Remote Sensing Image Change Detection and Location Based on Dynamic Level Set Model

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Abstract —Image change detection is established for extracting changed regions in multiple images of the same scene captured at different times. Recent research has demonstrated that the change detection methodologies using satellite images, such as multi-temporal visible light remote sensing image and synthetic aperture radar (SAR) image, are particularly useful for damage assessment after various disasters, e.g. earthquakes, fires, floods, landslides etc.

The level set method, because of its implicit handling of topological changes and low sensitivity to noise, is one of the most effective unsupervised change detection techniques for satellite images. The signed pressure force function (SPF) improved the performances of conventional level set methods through including two grayscale parameters, i.e. the average pixel intensity inside and outside the contour respectively. However, the mean of region pixel intensity is not a good indicator in case that the images are inhomogeneities grayscale, e.g. confused-edge objects in satellite images. In order to address this problem, we propose a novel model, denoted as dynamic SPF (D-SPF) model, which can dynamically learn a discriminative indictor for distinguishing the pixels inside or outside the contour. Specifically, the principle of maximizing entropy between the regions inside and outside the contour is used to learn the K distinguish parameters, which help to guide the segmentation contour to end on the object's edge.

The experiments are conducted on a public satellite image dataset, i.e. ERS, which contain 670 SAR and 670 optical images, each image covers approximately 150m^2 area including forests, lakes and cities etc. These images are challenging due to the inhomogeneities landforms and unknown natural disasters. The experimental results demonstrate that D-SPF model reduces almost 30.4% missed detection rate on the optical images and 41.2% missed detection rate on the SAR images in comparison with SPF, and obtains the best detection performances in ERS dataset.

Keywords *—Remote Sensing Image; Change Detection; Level Set Method; Dynamic Signed Pressure Force Model.*

INTRODUCTION

In the analysis and processing of remote sensing images, change detection is a very important field. Multi-temporal remote sensing image change detection is a process of quantitatively analyzing the changes of remote sensing images at the same place at different times. Change detection technology is widely used in various aspects: monitoring crop growth and changes, land type changes; monitoring changes before and after various types of disasters, such as location and loss assessment of strong earthquake areas; monitoring forest vegetation, snow cover, soil changes in moisture; monitoring the movement of ice floes on the sea, landslide movements on land glaciers; dynamic monitoring of objects of military interest and assessment of the effects of destruction after battlefield strikes.

Image segmentation is a very important part of traditional change detection methods. The method based on the level set method is a relatively advanced algorithm in image segmentation. It has the characteristics of high segmentation precision and insensitivity to noise, and is good at processing images with complex shapes and topological changes. The results of change detection often present a variety of complex shapes, so applying the level set segmentation method to change detection is theoretically feasible.

At present, there are many methods for multi-temporal remote sensing image change detection. Different scholars have established a large number of change detection methods and various models for different image characteristics. Singh. A concludes in the[1] that the common methods of change detection can be divided into direct comparison method and post-classification comparison method. The direct comparison method is to directly generate difference images from two remote sensing images (simple difference, ratio, etc.), then uses various methods to process the difference images and obtains the change detection results. This method is simple and intuitive which the implementation method is also very easy, but it is sensitive to the sensor itself and the noise in the transmission. The post-classification comparison method classifies the pixel-by-pixel points in the two remote sensing images, then performs the difference detection on the two categories of interest to obtain the change detection result. This method requires high classification accuracy and the classification error will directly lead to the error of the detection. Such as Bayesian method and so on. Whether it is direct comparison or post-classification comparison, image segmentation (category of categories, division of "change" and "invariant" regions) is inevitable. The level set based segmentation method is a more advanced technique in image segmentation. Most of the change detection studies use traditional segmentation methods such as threshold segmentation and the study on the use of level set methods in the detection of remote sensing images are relatively rare. Yakoub Bazi et al. in the paper[2] introduced a single-phase image classification method based on the MLS (multiresolution level set) level set model, and Turgay Celik et al. in 2011[3], The C-V model is proposed to divide the "variable" and "invariant" regions of the difference image after the non-sampling discrete wavelet transform.

Among them, the problems of remote sensing image change detection mainly conclude:

(1) How to improve the quality of the input image

Change detection is a method that is accurate to the pixel level, and any small error will seriously affect the detection result. Therefore, the prior image registration and denoising process is particularly important. Only the registration error of the two images is less than 1 pixel, so we can carry out the following detection steps very well[4].

(2) How to construct a satisfactory difference region

How to construct a difference image is a direct difference, a direct ratio or a filter to reduce the interference caused by noise.

(3) How to determine an appropriate change area

The key to change detection is actually to quantitatively find a change area. The determination of the change area is generally obtained by some threshold or classification methods which the threshold setting and category selection itself have certain uncertainty.

(4) How to improve the degree of automation

In the change detection method with supervision, many parameters need to be adjusted for different experiments. What’s more non-supervised change detection methods often have some threshold and other parameters and require manual intervention. This has affected the accuracy and speed of our detection.

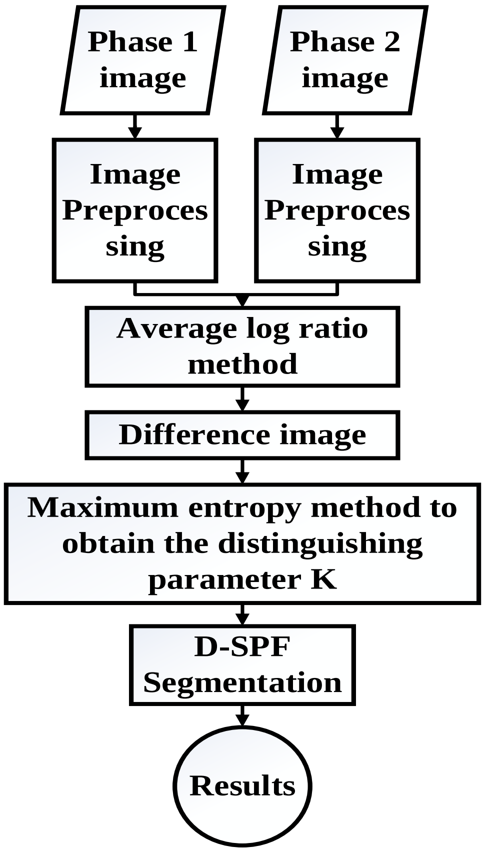
For the above problems, the method of this paper made mainly progress in (2) (3). Multi-temporal remote sensing image change detection has always been a research focus in the field of remote sensing applications, in addition, image segmentation based on level set is also an emerging method in the field of image segmentation. This paper attempts to combine the two directions to improve the precision and accuracy of remote sensing image change detection.

THE PROPOSED METHOD

A. Detection algorithm structure

The direct comparison is a method of obtaining a difference image of two images and then performing processing analysis of the difference phase image. The main idea of the change detection algorithm proposed in this paper is that the level set algorithm (mainly D-SPF model)[5] is used to segment and finally obtain the change region after the difference image is obtained by the direct comparison. The main algorithm flow chart is as follows in the Fig.1:

Fig.1 The Combination of Direct Comparison and Level Set.



The difference image acquisition method used in this paper is the average log ratio method, which is similar to the image ratio method. In order to reduce the noise interference and improve the discrimination of the foreground background, we have added the process of windowing and the natural logarithm of the result.

$$r = abs\left(\ln\left(\frac{\frac{1}{n}\sum_{i=1}^{n} I_1 + 1}{\frac{1}{n}\sum_{i=1}^{n} I_2 + 1}\right)\right) \tag{1}$$

Wherein, n is the number of pixels in the window. In the actual program, the window of the size is taken, so n=9. I_1, I_2 represent the gray values of the corresponding pixels on the phase 1 image and the time phase 2 image, respectively. The use of absolute values is used to prevent the occurrence of negative signs. In order to facilitate the comparison of various algorithms, all the algorithms mentioned below use the method of this section to obtain the difference image.

For the difference image, the part with the large gray value is the change area, and the part with the small gray value indicates that the change is not obvious. We use the level set segmentation algorithm to segment the difference image. The two parts that are separated are the areas of "change" and "unchanged". The "change" area is the purpose of our change detection.

There are many models of the level set segmentation algorithm, and a different potential energy function can construct a new segmentation model. I mainly use the C-V[8] model, the SPF model and my D-SPF model to segment. The first two level set segmentation models can achieve no-parameter segmentation. However, our D-SPF model needs to adjust the distinguish parameters k according to different images. We can use the maximum entropy algorithm to automatically obtain the distinguish parameter k for the difference image obtained by the average logarithmic ratio method for images such as satellite remote sensing images.

B. Dynamic Signed Pressure Force

Constructing the driving force of a curve and letting the curve gradually evolve into the shape of the target we are interested in is a very important purpose in the active contour model. Inside and outside the target, the opposite sign of the driving force function is the main feature of this driving force. After all, the only way to get the curve to receive the contraction force outside the target is to have an expansion force inside, and finally stay on the edge of the segmentation target. Based on the above characteristics, we call this driving force called Singed Pressure Force (SPF).

Kaihua Zhang etc. proposed a symbol pressure function based on the internal and external gray scale statistical information of the curve, and combined it with the level set to achieve image segmentation. This method of segmentation is called the SPF model. A brief introduction to SPF is as follows:

$$spf(I(x)) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max\left(\left|I(x) - \frac{c_1 + c_2}{2}\right|\right)} \tag{2}$$

Wherein, the parameters c1 and c2 are consistent with the parameters in the C-V model, respectively representing the average gray value inside and outside in which

$$c_1 = \frac{\iint_{\Omega_1} I dxdy}{\iint_{\Omega_1} dxdy}, \quad c_2 = \frac{\iint_{\Omega_2} I dxdy}{\iint_{\Omega_2} dxdy} \tag{3}$$

The evolution equation of the level set function is obtained after calculation.

$$\frac{\partial \phi}{\partial t} = spf(I(x)) \cdot \alpha \left|\nabla \phi\right| \tag{4}$$

Although the SPF model has been greatly improved and simplified based on the C-V[9]model and the GAC[7] model, the correctness of the algorithm is not satisfactory when the object grayscale features are not obvious.

Based on the SPF model introduced above, the main parameters used to distinguish the edges of the object are fixed $\frac{c_1+c_2}{2}$, as a result the model is not particularly effective in dealing with images with some grayscale features that are not obvious. Therefore, the proposal method in this paper makes some improvements on the basis of the above model, adding a distinguish parameter $k \in [0,1]$, which is used to adjust the strength of the segmentation.

Then the D-SPF function is defined as:

$$spf_k(I(x)) = \frac{I(x) - c_1 \cdot (\frac{c_2}{c_1})^k}{\max(\left|I(x) - c_1 \cdot (\frac{c_2}{c_1})^k\right|)} \tag{5}$$

Because of the definition of c1 and c2, $Min(I(x)) \le c_1, c_2 \le Max(I(x))$, so we can get the

$$\min(c_1, c_2) \le c_1 \cdot (\frac{c_2}{c_1})^k \le \max(c_1, c_2) \,. \tag{6}$$

For a more vivid description, we simply assume the object area and the background area of the image to be evenly gray, and the gray scale of the object is smaller than the background. Therefore, the object gradation is Min(I(x)), and the background gradation is Max(I(x)). Then for the points in the background area conform to formula (7). Otherwise, it is less than 0.

$$spf_{sign}(I(x)) = \max(I(x)) - c_1 \cdot (\frac{c_2}{c_1})^k > 0 \tag{7}$$

The SPF symbol [6]has the characteristics of internal and external signs. It is this law of force that causes the curve to eventually stop at the edge of the object. By replacing the original SPF function with the improved SPF function described above, we obtain the corresponding level and evolution equation as

$$\frac{\partial \phi}{\partial t} = spf_k(I(x))(div(\frac{\nabla \phi}{|\nabla \phi|}) + \alpha)|\nabla \phi| + \nabla spf_k(I(x)) \cdot \nabla \phi \tag{8}$$

Zhang [10] et al. mentioned in the paper, $div(\frac{\nabla \phi}{|\nabla \phi|})|\nabla \phi|$ is an adjustment in the level set function. Since it is satisfied $|\nabla \phi| = 1$ condition, the adjustment can be written as a Laplacian $\Delta \phi$. It can be known from the scale space theory[11] that the evolution of the Laplacian form of the equation is equivalent to initializing the initial condition of the equation with a Gaussian kernel filter. Therefore, we can add a Gaussian filter step to omit the $\Delta \phi$ calculation of this adjustment before the level set function evolves. By adjusting the standard error of the Gaussian filter, the depth of the curve evolution can be controlled. In addition, the SPF model utilizes regional statistical information, which has a larger search range and edge transition capability, so we can also omit $\nabla spf_k(I(x)) \cdot \nabla \phi$. Finally, our level set function became

$$\frac{\partial \phi}{\partial t} = spf_k(I(x)) \cdot \alpha |\nabla \phi| \tag{9}$$

Finally, we programmatically the above steps, we can get our algorithm flow as follows:

(1) Initialize level set function

$$\phi(x, t=0) = \begin{cases} 1, x \in \Omega_0 \\ -1, x \in \Omega - \Omega_0 \end{cases} \tag{10}$$

Where Ω is the area of the entire picture and Ω_0 is the inner area of initialization curve.

(2) Calculate c1 and c2 using equation (3).

(3) Evolve the level set function curve using equation (9)

(4) If $\phi > 0$,we made $\phi = 1$,otherwise $\phi = -1$.

(5) Filter the entire level set function with a Gaussian filter.

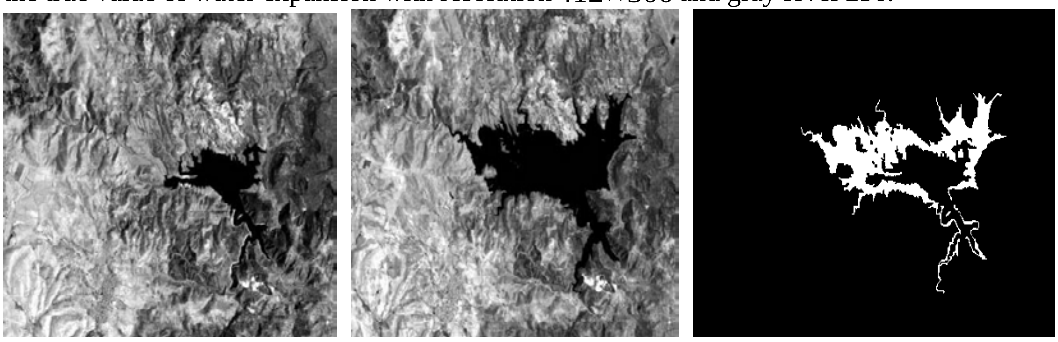
(6) Check whether the evolution of the level set function converges, if not, repeat to the step (2). If it converges, the algorithm ends and the output is outputted.

Through the above algorithm, image segmentation can be achieved. As for how to distinguish the parameter k in our D-SPF model, we will discuss it in the next chapter with the change detection algorithm.

EXPERIMENTAL RESULTS

A. Datasets and Experimental Setting

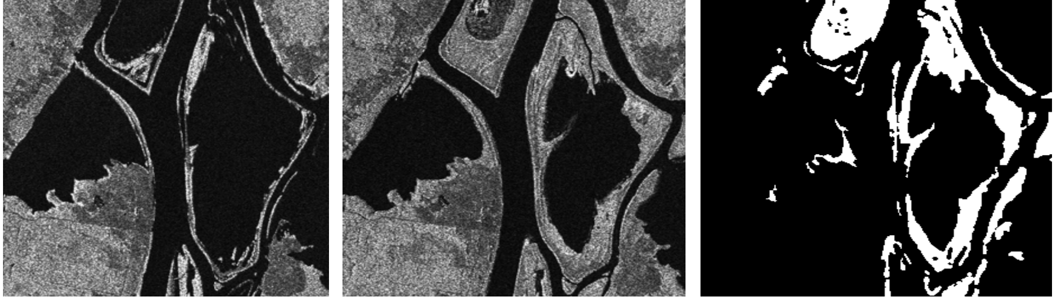
The first set of visible light images in our ERS, an optical remote sensing image taken by the thematic mapping instrument of the remote sensing satellite Landsat-5, reflects the changes in the waters of Sardinia in Italy. At the end of 1995, the area of a lake in the center of the island suddenly expanded rapidly and it is firstly necessary to test the area where the lake is enlarged. Because the lake is surrounded by mountains and mountains, it can be solved by remote sensing image change detection. Fig.2(a) and Fig.2(b) below show remote sensing images for September in 1995 and July in 1996, respectively, and Fig.2(c) represent the true value of water expansion with resolution 412×300 and gray level 256.



(a) September in 1995 (b) July in 1996 (c) True Value

Fig.2 Visible light Remote Sensing Image in Sardinia

The second set of SAR images in our ERS is a synthetic aperture radar (SAR) image taken by the RADARSAT satellite, reflecting the surface changes in the Ottawa region of Canada affected by the rainy season. It can be seen from Fig.3(a) and Fig.3(b) photographed at May in 1997 and August in 1997 respectively that the image data of this group is mainly composed of land and water, and the change information mainly comes from the surface changes caused by floods. Fig.3(c) shows the true value of the water change with resolution 290×350 and gray level 256.



(a) May in 1997 (b) August in 1997 (c) True Value

Fig.3 SAR Remote Sensing Image in Ottawa, Canada

B. Experimental Analysis

The overall appearance of the image can be represented by information entropy. If an image contains a target (a "variable" region in the difference image), then when we divide the image into target and non-target regions, the sum of information entropy on the two parts is the biggest. With the maximum entropy algorithm, we can get a segmentation threshold T. The traditional threshold segmentation is to directly use the threshold T to binarize the image and get the final result.

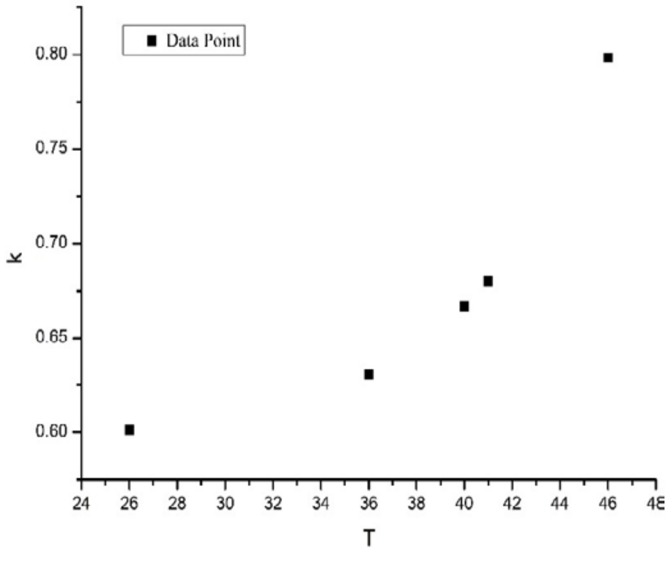
In the selection of the distinguishing parameter k of D-SPF model, we can learn from T algorithm. In the D-SPF of equation (5), because we need to segment a type of image such as a difference image. In general, our variation area has a grayscale greater than the non-target area. The internal average gray level of the curve is greater than the average gray level outside the curve. And as the discrimination parameter k increases, the curve tends to move to a place where the gradation is large (internal change region).

The larger the threshold T obtained by the difference image maximum entropy algorithm, the larger the interference of the non-changing region of the image. Therefore, a larger distinction between the distinguishing parameter k is required to allow the curve to "over" the interference areas, rather than detecting the interference areas together. As a result, the distinction between the parameter k and the maximum entropy threshold T should be a positive correlation.

For the difference image, the gray value of the edge of the final curve should be much larger than the background gray value c_1 and close to the target gray value c_2.We can limit the difference items $c_1 \cdot (\frac{c_2}{c_1})^k$ should be above $\sqrt{c_1 c_2}$,be equivalent to $k > 0.5$.

We first select five satellite remote sensing difference images obtained by the average log ratio method, then try to obtain the optimal distinguishing parameter k in the D-SPF model. We also calculate the maximum entropy threshold of each difference image. We can see the quantitative relationship between the distinguishing parameter k and threshold T in Fig.4.

Fig.4 Scatter Plot between the best distinguishing parameter k and T.



We can roughly see that as the maximum entropy threshold T increases, the distinguishing parameter k of the D-SPF model also increases. And, as can be seen in the Fig.4, the two parameters are roughly an exponentially increasing relationship. Therefore, we first define a formula (11) with parameters to describe the relationship between them.

$$k = ae^{bT} + c \tag{11}$$

Where T represents the maximum entropy threshold, and parameter k represents the optimal k value of our D-SPF model. We can use the ‘Curve Fitting Tool’ in MATLAB to get the values of the constants a, b, and c. The final output fitting results are a=0.000068, b=0.174, and c=0.595.

By substituting this result into our equation (11), we can construct a relation between the parameter k in the D-SPF algorithm and the threshold T in the maximum entropy threshold algorithm:

$$k = 6.8 \times 10^{-5} \times e^{0.174T} + 0.595 \tag{12}$$

C. Comparison with Other Methods

Five methods of maximum inter-class variance, maximum entropy and level set method of C-V model, SPF model and automatic D-SPF model were used to carry out change detection experiments, and the results of change detection were analyzed in our ERS.

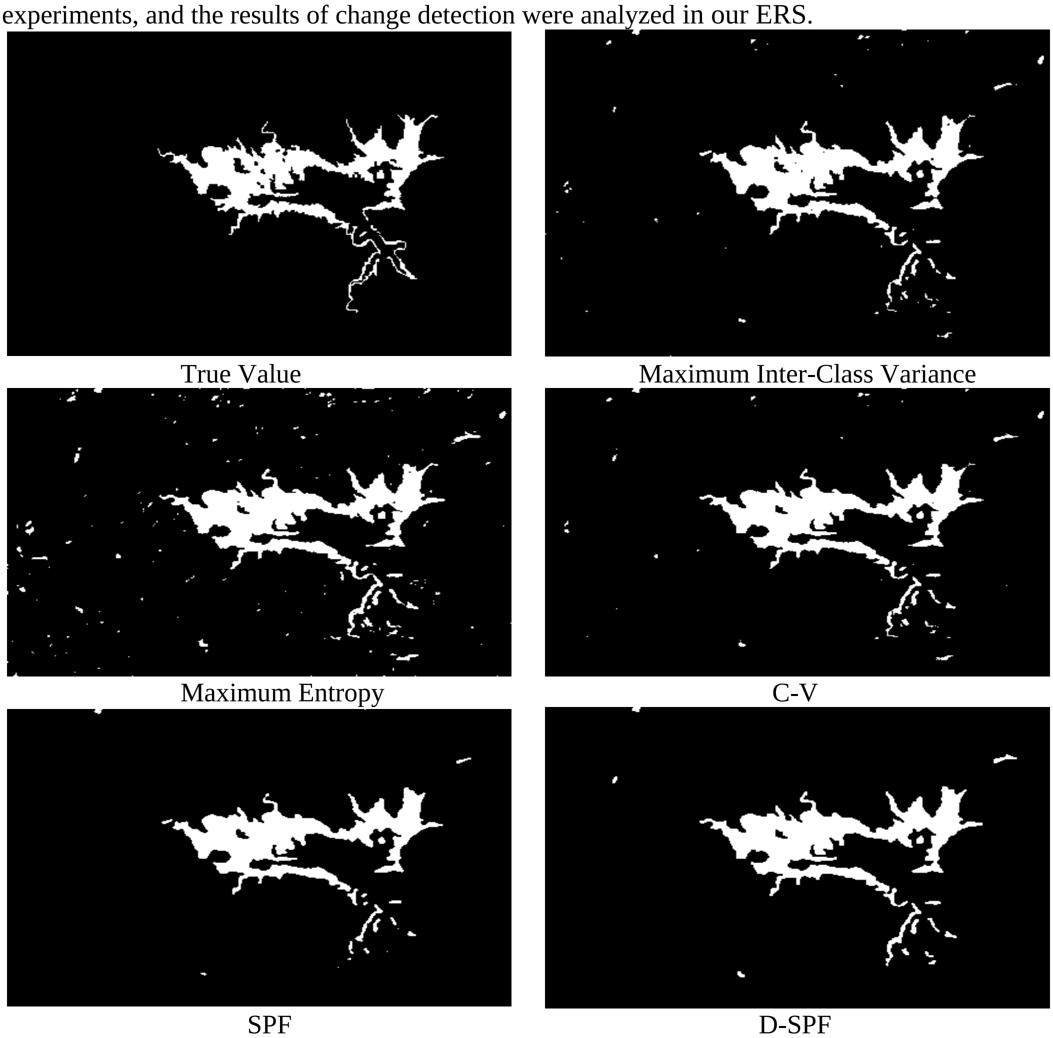


Fig.5 Visible Light Image Detection Results in Sardinia

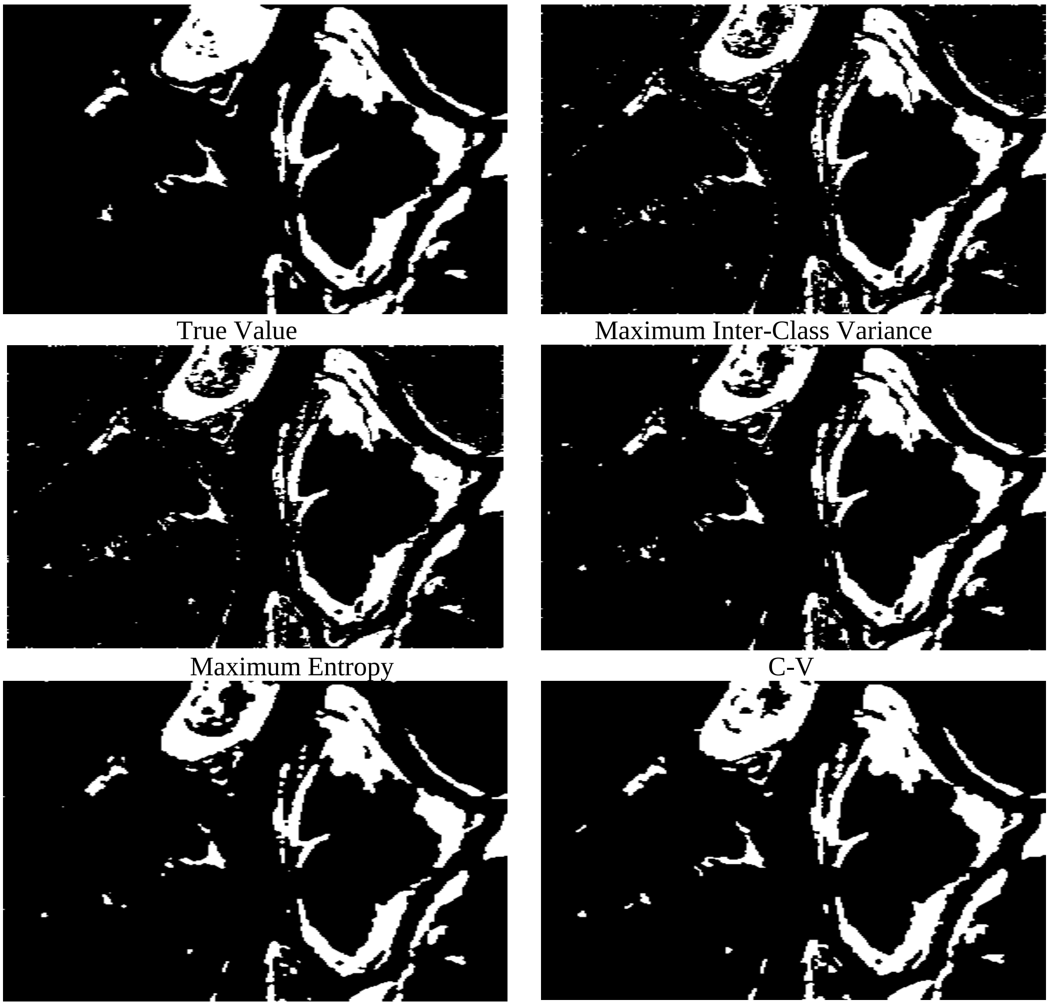


Fig.6 SAR Remote Sensing Image Detection Results in Ottawa, Canada

Table I Remote Sensing Image Detection Evaluation Index

Dataset	Evaluation index	Maximum Inter-Class Variance	Maximum Entropy	C-V	SPF	D-SPF
Visible Light Image	Error rate	1.6%	2.4%	1.7%	1.5%	1.5%
	False Alarm rate	1.1%	2.2%	1.4%	0.9%	1.3%
	Missed Detection rate	9.7%	5.9%	7.5%	10.2%	7.1%
SAR	Error rate	3.7%	3.8%	3.2%	3.3%	2.8%
	False Alarm rate	1.2%	1.1%	0.9%	0.6%	1.4%
	Missed Detection rate	17.1%	18.3%	15.5%	17.7%	10.4%

The most important parameter for change detection is the error rate in the Table I. In the two sets of data, the maximum entropy method has a higher error rate (the percentage of error pixels in the total pixels). From the segmentation results, it can be seen that there are many noises around the target, and the level set method can reduce the noise interference to the result to some extent. The reason why the missed detection rate (the number of missed detections as a percentage of the actual changed pixels) is larger than the false alarm rate (the number of false alarms as a percentage of the actual unchanging pixels) is that change region generally only occupied a small part of the whole image, so the actual number of changed pixel points is far less than the actual number of pixel points. In general, the missed detection rate should not be greater than 10%. In summary, our D-SPF change detection algorithm can balance the false alarm rate and the missed detection rate under the premise of ensuring excellent error rate.

CONCLUSION

This paper proposes a new level set segmentation model-- D-SPF model. The D-SPF model is based on the SPF model proposed by Zhang in this paper. It adds an improved model that distinguishes the parameter k and makes the segmentation result become controllable. For the change detection of the difference image based on the average logarithmic ratio method, this paper proposes an empirical formula that can automatically obtain the optimal distinguishing parameters k to make the detection process automatic. Finally, the change detection algorithm based on the D-SPF model has achieved good results in the experiment of change detection.

This paper attempts to combine the level set segmentation method with the change detection. From the experimental results of the change, the detection accuracy and accuracy are still very good. However, as a relatively new segmentation method, the level set segmentation method still has some limitations, such as the running speed and the distinguishing parameter k selection problem in the D-SPF model, etc. These problems also appear in our level-based change detection algorithm. If these problems can be solved effectively, our algorithm can be further improved.

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