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Iterative infrared ship target segmentation based on multiple features

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ABSTRACT

This paper presents an efficient method for ship target segmentation in infrared (IR) images. It consists of mainly two procedures: iterative image segmentation and ship target selection. First, based on the intensity distribution of an IR image, we design a global background subtraction filter (GBSF) to suppress the background, and an adaptive row mean subtraction filter (ARMSF) to enhance the target. After iteratively applying these two filters, we can obtain a proper threshold for image segmentation. Second, based on the geometric properties of the ship target, we construct four shape features and a selection criterion to identify the real target and remove the non-target regions. Experimental results demonstrate that the proposed method can effectively segment ship targets from different backgrounds in IR images. The advantage of the proposed method over the others in the previous literatures is validated in both visual and quantitative comparisons, especially for IR images with low contrast and uneven intensities.

1. Introduction

IR imaging systems detect relative differences of thermal radiations emitted from objects. The intensity of the emitted radiation depends on two factors: temperature and emissivity. Therefore, IR imaging systems could work during daytime and at night [1]. They are employed for both military and civil applications, such as long-range detection, automatic target recognition (ATR), video surveillance, and marine searching [2]. In recent years, IR imaging systems used for maritime surveillance have attracted much attention, including ship target detection, segmentation, tracking, and recognition [2,3]. Many researchers focus on IR dim ship targets which are usually small and lack of shape features [4]. For most of the present ATR systems, shape features of the segmented target are very important for target recognition. Therefore, precise IR ship target segmentation is desired, and this is the motivation of our work.

IR imagery may alleviate several problems in computer vision, such as the presence of shadow and sudden illumination changes. However, there are challenges with IR image itself. First, an IR image of sea surface records the total radiation of the ship target and background, including atmosphere and surface waves [3,5]. The intensity distribution is complex, and usually, the ship target is much smaller than the background. Second, heat exchange between the ship target and the background leads to a fuzzy outline of the target. Third, the ship target has uneven intensities because of the heating of the engine and chimney. In addition, limited by the imaging distance and IR imaging technology, IR images are characterized by low signal-to-noise ratio (SNR) and low target-to-background contrast [6]. All these challenges make ship target segmentation in IR images difficult.

To deal with the problem, many methods have been proposed. These methods could be roughly divided into four categories: methods based on thresholding [7], active contour models [8,9], mean-shift [10], and neural network [11,12]. Among the existing methods which are based on neural networks, Hopfield neural network (HNN) is commonly exploited for image segmentation. One identified problem of HNN is that it is difficult to choose penalty parameters. Although some criteria have been proposed to solve the problem, they are time-consuming [12].

Mean-shift is a robust feature-space analysis method, and it has been applied for image segmentation, clustering and tracking [13]. The segmentation is based on local regional merging. This may wrongly merge the target pixels into its neighborhood background when the contrast is low, or eliminate the target when its size is small [10].

The active contour model is defined based on curve evolution and geometric flows. The Chan–Vese model is one of the models which are effectively used for image segmentation [8]. Assuming that each image region is statistically homogeneous, the Chan–Vese model does not perform well for images having inhomogeneous

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intensities [9]. To overcome this weakness, a novel active contour model driven by local image fitting energy (AC-LFE) has been proposed [9]. Using local image information as constraints, AC-LFE works well for images with inhomogeneous intensities. Nevertheless, the performance of AC-LFE can be affected by different initializations.

The thresholding method is often used in IR image segmentation because of its simplicity and efficiency. A survey on the thresholding method can be found in [14]. The well-known methods are Otsu's [15], minimum error thresholding [16], entropy-based thresholding [17], and fuzzy *c*-means clustering [18]. One disadvantage of these classical methods is that spatial information in the image is not considered. In fact, the data in an image are inherently correlated [19]. To compensate for this shortcoming, local spatial information has been introduced, for example, local adaptive methods based on edge [19] and gradient information [20], 2D Otsu [21], 2D maximum entropy [22,23], and spatial fuzzy *c*-means [24]. These methods are less prone to noise, leading to more effective segmentation in images with low SNR. However, they are sensitive to the ratio between the pixel numbers in target and background regions. When the ratio is close to one, these methods perform well. When the target is much smaller than the background, these methods may wrongly classify the target as background. In addition, when the contrast is low between the target and the background, it is also hard to find a proper threshold for these methods.

In this paper, to segment the ship targets in IR images which are characterized by different sizes, low contrast, fuzzy outline, and uneven intensities, we propose a segmentation method based on multiple features, including the intensity properties and shape features. This method consists of two stages. First, we propose a global background subtraction filter (GBSF) to suppress the background, and an adaptive row mean subtraction filter (ARMSF) to enhance the target. After iteratively applying these two filters, a threshold is obtained to separate the target and the background. Then, we develop a target selection method based on shape features, including four shape descriptors and a selection criterion. Experimental results demonstrate that our method can effectively segment ship targets from different sea backgrounds. Comparison results indicate that our method achieves a better performance with lower misclassification error (ME) and lower relative foreground area error (RAE).

The rest of this paper is organized as follows. Section 2 presents the detailed procedure of our method. Section 3 demonstrates the main experimental results and discussions. Finally, Section 4 gives conclusions.

2. Segmentation algorithm

The flowchart of the proposed method is illustrated in Fig. 1. Details will be given in the following subsections.

2.1. Global background subtraction filter

Suppose the IR image is a gray scale image x, which is expressed as:

$$x = f + b, \quad x, f, b \in IR^N, \tag{1}$$

where f is the foreground or the target, b is the background, IR^N is the N-dimensional Euclidean space, where $N=2$ for gray scale image. The purpose of ship target segmentation is to obtain the exact ship target and remove the background. As a complex background will increase the difficulties of ship target segmentation, it is necessary to initially suppress the background.

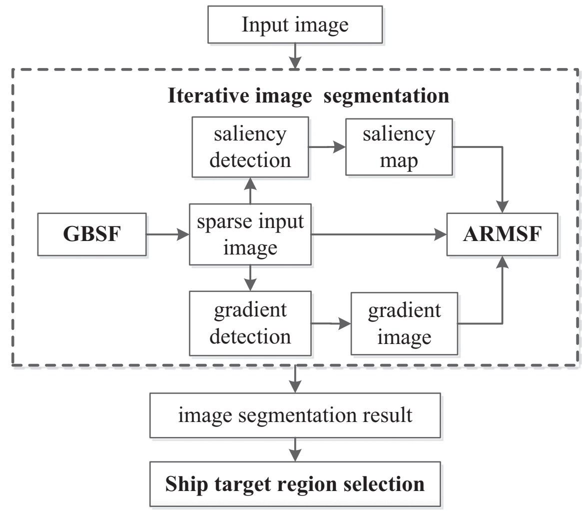

Fig. 1. Flowchart of the proposed method.

From sample IR images in maritime environment (Fig. 2), we can find three key characteristics. First, the ship target is small with the background occupying a large part of the image. Second, notable differences exist in the intensity distribution of different IR images, and it is difficult to model the distributions of the IR images. Third, in a single image, pixel intensities of the background concentrate in a narrow range because the thermal properties of the background are similar except for regions with some strong sea waves.

According to these characteristics, we propose a GBSF to suppress the background. As shown in Fig. 3, pixel intensities of the background form a significant peak in the histogram. A histogram analysis, which is an effective way for intensity distribution description [25], is applied to describe the intensity properties of the IR image. The idea of GBSF is to estimate the background by finding the peak of the histogram, and then to subtract it from the image. Thus, we can suppress most of the background and obtain a sparse foreground image, noted as f_x, and expressed as

$$f_x = \begin{cases} x - b_e, & x \ge b_e, \\ 0 & \text{otherwise}, \end{cases} \tag{2}$$

where b_e represents the estimated intensity of background pixels, and is determined as

$$b_e = k_{nmax} + ext_{min}. \tag{3}$$

In this expression, k_{nmax} is the pixel intensity corresponding to the peak of the histogram. Note that as the intensities of the background vary in a certain range, the background pixels occupy a certain width around the largest peak location in the histogram. To find the proper threshold, we extend k_{nmax} to the nearest valley location on the right hand side. The width of the extension is denoted as ext_{min}, as shown in Fig. 3(b). The k_{nmax} and ext_{min} are determined using the following equations:

$$k_{nmax} = \{k^* | hist(k^*) = \max(hist(k)),\ k \ge MeanI\}, \tag{4}$$

$$ext_{min} = \min\{ext \in N | dh(k_{nmax} + ext) < 0,\ dh(k_{nmax} + ext + 1) > 0\}, \tag{5}$$

$$dh(k) = hist(k+1) - hist(k) \ \text{ for } \ 0 \le k < 255; \quad dh(255) = 0, \tag{6}$$

where $hist(k)$ is the histogram; k is the gray level, $0 \le k \le 255$; $dh(k)$ is the difference of $hist(k)$ elements; $MeanI$ is the average intensity value of the image.