Ship Target Segmentation in SAR Images Using A Modified Nonlocal Active Contour

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Abstract. In ocean surveillance, ship targets are the focus of attention. The ship target segmentation of SAR images is still challenging due to not only speckle noise but also the variations of backscattering intensities. A new segmentation method for ship targets is proposed in this paper, based on the nonlocal processing principle. The level set is implemented by using nonlocal comparison of patches. In the procedure of pairwise interaction, only the local homogeneity of image features is utilized, and this is important in optimizing regions with homogeneous features. In order to make the method applicable for SAR images, a distribution metric is incorporated into the energy function to suppress the multiplicative noise. Experimental results based on TerraSAR data illustrate the effective performance of the proposed method on the ship target segmentation: It can overcome the speckle noise and intensity variations.

1. Introduction

Synthetic Aperture Radar (SAR) has been widely used in ocean surveillance due to its unique advantage of independence of both time and weather conditions. In many maritime SAR images, ship targets are the focus of attention. Ship target segmentation is the fundamental work of image interpretation, which is still challenging. The multiplicative noise effects are the traditional problem in SAR image processing. It may lead to intensity inhomogeneity and fuzzy edges, which frustrate the segmentation performance. For this problem, tremendous research efforts have been devoted to eliminating the speckle effects[1]. Efficient stochastic models of speckle noise, focusing on the multiplicative nature, are proposed[2]. Suitable distributions that fit SAR images better (e.g. K, Gamma and G⁰) are employed to eliminate the speckle effects[3]. By contrast, the work that aims at variations of backscattering coefficients is very limited. As known, the grey level of a pixel in the SAR image represents the proportion of microwave backscattered from the corresponding region. When we implement target segmentation form the background, the intensities of targets and background are usually supposed to be homogeneous. However, in SAR systems, multiplicative speckle noise and other factors usually make the regions of interest inhomogeneous. Furthermore, as for ships, there may be obvious intensity variations over the ship target due to the complicated structure of the ship’s hull, especially in high resolution images. In Figure 1, although the ship is a strong scattering-object, some dark regions familiar with the background are embedded in it, caused by shadows or flat surfaces. This kind of variations of local statistics bring much trouble to extract the ship from the background completely and precisely.
Figure 1. The difficulty of ship segmentation in SAR images. (a) shows a SAR chip containing a ship target with strokes in various colors. (b) and (c) display profiles of the SAR chip along the green and the red strokes.

The active contour model (ACM) has been widely used in image segmentation. It guides the evolution of contours toward a target’s boundary by means of minimization of an energy function. There are two kinds in ACMs: edge-based models and region-based models[4]. The snake and the geodesic active contour (GAC) models[5] are the classic edge-based models. They use some edge detector and guide the active contour towards sharp gradients of pixel intensity. These models are usually sensitive to noise. To solve this problem, region-based active contour models are proposed incorporating global information to optimize the homogeneity of regions inside and outside the contour. Region-based models (i.e. Chan–Vese (CV)[6], local and global intensity fitting (LGIF) [7], and local Gaussian distribution fitting (LGDF) models[8] have better anti-noise performance in optical and medical images. Besides, Some hybrid ACMs are proposed such as Lankton’s hybrid models[9] and selective binary and Gaussian filtering regularized level set (SBGFRLS) [10]. They absorb the advantages of those two kinds and have been demonstrated the great performance in optical and medical images. Due to the good performance, ACM has also been widely studied in SAR image processing. Many improved works are based on the classic ACMs. Germain et al. introduced a likelihood-ratio edge detector into the snake model to localize edges[11]. Shuai presented an improved level set algorithm with stationary global minimum using Gamma distributions[3]. Hu et al. utilized the Kullback–Leibler (KL) distance of Edgeworth to improve segmentation[12]. What’s more, Tu replaced the Euclidean distance by a new ratio distance and proposed the modified CV model and the modified LGIF model[13].

In the literature, most of these methods are based on the hypothesis that the regions inside and outside the contour are homogeneous or follow the same distribution. That’s to say, they may not deal with the intensity variations of ship targets. Focusing on this problem, a level set algorithm based on the nonlocal interactions between pairs of patches inside and outside the segmented regions is proposed in this paper. To improve the performance, a ratio distance, which is inspired by Tu’s idea in [13], is integrated in nonlocal comparisons of patches.

2. Nonlocal active contour model
Nonlocal image processing means nonlocal comparisons of patches that are extracted from the image. It is firstly proposed by Buades et al, and has been applied in denoising, inverse problems and classification[14]. Jung et al use the nonlocal energy to drive the active contour and optimize the homogeneity of the segmented region. It is called nonlocal active contour model[15].

In the image $f$, a patch around a pixel $x \in I$ can be defined as $p_x(t) = f(x+t), t \in \left[-\frac{\tau}{2}, \frac{\tau}{2}\right]$ and the size is $(\tau+1)^2$. The nonlocal active contour model is implemented by minimizing the following energy function,

$$E(\Omega) = E_{NL}(\Omega) + \lambda E_r(\Omega) \tag{1}$$
Where $R(\Omega)$ is a smoothing term regularizing the contour of the region, usually defined as the length of the boundary, and the parameter $\lambda$ is a weight controlling the regularity of the contour. More importantly, $E_{NL}(\Omega)$ is the nonlocal energy term describing the dissimilarity inside and outside Region $\Omega$, and it is defined as

$$E_{NL}(\Omega) = \overline{E}_{NL}(\Omega) + \overline{E}_{NL}(\Omega^c).$$

$$E_{NL}(\Omega) = \int_{\Omega} G_o(x,y)d(p_x,p_y) \, dx \, dy$$

Where $\Omega^c$ is the complementary region of $\Omega$, and $G_o(x,y)$, a Gaussian kernel of scale $\sigma$, is used as a decaying function of $|x - y|$. $d(p_x,p_y)$ evaluates the distance between patches $p_x$ and $p_y$. A specific metric can be used to deal with some images. This will be discussed in the next section.

For numerical implementation, the contour of the target can be evolved by a level set function $\phi$. Then, the energy function in (X) can be rewritten as

$$E_{NL}(\phi) = \int_{\Omega} \left[ 1 - \left| H(\phi(x)) - H(\phi(y)) \right| \right] G_o(x,y)d(p_x,p_y) \, dx \, dy$$

The regularization term can be defined as

$$E_R(\phi) = \int \left| \nabla H(\phi(x)) \right| \, dx$$

The contour evolution can be computed numerically by minimization of the energy functions.

3. Patch comparison in SAR images

As described above, the patch comparison metric $d(p_x,p_y)$ plays a crucial role in nonlocal image processing. To utilize pixel values, the orientation of textures and local statistical features, several metrics are introduced in patch comparison in , such as $L^2$ distance, $L^2$ distance based on Gabor filters and sliced Wasserstein distance. Although achieve success in optical and synthetic images, they are not suitable for measuring the distance between SAR image patches due to the speckle noise. On the one hand, the multiplicative nature of the speckle noise has been investigated by Feng et al, and it can be seen that the ratio distance is a useful metric for patch comparison in SAR images. On the other hand, according to the research of Deledalle et al, probabilities characteristics have satisfactory performance in SAR image processing. These two points of view has been further supported by the work of Tu et al.. They incorporate the ratio distance into the distribution metric, and modify the classic CV model by replacing the Euclidean distance. The energy function of the modified CV (MCV) model is defined as

$$E_{MCV}(\Omega) = \lambda_1 \overline{E}_{MCV}(\Omega) + \lambda_2 \overline{E}_{MCV}(\Omega^c)$$

$$E_{MCV}(\Omega) = \int \left[ \frac{\log^2 \left( \frac{p(x,\Omega)}{p_{img}} \right)}{\sigma^2} - \epsilon \left( \log \left( \frac{p(x,\Omega)}{p_{img}} \right) \right)^2 \right] \, dx$$

Where $p$ represents the probability density function of the region, $p_{img}$ represents the probability density function of the raw image, and $\epsilon(*)$ denotes the expectation.

The efficiency of the MCV model in image segmentation has been demonstrated based on the MASTAR data set. As previously mentioned, however, the classic scheme of the CV model has limited ability to deal with intensity variations.

Inspired by the preceding works, we introduce the distribution metric of the ratio distance into patch comparison to compute the nonlocal energy. Therefore, the dissimilarity measure can be rewrote as:
\[ E_{NL}(\Omega) = \int_{\Omega} G_{\sigma}(x,y) \left( \varepsilon \left\{ \left( \frac{P_x}{P_y} \right)^{\frac{1}{2}} \right\} - \varepsilon \left\{ \left( \frac{P_x}{P_y} \right)^{\frac{1}{2}} \right\} \right)^2 \, dx \, dy \\
+ \int_{\Omega^c} G_{\sigma}(x,y) \left( \varepsilon \left\{ \left( \frac{P_x}{P_y} \right)^{\frac{1}{2}} \right\} - \varepsilon \left\{ \left( \frac{P_x}{P_y} \right)^{\frac{1}{2}} \right\} \right)^2 \, dx \, dy \] (6)

Where \( P_x \) and \( P_y \) denote the probability density functions of the patches \( p_x \) and \( p_y \). The distance can be considered as the standard deviation between the log-likelihood of two distributions, \( P_x \) and \( P_y \). When the energy function is minimized, the minimum variances will be obtained. During this process, the contour will be driven close to the target boundaries so that the homogeneity of the regions inside and outside the contour will be optimized.

4. Experimental results and analysis
TerraSAR X-band images with 1m resolution are used in the experiment. To demonstrate the performance of the proposed segmentation method, we utilize 4 chips with apparent intensity variations, which are shown in Figure 2. What’s more, some traditional models, such as RSF, CV and LGIF, are added to comparison, and their results are displayed in Figure 3, figure 4 and figure 5. It can be seen that these method cannot deal with intensity variations and they fail to extract the ship from the background completely.

![Figure 2. Chips from SAR images](image1)

![Figure 3. RSF](image2)

![Figure 4. CV](image3)
Figure 5. LGIF

Figure 6 shows the results of the proposed method with the parameters $\lambda=10, \sigma=10, \tau=5$. Each target is completely segmented from the background.

Figure 6. The proposed method

Thanks to the advantage of level set, the proposed method can be used in multi target segmentation. In Figure 7, there are 3 ships in the sub-image of the TerraSAR X-band data. All of them are completely extracted by the proposed method.

Figure 7. Image of several ships. (a) is the original image, and (b) is the result of our method

5. Conclusion
A modified nonlocal active contour model for SAR image segmentation is proposed in this paper. On the one hand, the distribution metric of the ratio distance is used to overcome the multiplicative speckle noise. On the other hand, the patch comparison of the nonlocal scheme can deal with the intensity variations in SAR images, so that the proposed method can extract ship targets from the background completely. The real SAR images from TerraSAR X-band data with 1m resolution are
used in the experiments to demonstrate the performance of the proposed method. Compared with some popular ACMs, the proposed method achieves apparent development in accuracy and robustness of ship segmentation.

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