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A coastline detection method using SAR images based on the local statistical active contour model

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Abstract: A coastline detection method using synthetic aperture radar (SAR)images based on local statistical active contour model has been proposed in this paper. The method incorporates the local statistical active contour model to detect the coastline in SAR images. In order to remove the limitation of a rigid initial contour being requested in the local statistical active contour model, this method firstly utilizes a C-V model to gain an approximate segmentation. Thereafter, a local statistical active contour model based on G^0 distribution is proposed to achieve the accurate segmentation results. The new model adopted G^0 distribution to fit each neighborhood along the contour, enhancing the fitting ability for SAR images and improving the detection accuracy of the coastline. Through combining a penalizing term of level set function, the model eliminates the need of re-initialization procedure. The experiments of real SAR images demonstrate the proposed method has accurate coastline detection ability.

Key words: SAR, coastline detection, statistical active contour, C-V model

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1 INTRODUCTION

Detecting the coastline is of fundamental importance when monitoring various natural phenomena such as tides, coastline erosion and the dynamics of glaciers. Meanwhile it is also an important component of the ship detection system for shoreline synthetic aperture radar (SAR) images (Cerimele, *et al*., 2009). However, the coastline always contains signals both from the water and the land region, and in addition, SAR images are polluted by a strong multiplicative speckle noise because of the coherent imaging principle of the SAR system. Therefore, to detect the coastline from SAR images is very challenging. More specifically, the detection of coastline from SAR images is an image segmentation issue. In recent years, active contour models become widely used in the domain of image segmentation. It is actually a model which based on Variational approach and Partial Difference Equations (PDEs). The basic idea is (He, *et al*., 2009) to regard the target bound as a contour, and allow the contour to deform at the guide of a given energy functional so as to approach the target bound. It will not stop until the energy functional has a minimize value, and at this moment the contour represents the target boundary.

The active contour model can be classified into two main categories: edge-based and region-based. In edge-based model the contour evolves utilizing the local gradient and will stop at a local region with a relatively larger gradient value. The region-based model, on the other hand, utilizes the statistics of a specific region and the optimization process is actually to find the best match degree between the statistical model and the segmentation region. The edge-based model has local coherence and robustness in inhomogeneous regions. However, it is sensitive to the noise and the contour initialization and it may result in “leaks” when dealing with smooth region edges. In comparison, the region-based model is robust to contour initialization and is not that sensitive to image noises. However, it uses global statistics in the process of model and is not always perform well when dealing with the segmentation problems in inhomogeneous regions. It is mainly because that segmentation models often relay on global criteria, whereas images are almost based on local variations (*e.g*., intensity, contrast, noise) (Piovano & Papadopoulo, 2008).

To the question of the above two imperfect models, Piovano and Papadopoulo(2008), Brox, *et al*.(2007) and Mory, *et al*.(2007) come up with a new kind of segmentation model which based on local statistics. This model computes the statistics of the neighborhood regions of each point along the contour. In this way, the contour deforms to find the optimize match degree in each local region. Through the adjustments of the parameters of the neighborhood regions, this model has some interesting characteristics: when the parameter value is large, this model is similar to the region-based model, while when the parameter value is small, the model will be similar to the edge-based model. Therefore, this model combines

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both advantages of the two above models and greatly enhances its segmentation ability. Owning to the Gaussian distribution which is not suitable for SAR images, it requests rigid contour initialization.

It has been demonstrated through theory analysis and numerous field data that the G^0 distribution has reliable ability for the model of SAR images. A coastline detection method based on local statistical active contour model utilizing G^0 distribution for SAR images is proposed in this paper. In order to remove the limitation that a rigid initial contour being requested in the local statistical active contour model, this method firstly utilizes a C-V model (Chan & Vese, 2001) to gain an approximate segmentation. Then, it regards the approximate segmentation as the initialization of the local statistical active contour model and to acquire the final results.

2 IMPROVED LOCAL STATISTICAL ACTIVE CONTOUR MODEL

2.1 Classical statistical of active contour model

Let $\Omega \subset R^2$ denotes the image plane, $I:\Omega \to R$ is the image function based on definition domain of Ω, and the image segmentation issue is to find L optimal region partitions $R(\Omega)=\{\Omega_i\}_{i=1,\cdots,L}$, and in each sub-region Ω_i the image function I is uniform according to some attributions of the images. From the view of statistic, the optimal partitions $R(\Omega)$ can be gained through the maximum a posteriori (MAP) PDF$p(R(\Omega)|I)$ (Zhu &Yuille,1996; Cremers, *et al*., 2007). Maximization of the a posteriori probability is equivalent to minimizing its negative logarithm. Therefore, the image segmentation issue can be expressed as follows:

$$E\left(\{\Omega_1,\cdots,\Omega_L\}\right)=-\sum_{i=1}^{L}\int_{\Omega_i}\log p_i(I(x))\mathrm{d}x+\mu\,|C| \tag{1}$$

Eq. (1) is a general expression of the statistical active contour model. Where $|C|=\int_C \mathrm{d}s$ denotes the length of partition boundary, μ is a positive weighting parameter. Statistical active contour model is based on Bayesian theory and the basic idea is using the maximizing a posteriori probability of the region partition to find the optimal segmentation. The performance of the statistical active contour model is evaluated by the match degree between the image data and the statistical distribution. The higher of the match degree, the better performance of the method is. Because of influence of the speckle noises, SAR images can not be modeled by Gaussian distribution directly. It will result in errors if implement the statistical active contour model adopting Gaussian distribution in SAR images (He, *et al*., 2009). Previous research indicate that the G^0 distribution has reliable ability for the model of SAR multi-look images in a widely heterogeneity. It has many advantages, such as the easier estimation of the parameters and lower computational complexity. In this paper we adopt G^0 distribution as the statistical model for SAR images. However, the expression of G^0 distribution is very complex and it is not possible to obtain both the mean and variance of its components in closed form when using the high accurate maximum likehood estimation (MLE). In order to improve the computation efficiency, in practice, using Moment Estimation to estimate the parameters is preferred.

The expression of G^0 distribution for SAR intensity image is

$$p(I\,|\,\alpha,\gamma)=G^0(\alpha,\gamma,n)$$
$$=\frac{n^n\Gamma(n-\alpha)I^{n-1}}{\gamma^\alpha\Gamma(n)\Gamma(-\alpha)(\gamma+nI)^{n-\alpha}},\quad -\alpha,\gamma,n,I>0 \tag{2}$$

where I is the intensity image, n is the number of looks which can be obtained by the priori of SAR images. α is the shape parameter, γ is the scale parameter, which needs to be estimated, namely $\theta=[\alpha,\gamma]^{\mathrm{T}}$.

Using the Moment Estimation, we can reform the estimation expressions of α and γ are

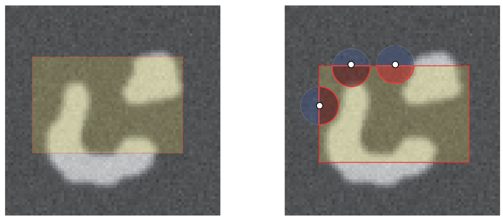
$$\hat{\alpha}=-1-\frac{n\hat{\lambda}}{n\hat{\lambda}-(n+1)\hat{\mu}^2} \tag{3}$$

$$\hat{\gamma}=(-\hat{\alpha}-1)\hat{\mu} \tag{4}$$

where $\hat{\mu}$ and $\hat{\gamma}$ are the sample mean and the sample square mean respectively.

2.2 Improved model

In the issue of coastline detection, the local statistics around the coastline are important factors. With the classical statistical active contour model utilizes the global statistics of partitions (Fig.1(a)), it leads to "over-segmentation" and the low accuracy.



(a) (b)

Fig.1 The global active contour model and the local active contour model
(a) the global active contour model: inside the red contour line is the interior, outside is the exterior; (b) the local statistical active contour model: for every point along the contour, calculate statistics of the neighborhood regions (the small circle), the red parts of the small circles are the local interiors and the blue parts of the small circle are the local exteriors

In order to obtain the local statistics of each point along the contour (Lankton & Tannenbaum, 2008), we introduce a characteristic function in terms of a radius parameter r:

$$B(x,y)=\begin{cases}1, & \|x-y\|<r\\ 0, & \text{otherwise}\end{cases} \tag{5}$$

where x, y are spatial variables, represent for the image pixel. x represents an point in the contour C. $B(x, y)$ masks the local regions which have the shape of a ball centered at x with a radius of r.

Introduce a Lipschitz constant function $\phi:\Omega\to R$ (called level set function),

$$\begin{cases}\phi(x)>0, & x\in\Omega_{\mathrm{in}}\\ \phi(x)<0, & x\in\Omega_{\mathrm{out}}\\ \phi(x)=0, & x\in C\end{cases} \tag{6}$$

This function, Ω_{in}, Ω_{out} represent the interior and exterior regions of contour C, respectively. Through combination of a penalizing term of level set function, the model eliminates the need of the time-consuming re-initialization procedure (Li, *et al*., 2005). Consider two regions' segmentation, we now define an energy function of the proposed local statistical active contour model based on G^0 distribution as follows:

$$E(\phi)=\int_{\Omega_x}\delta_\varepsilon(\phi(x))\int_{\Omega_y}B(x,y)\times$$
$$\begin{pmatrix}-H_\varepsilon(\phi(y))\log p(I(y)\,|\,\hat{\alpha}_{L1},\hat{\gamma}_{L1})-\\ \left[1-H_\varepsilon(\phi(y))\right]\log p(I(y)\,|\,\hat{\alpha}_{L2},\hat{\gamma}_{L2})\end{pmatrix}\mathrm{d}y\mathrm{d}x+$$
$$\mu\int_{\Omega_x}|\nabla H_\varepsilon(\phi(x))|\,\mathrm{d}x+\upsilon\int_{\Omega_x}\frac{1}{2}(|\nabla\phi(x)|-1)^2\mathrm{d}x \tag{7}$$

In the function, the last term is the penalizing term, $H_\varepsilon(\phi)$ is the Heaviside function:

$$H_\varepsilon(\phi(x)) = \begin{cases} 1, & \phi(x) < -\varepsilon \\ 0, & \phi(x) > \varepsilon \\ \left\{1 + \dfrac{2}{\pi}\arctan\left(\dfrac{z}{\varepsilon}\right)\right\}, & \text{otherwise} \end{cases} \tag{8}$$

where $\delta_\varepsilon(\phi) = H'_\varepsilon(\phi)$, Ω_x denotes the points set along the contour, $\delta_\varepsilon(\phi(x))$ ensures the energy function operating only on a local narrow band around the contour. Ω_y represents $B(x, y)$ neighborhood. It shows that in local statistical active contour model the energy function only calculates statistics of each $B(x, y)$ neighborhood along the contour. $\hat{\alpha}_{L1}$, $\hat{\gamma}_{L1}$ are local estimation parameters based on interior of $B(x, y)$ neighborhood, $\hat{\alpha}_{L2}$, $\hat{\gamma}_{L2}$ are local estimation parameters based on exterior of $B(x, y)$ neighborhood. They all can be obtained by equation (3) and (4). And the sample mean and the sample square mean based on local statistics are as follows:

$$\begin{cases} \hat{\mu}_{L1} = \dfrac{\int_{\Omega_y} B(x,y)I(y)H_\varepsilon(\phi(y))\mathrm{d}y}{\int_{\Omega_y} B(x,y)H_\varepsilon(\phi(y))\mathrm{d}y}, \\ \hat{\mu}_{L2} = \dfrac{\int_{\Omega_y} B(x,y)I(y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}{\int_{\Omega_y} B(x,y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y} \\ \hat{\lambda}_{L1} = \dfrac{\int_{\Omega_y} B(x,y)I^2(y)H_\varepsilon(\phi(y))\mathrm{d}y}{\int_{\Omega_y} B(x,y)H_\varepsilon(\phi(y))\mathrm{d}y}, \\ \hat{\lambda}_{L2} = \dfrac{\int_{\Omega_y} B(x,y)I^2(y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}{\int_{\Omega_y} B(x,y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y} \end{cases} \tag{9}$$

Using variational and steepest decent methods, the evolving equation of the level set function of the proposed local statistical active contour model based on G^0 distribution is as follows:

$$\begin{aligned} \frac{\partial\phi(x)}{\partial t} &= \delta_\varepsilon(\phi(x))\int_{\Omega_y} B(x,y)\times\delta_\varepsilon(\phi(y))\times \\ &\big(-\log p(I(y)\,|\,\hat{\alpha}_{L1},\hat{\gamma}_{L1}) + \log p(I(y)\,|\,\hat{\alpha}_{L2},\hat{\gamma}_{L2})\big)\mathrm{d}y + \\ &\mu\delta_\varepsilon(\phi(x))\mathrm{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right) - \nu\left[\mathrm{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right) - \Delta\phi(x)\right] \end{aligned} \tag{10}$$

where we can see that the global statistical active contour model uses the global statistics of region to find the optimum matching degree with the given statistical distribution and whereas the local statistical active contour model uses local statistics of each neighborhood of each point along the contour to find the optimum matching degree. The segmentation result is obtained when each point on the contour has moved, in which the local interior and exterior of each point along the contour are best approximated by local statistical parameters , $\hat{\mu}_{L1}$, $\hat{\mu}_{L2}$, $\hat{\lambda}_{L1}$ and $\hat{\lambda}_{L2}$. In the coastline detection for SAR images, owing to the effect of the mixture signals both from water, land and of continental shelf and reefs, the global statistical active contour model often leads to "over-segmentation" and has a local minimum. The proposed model in this paper can implement statistical model in the regions which are around the coastline and it is the reason for our model has a more accurate detection capability.

2.3 Algorithm flow

Both land and water regions are included in the SAR images used for coastline detection. Because of the mirror reflection of the water surface, the water regions are relevant dark and the land regions are relevant light in SAR images. This character is exactly suitable for the C-V model which is actually equivalent to the statistical active contour model which adopts Gaussian distribution with a fixed standard variance. Therefore, low precision of the segmentation is acquired for SAR images. With the C-V model that computes mean of the global region, the computational efficiency has been improved, and it is not sensitive to the contour initialization. The proposed method firstly utilizes a C-V model to gain an approximate segmentation. Then, it regards the approximate segmentation as the initialization of the local statistical active contour model and to gain the final result. In this way, we can avoid the limitation of the sensitivity of the contour initialization in local statistical active contour model. The idea that evolving using a big step when far from the target and implementing a careful adjustment when near can be found in various aspects of the automatic control domain.

The particular flow of the proposed method is in Fig. 2.

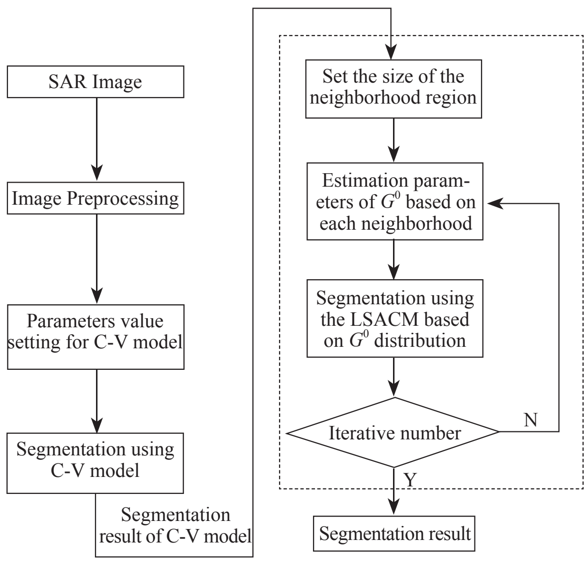


Fig. 2 The algorithm of the proposed method

The main steps of the proposed method are listed below:

(1) Image preprocessing. For the coherence of the parameters, normalize the original image to [0, 255].

(2) Segmentation using a C-V model. Utilize the C-V model to obtain an approximate result which can be used as the contour initialization for the following accurate segmentation step.

(3) Set the size of $B(x, y)$ neighborhood and compute the sample mean and square mean using Eq. (9), compute the local parameters $\hat{\alpha}_{L1}$, $\hat{\gamma}_{L1}$, $\hat{\alpha}_{L2}$, $\hat{\gamma}_{L2}$ using Eq. (3) and (4).

(4) Update the level set function using Eq. (10), acquire final results of the coastline detection in SAR images.

3 EXPERIMENTS AND ANALYSIS

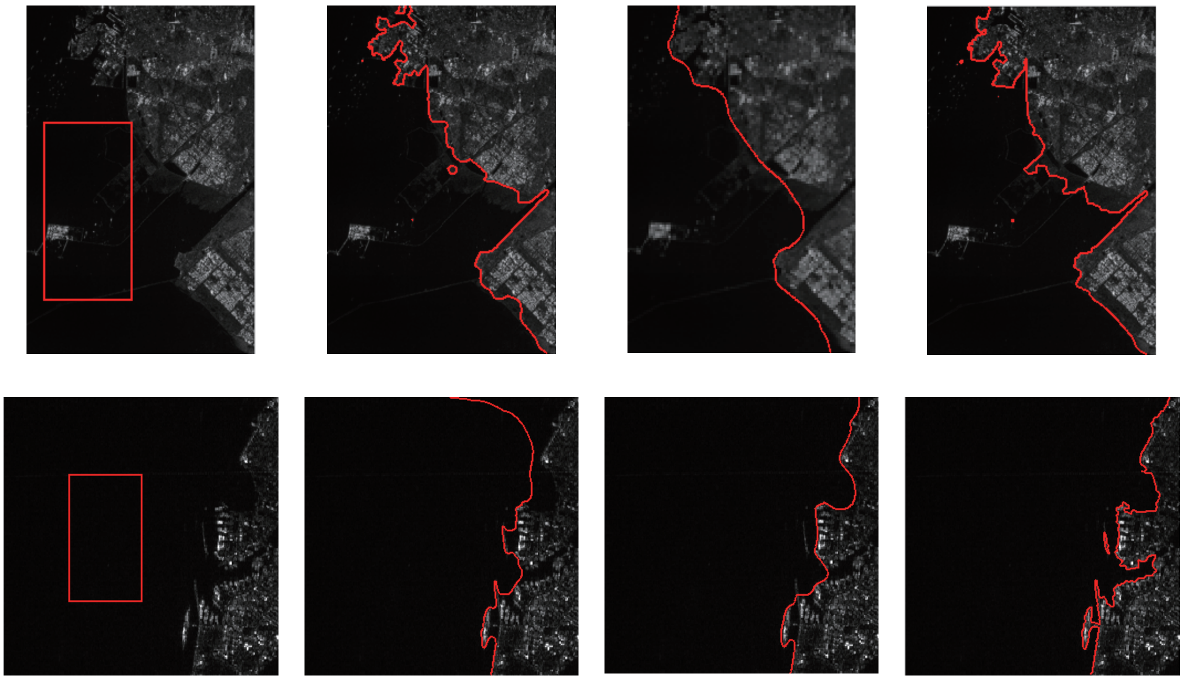
In order to demonstrate the performance of the proposed method, we implement experiments using real SAR images. Experiments condition: CPU is Pentium(R) Dual 1.8 GHz, 2 G RAM and the experiment software is matlab2008. Our method adopts the following parameters. The parameters of C-V are $\lambda_1=\lambda_2=1$, $\mu=0.02\times255^2$, $\Delta t=0.1$, $\varepsilon=1$. The parameters of the proposed model are: $\mu=0.2$, $\upsilon=2$, $\varepsilon=1$. Options of radius of the $B(x, y)$ neighborhood are 10, 15, and 20 pixels, respectively.

3.1 Performance of the proposed method

Fig.3 shows two Radarsat-2 SAR images of the seashore region of Seoul (resolution of 8 m and 4 looks). Fig.3(a) is the contour initialization. Fig.3(b) is the segmentation result of the C-V model for 20 times. Using the result as the initialization of the proposed model we can obtain the final segmentation result that shows in Fig.3(d). Fig.3(c) is the segmentation result of local statistical active contour model which uses Gaussian distribution. In comparison with the proposed method, it has lower accuracy.

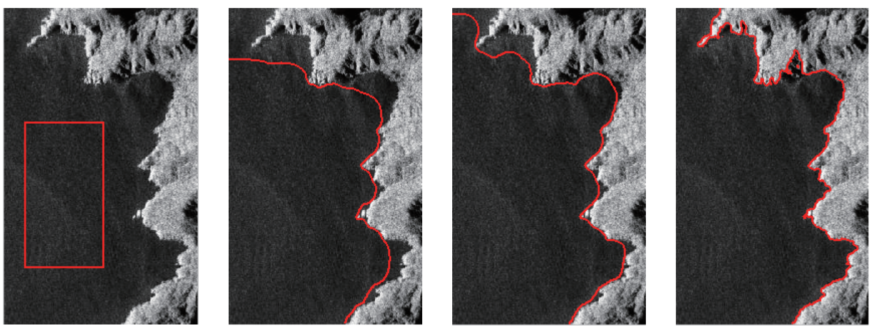
For the first image in Fig. 3, we can see that large area of the continental shelf shows high heterogeneity with many reefs. In this case, the classical global active contour model is not possible to obtain an accurate segmentation and will lead to "over-segmentation", However, the proposed method can still achieve a perfect segmentation result. This feature is especially useful when considering the second image, in which apart from the heterogeneous land region and the farraginous coastline, lands and water regions are mixed.

Fig.4 is a single look airborne SAR image which is obtained in SanYa China with a resolution of 1 m. Because this is an airborne SAR image, which has a high resolution, the complicate sea conditions request a high precision fitting ability for the statistical distribution. The comparison between Fig.4(c) and Fig.4(d) shows that Gaussian distribution fall short of ability for the model of SAR image data and the adoption of G^0 distribution in this paper has a strong capability for data fitting in the sea conditions.



(a)　(b)　(c)　(d)

Fig. 3　Coastline detection of the real Radarsat-2 SAR images



(a)　(b)　(c)　(d)

Fig.4　Coastline detection of the airborne SAR images

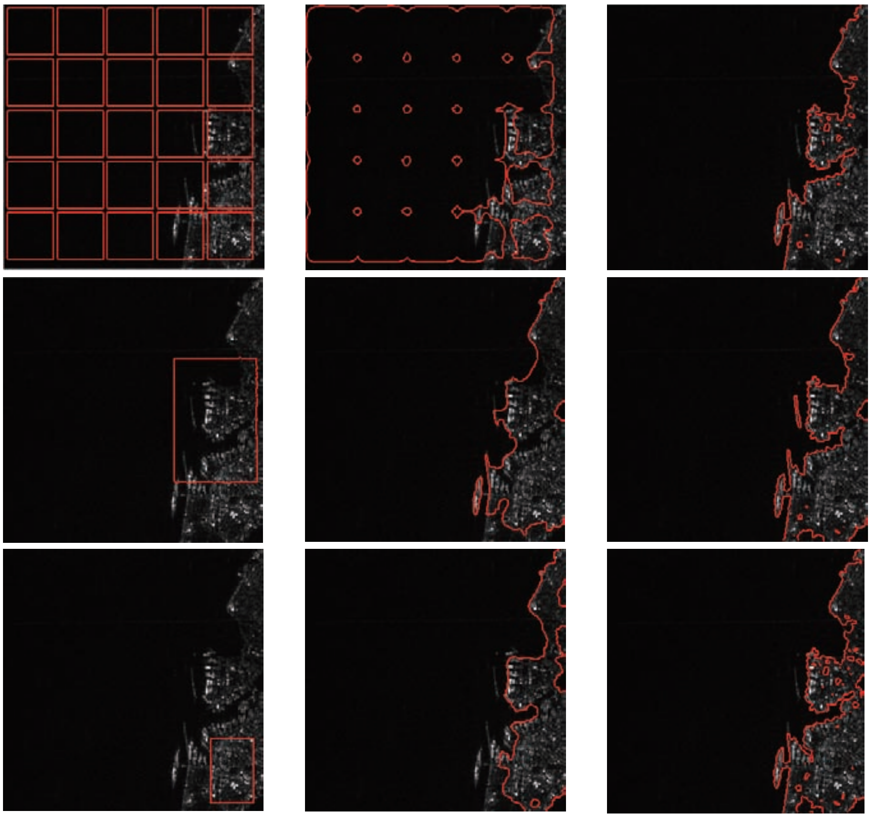
(a) the contour initialization; (b) the segmentation result of the C-V model for 40 times; (c) the segmentation result of the classical statistical active contour model using the Gaussian distribution; (d) the segmentation result of the proposed method

3.2 Analysis of the sensitivity of initialization`

Fig.5 shows the experiment of the proposed method in the case of different contour initializations. It can be seen that although the contour initialization is different, the proposed method can still detect the coastline accurately. It demonstrates the use of the C-V model in the proposed method successfully removes the limitation of requiring a rigid contour initialization in the local statistical active contour model. But the problem of minimum value of the proposed model will affect the contour initialization. It is mainly because of the convex contribution of the energy function which makes the model has local minimum values.

3.3 Quantitative evaluation of the proposed method

In order to evaluate the precision of the coastline detection of the proposed method, we compare the segmentation result with the field data in type of quantitative analysis. Here we gain the quantitative evaluation through calculating two types of errors, namely, False Positive Rate (FPR) and False Negative Rate (FNR) (Margarida, *et al*., 2009). The field data is drawn manually through visual inspection of SAR images. The FPR measures the rate of pixels classified as water by the automatic detection method that is not classified as such in the filed data, while the FNR measures the rate of pixels classified as water in the field that are missed by automatic detection method. These two errors are calculated as follows:



(a) (b) (c)

Fig.5 Experiment of different initialization contours
(a) different initializations; (b) the middle segmentation result; (c) the final result

$$\mathrm{FPR}(AC, GT) = \frac{\#(AC \cap \overline{GT})}{\#(GT)} \tag{11}$$

$$\mathrm{FNR}(AC, GT) = \frac{\#(\overline{AC} \cap GT)}{\#(GT)} \tag{12}$$

where AC denotes the segmentation results of the automatic detection method, GT denotes the filed data, and there are all binary images leading all pixels inside the contour having label 1 and the others label 0.

We select the second image in Fig.3 to implement the quantitative evaluation method. In comparison with the classical active contour model which uses Gaussian distribution, the results are shown in Table 1. *CE* is the total classification error (CE). From the results we can conclude the proposed method is more accurate.

Table 1 Quantitative evaluation results

Method	FPR(%)	FNR(%)	CE(%)
Proposed	4.2	5.7	9.9
Classical	6.8	13.5	20.3

In addition, we adopt a measurement of the uniformity of segmentation regions to further evaluate the performance of the proposed method. According to the definition of image segmentation, the interior of each region should be uniform after the segmentation and there should be a great difference between different regions. That is to say the uniformity degree of regions represents the quality of the segmentation. Therefore, we give the definition of the measurement of segmentation performance as follows (Ross & Mossing, 1999):

$$PP = 1 - \frac{1}{C}\sum_i \left\{ \sum_{x \in R_i} \left[I(x) - \frac{1}{A_i}\sum_{x \in R_i} I(x) \right]^2 \right\} \tag{13}$$

where R_i denotes different segmentation regions, C is the normalization constant, $I(x)$ is the gray value of point x in the image, A_i is the number of pixels in each region R_i. The closer to 1 the value of PP is, the more uniform the interior of the segmentation regions are and the better the quality of the segmentation is. From the results of Table 2, we can see that the values of PP are all close to 1 in both Fig.3 and Fig.4, which show high precision of the proposed method. From the values of PP in Fig.5 we can conclude that the proposed method is robust to initialization contour.

Table 2 Performance of the proposed method

Image	Fig.3		Fig.4	Fig.5 (up to down)		
PP	0.977	0.981	0.962	0.954	0.933	0.925

4 CONCLUSION

A coastline detection method for SAR images based on local statistical active contour model which adopts G^0 distribution is proposed in this paper, and achieves good performances in the detection of coastline. In order to remove the limitation of requesting a rigid contour initialization in the local statistical active contour model, this method firstly utilizes a C-V model to gain an approximate segmentation. Then, it regards the approximate segmentation as the initialization of the local statistical active contour model and to gain the final results. With combining a penalizing term of level set function, the model eliminates the need of re-initialization procedure. The theory and the experiments of real SAR images demonstrate the proposed method has accurate coastline detection ability, especially when comes to the problem of influences of continental shelf and reefs in the shoreline regions. The proposed method exhibits particular advantage. The main findings of the proposed method are listed below: (1) Utilizing the C-V model, the proposed method decreases the limitation of requesting a rigid contour initialization in the local statistical active contour model and speed up the segmentation. (2) The proposed local statistical active contour model based on G^0 distribution makes full use of the statistics of shoreline regions in SAR images, has accurate coastline detection ability and eliminates the influence of continental shelf and reefs. (3) In our model, we adopt G^0 distribution to represent SAR data which improves the image data representation ability.

The future work of this paper is as follows: (1) Low efficiency of local statistical active contour model is observed and therefore, the efficiency of the proposed method is an emphasis in future work. (2) In local statistical active contour model, the size of local neighborhood region would affect the precision and efficiency of the method. How to select a suitable size adaptively is also a task which needs an in-depth study in future.

REFERENCES

Brox T and Cremers D. 2007. On the statistical interpretation of the piecewise smooth Mumford-Shah functional. SSVM 2007, LNCS 4485Heidelberg: Springer: 203–213

Cerimele M M, Cinque L, Cossu R,and Galiffa R. 2009. Coastline detection from SAR images by level set model. ICIAP 2009, LNCS 5716: 364–373

Chan T F and Vese L A. 2001. Active contours without edges. *IEEE Trans on Image Process*, **10**(2): 266–277

Cremers D, Rousson M and Deriche R. 2007. A review of statistical approaches to level set segmentation: intergrating color, texture, motion and shape. *International Journal of Computer Vision*, **72**(2): 195–215

He Z G, Lu J and Kuang G Y. 2009. SAR image segmaentation method based on global active contour model. *Progress in Nature Science*, **19**(3): 344–360

Kuang G Y, Gao G and Jiang Y M. 2007. Synthetic Aperture Radar Target Detection Theory Algorithms and Applications. Changsha: NUDT Press: 48–52

Lankton S and Tannenbaum A. 2008. Localizing Region-Based Active Contours. *IEEE Trans on Image Processing*, **17**(11): 2029–2039

Li C, Xu C, Gui C and Fox M D. 2005. Level set evolution without re-initialization: a new variational formulation. IEEE Conference on Computer Vision and Pattern Recognition(CVPR), (1): 430–436

Mory B, Ardon R and Thiran J P. 2007. Variational Segmentation using Fuzzy Region Competition and Local Non-Parameteric Probability Density Functions. *ICCV*, 1–8

Piovano J and Papadopoulo T. 2008. Local statistic based region segmentation with automatic scale selection. ECCV 2008, Part Ⅱ: 486–499

Piovano J, Rousson M and Papadopoulo T. 2007. Efficient segmentation of piecewise smooth images. SSVM 2007, LNCS 4485, 709–720

Ross T D and Mossing J C. 1999. The MSTAR evaluation methodology. *Proceeding of SPIE*, **3721**: 705–713

Silveira M and Heleno S. 2009. Separation between water and land in SAR images using region-based level sets. IEEE Geoscience and Remote Sensing Letters, **6**(3): 471–475

Zhu S C and Yuille A. 1996. Region competition: unifying snakes, region growing, and Bayes/MDL for multiband image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **18**(9): 884–900

局部统计活动轮廓模型的SAR图像海岸线检测

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摘　要：首次将局部统计活动轮廓模型引入SAR图像海岸线检测问题中，提出了一种基于局部统计活动轮廓模型的SAR图像海岸线检测方法。首先利用C-V模型进行粗分割，消除局部统计活动轮廓模型对初始轮廓线设置要求严格的限制，然后提出了一种基于G^0分布的局部统计活动轮廓模型，进行精细分割。该模型采用G^0分布对轮廓线上每一点的邻域进行统计建模，增强了模型数据拟合能力，提高了海岸线检测精度，加入水平集函数惩罚项，消除了重新初始化过程。实测SAR图像实验表明，本文方法可用于精确海岸线检测。

关键词：合成孔径雷达，海岸线检测，统计活动轮廓，C-V模型

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Huang K H and Zhang J. 2011. A coastline detection method using SAR images based on the local statistical active contour model. *Journal of Remote Sensing*, **15**(4): 737–749

1　引　言

SAR图像海岸线检测在潮汐观测、沿海区域侵蚀情况及冰川变化等自然现象的监控中有至关重要的作用，同时也是SAR图像近岸舰船目标检测系统的重要组成部分。然而，海岸线往往同时结合了水陆混杂信号，并且由于SAR系统的相干成像原理，造成SAR图像被斑点噪声所污染，使SAR图像海岸线检测非常困难(Cerimele 等，2009)。从原理上讲，SAR图像海岸线检测就是一种图像分割问题。近年来，基于活动轮廓(active contour)模型的方法在图像分割领域得到了广泛的应用，它本质上是一种基于变分法和偏微分方程的模型，其基本思想是(贺志国 等，2009)：将待分割的目标边界视为一条可以活动的轮廓线，在特定能量泛函最小化过程的指引下，轮廓线不断朝目标的边缘方向变形，直至停留于目标的边缘位置，此时由轮廓线表征的就是待分割的边界。

活动轮廓模型一般可以分为两类：基于边缘信息和基于区域信息。基于边缘信息模型中轮廓线的演化利用图像的局部梯度信息，会在梯度值较大的局部停止演化。基于区域信息的模型利用图像的区域统计信息，最优化过程就是寻求统计分布模型与分割区域最优化匹配的过程。基于边缘信息模型有很好的局部一致性，对非均匀区域分割鲁棒性较强，但对噪声敏感，在边缘强度较弱的平滑边界，则可能越过边缘，出现“冒顶”现象，而且此类模型对初始轮廓线位置的设定非常敏感。与基于边缘信息的模型相比，基于区域信息的模型对初始轮廓线设定鲁棒性较强且对噪声不敏感。然而，此类模型在建模过程中使用的是全局统计信息，在处理混杂区域分割问题时通常不够理想，因为利用全局统计信息的模型获得的是全局标准，而图像的分割很多情况下却是基于局部信息(如灰度、对比度、纹理等)(Piovano和Papadopoulo, 2008)。

针对上述两类模型的不足，Piovano和Papadopoulo (2008)，Brox 和Cremers (2007)以及Mory等人(2007)提出一类基于局部统计信息的分割模型，这类模型对轮廓线上的每个点计算其邻域统计信息，这样轮廓线的演化变成寻求每个局部区域统计模型的最优匹配过程。通过对邻域参数的调整，这类基于局部统计信息的模型具有备受关注的特性(Piovano和Papadopoulo，

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2008)：当邻域参数设置比较大时，此模型类似于基于全局统计信息的模型，而当邻域参数设置比较小时，此类模型又类似于基于边缘信息的模型。所以，此类模型同时结合了上述两类模型的优点，分割能力得到很大的提升。但其在局部区域建模时通常采用高斯分布，不适合SAR图像的分割，而且基于局部统计信息的方法对初始轮廓线设置要求非常高。

理论分析和大量实测数据的实验已经证实了G^0分布对SAR图像有精确的建模能力(匡纲要 等，2007)，本文提出了一种基于G^0分布的局部统计活动轮廓模型的SAR图像海岸线检测方法。同时，为了消除基于局部统计信息对初始轮廓线设置要求严格的局限，采用对初始轮廓线设置要求较低的C-V模型(Chan和Vese，2001)，先用C-V模型进行粗分割，将粗分割的结果作为本文提出的局部统计活动轮廓模型的初始轮廓线，再进行精细分割。

2 改进的局部统计活动轮廓模型

2.1 经典的统计活动轮廓模型

令$\Omega \subset R^2$表示图像域，$I:\Omega \to R$为定义在图像域Ω中的图像函数，则图像分割问题就是寻求Ω的一种L区域分划$R(\Omega)=\{\Omega_i\}_{i=1,\cdots,L}$，使得每个子区域$\Omega_i$中的图像函数$I$依据某种属性而言是均匀的。从统计学的观点来看，$R(\Omega)$可以通过最大化后验PDF$p(R(\Omega)|I)$来获得(Zhu和Yuille，1996；Cremers，等，2007)。则图像分割问题可以表示为最小化如下能量泛函的问题：

$$E\left(\{\Omega_1,\cdots,\Omega_L\}\right)=-\sum_{i=1}^{L}\int_{\Omega_i}\log p_i(I(x))\mathrm{d}x+\mu|C| \quad (1)$$

式中，$|C|=\int_C \mathrm{d}s$表示分割边界的长度，μ为一个正的加权实数。式(1)即为统计活动轮廓模型的一般表达式。统计活动轮廓模型是一种基于贝叶斯推理的模型，其本质是通过最大化分割区域的后验概率来寻求最优分割，其性能取决于统计分布对图像数据的拟合程度。统计分布越合理，得到的分割越精确。经典的统计活动轮廓模型采用高斯分布拟合图像数据，大量的研究表明(贺志国 等，2009)，由于斑点噪声的影响，SAR图像数据无法采用高斯分布建模，因此若将采用高斯分布的统计活动轮廓模型应用于SAR图像，会产生错误的分割结果。理论分析和大量实测数据的实验都已经证实了G^0分布能够在一个广泛的均匀度变化范围内对SAR多视杂波图像进行较为精确的建模(匡纲要 等，2007)，而且其参数估计容易，计算复杂度低，因此本文采用G^0分布作为SAR图像数据的统计模型。但是G^0分布表达式复杂，若采用精度较高的最大似然估计(MLE)，将得不到参数的解析解，而且数值计算非常复杂，在实际应用中，为了提高计算效率，一般采用矩估计方法完成参数的估计。

SAR强度图像的G^0分布表达式为：

$$p(I\mid\alpha,\gamma)=G^0(\alpha,\gamma,n)=\frac{n^n\Gamma(n-\alpha)I^{n-1}}{\gamma^{\alpha}\Gamma(n)\Gamma(-\alpha)(\gamma+nI)^{n-\alpha}},\quad -\alpha,\gamma,n,I>0 \quad (2)$$

式中，I为强度图像，n为等效视数(可通过SAR图像的先验知识获得)。α为形状参数，γ为尺度参数，它们为待估计的分布参数，即：$\theta=[\alpha,\gamma]^{\mathrm{T}}$。

采用矩估计法，可得参数α和γ的估计式为：

$$\hat{\alpha}=-1-\frac{n\hat{\lambda}}{n\hat{\lambda}-(n+1)\hat{\mu}^2} \quad (3)$$

$$\hat{\gamma}=(-\hat{\alpha}-1)\hat{\mu} \quad (4)$$

式中，$\hat{\mu}$和$\hat{\gamma}$分别为样本均值和样本平方均值。

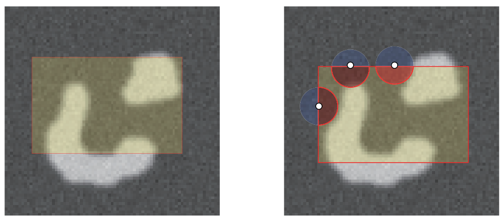
2.2 模型改进

在海岸线检测问题中，海岸线附近区域的局部统计信息对检测结果的影响往往更大，而经典的统计活动轮廓模型统计的是区域的全局信息(图1(a))，所以往往会出现“过度分割”现象，分割精度不够理想。

为了对轮廓线上每个点进行局部信息统计，借鉴Lankton和Tannenbaum (2008)的思想，引入一个滑窗因子：

$$B(x,y)=\begin{cases}1, & \|x-y\|<r\\ 0, & \text{其他}\end{cases} \quad (5)$$

式中，x，y为空间变量，代表像素点，r为滑窗半径，则$B(x, y)$代表轮廓线C上以点x为中心的半径为r的邻域。$B(x, y)$的内部点和外部点如图1(b)所示。



(a) (b)

图1 基于全局统计信息模型和基于局部统计信息模型示意图

(a)基于全局统计信息的模型：红色轮廓线内为内部区域(黄色)，红色轮廓线以外为外部区域；(b) 基于局部统计信息的模型：对轮廓线上每个点，计算其邻域(小圆)信息，小圆红色部分为局部内部区域，小圆中蓝色部分为局部外部区域

引入一个Lipschitz连续函数$\phi:\Omega\rightarrow R$(称为水平集函数)，使得：

$$\begin{cases}\phi(x)>0, & x\in\Omega_{\text{in}}\\ \phi(x)<0, & x\in\Omega_{\text{out}}\\ \phi(x)=0, & x\in C\end{cases}\tag{6}$$

式中，Ω_{in}，Ω_{out}分别表示轮廓线C的内部和外部区域，加入一个水平集函数惩罚项(Li 等，2005)，消除传统水平集方法迭代过程中耗时的重新初始化步骤，考虑两区域的情况，则本文提出的基于G^0分布的局部统计活动轮廓模型的能量泛函定义如下：

$$\begin{aligned}E(\phi)=&\int_{\Omega_x}\delta_\varepsilon(\phi(x))\int_{\Omega_y}B(x,y)\times\\&\begin{pmatrix}-H_\varepsilon(\phi(y))\log p(I(y)\,|\,\hat{\alpha}_{L1},\hat{\gamma}_{L1})-\\ \left[1-H_\varepsilon(\phi(y))\right]\log p(I(y)\,|\,\hat{\alpha}_{L2},\hat{\gamma}_{L2})\end{pmatrix}\mathrm{d}y\mathrm{d}x+\\&\mu\int_{\Omega_x}|\nabla H_\varepsilon(\phi(x))|\,\mathrm{d}x+\\&\upsilon\int_{\Omega_x}\frac{1}{2}(|\nabla\phi(x)|-1)^2\,\mathrm{d}x\end{aligned}\tag{7}$$

式中，最后一项为水平集函数惩罚项，$H_\varepsilon(\phi)$为Heaviside函数：

$$H_\varepsilon(\phi(x))=\begin{cases}1, & \phi(x)<-\varepsilon\\ 0, & \phi(x)>\varepsilon\\ \left\{1+\dfrac{2}{\pi}\arctan\left(\dfrac{z}{\varepsilon}\right)\right\}, & \text{其他}\end{cases}\tag{8}$$

式中，$\delta_\varepsilon(\phi)=H'_\varepsilon(\phi)$，$\Omega_x$为轮廓线上点的集合，$\delta_\varepsilon(\phi(x))$限定能量泛函的作用范围为轮廓线附近一个窄带内的点的集合，Ω_y代表滑窗因子$B(x, y)$定义的邻域，这表明在基于局部统计信息的活动轮廓模型中，能量泛函的计算只考虑轮廓线附近窄带内每个点的邻域的统计分布。$\hat{\alpha}_{L1}$和$\hat{\gamma}_{L1}$为基于$B(x, y)$局部区域内部数据的估计参数，$\hat{\alpha}_{L2}$和$\hat{\gamma}_{L2}$为基于$B(x, y)$局部区域外部数据的估计参数，都可以根据式(3)、(4)进行求解，易知此时基于局部统计信息的样本均值和样本平方均值分别为：

$$\begin{cases}\hat{\mu}_{L1}=\dfrac{\int_{\Omega_y}B(x,y)I(y)H_\varepsilon(\phi(y))\mathrm{d}y}{\int_{\Omega_y}B(x,y)H_\varepsilon(\phi(y))\mathrm{d}y},\\ \hat{\mu}_{L2}=\dfrac{\int_{\Omega_y}B(x,y)I(y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}{\int_{\Omega_y}B(x,y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}\\ \hat{\lambda}_{L1}=\dfrac{\int_{\Omega_y}B(x,y)I^2(y)H_\varepsilon(\phi(y))\mathrm{d}y}{\int_{\Omega_y}B(x,y)H_\varepsilon(\phi(y))\mathrm{d}y},\\ \hat{\lambda}_{L2}=\dfrac{\int_{\Omega_y}B(x,y)I^2(y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}{\int_{\Omega_y}B(x,y)[1-H_\varepsilon(\phi(y))]\mathrm{d}y}\end{cases}\tag{9}$$

采用变分法和最速下降法，可得到本文提出的基于G^0分布的局部统计活动轮廓模型的水平集函数演化方程：

$$\begin{aligned}\frac{\partial\phi(x)}{\partial t}=&\delta_\varepsilon(\phi(x))\int_{\Omega_y}B(x,y)\times\delta_\varepsilon(\phi(y))\times\\&\left(-\log p(I(y)\,|\,\hat{\alpha}_{L1},\hat{\gamma}_{L1})+\log p(I(y)\,|\,\hat{\alpha}_{L2},\hat{\gamma}_{L2})\right)\mathrm{d}y+\\&\mu\delta_\varepsilon(\phi(x))\mathrm{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right)-\\&\nu\left[\mathrm{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right)-\Delta\phi(x)\right]\end{aligned}\tag{10}$$

可以看出，基于全局统计信息的活动轮廓模型是基于区域的全局信息寻求统计分布的最优匹配过程，而基于局部统计信息的活动轮廓模型是对轮廓线上的每个点寻求其局部区域统计分布的最优匹配过程。在用于SAR图像海岸线检测时，由于海陆信号的混杂作用以及大陆架、暗礁区域的影响，基于全局统计信息的分割模型通常会出现“过度分割”现象，而且存在局部极小值。本文提出的这种基于局部统计信息的模型可以更有针对性的对海岸线附近区域进行统计建模，无疑具有更加精确的检测能力。

2.3 算法流程

进行海岸线检测的SAR图像同时具有海洋区域和陆地区域，而由于海面的镜面反射作用，SAR图像中海域通常表现为较暗的区域，陆地表现为较亮的区域，这种特点正适合于C-V模型的分割应用。由于C-V模型本质上是假设区域为标准差固定的高斯分布的统计活动轮廓模型，所以在SAR图像的分割中精度较差。C-V模型只计算全局均值信息，计算速度较快，而且对噪声和初始轮廓线位置的设定不敏感，将C-V模型分割结果作为基于G^0分布局部统计活动轮廓模型的初始轮廓线可以很好的弥补局部统计活动轮廓模型对初始轮廓线位置非常敏感的缺陷。这种在离分割目标较远时采用大步长演化，接近目标时进行精准调整的思想在自动控制领域的很多方面都有体现。

归纳起来，本文算法的详细流程如图2所示：

主要步骤为：

(1)图像预处理。为了参数设置的一致性，首先将原始图像数据取值区间设置为[0，255]。

(2)C-V模型分割。使用C-V模型对SAR图像进行粗分割，粗分割的结果作为下一步精细分割的初始轮

廓线。

(3)设定邻域滑窗大小，对轮廓线上每个点利用式(9)计算其样本均值和样本平方均值，利用式(3)(4)估计G^0分布的局部参数$\hat{\alpha}_{L1}, \hat{\gamma}_{L1}$和$\hat{\alpha}_{L2}, \hat{\gamma}_{L2}$。

(4)利用式(10)对水平集函数进行更新，实现对SAR图像海岸线的精确检测。

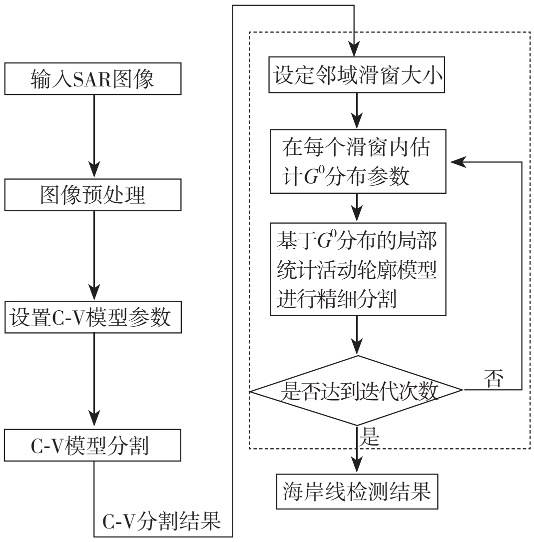


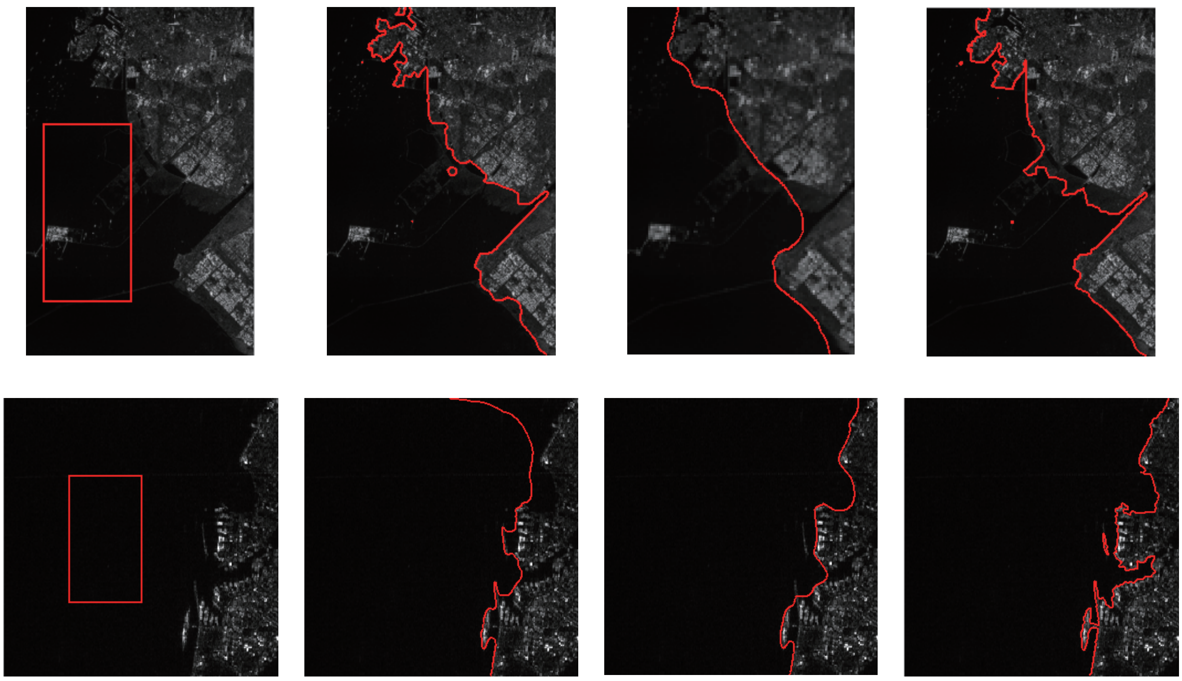
图2 本文算法流程

3 实验结果与分析

为了验证算法的分割性能，采用真实SAR图像数据进行实验分析。实验环境：CPU为Pentium(R) Dual 1.8 GHz，2 G内存，实验软件为matlab2008。C-V模型参数设置为：$\lambda_1=\lambda_2=1$，$\mu=0.02\times255^2$，$\Delta t=0.1$，$\varepsilon=1$。模型参数设置为：$\mu=0.2$，$\upsilon=2$，$\varepsilon=1$，滑窗半径设置一般为10，15，20。

3.1 算法有效性验证实验

图3是两幅分辨率为8 m，4视的Radarsat-2汉城滨海区域的SAR图像。仔细观察图3中的上图，可以看到图中有较大面积的大陆架延伸区域，滨海区域极不均匀，有大片的暗礁区影响，基于全局统计信息的方法存在“过分割”现象，分割的细节处理能力不足，但本文算法仍能精确的实现海岸线的检测。图3下图中海岸线和临海区域分布更为复杂，图中陆地区域分布极不均匀，海岸线轮廓不光滑，有几处向内陆区域的延伸，也有内陆向水域的突出，传统的局部统计活动轮廓模型在细节的刻画上显得不足，而本文算法有精细的分割能力。



(a) (b) (c) (d)

图3 实测Radarsat-2 SAR图像海岸线检测实验

(a)原始图像及初始轮廓线设置；(b)C-V模型的分割结果(20次)；将图3(b)结果作为本文算法的初始轮廓线继续进行精细分割得到图3(d)的最终结果；(c)传统的基于高斯分布的局部统计活动轮廓的分割结果；(d)本文算法结果

图4是一幅三亚海域附近的机载、单视SAR图像，分辨率为1 m。由于该图像为机载SAR数据，分辨率较高，所以海况比较复杂，海面杂波对统计分布模型的拟合精度要求更高，图4(c)和(d)的分割结果表明高斯分布模型对SAR数据的建模能力不足，而本文所采用的G^0分布具有较强的复杂海况下的数据拟合能力，使得本文算法取得比较精确的海岸线检测结果。

3.2 对初始轮廓线设定鲁棒性分析

图5为本文方法在不同初始轮廓线位置情况下的海岸线检测实验。可以看出，虽然初始轮廓线设置不同，本文算法却都能够精确的检测出海岸线。这说明由于本文算法利用了C-V模型，消除了局部统计活动轮廓模型对初始轮廓线设定要求严格的局限。但不足在于模型分割产生的极小值点问题会受到初始轮廓线位置的影响。这主要是由于能量泛函的非凸性，导致模型在本质上仍然存在局部极小值点，因而初始条件的设定对局部极小值点会产生影响。

3.3 本文算法海岸线检测精度定量化评估

为了更为客观的衡量本文算法的海岸线检测精度，和实测结果(Ground Truth)进行定量化比较，主

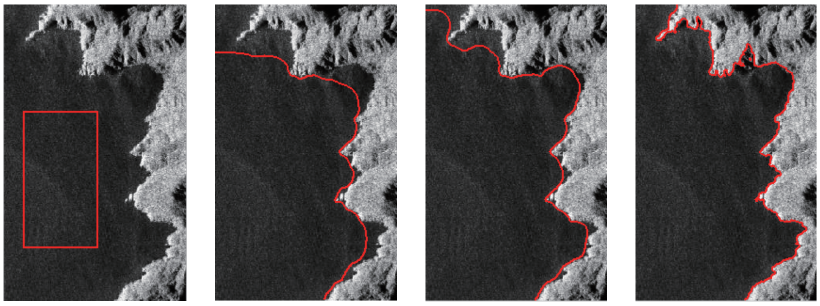


图4 机载SAR图像海岸线检测实验

(a)原始图像及初始轮廓线设置；(b)C-V模型的分割结果(40次)；(c)传统的基于高斯分布的局部统计活动轮廓的分割结果；(d)经过本文算法精细分割得到的结果

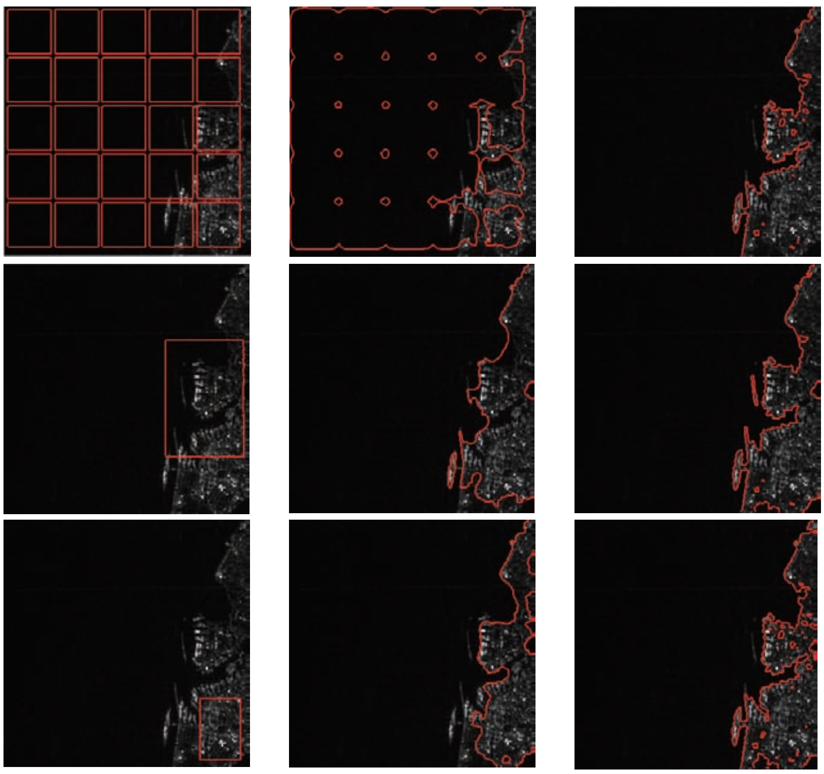


图5 不同初始轮廓线对分割结果的影响

(a)不同的初始轮廓线设置；(b)中间分割结果；(c)最终分割结果

要计算FPR(False Positive Rate)和FNR(False Negati-ve Rate)两种错误率(Margarida等，2009)。实测结果通过人工的对实际SAR图像的肉眼观测勾绘得到。FPR衡量了和实测结果相比较，自动检测算法将实测为陆地的像素划分为水域的错误率；FNR衡量了和实测结果相比较，自动检测算法将实测为水域的像素漏检的错误率。两种错误率的计算公式如下：

$$\mathrm{FPR}(AC,GT)=\frac{\#(AC\cap\overline{GT})}{\#(GT)} \tag{11}$$

$$\mathrm{FNR}(AC,GT)=\frac{\#(\overline{AC}\cap GT)}{\#(GT)} \tag{12}$$

式中，AC表示自动检测算法海岸线检测结果图像，GT表示实测结果的图像。AC和GT都是二进制图像，检测轮廓线以内的像素被标记为1，检测轮廓线以外的像素被标记为0。

采用上述定量化分析方法，选用比较有代表性的图3中第二幅图像进行海岸线检测精度分析，并和传统的基于高斯分布的活动轮廓方法进行比较，结果如表1所示，式中CE表示总的错误率。从表1的结果可以看出，本文算法更为精确。

另外，本文还采用了一种区域内部均匀性度量的方法来对海岸线检测精度进行评估。根据图像分割的定义，分割后图像每个区域内部应该是均匀的，不同区域之间存在较大的差异，所以区域内部的均匀程度表征了图像分割的质量。定义分割精度度量如下(Ross和Mossing, 1999)：

$$PP=1-\frac{1}{C}\sum_i\left\{\sum_{x\in R_i}\left[I(x)-\frac{1}{A_i}\sum_{x\in R_i}I(x)\right]^2\right\} \tag{13}$$

式中，R_i为图像中的不同分割区域，C为归一化系数，$I(x)$为图像中点x处的灰度值，A_i为区域R_i中的像素个数。PP值越接近于1，表明分割图像内部各区域越均匀，图像的分割质量越好。从表2的结果可以看出，图3和图4的PP值都接近1，说明本文算法分割精度较高。图5的PP值验证了本文算法对初始轮廓线位置设定鲁棒性较强。

表1 定量化比较结果

方 法	FPR/%	FNR/%	CE/%
本文算法模型	4.2	5.7	9.9
经典算法模型	6.8	13.5	20.3

表2 本文算法分割质量评估

图 像	图3		图4	图5(从上至下)		
PP	0.977	0.981	0.962	0.954	0.933	0.925

4 结 论

提出一种基于G^0分布的局部统计活动轮廓模型的SAR图像海岸线检测方法，实现了对海岸线的精确检测。为了消除局部统计活动轮廓模型对初始轮廓线设定要求严格的局限，首先利用C-V模型进行粗分割，将粗分割的结果作为局部统计活动轮廓模型的初始轮廓线再进行精细分割。加入水平集函数惩罚项，去除了耗时的重新初始化过程。实验结果表明，本文算法具备精确的海岸线检测能力，尤其是针对SAR图像中滨海区域大陆架、暗礁的影响使海岸线检测不够精确的问题，展现了独有的优越性。本文算法的新颖之处在于：(1)利用C-V模型分割方法，降低了局部统计活动轮廓模型对初始轮廓线设定严格的局限，同时加快了整体分割速度。(2)提出的基于G^0分布的局部统计活动轮廓模型充分利用了SAR图像近海岸区域的统计信息，有精确的海岸线检测能力，可以很好的消除大陆架、暗礁对海岸线检测带来的影响。(3)在模型中，采用G^0分布拟合SAR图像数据，提高了模型对图像数据的拟合能力。

下一步的工作主要有：(1)基于局部统计信息的活动轮廓模型在算法的执行效率方面相对较差，提高算法的执行效率是下一步关注的重点问题；(2)基于局部统计信息的模型，邻域参数尺度大小会影响检测算法的精度和执行效率，如何自适应的进行邻域参数尺度选择是需要进一步研究的课题。

REFERENCES

Brox T and Cremers D. 2007. On the statistical interpretation of the piecewise smooth Mumford-Shah functional. SSVM 2007, LNCS 4485Heidelberg: Springer: 203–213

Cerimele M M, Cinque L, Cossu R,and Galiffa R. 2009. Coastline detection from SAR images by level set model. ICIAP 2009, LNCS 5716: 364–373

Chan T F and Vese L A. 2001. Active contours without edges. *IEEE Trans on Image Process*, **10**(2): 266–277

Cremers D, Rousson M and Deriche R. 2007. A review of statistical approaches to level set segmentation: intergrating color, texture, motion and shape. *International Journal of Computer Vision*, **72**(2): 195–215

He Z G, Lu J and Kuang G Y. 2009. SAR image segmaentation method based on global active contour model. *Progress in Nature Science*, **19**(3): 344–360

Kuang G Y, Gao G and Jiang Y M. 2007. Synthetic Aperture Radar Target Detection Theory Algorithms and Applications. Changsha: NUDT Press: 48–52

Lankton S and Tannenbaum A. 2008. Localizing Region-Based Active Contours. *IEEE Trans on Image Processing*, **17**(11): 2029–2039

Li C, Xu C, Gui C and Fox M D. 2005. Level set evolution without re-initialization: a new variational formulation. IEEE Conference on Computer Vision and Pattern Recognition(CVPR), (1): 430–436

Mory B, Ardon R and Thiran J P. 2007. Variational Segmentation using Fuzzy Region Competition and Local Non–Parameteric Probability Density Functions. *ICCV*, 1–8

Piovano J and Papadopoulo T. 2008. Local statistic based region segmentation with automatic scale selection. ECCV 2008, Part Ⅱ: 486–499

Piovano J, Rousson M and Papadopoulo T. 2007. Efficient segmentation of piecewise smooth images. SSVM 2007, LNCS 4485, 709–720

Ross T D and Mossing J C. 1999. The MSTAR evaluation methodology. *Proceeding of SPIE*, **3721**: 705–713

Silveira M and Heleno S. 2009. Separation between water and land in SAR images using region-based level sets. IEEE Geoscience and Remote Sensing Letters, **6**(3): 471–475

Zhu S C and Yuille A. 1996. Region competition: unifying snakes, region growing, and Bayes/MDL for multiband image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **18**(9): 884–900

附中文参考文献

贺志国, 陆军, 匡纲要. 2009. 基于全局活动轮廓模型的SAR图像分割方法. 自然科学进展, **19**(3): 344–360

匡纲要, 高贵, 蒋咏梅. 2007. 合成孔径雷达目标检测理论、算法及应用. 国防科技大学出版社: 48–52