IR Target Detection via Lateral Inhibition and Singular Value Decomposition

Yufei Zhao\textsuperscript{1,2}, Yong Song\textsuperscript{1,2,*}, Yao Wu\textsuperscript{3}, Feifei Teng\textsuperscript{3}, Yun Li\textsuperscript{1,2} and Shangnan Zhao\textsuperscript{1,2}

\textsuperscript{1} School of Optics and Photonics, Beijing Institute of Technology, Beijing, 100081 China
\textsuperscript{2} Beijing Key Laboratory for Precision Optoelectronic Measurement Instrument and Technology, Beijing, 100081 China
\textsuperscript{3} Xi'an Research Institute of Applied Optics, Xi'an, 710065, China

\textsuperscript{*} E-mail: yongsong@bit.edu.cn

Abstract. IR (infrared) target detection has been an important technology in the field of target search and tracking. Generally, due to the influence of IR detector noise, cloud interference and other factors, IR image is blurred, the contrast is low, and the background clutter is heavy. As a result, detecting IR targets from complex background has become a challenging task, especially when the target is small, dim and shapeless. Meanwhile, when detecting and tracking a moving IR target, the method should be able to detect both small target and area target. In this paper, an IR target detection method via LI (lateral inhibition) and SVD (singular value decomposition) is proposed. Firstly, a local structure descriptor based on SVD of gradient domain is constructed, which reflects the basic structures of the local regions of an IR image. Then, combining with the local structure descriptor, a modified LI network is established to enhance target and suppress background. Meanwhile, to calculate lateral inhibition coefficients adaptively, the direction parameters of LI network are determined according to the dominant orientations obtained from SVD. Experimental results show that compared with the typical methods, the proposed method not only can detect small and area target under complex backgrounds, but also has excellent abilities of background suppression and target enhancement.

1. Introduction
Infrared (IR) target detection is of great significance in target search and tracking \cite{1, 2}. Generally, IR images tend to be blurred, low contrast, and have heavy background clutter due to factors such as noise and interference. Therefore, IR target detection has become a challenging task \cite{3}.

There are lots of IR target detection method, such as background suppression \cite{2, 4}, morphology \cite{5, 6}, wavelet transform \cite{7}, and image segmentation \cite{8}. However, background suppression is not capable to detect a blurred target; Top-hat, a typical morphology method, usually leaves some background clutter; Wavelet transform is complex, causing too much calculation.

The Human Vision System (HVS) has an extraordinary mechanism for object detection, recognition, and understanding \cite{9}. As one of them, LI (lateral inhibition) has better capabilities to enhance contrast and suppress clutters. Thence, LI has the potential in IR target detection \cite{10, 11} and image enhancement \cite{12, 13}. However, traditional LI has certain limitations when the background is complex.

In this paper, we proposed an IR target detection method via LI and singular value decomposition (SVD). A modified LI combining LI with local structure descriptors (LSD) is designed to enhance the
target and suppress the background. At the same time, the direction parameter of LI is determined by SVD [14]. The experimental results show that the proposed method can detect both small and area target.

2. Theory

2.1. LI network

A 2D LI network is

\[
G(x, y) = F(x, y) - \sum_{m=-l}^{l} \sum_{n=-l}^{l} h(m, n) F(x + m, y + n),
\]

(1)

where \(F(x, y)\) and \(G(x, y)\) are the input and output, respectively, \(h(m, n)\) is LI coefficient, and \(l\) denotes inhibitory field radius.

An anisotropic Gauss kernel function was adopted to determine LI coefficients [11]. If the scales in \(x\) and \(y\) directions are different, the \(x - y\) plane of Gauss kernel function will be an ellipse, as

\[
G(x, y, \sigma) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right],
\]

(2)

where \(\sigma_x^2\) and \(\sigma_y^2\) are the variances of \(x\) and \(y\) directions, respectively. Rotate the ellipse by \(\theta\), the \(x - y\) is transformed into \(u - v\) by

\[
\begin{bmatrix}
u \\
v
\end{bmatrix} = \begin{bmatrix}
\cos \theta & \sin \theta \\
-\sin \theta & \cos \theta
\end{bmatrix} \begin{bmatrix}x \\
y\end{bmatrix},
\]

(3)

where \(\theta\) is the rotation angle of anisotropic Gaussian filter. Combine above equations, the LI coefficient can be calculated by

\[
G_{\theta}(u, v; \sigma_u, \sigma_v, \theta) = \frac{1}{2\pi\sigma_u\sigma_v} \exp \left[ -\frac{1}{2} \left( \frac{1}{\sigma_u^2}(x \cos \theta + y \sin \theta)^2 + \frac{1}{\sigma_v^2}(-x \sin \theta + y \cos \theta)^2 \right) \right].
\]

(4)

2.2. SVD of the gradient domain

The SVD of the local gradient field is calculated to determine the direction parameters in LI.

First, obtain gradient of \(I(x, y)\) at \((x_i, y_i)\) by

\[
\nabla I(i) = \nabla I (x_i, y_i) = \begin{bmatrix} \frac{\partial I (x_i, y_i)}{\partial x} & \frac{\partial I (x_i, y_i)}{\partial y} \end{bmatrix}^T,
\]

(5)

Then, sort \(\nabla I (i)\) into an \(n \times 2\) matrix \(G\) and perform SVD operations on it by

\[
G = \begin{bmatrix} \nabla I(1)^T \\ \nabla I(2)^T \\ \vdots \\ \nabla I(n)^T \end{bmatrix} = U S V^T,
\]

(6)

where \(n\) is the amount of pixels in each block, \(U\) is an orthogonal matrix with the size of \(n \times n\), \(S\) is a matrix with the size of \(n \times 2\) and \(\lambda_1\) and \(\lambda_2\) reflect the energy of the eigenvector direction. \(V\) is a matrix with the size of \(2 \times 2\). The dominant orientation \(O_d\) can be achieved by

\[
O_d = \arctan \left( \frac{v_1}{v_2} \right).
\]

(7)
3. Algorithm Design

3.1. Local structure descriptor
There are generally three situations in an image: (1) in the plat area, $\lambda_1 \approx \lambda_2 \approx 0$; (2) in the edge area, $\lambda_1 > \lambda_2 \approx 0$; (3) in the detailed area, $\lambda_1 > \lambda_2 > 0$. In the proposed method, to classify the pixels, a LSD $D_{LS}(0 \leq D_{LS} \leq 1)$ is established. The larger $D_{LS}$ is, the greater changes of the image.

$$
\begin{align*}
D &= \lambda_1 + \lambda_2 \\
D_{LS} &= \frac{D - D_{min}}{D_{max} - D_{min}}. 
\end{align*}
$$

3.2. Modified adaptive LI network
In the proposed method, $O_d$ is adopted to determine the direction parameter $\theta$ in Eq. (4). In the case that $O_d$ does not exist, set $\theta = 0$ to suppress clutters. In additional, set $\sigma_u = C_1 = 1$ and $\sigma_v = C_2 = 1$ according to [15, 16]. Finally, we can obtain the LI coefficients by

$$
G_{\theta}(\theta) = \frac{1}{2\pi C_1 C_2} \exp \left[ -\frac{1}{2} \left( \frac{1}{C_1^2} (x \cos O_d + y \sin O_d)^2 + \frac{1}{C_2^2} (-x \sin O_d + y \cos O_d)^2 \right) \right].
$$

Then a modified LI network can be achieved by the processes shown in Figure 1, in which $F(x, y)$ is input image (a) and the corresponding 3D plot (b), $D_{LS}(x, y)$ in Figure 1(c) denotes the LSD, $R(x, y)$ in Figure 1(d) is the result of adaptive LI, and $G(x, y)$ in Figure 1(e) is the final result.

![Figure 1. The modified adaptive LI.](image)

3.3. Algorithm process
Because noises may affect the dominant orientation [17], we adopted a filter process as pre-process step. The process are presented in Figure 2. Initially, the local block can be decomposed by SVD, and $S$ and $V$ are obtained. Then, the $D_{LS}$ (LSD) can be obtained according to $S$. Next, $\theta$ (rotation angle) can
be determined by $O_d$ (dominant orientation). Moreover, to make the target more obvious, gray value compensation of the image by

\[
\begin{align*}
K &= 255 \cdot \frac{n}{\sum_{i=1}^{n} G_{\text{order}}(i)}, i = 1, 2, \cdots, n \\
G(x, y) &= K \cdot G(x, y)
\end{align*}
\]

where $n$ is the amount of pixels with higher gray value in $G_{\text{order}}$; $K$ is the compensation coefficient.

4. Experimental results

4.1. Experiment setup

The experiments include two parts: small and area target detection, in which the target with less than 81 (9 × 9) pixels is defined as small target [18], otherwise defined as area target.

And the following two metrics are adopted to be the evaluation parameters:

\[
\begin{align*}
GSCR &= \frac{(S/C)_{\text{out}}}{(S/C)_{\text{in}}} \\
BSF &= \frac{C_{\text{in}}}{C_{\text{out}}}
\end{align*}
\]

4.2. Small target detection experiments

In this part, the input images are three images with dim targets. Figure 3 and Figure 4 show the detection results and corresponding GSCR and BSF, respectively. As we can see, the first three methods can enhance the target, yet fail to suppress clutters (Figure 3(b)). Top-hat and Shi’s are capable to suppress background, but reserve some clutters, (Figure 3(c)). In addition, if the targets tend to be very small, the performance became weak (Figure 3(a) and (b)). In comparison, the proposed method not only enhance the targets, but also suppress the clutters well, which makes the proposed method has good detection performance, with higher GSCR and BSF.
4.3. Area target detection experiments
In this part, the input images are three images with area targets. Figure 5 and Figure 6 show the detection results and corresponding GSCR and BSF, respectively. As we can see, Max-median almost fails to detect the area target; For Max-mean, TDLMS and Shi’s, they are able to detect target, but the clutter suppression performance is quite weak; Top-hat cannot enhance the area target and reserves clutter; In comparison, the proposed method not only enhance the targets, but also suppress the clutters well, with higher GSCR and BSF.

![Figure 3. The results of small target detection.](image)

![Figure 4. The corresponding GSCR and BSF of Figure 3.](image)

![Figure 5. The results of area target detection.](image)
5. Conclusion

We proposed an IR target detection method via LI and SVD. This method established an LSD based on SVD, and adopted to modify LI network, so that achieve the abilities of enhancing target and suppressing clutters. Some experiments are conducted, and the results indicated that the proposed method is capable to detect both small and area target, and has good abilities of target enhancement and clutter suppression.

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