Robust Principal Component Analysis-Based Infrared Small Target Detection

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Abstract

A method based on Robust Principle Component Analysis (RPCA) technique is proposed to detect small targets in infrared images. Using the low rank characteristic of background and the sparse characteristic of target, the observed image is regarded as the sum of a low-rank background matrix and a sparse outlier matrix, and then the decomposition is solved by the RPCA. The infrared small target is extracted from the single-frame image or multi-frame sequence. In order to get more efficient algorithm, the iteration process in the augmented Lagrange multiplier method is improved. The simulation results show that the method can detect out the small target precisely and efficiently.

Introduction

As an important means of remote sensing and battlefield perception, infrared small target detection on sky background has a wide range of applications in defense technology (Caefer, Silverman, and Mooney 2000). In order to provide the target information as quickly as possible, and to obtain a sufficiently long reaction time for the defense system, the infrared imaging system is required to perform detection on the target at a long distance. At this time, the target imaging area is small, the contrast is low, and structural information such as shape, size, and texture is lacking. At the same time, due to the complex scenes and large span scenes in the air scene, long-distance imaging effects are often affected by many factors such as field of view selection, weather, day and night and clouds, which may cause the infrared targets to be submerged in complex backgrounds. Therefore, the detection of small targets is very difficult (Zhao et al. 2011).

Traditional infrared target detection methods include the background difference method, the inter-frame difference method and the optical flow field method (Beck and Teboulle 2009). The background difference method subtracts the current image from the background reference model, and is sensitive to background light changes. The inter-frame difference method is based on the difference between the front and back frames, and can adapt to changes in the external environment. But when the change between the target frames is not obvious, the detection will be difficult. The optical flow field method detects the motion state of the object by the motion vector, and the calculation complexity is high. Aiming at these problems, this paper proposes an infrared small target detection method based on RPCA (Candes et al. 2009). Under the augmented Lagrangian multiplier, the original iterative process is improved to make the algorithm more simple and effective.

RPCA-based detection model

For infrared small target detection, the basic requirement is to separate the moving target from the background. The background area of the infrared image is mainly a smooth scene with a large area of gentle and subtle changes. They tend to exhibit a large continuous distribution in space and a gradual transition state in strength. The small target of the infrared image generally refers to a target that has a small pixel and a low signal-to-noise, and appears as an isolated point whose brightness is higher than the surroundings.

If the image is divided into blocks and then each image block is sequentially converted into a column vector, we can form an observation matrix. Since the background has a strong correlation in the gray space, only the matrix composed of the background pixels has the low rank, and the target itself has the sparse property. Thus the observation matrix can be considered to having a low rank matrix and a sparse matrix. In RPCA, if one part of a matrix has low rank and the other part has sparsity, then we can separate and recover these parts of the matrix by convex optimization.

(i) **RPCA model:** Suppose there is an observation matrix of size $m \times n$, which can be decomposed into $M = L + S$, where L is a sparse matrix of $m \times n$. The low rank matrix L can be recovered from the observation matrix M:

$$\min rank(L) + \lambda \left\| S \right\|_0 \qquad s.t. \quad M = L + S \tag{1}$$

where $rank(L)$ represents the rank of the matrix L, $\left\| S \right\|_0$ represents the l_0-norm of the matrix S, i.e. the number of non-zero values in the S. In fact, Equation (1) is an NP problem that is difficult to solve. It can be transformed into:

$$\min \left\| L \right\|_* + \lambda \left\| S \right\|_1 \qquad s.t. \quad M = L + S \tag{2}$$

where $\left\| L \right\|_*$ represents the kernel norm of the matrix L, which is the sum of the singular values of the matrix L. $\left\| S \right\|_1$ represents the l_1-norm of S, λ is the weighting parameter. For the $m \times n$ matrix, λ is set to $1/\sqrt{\max(m, n)}$.

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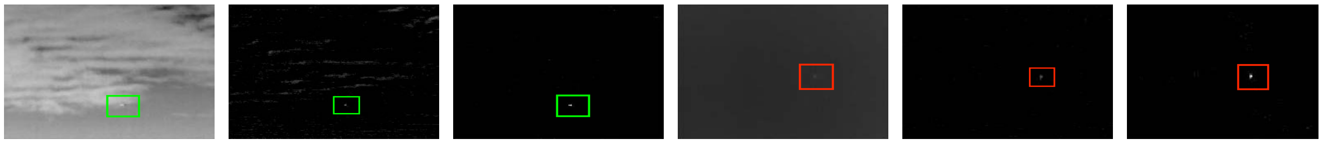

(a) Original image #1 (b) Background diff. (c) Our method (d) Original Image #2 (e) Background diff. (f) Our method

Figure 1: Performance comparison of infrared image target detection methods

(ii) **Augmented Lagrangian multiplier:** The augmented Lagrange multiplier method can transform the original constrained problem into an unconstrained problem. The principle is to alternately optimize the unconstrained problem for each variable in each iteration and finally solve the entire constrained problem. The Lagrangian function of Equation (2) is $\Gamma(L,S,Y) = \|L\|_* + \lambda \|S\|_1 + \langle Y, M-L-S\rangle + \frac{\mu}{2}\|M-L-S\|_F$, where Y is the Lagrange multiplier matrix, $\langle * \rangle$ is the standard inner product, $\mu > 0$ is the penalty parameter and $\|M-L-S\|_F$ is the Frobenius norm.

The minimization of $\Gamma(L,S,Y)$ can be solved by the following iterative approach. Firstly, in the case of fixing L, we find the function Γ with the minimum value of S, that is, $\arg\min_s \Gamma(L,S,Y)$. If we define a contraction function $S_\tau(t) = sgn(t)\max(|t|-\tau,0))$, then $\arg\min_s \Gamma(L,S,Y) = S_{\lambda/\mu}(M-L+Y/\mu)$. Secondly, in the case of fixing S, we find the function Γ with the minimum value of L $\arg\min_s \Gamma(L,S,Y)$. If we define a matrix operation function $D_\tau(X) = US_\tau(\sum)V^*$ where $X = U\sum V^*$, then $\arg\min_s \Gamma(L,S,Y) = D_{l/\mu}(M-S+Y/\mu)$. Finally, we update the Lagrangian multiplier matrix Y and the penalty parameter μ using the value of $M-L-S$: $Y_{k+1} = Y_k + \mu_k(M-L_{k+1}-S_{k+1})$ and $\mu_{k+1} = \rho \cdot \mu_k$. where $\rho > 1$ is a constant. When the iterative result reaches the convergence value, the calculation will end and the low rank matrix L and the sparse matrix S will be obtained.

(iii) **Improved Lagrangian multiplier:** For higher efficiency, the rapid iterative contraction algorithm is used to improve the above conventional method. We make the iterations for the S and L in the k-th and $(k+1)$-th episodes:

$$\tilde{S}_{k+1} = S_{k+1} + (t_k - 1/t_k)(S_{k+1} - S_k) \tag{3}$$

$$\tilde{L}_{k+1} = L_{k+1} + (t_k - 1/t_k)(L_{k+1} - L_k) \tag{4}$$

where the step size is $t_{k+1} = (1+\sqrt{1+4\,t_k^2})/2$. Here $t_0 = 1$. Thus, in the iterative process, not only the S_k and L_k of the current episode are used, but also the S_{k-1} and L_{k-1} are also used. The number of iterations is reduced and the iterative structure is more accurate. The second iteration itself is simple and does not increase the complexity.

Table 1: SNRs on the original image #1 and #2

	G_T	G	σ	SNR
Original image #1	168.33	158.37	17.39	0.57
Background difference	35.30	0.32	1.61	9.35
Our method	**39.67**	**0.15**	**1.02**	**38.58**
Original image #2	52.78	44.48	3.48	2.39
Background difference	27.50	0.78	2.26	11.82
Our method	**92.67**	**2.12**	**6.63**	**13.67**

Simulation experiment and analysis

In order to illustrate the effectiveness of the method, we selected two real-time infrared small target images for simulation experiments. Figure 1(a) is a small target image in the day sky, and 1(d) is a small target image in the night sky. In the experiment, the original infrared image was first divided into blocks with the size of 8×8. These blocks were converted to column vectors and arranged in order. We can construct a new observation matrix M with a size of 64×800. Then, using the augmented Lagrangian multiplier, the image was manipulated to RPCA, and L and S were obtained. Furthermore, by restoring S, the target image was obtained.

To comprehensively analyze the performance of infrared small target detection, the signal to noise ratio (SNR) indicator was adopted. The SNR of the image is defined as $SNR = (G_T - G)/\sigma$, where G_T is the grayscale mean of the target, G is the grayscale mean of the image, σ is the mean square error of the image. The SNRs of the original and final images are shown in the Table 1. The results show that our method is well extracted to the target, and the target display is more obvious than the traditional method.

Conclusion

Based on the RPCA algorithm, the paper proposes a method for detecting infrared small target images. When detecting, the infrared image is decomposed into a background part with low rank characteristics and a target part with sparse characteristics. By improving the iterative process of the augmented Lagrangian multiplier, the algorithm is more effective. Simulation experiments show the good results.

References

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