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An Evaluation Method of Dynamic Camouflage Effect Based on Multifeature Constraints

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ABSTRACT Most of the existing camouflage effect evaluation methods are for static images, and the evaluation methods have problems of singularity and subjectivity. Therefore, this paper takes the camouflage of moving objects in video as the research object and proposes a comprehensive camouflage effect evaluation method based on multifeature constraints. This method has two parts: the Homo-F (homography transformation and optical flow) target detection module and the camouflage effect evaluation module. The former uses the optical flow method to correct the target detection results obtained by the homography transformation. The latter performs statistical analysis on the target detection results and the feature information of the neighborhood background and describes the effect of camouflage from multiple angles such as the degree of target fusion, the repetition rate and the target detection stability in the video sequence. The experimental results of the comprehensive camouflage evaluation of moving targets show that the proposed method can objectively and accurately evaluate moving targets with different levels of camouflage, which verifies the reliability and effectiveness of the method.

INDEX TERMS Image sequence analysis, object detection, camouflage effect evaluation.

I. INTRODUCTION

Modern warfare, especially high technology local wars, is developing towards intelligence and high intensity. In this process, the effective battlefield information capture capabilities of the warring parties determine the initiative of the war, and military target camouflage technology plays an important role as an important means of anti-reconnaissance and anti-precision strikes [1]–[5]. Effective military target camouflage can not only greatly reduce the probability of the exposure of battlefield information, but it can also have an extremely important role in improving the combat effectiveness and battlefield survivability of personnel and equipment [6]–[9].

Camouflage technology refers to the various technical methods used to conceal oneself and confuse the other party in a planned way. Any target can be disguised to achieve the purpose of hiding the truth and revealing the false. The pre-assessment of the camouflage effect of the target can understand the target exposure probability, and it also has guiding significance for the development of camouflage technology.

The traditional camouflage effect evaluation method relies on the target discovery probability. This process mainly relies on the subjective factors of the interpreter. Lin *et al.* [10] first put forward an evaluation method based on the psychological perception after considering the psychological factors of the observer, but the results still have strong subjectivity. Wang *et al.* [11] comprehensively selected 5 typical characteristic parameters of brightness contrast, color characteristics, texture characteristics, edge shape and spot size and evaluated the camouflage effect based on the grayscale theory, achieving more objective results. At the end of the 20th century, the introduction of neural networks [12], which can change the weights of indicators during training so that the evaluation model can be continuously updated during training and learning, broke the tradition of optical image camouflage evaluation.

However, the above methods are all based on static target camouflage effect evaluation methods, and the neural network method requires a large number of training samples, which makes it difficult to apply to military tasks. Liu *et al.* [13], Fang *et al.* [14] and Ma *et al.* [15] used

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abundant hyperspectral information as a similarity evaluation index to quantitatively and objectively describe the camouflage effect of a target. Hyperspectral information can accurately identify camouflage targets by detecting the fine spectral curves of each point of the target scene according to the spectral "fingerprint" effect of different substances. However, since a hyperspectral image contains a massive amount of data, real-time detection cannot be achieved, and the existing technology makes it currently only suitable for the detection of fixed targets. In 3D computer graphics, a depth map is similar to a grayscale map, and the value of each pixel is the actual distance from the sensor to the object. The fusion of RGB features and depth features can effectively perform target recognition and extraction [16]. However, in practice, a camouflaged target is hidden in the background. For example, the spot features of camouflage and the jungle are similar, the texture patches of the target intersect with the complex background, and the depth information cannot be used to detect a camouflaged target well. Therefore, the spectral and depth information is not considered in this paper.

The actual battlefield, especially a battlefield with complex ground, is usually dominated by high-speed mobile special military equipment. As the mobility of vehicles on the battlefield increases, the camouflage effect evaluation plan must have good characteristics to comprehensively evaluate moving targets. Therefore, it is necessary to introduce a moving target detection algorithm. GMM (Gaussian Mixture Model) is widely used in the background modeling of scenes [17], but it is only suitable for situations with large differences in foreground pixels, and has certain limitations for camouflage foreground detection. Li *et al.* [18] proposed a TGWV (texture guided weighted voting) method to detect camouflaged targets and analyzed the difference between the foreground and the visually similar background in the wavelet domain based on texture features. Zhang *et al.* [19] proposed a CM (Camouflage Modeling) model combines CM and DM (Discriminative Modeling) in the Bayesian framework to detect camouflage that is highly similar to the scene of the moving object. The abovementioned methods use different ideas to detect camouflage targets; however, they are only suitable for monochromatic camouflage target detection and do not consider the distorted facts of polychromatic camouflaged targets on texture features, which leads to the failure of the methods.

For moving target detection with a dynamic background, it is difficult to achieve complete foreground detection only by updating the background model with the limited pixels provided by similar frames. Malathi and Bhuyan [20] proposed a multiview foreground segmentation method considering the differences in views to correct detection results. Based on the theory of epipolar geometry, Dey *et al.* [21] proposed using multiple sets of basic matrices for background modeling to achieve moving target detection in video sequences. The optical flow field proposed by Horn and Schunck in 1981 utilizes the temporal changes and correlation of image pixel intensity data [22], which can effectively describe the motion vector of each pixel and reflect the motion information between the adjacent frames of a video. Pan *et al.* [23] analyzed the detection ability before and after a target is camouflaged based on the optical flow information. The Horn-Schunck optical flow algorithm can obtain accurate instantaneous positions and velocities, but there are certain defects in the detection of the target's edges.

It is found that the accuracy of target detection is closely related to the evaluation results of the camouflage effect. Meanwhile, the detection of camouflaged targets is posed the challenge to the feature extraction algorithm. This huge amount of data in the video sequence makes most feature extraction algorithms unable to achieve the real-time performance. Abdulhussain *et al.* proposed two algorithms including a fast feature extraction algorithm for Video Processing [24] and an image edge detection algorithm based on the orthogonal polynomial [25], which can effectively detect the edges of the moving objects in a distorted image. The shot boundary detection (SBD) processing algorithm proposed by Abdulhussain also can effectively reduce the computational cost. Therefore, in the later stage, we will make an in-depth study on the effectiveness and real-time of the feature extraction algorithm.

In this paper, the two parts of camouflage target detection and camouflage effect evaluation technology are used to assess the camouflage effect evaluation method for moving targets with camouflaged clothing that reduces the distinguishability of a target in the jungle. Ideally, the target after camouflage should be completely fused with its background, and the feature information of the image should be random and uniform. To solve the detection problem of multicolor camouflage in a complex background, we proposed the Homo-F (homography transformation and optical flow) detection method. We use Gaussian pyramid hierarchical preprocessing to reduce the unnecessary redundant information in the image, perform homography transformation on the interframe image, and use the global robustness of the optical flow method to achieve complete target detection. Second, the target detection result intuitively describes the position and size of the camouflaged target in an image to the observer and compares the detection result with the prior knowledge of the camouflage target to obtain the repetition rate index and stability index of the camouflaged target during the movement process. The degree of fusion between the external camouflage target and the background can be obtained using the similarity of each feature vector and finally weighted to obtain the evaluation result of the comprehensive camouflage effect. The degree of fusion between the external camouflage target and the background can be obtained using the similarity of various feature vectors. Finally, each index is weighted to obtain the evaluation result of the comprehensive camouflage effect. The detailed process of the dynamic evaluation of camouflage targets is shown in Fig. 1.

The rest of this paper is organized as follows. Section II reviews the related works, Section III and Section IV introduce the moving target detection model and the camouflage

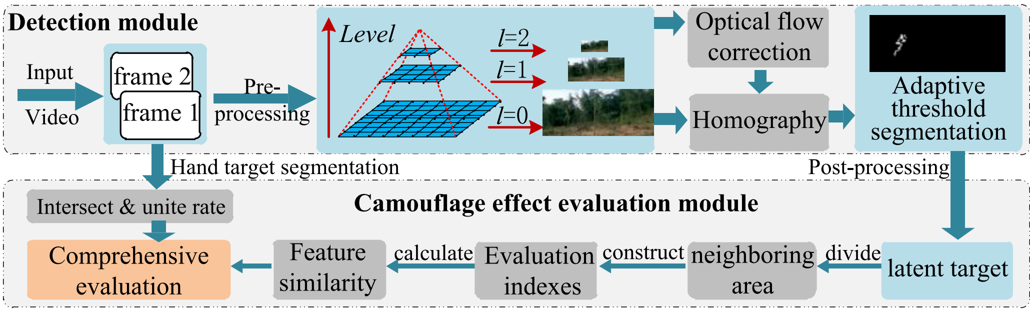

FIGURE 1. Camouflage target dynamic evaluation flowchart.

effect evaluation model, respectively. Section V describes our experimental process and results. Finally, Section VI presents the concluding remarks.

II. RELATED WORK

At present, the methods for evaluating the effectiveness of camouflage for fixed targets are relatively mature, but there are few studies on the methods for evaluating the effectiveness of camouflage for as the movements of personnel, vehicles, ships and so on. Yang *et al.* [26] proposed a camouflage effect detection method for mobile equipment camouflage based on the Surendra background update modeling algorithm. This method uses the target detection result to evaluate the camouflage effect. Due to the lack of target and background feature analysis, different camouflage techniques cannot be explained. Due to the lack of target and background feature analysis, the pros and cons of different camouflage techniques cannot be explained. In addition, this method is only suitable for a motion scene with a single background and is not suitable for a complex and changing motion scene. Ying *et al.* [27] and Ying *et al.* [28] proposed an infrared dynamic camouflage effect evaluation method based on image feature synthesis technology that used the brightness contrast, histogram feature, texture and edge feature indicators to calculate the similarity value. Yang *et al.* [29] used mean shift target tracking technology and proposed a dynamic camouflage effect evaluation method based on feature statistics. The method analyzed the camouflage effect of the target by counting the correlation feature data between the target and the background over 8 communication domains. The two methods of Ying *et al.* [28] and Yang *et al.* are designed for infrared and visible images, respectively. Both focus on the similarity between the target and the background and evaluate the camouflage effect using the difference of the image features, ignoring the detection results of the active camouflage target. Rong *et al.* [30] modeled the difference of the moving background and used moving target detection to evaluate the effect of a camouflage pattern. Yang *et al.* [31] calculated the image distortion rate from the detection results of the moving target and evaluated the camouflage effect of the moving target based on the similarity of the target and the background. The difference in the effect of the target before and after camouflage is described successfully, but the image distortion rate index has no obvious differentiation when facing a scene and background with complex textures.

III. MOVING TARGET DETECTION MODULE

The core idea of sequential image analysis is to repeatedly compare the image information of adjacent frames. Based on this, the homography transform of a two-dimensional plane defines the mapping relationship between two planes [32], but it must satisfy one of the following two conditions: one is that the device that obtains the image needs to be fixed, that is, there is no spatial displacement; and the other is that the device takes the same plane scene in any form [33], [34] (the second point can be equivalent when the target distance is relatively remote).

By combining the advantages of different algorithms, this paper proposes a multiconstrained feature motion camouflage target detection method based on the homography transformation. To reduce the algorithmic complexity, this paper uses a Gaussian pyramid layer for video frames according to the textural complexity of the input video frames. This method can eliminate much redundant information and then apply the optical flow method to correct the results and improve the detection efficiency.

A. TARGET DETECTION MODEL

Due to the irregularity of a target's motion, the appropriate frame difference l can not only highlight the change of the target's motion but also reduce the amount of calculations exponentially and improve the efficiency of the algorithm. We set $P^k = \{P^k_{i,j}\}(1 \leq i \leq \text{m}, 1 \leq j \leq \text{n})$ as the pixel set of the k-th frame after the video sequence is preprocessed by the Gaussian layer, the size of image is m x n, and $P^{k,l} = \{P^{k,l}_{i,j}\}$ represents the pixel set of the (k+l)-th frame. The relationship between the two can be expressed as: $P^{k,t}_{i,j} \simeq H^{k,t} P^k_{i,j}$.

Similarly, set $I^k_{i,j}$ as the brightness of the pixel coordinate (i, j) of the k-th frame image. Since the brightness of adjacent frames of image is consistent, $dI/dt = 0$, that is, $I^k_{i,j} = I^{k+t}_{i+\Delta i, j+\Delta j}$. We use the classic Horn-Schunck optical flow method to further correct the detection results. The horizontal and vertical optical flow vectors at pixel point (i, j) are given

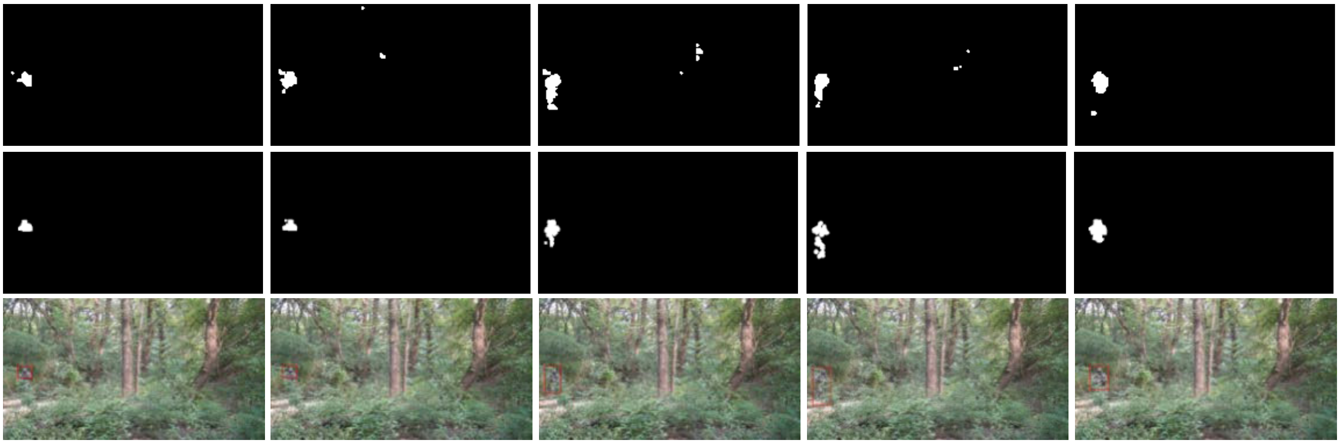

FIGURE 2. Camouflage target depth motion detection results. First row: Binary images of optical flow method; Second row: Binary images of CEDM; Third row: results of Homo-F in five frames.

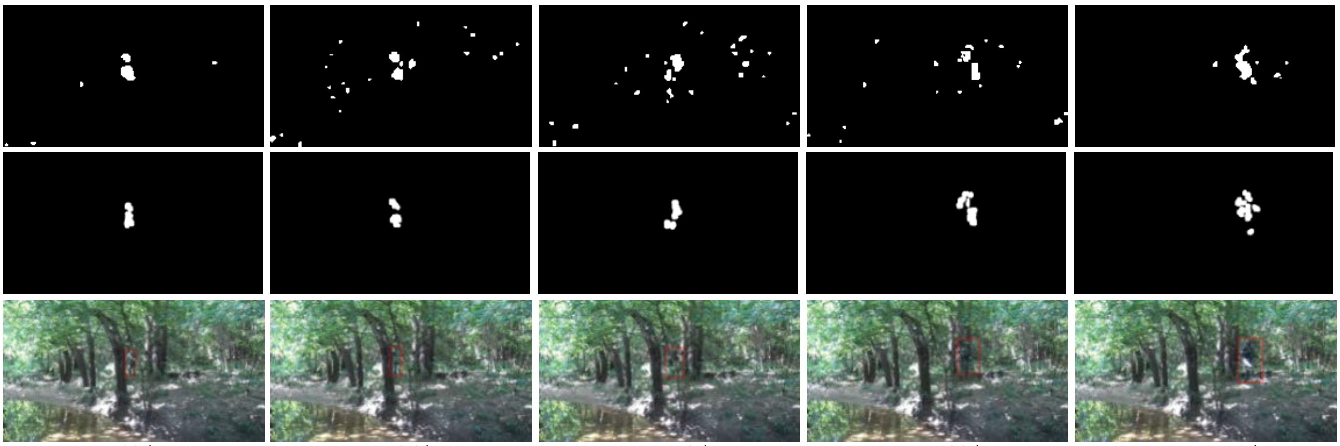

FIGURE 3. Camouflage target lateral motion detection results. First row: Binary images of optical flow method; Second row: Binary images of CEDM; Third row: results of Homo-F in five frames.

as $u = dI_i/dt$ and $v = dI_j/dt$, respectively. After multiple smooth constraints, the optical flow vector is iteratively estimated using the Gauss-Seidel [35] as

$$o^{k+1} = \bar{o}^k - I_i^k \cdot \frac{I_i^k \bar{o}^k + I_j^k \bar{o}^k + I_t^k}{\alpha^2 + I_i^2 + I_j^2} (o = u_{i,j}, v_{i,j}) \quad (1)$$

By calculating the module length q of the visible light flow vector area, the difference between frames is obtained by correcting the homography transformation with the optical flow results of the current frame, thereby detecting the moving target.

$$Target_{detect} = \left\| q_{i,j}^k \right\|_2 \geq \varepsilon_f \cap \left\| P_{i,j}^{k,l} - P_{i,j}^k \right\|_2 \geq \varepsilon_h \quad (2)$$

where $q_{i,j}^k = \left\| \lambda(u_{i,j}^k + v_{i,j}^k) \right\|_2$, $\|\cdot\|_2$ represents the 2-norm, λ represents the optical flow field scale, and ε_f and ε_h represent the adaptive thresholds.

B. TARGET DETECTION RESULTS ANALYSIS

To verify the effectiveness of the algorithm, this paper takes jungle digital camouflage clothing as the detection object and conducts camouflage moving target detection under a complex jungle background. Two backgrounds were set in the experiment: one is a simple jungle grass background, and the other is a jungle background with flowing water. Fig. 2 and Fig. 3 are the binary images of the target detection results of the video sequences under the two backgrounds using the traditional optical flow method and the Homo-F algorithm, respectively.

To quantitatively describe the target detection accuracy, this paper analyzes the detection results by calculating the patch dispersion of binary images. It can be seen from Fig. 4 that under the influence of illumination and the reflection from flowing water, the dispersion of the optical flow method fluctuates greatly, and a large number of interfering "fake targets" are detected in some frames, which greatly reduces the detection accuracy of the target; conversely, the

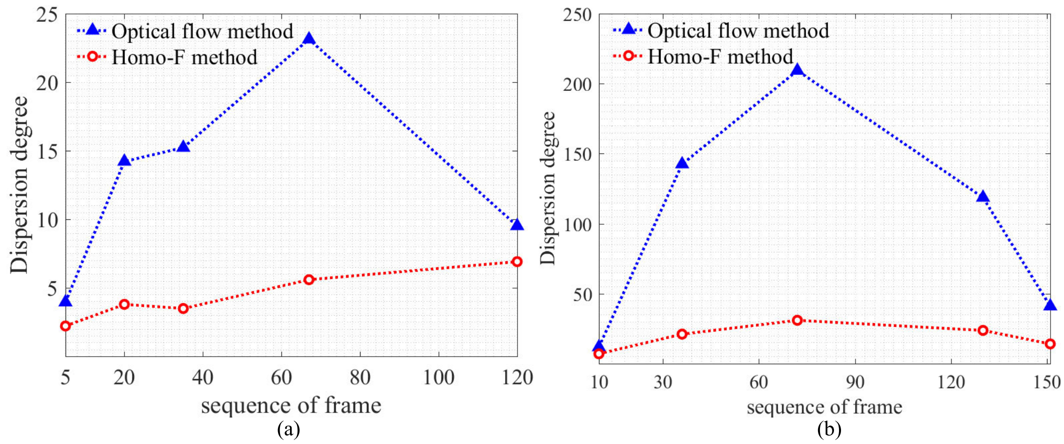

FIGURE 4. Dispersion curve of target detection result. (a) Dispersion curve of camouflage target in depth motion; (b) Dispersion curve of camouflage target doing lateral motion.

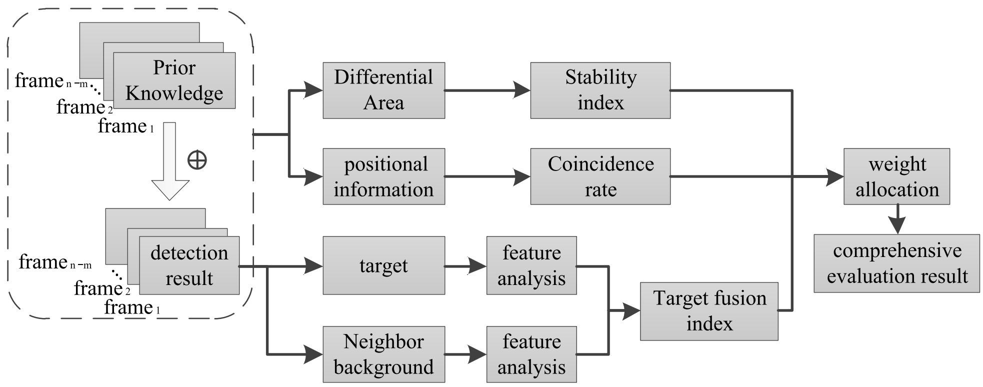

FIGURE 5. Comprehensive evaluation of camouflage effectiveness flow chart.

dispersion of the detection results of Homo-F algorithm is always maintained at a low level.

IV. CAMOUFLAGE EFFECT EVALUATION MODULE

Regarding the human visual attention mechanism, the observer has strong perception ability for feature information such as brightness and texture. Therefore, the similarity measurement between the target and the background based on the image feature information has been used as an important means of camouflage effect evaluation. In addition, the detection accuracy of moving targets is also an important indicator to measure the quality of the camouflage effect of moving targets. Hence, this paper proposes a comprehensive camouflage effect evaluation method based on multifeature constraints such as the degree of target fusion, the repetition rate and the detection stability. Fig. 5 is a detailed flowchart of the comprehensive evaluation of the camouflage effect.

A. CAMOUFLAGE BACKGROUND DEFINITION

Since the degree of fusion of a camouflage target is reflected in the characteristic difference between the target and background, the traditional 8-neighbor background model can effectively eliminate the influence of the background part far away from the target on the evaluation results. However, the neighborhood background of a moving target is complex and changeable due to clutter such as illumination and shadows. To fully reflect the degree of fusion of a camouflage target and the neighborhood background and to eliminate the influence of large differences between the neighborhood background on the camouflage effect evaluation results, the target in the frame to be detected is defined as the central template, and the direct background is selected by the neighborhood including it proportional to the area, as shown in Fig. 6.

The probability density distribution of the image has strong sensitivity to natural factors such as illumination changes and tree shadow interference. It can be seen from Fig. 7 that the distribution of the image probability density of the background in each layer in the neighborhood domain is roughly stable while there is a strong difference between the 8-neighbor background blocks. The background layer of the neighborhood center defined in this paper contains the target template. Theoretically, the similarity value of each background layer can be directly quantified to obtain the comprehensive degree of integration between the target and the background. Compared with the traditional 8-neighbor

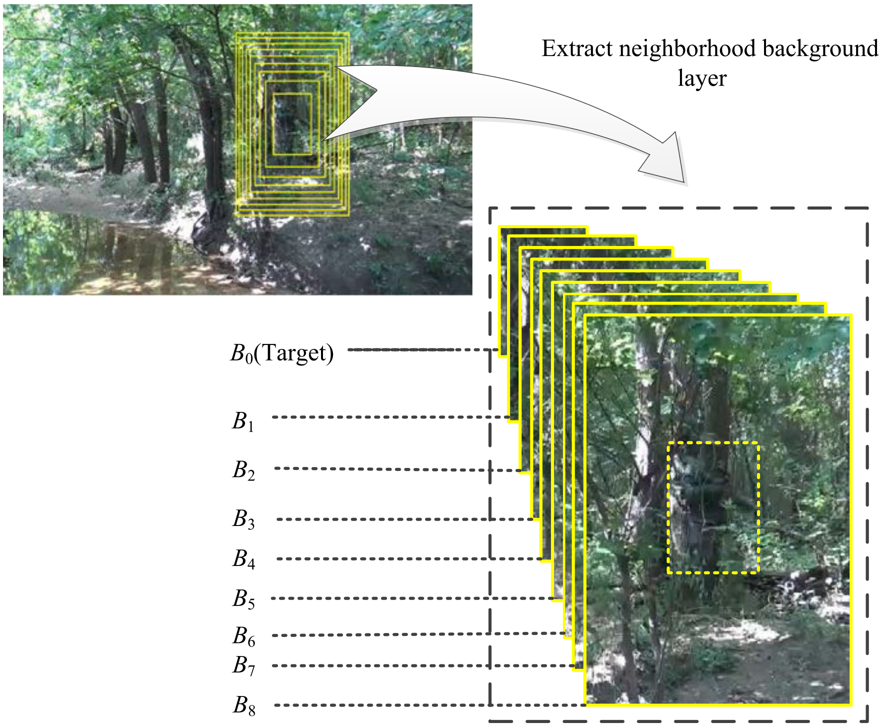

FIGURE 6. Neighborhood Background Hierarchy.

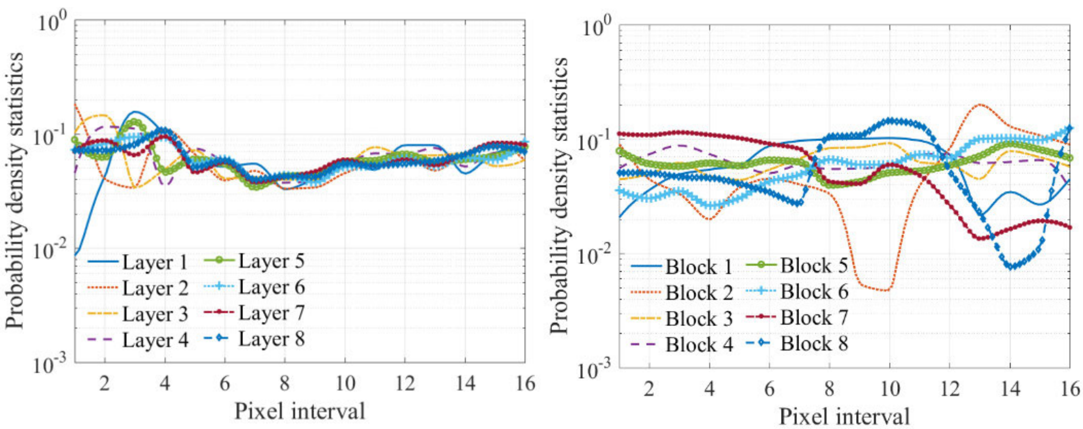

FIGURE 7. Probability density curves fitting in interval pixel. (a) Probability density curves of eight neighborhood background layers; (b) Probability density curves of eight neighborhood background blocks.

background block, the stability of the evaluation results is maintained to a certain extent.

B. TARGET FUSION INDEX

The degree of fusion of the camouflage target in the background is directly reflected in the similarity of the image feature information. Because the target has the characteristics of camouflage, the comparison of the pure grayscale or texture features lacks comprehensiveness. Based on Section 2.3 and Section 3.1, we comprehensively consider five typical types of image feature information such as the brightness (L), hue (C), texture (T), shape (S), and patch (D). According to whether there are spatial relations (spatial relations, Sr), we divide the similarity into $NSr = \{S_L, S_C\}$ and $Sr = \{S_T, S_S, S_D\}$ and construct a linear weighting function $Q(w)$. Then, the expression of the image feature similarity is

$$S_{NSr} = \sum_{i=1}^{2} Q_{NSr}(w_i) \cdot NSr\{i\}$$
$$S_{Sr} = \sum_{j=1}^{3} Q_{Sr}(w_j) \cdot Sr\{j\} \quad (3)$$

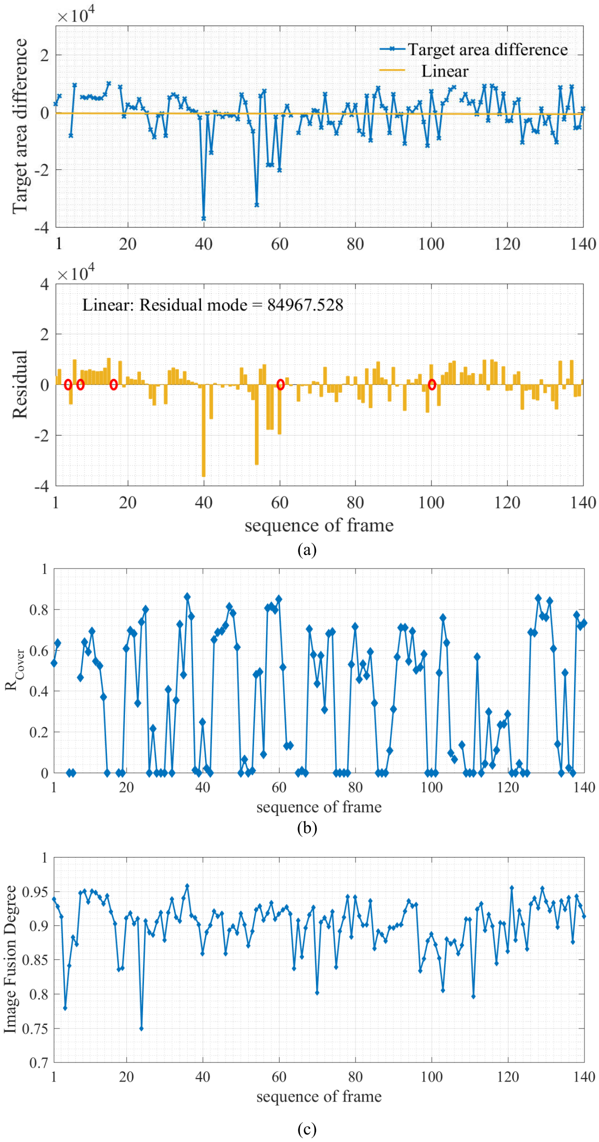

FIGURE 8. **Camouflage target dynamic analysis curve. (a) The target detection result and the actual target difference curve are linearly fitted to obtain the residual mode; (b) Target repetition rate of each frame; (c) Target fusion for the entire time interval.**

Among them, the weight w is determined by the entropy weight method. Hence, the target fusion quantization index based on image feature information can be determined as

$$Sim_{feature} = Ave[S_{NSr}, S_{Sr}] \tag{4}$$

C. CAMOUFLAGE TARGET COINCIDENCE RATE

The above $Sim_{feature}$ calculation results are carried out under the target detection results of the sequence image without any prior information. However, during the evaluation of the camouflage effect, the information such as the size and position of the camouflage target are known, and the coincidence rate R_{Cover} between the target detection result and the actual area is inversely proportional to the camouflage level of the target. The lower the coincidence rate is, the higher the camouflage level of the target, that is, the better the camouflage effect. Therefore, the coincidence rate can be used as an important index to reflect the evaluation results of the camouflage effect.

Suppose there are m potential targets in the image detection results of the k-th frame, where T_i represents the i-th potential target area in T_{latent}. The potential targets are classified according to their intersecting relationship with the area of the actual target (Target):

$$\delta(T_i \Theta Target) = \begin{cases} 1, T_{useless} = \{T_i\} \\ 0, T_{latent} = \{T_i\} \end{cases} \tag{5}$$

where $\delta(\cdot)$ is the impulse function, and Θ represents the intersection between the two regions. The useless target region can be eliminated by the upper formula calculation, and the classification result meets $T_{latent} \cup T_{useless} = T_i (i = 1, 2, \cdots m)$.

The set represents the position and size of the u-th of latent target (T_u) in T_{latent}. The rate of camouflage target coincidence is

$$R_{Cover} = \frac{\hat{T}_{latent} \Theta Target}{Area(\hat{T}_{latent}) + Area(Target) - \hat{T}_{latent} \Theta Target} \tag{6}$$

$$\hat{T}_{latent} = [\min\{X_u\} \min\{Y_u\} \max\{X_u + W_u\} \max\{Y_u + H_u\}] \tag{7}$$

D. TARGET STABILITY ANALYSIS

In the detection range, the moving target presents a relative motion state with the background. Without any prior information, the discovery rate of the dynamic target depends on the time when it appears in the detection range. Therefore, the evaluation of the camouflage effect of the moving target needs to be carried out within a certain period of time.

Once the target is "locked", even if there is irregular deformation movement, its overall proportion in the background module can be regarded as fixed. It can be inferred that in the image sequence analysis process, the greater the difference between the detection results of the front and back frames is, the better the camouflage effect. Suppose that the target starts from the t_0-th frame, and the cumulative detection accuracy rate within the interval Δt is defined as follows:

$$\rho(t_0, \Delta t) = 1 - \frac{1}{\ln(e + \frac{M}{\alpha \cdot M^{\beta}})}$$
$$M = \sum_{k=t_0}^{k=t_0+\Delta t} Rm^k \tag{8}$$

where Rm^k represents the residual modulus of the target detection result of the k-th frame image and the linear fitting curve in the interval $(t_0, t_0 + \Delta t)$, and α and β are constant coefficients.

According to the above model, the final evaluation result of each index through a linear weighting function is

$$Mark(t_0, \Delta t) = \sum_i W_i \cdot \left[\widetilde{Sim}_{feature}, \left(1 - \widetilde{R}_{Cover}\right), \rho(t_0, \Delta t)\right]^{\mathrm{T}}$$
$$W_i = [w_1, w_2, w_3] \tag{9}$$

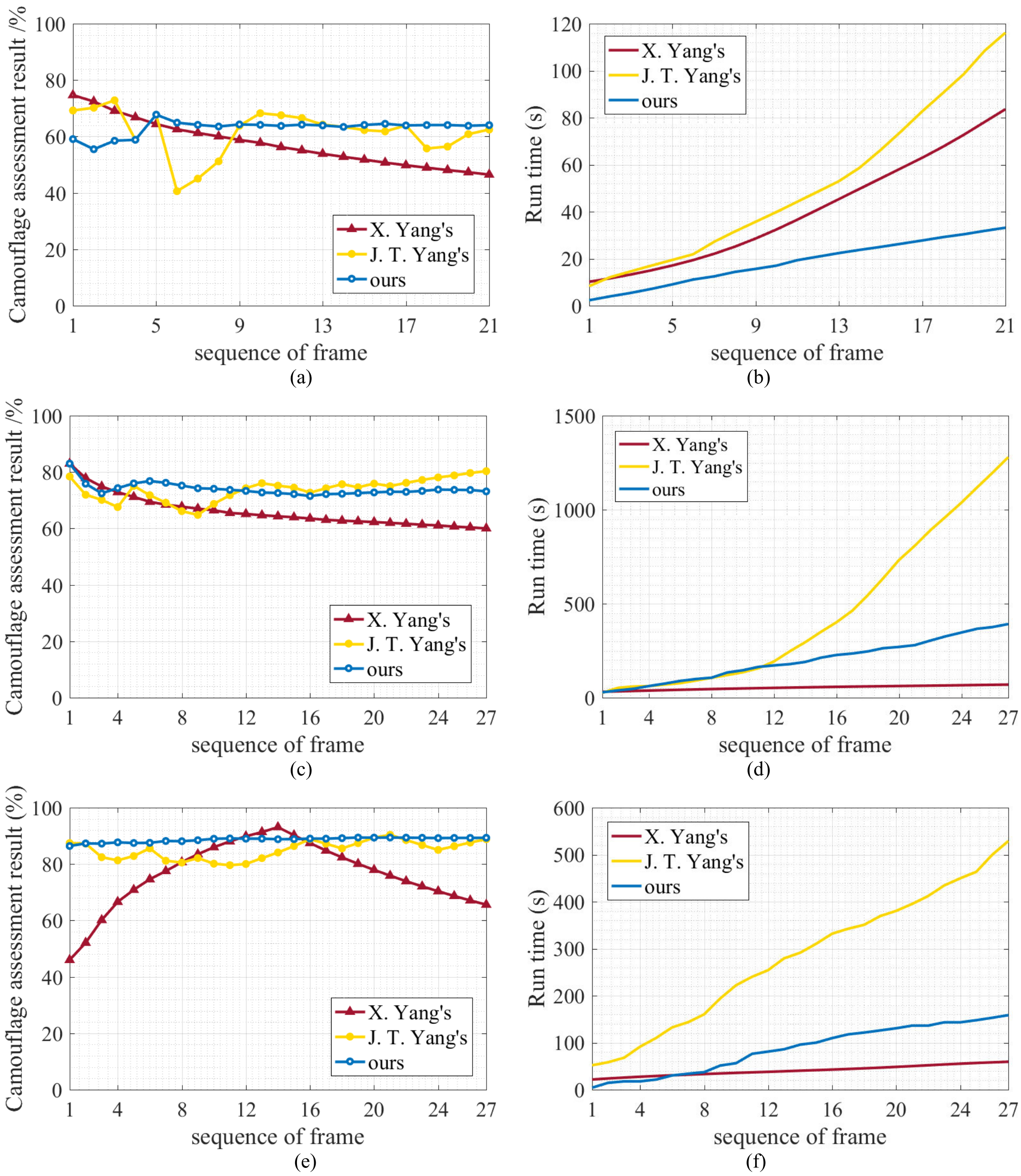

FIGURE 9. Results of evaluation given by different methods. (a) results of undisguised targets in a single background video; (b) Different methods running time; (c) result of camouflage target in single background video; (d) Different methods running time; (e) Camouflage target in a complex background video; (f) Different methods running time.

V. EXPERIMENTS

A. COMPREHENSIVE EVALUATION RESULTS

To test the reliability of the comprehensive camouflage effect evaluation method, we take the 128th frame of the camouflage target's lateral motion video as an example. According to the feature similarity of the feature extraction, we use the entropy weight method to obtain the weight of each feature $Q_{NSr}\{0.4431, 0.0569\}$ and $Q_{Sr}\{0.3292, 0.0128, 0.1580\}$, and then the comprehensive similarity measurement value in the background of each layer of the camouflage target is obtained, as shown in Table 1.

The closer the background layer is to the target, the greater the reference value. Therefore, according to the principle of isodyne allocation, the degree of background fusion of the camouflage target in the 128th frame image is calculated as 0.9586.

Using the camouflage evaluation model, the lateral motion video of the camouflage target is analyzed and processed, and the dynamic analysis curve of the camouflage target is calculated and drawn, as shown in Fig. 8.

If the target is far enough away from the detection device, no matter how deformed the target is, the size of its background pixels can be regarded as constant. From the results

TABLE 1. Similarity Statistics of Sample Features.

Background layer.	No spatial relationship		Spatially related			comprehensive similarity
	Light	Color	Texture	Shape	Dot	
1	0.9926	0.9624	0.9998	0.9851	0.9194	0.9816
2	0.9826	0.9506	0.9889	0.9740	0.9889	0.9838
3	0.9495	0.9377	0.9329	0.9766	0.9972	0.9512
4	0.9443	0.9356	0.9208	0.9928	0.9917	0.9442
5	0.9360	0.9365	0.9096	0.9791	0.9972	0.9376
6	0.9305	0.9375	0.9098	0.9672	0.9917	0.9342
7	0.9246	0.9381	0.9102	0.9773	0.9972	0.9328
8	0.9209	0.9389	0.9063	0.9840	0.9639	0.9247

TABLE 2. Camouflage Effect Level Standard.

Grade.	Quantified percentage	Camouflage level
1	≥ 95%	I
2	≥ 85%	II
3	≥ 75%	III
4	< 75%	IV

shown in Fig. 8 (a), the difference between the entire video detection result and the actual target area is fit to a straight line with y =0, which is in line with the theoretical assumptions. The residual modulus reflects the fluctuation range of the detection result of the camouflage target; and the larger the residual modulus is, the more successful the camouflage of the moving target. Additionally, the 5 discontinuity points marked by circles indicate that no target is detected in the frame image (the camouflage effect is excellent). In addition, statistics show that there are 36 zero points in Fig. 8 (b). The repetition rate is zero due to the detection of ''fake targets''. This phenomenon is also called false alarm in the field of target detection. Fig. 8 (c) is a line graph of the degree of image fusion between the video sequence detection target and the background of its neighborhood. It can be seen that the overall average of the degree of fusion with the background is 0.9005 regardless of whether the target is a disguised target or ''fake target''.

According to reference [6], a difference between images below 25% means that the images can be considered to be similar. Thus, the grade standards of the correlation coefficient of degree of target fusion can be reverted, as shown in Table 2.

In summary, through the calculation and analysis of (9) and Table 2, the evaluation results of the camouflage effect of the moving target in the video are determined, and the camouflage level is identified as level II.

B. COMPARISON OF EVALUATION RESULTS

To verify the effectiveness and advancement of the proposed method, we choose a series of common methods to serve as comparisons in the following experiments, such

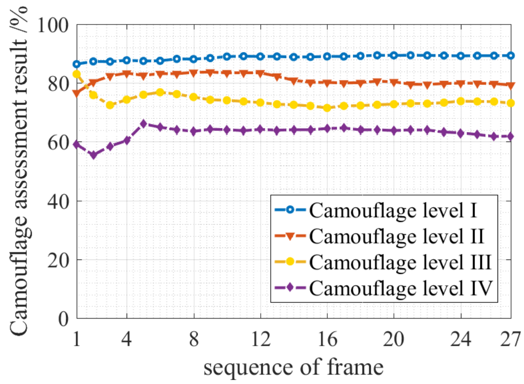

FIGURE 10. Comprehensive evaluation results of different camouflage levels diagram.

as the method proposed by Yang *et al.* [26] and the method proposed by Yang *et al.* [29], which serves as the baseline.

It can be seen from Fig. 9 that the method proposed by Yang *et al.* [29] shows a certain trend over the entire evaluation interval; and as the complexity of the target and the background increases, the target detection deviation increases, and target detection errors occur (the turning point in Fig. 9 (e)). This method cannot be applied to the evaluation of the camouflage effect in complex backgrounds. The method proposed by Yang *et al.* [26] has certain fluctuations over the evaluation interval, but compared to the running time curve of the method, its time costs are relatively large. Compared with the other two methods, our method has better stability, and the running time of our method is approximately 3 times shorter than J. T. Yang's.

When the target detection and tracking tasks are carried out by calculating image features of the spatial domain, the target will be missing or even lost due to the change of illumination. The Homo-F method proposed in this paper integrates the homography transformation and optical flow correction methods, and combines the spatial displacement and light field characteristics, which make the detection results of camouflage targets maintain a stable level. Different from the previous evaluation methods, we comprehensively considered three representative indicators including the degree of the target fusion, the repetition rate and the target detection stability, and dynamically weighted the indicator changes in the entire evaluation interval. Then, the camouflage effect of the target was evaluated comprehensively, which avoided the bias caused by a single image feature index. Meanwhile, the proposed method was operated in an inter-frame, which did not require the iteration or the memory, and had the small calculation loss. Therefore, our method has the good reliability and the real-time performance.

To further verify the effectiveness of the proposed camouflage evaluation method, we choose different camouflage levels to move the target video data for analysis and to obtain the comprehensive evaluation results, which were drawn in Fig. 10.

From the results shown in Fig. 10, as the camouflage level improves, the percentage of the camouflage evaluation results also increases, and the calculation results meet the requirements of the camouflage effect grading standard, which fully illustrates the accuracy and stability of the comprehensive camouflage effect evaluation method based on multifeature constraints.

VI. CONCLUSION

This paper proposes a method for evaluating the effects of camouflage for moving targets based on moving target detection and target fusion analysis. First, an image is transformed via homography to obtain the potential target area, and the target position is confirmed by using the optical flow method and adaptive threshold segmentation correction. Then, we build an index system containing the degree of fusion of the target and background, the repetition rate, the target stability and other characteristic parameters, and the camouflage effect of the target is comprehensively evaluated from multiple frame images and multiple angles.

The experimental results show that compared with the traditional optical flow method, the camouflage moving target detection method based on homography can effectively weaken the natural interference such as illumination and reflections from flowing water. The comprehensive evaluation method of the camouflage effect based on multifeature constraints has achieved the nonlinear fusion of camouflage target detection results and the degree of fusion of the target and background, which can objectively and accurately describe the camouflage effect of a target in a moving state.

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