Pattern Recognition 76 (2018) 463–475

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/patcog

Infrared small-dim target detection based on Markov random field guided noise modeling

Chenqiang Gao[a,*], Lan Wang[a], Yongxing Xiao[a], Qian Zhao[b], Deyu Meng[b]

[a] Chongqing Key Laboratory of Signal and Information Processing, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
[b] Institute for Information and System Sciences and Ministry of Education Key Lab of Intelligent Networks and Network Security, Xi'an Jiaotong University, Xi'an 710049, China

ARTICLE INFO

Article history:
Received 23 February 2017
Revised 19 October 2017
Accepted 16 November 2017
Available online 20 November 2017

MSC:
00-01
99-00

Keywords:
Infrared image
Small target detection
Mixture of Gaussians
Markov random field
Variational Bayesian

ABSTRACT

Small target detection is one of the key techniques in infrared search and tracking applications. When small targets are very dim and of low signal-to-noise ratio, they are very similar to background noise, which usually causes high false alarm rates for conventional methods. To address this problem, we novelly treat the small-dim targets as a special sparse noise component of the complex background noise and adopt Mixture of Gaussians (MoG) with Markov random field (MRF) to model this problem. Firstly, the spatio-temporal patch image is constructed using several consecutive frames to utilize the temporal information of the image sequence. Then, the MRF guided MoG noise model under the Bayesian framework is proposed to model the small target detection problem. After that, by variational Bayesian, the small target component can be effectively separated from complex background noise. Finally, a simple adaptive segmentation method is used to extract small targets. Several series of experiments are done to evaluate the proposed method and the results show that the proposed method is robust for real infrared images with complex background.

1. Introduction

Infrared small target detection is a key technique in many areas, including space surveillance systems, early-warning systems, object tracking systems, etc. Its task is to localize targets, e.g., boats in the sea, airplanes in the sky, vehicles in the land, etc., as shown as Fig. 1 [1], in infrared images. Due to the long imaging distance, these targets are usually of very small sizes. Besides, the cloudy clutter, sea clutter or other clutter makes the background very complex and thus the targets are usually of low signal-to-noise ratio (SNR). Although the community has made a good progress on this task in past decades [1–4], it still remains an open problem, due to these challenges.

Up to now, a large number of approaches have been proposed. Some of them use the spatio-temporal cues to detect small targets. There are two representative categories among these methods: detection before track (DBT) [5–7] and track before detection (TBD) [8–10]. DBT can exploit the continuity of target's trajectories to reject the false targets in primary detection results obtained by single frame based detection methods. Thus, the performance of this kind of methods greatly depends on detection results from the single frame. In contrast, TBD can enhance the target signal energy by seeking the potential target trajectory and then accumulating the signal energy of the target along the trajectory before detecting targets. In this way, the enhanced target can be more robustly detected. The classical methods include 3D matched (directional) filters [11–13] and other spatio-temporal methods [14–17]. Generally, the methods using spatio-temporal information depend on the assumption of the motion continuity of targets. Whether this assumption is true in practical applications would influence the final detection performance.

Different from previous methods, many other methods just use spatial information to detect targets. It is usually assumed that an infrared image $f_F(x, y)$ can be formulated as a combination of three components, which are a background component $f_B(x, y)$, a target component $f_T(x, y)$, and a noise component $f_N(x, y)$, respectively. Some methods attempted to firstly predict the background component $f_B(x, y)$, and then extract targets from the difference image between $f_F(x, y)$ and $f_B(x, y)$. The representative methods include Top-Hat filtering [18], Max-Median filtering [19] and others methods [20–22]. In contrast, other methods directly model the target component $f_T(x, y)$ based on the infrared small target characteristics, such as GST [3], edge directional 2D LMS filter [23], sparse ring representation [24], modified gaussian function [25]. Since these methods just focus on one aspect of the infrared image compo-

* Corresponding author.
E-mail address: gaocq@cqupt.edu.cn (C. Gao).

https://doi.org/10.1016/j.patcog.2017.11.016

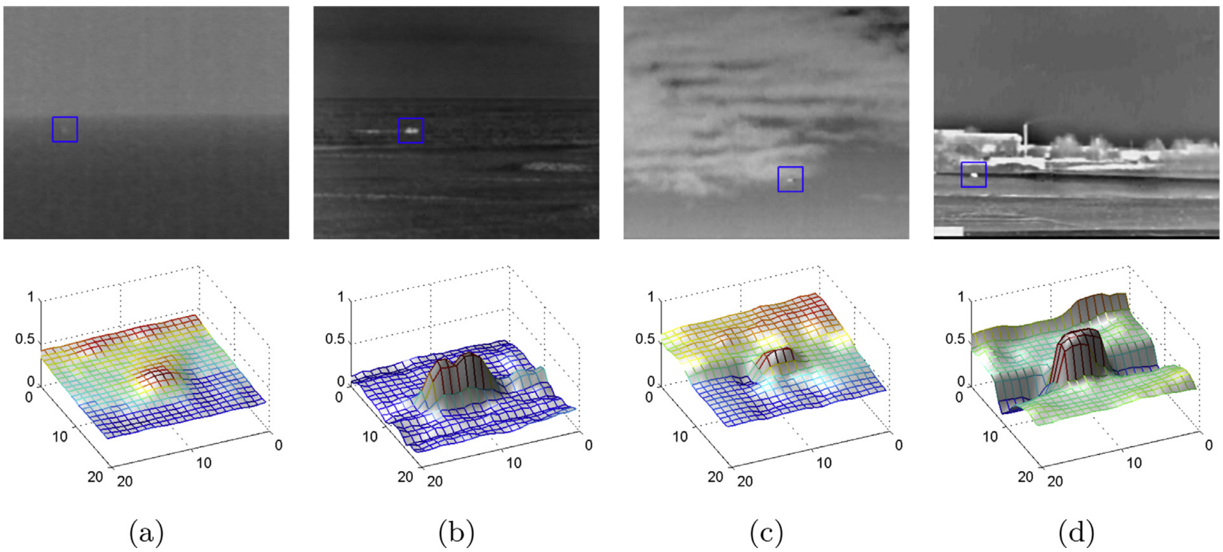

Fig. 1. Representative targets (upper) and the corresponding 3-D surfaces (lower) in different backgrounds (normalized) [1]. (a) A dim small ship target in sea-sky background. (b) A bright ship target in sea-sky background. (c) A dim aeroplane target in sky cloud background. (d) A bright vehicle target in sky-ground background.

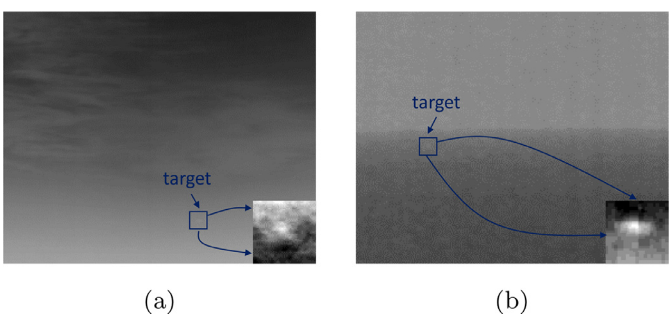

Fig. 2. Two representative small-dim target images. (a) A dim small ship target in sea-sky background. (b) A dim aeroplane target in sky cloud background.

nents with slightly strong assumptions, they are usually suitable for specific applications while not generalizing well to others.

Inspired by the recent advances in low-rank matrix analysis [26–29], the state-of-the-art method [1] is to jointly consider all three components, namely $f_B(x, y)$, $f_T(x, y)$ and $f_N(x, y)$, in the low-rank framework. With an effective image construction method, the background and target components are approximately transformed into a low-rank matrix and a sparse matrix, respectively, and thus an infrared image can be seen as a combination of a low-rank matrix, a sparse matrix and a noise matrix. By applying the accelerated proximal gradient (APG) approach [30], the target and background components can be concurrently and effectively recovered.

However, for the case of complex background noise, the current assumption for noise is simple, which slightly ignores the influence of noise for the small target detection task. As a result, the model could not well match the practical problem with heavy noise and this would influence the robustness of small target detection.

In this paper, we focus on the problem of small target detection in the case that targets are not only small, but also dim. These characteristics make their SNRs so low that targets almost approximate to noise, as shown as Fig. 2. In this situation, it is difficult to model separately the small target and noise components. The conventional methods usually have high false alarm rates on this task since there would be a lot of noise/clutter residual in the target image. To address this challenging problem, we do not explicitly discriminate the target from noise. Instead, we model the target component $f_T(x, y)$ and noise component $f_N(x, y)$ together, and assume that the target is a component of complex noise. Then we adopt the mixture of Gaussians (MoG) noise model [29] to model the complex noise. Due to the sparse property of the small target, the corresponding component is generally significant different from the rest components of the MoG. Thus, the small target can be separated from the complex noise. Besides, the adjacent pixels of small targets are usually dependent each other, while the noise pixels are random. Thus, we adopt the Markov random field (MRF) model to guide the separation of small targets from noise, which makes the detected small targets full shapes. In order to tackle the challenge of the low SNR, the spatio-temporal information is utilized and this is different from the state-of-the-art work [1] which is just based on spatial information in a single image.

The remainder of this paper is organized as follows. Section 2 describes the proposed method in detail, including the spatio-temporal patch image model, problem formulation, solution and the small target extraction framework. Experiments and comparisons between the proposed method and the baseline methods are provided in Section 3. Conclusions are given in Section 4.

2. The proposed method

In this section, we first introduce the construction and reconstruction method of a spatio-temporal patch image. Then, we describe the formulation of small target detection problem based on MoG and its solution in detail. After that, we present small target extraction and introduce the full framework of the proposed method, including the implementation steps. Finally, we analyze the computational complexity of the proposed method.

2.1. Spatio-temporal patch image

Similar to our previous work [1], given an image sequence f_1, f_2, $\cdots$, f_d and a cubic sliding window with a size of $w \times h \times d$, we can obtain a series of cubic patches. Then, a 2D matrix can be constructed by orderly vectorizing cubic patches as its columns, as shown in Fig. 3. Contrariwise, as shown in Fig. 4, after being processed, the constructed 2D matrix can be reconstructed into an image sequence with d frames by the inverse processing with a minor modification. Namely, for the pixel with overlap patches, its value is determined by pooling multiple different values into one. In this