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A Multi-scale Segmentation Method of Oil Spills in SAR Images Based on JSEG and Spectral Clustering

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Abstract

Image segmentation is a key step of oil spills detection in SAR images. For the problem that the traditional multi-spectral clustering algorithm with the features extraction by GLCM (Gray-Level Co-occurrence Matrix) has such limitations as direction sensitivities and difficulties in selecting the best feature combination etc., this paper proposes a multi-scale segmentation method of oil spills in SAR images based on JSEG and spectral clustering. Multi-scale J-images are used to extract the multi-features and the Laplace matrix is clustered by the K-means method. Finally, a decision-level fusion strategy is used to fuse the segmentation results from different scales. Two sets of experiments show that, compared to the traditional spectral clustering methods based on the gray feature and multi-textual features, the proposed method has higher accuracy and stronger robustness.

Keywords: *SAR; JSEG; Spectral clustering; Image segmentation; Oil spills detection*

1. Introduction

Oil spill pollution has brought serious problems to the marine ecosystem, environment and economic development of coastal cities, and has become one of the major marine pollutions. Synthetic Aperture Radar (SAR) can effectively penetrate clouds with all-day and all-weather monitoring capabilities, so it has been widely applied to oil spills detection [1-7]. The oil spills, which usually appear as dark bands or spots in SAR images, have the characteristics of radar backscatter that may cause attenuation of Bragg wave, and reduce the roughness of the sea surface. Meanwhile, some other factors like raining areas, upwelling zones, natural marine hydrocarbon seepages etc. have similar spectral and textural features with oil spill regions, which bring great difficulties in image segmentation [8, 9]. Furthermore, due to the imaging mechanism of SAR image, vast amount of coherent noises are produced, which may cause significant interference of the subsequent image processing. As a result, accurate and efficient image segmentation is a key step of oil spills detection in SAR images.

The idea of spectral clustering is based on the graph spectrum division theory [10]. Compared with traditional clustering methods, spectral clustering has the major advantage of convergence to the global optimum. Spectral clustering has been successfully applied in image segmentation field and is one of hot spots in recent years [11, 12]. It can build similarity matrix by utilizing similarities between data points, and then obtain the segmentation results by clustering the extracted eigenvectors. For example, the literature 13

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divided high-dimensional images into a plurality of sub-graph by using partitioning strategy, and then classified each sub-graph by spectral clustering based on the gray feature, thus reducing the complexity of the algorithm effectively. This method only uses gray feature that is more susceptible to coherent noises, thus the connectivity of obtained oil spills areas are unsatisfactory and the accuracy is low. For these reasons, more features of image such as textural features etc. should be further extracted.

Currently, textural features extraction of oil spills in SAR images is mainly achieved by analysis method GLCM (Gray-Level Co-occurrence Matrix) [14]. The GLCM method, first proposed by Haralick [15], can effectively describe the spatial correlation between pixels in image. For example, in the literature 16, GLCM was used to extract multi-textural features in SAR images to build similarity matrix, which effectively improved the accuracy of segmentation based on spectral clustering. However, there are three parameters should be determined before conducting GLCM: direction, step length and window size for calculating texture features. Different combinations of parameters will produce different segmentation results. However, these parameters are usually determined in accordance with the SAR image itself or experience. On the other hand, taking a certain combination of parameters determines for calculating GLCM is simply sensitive to the textural features in a special scale, thus ignoring the scale information in the image. According to expert knowledge, the multi-scale analysis tools can help to better indentify the differences between objects of different categories and effectively improve the accuracy [17]. Finally, there is no unified standard in choosing applicable combinations of textural features extracted by GLCM to conduct the feature matrix.

According to the analyses above, we propose a multi-scale segmentation method of oil spills in SAR images based on JSEG and spectral clustering. The JSEG algorithm proposed by Deng and Manjunath [18] is one of most popular color texture segmentation algorithms. The J-image is a sequence of multi-scale images which are calculated during the segmentation by JSEG. The multi-scale J-images can well integrate the spectral and features as well as scale information. So taking J-images to extract the objects can effectively overcome the limitations existing in directly using the original eigenvectors. Therefore, this paper uses sequence of J-images to extract textural and textural features in multi-scales and conducts the similarity matrix on this basis. Then, the eigenvectors corresponding to the second-smallest eigenvalue are extracted according to the Normalized Cut Criteria [11] and the K-means method is used for clustering. Finally, the inconsistent pixels of clustering results between different scales are discriminated by a decision fusion strategy based on the voting mechanism to obtain the final segmentation results.

This paper consists of four parts. Next chapter describes the basic principles and the implementation of the proposed method. The third section compares and analyzes the experimental results. The last section draws the conclusion.

2. Method

In order to effectively extract the oil spill areas in SAR images, the proposed method includes three steps: Color quantization and feature extraction; multi-scale segmentation by spectral clustering; decision-level fusion based on voting mechanism.

2.1. Color Quantization and Feature Extraction

Given the serious impacts of coherent noise on the segmentation in SAR images, image denoising should be conducted first before feature extraction. Meanwhile, to further reduce the computation and remain the image features as possible, the proposed algorithm uses the method proposed by Y. Deng which has been proved to be able to obtain good effects in JSEG to compress the gray levels of image [19]. Firstly, covert the color space of image into LUV space and use the peer group filtering to conduct image denoising and smoothing. Then, quantize the image by classical K-means method to obtain quantitative image, namely "class-map". After that, the sequence of J-images is calculated based on the "class-map". The J-value is defined as follows:

Let the location $Z(x,y)$ of pixel z in quantitative image be the pixel value of z. $z(x,y) \in Z$. Z is a set of pixels which belong to a specific sized window centered at pixel z. Figure 1 and Figure 2 are respectively the windows with the size of 9 × 9 pixels and 18 × 18 pixels centered at z. To ensure the consistency in all directions, the corners of windows are removed.

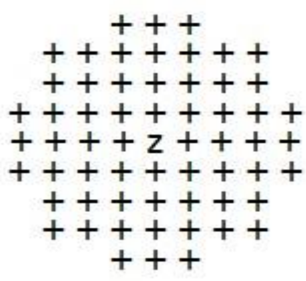


Figure 1. Window of 9×9 Pixels at z

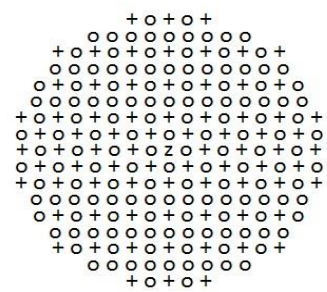


Figure 2. Window of 18×18 Pixels at z

S_T is defined as the population variance of the pixels in Z, S_W is the sum of variance of the pixels that belong to the same gray-levels. The J-value is defined as follows:

$$J=(S_T - S_W)/S_W \tag{1}$$

Replace the pixel value of z by the J-value calculated with the same sized window at the center of z and iterate over all the pixels. Then, we can obtain a J-image at single scale. By changing the window size, a sequence of J-images can be calculated. J-image is in essence a gradient image. It integrates the spectral and textural features in different scales of the original image, while they are not sensitive to direction and can effectively eliminate the influence of noise, so this paper chooses the J-images to conduct the similarity matrix.

2.2. Multi-scale Spectral Clustering Segmentation

The first step of spectral clustering algorithm is constructing the similarity matrix. The formula for conducting the similarity matrix W is as follows:

$$W_{ij} = \exp(-\|x_i - x_j\|^2 / 2\sigma^2) \tag{2}$$

In formula (2), x_i, x_j are any two data points in image and σ is the kernel parameter. Then, calculate eigenvalues and the corresponding eigenvectors of the matrix and cluster the eigenvectors to complete the segmentation of J-image at single scale.

Currently, the common classification criteria for binary-class include Ratio cut [20], Normalized cut and Min-max cut [21]. The literature 16 had proven that Normalized cut criteria could be successfully used in detection of oil spills in SAR images. For ease of comparison between different methods, this paper uses Normalized cut criteria and K-means method to achieve the spectral clustering segmentation.

2.3. Decision Fusion based on the Voting Mechanism

In order to fuse the segmentation results from multi-scale J-images, this paper proposes a decision-level fusion strategy based on the voting mechanism:

1) Compare the multi-scale segmentation results and divide all pixels into three categories. Pixels with the same results can be classified in the same category. Pixels can be defined as oil spill category, non-oil spill category and suspected oil spill category which needs to be further discriminated.

2) Discriminate which pixel belongs to suspected oil spill category by voting. The classification which gets more votes can be considered as the correct one.

3) Since the minimum window size can more accurately reflect the details of image, when a pixel wins the same number of votes, the classification result in J-image at this scale should be taken.

2.4. Implementation of Proposed Method

The implementation process of the proposed method is as follows:

1) The first step is image denoising and grayscale compression by quantization method of JSEG algorithm. Then, determine the set of window sizes and calculate J-values by formula (1) to produce multi-scale J-images. A large window size is better to extract the block oil spill areas with similar textural features. On the other hand, large window size can effectively reduce the interference caused by noise and other isolated points in these block areas. Small window, however, is suitable for extracting sporadical floating oil areas, in addition to accurately locate edges of spill areas. The more J-images at different scales, the more realistic reflection of the image textural information and the computation grows exponentially. Thus, the set of window sizes can be selected according to the characteristics of actual oil spills in SAR images. This paper sets window sizes with 5×5 pixels, 10×10 pixels, 15×15 pixels and 20×20 pixels in experiments.

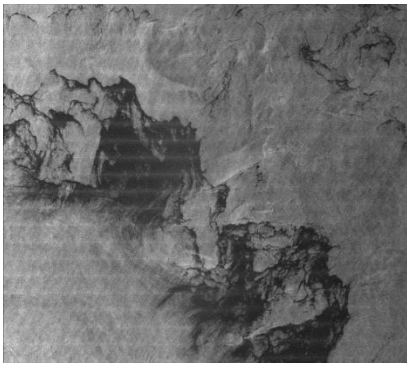
2) In a single-scale J-image, calculate the similarity matrix $W \in R^{n\times n}$ by the formula (2), and then construct the Laplace matrix $L = W$. The kernel parameter σ in formula (2) is usually determined by experience. Calculate the eigenvalues and the corresponding eigenvectors of L . Take the eigenvector corresponding to the second-smallest eigenvalue and obtain the segmentation results at a single scale by K-means method.

3) Fuse the results from different scales by the fusion strategy defined in section 2.3. In order to further eliminate isolated points in segmentation results, change the classification result of a pixel if it is different from the adjacent eight pixels. Repeat these steps with all the pixels and gain the final clustering results.

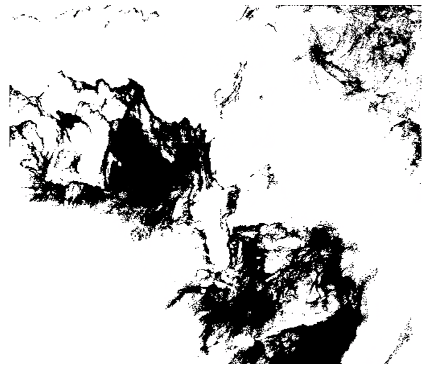
3. Analysis of Experimental Results

For the purpose of comprehensively verifying the performance of the proposed algorithm, the experimental results are respectively compared with the traditional spectral clustering algorithm based on gray feature and the improved clustering algorithm based on multi-textural features proposed in literature 16.

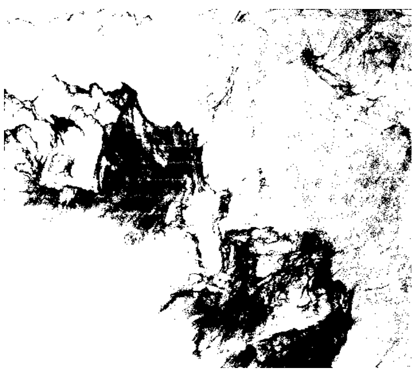
We take two oil spill SAR images which were acquired by the German Terra SAR-X radar satellite on 21 September, 2009, while operating in Scan SAR mode and have a resolution of around 18 meters. The images show the Montara offshore oil platform in the Timor Sea, northeast of Australia, with an oil slick of around 2000 square kilometers spreading out from it, which was revealed as a dark area. The sizes of two images are both 512×512 pixels. The Kernel parameter σ is determined by the shape and size of oil spill areas. Let $\sigma = 0.08$ and $\sigma = 0.13$ respectively in two experiments and the results are shown in Figure 3 and Figure 4.



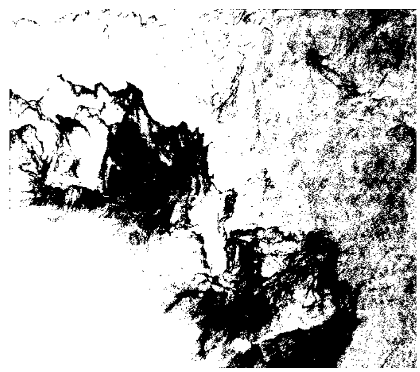
(a) Oil Spills in SAR Image



(b) Segmentation Results of Proposed Method

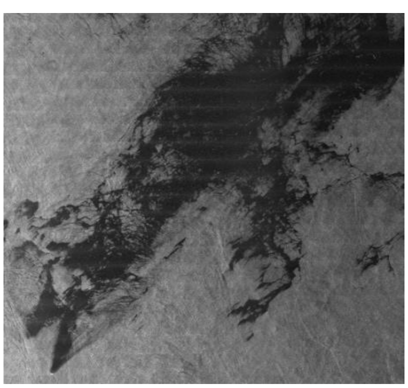


(c) Segmentation Results of Spectral Clustering based on Multi-texture Features



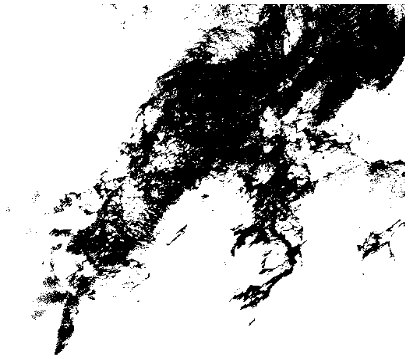
(d) Segmentation Results of Spectral Clustering based on Gray Feature

Figure 3. Experiment 1

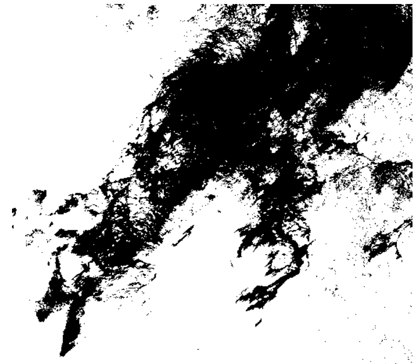


(a) Oil Spills in SAR Image

(b) Segmentation Results of Proposed Method



(c) Segmentation Results of Spectral Clustering based on Multi-texture Features



(d) Segmentation Results of Spectral Clustering based on Gray Feature

Figure 4. Experiment 2

It can be seen by visual analysis that the spectral clustering based on gray feature could extract the main oil spill areas, but there are a lot of isolated points and crushing plaques caused by the noise, resulting in serious loss of details. The anti-noise performance of the spectral clustering based on multi-textural features is good, but segmentation accuracy is low, especially in the areas where the textures of oil spills and the surface of ocean are similar. So these areas have serious under-segmentation phenomenon. The proposed method can more accurately extract the oil spill areas of the image, effectively eliminate coherent noise and meanwhile ensure the accuracy of segmentation. For further quantitative analysis of segmentation accuracy by the three algorithms, this paper selects a group of sample set including 5000 pixels in two experiments respectively, and regards the set as real data to evaluate the accuracy of the three algorithms. The results are shown in Table 1:

Table 1. Accuracy Evaluation of Algorithms

Parameters/ Methods	Experiment 1				Experiment 2			
	Overall accuracy %	False alarm rate%	Miss detection rate%	Kappa	Overall accuracy %	False alarm rate%	Miss detection rate %	Kappa
The proposed algorithm	84.1	13.83	14.42	0.6566	87.4	13.83	14.22	0.6996
Spectral clustering based on multi-texture features	82.7	14.02	15.25	0.6357	82.4	14.02	19.25	0.6539
Spectral clustering based on gray feature	80.2	15.59	19.57	0.6047	81.2	16.59	18.57	0.6104

4. Conclusion

We can see from Table 1 that the quantitative analysis conclusion is consistent with the conclusion by visual analysis. Therefore, the following conclusions can be drawn: the proposed multi-scale segmentation method of oil spills in SAR images based on JSEG and spectral clustering can effectively extract the oil spill areas with good robustness for coherent noise.

Compared with the traditional spectral clustering methods based on the gray features and multi-textural features, the proposed algorithm uses the gray feature and textural features of the image as well as the scale information contained in images, and effectively overcome the disadvantage of poor anti-noise performance when doing the segmentation by the traditional spectral clustering based on gray feature. On the one hand, in order to make a contrast with the spectral clustering segmentation algorithm that uses multi-textures features, this paper introduces the JSEG algorithm by using the J-images to extract the local homogeneity textural features and scale information of the image for higher segmentation accuracy. On the other hand, the proposed algorithm can effectively avoid the uncertainty during the segmentation due to the selection of different combination of texture features when using the spectral clustering method based on the GLCM. The authors will focus on investigating the influence of segmentation parameter settings on segmentation accuracy in the future.

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