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Small target detection based on weighted self-information map

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HIGHLIGHTS

- A weighted self-information map is proposed to overcome the target growing effect.
- The seed point and stopping criterion are selected automatically in the improving region growing technique.
- The presented approach yields high detection probability and low false alarm probability.

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ABSTRACT

The target growing effect and large calculation are two major drawbacks in small target detection based on the self-information map. Consequently, a weighted self-information map is proposed to overcome those disadvantages in this paper. The removal of the target growing effect from the weighted self-information map is proved theoretically, which is capable of improving the capability of small target detection. Based on the weighted self-information map and the improved region growing technology, a small-target detection approach is constructed. The signal-to-noise ratio, peak signal-to-noise ratio, region nonuniformity, the probability of detection and the probability of false alarm are adopted to demonstrate the performance of the proposed approach. Both quantitative analysis and qualitative comparison confirm the validity and efficiency of the proposed approach.

1. Introduction

Small-target detection technologies have been broadly adopted both in military and civil fields, e.g. missile guidance, early warning system, anomaly detection of medical image, and industrial flaw detection. Small-target detection technologies can be classified into two categories: detect-before-track (DBT) and track-before-detect (TBD) [12]. DBT is a powerful detection technique owing to its shorter computation time and less memory requirement. DBT contains two successive procedures [8,9]: the pre-detection procedure in a single-frame image and the track procedure in multiple frames. The result of the former procedure has a great effect on the computation and accuracy of the latter one.

The research on small-target detection technologies is a hot and difficult spot in computer vision, and lots of related detection methods have been explored in recent decades [1–12]. It is known that background suppression and image segmentation are two crucial steps in the pre-detection procedure. However, in these two steps there are some unresolved problems that the research aims to solve.

A small target is of small size and weak intensity, and it usually submerges in the complex background and noise. Background suppression is to suppress the intricate background, enhance targets and then improve signal-to-noise ratio of the small target image. To suppress those small-target image backgrounds whose statistical characteristics are constant or slowly varying, the previous researches have put forward the algorithm based on the finite or infinite impulse response filter, the integration approach based on the point estimation [4], top-hat transformation [3], and adaptive filtering techniques [6] etc. Some methods, such as Butterworth high-pass filter, wavelet analysis, and others based on the biorthogonal wavelet or integrated high order cumulant with wavelet transformation [10] have been explored to suppress nonstationary, nonlinear and rapidly varying backgrounds. For those methods, their performance of background suppression is limited, since those methods root in Fourier transform restricted by Heisenberg uncertainty principle. Therefore, the study on background suppression methods, whose advantages are simple structure, good filtering effect, and strong robustness, is the key issue in the development of small target detection.

Information entropy is a measure of the average amount of information, which has many useful characteristics, so it has broad applications in image recovery, edge detection, target detection,

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image matching, and so on. In recent years, the local entropy operator has been applied to suppress small-target image backgrounds [11], since the emergence of the target damages the characteristics of image texture in the local region. Similar to the local entropy operator, the concept of local self-information operator has been proposed to suppress small-target image backgrounds [12]. For a small target image, the value of self-information should be identified because its texture characteristics is definitive, while the appearance of a target destructs the characteristics of the image texture in a local window, and then arouses the change of the value of local self-information operator. The small-target detection method based on self-information map (SINM) can effectively detect small targets under complex backgrounds [12]. However, the disadvantages of that method are the target growing effect and huge workload.

Image segmentation in DBT is to separate candidate targets through a threshold from the image after background suppression, and it is one of the most critical tasks in automatic image analysis. The choice of threshold is of great significance in the threshold segmentation. The threshold segmentation contains global and local threshold methods. The most conventional methods are global threshold methods. In global threshold approach, a single threshold is selected for the entire image according to global/local information. While in local threshold approach, the threshold value is determined locally, e.g. pixel by pixel, or region by region. The region growing technique is an effective small-target segmentation method, and it is an iterative process that groups pixels or sub regions into larger regions based on the predefined criteria. However, the choice of the seed point and the stopping criterion are difficulties in the application of the region growing method.

In order to suppress the target growing effect, decrease the amount of computation of SINM, self-adaptively choose the seed point and the stopping criterion in the region growing technique, the research presents a small-target detection approach based on the weighted self-information map and the improved region growing technique. By comparing the presented approach with other methods such as the maximum background prediction model (MBPM), the top-hat transformation (THT), empirical mode decomposition method (EMD), and the self-information map (SINM) [12] from different perspectives, the research expects that the presented approach can detect small targets image more efficiently, rapidly and robustly.

The organization of the remainder of this paper is as follows: Section 2 reviews the relevant concepts of self-information map, and the weighted self-information map (WSINM) is constructed in Section 3. The small-target detection approach integrated WSINM with the improved region growing technology is presented in Section 4 and the proposed method is tested and verified to be a useful small-target detection approach in Section 5. Section 6 summarizes the contributions of the paper and proposes an outlook to future work.

2. Self-information map

2.1. Neighborhood system

An image is assumed as the random vector $X(\Omega;\ \Theta)$, where Ω is sample space and Θ is a set of points defined on a discrete Cartesian grid, then a neighborhood system $N = \{N_i\}_{i\in\Theta}$ $(i\notin N_i)$ is constructed if N satisfies the property: $N_i \subset \Theta$, $N_j \subset \Theta$, $j \in N_i$ if and only if $i \in N_j$, where N_i and N_j is the neighborhood of the respective point i and j. If x_i represents a specific realization of $X(\Omega;\ \Theta)$ at the point i, those points $Y(i) = \{x_j\}_{j\in Ni}$ contained in N_i will be viewed as a random vector. Therefore, the statistical relationship between x_i and its neighbors can be denoted as

$$h(X|Y) = h(X,Y) - h(Y) = \sum_{j\in Ni} p(Y = x_j)h(X = x_i|Y = x_j) \tag{2.1}$$

where $h(Y)$ is the information entropy of the random variable Y, and $h(X,Y)$ is the joint entropy of variables X and Y. The conditional probability density function of each point-neighborhood pair $(X = x_i, Y = y_j)$ is multiplied by the conditional entropy $h\ (X|Y)$.

2.2. The concept of SINM

For a point i and its neighborhood N_i, the estimation of probability density function (PDF) of x_i is a difficult task, which needs to deal with the high-dimensional, scattered-data interpolation process. A Parzen window-based density estimation method is an effective nonparametric density estimation technique [13]. In n-dimensional space, the PDF of x_i is estimated as

$$p(x_i) = \sum_{j\in N_i} \frac{1}{|N_i|} \cdot G(x_i - x_j, \Psi) \tag{2.2}$$

where $|N_i|$ is the cardinality of the set N_i, x_j is the neighbor of x_i, and $G(x_i\text{-}x_j,\ \Psi)$ is the Parzen-window function, and it is usually chosen as the n-dimensional Gaussian kernel:

$$G_n(x_i - x_j, \Psi_n) = \frac{1}{(2\pi)^{n/2}|\Psi_n|^{1/2}} \times \exp\left(-\frac{1}{2}(x_i - x_j)^T \Psi_n^{-1}(x_i - x_j)\right) \tag{2.3}$$

where Ψ_n is the $n \times n$ covariance matrix.

According to formula (2.2), the probability of a point with the particular intensity depends on the intensities of its spatial neighbors [14]. If the self-information of the center in the Parzen window is adopted to measure the information contained in the window, and the local window shifts in the image plane from left to right and from top to down, a self-information matrix S will be constructed. When S is normalized to [0,1], the self-information map (SINM) will be founded.

3. Weighted self-information map

3.1. Target growing effect

If no priori information about the structure of the PDF of x_i is obtained, an isotropic Gaussian function will be usually chosen as the descriptor of the Parzen-window function in formula (2.3). The size of the self-information matrix S is the same as that of the original image, and the matrix element $S(i)$ $(i = 1,2,\ldots,M)$ is described as

$$\begin{aligned} S(i) &= -\log p(x_i) \\ &= -\log \frac{1}{|N_i|} \sum_{j\in N_i} \frac{1}{(2\pi)^{n/2}|\sigma^2 I_n|^{1/2}} \\ &\quad \times \exp\left(-\frac{1}{2}(x_i - x_j)^T(\sigma^2 I_n)^{-1}(x_i - x_j)\right) \end{aligned} \tag{3.1}$$

where σ is the standard deviation of the Gaussian function, and I_n is the n-dimensional identity matrix. Then, for an image, $S(i)$ is viewed as a function with three parameters which are the width p and the height q of the Parzen window, and the standard deviation σ respectively. The parameters p, q, σ are denoted by the parameter pair (p, q, σ).

A simulated small target image with two bright point targets is shown in Fig. 1a, which is normalized to [0, 1] in advance. The size of simulated image is 256×256, and the positions of two targets are (125, 75) and (156, 175) respectively. The noise image shown in Fig. 1b is obtained by adding Gaussian white noise with zero mean and 0.01 variance to Fig. 1a. The corresponding SINMs with