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Advanced SURF Features Based Flexible Object Detection

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Abstract—On the modern assembly line, the posture of flexible products can be distorted or stacked on each other, which is difficult for methods currently in effect to ensure the precision with current methods. To solve this problem, we demonstrate our method on ABB Yumi robot for flexible object detection based on SURF features with color channel prior and marginal feature optimization. Our method achieved 97.99% accuracy, which is 7.67% better than vanilla SURF.

Index Terms - SURF; Computer vision; Flexible Object

I. Introduction

Machine vision has a very broad prospect in the global market. Machine vision is the use of machines to replace the human eye. Machine vision systems refer to the conversion of captured images into image signals through machine vision products, which are transmitted to a specific image processing system and converted into digital signals for calculation, with the pixel distribution, brightness, color and other information for benchmark target feature extracting, and control equipment of the live action according to the results of the discriminant.

The characteristic of machine vision system is that it can improve the degree of automation and flexibility of industrial production. In some situations, where manual operation is not suitable or cannot meet the work requirements, machine vision is commonly used to replace manual vision. In the large-scale industrial production process, machine vision has an efficiency than the manual work. Using machine vision can greatly improve the production efficiency and the degree of automation of production. And machine vision is easy to achieve information integration, which is one of the basic technologies to achieve industrial automation.

In the background of industrial automation trend becoming more and more common, Flexible products produced on modern assembly line. like cloths or rubber, are available to each other or stack on each other. The product efficiency will be severely influenced. Generally speaking, the current methods are on single feature like color or shape works well on non - flexible product; Or we can count and identify positions and postures of multiple work piece by obtaining 3D point cloud information of the work piece, but point cloud information cannot exclude debris in the field of vision, if we need to keep flexible products stable, then extra flatten process is needed, which bring more costs.

Considering the problems in the actual industrial production environment, this study plans to solve the following bottleneck problems in related fields by studying the detection algorithm based on the monocular machine vision with the lowest relative cost. The detection algorithm based on the monocular machine vision with the lowest relative cost.

1. The problem of object recognition of flexible parts with distorted posture and mutual folding under different lighting conditions;

2. The problem of precise counting and position ordering of cluttered stack artifacts based on vision;

3. When different types of flexible parts are stacked together, the problem of debris elimination and the problem of accurate counting and position and posture ordering of target work piece.

II. Related Work

A. Feature matching for pattern recognition

Krikegaard et al. first apply Harmonic Shape Contexts (HSC) features since these are invariant to translation, scale, and 3D rotation, and divide each object into a number of sub-models each represented by a number of HSC features. Using this method, we can recognize one object at least, but it's sensitive to noise, and unable to count the number of objects in view [1].

Deep neural network has a great performance on image classification and object detection, since Max Schwarz et al. use convolutional neural network with a large dataset, and use SVM classifier to recognize the object, use support vector regression to estimate posture of the object [2]. Kensuke Harada et al. also use deep neural networks for object detection [3], but deep learning methods require large datasets and long-term training, which may bring a lot extra costs.

B. Pose estimation based on 3D point cloud

Random sample matching (RANSAM) [4] proposed by Buchholz present a solution based on a standard 3d-sensor, match point cloud data to CAD model, and get the posture of the object. This method has high precision but poor real-time performance, it would take about 5.5s for point cloud processing.

Choi C et al. proposed another method for posture estimation [5]. This method treats oriented surface point, boundary points with directions and boundary line segments as the key role of 3D object detection as the edge played in 2D object detection. They demonstrated several algorithms to show that these primitives encode more information compactly and provide higher accuracy. But this method requires the object with obvious edges and pose feature, the accuracy can't be ensuring detecting distorted flexible object.

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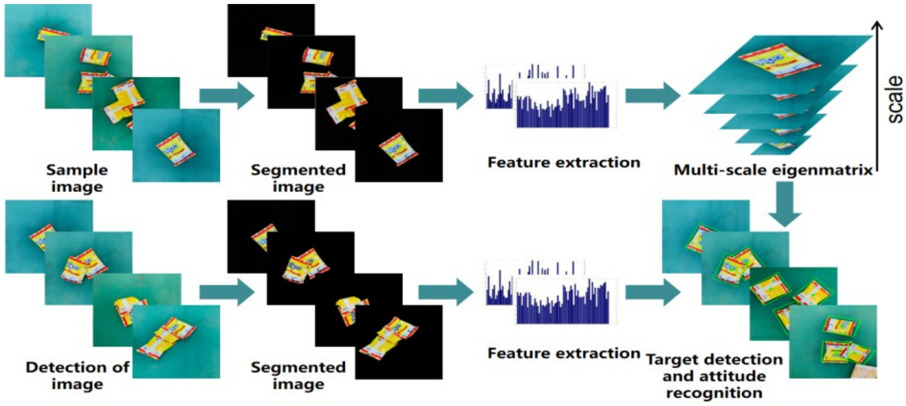


FIG. 1 Flexible parts detection system

III. ADVANCED SURF FOR FLEXIBLE OBJECT DETECTION

To solve problem, we stated above, we demonstrate our method on flexible food packages. We use multi-feature integration for distorted flexible product detection, and do object detection and sorting by separately quantizing multi-feature of the object. Experiments showed our method performed well on distorted, folded, stacked objects with great accuracy, and already be used on industrial assembly line.

A. Image Preprocessing

The original image collected by the system is the full-color picture of the packaging food bag taken by the CCD camera. In order to accurately identify the target and capture it, the collected image needs to be preprocessed. The pre-processing process is shown in the figure.1. Because in industry the accuracy of CCD camera is limited, video frames extracted in the original video will have obvious noise. In order to ensure the accuracy of the recognition results, it is necessary to de-noise them. The noise is shown in the figure.2.

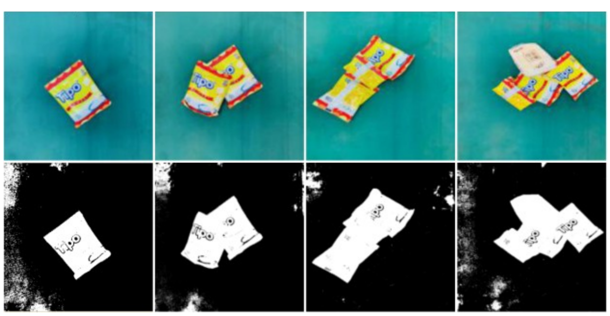


FIG. 2 original image background noise

Median filter denoising method with adaptive scaling update: Most of the noise in the original picture is caused by irregular stains generated by the stains of the production line, which is more suitable for nonlinear denoising method, so nonlinear de-noising method is adopted for denoising. Taking the 3×3 filtering window as an example, the principle is shown in the figure.3:

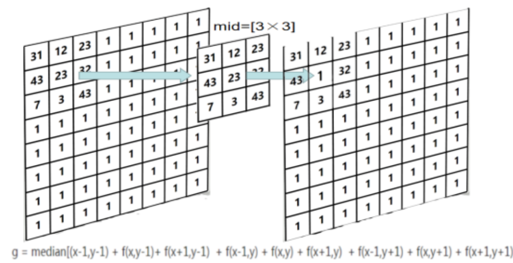


FIG. 3 median filtering

Median filtering has a good effect on nonlinear noise removal, but it is easy to destroy image edge features. Therefore, this study makes some improvements to it, and the basic principles are as follows:

The convolution window corresponding to the point (x,y) is $Z_{(x,y)}$, $T_{(x,y)}$ is corresponding gray value, the maximum value is denoted as T_{max}, the minimum value as T_{min}, the median value as T_{med}, and the mean value as T_{mean}. Z_{max} is the maximum traversal scale allowed when no boundary effect is generated. In the traversal of the detected image, it is also limited by the requirement of real-time matching. In order toretain boundary features during denoising, the difference allocation of T_{med} and T_{mean} in the convolution window (weight is Q) was carried out, denoted as Q-T_{med} =0.4, Q-T_{med} =0.6. Q-T_{med} was updated with the gray median value obtained after allocation.Through:

Step1: mark $T_{11}=T_{med}-T_{min}$,$T_{12}=T_{max}-T_{med}$; if T_{11},T_{12}>T, Step2; otherwise, increase Z; if Z < Z_{max}, repeat Step1; otherwise, output $T_{(x,y)}$;

Step2: mark $T_{21}=T_{(x,y)}-T_{min}$,$T_{22}=T_{max}$- $T_{(x,y)}$,T21, if T_{22}>T, then output $T_{(x,y)}$; otherwise, output T_{med}.

The threshold value T is calculated from the original image SNR and acceptable SNR.

B. Feature Extraction

Due to the characteristics of mass production in modern industry, the same batch of products on assembly line have the consistency in appearance. Therefore, the pattern recognition based on prior knowledge would perform well on flexible object recognition under such complicated conditions.

Color features quantification: In this paper, we take food packaging as an example, and there are obvious color differences between the foreground area and industrial background area. Our study introduced the notion of connected domain, use morphological calculation to further eliminate the background area and excluding different Chroma regions. The Original image RGB color distribution is shown in the figure.4.

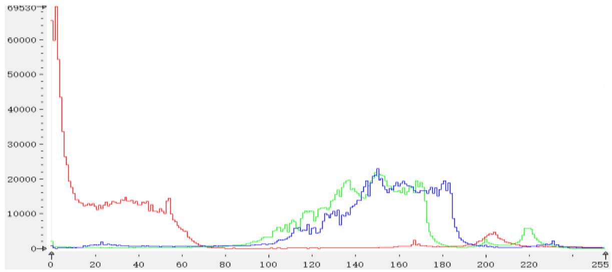


FIG. 4 Original image RGB color distribution

The foreground area can be extracted from the range shown in the table 1 from result of the original images.

Table 1: foreground area color threshold

	R	G	B
Color threshold	R≥80	G≤60，G≥185	B≤85，B≥195

Based on large number of image samples, we set the threshold of the total number of pixels in the foreground area of flexible part in the connected domain A∈ [10000, 20000] to filter obvious interference areas. The results are shown in figure.5 .

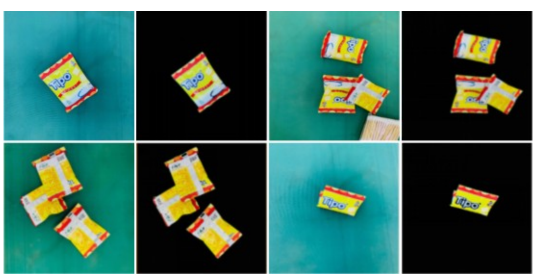


FIG. 5 Color threshold extraction effect

Edge features quantification: This study uses the canny operator to extract the edge of the flexible object. The Canny operator is an effective edge detection algorithm with good noise immunity and can detect weak edges of images. The process of Canny edge detection algorithm can be broken down into 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise
2. Find the intensity gradients of the image
3. Apply non-maximum suppression to get rid of spurious response to edge detection
4. Apply double threshold to determine potential edges
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Vanilla Canny algorithm doesn't work well on flexible object feature extraction; the reasons are listed as below.

1. Vanilla Canny use Gaussian filter to smooth the image, which cannot handle the noise in the raw image.

2. The traditional algorithm uses 2×2 finite difference for gradient calculation. This calculation method is very sensitive to noise and affects the accuracy of edge extraction.

To solve this problem, we use improved median filter to denoise the raw image and eliminate nonlinear noise while preserving the edge features, and based on traditional Canny algorithm, we obtain the gradient templates of different angle and amplitudes by affine transformation, and solve the gradient components of different orientations separately.

In this study, gradient templates of 0°, 45°, 90°, and 135° were selected to solve the gradient components. The transformation matrix is shown in the figure.6 .

$$\begin{array}{cccc} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} & \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} & \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} \\ \text{(a)} & \text{(b)} & \text{(c)} & \text{(d)} \end{array}$$

FIG. 6 Four filters for detection of (a) horizontal (b) vertical (c) diagonal at 45 and (d) diagonal at 135°edges

The gradient components in the four directions can be obtained by convolution of the template in the above figure, and then the gradient amplitude $P(x,y) = \sqrt{C(x,y)}$ is obtained by combining the four components.

Object Detection with multi-feature: After testing, when the detection target causes edge blur due to occlusion, stacking, posture distortion, etc., the detection effect of the traditional SURF algorithm is not ideal. In response to these problems, this study is based on the traditional Surf algorithm, which is optimized as follows:

1. Using a priori method of color feature based on prior knowledge, the foreground area of the image to be inspected is extracted to improve the real-time performance of the algorithm.

2. Replace box filter smoothing image of the conventional SURF algorithm with a median filter of adaptive scale update. In order to ensure the real-time performance, an upper limit is set for the update scale of the detected image.

3. The improved Canny edge extraction algorithm is used to replace the simple gradient calculation in the traditional Surf algorithm to optimize the edge feature extraction.

4. A feature matching method based on local statistics and scale transformation is proposed to replace the global matching method in the traditional Surf algorithm to improve the efficiency of the algorithm.

In the target recognition, the normalized method is used to perform similarity quantification on the extracted foreground region, so that the matching template has illumination invariance. Assume the gradient of the template image in the X, Y direction $P_i^T = (X_i^T, Y_i^T)$, the gradient of the target image in the X, Y direction $G_i^T = (G_{xi}^T, G_{yi}^T)$.

Assume the edge feature $G_{u,v}^S = (Gx_{u,v}^S, Gy_{u,v}^S)$, Where u is the number of rows traversed and v is the number of columns traversed. In the detection process, the similarity measurement model is used to extract the edge of the detected image, and the sum of the normalized dot products of the template image feature points is obtained, and the matching solution is performed in the similar data set of the detected image.

$$S_{u,v} = \frac{1}{n}\sum_{i=1}^{n} \frac{\left(Gx_i^T \cdot Gx^S_{(u+X_i,v+Y_i)}\right)+\left(Gy_i^T \cdot Gy^S_{(u+X_i,v+Y_i)}\right)}{\sqrt{{Gx_i^T}^2+{Gy_i^T}^2}\cdot\sqrt{{Gx^T_{(u+X_i,v+Y_i)}}^2+{Gy^T_{(u+X_i,v+Y_i)}}^2}}$$

S is the matching degree between the detected feature and the template feature, S∈[,0,1].

In actual operation, the way of global traversal solution of the detected image will greatly affect the real-time performance of the matching algorithm. In order to improve the efficiency of the solution, the original algorithm is optimized by local statistics and scale transformation.

First, set the solution domain for the similar normalized dot product region to be solved. Set the minimum similarity S_{min}, then the local feature matching value S_m can be recorded as below.

$$Sm_{u,v} = \frac{1}{m}\sum_{i=1}^{m} \frac{\left(Gx_i^T \cdot Gx^S_{(u+X_i,v+Y_i)}\right)+\left(Gy_i^T \cdot Gy^S_{(u+X_i,v+Y_i)}\right)}{\sqrt{{Gx_i^T}^2+{Gy_i^T}^2}\cdot\sqrt{{Gx^T_{(u+X_i,v+Y_i)}}^2+{Gy^T_{(u+X_i,v+Y_i)}}^2}}$$

When the sum of remaining items is less than or equal to 1, which refers to $S_m > S^{min} - 1 + \frac{m}{n}$, stop solving.

Second, when performing feature matching in any region, the matching degree of any matching region should be higher than the lower bound of similarity, and the phenomenon of missed detection is optimized. Define the subject description ratio as the prior coefficient, denoted as g, then satisfy the condition below, stop matching.

$$S_m < MIN\left(\left(S^{min} - 1 + \frac{1-g \cdot S^{min}}{1-g} \cdot \frac{m}{n}\right), \left(S^{min} \cdot \frac{m}{n}\right)\right)$$

IV. RESULT

A. *Authors and Affiliations*

In order to verify the improved denoising effect of median filtering, this study selected a variety of traditional algorithms to compare with many improved denoising algorithms in recent years. The experimental results are shown in figure.7 .

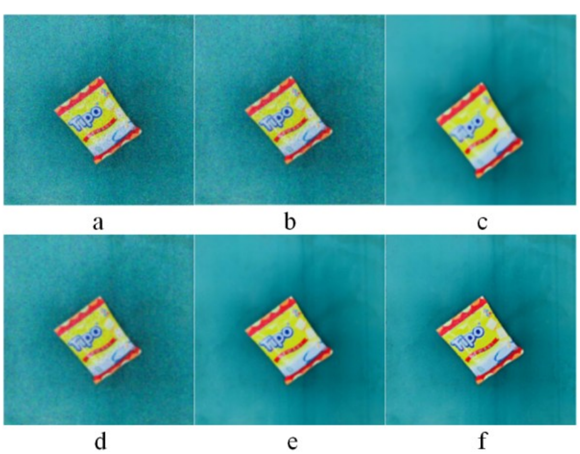
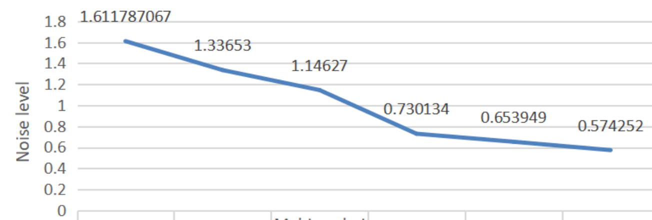


FIG. 7 Different denoising effects

a: original image
b: Ito K. Gaussian [6]
c: Multiresolution bilateral [7]
d: adaptive vector median [8]
e: median and wavelet [9]
f: Our study

According to the figure.8, it can be seen that for the same image, the algorithm proposed in this study has better denoising effect, and the image noise value after denoising is the lowest, and compared with other denoising methods, the denoising algorithm proposed in this study is better in the edge information of the image.



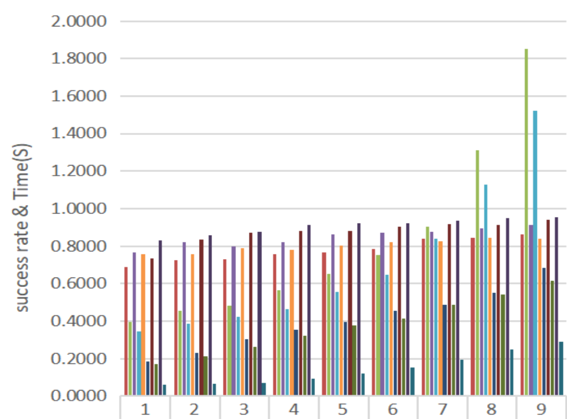
	original image	Ito K. Gaussian[6]	Multiresolution bilateral[7]	adaptive vector median[8]	median and wavelet[9]	Our study
noise	1.611787067	1.33653	1.14627	0.730134	0.653949	0.574252

FIG. 8 Image noise statistics after different ways of denoising

B. *Color feature prior*

Our research utilizes a priori knowledge of color feature prior methods to optimize the traditional Surf matching method. The foreground area of the image to be inspected is extracted first to improve the real-time performance of the algorithm.

In order to verify the actual effect of this improved method, a variety of algorithms were selected in this study, and the pyramid scale space of different layers was constructed to match the test images. The matching results are shown in figure.9.



	1	2	3	4	5	6	7	8	9
traditional SIFT[10]accuracy	0.689	0.723	0.731	0.756	0.765	0.785	0.841	0.842	0.861
traditional SIFT[10]time(s)	0.396	0.456	0.484	0.564	0.651	0.754	0.905	1.312	1.851
modified SIFT[11]accuracy	0.765	0.820	0.796	0.821	0.861	0.871	0.874	0.896	0.912
modified SIFT[11]time(s)	0.345	0.384	0.423	0.465	0.556	0.645	0.841	1.126	1.523
traditional SURF[12]accuracy	0.757	0.757	0.787	0.779	0.802	0.823	0.824	0.842	0.839
traditional SURF[12]time(s)	0.185	0.232	0.305	0.356	0.395	0.456	0.486	0.552	0.683
modified SURF[13]accuracy	0.733	0.834	0.871	0.881	0.881	0.905	0.915	0.912	0.939
modified SURF[13]time(s)	0.169	0.214	0.262	0.323	0.375	0.415	0.485	0.541	0.613
our study accuracy	0.832	0.856	0.875	0.912	0.923	0.921	0.934	0.951	0.952
our study time(s)	0.059	0.064	0.070	0.092	0.120	0.153	0.196	0.250	0.292

FIG. 9 Color feature priori effect in different layers of scale space

As can be seen from the experimental statistical results, compared with the traditional SIFT and SURF algorithms and the improved SIFT and SURF algorithms in recent years, under the same detection environment, the improved method of color domain prior proposed by this research can achieve better detection success rate and shorter detection time.

C. Edge quantization

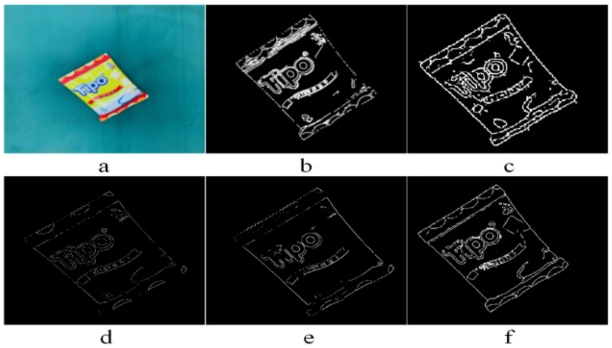
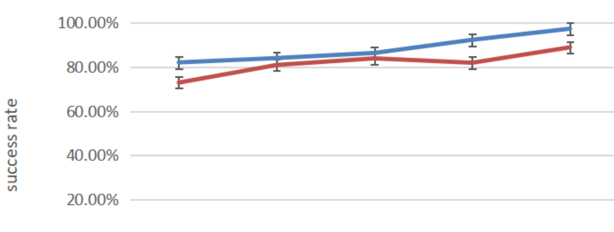


FIG. 10 Different edge detection algorithm

a: original image;
b: Method 1[14];
c: Method 2[15];
d: traditional canny [16];
e: modified Canny [17];
f: our research

As can be seen from the figure.10, the edges extracted by the gradient calculation are not continuous, and the traditional Canny operator extracts a large number of noises that affect the matching. Our improved algorithm removes the features from the continuous feature edges and removes the distortion from the noise that affects the matching.

According to the statistical results, this research proposed to improve the edge features extracted by the edge detection algorithm, which can significantly improve the final detection accuracy. The statistical results are shown in figure.11.



	Method 1[14]	Method 2[15]	traditional canny[16]	modified Canny[17]	our study
accuracy	82.15%	84.13%	86.45%	92.40%	97.43%
Average similarity	0.73	0.81	0.84	0.82	0.89

FIG. 11 The effect of different edge detection methods on matching results

D. Object Detection

We selected 500 images in different lighting and background environments for testing. The choice of parameters is the key to optimize performance. We have determined that the dataset retention resolution is 360×240 through multiple experiments, and add different degrees of salt-and-pepper noise to verify its anti-interference performance. The camera is settled at 1 meter above the production line.

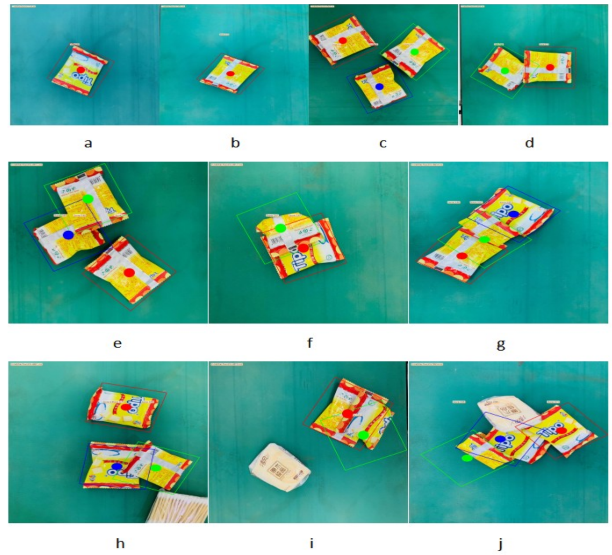


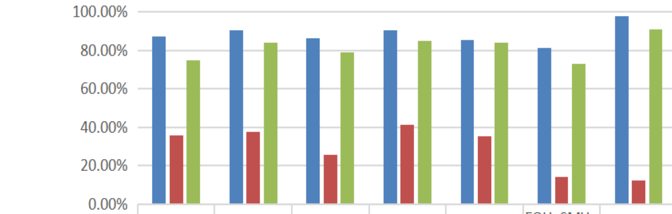
FIG. 12 Test results

In the Figure.12, Figure12.a,b is the detection result of a single work piece in different postures; Figure12.c, d, e are the detection results when the work piece is not seriously distorted, but stacked on each other;Figure12.f, g are the distortion of the work piece itself, and the detection is performed under the mutual stacking As a result, Figure12.h,i are the detection results when the work piece is distorted itself, stacked on each other, and there are still similar objects in the industry;Figure12.j is the detection result when the work piece itself is distorted, stacked on each other, and stacked with similar objects.

It can be seen from the result that the matching algorithm proposed by us can achieve object detection and debris removal in the case of complex work piece self-distortion, stacking, and even stacking debris with similar postures, and can calculate the posture information of the work piece. The sorting information of the target objects stacked on each other is given based on the matching result.

In order to further quantify and verify the work made in this study, six detection methods that have been used in recent years were selected to conduct verification experiments on target data sets under the same conditions. Among them, method 1 is CSIFT algorithm proposed by Abdel-Hakim et al in 2006 [18]. Reference 2 is an improved SIFT algorithm proposed by Zhou X et al in 2017 [19]. Literature 3 is the traditional SIFT algorithm summarized by Wang Z et al. [20]; Literature 4 is traditional SURF algorithm [21]. Reference 5 is the target detection method based on cascade classifier proposed by Triggs B et al in 2017 [22]. Reference 6 is the overlapping target detection algorithm of EOH + SMH + AdaBoost proposed by Ahmad J et al in 2018 [23]. The experimental results are summarized as follows.

According to the statistical results, compared with the other six detection methods, the algorithm proposed in this study can achieve the highest detection accuracy under the premise of ensuring the real-time performance of the algorithm, and has a good matching degree to the detected target objects. The experimental results are shown in figure.13.



	CSIFT[18]	modified SIFT[19]	traditional SIFT[20]	traditional SURF[21]	cascades classifiers[22]	EOH+SMH+AdaBoost[23]	our study
Accuracy	87.38%	90.32%	86.55%	90.32%	85.35%	81.23%	97.99%
Time（s）	0.3561	0.3763	0.2569	0.4126	0.3512	0.1435	0.1235
Average similarity	0.75	0.84	0.79	0.85	0.84	0.73	0.91

FIG. 13 The experimental results

V. CONCLUSION

In this paper, the target detection algorithm commonly used in the flexible parts industry is proposed to solve the problems of attitude distortion, poorly recognized objects, poor real-time performance and high false detection rate. The algorithm uses improved median filtering for image preprocessing, and uses the Surf algorithm based on color channel prior and edge feature optimization for target matching. The local feature matching degree and prior coefficient are used to ensure real-time detection. The experimental results shown proposed method can detect the target and the attitude of the work pieces with different poses and backgrounds in different illumination and background environments. The matching results can be used to give the target object sorting information based on the matching results. The detection success rate is up to 97.99%, compared with the original Surf algorithm, the accuracy is improved by 7.67%, and it is greatly optimized in real-time. Compared with other research methods, this study proposes that the algorithm can achieve the highest detection accuracy under the premise of ensuring the real-time performance of the algorithm, and has a good matching degree to the detected target object.

VI. FUTURE WORK

The algorithm proposed in this study is based on the feature matching method of the template sample set. The detection effect is closely related to the quality of the template sample set and the matching degree between the template sample set and the detected sample set. In the future research, we will optimize the feature network concept and further optimize the test results using a more accurate feature engineering implementation.

ACKNOWLEDGMENT

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