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RESEARCH ARTICLE

An Infrared Target Images Recognition and Processing Method Based on the Fuzzy Comprehensive Evaluation

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ABSTRACT In response to the issues of relatively low image contrast, blurry boundaries of infrared small targets, and various environmental noise interferences in thermal imaging systems, resulting in reduced target recognition rates and tracking effectiveness. This paper proposes an infrared target image recognition algorithm based on fuzzy comprehensive assessment. Built upon infrared image sequences captured by an on-board thermal imager, the algorithm employs grayscale processing, neighborhood mean filtering, and second-order difference method to filter and enhance the infrared target images. This process improves the quality of infrared target images and enhances the contrast between targets and backgrounds. The algorithm utilizes the maximum interclass variance method for segmenting the infrared target images, combining it with the Canny operator to extract target edges, thereby obtaining clearer details of the infrared target edges. Finally, based on the extracted target feature information, the algorithm calculates the confidence of each marked region, establishes the membership function of target likelihood, employs a comprehensive weighted approach to construct the target confidence function, and compares the confidence of marked regions with that of the template image to achieve precise target recognition. Experimental validation against theoretical methods and comparisons with other approaches demonstrate the effectiveness and feasibility of the proposed method, providing theoretical support for reliable target tracking in electro-optical imaging systems.

INDEX TERMS Infrared target images, neighborhood average filtering, maximum interclass variance, fuzzy comprehensive evaluation, target recognition.

I. INTRODUCTION

A. RESEARCH BACKGROUND

With the application and development of target recognition technology in the military field, accurate and rapid recognition of targets is of great significance for reliable tracking effect. Due to the complex environment of military scenes and mostly night conditions, the visible light imaging system can hardly recognize the moving target in this scene. In recent years, with the continuous development of infrared technology and the expansion of application fields, the research of infrared target images has become more and more important in military, security, monitoring and other fields. Infrared images have become an indispensable part of modern sensing technology because of their unique advantages in achieving target detection and recognition at night or in low-illumination environments. The performance of infrared target image recognition system directly affects the execution of tasks in key areas such as military reconnaissance, border monitoring, and drone navigation. To solve the stable tracking of the moving target in the night environment with weak illumination, the infrared thermal imager is used

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to convert the invisible infrared energy emitted by the target into a visible thermal image, due to the fact that infrared images are obtained by measuring the heat radiated from objects, they have disadvantages such as poor resolution, low contrast, low signal-to-noise ratio, blurred visual effects, and limited information compared to visible light images. The comfortable visual imaging effects are obtained by a series of image processing, among them, image denoising and enhancement are particularly important. In various stages of imaging, infrared images are subject to external influences and generate noise, such as thermal conduction effects and air scattering, resulting in blurred image edges and low contrast; the uneven temperature distribution will cause speckle noise, which seriously affects the visual effect. The denoising method based on infrared image has important research value for infrared detection equipment to accurately recognize targets [1], [2]. Infrared image target recognition technology can rely on observation images to obtain the category of interested targets, and provide support for intelligence interpretation.

However, infrared target images also face typical challenges, including illumination changes, weather effects, target and background fusion. In response to these challenges, researchers are committed to finding effective image processing and recognition methods to improve the recognition performance of infrared target images. In this context, this study aims to explore the application of fuzzy comprehensive evaluation method in infrared target image recognition and processing. As a flexible and adaptable method, fuzzy comprehensive evaluation has natural advantages in dealing with ambiguity and uncertainty in infrared images. By introducing fuzzy logic and fuzzy set theory, we try to improve the robustness of infrared target image recognition system to complex environment and uncertain factors.

B. THE MAIN CONTRIBUTION OF THE THESIS

The main contributions of this work are as follows:

(1) When we collect infrared images, the temperature of the target area is close to the temperature of the interference source in the surrounding environment, which leads to the high similarity between the target area and the interference source in the collected infrared image and the low signal-to-noise ratio and low clarity of the original image. In this paper, we use the neighborhood average filtering and second-order differential processing methods to filter and denoise, thereby enhancing the contrast between the target and the background.

(2) In view of the relatively complex background of the target, the large noise of the collected image and the loss of the edge details of the target when collecting the infrared image of the moving target, we put forwards the maximum inter-class variance method to segment the target and background in the infrared image after noise reduction and filtering, and uses the Canny operator to extract the edge information of the image, so that the edge details of the target are clearer.

(3) Based on the extracted feature information, we construct a membership function to determine the likelihood of the target, form a target confidence function combining the feature information of the target itself, and propose the recognition algorithm of target using fuzzy comprehensive evaluation method.

The remainder of this paper is organized as follows: Section II states the related work of this paper. Section III elaborates infrared target images recognition and processing based on the fuzzy comprehensive evaluation. Section IV gives experimental analysis. Section V provides a summary of this paper.

II. RELATED WORK

In view of the fact that target recognition in infrared target images has become a research hotspot, for example, Li et al. [3] proposed a fuzzy comprehensive evaluation method to recognize target by calculating the confidence of the target area. Wang et al. [4] studied a target recognition method based on infrared visible light fusion, and realized image target recognition through the principle of local invariance matching. Based on the infrared image recognition and tracking algorithm of the aircraft, Wang and Liu [5] simulated and analyzed the infrared image of the aircraft by establishing an algorithm model, and realized the recognition and tracking of the target. Zhan et al. [6] proposed a vehicle target recognition algorithm based on the fusion of lidar and infrared target image, which used the target matching threshold to iteratively screen by fusing infrared features and point cloud features, and finally recognized vehicle target. Lan and Yang [7] used an average drift target tracking algorithm to accurately track the intelligent networked vehicles obtained by using the infrared imaging principle. Ning and Zheng [8] studied a decision-level fusion strategy based on model reliability to detect infrared target images, and fused the model detection results according to the fusion strategy to obtain the final target detection results. Miao and Wang [9] put forward a single-frame infrared weak target detection algorithm based on improved Sobel operator, the improved Sobel operator is used to convolve the image, and finally detected infrared weak and small targets after median filtering. He et al. [10] researched an infrared weak target detection algorithm based on randomized tensor algorithm, which not only reduced the computational complexity, but also improved the detection performance of infrared weak and small targets compared with the traditional algorithm based on low-rank sparse decomposition. Xiong et al. [11] presented a millimeter-wave radar and infrared camera fusion system, which extracts and combines the advantage information of each sensor through target-level fusion, and finally output stable target perception results. Zhang et al. [12] proposed image registration based on gray peak and Fourier phase correlation algorithm, and recognized the moving point target by calculating the absolute value of the difference between the overlapping parts of the two images. Wu et al. [13] proposed a low-visibility road target detection algorithm based on infrared visible light fusion, which can optimize the road target detection model by fusing five parameters, including mean, standard deviation, information entropy, average gradient and spatial frequency, this measure can improve the target detection accuracy. Ma et al. [14] researched a feature fusion algorithm based on the target detection task, which simultaneously input visible light and infrared target images into the end-to-end neural network to perform feature extraction and feature fusion, and finally output the target detection results. Wang et al. [15] put forward an infrared saliency target detection algorithm based on the similarity Bayesian model, which enhanced the contrast between the target and the background and improved the target detection accuracy by suppressing noise interference in the infrared image. Yang and Li [16] analyzed an infrared weak target detection algorithm based on Bayesian estimation, and a large number of experimental tests showed that the algorithm could detect moving targets with a lower signal-to-noise ratio and is more robust. Shen et al. [17] proposed a semi-supervised infrared image target detection algorithm based on CenterNet and OMix enhancement, used CenterNet as the backbone model to detect target in infrared target images according to key points, and achieved good detection performance by training and testing on public datasets. Liu et al. [18] set up the lightweight infrared real-time target detection model MCA-YOLO, which improved the real-time performance of target detection by reducing the model parameters and ensured the detection accuracy. Sun et al. [19] proposed a simple and fast infrared image salient target detection algorithm, extracted the spectral residuals in the log spectrum by enhancing the contrast between the target and the background, and used a sliding window to search in the target candidate area until the accurate position of the target is determined. Li et al. [20] studied a lightweight infrared image target detection algorithm GPNet, fused GhostNet and improved PANet to reduce network parameters and extract more feature information. Li et al. [21] proposed an infrared pedestrian small target detection algorithm based on YOLOv3, fused SE block and YOLOv3 models to perform weight calibration to improve the feature description ability of target detection network. Wang et al. [22] researched an infrared time-sensitive target detection method based on cross-modal data enhancement, realized accurate detection of infrared time-sensitive targets by integrating SE module and CBAM module in the YOLOv5 target detection framework. In [23], the Traffic Salient Object Detection Using a Feature Deep Interaction and Guidance Fusion Network (TFGNet) is proposed. In [24], a novel artificial intelligent evaluation method for the selection of a levitation controller is developed based on a 3-grade fuzzy method and analytic hierarchy process (AHP). The improvement of target detection accuracy provides a good prerequisite for subsequent target tracking. Yang et al. [25] proposed an infrared target recognition algorithm for air defense weapons based on deep learning for the operational requirements of air defense weapons. The YOLO network model was used to realize the multi-target recognition and positioning of the whole image. In the target tracking stage, the super-resolution reconstruction algorithm is used to improve the local image resolution of the target, and the deep residual network model is used to realize the recognition and classification of the tracking target. Zhang et al. [26] studied a method of detecting moving targets using infrared video images to solve the problem that it is difficult to image visible light equipment at night. The improved median filtering algorithm, the idea of grayscale and wavelet transform and the target positioning algorithm based on the center of gravity of the object are used to detect and locate the target. Then the Haar-like feature is used to characterize the characteristics of the moving target. Finally, the AdaBoost algorithm is used to identify the moving target in real time. Li et al. [27] studied an aircraft infrared target recognition method based on infrared image and feature fusion to solve the problem that the high complexity of the shape, attitude and size of the infrared image of the aircraft makes the recognition rate and robustness of the existing infrared target recognition methods not high. Wang et al. [28] proposed an adaptive enhancement framework for a single low-light image, the exposure control parameters are adaptively generated and a virtual exposure enhancer constructed by a quadratic function is applied to generate several image frames from a single input image. Li et al. [29] propose a knowledge distillation method for low light image enhancement, uses a teacher-student framework in which the teacher network tries to transfer the rich knowledge to the student network, and designed a gradient-guided low-light image enhancement network. Although the research on infrared image recognition based on image processing and deep learning has made great progress, there are still some problems:

(1) The infrared image recognition method based on deep learning requires collecting a large number of training samples and annotating them, and the network model is composed of a large number of parameters, which requires high computational resources.

(2) The infrared image recognition methods based laser is prone to strong environmental light interference, leading to a decrease in image quality. In outdoor or complex environments, laser signals may undergo multiple reflections, scattering, and refraction, resulting in multipath effects that interfere with target recognition rate and tracking effect.

(3) The infrared image recognition method based on radar has relatively low resolution, which may lead to unclear boundary and texture information of the target. Moreover, the radar signal is affected by material absorption, reflection, and diffraction during propagation, which can lead to certain errors in the measurement results of the infrared image.

(4) When the temperature of the target area is close to the temperature of the interference source in the surrounding environment, the target area in the collected infrared image has a high similarity with the interference source, which affects the target recognition accuracy.

Due to limitations in testing conditions, this study only collected a small number of infrared images of tank targets, making it impossible to construct a large sample dataset and adopt deep learning methods that require large samples for target recognition; therefore, this paper proposes a method for infrared target image recognition and processing based on fuzzy comprehensive evaluation, because the fuzzy comprehensive evaluation method can effectively solve fuzzy and difficult to quantify problems. Based on the infrared target image sequence obtained in this paper, the target in the image has various feature information, such as target shape features, moment features, statistical distribution features, etc. These can be applied as input variables to determine the possible membership function of the target. These target features are described adopting fuzzy language, and corresponding membership functions are constructed based on these fuzzy languages. To realize the transformation of qualitative evaluation into quantitative evaluation based on the membership degree theory of fuzzy mathematics, and obtain target recognition results.

III. INFRARED TARGET IMAGES RECOGNITION AND PROCESSING BASED ON THE FUZZY COMPREHENSIVE EVALUATION

A. THE PRINCIPLE OF INFRARED TARGET IMAGES RECOGNITION

Accurate and rapid recognition of targets by shooting multi-frame images by photoelectric imaging equipment is an important prerequisite for achieving stable target tracking effect. Under the condition of sufficient ambient illumination, the visible light imaging system is used to recognize and track moving target, if the ambient illumination decreases, such as cloudy days or night scenes, the visible light imaging system can hardly recognize and track the target [24]. The infrared imaging system can make up for the shortcomings of the visible light imaging system in the weak illumination, because the wavelength of the infrared imaging equipment is 0.75μm $\sim 1000\mu$m, which is much larger than the wavelength of the visible light imaging equipment, and the moving target can be tracked even at night.

Based on the infrared image of the moving target sequence taken by the infrared thermal imager, this paper proposes a target recognition method for infrared image, recognizes the target as a military tank. The photoelectric imaging equipment is an infrared thermal imager, and installs it in the armored vehicle. Because the target (tank) is in motion, the vehicle-mounted infrared thermal imager shoots the target in the road, the clouds, fog, smoke and other particles in the external environment, and the imaging interference and jitter effect of the infrared image taken by the infrared imaging equipment by the driving state of the armored vehicle [30]. The quality and clarity of every infrared image captured by the system cannot be guaranteed. To improve the stable target tracking effect of infrared imaging system, it is necessary to preprocess the captured sequence of infrared target images. Because infrared target images inevitably generate some noise during the collection process, which can affect the clarity and details of the image, reduce image quality, and interfere with feature information such as edges, textures, and details, even leading to target misrecognition. Accordingly, by removing noise from infrared target images and performing image enhancement processing to improve contrast, the interference of background noise on the target can be reduced. Which can apply the features of the target more obvious and accurate, improve the effectiveness of feature extraction, and make it easier to segment and recognize in the image, thereby further increasing the accuracy of target segmentation and recognition. Based on the preprocessed infrared target image, the maximum interclass variance method is used to segment the image and the separated target and the background is obtained, and the accurate recognition of the target is realized by combining the characteristics of the target in the infrared target images. This result provides a reference for the system's reliable tracking of targets. The flowchart of the infrared target image recognition method is shown in Figure 1.

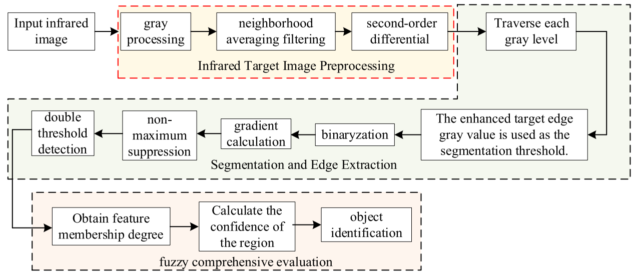


FIGURE 1. Flow chart of infrared target image recognition principle.

Figure 1 illustrates the specific design steps of the infrared target image recognition and processing method. Firstly, the onboard infrared thermal imager captures military targets in motion, forming multiple sequences of infrared target images. Subsequently, preprocessing of the infrared target images takes place, including grayscale processing, neighborhood averaging filtering, and second-order difference. Different template sizes for neighborhood averaging filtering are employed for denoising and image enhancement operations to suppress imaging interference and shake during the capture process [31]. This step aims to enhance the quality and recognizability of the original images. The next stage involves segmentation and edge extraction. The enhanced infrared target images are segmented using the maximum inter-class variance method to separate targets from the background. The Canny operator is then applied to extract target edges. This stage includes traversing each grayscale level, using the enhanced target edge grayscale value as the segmentation threshold, binarization, gradient calculation, non-maximum suppression, and double threshold detection. These steps accurately extract the edge information of the targets for subsequent target recognition. Finally, the fuzzy comprehensive evaluation stage comprises obtaining feature membership, calculating regional confidence, and target recognition.

In this stage, a fuzzy comprehensive evaluation is conducted by considering multiple features of the targets, such as feature membership and regional confidence, to achieve precise identification of infrared targets.

B. INFRARED TARGET IMAGE PREPROCESSING

Due to the interference caused by the shake of the vehicle-mounted infrared thermal imager during movement and the suspended smoke and dust particles in the surrounding environment, the captured infrared target images exhibit characteristics such as unclear imaging, low contrast, blurry edges, and strong sudden noise. To achieve stable and reliable target tracking effect, preprocessing is applied to the infrared target images to improve the contrast of the target and suppress the influence of interference signals. The infrared target image preprocessing process consists of three parts: grayscale processing, filtering and denoising, and image enhancement. The grayscale processing reduces the amount of data in the infrared target image, the original infrared target image is filtered and denoised using neighborhood average filtering and second-order differential processing, and the contrast between the target and background is enhanced to improve the accuracy of target recognition in the infrared imaging system.

The complexity of the military target driving environment and the intrinsic properties of the infrared detector result in a high probability of low contrast and high noise in the infrared target images captured by the system, which greatly affects the system's ability to recognize targets [32]. To mitigate the impact of noise on target recognition, grayscale processing and denoising filtering are performed on the infrared target images. The weighted average method is used to allocate the three RGB components in the infrared target image according to the sensitivity of the human eye. Assuming the original infrared target image is $f(x, y)$ and the infrared target image after grayscale processing is $f_{gray}(x, y)$, the grayscale value in the two-dimensional image is represented as (x, y), then $f_{gray}(x, y)$ is represented by equation (1).

$$f_{gray}(x, y) = 0.2R(x, y) + 0.59G(x, y) + 0.11B(x, y) \quad (1)$$

where $R(x, y)$, $G(x, y)$, and $B(x, y)$ represent the values of point (x, y) in the R, G and B channels, respectively.

Linear filtering methods such as mean filtering and non-linear filtering methods such as median filtering are commonly used for image denoising. Mean filtering is a linear filtering method that mainly uses neighborhood averaging to denoise images. This method is computationally simple and effective in suppressing Gaussian noise [33]. Median filtering is a non-linear filtering method that can overcome the blurring problem caused by linear filters and is effective in removing particle noise. Due to the special nature of the experimental environment and shooting conditions, this paper adopts the neighborhood averaging filtering method to process infrared target images. Assuming that $f_{gray}(x, y)$ is the function of the infrared target image to be filtered, the filtered infrared target image function is denoted as $g(x, y)$.The function for describing the neighborhood averaging filtering method is used to process the infrared target image, and which is shown in equation (2).

$$g(x, y) = \frac{1}{Q} \sum_{(x,y)\in M} f_{gray}(x, y) \quad (2)$$

where, the coordinates of each neighboring pixel within the selected neighborhood are denoted by M, while the total number of coordinates within set M is denoted by Q [34]. Effective reduction of speckle noise in infrared target images can be achieved through the application of neighborhood mean filtering, and the smoothness of the resulting denoised image is dependent on the size of the selected neighborhood. A superior denoising effect is obtained for infrared target images with larger neighborhood sizes.

The edge of the infrared target image after neighborhood average filtering processing is blurred, and the distortion is obvious, which interferes with the extraction and recognition of image edge information, so it is necessary to implement edge image enhancement operation on the target contour of the infrared target image after filtering processing. The differential calculus method of reverse operation is used to improve the rendering effect of high-frequency components in the image, so that the edge outline of the infrared target image is clearer. Compared with first-order differential processing, second-order differential processing has a more obvious effect on improving the high-frequency components of the image, and the Laplace operator expression representing the second-order differential is expressed by equation (3).

$$\nabla^2 g(x, y) = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \quad (3)$$

The equation (3) is discretized, and which is expressed as:

$$\begin{aligned}\nabla^2 g(x, y) = {} & [g(x+1, y) + g(x-1, y) + g(x, y+1) \\ & + g(x, y-1)] - 4g(x, y) \quad (4)\end{aligned}$$

After the second-order differential processing, the gray value of each pixel of the infrared image can be effectively saved, and at the same time, the contrast effect between the target and the background where the gray value difference is large is obvious through the enhancement processing of the infrared target image, and the detailed information of the edge outline of the infrared target image is significantly presented, which provides a basis for the next target and background segmentation.

C. INFRARED TARGET IMAGE SEGMENTATION AND EDGE EXTRACTION

The maximum interclass variance method is a global-based binarization algorithm that mainly splits the target and background according to the grayscale characteristics of infrared target images. The larger the interclass variance between the target and the background in the infrared target image, the greater the difference between the target and the background that constitutes the image. When part of the target is misdivided into the background or part of the background is misdivided into the target, it will lead to the difference between the target and the background becomes smaller; when the segmentation of the threshold makes the variance between the classes the largest, it means that the probability of misdivision is the smallest [35].

Assuming $h(x, y)$ represents the gray value of image $f_{M\times N}$ at point (x, y), K represents the gray level, and $h(x, y) \in [0, K-1]$. Let h_i denotes the number of pixels with gray level i, and P_i denotes the probability of the occurrence of the i th gray level, there is:

$$P(i) = h_i / (M \times N) \tag{5}$$

where $i = 0, 1, \cdots, K-1$, and $\sum_{i=0}^{K-1} P(i) = 1$.

Threshold T is set as the segmentation threshold between targets and backgrounds in infrared target images, among, T_b denotes the background with a gray level of $0 \sim k-1$, and T_t denotes the target with a gray level of $k \sim K-1$. The pixels corresponding to the background T_b and target T_t are represented by $h(x, y) < k$ and $h(x, y) \geq k$, respectively.

The probability of the appearance of background T_b is represented by P_{T_b}:

$$P_{T_b} = \sum_{i=0}^{k-1} P(i) \tag{6}$$

The probability of the appearance of background T_t is represented by P_{T_t}:

$$P_{T_b} = \sum_{i=k}^{K-1} P(i) \tag{7}$$

where, $P_{T_b} + P_{T_t} = 1$.

The average gray value of background T_b is represented by β_{T_b}:

$$\beta_{T_b} = \sum_{i=0}^{k-1} i\left(P(i)/P_{T_b}\right) \tag{8}$$

The average gray value of background T_t is represented by β_{T_t}:

$$\beta_{T_t} = \sum_{i=k}^{K-1} i\left(P(i)/P_{T_t}\right) \tag{9}$$

The average gray value of the infrared image is represented by β:

$$\beta = \sum_{i=1}^{K-1} iP(i) \tag{10}$$

The interclass variance between the background and targets in the infrared target image is represented by δ:

$$\delta^2(t) = P_{T_b}\left(\beta - \beta_{T_b}\right)^2 + P_{T_t}\left(\beta - \beta_{T_t}\right)^2 \tag{11}$$

The range of values for threshold t is set to $(0, K-1)$ [36]. When the variance $\delta^2(t)$ is maximal, the optimal threshold t is obtained, which maximizes the contrast between the targets and background in the infrared target image. The maximum interclass variance method is sensitive to noise and target size, and it only produces satisfactory segmentation results for images with unimodal interclass variances. The specific process of segmentation is as follows: Firstly, globally traverse the entire infrared target image. Then determine the grayscale values of the target edge after image enhancement, and set them as the segmentation threshold. Finally, set the grayscale values higher than the target part and lower than the target part respectively to obtain the binarized target image. When the size ratio between the target and background is significantly different, the interclass variance criterion function may exhibit bimodal or multimodal characteristics, which leads to unsatisfactory results. Morphological closing operation is performed on the segmented infrared target image using an appropriate structural element, which effectively fills the gaps in the threshold-segmented image. Morphological closing operation is defined as dilation followed by erosion, and $A \cdot B$ denotes the closing operation of B with respect to A, whose result is shown in equation (12).

$$A \cdot B = (A \oplus B) \Theta B \tag{12}$$

After the threshold segmentation and closing operation processing of the infrared target image, the "logic" and "and" operations are required, which can realize the effective superposition of different infrared target images and better realize the segmentation of the target and background.

The edge of the infrared target image contains rich feature information, and the edge detection and extraction can provide accurate edge feature information for subsequent image processing. In this paper, the Canny edge detection operator is selected for image edge detection, and the edge detection process steps are shown in Figure 2.

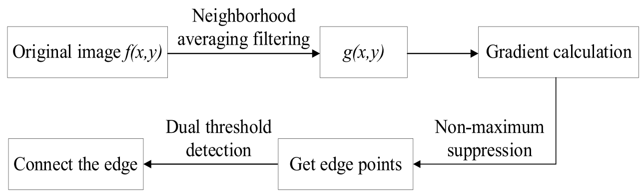


FIGURE 2. Canny edge detection process.

Based on the above information, the smooth image obtained by using two determinants of 2×2 is used to convolute the image information, and the two determinants are shown in equation (13).

$$\begin{cases} H_1 = \begin{pmatrix} -0.5 & 0.5 \\ -0.5 & 0.5 \end{pmatrix} \\ H_2 = \begin{pmatrix} 0.5 & 0.5 \\ -0.5 & -0.5 \end{pmatrix} \end{cases} \tag{13}$$

The above pixels are calculated in the x and y axes to obtain gradient information $d_x(x, y)$ and $d_y(x, y)$ for the pixels, which are shown in equation (14).

$$d_x(x,y) = g(x,y) * H_1, d_y(x,y) = g(x,y) * H_2 \quad (14)$$

The purpose of gradient calculation is to obtain the amplitude information $M(x,y)$ and direction information $\theta(x,y)$ of the specific image pixel in the smoothed image $g(x,y)$ after filtering process, among them, $M(x,y)$ represents the amplitude information of the pixel and $\theta(x,y)$ represents the direction information of the pixel, which can be obtained by equations (15) and (16).

$$M(x,y) = \sqrt{d_x^2(x,y) + d_y^2(x,y)} \quad (15)$$

$$\theta(x,y) = \arctan\left(\frac{d_y(x,y)}{d_x(x,y)}\right) \quad (16)$$

The purpose of non-maximal suppression is to determine whether point $M(x,y)$ is an edge point. The judgment condition is whether the point is a local maximum point, if it is a local maximum point, it is an edge point, and if not, it is $M(x,y) = 0$.

D. TARGET FEATURE EXTRACTION AND RECOGNITION BASED ON THE FUZZY COMPREHENSIVE EVALUATION

The fuzzy comprehensive evaluation method is a comprehensive evaluation method based on fuzzy mathematics. This comprehensive evaluation method transforms qualitative evaluation into quantitative evaluation based on the membership theory of fuzzy mathematics, which applies fuzzy mathematics to make a comprehensive evaluation of things or objects constrained by multiple factors. It has the characteristics of clear results and strong systematicity, which can effectively solve fuzzy and difficult to quantify problems, and is suitable for solving various non-deterministic problems. According to the specific characteristics of target infrared imaging and actual imaging conditions, the characteristic information of the infrared target image is selected, and the target shape feature, moment feature and statistical distribution feature are used as input variables to judge the target possibility membership function, and these target features are described in fuzzy language, specifically: (1) The larger the segmentation area duty cycle is away from a certain range, the smaller the probability of the target. (2) The larger the aspect ratio of the divided area away from a certain range, the less likely it is to be the target. (3) The larger the roundness of the segmented area away from a certain range, the less likely it is to be the target. (4) The larger the complex moment of the division area away from a certain range, the less likely it is to be the target. (5) The greater the mean contrast in the segmentation area, the greater the probability of being the target.

According to the description of the four fuzzy languages (1)-(4), To conform to the essential characteristics of the fuzzy variable as much as possible, the intermediate normal distribution function is selected to construct the corresponding membership degree function as shown in equation (17).

$$\mu(i) = \begin{cases} e^{-\left(\frac{i-a}{\sigma}\right)}, & i < a \\ 1, & a \leq i \leq b \\ e^{-\left(\frac{i-b}{\sigma}\right)}, & i > b \end{cases} \quad (17)$$

where a, b and σ are the parameters determined in the experiment [37].

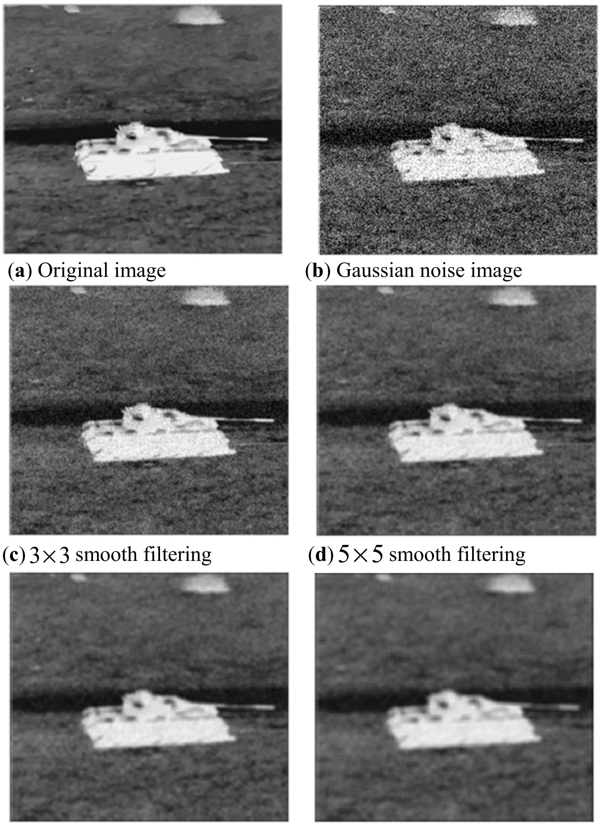
According to the description of above fuzzy languages, To conform to the essential characteristics of the fuzzy variable as much as possible, the corresponding membership degree function can be constructed by selecting the large normal distribution function as shown in equation (18).

$$\mu'(i) = \begin{cases} 0, & i < a \\ 1 - e^{-\left(\frac{i-a}{\sigma}\right)}, & i \geq a \end{cases} \quad (18)$$

When real targets and false targets appear in the sequence images taken by the vehicle-mounted infrared thermal imager, it is necessary to recognize the targets in the sequence infrared target images. This paper utilizes the fuzzy comprehensive evaluation method to evaluate the segmented target and compares it with the confidence level of the template image. Finally, the target part with a confidence level similar to the template image is extracted as the real target. After segmenting the sequence images captured by the vehicle mounted infrared thermal imager, it is necessary to distinguish between the real target and other interfering objects. The segmented image containing only the real target is employed as the template image, and the confidence of the suspected target part in the sequence infrared target image and the template image is compared in a one-to-one manner, including the proportion area feature, perimeter feature, eccentricity feature, complex moment feature, and target mean contrast feature, obtain the similarity between the target image and the template image in each image, and its value represents a function of the target features to determine which category the target falls into [38]. Based on the extracted target features, the fuzzy comprehensive evaluation method is adopted to represent the extracted features as the membership parameters of the target. These membership functions are combined with the comprehensive weighting method to construct the target confidence function, which is:

$$I = (t_1\gamma_{R1} + t_2\gamma_{R2} + t_3\gamma_{R3}) \times (t_4\gamma_P + t_5\gamma_C) \quad (19)$$

where γ_{R1} is the proportion area characteristic of the target; γ_{R2} is the perimeter feature of the target; γ_{R3} is the eccentricity characteristic of the target; γ_P is the complex moment characteristic of the target; γ_C is the mean contrast characteristic of the target; $t_1 + t_2 + t_3 = 1$, $t_4 + t_5 = 1$. The three parameters t_1, t_2, t_3 control the weight of the area, perimeter and eccentricity characteristics of the target in the target confidence function respectively. When t_1, t_2, t_3 changes, it will affect the contribution of different features in the overall confidence. The two parameters t_4 and t_5 control the weight of the complex moment feature and the



(**a**) Original image (**b**) Gaussian noise image

(**c**) 3×3 smooth filtering (**d**) 5×5 smooth filtering

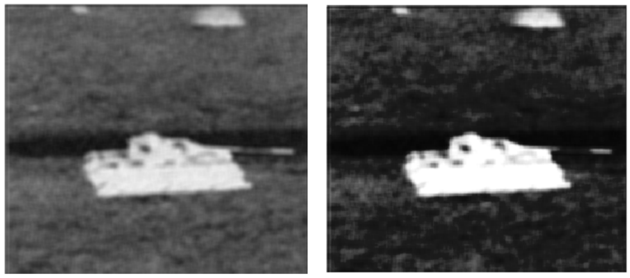
(**e**) 7×7 smooth filtering (**f**) 9×9 smooth filtering

FIGURE 3. Filtering results of infrared target image.

average contrast feature in the target confidence function. The change of these two parameters may lead to the adjustment of complexity and contrast, which affects the sensitivity to target structure and brightness difference. The specific process is: for each labeled area, the membership degree of the characteristic is obtained and the confidence degree of the region is calculated, and compared with the confidence of the template image, the segmented region is the target when I and $I_{\text{mod }e}$ are close, and the segmented region is not the target when the difference between I and $I_{\text{mod }e}$ is far. When multi-target occurs, select the target with the highest confidence in the target to recognize. Due to the differences among multiple targets, the lowest gray value of suspected targets is still used to determine the threshold value of the maximum inter-class variance method, which weakens the characteristics of other real targets. In this case, an appropriate threshold method should be determined according to the characteristics of multiple targets, which is not the research object of this paper. In the future, we will continue to carry out research on multi-object recognition methods in complex situations.

IV. EXPERIMENTAL ANALYSIS

To verify that the recognition effect of infrared target image after preprocessing, image enhancement and feature extraction operation is significantly improved, the sequence



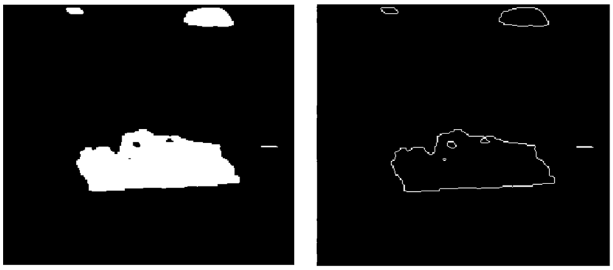
(**a**) Before image enhancement (**b**) After image enhancement

FIGURE 4. Infrared target image enhancement result.

infrared target images taken by the vehicle-mounted thermal imager is selected in the military scene to track it.The experimental environment is: Windows11 operating system, NVIDIA GeForce RTX 3050 Laptop GPU, i5-11400H CPU, 32GB memory, cUDA Version: 12.1, the application software includes Pycharm compilation environment and Python3.9. Considering the operability of the experiment, a certain frame of the infrared target motion state is selected by default for tracking, and the infrared target image is preprocessed, and the 3×3, 5×5, 7×7, 9×9 different templates are used to filter the infrared target image. The filtering results are shown in Figures 3(a)-(f).

Figure 3(a) is the original infrared target image, 3(b) is the infrared target image, containing Gaussian noise, 3(c) is the filtering results of 3×3 template smoothing filtering on infrared target image, 3(d) is the filtering results of 5×5 template smoothing filtering on infrared target image, 3(e) is the filtering result of the 7×7 template smoothing filter on the infrared target image, and 3(f) is the filtering result of the 9×9 template smoothing filter on the infrared target image. Comparing Figures 3(a) and 3(b), which can be seen that the background of infrared target image containing noise is complex, leading to a decrease in the quality of infrared target image and interfering with target recognition. Utilizing different templates to filter Figure 3(b), it was found that the filtering effect of adopting a 3×3 template had the worst filtering effect, and the infrared target image was still blurry after filtering the noise. The filtering effect of adopting a 5×5 template is poor, and the infrared target image is blurry after filtering noise. The filtering effect of adopting a 7×7 template is general, and Gaussian noise still exists in the infrared target image after filtering noise. The filtering effect of adopting a 9×9 template is good, and Gaussian noise has disappeared after filtering the noise. The larger the neighborhood, the better the noise removal effect. Consequently, the Gaussian noise in infrared target images can be well suppressed by employing appropriate templates and neighborhood average filtering.

The 9×9 template was selected for image enhancement after smoothing and filtering of the infrared target image, and the result is shown in Figure 4. Figures 4(a) show infrared target images without enhancement processing, as well as grayscale histograms. Figures 4(b) show the enhanced external infrared target image and grayscale histogram. Through



(a) Image segmentation (b) Edge extraction

FIGURE 5. Image segmentation and edge extraction results.

TABLE 1. Calculation results of infrared image features.

	γ_{R1}	γ_{R2}	γ_{R3}	γ_P	γ_C	I
Template target image	27252.00	893.52	0.93	38.46	246.56	8.1501e+05
The part I of infrared target image	385.00	80.69	0.92	44.40	251.08	1.5008e+04
The part II of infrared target image	29169.00	846.75	0.93	37.01	253.11	8.8319e+05
The part III of infrared target image	3300.00	245.16	0.91	72.58	252.20	1.1918e+05

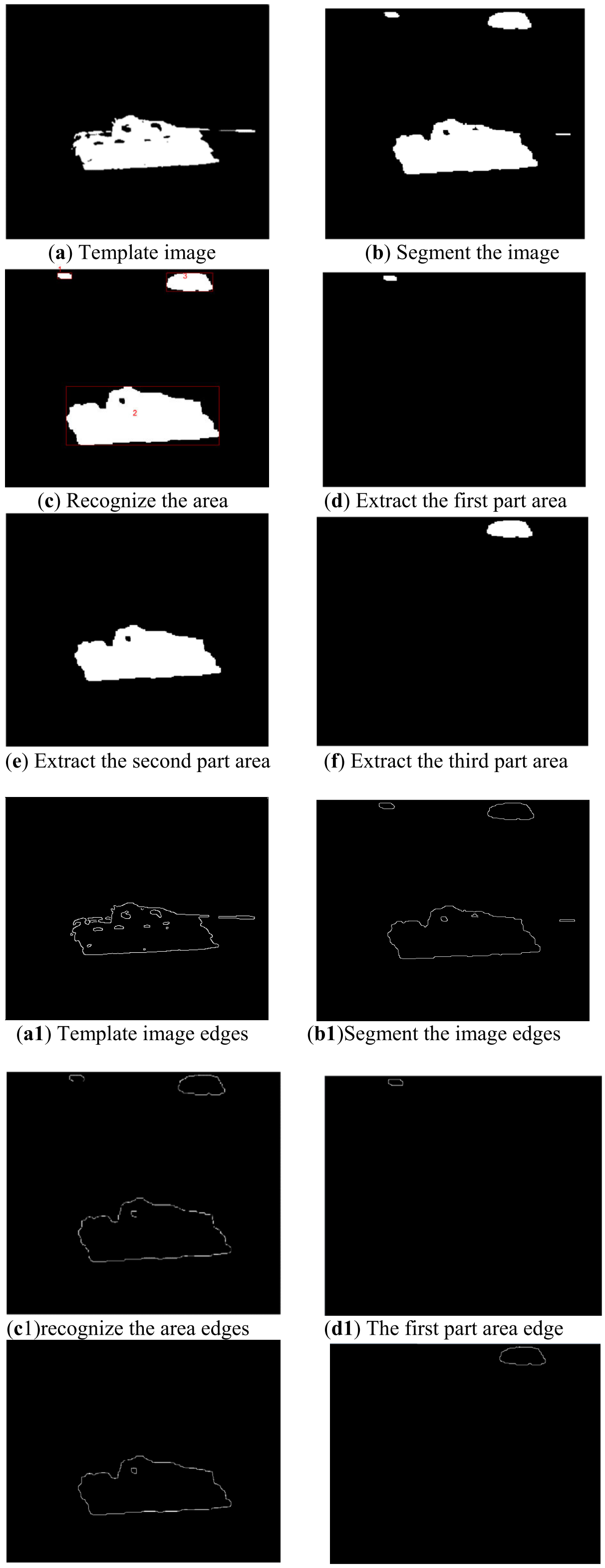
comparison, it can be concluded that the enhanced infrared target image has a more pronounced contrast and better visual effect, and from the distribution comparison of the histogram, the grayscale values of the enhanced infrared target image are more concentrated.

The enhanced infrared target image is segmented taking the maximum interclass variance method. The target grayscale value after image enhancement is applied as the threshold for target image segmentation, and the maximum interclass variance method is adopted to globally traverse the entire image. The grayscale value above the target is set to 255, and the grayscale value below the target is set to 0. In Figure 4(b), there are four suspected targets, after performing expansion and corrosion operations on it, there are three suspected targets remaining, among which the lowest grayscale value of the suspected target is 146, and this grayscale value is employed as the threshold for the maximum inter class variance method, and obtained the segmented image, as shown in Figure 5 (a). The Canny operator was used for edge extraction, and the processing results are shown in Figure 5 (b).

When the difference between I and $I_{\mathrm{mod}\ e}$ is small, the result is that the segmented area is the target, otherwise, the segmented area is not the target. Infrared image target recognition result and corresponding edges extraction result are shown in Figure 6.

The feature extraction of the segmented infrared target image is carried out, the region of interest is retained, and the target recognition is carried out. The confidence level of each labeled region is calculated according to formula (14), and the results are shown in Table 1.

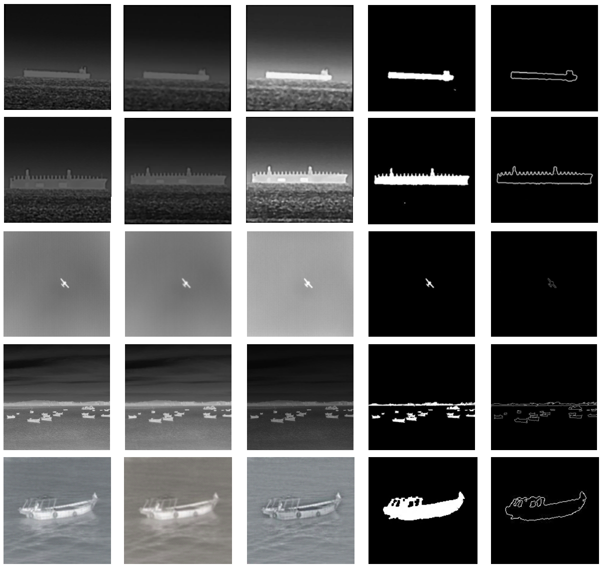
To verify the reliability and recognition accuracy of the method in this paper, a comparative test of recognition



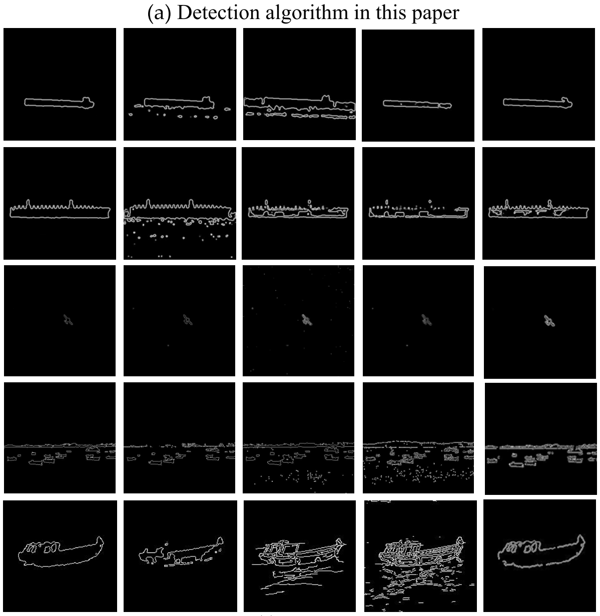
(**a**) Template image (**b**) Segment the image
(**c**) Recognize the area (**d**) Extract the first part area
(**e**) Extract the second part area (**f**) Extract the third part area
(**a1**) Template image edges (**b1**)Segment the image edges
(**c1**)recognize the area edges (**d1**) The first part area edge
(**e1**) The second part area edge (**f1**) The third part area edge

FIGURE 6. Infrared image target recognition result. (a)-(f) are image processing; (a1)-(f1) are edge extraction process.

accuracy is carried out. Three original infrared target images captured by the vehicle thermal imager are randomly selected, and the noise is removed by neighborhood filtering.



(a) Detection algorithm in this paper



(b) Infrared detection comparison results

FIGURE 7. Infrared target detection results.

Then the image is enhanced according to the differential method of reverse operation to improve the image quality and contrast. Finally, the image is segmented by the maximum inter-class variance method, and the target features are extracted to obtain the region of interest of the infrared image. The recognition results of this paper are shown in Fig.7 (a). The proposed algorithm is compared with infrared target detection algorithms such as cascaded nested U-Net [39], target segmentation method based on adversarial domain adaptation [40] and multi-target segmentation method based on multi-level feature fusion [41]. The comparison results of infrared target detection are shown in Fig.7(b).

By observing the infrared target detection results in Fig.7, the cascaded nested U-Net recognition algorithm in [39], the target segmentation method adapted to the adversarial domain in [40], and the multi-target segmentation method of multi-level feature fusion in [41]. When the target with complex background and multi-target are identified, the target edge will be lost, and the target cannot be accurately identified. At the same time, the target segmentation method adapted to the adversarial domain in [40] and the multi-target segmentation method of multi-level feature fusion in [41] are affected by the noise in the collected original image. When identifying the target, these noises will interfere with the recognition results. Compared with the other three comparison methods, the target recognition method in this paper has better detection effect and higher recognition accuracy. This is because the neighborhood filtering can effectively remove the noise. At the same time, the image enhanced by the differential method of inverse operation has clearer edge contour, which can accurately identify the target with large noise and complex background.

To illustrate the applicability and advantages of the proposed method, based on the data set containing a large number of sample information, the methods in [42] and [43] are compared with the methods proposed in this paper. In [42], an improved algorithm for visual target recognition based on variable component model is proposed. By removing background, extracting foreground and reducing the number of useless sliding windows, the target recognition and detection rate can be rapidly improved, so as to reduce the time required for target recognition and detection. In [43], RCN-based UAV inspection image power component recognition methods are studied, and DPM, SPPnet and Faster R-CNN recognition methods are compared and analyzed. The specific details of the test are as follows: the public data set PASCAL VOC 2007 was used to conduct the simulation experiment, which contains 9963 labeled pictures, and the labeled objects are mainly people, animals, vehicles, furniture and other 20 categories. The data set is taken as the input of DPM and RCNN algorithms respectively, and the average recognition time of a single image and the average accuracy rate of target recognition are taken as output. Taking the vehicle in the data set as an example, the algorithm comparison results are shown in Table 2.

As can be seen from the comparison results in Table 2, although the recognition rate of the proposed method is not very high compared with the other two methods, the recognition time of the proposed method is short, and it can provide reference value for target recognition methods in complex environments.

In addition, the target recognition method based on infrared image in this paper is compared with the method in [9], [21], and [44] to track the target, and the target recognition rate of the three methods is compared with different shooting distances, and the change curve is shown in Figure 8.

TABLE 2. The algorithm comparison results.

	Average recognition Time/s	map rate /%
The method proposed in this paper	77	80.2
The method proposed in [42]	224	70.6
The method proposed in [43]	168	77.3
The method proposed in [44]	192	79.8

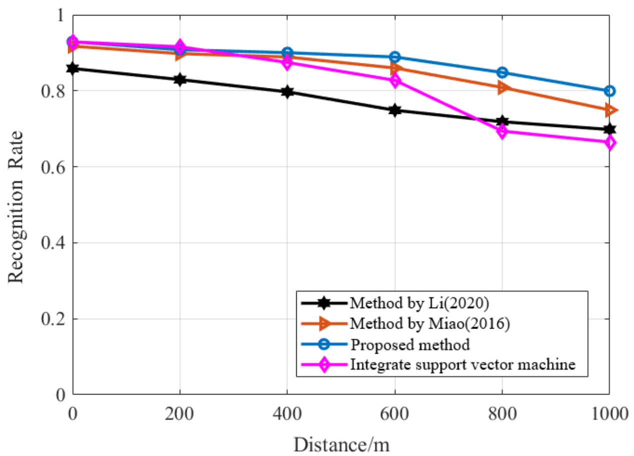


FIGURE 8. The target recognition rate of the three methods with different shooting distances.

It can be found from the Figure 8 that in the process of close-up shooting, with the increase of shooting distance, the recognition rate of the method in [9], [21], and [44] and the recognition method proposed in this paper all gradually decreases. But, compared with the recognition method in [9], [21], and [44], In particular, the recognition rate of the method in [44] shows a significant downward trend when the distance exceeds 600 meters. when the distance exceeds 600m, the recognition method proposed in this paper have achieved a better recognition rate, and is simple, can quickly and intuitively obtain the results of the experimental requirements, especially to meet the needs of current scientific research projects. The research achievement can provide better technical support for the subsequent stable tracking of the target.

V. CONCLUSION

To solve the problem of visible light unable to recognize night targets in actual battlefield, this paper proposes a target recognition method based on fuzzy comprehensive evaluation. According to the original infrared target image captured by the vehicle-mounted thermal imager, neighborhood filtering is used to remove noise, image enhancement is carried out to improve image quality and contrast, and maximum inter-class variance method is used to segment the image and extract the target features to obtain the region of interest of the infrared image. According to the fuzzy comprehensive evaluation method, the membership degree represented as the feature is obtained for each marked region and the confidence degree of the region is calculated. The target is recognized by comparing the results with the confidence degree of the template image. The experimental comparisons were conducted with the method in [9] and [21] at different shooting distances, proving that the proposed method still has a high recognition rate when shooting at long distances.

While the proposed target recognition method based on fuzzy comprehensive evaluation in this paper successfully addresses the challenge of visible light's inability to recognize nighttime targets, there is a need for further in-depth exploration in future research, particularly in the domain of target recognition within extremely complex environments. This encompasses the study of adverse weather conditions, complex terrains, and performance under varying lighting conditions. To ensure the robustness of the system across diverse and challenging scenarios, it may be necessary to employ more sophisticated image processing techniques and adaptive algorithms. In the realm of multi-target recognition and tracking, future studies could delve into advanced target segmentation and tracking algorithms, aiming for more precise and real-time monitoring of multiple targets. This might involve considerations for factors such as mutual occlusion between targets, variations in speed, and different motion patterns. The fusion of multiple data sources, including radar, infrared, and lidar, stands out as a pivotal task for enhancing the overall performance of target recognition systems. In future research, a paramount focus should be placed on further optimizing the real-time performance and efficiency of the system. This optimization is crucial to better adapt the technology to the diversity and complexity of real-world battlefield scenarios, ultimately contributing to a comprehensive and efficient enhancement of target recognition technology in practical applications.

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