ISTD Based on Background-SuppressionProximal Gradient and GPU Acceleration

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Infrared Small-Target Detection (ISTD) is an important component of infrared search and tracking, aiming to exploit the thermal radiation difference between a target and its background to achieve long-range target detection. According to the definition by the Society of Photo-Optical Instrumentation Engineers (SPIE), small targets typically refers to objects in a 256 × 256 image with an area of fewer than 80 pixels, accounting for approximately 0.12% of the total image area.

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1. Introduction

Infrared Small-Target Detection (ISTD) is an important component of infrared search and tracking, aiming to exploit the thermal radiation difference between a target and its background to achieve long-range target detection. According to the definition by the Society of Photo-Optical Instrumentation Engineers (SPIE), small targets typically refer to objects in a 256 × 256 image with an area of fewer than 80 pixels, accounting for approximately 0.12% of the total image area [1]. These small targets usually appear as faint, tiny points, characterized by their diminutive size and a lack of clear texture and shape features. Moreover, the background in infrared images is often affected by random noise, clutter, and environmental factors, making small targets vulnerable to interference. Furthermore, some practical applications have strict requirements for the real-time performance of detection algorithms. Therefore, the rapid and accurate detection of small targets in complex backgrounds poses a significant challenge.

Two primary methods are employed in ISTD for target detection: Tracking-Before-Detection (TBD) and Detection-Before-Tracking (DBT). TBD relies on the temporal information of consecutive frames to capture the movement and features of potential targets. It struggles with stationary or sporadically moving targets and is constrained by computational resources. On the other hand, DBT applies single-frame ISTD to infrared data, identifying potential targets based on features such as contrast and low-rank sparsity. Single-frame infrared small target detection has been widely concerned because of its simple data acquisition, low computational complexity, not affected by target motion and wide applicability.

The categorization of single-frame ISTD can be determined by the structure of the image; that is, whether (1) the original image or (2) the patch image is used [2]. The first category detects the target directly from the original image; for example, by filtering or Human Vision System (HVS). Filter-based methods [3][4][5][6] have limited utility in ISTD, due to their strict requirements on the background variation and prior knowledge. Meanwhile, HVS-based methods [7][8][9][10][11] use the contrast mechanism to quantify the difference between the target and the background, thereby enhancing small targets. However, these methods are limited by the local saliency of the target, rendering them ineffective when detecting targets that are dark or similar to the background. Some deep learning technologies [12][13][14][15] have recently been applied to this category, but a lack of large data sets limits their performance.

The other category—namely, patch-based methods—transforms small target detection into a low-rank matrix recovery problem [16]. This transformation can circumvent the aforementioned limitations, such as the dependence on prior knowledge and target saliency, as well as the false detection of dark targets. The most popular method is Infrared Patch-Image (IPI) [17], which uses a sliding window technique to generate a corresponding patch image from the original image. Due to its outstanding performance, many studies [18][19][20][21][22][23][24][25][26] have been conducted on IPI, which typically yields superior results. However, patch-based methods still have two problems: (1) The misclassification of strong edges as sparse target components, and (2) the time-consuming nature of the method.

The above-mentioned misclassification arises from the limited ability of the model to distinguish strong edges from sparse components. To address this issue, we propose a Background Suppression Proximal Gradient (BSPG) method, incorporating a novel continuation strategy during the alternating updating of low-rank and sparse components. Our proposed continuation strategy can preserve more components while updating the low-rank matrix, while also reducing the update rate of sparse matrix. As strong edges frequently correspond to larger singular values than targets, the former facilitates the transition of strong edges from sparse components to low-rank components, thereby enabling the model to eliminate the effect of strong edges. Meanwhile, the latter ensures the convergence of the algorithm. The time-consuming nature of patch-based methods is due to the complex nature of solving the method, mainly including solving the LRSD problem and constructing/reconstructing patch images. To address this issue, we utilize both algorithmic optimizations and hardware enhancements. At the algorithmic level, we propose an approximate partial SVD (APSVD) for efficiently solving the LRSD problem and use a rank estimation method to ensure the accuracy of the solution. At the hardware level, we propose the use of GPU multi-threaded parallelism strategies to expedite the construction and reconstruction modules, as these modules can be decomposed into repetitive and independent sub-tasks.

2. Infrared Small-Target Detection Based on Background-Suppression Proximal Gradient and GPU Acceleration

2.1. HVS-Based Methods

HVS-based methods detect small targets by utilizing the contrast differences between the target region and its surrounding background. These methods can be categorized based on the type of information they use: grey scale information, gradient information, and a combination of both greyscale and gradient information. Local Contrast

Measure (LCM) [1] proposes a novel method for detecting small targets by leveraging grey scale contrast. This method uses a contrast mechanism designed to enhance small targets while effectively suppressing the background noise. Based on the improvement of the LCM algorithm, Relative Local Contrast Measure (RLCM) [8], Multiscale Patch-based Contrast Measure (MPCM) [9], Weighted Local Difference Measure (WLDM) [27] and other methods were proposed. Gradient-based contrast methods use first-order or second-order derivatives of the image to extract gradient information. They then utilize this information to design a gradient difference measure that effectively discriminates between small targets and the surrounding background. Building on this concept, Derivative Entropy-based Contrast Measure (DECM) [28] and Local Contrast-Weighted Multidirectional Derivative (LCWMD) [29] propose the use of multidirectional derivative to incorporate more gradient information. In addition, Local Intensity and Gradient (LIG) [30], and Gradient-Intensity Joint Saliency Measure (GISM) [31] fuse gradient and intensity information to further highlight small targets. Although HVS-based methods can be effective in many scenarios, they are susceptible to missed detections and false positives in images characterized by low signal-to-clutter ratios and high-intensity backgrounds.

2.2. Deep Learning-Based Methods

In recent years, there has been a significant research focus on deep learning-based methods for infrared small target detection, which seek to achieve high-accuracy detection rates. These deep learning models are trained to discern features within infrared images using vast datasets, thereby enhancing their detection capabilities. To address the problem that infrared small target features are easily lost in deep neural networks, Attention Local Contrast Network (ALCNet) [32] proposes asymmetric contextual modulation to interact with the feature information between the high and low levels. Dense Nested Attention Network (DNANet) [15] adequately fuses feature information through densely nested interaction modules to maintain small targets in deep layers. Miss Detection vs. False Alarm (MDvsFA) [33] proposes dual generative adversarial network models, trained inversely to decompose the detection challenge into sub-problems, aiming to strike a balance between miss detections and false alarms. While publicly available datasets have advanced deep learning for infrared small target detection, the scant features of small targets and the dependency on training samples limit the applicability of the model in varied real-world scenarios.

2.3. Patch-Based Methods

A significant amount of research has been conducted to improve the detection ability of IPI [17]. On one hand, some methods have used prior constraints, including ColumnWeighted IPI (WIPI) [18], Non-negative IPI with Partial Sum (NIPPS) [20], and Re-Weighted IPI (ReWIPI) [21]. On the other hand, some studies have identified limitations in the nuclear norm and L1 norm and, so, alternative norms to achieve improved target representation and background suppression have been proposed; for example, Non-convex Rank Approximation Minimization (NRAM) [22] and Non-convex Optimization with Lp norm Constraint (NOLC) [23] introduce non-convex matrix rank approximation coupled with L2,1 norm and Lp norm regularization, while Total Variation Weighted Low-Rank (TVWLR) [24], Kernel Robust Principal Component Analysis (KRPCA) [25] introduce total variation regularization, High Local Variance (HLV) [26] method present LV* norm to constrain the background's local variance. Patch-based methods mainly consider the low-rank nature of the background, affecting their performance in the presence of strong edges. However, our method pays additional attention to heterogeneous background suppression in low-rank constraints, to avoid this problem.

2.4. Acceleration Strategies for Patch-Based Methods

Acceleration strategies for patch-based methods can be categorized into algorithm-level and hardware-level acceleration. The first category mainly relies on the strategy of reducing the number of iterations. Self-Regularized Weighted Sparse (SRWS) [34] and NOLC [23] improve the iteration termination condition for acceleration but still suffer from the time consumption associated with decomposing large matrices. The other category (i.e., hardware acceleration) relies on the use of computationally powerful hardware and efficient parallelization strategies. In Ref [35], the researchers proposed Separable Convolutional Templates (SCT); however, this method has poor performance under complex backgrounds. In addition, extending the patch model to tensor space can also achieve acceleration [36][37][38][39][40][41]. Representative methods in this direction include Re-weighted Infrared Patch-Tensor (RIPT) [36], LogTFNN [39] and the Pareto Frontier Algorithm (PFA) [37]. However, unfolding the tensor into a two-dimensional matrix before decomposition increases the algorithm's complexity. Partial Sum of the Tensor Nuclear Norm (PSTNN) [38] and Self-Adaptive and Non-Local Patch-Tensor Model (ANLPT) [42] utilize the t-SVD speed up tensor decomposition with t-SVD. However, these methods are limited by the complexity of finding the applicable constrained kernel norm. Our work investigates accelerated patch-based methods at both the algorithmic and hardware levels.

References

1. Chen, C.P.; Li, H.; Wei, Y.; Xia, T.; Tang, Y.Y. A local contrast method for small infrared target detection. IEEE Trans. Geosci. Remote Sens. 2013, 52, 574–581.
2. Zhang, C.; He, Y.; Tang, Q.; Chen, Z.; Mu, T. Infrared Small Target Detection via Interpatch Correlation Enhancement and Joint Local Visual Saliency Prior. IEEE Trans. Geosci. Remote Sens. 2021, 60, 5001314.
3. Bai, X.; Zhou, F. Analysis of new top-hat transformation and the application for infrared dim small target detection. Pattern Recognit. 2010, 43, 2145–2156.
4. Zhao, Y.; Pan, H.; Du, C.; Peng, Y.; Zheng, Y. Bilateral two-dimensional least mean square filter for infrared small target detection. Infrared Phys. Technol. 2014, 65, 17–23.
5. Deshpande, S.D.; Er, M.H.; Venkateswarlu, R.; Chan, P. Max-mean and max-median filters for detection of small targets. In Proceedings of the Signal and Data Processing of Small Targets, Denver, CO, USA, 20–22 July 1999; Volume 3809, pp. 74–83.

6. Liu, X.; Li, L.; Liu, L.; Su, X.; Chen, F. Moving dim and small target detection in multiframe infrared sequence with low SCR based on temporal profile similarity. IEEE Geosci. Remote Sens. Lett. 2022, 19, 7507005.
7. Qin, Y.; Li, B. Effective infrared small target detection utilizing a novel local contrast method. IEEE Geosci. Remote Sens. Lett. 2016, 13, 1890–1894.
8. Han, J.; Liang, K.; Zhou, B.; Zhu, X.; Zhao, J.; Zhao, L. Infrared small target detection utilizing the multiscale relative local contrast measure. IEEE Geosci. Remote Sens. Lett. 2018, 15, 612–616.
9. Wei, Y.; You, X.; Li, H. Multiscale patch-based contrast measure for small infrared target detection. Pattern Recognit. 2016, 58, 216–226.
10. Chen, Y.; Zhang, G.; Ma, Y.; Kang, J.U.; Kwan, C. Small infrared target detection based on fast adaptive masking and scaling with iterative segmentation. IEEE Geosci. Remote Sens. Lett. 2021, 19, 7000605.
11. Cui, H.; Li, L.; Liu, X.; Su, X.; Chen, F. Infrared small target detection based on weighted three-layer window local contrast. IEEE Geosci. Remote Sens. Lett. 2021, 19, 7505705.
12. Du, J.; Lu, H.; Hu, M.; Zhang, L.; Shen, X. CNN-based infrared dim small target detection algorithm using target-oriented shallow-deep features and effective small anchor. IET Image Process. 2021, 15, 1–15.
13. Du, J.; Lu, H.; Zhang, L.; Hu, M.; Chen, S.; Deng, Y.; Shen, X.; Zhang, Y. A spatial-temporal feature-based detection framework for infrared dim small target. IEEE Trans. Geosci. Remote Sens. 2021, 60, 3000412.
14. Zhang, M.; Dong, L.; Ma, D.; Xu, W. Infrared target detection in marine images with heavy waves via local patch similarity. Infrared Phys. Technol. 2022, 125, 104283.
15. Li, B.; Xiao, C.; Wang, L.; Wang, Y.; Lin, Z.; Li, M.; An, W.; Guo, Y. Dense nested attention network for infrared small target detection. IEEE Trans. Image Process. 2022, 32, 1745–1758.
16. Zhong, S.; Zhou, H.; Cui, X.; Cao, X.; Zhang, F. Infrared small target detection based on local-image construction and maximum correntropy. Measurement 2023, 211, 112662.
17. Gao, C.; Meng, D.; Yang, Y.; Wang, Y.; Zhou, X.; Hauptmann, A.G. Infrared patch-image model for small target detection in a single image. IEEE Trans. Image Process. 2013, 22, 4996–5009.
18. Dai, Y.; Wu, Y.; Song, Y. Infrared small target and background separation via column-wise weighted robust principal component analysis. Infrared Phys. Technol. 2016, 77, 421–430.
19. Wang, X.; Peng, Z.; Kong, D.; Zhang, P.; He, Y. Infrared dim target detection based on total variation regularization and principal component pursuit. Image Vis. Comput. 2017, 63, 1–9.

20. Dai, Y.; Wu, Y.; Song, Y.; Guo, J. Non-negative infrared patch-image model: Robust target-background separation via partial sum minimization of singular values. Infrared Phys. Technol. 2017, 81, 182–194.

21. Guo, J.; Wu, Y.; Dai, Y. Small target detection based on reweighted infrared patch-image model. IET Image Process. 2018, 12, 70–79.

22. Zhang, L.; Peng, L.; Zhang, T.; Cao, S.; Peng, Z. Infrared small target detection via non-convex rank approximation minimization joint l 2, 1 norm. Remote Sens. 2018, 10, 1821.

23. Zhang, T.; Wu, H.; Liu, Y.; Peng, L.; Yang, C.; Peng, Z. Infrared small target detection based on non-convex optimization with Lp-norm constraint. Remote Sens. 2019, 11, 559.

24. Chen, X.; Xu, W.; Tao, S.; Gao, T.; Feng, Q.; Piao, Y. Total Variation Weighted Low-Rank Constraint for Infrared Dim Small Target Detection. Remote Sens. 2022, 14, 4615.

25. Yan, F.; Xu, G.; Wu, Q.; Wang, J.; Li, Z. Infrared small target detection using kernel low-rank approximation and regularization terms for constraints. Infrared Phys. Technol. 2022, 125, 104222.

26. Liu, Y.; Liu, X.; Hao, X.; Tang, W.; Zhang, S.; Lei, T. Single-Frame Infrared Small Target Detection by High Local Variance, Low-Rank and Sparse Decomposition. IEEE Trans. Geosci. Remote Sens. 2023, 61, 5614317.

27. He Deng; Xianping Sun; Maili Liu; Chaohui Ye; Xin Zhou; Entropy-based window selection for detecting dim and small infrared targets. *Pattern Recognit.*. **2017**, *61*, 66-77.

28. Xiangzhi Bai; Yanguang Bi; Derivative Entropy-Based Contrast Measure for Infrared Small-Target Detection. *IEEE Trans. Geosci. Remote. Sens.*. **2018**, *56*, 2452-2466.

29. Yunkai Xu; Minjie Wan; Xiaojie Zhang; Jian Wu; Yili Chen; Qian Chen; Guohua Gu; Infrared Small Target Detection Based on Local Contrast-Weighted Multidirectional Derivative. *IEEE Trans. Geosci. Remote. Sens.*. **2023**, *61*, 1-16.

30. Hong Zhang; Lei Zhang; Ding Yuan; Hao Chen; Infrared small target detection based on local intensity and gradient properties. *Infrared Phys. Technol.*. **2018**, *89*, 88-96.

31. Yongsong Li; Zhengzhou Li; Weite Li; Yuchuan Liu; Infrared Small Target Detection Based on Gradient-Intensity Joint Saliency Measure. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.*. **2022**, *15*, 7687-7699.

32. Yimian Dai; Yiquan Wu; Fei Zhou; Kobus Barnard; Attentional Local Contrast Networks for Infrared Small Target Detection. *IEEE Trans. Geosci. Remote. Sens.*. **2021**, *59*, 9813-9824.

33. Huan Wang; Luping Zhou; Lei Wang. Miss Detection vs. False Alarm: Adversarial Learning for Small Object Segmentation in Infrared Images; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, United States, 2019; pp. 8509-8518.

34. Tianfang Zhang; Zhenming Peng; Hao Wu; Yanmin He; Chaohai Li; Chunping Yang; Infrared small target detection via self-regularized weighted sparse model. *Neurocomputing*. **2020**, *420*, 124-148.
35. Xin Wu; Jian-Qi Zhang; Xi Huang; De-Lian Liu; Separable convolution template (SCT) background prediction accelerated by CUDA for infrared small target detection. *Infrared Phys. Technol.*. **2013**, *60*, 300-305.
36. Yimian Dai; Yiquan Wu; Reweighted Infrared Patch-Tensor Model With Both Nonlocal and Local Priors for Single-Frame Small Target Detection. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.*. **2017**, *10*, 3752-3767.
37. Long Xu; Ying Wei; Haoyun Zhang; Shengxing Shang; Robust and fast infrared small target detection based on pareto frontier optimization. *Infrared Phys. Technol.*. **2022**, *123*, 104192.
38. Landan Zhang; Zhenming Peng; Infrared Small Target Detection Based on Partial Sum of the Tensor Nuclear Norm. *Remote. Sens.*. **2019**, *11*, 382.
39. Xuan Kong; Chunping Yang; Siying Cao; Chaohai Li; Zhenming Peng; Infrared Small Target Detection via Nonconvex Tensor Fibered Rank Approximation. *IEEE Trans. Geosci. Remote. Sens.*. **2021**, *60*, 1-21.
40. Guanghui Wang; Bingjie Tao; Xuan Kong; Zhenming Peng; Infrared Small Target Detection Using Nonoverlapping Patch Spatial–Temporal Tensor Factorization With Capped Nuclear Norm Regularization. *IEEE Trans. Geosci. Remote. Sens.*. **2021**, *60*, 1-17.
41. Jie Li; Ping Zhang; Lingyi Zhang; Zhiyuan Zhang; Sparse Regularization-Based Spatial–Temporal Twist Tensor Model for Infrared Small Target Detection. *IEEE Trans. Geosci. Remote. Sens.*. **2023**, *61*, 1-17.
42. Zhao Zhang; Cheng Ding; Zhisheng Gao; Chunzhi Xie; ANLPT: Self-Adaptive and Non-Local Patch-Tensor Model for Infrared Small Target Detection. *Remote. Sens.*. **2023**, *15*, 1021.