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Wheel Model Recognition Based on Minimum Distance

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Abstract. *A shape recognition based on minimum distance has been proposed which aims at the wheel model recognition. First, a standard template has been defined and its outline was regard as a hidden information of the wheel model feature, taking the template as a window to shift matching at an edge detection image of the identified wheel image, and then figure out the minimum two-dimensional Euclidean distance between template and ROI(region of interest) of the identified wheel image. After calculating the minimum distance, it is compared with a specific threshold, and if the minimum distance is less than a certain threshold, we assume that we get the shape consistent with the template. Finally, the meanshift adaptive clustering algorithm is used to filter shapes what we obtained above. This matching algorithm is an one-to-one mapping model, namely, a pose of template corresponds to just one wheel shape in the wheel image. The process of the recognition with advantages of non-contact, good flexibility and high accuracy, and has strong robustness for the image with heavy disturbance.*

Keywords: Automobile hub, Wheel model recognition, Minimum distance, Shape recognition, Template matching.

1. **Introduction.** In the field of computer vision, shape recognition technology has become a hot topic[1-2]. M Greg proposed a modified algorithm of Shape Context[3], working out the coincidence degree between template and the identified image by calculating the number of contour points in each dimension and each corner under the polar coordinates, as a results, the speed of operation was increased, and the amount of calculation was reduced. But the identification of the wheel model should have a certain degree of flexibility, which is very important to make the shape recognition with rotation invariance. Based on this, ŽunicD proposed a moment invariant theory[4], and DM Tsai proposed a wavelet decomposition theory based on circular projection[5]. The former constructed an invariant moments by extracting the displacement , rotation and scale invariant features of shapes. The latter defined the matching degree of template and identified image by counting the number of points within the circle with specified radius, overcame the problem that the template can not rotate. But its stability is not good enough, and with poor accuracy of recognition, so it can only be used to extract shape roughly. Based on this, W. Li proposed an algorithm to extract aircraft targets from coarse to fine, this algorithm with advantages of high precision and strong robustness. But as a wheels, its interior

region often occupied with many overlapped outlines, it will cause greate disturbance to target and lower the recognition rate. MY Liu [7] and O. Danielsson [8] combined with the PF Felzenszwalb [9] edge distance calculation to propose chamfer template matching method, and use line segment instead of boundary point, and then through the boundary fitting and the overall distance tensor to determine the matching shape, Reduce the amount of calculation, and improve the anti-jamming capability. The above methods can be used for shapes recognition in the specific environment, but the wheels are required to be recognized directly in kun-stick on the production lines, so the background disturbance, illumination disturbance and the requirement of production rhythm should be take into consideration. In conclusion, we proposed an algorithm of wheel model recognition based on Minimum Distance. Firstly, defining a spoke shape as a standard template, then puts the template contours in the edge detection figure of the identified image, and figure out the distance from template contours to the nearest edge detection lines of the identified image one by one. Each pixel on the template contours corresponds to one such distance. The average of these distance is the minimum distance, if the minimum distance is less than the given threshold value, then we assume that we found a shape consistent with the template.

2. **Principle.**

2.1. **The process of wheel recognition.** Figure 1 shows the process of wheel model recognition. First define a spoke shape as a standard template, with the template in the edge of the wheel sample map to match, and then according to the wheel of the central symmetry number nt to calculate the angel template needs to rotate. (The central symmetry number nt is defined as: the entire wheel has nt shaped identical spokesand all spokes are centrally symmetrical.) Successively match the template in the edge graph until nt times are completed. If the number of shapes that consistent with template is nt, it indicates the wheel model matching is successful.

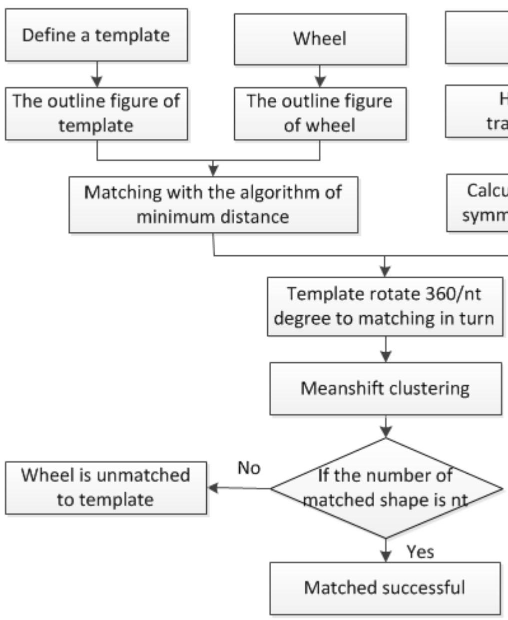

Figure 1. The process of wheel model recognition.

2.2. **Hough-circle transformation.** For an identified wheel image. Firstly, we should confirm the location of the wheel area, because the wheels are roundness certainly, so it is convenient to use Hough-circle transformation[10] to search. We remove the high frequency noise in the image by Gaussian filters, and then calculate the amplitude and direction of gradient by Sobel operator. The gradient direction θ expressed as:

$$\theta = arctan\left(\frac{G_x}{G_y}\right) \tag{1}$$

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} A \qquad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} A \tag{2}$$

The Sobel operator consist of two sets 3×3 matrix, as equation(2) shown, the left one is transverse operator, and the right one is longitudinal operator. Have convolution operation between original image and two operators and obtain Gx and Gy, the symbol A represents the original image, Gx represents the transverse edge detection image, and Gy represents the longitudinal edge detection image. So the gradient amplitude G expressed as:

$$G = \sqrt{G_x^2 + G_y^2} \tag{3}$$

Sobel algorithm operation effect as shown in figure 2:

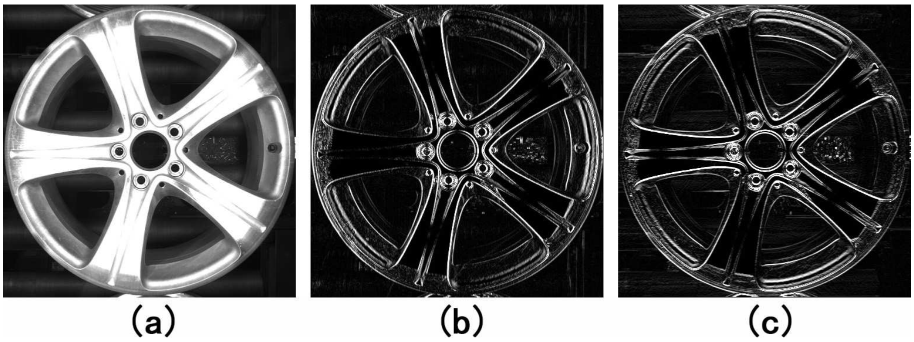

FIGURE 2. The effect of Sobel operator convoluted with original image. (a)Original image. (b)Transverse Sobel operator operation results. (c)Longitudinal Sobel operator operation results.

According to the Sobel algorithm we can obtain the rough edge of the image, shown in figure 4(b). If we want to locate image edges precisely, we need non-maximal value suppression method, as shown in figure 3, black box represents the pixels in the image, the direction of the pixel represents the gradient direction of image edge. For example, we take pixel I(i-1) as a local maximal value candidate, and compare it with the left and right pixel adjacent. Supposing pixel I(i) is a local maximal value, then I(i)>I(i-1), pixel I(i-1) is not a local maximal value, reset the pixel I(i-1). After that, take pixel I(i) as a local maximal value candidate, we know I(i)>I(i+1), then reset pixel I(i+1), and it is not necessary to take pixel I(i+1) as a local maximal candidate, directly jumping to pixel I(i+2), taking pixel I(i+2) as a local maximal candidate. After above steps,we can eliminate the non-edge pixels, just keep some thin lines of the edges. The results shown in figure 4(c).

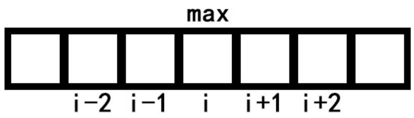

FIGURE 3. The schematic of non-maximal value suppression algorithm.

After that, the hysteresis threshold value is used to optimize the edge lines we obtained above. We set a high threshold value and a low threshold value, then we judging the amplitude of a pixel, if the amplitude exceeds the high threshold value, we reserve this pixel as an edge pixel; If the amplitude less than the low threshold value then it will be ruled out; If the amplitude between two thresholds, only when this pixel connected to anther pixel which amplitude value exceeds the high threshold, then this pixel will be reserved. The results shown in figure 4(d).

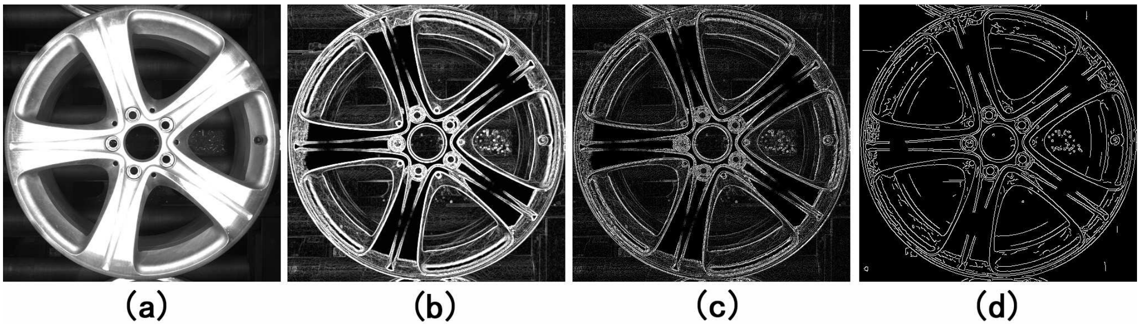

FIGURE 4. The steps of edge detection. (a)Original image. (b)Sobel transformation. (c)Non-maximal values suppression. (d)Hysteresis thresholding.

The edge lines with high strength edge information is selected by the gradient amplitude information, and we obtain the normal lines of the edge lines through the direction of gradient information and the coordinates of edge line pixels. The coordinates of point A in figure 5 set as (Xa,Ya), and the direction of gradient of point A set as θ_a then the normal lines of point A can be expressed as:

$$(Y - Y_a)\, sin\theta_a = (X - X_a)\, cos\theta_a \tag{4}$$

After we obtain the edge lines, Sobel algorithm is used to calculate the gradient and the amplitude information to confirm the normal lines of the edge lines. As shown in figure 5, the lines between points ABCDEF and O, and the direction point to O is the normal lines on circumference. The intersection point O of normal lines is a candidate center, then accumulate these intersection points, if the cumulative frequency exceeds the threshold value, then we regard this intersection point as a center.And then the radius is determined by the center, calculate the distance of the center to all the circumference. We know the number of radius is far more than others lines which with same length, screen for the radius above, making them satisfy the extent we set. In order to prevent noise disturbance near the wheel circumference and avoid mistaking the larger or smaller circle for wheel area, so the algorithm in this article only to find out the most perfect roundness when use Hough-circle transformation, rather than to find out all roundness which satisfy the radius extent we set. Because the edge of wheel is generally the most high-frequency part of the image, and it has better continuity after the edge detection operation, so it has greatest possibility to be judged as a perfect roundness.

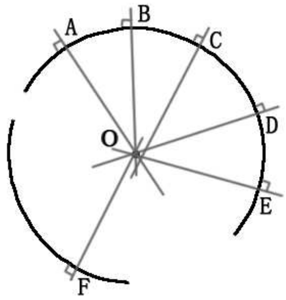

Figure 5. Look for centroid

2.3. **Calculating the center symmetry number.** Locating to wheel area, we will obtain the radius and center of wheel. According to the hole position on wheels, we cut and obtain an annular region of the wheel-hole in a certain proportion, see as figure 6(b). Then we obtain the center symmetry number of wheel by binaryzation.

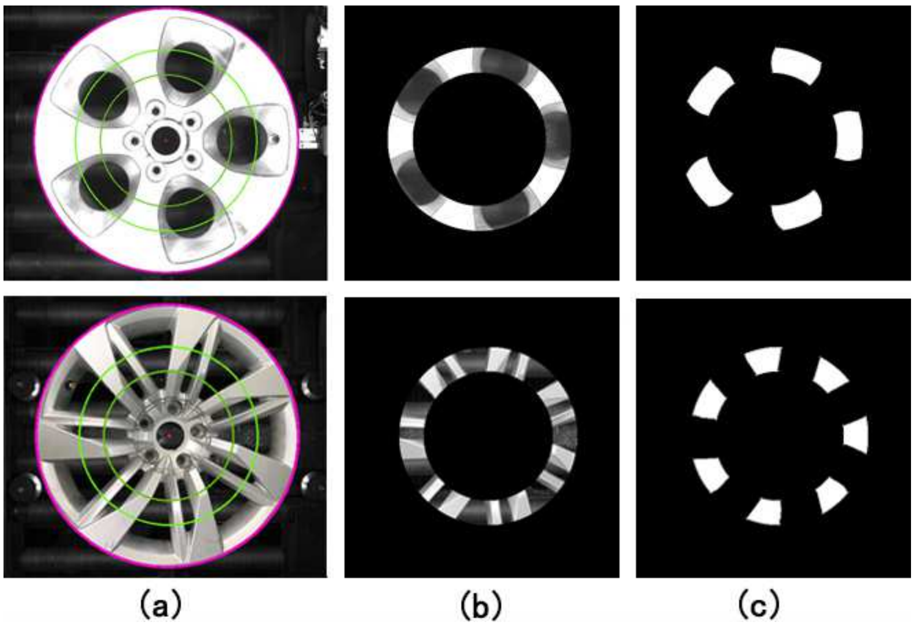

Figure 6. Calculating the center symmetry number. (a)Locating the extent of annular. (b)Extract annular region. (c)Binaryzation.

2.4. **Template matching by minimum distance.** The core algorithm of this paper is a kind of shape matching based on minimum distance. First take a standard wheel shape as a template, and then obtain the outline of the template(as the blue line shown in figure 7), adjusting the size of the template and make it consistent with the identified wheel, assuming this template contour has n pixels. Then detect edges for the identified wheel image by Canny algorithm, and show the high frequency part in a form of binarization image(as the red line shown in figure 7), namely, the grey value of edge lines are 255, and the grey value of background is 0. Then we use a small square as a window to scan template contours for a circle, check if there exist edge points(the points of red line in figure 7) in this square window, if so, figure out the distance from this point to the center of square window, and we only pick out an edge point which has the shortest distance to the center of window if there exist many edge points in this square window. We denote this distance as di, if di less than a quarter of window length, we define this point as a Near-Point; If there are no edge points in square window, then we set di as a larger value. Scanning the template contour for a circle and we can obtain n points like this, we denote these points as d1,d2,...di,...dn, and we get m Near-Points. Figuring out the average distance of these n points:

$$Dis = \frac{1}{n}\sum_{i=1}^{n} d_i \tag{5}$$

Comparing Dis with Dt, if Dis is less than the threshold value Dt and m exceeds the threshold value mt, that means we have matched a shape consistent with template. In this paper, we select the length of Dt for four pixels, and mt for a half of n artificially.

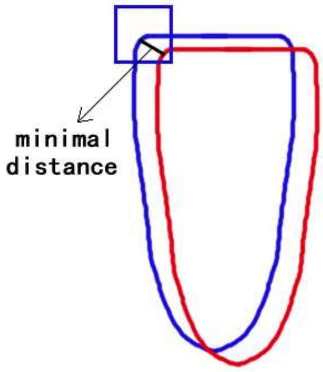

FIGURE 7. The principle of minimal distance.

We rotate the template with 360/nt degree to match again according to the center symmetry number nt, after completing with nt times match, check if there exist nt shapes consistent with the template, if so, we define the wheel model matching is successful, otherwise it is failed.

2.5. **Traverse from inside to outside.** When we scan the template contours with a small square window, we use a method with from inside to out traversal, Because it is faster than traditional traversal.

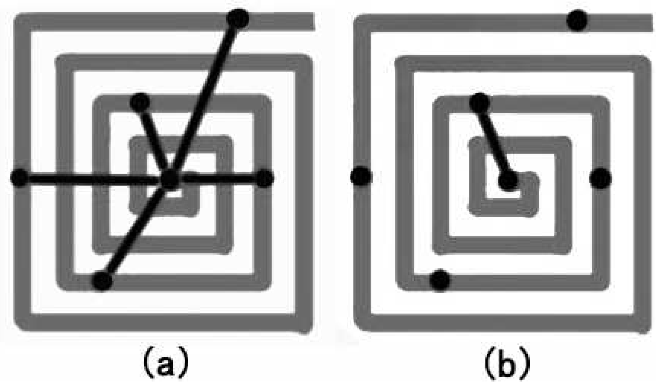

FIGURE 8. Traversal from the inside out. (a)Traditional traversal. (b)Proposed traversal.

In traditional traversal, it is necessary to figure out all distance from edge points to the center of square window, comparing these distances and choose the nearest one, as shown in figure 8(a). But the method in this paper, we use a circular scanning from window center to outside, so the first edge point we get within the window is the minimal distance, as shown in figure 8(b). In this way, we need only one calculation while complete the traversal of whole window. Comparing to traditional methods, this way of traversal greatly saves the operation time, although there exist a little deviation about the calculation of minimum distance, but considering the accuracy and operation rate synthetically, our approach in this paper is superior to the traditional algorithm.

3. Experimental results and analysis.

3.1. Recognition results and analysis. To verify the feasibility of the algorithm that proposed above, we debug and program under the environment of Opencv2.4.9, The experimental image is 480×480 pixels. As figure 9 shows, figure 9(a) presents the templates obtained in three standard wheels respectively, figure 9(b) are identified image with wheel model A1-A3, figure 9(c) are matching results of template and identified wheel, and figure 9(d) are matching results after sifting by meanshift cluster[11]. As the recognition results shown, we located nt shapes consistent with the template when use proposed algorithm, namely, we can identify the wheels with same model accurately.

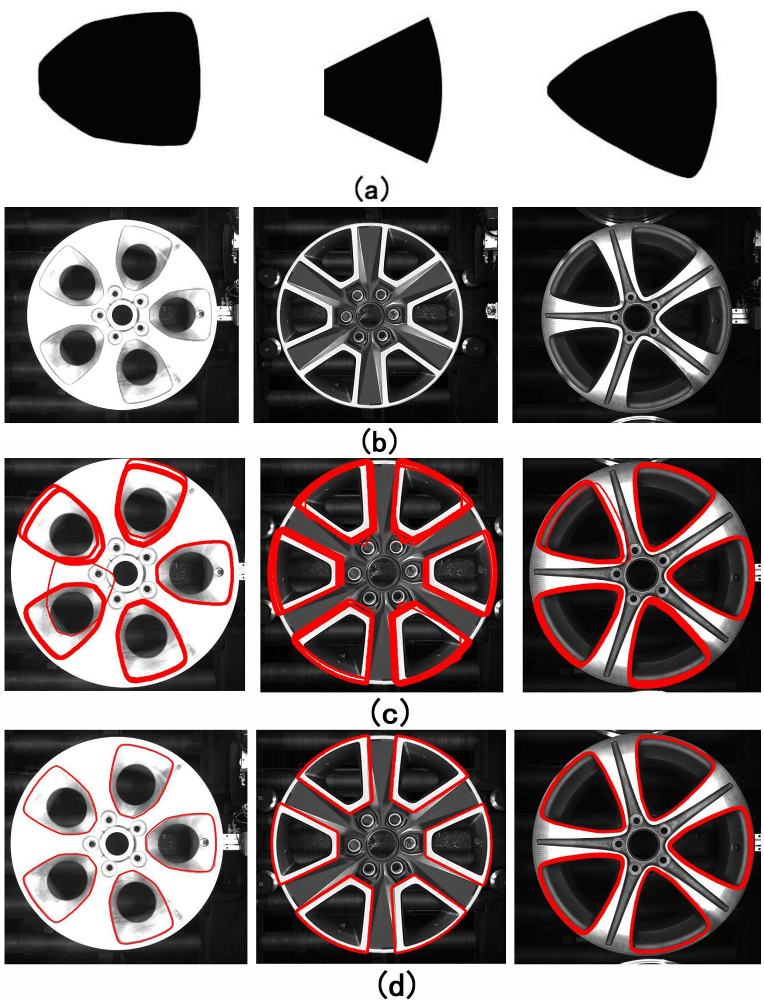

FIGURE 9. (a)Template of wheels A1-A3. (b)Wheel original images. (c)The matching results. (d)The result of the use of cluster meanshift.

3.2. **The effectiveness and instantaneity of this algorithm.** In order to further verify the effectiveness and instantaneity of the algorithm proposed, we make comparison between the algorithm proposed and the template match method based on pixel gray scale difference. Figure 10(a) are original image of identified wheel A4-A5, figure 10(b) are standard templates of the minimum distance algorithm proposed, and figure 10(c) are standard templates of pixel gray scale difference.

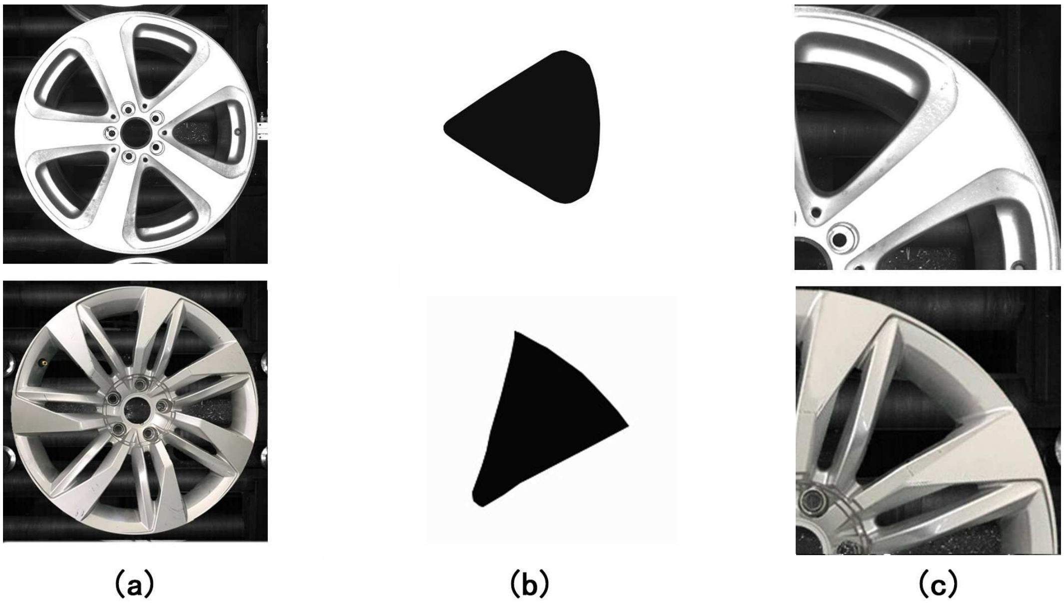

FIGURE 10. (a)Wheel original image. (b)Templates of proposed algorithm. (c)Templates of pixel gray scale difference.

The recognition results shown in figure 11, figure 11(a) are the recognition results of proposed algorithm, and figure 11(b) are the recognition results of pixel gray scale difference.

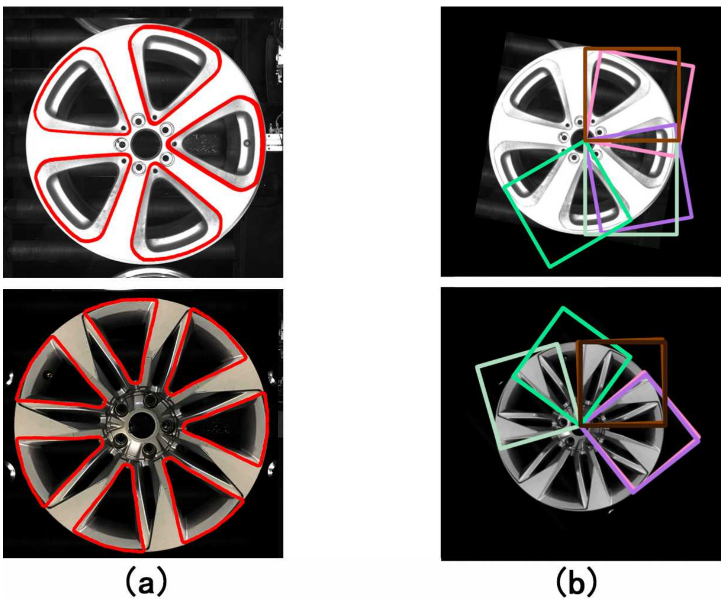

FIGURE 11. Comparing the results of two algorithm. (a)Results of proposed algorithm. (b)Results of pixel gray scale difference.

For the wheel with wheel model A4-A5, in the process of recognition we use the normal illumination for wheel A4, and we reduce the intensity of illumination for wheel A5. By the recognition results can be seen, The recognition results shows the algorithm proposed in this paper could identify the location of each wheel spokes accurately, and it could not identify all these wheel spokes accurately when use pixel gray scale difference, In addition, when the pixel gray scale difference is used, there is a case of false recognition, namely, mistaken the region different with template for template region. In figure 11(b), the region circled by colorized lines are the matching results of pixel gray scale difference.

For the further comparison of effectiveness and instantaneity of wheel model recognition, we tested five wheels with wheel model A1-A5, table 1 given the results of recognition rate and false alarm rate of wheel model recognition. Matching a template with an identified wheel which consistent with the template, we called the results TP if matched successfully, else we called TN. Matching a template with a wheel which has different wheel model from the template, under this circumstance, we called the results FN if matched successfully, else we called FT, then we define the recognition rate R and the false alarm rate F as:

$$R = \frac{TP}{TP + TN} \qquad F = \frac{FN}{FN + FT} \tag{6}$$

Table 2 given the average recognition time of five wheel with wheel model A1-A5.

Table 1. The recognition rate and false alarm rate results of wheel

	A1		A2		A3		A4		A5	
	R	F	R	F	R	F	R	F	R	F
Proposed algorithm/(%)	94.17	10.13	96.67	10.34	93.33	9.06	95.83	8.90	92.23	5.32
pixel gray scale difference/(%)	87.90	12.30	87.90	11.42	90.32	11.74	88.71	11.39	90.56	8.96

Table 2. The average recognition time of wheel

	A1	A2	A3	A4	A5
Proposed algorithm/(ms)	420	402	367	396	404
pixel gray scale difference/(ms)	655	670	630	580	532

After compared the effectiveness and instantaneity of two algorithms, It can be seen that the proposed algorithm has more advantages in the recognition rate, false alarm rate and real-time performance. The table also shows lower recognition rate when use pixel gray scale difference, the main reason is that the method can not eliminate the background disturbance, and it must calculate every pixel gray scale difference between template and corresponding region of wheel when calculate the gray scale difference, so the hole region of wheel may cause great disturbance to recognition. Instead, the algorithm of this paper is to match the edge lines of the image directly, so it can eliminate the background disturbance, and has strong robustness.

4. **Conclusion.** In order to classify the wheel on the production lines, this paper proposed a shape recognition algorithm based on minimum distance. The core of the proposed algorithm is to figure out the minimum two-dimensional euclidean distance between template and region of interest of the identified image. Firstly, locating the region of wheel

spokes which consistent with the template approximately, then meanshift adaptive clustering algorithm is used to filter these regions to confirm the specific location of corresponding wheel spokes. This algorithm could eliminate the background disturbance of wheel image and with strong robustness. As we can see from the data of the test results, it has higher recognition rate while using proposed algorithm. However, for the wheel without obvious spoke shape, the proposed algorithm has yet to be improved.

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