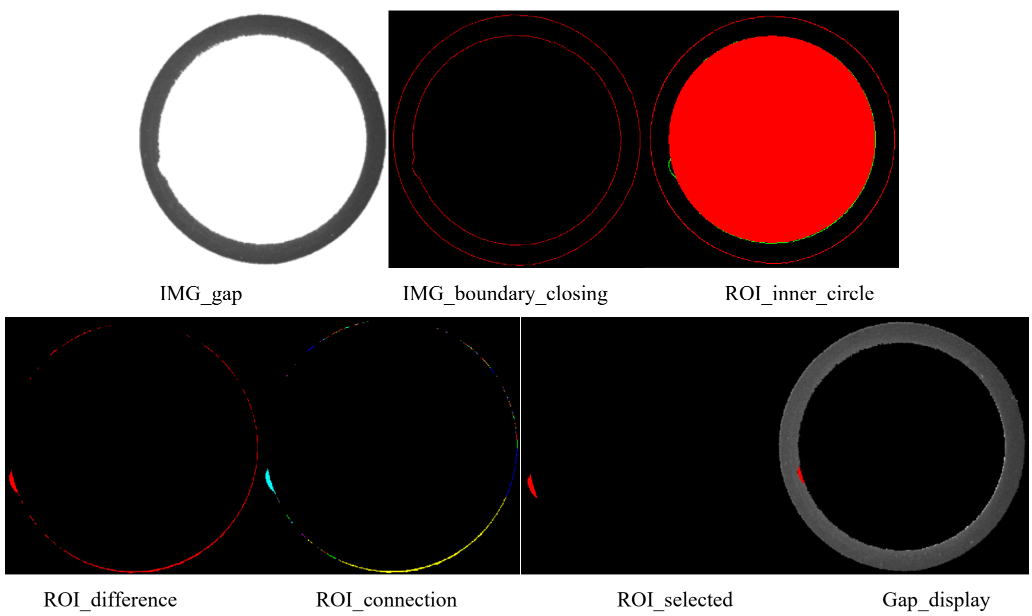
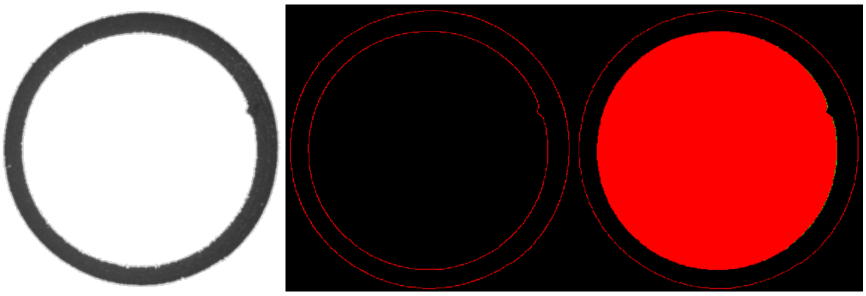


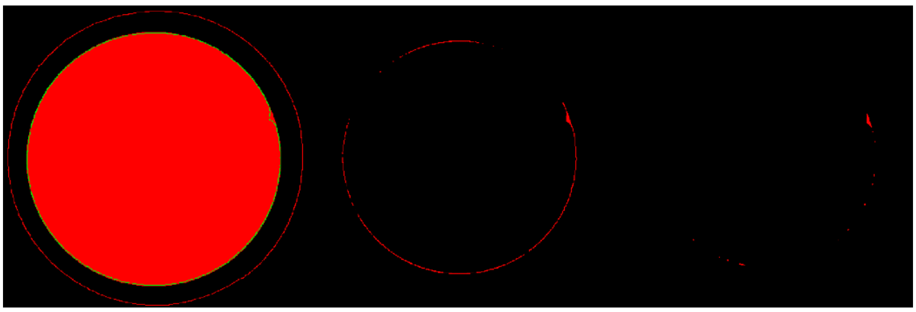
Figure 6. Notch defect feature extraction.

(2) Extraction of oil seal burr defect features

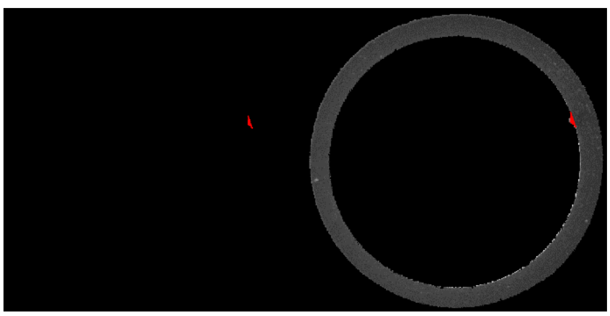
The burr defect and gap defect in the oil seal are located in the same region. The only difference is that the burr defect is a protrusion feature. Therefore, when extracting the features of the burr defect, the same algorithm and parameters used for the gap defect feature extraction can be applied. The opening operation and inner edge filling operations should be performed with the same parameters. Then, the minimum bounding circle region (ROI smallest circle) of the filled region is calculated, and the region subtraction operation is applied between the two regions to obtain the burr defect area (ROI difference). Next, an opening operation using a circular structuring element with a radius of 2 pixels is performed to eliminate minor edges. Based on the area feature, the largest region is selected as the burr defect area. Finally, this area is displayed on the image of the region where the burr is located. At this point, the feature extraction of the burr defect is completed, as shown in Figure 7.



IMG_burr IMG_boundary_opening ROI_fill



ROI_smallest_circl ROI_ difference ROI_opening_circle



ROI_burr burr_display

Figure 7. Burr defect feature extraction.

(3) Extraction of defective features of oil seal cuts

Manually build a Gaussian filter (Gauss Filter); then convert the defective region image to a frequency domain image (IMGFFT) for processing, using the Gaussian filter to process the frequency domain image; then calculate the grayscale difference between this image and the original image to obtain the difference image (Sub IMG). At this point, it can be clearly observed that the cut defect features are more prominent compared to the original defective region image. Next, use the threshold segmentation algorithm (Threshold) to extract defects; due to the presence of many small impurity regions, morphological processing is applied to them, combining dilation and opening operations, and then the non-connected regions are split using a region connectivity algorithm (Connection). Finally, the cut defects are filtered based on area features and displayed in the original image (cutmark display), as shown in Figure 8.

(4) Extraction of defective features of oil seals

The defect region image of an oil seal bruise (IMG bruise) can be obtained from the previous text. The defect features of this bruise are similar to the cut defect features, except for their shape. Therefore, the extraction algorithm is similar to the cut extraction method, as shown in Figure 9.

4. Detection experiments and results analysis

For the oil seal defect detection algorithms demonstrated in the previous section, this section selects a total sample of 930 detection images (sample, S), including 840 defect image samples and 90 non-defect image samples (non-defect sample, NDS). Among the defect image samples, there are 210 samples for each type of defect image (defect sample, DS). The detection data includes the general detection time (GDT), the number of defects not detected (DND), and the number of non-defects incorrectly detected as defects (false drop, FD). The detection performance metrics include defect detection speed (DS), individual defect recall (REC), false positive rate (FP), and general defect recall (GREC).

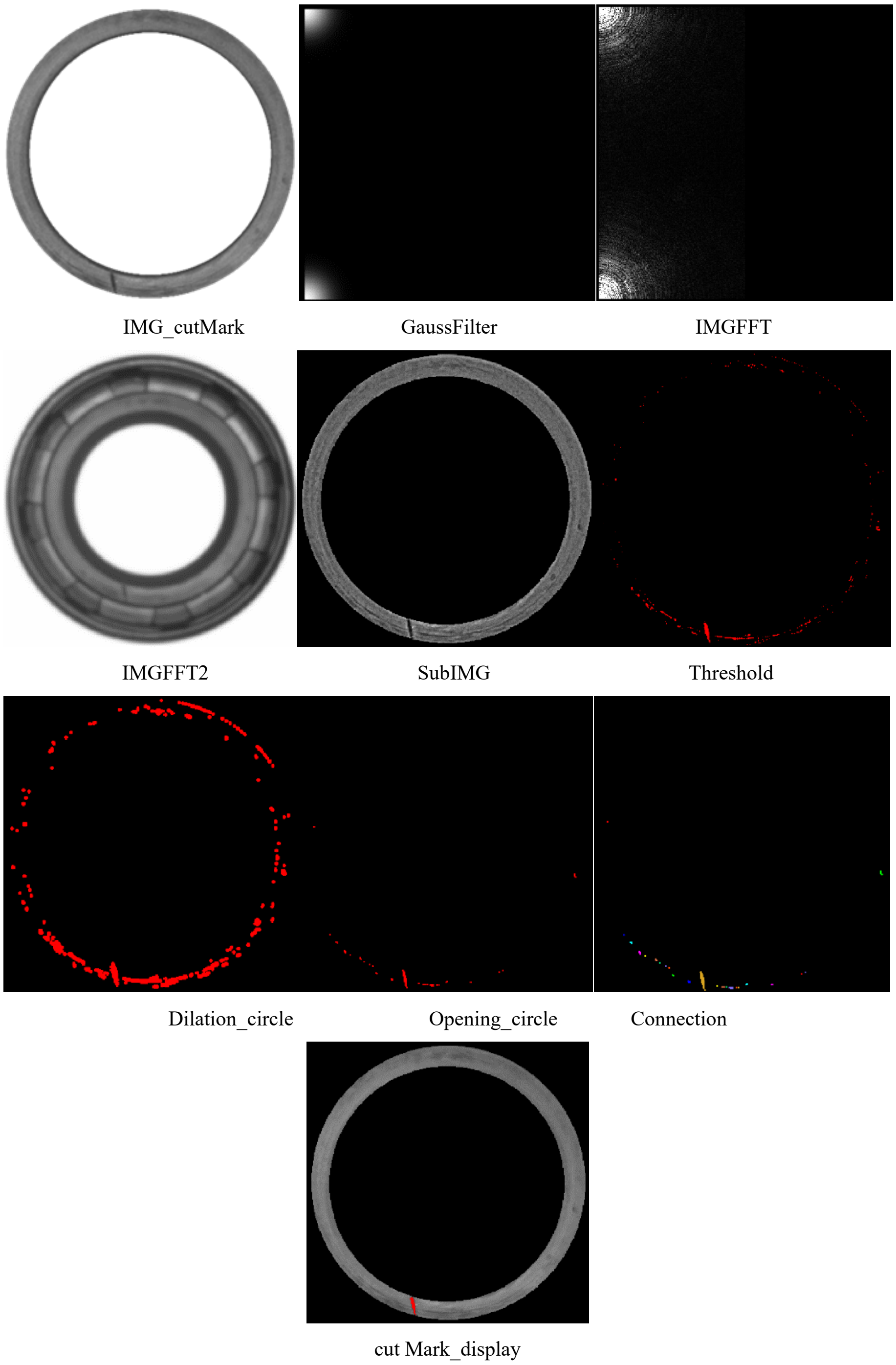


Figure 8. Cut defect feature extraction.

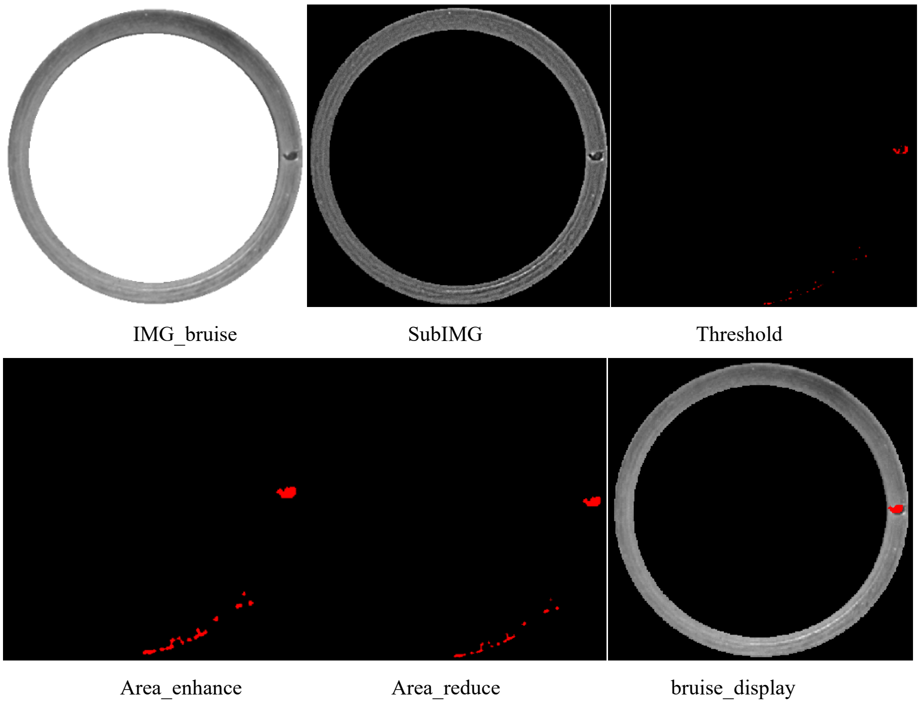


Figure 9. Feature extraction of bruise defects.

The detection result metrics are calculated as follows:

$$DS = \frac{DT}{S}$$

$$REC = 1 - \frac{DND}{DS}$$

$$FP = 1 - \frac{FD}{S}$$

$$GR = 1 - \frac{\sum DND}{S}$$

The test results are shown in Figure 10 and Table 1.

Figure 10. Test results.

Table 1. Test results

defect	DND	FD	FP	REC	GREC	GDT	DS
gap	2 sheets	41 sheets	0.044	0.990	0.987	664s	1.4 sheets /s
cutMark	4 sheets	264 sheets	0.284	0.981			
burr	0 sheets	55 sheets	0.059	1			
bruise	5 sheets	61 sheets	0.066	0.976			

5. Conclusion

By using a visual algorithm-based method for oil seal defect detection, effective classification and localization of oil seal defects can be achieved. Based on the characteristics of the defects, image processing algorithms are used for defect region segmentation and feature extraction, and the defects are finally displayed and plotted in the original image. Experimental results show that this method has achieved good performance in terms of detection speed, single defect recall rate, false detection rate, and overall defect recall rate.

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