Infrared Physics & Technology 67 (2014) 202–209

Contents lists available at ScienceDirect

Infrared Physics & Technology

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

Multiscale facet model for infrared small target detection

Changcai Yang [a], Jiayi Ma [b,*], Meifang Zhang [c], Sheng Zheng [d], Xin Tian [b]

[a] College of Computer and Information Science, Fujian Agriculture and Forestry University, Fuzhou 350002, China
[b] Electronic Information School, Wuhan University, Wuhan 430072, China
[c] Basic Subject Department of Fujian Health College, Fuzhou 350101, China
[d] Institute of Intelligent Vision and Image Information, College of Science, China Three Gorges University, Yichang 443002, China

HIGHLIGHTS

- The directional second-order directional derivative filters are deduced to enhance the targets.
- A multiscale representation provided by the proposed method is used to reduce the false alarm rate.
- The proposed method is effective to detect the small target in complex background with low SCR.

ARTICLE INFO

Article history:
Received 1 June 2014
Available online 5 August 2014

Keywords:
Directional second-order directional derivative filter
Facet model
Multiscale facet model matrix
Small target detection

ABSTRACT

In this paper, we proposed a new robust infrared small target detector that is more suitable for complex background with low signal-to-clutter ratio. The original image is decomposed into sub-bands in different orientations by using the directional second-order directional derivative (DSODD) filters deduced from the facet model. The multiscale facet model (MFM) analysis is developed by using a series of multiscale DSODD filters, which are obtained by filling zeros in the basic DSODD filter. Based on MFM, an MFM matrix is constructed, and the normalized determinant of this matrix is then defined as the target measure. The corresponding multiscale correlations of the target measures are computed to enhance the target signal and suppressing the background clutter. The experimental results on a set of real infrared images demonstrate that the proposed approach is effective and is superior to the traditional small target detection methods in terms of the pertained quantitative detection evaluation indexes, such as the signal-to-clutter ratio gain and the background suppression factor.

1. Introduction

The robust detection of infrared small targets in clutter is an issue of critical importance to infrared search and track (IRST) applications for self-defense or attacks [1–6]. Due to that the target is at a far distance, its projected image is usually very small and does not have available shape and texture for detection or matching [7–9]. Furthermore, because of the effects of inherent sensor noise or environment, the obtained infrared small targets are often buried in a complex background with low signal-to-clutter ratio (SCR). Therefore, it is difficult to detect the small targets in complex infrared background.

In order to detect a small target effectively, many approaches have been proposed in the past few decades. The small target regions are typically different from the surrounding clutter background. Based on this fact, some background prediction model based methods are proposed to detect targets. Gu et al. proposed a kernel-based nonparametric regression method for background prediction and clutter removal [1]. Each pixel of the observed infrared imagery is represented by using a linear mixture model. The clutter background is estimated by using kernel regression and small target is subsequently detected from the "pure" target-like region. Deng and Liu introduced an efficient method for background prediction based on the concept of self-information [2]. The self-information map (SINM) is constructed by a Parzen window function. Then the adaptive thresholding method followed by a region growing technique is adopted to detect the target from SINM. The major drawbacks of this method are the target growing effect and large calculation. To overcome these disadvantages, Deng et al. developed a weighted SINM based method and improved the region growing technique [3]. The spatial bilateral filter (BF) is integrated with temporal profile to predict background without targets [4]. An infrared patchimage (IPI) model based on

* Corresponding author.
E-mail addresses: changcaiyang@gmail.com (C. Yang), jyma2010@gmail.com (J. Ma), mfzhang85@163.com (M. Zhang), zsh@ctgu.edu.cn (S. Zheng), xin.tian@whu.edu.cn (X. Tian).

http://dx.doi.org/10.1016/j.infrared.2014.07.029
1350-4495/

the non-local selfcorrelation property of the infrared image for small target detection was proposed by Gao et al. [6]. They assume that the target and background patch-images are a sparse and a low-rank matrix, respectively. Then the background image is reconstructed by recovering the low-rank and sparse matrices. Bae et al. [5] introduced an edge directional 2D least mean squares (LMSs) filter to predict the background excluding small targets. Small targets can be extracted by subtracting the predicted background from the original infrared image.

Traditional small target detection methods including Top-hat filtering [10], max-mean/max-median filter [11] and so on, are widely used to suppress the background clutter or enhance the small target. Based on Top-hat filtering, some new related methods have been presented. The Top-hat filtering parameters are optimized by using neural network and genetic algorithm [12]. A new Top-hat transformation method was proposed by Bai et al. [13]. They reorganized the classical Top-hat transformation by using two different but correlated structuring elements. The different information between the target and surrounding regions is also taken into account. Meng et al. proposed an adaptive method for small target detection [14]. The modified top-hat transformation using interrelated structuring elements is used to adaptively detect the darker and brighter targets and suppress the cluttered background. However, they sometimes did not give truly satisfactory results. The main difficulty is that the size of the small target may vary from 2×2 to 12×12 pixels [15].

In order to solve the scale problem, many multiscale based methods have been proposed. According to the principle of human discrimination of small targets from a natural scene, an efficient multiscale small target detection using template matching based on the average gray absolute difference maximum map was proposed by Wang et al. [16]. A small targets detection method based on support vector machines (SVM) in the wavelet domain has been presented [17]. Motivated by the robust properties of the human visual system (HVS), Kim and Lee proposed a scale invariant small target detection for solving the scale and clutter suppression problem [15]. They applied the row-directional-local background removal filter (RD-LBRF) to estimate background image. The possible target position parameters are obtained by searching local extrema from the Laplacian scale-space images. Then the maximum of SCR is obtained by using the Tune-Max method. Other related work includes the least squares support vector machine (LS-SVM) based method [18], directional saliency based method [19], image layering based method [20], as well as local contrast method [21]. These methods can achieve good performance in typical applications but may become less effective for the small target in complex background with low SCR.

In this paper, we explore a new robust infrared small target detector that is more suitable for different cluttered and noisy backgrounds and target types. The key ideas of the proposed method are to use the directional second-order directional derivative (DSODD) filters to enhance targets and the multiresolution representation to reduce the false alarm rate. The DSODD filters are used to decompose the original image into sub-bands in horizontal, vertical and diagonal orientations. The multiscale analysis is developed by using a series of multiscale DSODD filters, which are obtained by filling zeros in the basic DSODD filter. Based on multiscale DSODD filters, a multiscale facet model (MFM) matrix is constructed, and the normalized determinant of this matrix is then defined as the target measure. The corresponding multiscale correlations of the target measures are computed for enhancing the target signal and suppressing the background clutter.

The rest of the paper is organized as follows. In Section 2, the multiscale DSODD filters is developed to decompose the original image. In Section 3, we introduce the target detection method based on multiscale facet model. The experiments are provided in Section 4. We conclude this paper in Section 5.

2. Multiscale facet model

In the following, we describe the necessary algorithm on which our algorithm is based, and then a multiscale representation is developed by using a series of multiscale DSODD filters.

2.1. DSODD

Let R and C be the index sets of the neighborhood that satisfy the symmetric conditions, i.e., $r\in R$ implies $-r\in R$ and $c\in C$ implies $-c\in C$. Similar to the second-order directional derivative (SODD) based method [22,23], we deduce the DSODD filters from the facet model [24]. The set $\{P_1(r,c),\cdots,P_N(r,c)\}$ of discrete orthogonal polynomials over $R\times C$ can be constructed. Then the fitted intensity surface function over the constant vector space, $R\times C$, can be written as follows:

$$f(r,c)=\sum_{n=1}^{N}a_nP_n(r,c), \tag{1}$$

where $f(r,c)$ is the corresponding intensity value. For the 5×5 neighboring window in which $R=\{-2-1012\}$ and $C=\{-2-1012\}, P_n(r,c)$ are shown as $\{1,r,c,r^2-2,c^2-2,r^3-\frac{17}{5}r,(r^2-2)c,(c^2-2)r,c^3-\frac{17}{5}c\}$.

The fitting coefficients can be estimated by minimizing a residual error and can be written as

$$a_m=\frac{\sum_{r\in R}\sum_{c\in C}f(r,c)P_m(r,c)}{\sum_{r'\in R}\sum_{c'\in C}P_m^2(r',c')}. \tag{2}$$

From Eq. (2), we can seen that each fitting coefficient a_m can be computed as linear combination of the data values. For each index (r,c) in the index set, the intensity value $f(r,c)$ is multiplied by the weight

$$W_m=\frac{P_m(r,c)}{\sum_{r'\in R}\sum c'\in CP_m^2(r',c')}. \tag{3}$$

If we substitute $P_n(r,c)$ into Eq. (3), the weight kernels $W_m, m=4,5,6$ can be obtained as follows:

$$W_4=\frac{1}{70}\begin{bmatrix}2&2&2&2&2\\-1&-1&-1&-1&-1\\-2&-2&-2&-2&-2\\-1&-1&-1&-1&-1\\2&2&2&2&2\end{bmatrix},$$

$$W_5=\frac{1}{100}\begin{bmatrix}4&2&2&-2&-4\\2&1&-1&-1&-2\\0&0&0&0&0\\-2&-1&-1&1&2\\-4&-2&2&2&4\end{bmatrix},$$

$$W_6=W_4^T.$$

Assume that in each neighborhood of the image the intensity surface function f takes the parametric form of a polynomial in the row and column coordinates. Thus, in each neighborhood f can be written as:

$$f(r,c)=k_1+k_2r+k_3c+k_4r^2+k_5rc+k_6c^2+k_7r^3+k_8r^2c + k_9rc^2+k_{10}c^3. \tag{4}$$

Evaluating the second row and column partial derivatives at the center point $(0,0)$ from Eq. (4) yields the second order directional derivatives