A Novel Filtering Method for Infrared Image

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Abstract. The image filtering technology is widely used in many fields, such as environmental monitoring and assessment, space remote sensing, recognition and tracking of infrared target. In this paper, aiming at the problem of poor generalization capability and over-fitting with artificial neutral network for infrared image filtering, a new filtering method is presented. The structure elements are used to set up the training samples. And then, based on support vector machine theory, it builds the learning ma-chine with proper model and trains the samples. The result can be used to suppress the background SNR of following image. The experimental result with infrared image shows that the method can obtain higher SNR than conventional neutral network and fixed Top-Hat operator method, especially in low SNR.

Keywords: Image filtering · Neutral network · Support vector machine · Top-Hat operator

1 Introduction

The technology of image filtering is widely used in many fields, such as environmental monitoring and assessment, space remote sensing, recognition and tracking of infrared target, and so on. With the development of mathematical morphology, it has become a important method for image filtering and many researchers use it to filter the background noise. But, the traditional morphology filter all depends on the experience of the designer, which is difficult to select the optimal structural elements [1]. So, a morphology weighted neural network is used for target recognition by Won [2], and the learning ability of morphology neural network is researched by Ritter [3]. The application of the morphology neural network is summed up by Grana [4]. But, in practice, the neural network has the problem of over-fitting and poor generalization capability. In the paper. the training algorithm based on Support Vector Machine (SVM) is presented. SVM [5] realizes the structural risk minimum, and minimums the experience

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risk and the bound of VC dimension. SVM can get less practice risk and better generalization. In this paper, it is used for the filtering of infrared image.

2 Target Observation Models

For the infrared image, the targets are close to a point source (several pixels), because of aerooptic disturbance and air turbulence. The model of targets can be substitute by a 2D IR optical blur function, which is shown as follow:

$$f_T(x,y) = \tau * \exp\left\{ -\frac{1}{2}\left(\frac{x}{\delta_x}\right)^2 + \left(\frac{y}{\delta_y}\right)^2 \right\} \tag{1}$$

Where, $f_T(x,y)$ is the targets intensity; τ is the targets intensity amplitude, δ_x and δ_y are horizontal and vertical extent parameter, x and y are the coordinates of targets.

The observation sequence of a random infrared image embedded with moving targets can be modeled as follow

$$f(x,y,k) = f_T(x,y,k) + B(x,y,k) + N(x,y,k)$$

Where, $B(x, y, k)$ is the exterior clutter background; $N(x, y, k)$ is the noise of the image; k is the sampling time.

Figure 1 is the real infrared image, which is get from thermal infrared imager, which is made by Sofradir company, France. It is 320 × 240, 8 bit infrared target image sequence. According to Fig. 1, the local properties of infrared targets are convex.

3 Grayscale Morphology Filter Algorithm

The basic operation of grayscale morphology is erosion, dilation, open and close, which are defined as follow.

Defining one:

Structural element B erodes image f:

$$(f\Theta\mathrm{B})(x) = \min_{t\in B} f(x+t)$$

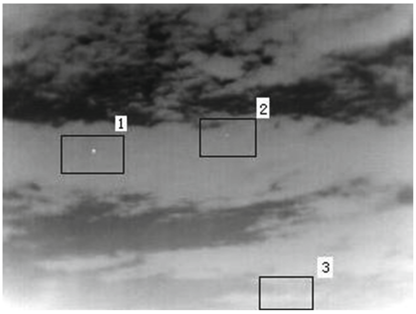
Structure element B dilates image f:

$$(f \oplus \mathrm{B})(x) = \min_{t\in B} f(x-t)$$

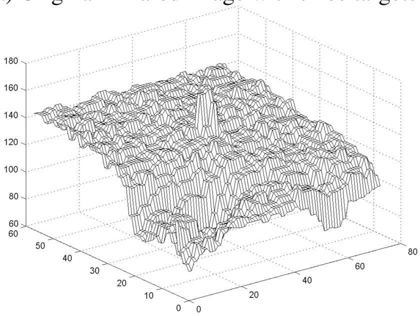
Defining two:

Opening

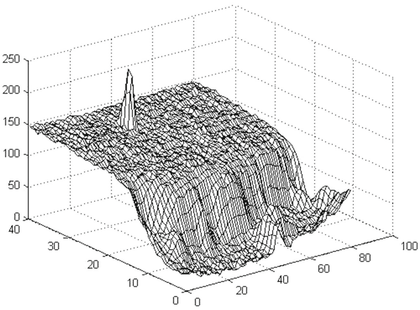
$$f \circ \mathrm{B}(x) = (f\Theta\mathrm{B})(x) \oplus \mathrm{B}$$



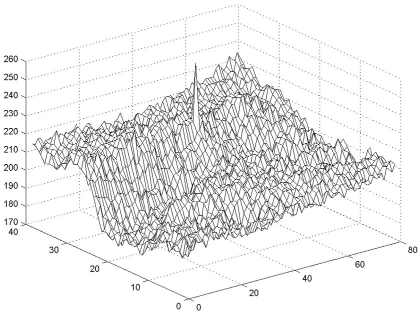
(a) Original infrared image with three targets



(b) Target one



(c) Target two



(d) Target three

Fig. 1. The local property of infrared target.

Closing

$$f \circ \mathrm{B}(x) = (f \oplus \mathrm{B})(x) \Theta \mathrm{B}$$

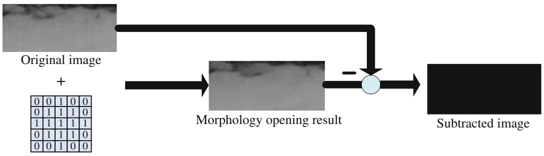
Open operation likes a non-linear low-pass filter, but it is different from the frequency domain low-pass filter. When the big and small structures both have high frequencies in one image, the open operation only allows the big structures passing and prevents the small structures passing.

As discussing above, the target is the "convex" structure in infrared image. After filtering, original image subtracting the background can immediately get the candidate targets.

Open Top-Hat operation and Close Top-hat operation is defined as follow and Fig. 2.

$$\mathrm{OTH}_{f,B}(x) = (f - f \circ \mathrm{B})(x)$$

$$\mathrm{CTH}_{f,B}(x) = (f \circ \mathrm{B} - f)(x)$$



4 An Illustration of Mathematical Morphological Top-Hat Transform

Open Top-Hat operation can find the peak of one image. Close Top-Hat operation can find the valley of one image. Morphological Top-Hat operation can effectively identify spot targets in a complicated background. But for spot targets in high noise image, the traditional Top-Hat Morphology operation is helpless. So, the learning algorithm based on Support vector machine (SVM) is provided.

5 Training Method Based on SVM

The size of structural elements decides the input vector dimension of learning machine. For example, if the length of structural elements is $n \times n$, the input vector dimension must be n^2.

Suppose the set of training samples is

$$(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l) \in \mathrm{R}^l \times \{-1, 1\}$$

Where, x_i is a n^2 dimension vector and $y_i \in \{-1, 1\}$. The standard format of SVM is shown as follows:

$$\min_{\omega,b,\varepsilon}(\frac{1}{2}\omega^T\omega + C\sum_{i=1}^{l}\xi_i), y_i[\omega^T\phi(x_i) + b] \geq 1 - \xi_i \tag{2}$$

Where, ξ_i usually is called punishing coefficient, which satisfies $\xi_i \geq 0, i = 1, 2, \ldots, l$. ω is called weighted vector. When $\phi(x_i) = x_i$, formula (2) is called linear kernel under linear separable conditions. For the non-linear inseparable problem, x_i is usually mapped to a high dimension space, then it becomes a SVM of non-linear kernel. In order to solve the objective function under restricting condition, it must solve the following dual problem.

$$\min_{\alpha}(\frac{1}{2}\alpha^T Q\alpha - e^T\alpha), y^T\alpha = 0 \tag{3}$$

Where, $0 \leq \alpha_i \leq C_i = 1, \ldots, l, \alpha_i$ is the undetermined coefficient, Q is $l \times l$ positive semidefinite matrix. $Q_{ij} = y_i y_j \phi(x_i)^T \phi(x_j)$, e is the matrix whose elements all are one. $K(x_i, x_j) = \phi(x_i)^T \phi(x_i)$ is called kernel function. It can be seen from the solution $\omega = \sum_{i=1}^{l} y_i \cdot \phi(x_i) \cdot \phi(x_j)$. The only input vector, which satisfies $\alpha_i > 0$, is called support. According to the training sample, the decision-making function is shown as follow.

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{ns} \alpha_i y_i K(x_i, x) + b) \tag{4}$$

Where, ns is the number of support vectors, b is a constant number. For a testing vector x, if $\sum_{i=1}^{ns} \alpha_i y_i K(x_i, x) + b > 0$, it will be classified as the class of "1", otherwise classified as the class of "-1", the learning machine can be generalized by radius basis function (RBF), which is shown as follows:

$$K(x_i, x) = \exp\left(\frac{\|x - x_i\|^2}{-2\sigma^2}\right) \tag{5}$$

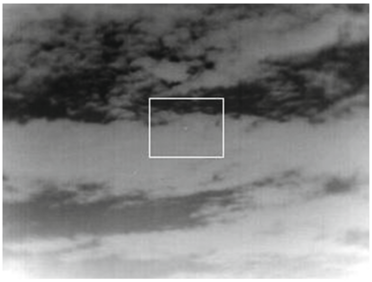
Where, σ is the parameter of kernel function.

Synthesize this two kernel function; a mixed kernel is shown as follows:

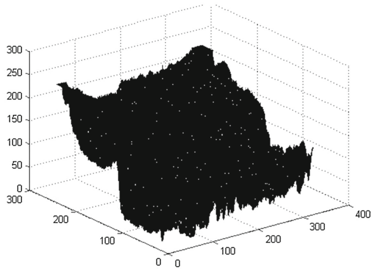
$$K_{mix} = \rho K_{poly} + (1 - \rho)K_{rbf} \tag{6}$$

According to the decision-making function, for a image of $R \times L$, the operation times is $ns \times R \times L$, the complicated extent of the calculation is depend on the size of the image O($R \times L$), the support vector number of the learning machine O(ns) and the $n \times n$ structural element. So, the operation times is shown as follow

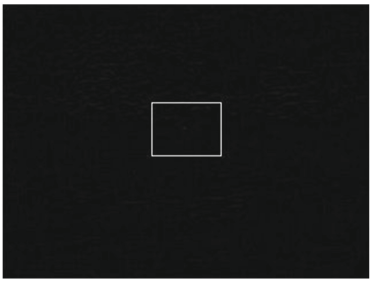
$$Operations \approx ns \times R \times L \times n^2$$



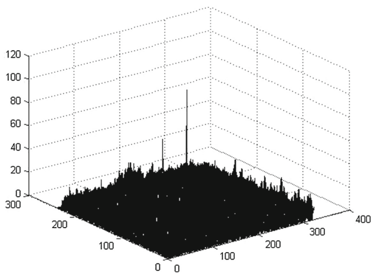
(a) Original image



(b) 3D image of the original image



(c) Filtering image



(d) 3D image of filtering image

Fig. 2. The filtering result

6 Experiment Result

In this experiment, it gets a real infrared target image sequence, which is used to verify the ability of the algorithm, which is presented in this paper. Figure 2 shows the filtering result. Figure 2(a) is the original image. Figure 2(b) is the 3D image of the original image. Figure 2(c) is the image, which is filtered using SVM. Figure 2(d) is the 3D image after filtering. The size of the target is only several pixels, and because of the sunshine's irradiation, the gray degree value at the right bottom is much higher than another place. Figure 2(b) shows an obvious staircase, the target is hard to distinguish. According to Fig. 2(c) and (d), the background is flat after filtering and the SNR increases.

In order to compare the algorithm, it defines the SNR as follow:

$$SNR = \frac{f_{Tm} - u}{\sigma} \tag{7}$$

Where, f_{Tm} is the minimal gray value of the targets; u is the average value of gray value; σ is the standard deviation of gray value. The result is shown in Table 1.

Table 1. SNR after filtering

SNR	SNR after filtering		
	Method one	Method two	Method three
1.7	8.37	13.41	19.70
2.1	15.22	20.18	25.37
4	37.56	38.46	40.15

Method one is using SVM. Method two is using neural network. Method three is using Top-Hat operator, which is fixed. As shown above, three methods are both performing well in high SNR, but in low SNR, the SVM method has the best filtering result.

7 Conclusion

In this paper, a new filtering method of infrared image is presented. The structure elements is taken to set up the training samples, and then, based on support vector machine theory, it builds the learning machine with proper model and trains the samples. The results can be used to suppress the background SNR of following image. The experiment result with infrared image shows that the method can obtain higher SNR than traditional neutral network and fixed Top-Hat operator method, especially in low SNR.

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