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Infrared small target and background separation via column-wise weighted robust principal component analysis

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HIGHLIGHTS

- WIPI model incorporates structural prior into the target-background separation.
- Weight is adaptive for each column in patch-image according to its patch structure.
- The adaptive weight for each column is designed based on the steering kernel.
- To solve the CWPRCA problem, an algorithm is developed based on ADM.

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ABSTRACT

When facing extremely complex infrared background, due to the defect of l_1 norm based sparsity measure, the state-of-the-art infrared patch-image (IPI) model would be in a dilemma where either the dim targets are over-shrinked in the separation or the strong cloud edges remains in the target image. In order to suppress the strong edges while preserving the dim targets, a weighted infrared patch-image (WIPI) model is proposed, incorporating structural prior information into the process of infrared small target and background separation. Instead of adopting a global weight, we allocate adaptive weight to each column of the target patch-image according to its patch structure. Then the proposed WIPI model is converted to a column-wise weighted robust principal component analysis (CWRPCA) problem. In addition, a target unlikelihood coefficient is designed based on the steering kernel, serving as the adaptive weight for each column. Finally, in order to solve the CWPRCA problem, a solution algorithm is developed based on Alternating Direction Method (ADM). Detailed experiment results demonstrate that the proposed method has a significant improvement over the other nine classical or state-of-the-art methods in terms of subjective visual quality, quantitative evaluation indexes and convergence rate.

1. Introduction

Due to the large dynamic range, long operating distance and all-day use of infrared imaging, infrared small target detection is a key technique in early-warning systems and precision guide weapons. However, with the development of long-range weapons, the targets occupy merely several pixels, even only single pixel in the whole image. What's worse, these small targets are often surrounded by very complex background, including heavy cloud clutter, urban buildings and other artificial interference objects. In addition, in many situations, the relatively rapid movement between small target and infrared sensor results in the fast change of backgrounds, making it hard to utilize the spatial and temporal information which is usually exploited by the sequence detection methods [1,2]. Therefore, the research work of infrared small target detection in single frame still remains challenging.

Traditionally, a single frame infrared small target image can be formulated as:

$$f_D = f_B + f_T \tag{1}$$

where f_D, f_T, f_B represent original image, background image and target image, respectively. Recently, robust principal component analysis (RPCA) [3] shows a nice framework to separate the background

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and foreground. Based on RPCA, Gao et al. firstly proposed the low-rank based infrared patch-image (IPI) model [4]. IPI model assumes that the input patch-image matrix $\boldsymbol{D}$ can be separated into a sparse matrix $\boldsymbol{T}$ called target patch-image and a low-rank matrix $\boldsymbol{B}$ named background patch-image, respectively. Then the small target-background separation task was transformed into a RPCA problem as follows:

$$\min_{\boldsymbol{B},\boldsymbol{T}} \|\boldsymbol{B}\|_* + \lambda\|\boldsymbol{T}\|_1, \quad \text{s.t.} \quad \boldsymbol{B}+\boldsymbol{T}=\boldsymbol{D} \tag{2}$$

where $\|\cdot\|_*$ is the nuclear norm of a matrix (i.e. the sum of singular values), $\|\cdot\|_1$ is the l_1-norm (i.e. $\|\boldsymbol{X}\|_1 = \sum_{ij}|\boldsymbol{X}_{ij}|$). In Ref. [4], the above convex optimization problem is solved via Accelerated Proximal Gradient (APG) [5] approach.

Although as a state-of-the-art method, IPI model has achieved a great success in small target detection. In our observation, there are still two limitations that prevent it from achieving better performance. One limitation is the sparsity measure of small targets depicted by l_1 norm. It might not be suitable while dealing with some extremely complex backgrounds. Because besides the target, some rare structures like edges and corners in the background would also be considered as sparse components under l_1 norm. They might be separated into the target component, which would result in a lot of false alarms. The other limitation is the constant weighting parameter λ in Eq. (2), which controls the trade-off between the low-rank component and the sparse component for each patch, namely each column in the patch-image. Since neither the low-rank property of background image nor the sparsity of target image is consistent, it is unwise to adopt a global constant weighting parameter for all different patches. With the constant weight, the solution to Eq. (2) is merely a simple separation of the input patch-image. The infrared small target in the target component is inevitably surrounded by background clutters with less intensity, which would raise a lot of false dismissals.

Aiming to eliminate the forementioned limitations, we propose a weighted infrared patch-image (WIPI) model for small target-background separation in this paper. Besides the background low-rank prior and target sparse prior, WIPI model incorporates more prior information of the patch structure into the separation process. Instead of the constant weight, different and adaptive weights are assigned to each column of the target patch-image matrix $\boldsymbol{T}$. With well-designed weights, the target enhancement and background suppression can be accomplished simultaneously during the separation process, eliminating the clutters in the target component cleanly and making the target detection easier. In WIPI model, the target unlikelihood coefficient (TUC) is designed as the column-wise weight based on the steering kernel weights [6]. Since the steering kernels are exceedingly informative and robust in conveying reliable local structural information about the image patches, the TUC can distinguish the small target from the edges well. By assigning the patches containing high-contrast edges with larger weights, we can remove the undesirable non-target but sparse structures in the target patch-image caused by the imperfection of the l_1 norm sparsity measure. Finally, in order to solve the column-wise weighted robust principle analysis (CWRPCA) problem for the proposed WIPI model, a solving algorithm based on the Alternating Direction Method (ADM) [7,8] is provided.

The remaining part of this paper is organized as follows. In Section 2, we briefly the existing works about infrared target-background separation or small target detection. In Section 3, the proposed WIPI model is detailedly described, including the design of the target unlikelihood coefficient, the solution to the CWRPCA problem as well as the mathematical explanation of the adaptive shrinkage in the target image. Detailed experimental results are presented and analyzed in Section 4. Finally, we conclude this paper in Section 5.

2. Related works

Many algorithms have been proposed for infrared small target and background separation. There are also a few different ideas about how to categorize them. In this section, we conduct a brief review for the existing algorithms and divide them into three categories based on the data structure level on which they are designed.

2.1. Pixel-level methods

As far as we know, most of the existing algorithms can be attributed as pixel-level methods. The typical approaches estimate the background by regression [9] or image filters such as max-mean and max-median filters [10], two-dimensional least mean square (TDLMS) filter [11]. Then the potential targets are enhanced by subtracting the estimated background from the original image. However, in the presence of complicated cloud-edge shapes, the above methods are unable to detect small targets accurately. In an attempt to overcome some of the disadvantages of these filtering based methods, some improved methods like edge component based bilateral filter [12], Bilateral TDLMS (BTDLMS) filter [13] Edge Directional TDLMS (EDTDLMS) filter [14] were proposed which directly incorporated the edge analysis results into the filtering processing. Another kind of the pixel-level methods directly enhances the targets by filtering them out from the original images. These methods are often based on morphological processing [15] including Top-Hat filter [16,17], toggle contrast operator [18]. It should be noticed that all the above-mentioned methods require that the designed filter must be able to meet the target characteristics. Otherwise, they might fail to distinguish the targets from backgrounds.

Recently many efforts are focused on imitating robust human visual system (HVS) to improve the performance of small infrared target detection, most of which use multiscale filtering or transform to compute the saliency map, such as Laplacian of Gaussian (LoG) filter [19], Difference of Gaussians (DoG) filter [20]. Actually, the contrast definition between the target and background is one of the most important tasks for HVS based methods. In Ref. [21], the local contrast is measured by the dissimilarity between the current location and its neighborhoods. Ref. [22] proposed another local contrast measure method called multiscale patch-based contrast measure (MPCM). Inspired by Ref. [21], we implement MPCM in a filtering manner, thus we still classify it in the pixel-level category.

2.2. Patch-level methods

Patch-level approaches divide the image into a set of image patches, and then estimate the background or detect the target individually for each patch. Analogous to the face detection scheme based on principal component analysis (PCA) or sparse presentation [23], most patch-level methods firstly build a set of target or background patch samples. Then the tested patch is projected onto a subspace constructed by the sample dictionary. The distance between the original patch and the reconstructed patch indicates the possibility of containing a target. This projection can be conducted by PCA [24], probabilistic principal component analysis (PPCA) [25], nonlinear principal component analysis (NLPCA) [26], kernel principal component analysis (KPCA) [27], sparse representation [28,29].

It should be noted that those target samples in these methods are produced by 2D Gaussian function. However, in some real-life applications, these approaches might not be robust enough since we usually cannot know the target information in advance.