Research on High Robust Infrared Small Target Detection Method in Complex Background

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Abstract— **Realizing high robust infrared (IR) small target detection is of great significance in the face of complex and ever-changing IR image sequences. In this letter, we analyze the inherent relationship between local contrast, local gradient, and local background gray value of IR small targets from a new perspective. Based on this, a method for IR small target detection based on local contrast and the local gradient is proposed. In addition, a four-direction model is proposed to reduce the interference of bright background clutter in the target neighborhood. The experimental results show that the method proposed in this letter has high robustness and is suitable for detecting small IR targets in complex backgrounds.**

Index Terms— **Detection probability, false alarm rate, four-direction model, infrared (IR) small target detection, small target detection.**

I. Introduction

SMALL target detection plays an important role in applications such as early warning systems and surveillance systems [1], [2], [3], [4]. Due to the long imaging distance, infrared (IR) targets usually only occupy a few pixels in the image, lacking texture or shape features [5], [6]. Faced with complex imaging environments, small targets are often submerged in the background and affected by bright backgrounds, edges, and noise [7]. Faced with rapidly moving targets, rapid background changes and motion blur significantly reduce detection performance [8]. Therefore, improving the performance of IR small target detection is a challenging task that must be faced at present.

In recent years, extensive research has been conducted on detection methods based on human vision. These methods focus on the contrast and differences between the target and its surrounding background. Chen et al. [9] proposed a local contrast measure (LCM) algorithm that utilizes nested windows to divide the surrounding area into eight directions to suppress background edges. Wei et al. [10] proposed a multiscale patch-based contrast measure (MPCM) that can detect both bright and dark targets simultaneously. Han et al. [11] proposed the relative LCM (RLCM) algorithm, which can adapt to more IR image sequence scenes by adjusting flexible parameters. Han et al. [12] proposed a weighted strengthened LCM (WSLCM). At the same time, the Gaussian filter was introduced to enhance the background suppression and improve the performance of small target detection. Han et al. [13] proposed a new detection framework named multiscale tri-layer LCM (TLLCM) to enhance the target before local contrast calculation. Nasiri and Chehresa [14] proposed an IR small target enhancement method based on variance difference, which has a good background suppression performance. Tang et al. [15] proposed a global contrast measure (GCM), which has both high performance and efficiency.

Generally speaking, these methods are not very stable when faced with complex backgrounds. In order to better adapt to different scenes for IR small target detection, this letter analyzes the relationship between local contrast, local gradient, and local background gray value, and establishes a calculation model based on local contrast and local gradient. In addition, a four-direction contrast model is designed to reduce the interference of bright background clutter in the target neighborhood. The experimental results show that the method proposed in this letter has good robustness and broad adaptability. It can overcome the application limitations of traditional methods and has certain advantages over existing methods.

II. Proposed Algorithm

The flowchart of this algorithm is shown in Fig. 1. First, the four-direction model is used to calculate the local contrast and gradient measure (LCGM) to enhance the target and suppress the background at the same time. In some complex backgrounds, the four-direction model can reduce the interference of bright backgrounds and noise in the target neighborhood. Fig. 2 shows the comparison between the four-direction model and eight-direction model. Then, the adaptive threshold segmentation algorithm is used to detect the target.

A. LCGM Calculation

In this letter, inspired by LCM [9] and MPCM [10], we redefined local contrast and local gradient, as shown in the following equations:

$$\mathrm{LC} = \mathrm{IT}/\mathrm{LBG} - 1 \tag{1}$$

$$\mathrm{LG} = \mathrm{IT} - \mathrm{LBG} \tag{2}$$

where LC and LG represent the local contrast and the local gradient, respectively. LBG represents the local background

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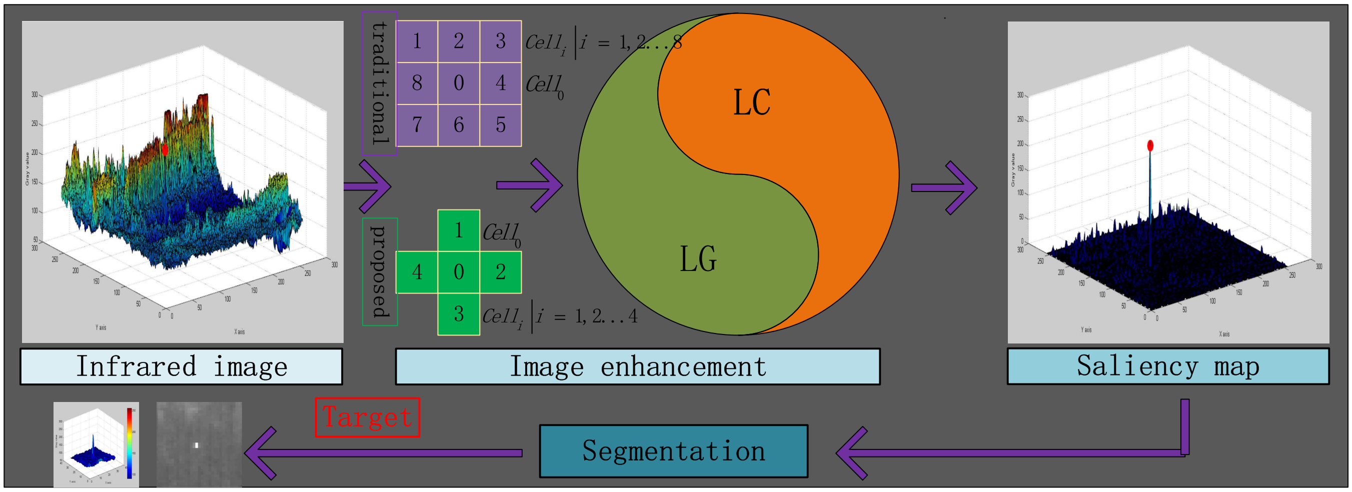

Fig. 1. Flowchart of the proposed method.

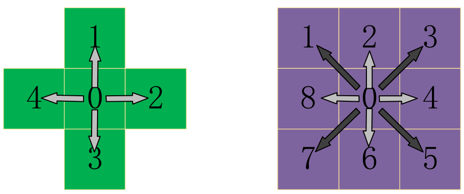

Fig. 2. Comparison between the four-direction model and the eight-direction model.

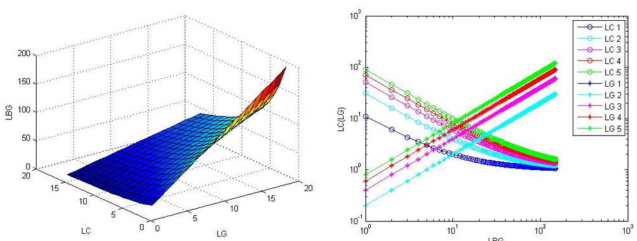

Fig. 3. Relationship between local contrast, local gradient, and local background gray value.

gray value. IT represents the gray value of the target. The following relationship can be obtained from (1) to (2):

$$\mathrm{LC} = (\mathrm{LBG} + \mathrm{LG})/\mathrm{LBG} - 1 = \mathrm{LG}/\mathrm{LBG} \tag{3}$$

i.e.,

$$\mathrm{LBG} = \mathrm{LG}/\mathrm{LC}. \tag{4}$$

The relationship between local contrast, local gradient, and local background gray value is shown in Fig. 3. It is easy to draw the following conclusion. When the local gradient is constant, the smaller the local background gray value, the greater the local contrast. When the local contrast is constant, the larger the local background gray value, the greater the local gradient. Based on the above assumptions, when the local background is relatively dark, the local contrast calculation can achieve good detection results for small targets. When the local background is relatively bright, the local gradient calculation can achieve good small target detection results.

Therefore, there is a certain complementary relationship between LG and LC, and LCGM is designed using this feature, which can increase the adaptability of IR small target complex scenes, as shown in the following equation:

$$\mathrm{LCGM} = \mathrm{IT} * \left(\lambda * \alpha * \mathrm{LC} + \left(1 - \lambda\right) * \beta * \mathrm{LG}\right) \tag{5}$$

where α and β represent the normalization coefficient which can be calculated by the following equation:

$$\alpha = \frac{1}{\mathrm{MAX(LC)}} \tag{6}$$

$$\beta = \frac{1}{\mathrm{MAX(LG)}}. \tag{7}$$

IT denotes the average gray value of the $N1$ max pixels in Cell_0, as shown in the following equation:

$$\mathrm{IT} = \frac{1}{N1}\sum_{k=1}^{N1} I^k(x, y), (x, y) \in \mathrm{Cell}_0 \tag{8}$$

where $N1$ is the number of maximal gray values considered in Cell_0. $I^k(x, y)$ is the kth maximal gray value. LBG is calculated by the following equation:

$$\mathrm{LBG} = \mathrm{MAX}\{\mathrm{IB}_i | i = 1, 2, \ldots, 4\} = \mathrm{MAX} \left\{\frac{1}{N2}\sum_{k=1}^{N2} I^k(x, y) | (x, y) \in \mathrm{Cell}_i, i = 1, 2, \ldots, 4\right\} \tag{9}$$

where $\mathrm{IB}_i | i = 1, 2, \ldots, 4$ represent the local background gray values in the 4 directions. $N2$ is the number of maximal gray values considered in $\mathrm{Cell}_i | i = 1, 2, \ldots, 4$.

Therefore, we obtained the calculation method in this letter

$$\mathrm{LCGM} = \mathrm{IT} * \left(\lambda * \mathrm{MIN}\left(\frac{1}{\mathrm{MAX(LC)}} * \left(\frac{\mathrm{IT}}{\mathrm{IB}_i} - 1\right)\right) + (1 - \lambda) * \mathrm{MIN}\left(\frac{\mathrm{IT} - \mathrm{IB}_i}{\mathrm{MAX(LG)}}\right)\right), \quad i = 1, 2, \ldots, 4 \tag{10}$$

where λ is the weight coefficient with a value range of 0–1. The larger the value of λ, the higher the local contrast weight,

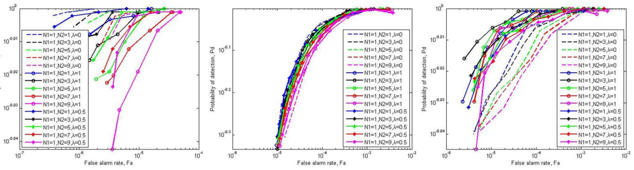

Fig. 4. Influence of weight coefficients on detection performance.

and the smaller the value of λ, the higher the local gradient weight. Fig. 4 shows the impact of different weight coefficients on the performance of IR small target detection.

From (10), it is easy to draw the following conclusion, that is, the characteristics of LCGM.

1) If the current area is larger than the surrounding area, then LCGM > 0, the target is retained or enhanced.
2) If the current area is equal to the surrounding area, then LCGM $= 0$, so as to suppress the dark background area and light background area.
3) If the current area is smaller than the surrounding area, then LCGM < 0, so as to suppress the complex bright background edges.

B. Multiscale LCGM Calculation

For known IR small target image sequences, $N1$ is recommended to be similar to the effective number of pixels of the target, and $N2$ is recommended to be similar to $N1$. Faced with different image sequences, parameters need to be adjusted according to the actual situation to achieve optimal detection performance. For image sequences with unknown targets, multiscale calculation methods can be used

$$\text{MLCGM} = \text{MAX}\left\{\text{LCGM}_M^{(N1,N2)}(i, j)|M = 1, 2, \ldots, S\right\} \tag{11}$$

where MLCGM represents parameter multiscale calculation result. S is the number of scales been used. S corresponds to the number of groups for parameter $N1$ and parameter $N2$. $N1$ and $N2$ represents the number of max pixels considered in Cell_0 and Cell_i. The recommended parameters $N1$ and $N2$ for each group are different.

C. Threshold Segmentation Algorithm

First, (12) is used for threshold segmentation of the image. After processing by the LCGM method, part of the background becomes zero, so we use the mean value of removing zero for the calculation

$$\text{Th} = k \times I_{\max} + (1 - k) \times I_{\text{mean}(\sim 0)} \tag{12}$$

where $I_{\max}$ is the maximum gray value in the image, and $I_{\text{mean}(\sim 0)}$ is the mean value of the image excluding zero. k is the threshold coefficient, with a value range of 0–1.

III. Simulations and Experimental Results

In order to verify the effectiveness and high robustness of the proposed algorithm, four real IR sequences are used for experiments. The detailed information of the image sequences is shown in Table I. We compare six methods as follows. LCM [9], RLCM [11], WSLCM [12], TLLCM [13], VARD [14], and GCM [15].

TABLE I
Details of the IR Sequences

	Frames	Size	Target number	Target size	Target Type
Seq.1	399	256*256	1	2*2 to 3*3	Plane
Seq.2	399	256*256	1	2*2 to 3*3	Plane
Seq.3	500	256*256	1	2*2 to 3*3	Plane
Seq.4	399	256*256	1	3*3 to 5*5	Plane

In the original IR image sequences, the background is relatively complex. From Fig. 5, it can be seen that after LCM calculation, the target is prominent and the complex background is suppressed, but the salient image still has background features. After RLCM calculation, most of the background feature information is eliminated, and the number of pixels involved in the calculation can be adjusted to increase the flexibility of the algorithm. However, in the face of complex background IR images, they are still subject to interference from background clutter. The WSLCM method and the TLLCM method perform poorly when dealing with dim and small targets. The VARD algorithm uses variance for calculation, and the highlight background clutter is easily mistaken for a target and thus enhanced. The GCM algorithm adopts a dilation operation, which has poor performance for some complex and slightly larger targets. It can be seen that our proposed algorithm achieves most of the background elimination. In addition, we use a four-direction model to reduce the interference of high-brightness background and noise in the neighborhood of the target and integrate local gradient and local contrast to enhance the algorithm's adaptability to bright and dark backgrounds. Compared to other algorithms, our algorithm is more balanced and has better stability.

The processing results of a single image can only reflect the algorithm's processing effect on a certain image, so we calculated the receiver operating characteristic (ROC) curves, which can well represent the processing effect of different algorithms on image sequences. As shown in Fig. 5, for image sequences with dim and small targets, the WSLCM method and the TLLCM method have poor detection performance. LCM is a classic algorithm based on human vision that can achieve basic small target enhancement and background suppression, but its robustness is poor when faced with complex IR image sequences in the background. The RLCM algorithm is an improved algorithm based on LCM, which can eliminate most of the background. At the same time, the adjustable design of the number of pixels involved in the calculation increases its adaptability to image scenes. However, when faced with complex background IR image sequences, the detection performance is not very ideal. The VARD algorithm utilizes variance to enhance targets and is susceptible to interference from bright background clutter. The GCM algorithm combines high performance and efficiency. Due to the fact that the dilation operation only outputs one maximum pixel as the background gray value, when the target is large in complex backgrounds, the calculation accuracy is poor. The algorithm proposed in this letter has the best calculation results for ROC, indicating

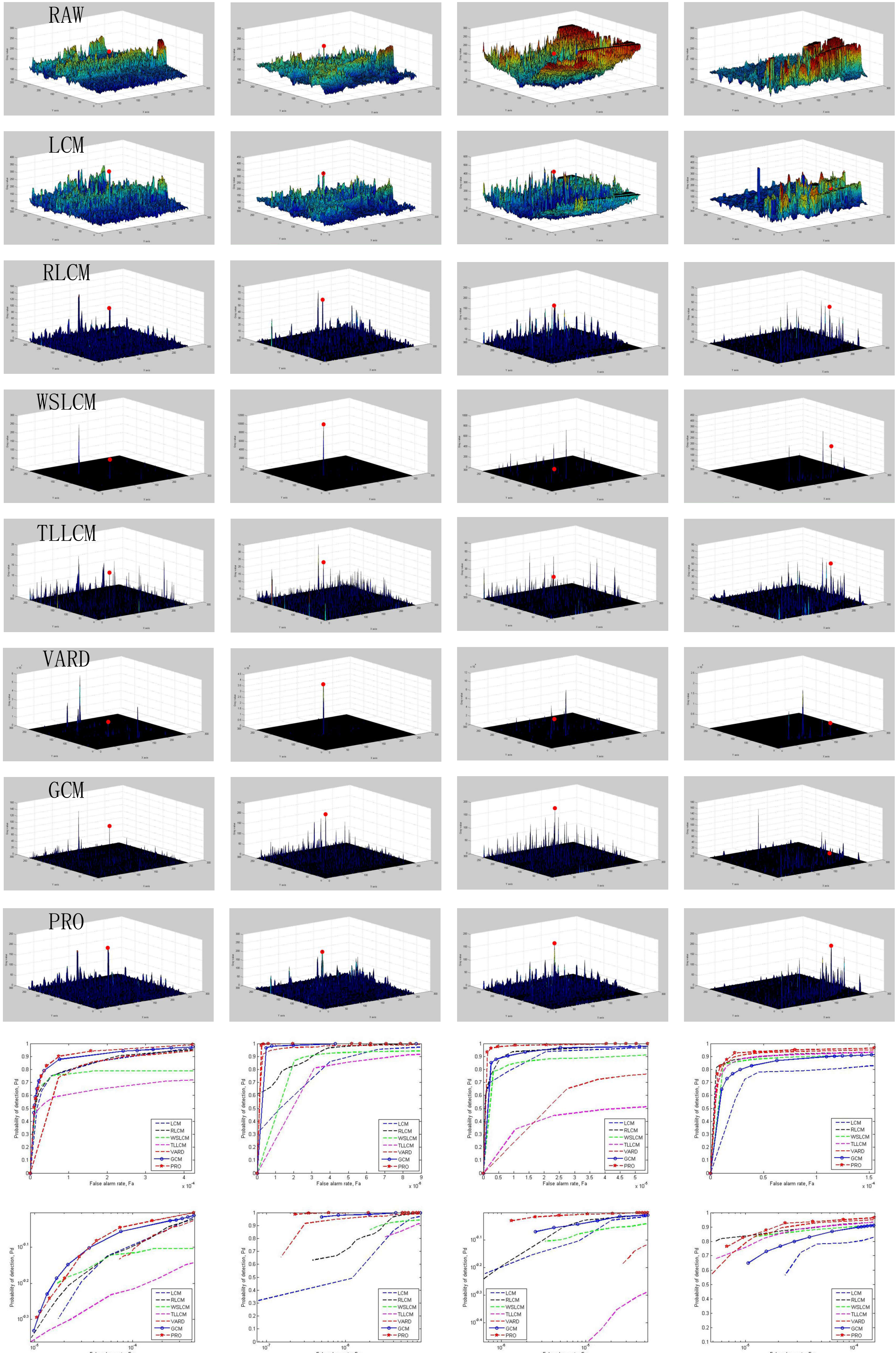

Fig. 5. From (left to right): sequences 1–4. From (top to bottom): Raw images, LCM results, RLCM results, WSLCM results, TLLCM results, VARD results, GCM results, LCGM results, the ROC curves of sequences 1–4, and the ROC curves of sequences 1–4 in the log scale.

the best performance for small target detection. At the same time, we calculated the area under the curve, as shown in Table II. Our proposed algorithm has the largest area, further demonstrating the best detection performance of our algorithm. The following improvements have improved the performance of the algorithm. First, our algorithm integrates local contrast

TABLE II
AREA UNDER CURVE

	LCM	RLCM	WSLCM	TLLCM	VARD	GCM	PRO
Seq.1	0.835	0.848	0.757	0.651	0.796	0.895	0.913
Seq.2	0.789	0.919	0.824	0.715	0.964	0.964	0.987
Seq.3	0.894	0.936	0.852	0.433	0.551	0.928	0.978
Seq.4	0.715	0.891	0.859	0.885	0.904	0.830	0.917

and local gradient, which can better adapt to dark and bright backgrounds. Second, for the traditional eight-direction model, when there is a bright background and noise near the small target, the enhancement effect of the small target will be weakened, thereby reducing the detection rate of the target. The design of the four-direction model reduces the number of cells in the calculation, which can appropriately reduce the interference of bright background and bright background noise while suppressing the background. These clever designs have improved the robustness of the algorithm in this letter from multiple aspects.

IV. Conclusion

From a new perspective, the inherent relationship between the local gradient, local contrast, and local background gray value of IR small targets is analyzed. Based on this, we propose a method for IR small target detection based on local contrast and local gradient, which can effectively suppress bright backgrounds, complex bright background edges, and enhance small targets. The traditional eight-direction model weakens small targets when faced with locally highlighted backgrounds. A four-direction model is proposed, which only uses four cells that are relatively close to small targets for calculation. This can reduce the impact of locally highlighted backgrounds and improve detection performance. Four sequences and six algorithms are compared. The experimental results show that the algorithm proposed in this letter has high robustness and is suitable for detecting small IR targets in complex backgrounds.

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