Infrared Physics & Technology 65 (2014) 17–23

Contents lists available at ScienceDirect

Infrared Physics & Technology

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

Bilateral two-dimensional least mean square filter for infrared small target detection

Yao Zhao [a,b], Haibin Pan [a,b,c,*], Changping Du [a], Yanrong Peng [a], Yao Zheng [a,b]

[a] Institute of Aerospace Information Technology, Zhejiang University, Yuquan Campus, Hangzhou, Zhejiang 310027, PR China
[b] Joint Laboratory of Flight Vehicle Ocean-based Measurement and Control, Zhejiang University, Yuquan Campus, Hangzhou, Zhejiang 310027, PR China
[c] Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

HIGHLIGHTS

- Variance of Gaussian filter and step size are adjusted adaptively.
- Leftward filter is added.
- Prediction error is separated by its plus–minus sign.
- Four images of prediction error are fused.
- Clouds and noises are significantly suppressed.

ARTICLE INFO

Article history:
Received 18 October 2013
Available online 28 March 2014

Keywords:
Small target detection
TDLMS
Bilateral filtering
Image fusing

ABSTRACT

The basic TDLMS (Two-Dimensional Least Mean Square) filter fails to detect infrared small targets consistently, especially under conditions of heavy noise and distinct cloud edges. This paper proposes a robust and efficient small-target detection method based on the basic TDLMS filter. The method first smooths the input image with a Gaussian filter of adaptive variance, and then employs TDLMS with a selected step size to filter the image with rightward and leftward iterations. Two prediction error images are obtained by subtracting the prediction images of the bilateral filtering from the original input image. Each prediction error image is separated into positive and negative prediction error images. That is, four images are generated in the bilateral filtering. The final image is obtained by fusing these four images. Experimental results show that the proposed method achieves significant improvement in background suppression and detection performance over the basic TDLMS filter and other improved TDLMS filters.

1. Introduction

Automatic target detection based on infrared imaging systems has the advantages of large dynamic range, long operating distance, and all-day use [1]. It applies to many areas including infrared imaging guidance systems, space surveillance systems, astronomy prognosticates, remote sensing, and forest warning [2]. Infrared small-target detection is an important part of the infrared imaging system. In recent years, significant research dedicated to infrared small-target detection has been undertaken [3–12]. In general, a detection algorithm includes background suppression and detection/tracking (tracking before detection or detection before tracking). The existing background-suppression algorithms can be divided into three classes [1]: (1) Spatial filter-based algorithms [3–6]. These algorithms are based on the assumption that the background pixels are spatially correlated and target pixels are the opposite. Therefore, the predicted background can be obtained by a spatial filter, and the background clutters can be suppressed by subtracting the filtered image. (2) Temporal filter-based algorithms [7–9]. Background pixels are often stationary in the time domain, whereas the moving target pixels are non-stationary. Therefore, the background clutters can be suppressed by subtracting the time domain filtered/predicted background. (3) Transformation domain-based algorithms [10–12]. The original image is first transformed to a frequency or wavelet domain. The background clutters are usually in the low-frequency band and the targets are usually in the high-frequency band. The background can be suppressed when the low-frequency band is removed. However, the temporal-based algorithms fail to detect a target on a non-stationary background. The transformation domain-based algorithms are time-consuming

* Corresponding author. Present Address: Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong. Tel.: +86 13396518496.

E-mail address: phbzll@zju.edu.cn (H. Pan).

http://dx.doi.org/10.1016/j.infrared.2014.03.006
1350-4495/

and cannot satisfy the real-time requirement. Therefore, we propose an improved TDLMS, a spatial filter-based algorithm, for infrared small-target detection.

TDLMS was first proposed by Hadhoud and Thomas in 1988 [13]. The TDLMS filter is a two-dimensional adaptive filter. It is an extension of the one-dimensional least mean square (LMS) filter. It attempts to minimize the mean square error between the expected response and the output signal. The TDLMS filter predicts the pixel intensity using the weighted intensity of nearby pixels. The prediction error is large near the target and is close to zero in the background. This is because the intensity of the pixels near the target changes rapidly and is hard to predict accurately. Conversely, the intensity of the background pixels is homogeneous and easy to predict. Utilizing this feature, the TDLMS filter can enhance small targets and suppress backgrounds.

TDLMS is a widely used method in the field of infrared small-target detection. Azimi et al. [14] proposed the two-dimensional BDLMS (Block Diagonal Least Mean Square) method. The weight matrix is updated once per block rather than once per pixel. The diagonal scanning is adopted to avoid the problems inherent in the one-dimensional (1D) standard scanning schemes. Bae et al. [15] presented a mask-weighted TDLMS method that places the predicted pixel in the center of the masked prediction matrix. The method can obtain more neighborhood information than the conventional method. Problems related to the step-size adjustment of TDLMS have been extensively researched [16–18]. Cao et al. [17] made use of five prediction matrixes to obtain the neighborhood information to determine the step size. The step size is a function of the variance of the four prediction values in the four directions. It becomes long near the changeable area such as the cloud edges and short in the homogeneous backgrounds. Similar to Cao, Bae et al. [18] made use of eight prediction matrixes to obtain the neighborhood information. This improved the TDLMS algorithms by fully utilizing the neighborhood information to determine whether the pixel was near the edge of the cloud or near the target. Then, accordingly, the step size near the edge of the cloud was increased and the step size near the target was reduced. However, in the presence of complicated cloud-edge shapes and serious noise, the above TDLMS filters are unable to detect small targets accurately. In addition, the above improved TDLMS algorithms are time-consuming and do not perform well in real-time applications.

In an attempt to overcome some of the disadvantages of these improved TDLMS methods, we propose a bilateral filtering method. The method filters the images rightwards and leftwards and then fuses the prediction error images. With the addition of the leftward filtering and fusing processes, the cloud edges and noise spots are suppressed sharply and the targets are significantly enhanced. We also use a selected, fixed step size and simplified filter structure to improve the computing speed. Experimental results show that the algorithm has significantly better detection performance as well as competitive execution efficiency.

2. Overview of TDLMS

As shown in Eq. (1), the TDLMS filter predicts the image pixels according to the reference input image, X, with the size $M \times M$:

$$\mathbf{Y}(m,n) = \sum_{l=0}^{N-1}\sum_{k=0}^{N-1}\mathbf{W_j}(l,k)\mathbf{X}(m-l,n-k) \quad m,n = 0,\ldots,M-1 \tag{1}$$

where $\mathbf{Y}$ is the predicted image, and j is the iteration number given by $j = m * M + n$. The filter window, $\mathbf{W}_j$, with the size $N \times N$, is the weight matrix at the jth iteration.

By comparing the predicted image with the desired value of the input image, the prediction error is generated. The prediction error value, e_j, at the jth iteration is calculated as:

$$e_j = \mathbf{D}(m,n) - \mathbf{Y}(m,n) \tag{2}$$

where $\mathbf{D}(m,n)$ is the desired value of the input image. The prediction error value is used to update the coefficients of the weight matrix.

The coefficient updating equation of the weight matrix, $\mathbf{W}_j$, is given by the following:

$$\mathbf{W}_{j+1}(l,k) = \mathbf{W}_j(l,k) + \mu \cdot e_j \cdot \mathbf{X}(m-l,n-k) \quad l,k = 0,\ldots,N-1 \tag{3}$$

where μ is the step size to control the prediction error value between the desired value and the predicted value. The TDLMS algorithm is based on the method of steepest descent. The difference between the updated weight matrix and the present weight matrix is proportional to the negative gradient of the error power.

3 Proposed bilateral TDLMS filter

3.1. Structure of proposed bilateral TDLMS filter

To address the deficiencies of the basic TDLMS filter in small target detection, we propose TDLMS with bilateral filtering and image fusing. We add Gaussian blurring and select an efficient step size for better performance. The structure of the proposed algorithm is shown in Fig. 1.

3.2. Optimized Gaussian blurring variance and step size

The Gaussian blurring process is given by:

$$\begin{aligned} I_{gauss}(\sigma) &= I_{org} * g \\ g(u,v,\sigma) &= \frac{1}{2\pi\sigma^2}e^{-(u^2+v^2)/(2\sigma^2)} \end{aligned} \tag{4}$$

where * denotes the convolution operation and σ^2 is the variance of the Gaussian function.

The signal-clutter ratio in the infrared images is relatively low; therefore, bright noise spots may cause the TDLMS filter to output a large prediction error that increases the probability of a false alarm. The Gaussian blurring can smooth the images and suppress the response of the small, bright noise spots. The variance of the Gaussian blurring is set to be proportional to the variance of the noise as follows:

$$\sigma = S \cdot \sigma_{noise} \tag{5}$$

where S is the variance coefficient.

The noise variance is estimated as follows:

$$\begin{aligned} \sigma_{noise}^2 &= D(I_{org} - I_{org} * g) \\ g &= g(u,v,\sigma_n) \end{aligned} \tag{6}$$

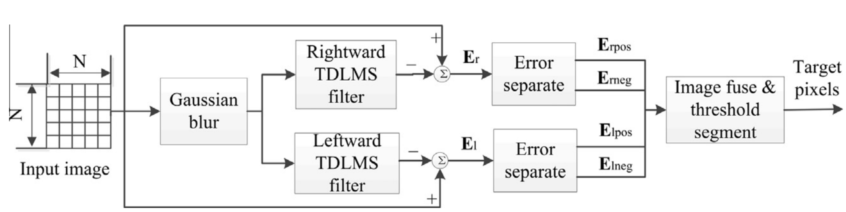

Fig. 1. Structure of the proposed filter.