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• **LETTER** •

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A novel sea-land segmentation based on integral image reconstruction in MWIR images

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Dear editor,

Middle wave infrared remote (MWIR) technology is the main approach in remote sensing applications, because thermal infrared can work all-time. The MWIR technology can provide valid object information in remote sensing technology than optical and synthetic aperture radar (SAR) images caused by mechanism of thermal imaging.

MWIR images are widely used in many remote sensing applications. In remote sensing image processing applications, sea-land segmentation results influence the processing of the target level, so better results in sea-land segmentation can improve the accuracy of remote sensing applications [1]. The general land mask removal method uses geographic information system (GIS) database, but this database has low localization accuracy [1]. Based on some special task demands, the GIS database's accuracy is insufficient, so an accurate sea-land segmentation algorithm is necessary.

Sea-land segmentation using MWIR images have more challenges than using optical images; in actual application, MWIR image suffers from complex scene information, low contrast ratios, and the bipolar problem [2]. Currently, the popular sea-land segmentation algorithms all mainly focus on optical and SAR image processing [3–5]. The traditional sea-land segmentation method cannot find a suitable threshold to separate a complex scene into two parts. Since most methods are based on gray level intensity, they cannot address the bipolar problem and low contrast ratios in MWIR images.

Classical sea-land segmentation algorithms fall into two categories based on the gray value histogram and texture character. The Otus's method and maximum likelihood in Bayesian segmentation use the maximum variance between two classes. Whereas for determining texture information, different methods are used. Zhang and Wang [6] extracted the coastline based on improved minimum filter with extracted texture feature. Xia et al. [7] used the local binary pattern model to achieve sea-land segmentation. The classical methods are mostly used in optical remote sensing applications, but these methods are not suitable for being used in MWIR.

Our proposed novel algorithm is related to integral image [8], and using the integral image reconstruction of flat and coarse texture areas, to achieve the sea-land segmentation in MWIR images. First, we obtain a gradient feature map

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(GFM), which is used to prepare sum area table (SAT) and reconstruct an integral image. The integral image reconstruction operation solved the low contrast ratio and bipolar problems. Then, an adaptive threshold method is employed for integral image segmentation. The last stage is morphology operations to fill the holes of the binary pattern. Our experiments are performed on MWIR images obtained from the U.S. geological survey (USGS) Landsat 8, to demonstrate the performance of the proposed method in Figure 1. In this letter, the gradient feature map can be expressed below:

$$G_{\mathrm{horz}} = \frac{1}{rc} \cdot \sum_{x=1}^{r} \sum_{y=1}^{c} \left[1 - \left(\frac{I_{x,y} - I_{x,y+1}}{255} \right)^2 \right], \quad (1)$$

$$G_{\mathrm{vert}} = \frac{1}{rc} \cdot \sum_{x=1}^{r} \sum_{y=1}^{c} \left[1 - \left(\frac{I_{x,y} - I_{x+1,y}}{255} \right)^2 \right], \quad (2)$$

$$G = \max(G_{\mathrm{vert}}, G_{\mathrm{horz}}), \quad (3)$$

where r and c are the rows and columns of one image, x and y are the coordinates of each pixel. $I_{x,y}$ is the gray-scale value of coordinates x and y, the parameter G_{vert} is the approximate vertical gradient, and G_{horz} is the approximate horizontal gradient. Eq. (3) defines the maximum gradient value between vertical and horizontal as G. Through this step, the GFM can get the textural and structural statistical feature map from a MWIR image.

When the GFM is obtained, the algorithm needs to generate an SAT map from the GFM. The SAT initialization is the key process in integral image generation; in addition, it can rapidly establish an integral image at any visual scale by choosing different filtering window sizes. The SAT map can be expressed below:

$$S_{x,y} = \sum_{i=0}^{x-1} \sum_{j=0}^{y-1} \mathrm{GFM}_{i,j}, \quad (4)$$

$$S_{x,y} = S_{x+a,y+b} - S_{x+a,y} - S_{x,y+b} + S_{x,y}. \quad (5)$$

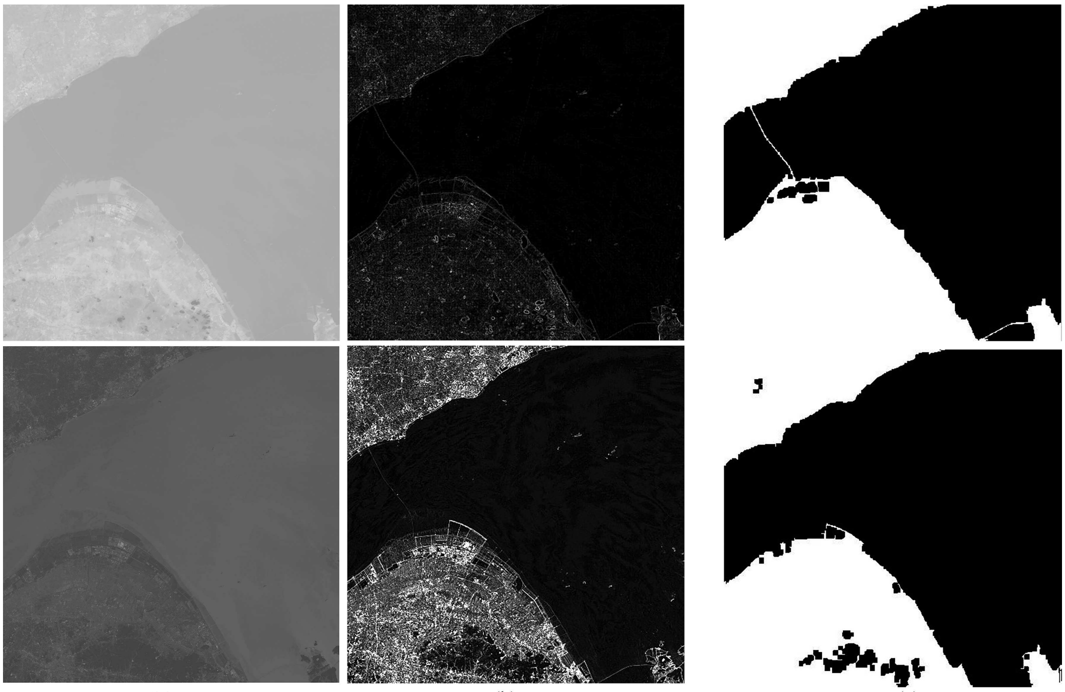
$S_{x,y}$ is the sum of texture regions from the GFM based on region size, where x and y are the width and length of the region. S_{texture} represents local texture integration calculated by neighbours $S_{x,y}$, $S_{x+a,y+b}$, $S_{x+a,y}$, $S_{x,y+b}$ in the SAT map.

The integral image reconstruction can be generated by following SAT map set up. The filtering operation combined with local texture integration, and the texture integral value of the local area will set to a central pixel in the filtering window; window sizes of 3×3, 5×5 and 7×7 can be chosen. This function is expressed in Eqs. (6) and (7). Eq. (6) represents the SAT map, which is the summation of GFM in a region, where m and n are the region size. $T(i, j)$ is the texture information by summing of gradient values. The integral image reconstruction function (7) is calculated by Eqs. (5) and (6), where the parameter n is the filtering window size.

After the integral image generation process, an adaptive threshold method is employed. When the integral image obtains the adaptive threshold value of texture and structure information, the texture integral image will be separated into two parts. Then, the process of refine binary pattern is including down-sampling of medium filtering combined with erosion, dilation, and connected domain area filling. Hence, the final integrated sea-land mask of the MWIR is obtained.

$$\mathrm{SAT\_map} = \mathrm{GFM} \begin{bmatrix} \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} T(i,j) & \cdots & \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{N} T(i,j) \\ \vdots & \ddots & \vdots \\ \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{n} T(i,j) & \cdots & \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} T(i,j) \end{bmatrix}, \quad (6)$$

$$\mathrm{Integral\_image} = \mathrm{SAT} \begin{bmatrix} S(\frac{n+1}{2}, \frac{n+1}{2})_{\mathrm{texture}} & \cdots & S(\frac{n+1}{2}, N - \frac{n+1}{2})_{\mathrm{texture}} \\ \vdots & \ddots & \vdots \\ S(M - \frac{n+1}{2}, \frac{n+1}{2})_{\mathrm{texture}} & \cdots & S(M - \frac{n+1}{2}, N - \frac{n+1}{2})_{\mathrm{texture}} \end{bmatrix}. \quad (7)$$



(a) (b) (c)

Figure 1 Result in day and night imaging condition. (a) Original input image of day and night; (b) integration image reconstruction; (c) day and night segmentation result.

To validate the effectiveness of the method proposed by this study, we used MWIR images. The 40 Landsat 8 images are from the U.S. Geological Survey (USGS). They are 3000×3000 pixels with 30 m spatial resolution. The parameter optimization part is in Figure S1, and the black line inflection point shows the best performance of parameters tuning. Appendix A is the definition of accuracy calculating, Appendix B shows the RPC curve of our proposed algorithm model in Figure S1.

Conclusion and future work. In this letter, a novel sea-land segmentation algorithm for MWIR images based on integral image reconstruction, has been proposed. The future work will focus on modifying the down-sampling of a medium filter module to refine the binary land mask, which can improve the slight deformation evident in the current land mask result.

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Supporting information Appendix A, B, and Figure S1. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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