Rectangular Feature Recognition Method Based on Whale Algorithm in Complex Background

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Abstract: Due to the complex background of the observation target, traditional feature extraction methods cannot effectively acquire the target features. Based on the research of target recognition technology and its engineering application, this paper proposes a target recognition method based on rectangular geometric features. Firstly, a linear feature extraction method based on this condition is proposed, which is used to identify the straight line on the edge of a rectangular object. Based on the Hough transform, the problem is transformed into a multi-constraint optimization model, and the whale optimization algorithm is used to solve the model to achieve accurate identification of features in complex backgrounds. The experimental results show that the method can effectively detect the target features even if the number of lines in the image varies greatly, which has better robustness and can improve the engineering execution efficiency.

1 INTRODUCTION

With the continuous development of computer vision technology, people try to apply it to more tasks. In recent years, feature recognition technology has become more and more important in computer vision technology, and it has played an increasingly prominent role in various fields. In the aerospace industry, scientists are trying to use feature recognition technology to solve problems such as space debris recovery and spacecraft on-orbit services, such as the US abandoned satellite recycling program "PHOENIX" (DARPA 2014), the European Space Agency (ESA) Robotic Geostationary Orbit Restorer program (Bischof et al. 2004),etc. in the field of industrial manufacturing, part detection and processing technology based on feature recognition technology is widely used (Yuyuan et al. 2019) in the medical field, the extraction of key information such as lesion area also begins to rely on feature recognition technology detection (Yuqing et al. 2008). In the Internet of Things, quickly and accurately identifying packages and accurately classifying them can greatly improve their work efficiency (Zhongtai 2018). In summary, identifying targets through spatial geometric information of foreground targets is an important issue in an unknown complex context.

At present, dealing with this problem in engineering mainly involves two aspects, image preprocessing and target recognition. In terms of image preprocessing, the widely used processing methods include multi-channel image grayscale, quadrature equalization processing, denoising by Gaussian filtering, etc., using some classical operators to detect significant edges in the image. Reference (Montague et al. 2005) built a visual inspection system to measure the curvature of the strip during hot rolling; Cheng Peng et al. (2013) preprocessed the image in a specific context and applied morphological theory to identify the circular object; Another study (Wang et al. 2013) use the Sobel vertical edge detection operator to identify and locate the license plate for a license plate image acquired in a complex background.

In terms of target recognition, Tokuhiro AT (2005) used machine vision to detect the corrosion of the control rod surface in the reactor; Amavasai B. P. et al. (2005) added machine vision to the micro-robot system, achieved the detection and identification of the external environment; Singh V et al. (2006) developed a machine vision-based inspection system and classified metal sheets by

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combining image processing with artificial neural networks; Liu Y C et al. (2007) studied the characteristics of laser fuze in complex environment, and proposed a parallel artificial neural network algorithm to detect and identify the edge features of fuze.

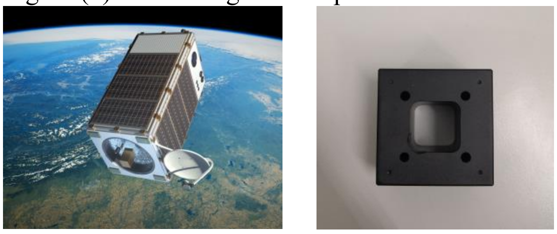
Most current research on target recognition focuses on target feature recognition for simple backgrounds or specific contexts. These methods use their own geometric feature constraints to extract the target contour. The commonly used methods are mainly iteration and enumeration. The main disadvantage of this method is that its robustness is not high and the computational efficiency is not high. In some complex feature collection scenarios, or real-time online processing projects, a more efficient way to extract contours is needed. To solve these kinds of complicated, large-scale optimization problem, meta-heuristic optimization algorithms emerged. By virtue of its obvious advantages, mainly including easy to implement, do not require specific parameters information and being able to bypass local optima, these meta-heuristic optimization algorithms have been utilized in engineering applications widely.

Based on the previous research, this paper proposes a target recognition method based on whale optimization algorithm. In this paper, the geometric features of rectangular objects of different scales are used as features to be identified and tested in complex backgrounds. At the same time, a multi-constraint condition based on its spatial geometry is proposed, which can extract the target contour quickly and accurately after image preprocessing. The simulation results show that the proposed method can accurately extract rectangular targets with complex background and has a certain degree of robustness.

2 OBJECT STRUCTURE AND FEATURE RECOGNITION

2.1 Rectangular Object Feature Analysis

The main target of the proposed object in this paper is Rectangular object. There are many rectangular features in the identification problem that need to be identified, such as satellites, parts, containers, etc. There is no cooperation mark on it, and its motion cannot be predicted. Therefore, its recognition mainly depends on its geometric features. The satellite body in Figure (a) has a rectangular feature, Figure (b) is a rectangular component.



(a) Satellite (b) Rectangular component

Figure 1: Rectangular object structure.

2.2 Rectangular Feature Recognition Process

In general, the feature recognition process in this paper is mainly divided into two parts: image preprocessing and line detection. In the process of image shooting, it is easy to be affected by random noise, weakening the morphological features of the target, causing the target edge to be blurred, which has adverse effects on image recognition. Therefore, in order to facilitate the accuracy of image recognition, it is necessary to perform a pre-processing operation first, and then complete the line detection on this basis.

2.2.1 Image Preprocessing

In this paper, the target is captured by a grayscale camera. According to the acquisition equipment, the image noise collected by this device is mainly normal distributed noise. Denoising grayscale images with Gaussian filter, which can eliminate the interference caused by environment and equipment. . The two-dimensional Gaussian distribution is as follows:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

Where (x,y) is the image coordinate and σ is the standard deviation. The Gaussian function is discretized and combined with the original pixels to obtain a Gaussian function value. This value is the new pixel value in the current coordinates of the image, and then the denoised image is obtained.

The first processing to be performed on the denoised image is threshold segmentation, which divides the object in the image from the partial background to serve the edge detection of the object to be measured. The threshold segmentation method adopted in this paper is Otsu algorithm (Nobuyuki Otsu 1979), which is a method for determining the adaptive threshold. This method can maximize the inter-class variance between the background and the target, thus minimizing the probability of mis-segmentation. It is a widely used fast image segmentation method.

In terms of edge detection of images, a variety of detection operators are widely used, and each operator has its advantage. For example, the Reborts operator uses local differences to find edges; the Sobel operator combines direction difference operations with local weighted averages to extract edges; the Prewitt operator is similar to Sobel, except that it uses first-meanization and then differential. In this paper, the Canny operator is used, which uses the variational method to find the pixel boundary, and uses the double threshold to segment the strong and weak edge points. This operator is the theoretically relatively perfect edge detection algorithm.

In this paper, the simulation experiment data is collected by the gray scale camera. The Gaussian filter denoising, adaptive threshold image segmentation, edge detection and Hough transform line extraction are used to identify the spatial geometric features of the space. The specific process of image preprocessing is shown in Figure 2.

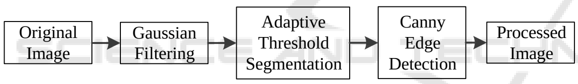


Figure 2 Image Preprocessing

2.2.2 Line detection based on Hough Transform

The non-cooperative spacecraft body has a rectangular geometric feature, and the spacecraft body is identified by the preprocessed image. In this paper, the Hough transform is used to extract the linear features in the image, and then the rectangular features of the spacecraft are obtained. The basic idea of Hough transform is to transform the points in the image space into the parameter space and accumulate them by using the duality of the image space and the parameter space, achieve the purpose of detecting the line in the image space.

In two-dimensional space, the equation for a straight line in a Cartesian coordinate system is:

$$y = kx + b \tag{2}$$

To avoid the case where the slope or intercept is ∞, convert the linear equation to the form under parameter space (r, θ):

$$r = x\cos\theta + y\sin\theta \tag{3}$$

r is the distance from the origin to the nearest point on the line, and θ is the angle between the x-axis and the line connecting the origin and the nearest point to it.

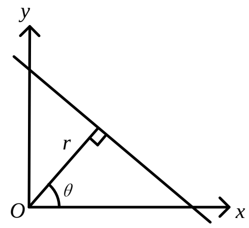


Figure 3: Hough transform.

Figure 3 shows the principle of the Hough transform, the points on the same line are converted to the parameter space, and these points are accumulated in the parameter space, so that the line exceeding the target threshold is detected. However, due to the complicated background, the selection of the target threshold is very strict, and it is difficult to accurately identify the target. Therefore, this paper uses the whale optimization algorithm to screen straight lines based on morphological constraints to identify the correct target.

3 OPTIMIZATION MODEL

3.1 The Whale Optimization Algorithm

Whale Optimization Algortihm(WOA) is a novel excellent meta-heuristic intelligence algorithm proposed by Seyedali Mirjalili (2016), which is inspired by the hunting rules of humpback whales. WOA has been proved equipped prominent search ability than most of the traditional intelligence algorithm, such as Particle Swarm Optimization (PSO) (Kennedy Eberhart 1995), gravitational search algorithm (GSA) (Rashedi 2009), Differential Evolution (DE) (Storn R Price K 1997.), et.al, since it has the ability of avoiding in trapping in the local optima and being able to converge to global optima in a fast speed, and it is worth to be mentioned that WOA has good performance in solving constrained problems (Yuyuan 2019).

The primary rule of WOA is to update each whale' position towards the best solution up to now, which is mainly composed by two parts, bubble-net attacking method (exploitation phase), search for prey (exploration phase).

1. Exploitation Phase (local search)

Here set the population size as NP and the maximum iteration number as $T_{\max}$.

The exploitation phase happens in most of the situations, by updating the position to the best solution.

$$\boldsymbol{X}(t+1)=\begin{cases}\boldsymbol{X}^*(t)-A\cdot\boldsymbol{D}, & p<0.5 \ and \ |A|<1\\ \boldsymbol{X}^*(t)+\boldsymbol{D}'e^{bl}\cos(2\pi l), & p\ge 0.5\end{cases} \quad (4)$$

where t means the iteration time currently, X is the position vector, X^* represents the position of the best individual so far and p is the random number between 0 and 1.

The other parameters are calculated as follows:

$$\boldsymbol{D}=C\cdot\boldsymbol{X}^*(t)-\boldsymbol{X}(t), \boldsymbol{D}'=X^*(t)-X(t) \quad (5)$$

$$a=2\text{-}\frac{2}{N-1}(i\text{-}1),(i=1,2,...,T_{\max}) \quad (6)$$

$$A=a(2r-1), C=2r \quad (7)$$

where r is the random number between 0 and 1, l is the random number between 0 and 1and b is constant, which influences the speed of convergence.

2. Exploration Phase (Global Search)

In this case, the position of the selected whale updates towards a random individual, which aims to avoid trapping in the local optima.

$$X(t+1)=X_{rand}(t)-A\cdot\boldsymbol{D}_{rand}, |A|\ge 1 \ and \ \ p<0.5 \quad (8)$$

$$\boldsymbol{D}_{rand}=C\cdot X_{rand}(t)-X(t) \quad (9)$$

where $X_{rand}(t)$ indicates the position of random individual in the population, the other parameters is obtained in the same way as exploitation phase situation.

3.2 Mathematical Model

To build the mathematical model of the feature recognition system, we transfer this problem into finding two groups of parallel lines meeting the requirement.

After the camera calibration, combined with the calibration parameters and the size of the target, it is known that the target size in the image is about 284×284 pixels, so b_0 is set 284. Therefore, this feature recognition problem is transferred into a optimization problem, which is to screen out the parallel lines which satisfy the distance requirement. Then the selection mechanism in this paper is concluded in Figure 4.

if $|k_i-k_j|<\text{V}k$ %Compare the gradient between the two lines

if $-\text{V}b<|b_i-b_j|-b_0<\text{V}b$ %Compare distances between two lines

Save lines *i* and *j* to the memory archive

end

end

Determine if the lines intersect in the range of the errors permitted

Figure 4: Selection Mechanism of WOA.

Considering the instrument precision, we choose $\text{V}k=10^{-1}, \text{V}b=20$ in this paper.

In the end, determine whether the endpoints of the real line segments on the parallel lines intersect (allowing for some error), and finally select the two sets of parallel lines of the target.

3.3 Experimental Flow Chart

Through the above modeling process, the flow chart for the full experimental process is shown in the Figure 5.

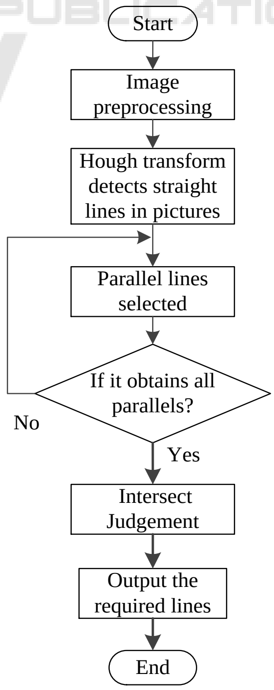


Figure 5: Algorithm Flowchart.

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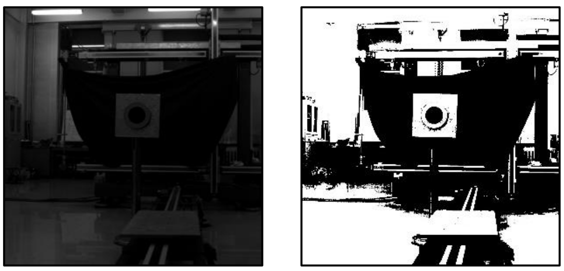
4 EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the feasibility of the rectangular geometric feature recognition algorithm for non-cooperative spacecraft, this paper builds a simulation experiment environment and carries out experimental verification. The experimental environment consists of a high-resolution grayscale vision module, a non-cooperative spacecraft model, an image acquisition control and data processing module, and an algorithm execution computer.

The camera used is a high-speed CMOS digital monochrome camera from Mikrotron, Germany, with a pixel resolution of 1680×1710 . The data acquisition module consists of NI high-speed real-time data collectors and storage devices. All algorithms are coded in Matlab 2012a and performed on a computer with Intel Core i7-8565 CPU,1.99 GHz and 8 GB RAM, under Windows 10 pro, 64-bit OS.

The above image acquisition device is used to shooting the experimental image. The feature detection algorithm proposed in this paper is used to detect rectangular parts with different scales in the Figure 6(a), Figure11 and Figure15.
Firstly, the detection process of a large-sized rectangular object will be described. The large part is made of KT board and reflective material. In this paper, the size of the large part is 350×350 mm.



(a)Original Image (b) Processed Image

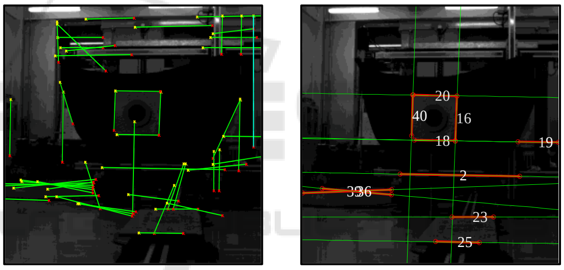
Figure 6: Image Preprocessing.

In order to verify the accuracy and robustness of the algorithm, three different thresholds were chosen to perform a Hough transform on the test image to obtain a different number of straight lines, in this way three experiments are solved in this section, the thresholds set and the number of detected lines are shown in table 1.

Table 1: Set of Experiments.

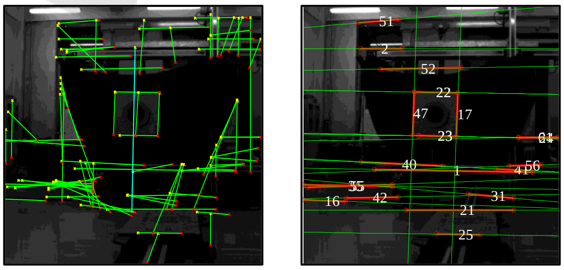
	FillGap	MinLength	Lines' number
1	100	350	21
2	120	200	84
3	120	80	133

For the above three images with different numbers of lines, use the optimization algorithm proposed in this paper for processing. The line detection image and results after parallel constraining optimization for the three experiments are shown in the Figure 7, Figure 8, and Figure 9 separately.



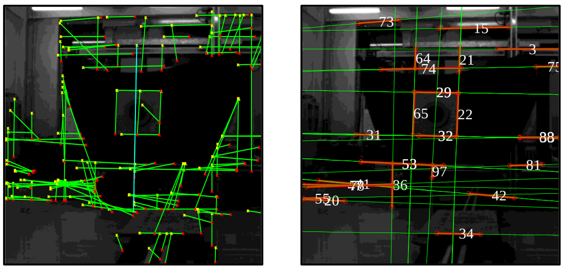
(a) Line Detection (b) Parallel Obtained

Figure 7: Experiment One.



(a) Line Detection (b) Parallel Obtained

Figure 8: Experiment Two.



(a) Line Detection (b) Parallel Obtained

Figure 9: Experiment Three.

The search population of in WOA is set as 100, and each experiment is repeated a 10000 times, then the average iteration times, number of parallel obtained and correct rate are recorded in Table 2. Noted that the average iteration times means the best result will not improve in 10 times iteration.

Table 2: Optimization Results.

	Average Iteration Times	Number of Parallel	Correct Rate (%)
1	11.4832	5	99.84
2	11.5543	12	99.99
3	11.7710	17	99.95

It can be concluded from Table 2 that the sets of parallel lines obtained for these three tests are 5, 12, and 17. Furthermore, with the increase of problem complexity the average iteration times needed are added slightly and the correct rate is fluctuate between 99.99% and 99.84%, which means the proposed method is feasible to solve this line detection problem with strong adaptive capacity.

After parallel constraining selection by WOA, most of the interference lines in the picture have been filtered out. After performing the intersection constraint, the three images get the same result, as shown in the Figure10.

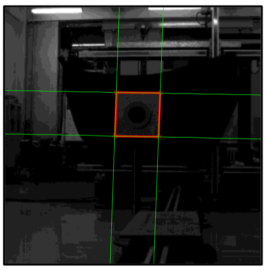
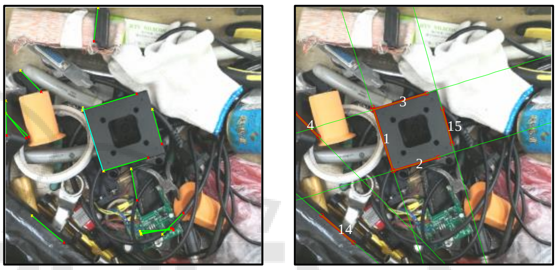


Figure 10: Final Recognition Result.

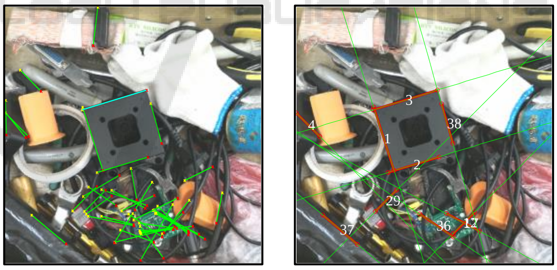
In order to verify the versatility of the algorithm, other parts are identified by the above algorithm. This time, this article uses color camera to collect data. The same algorithm is used to identify a small rectangular part(55×55 mm)shows in Figure 11. As shown in the Figure 12 and Figure 13, two sets pictures are used in the experiments (Experiment Four and Experiment Five), with different threshold set.

Figure 11: Original Image.



(a) Line Detection (b) Parallel Obtained

Figure 12: Experiment Four.



(a) Line Detection (b) Parallel Obtained

Figure 13: Experiment Five.

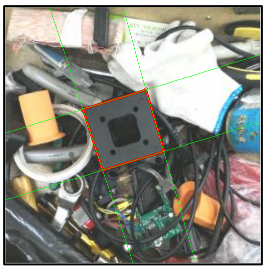


Figure 14: Final Recognition Result.

It can be seen from the above output image that the test image is identified by the algorithm proposed in this paper, and the rectangular contour of the object can still be detected in the case of more interference, indicating that the algorithm has better robustness; From the above point of view, the optimization model proposed in this paper is highly efficient and has better applicability.

Next, another figure with two rectangular parts is test in this paper, and the original figure is shown in Figure 15. The size of the part is 75×75 mm. Then the result of this test (Experiment Six), including the line detection figure and final recognition figure are displayed in Figure 16.

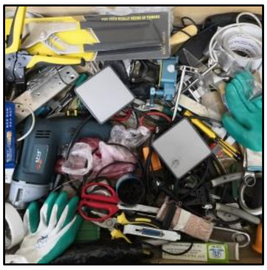


Figure 15: Original Image.

(a) Line Detection (b) Final Recognition Result

Figure 16: Experiment Six.

5 CONCLUSIONS

Target recognition technology in complex background is one of the key technologies at present. For example, when performing part inspection and recycling, it is necessary to accurately identify targets with specific geometric features. This paper presents a rectangular feature recognition method based on whale optimization algorithm. There is no need to exclude complex backgrounds during the identification process. Once the target is successfully identified, it can be used for subsequent tasks such as pose measurement. After the image is pre-processed, the Hough transform is applied to detect the line, thereby extracting the line set to be identified. Then, combined with the spatial geometric feature constraints of the image, the mathematical model is used to optimize and finally identify the target object. The simulation experiment proves that when the number of lines to be screened in the picture is different, the optimization model established in this paper can quickly and accurately identify the rectangular features in the image, and has high execution efficiency and strong robustness. Moreover, this paper tests the image with multiple rectangular features in the image. The results show that the proposed algorithm can effectively extract the features of similar rectangular objects in images.

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