Synthetic aperture radar oil spills detection based on morphological characteristics

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In recent years, oil spills in coastal regions have received a lot of public concern for its strong impact on the coastal ecological system. Synthetic aperture radar (SAR) is regarded as one of the most suitable sensors for oil spill monitoring for its wide-area and all-day all-weather surveillance capabilities. However, due to its special imaging mechanism, multiplicative speckle noise and dark patches caused by other physical phenomena always affect the accuracy of oil spill detection. In this work, an oil spill detection method based on dual-threshold segmentation and support vector machine was proposed. Experiments on SAR images illustrated the effectiveness of the proposed method in detecting and tracing oil spill from SAR images.

**Keywords:** synthetic aperture radar (SAR); oil spill; classification; support vector machine (SVM)

1. Introduction

Marine oil slicks are usually caused by accidents such as ship collision, drilling platform accidents, crack of oil pipeline, and deliberate discharges (1). They have become one of the most significant environmental concerns (2). With continuous economic growth, the occurrence of oil spills in China’s coastal region is increasing correspondingly (1).

The Pearl River Delta lies along the Southeast China Sea, which is among the busiest international sea-lanes in the world. Several major international shipping routes pass through this region connecting the Pacific Ocean to the Indian Ocean (3). Countless oil tankers shuttle through this region every day, most of which are from the Middle East to China, Japan and other Asia countries. There are also abundant oil and natural gas resources in this region. A lot of offshore drilling platforms are established by domestic or foreign petrol companies. All these factors enlarge the possibility of oil spill in this region. While macro slicks caused by accidents are infrequent, micro slicks caused by illegal tank cleaning and deliberate discharge can be found almost every day. As a result, early detection and clean-up of oil spill plays a very important role in the reduction of economic and environmental losses (4).

At present, there are several widely used methods for oil spill monitoring, which include ship tracking, aerial surveillance, and satellite remote sensing (5). Compared with other methods, satellite remote sensing has larger coverage range, which is especially suitable for large-scale marine monitoring. A lot of spaceborne sensors have been used for oil spill monitoring such as visible light, infrared, ultraviolet, and synthetic aperture radar (SAR) (5). Among these, SAR is the most popular one at present for its all-day and all-weather observation capability (6, 7). This is especially helpful for this task since optical sensors have limitations at night or during adverse weather conditions when a large number of oil spill accidents take place.

SAR is an active sensor that captures the microwave reflected from the targets (5). The presence of oil films suppresses the backscattering of the sea surface by dampening the short gravity and capillary waves stimulated by the wind, which are observed as dark regions in SAR images. However, SAR images unavoidably suffer from the effect of speckle noise. A lot of study has been done on segmenting dark patches that likely represent oil slicks from the sea background. Both adapted and non-adapted threshold algorithms have been applied. Solberg et al. (8) set the threshold to be k dB below the mean value of the moving window and used a multi-scale pyramid approach and clustering step in the calculation. Li et al. (9) made use of spatial density feature to separate the dark spots and the background. Migliaccio et al. (10) implemented oil spill detection processing over single-look SAR images based on a physical model. Huang et al. (11) adopted level-set method to carry on oil spill detection. Oil slicks can be accurately extracted using level-set method. However, it is much more time-consuming in actual implementation.

The movement and spreading track of oil spill have also been investigated by researchers. Li et al. (12) set up a model based on the hydrodynamic model and oil spill schema to simulate continuous oil spill from moving point source. Together with information such as wind field and current field, this model can be used to track oil spill and guide the clean-up operation. The effect of oil spill on the ecological system was also investigated.
by Tang et al. (13). Based on time-series analyses of multi-source remote sensing data, the 2006 Lebanon oil spill was studied. A large phytoplankton bloom was found 10 months after the accident, which revealed the effect of oil spill on the environment.

Due to special imaging mechanism, sometimes it is very difficult to identify real oil spills in SAR images (4). Objects having similar low backscattered signal are called “look-alikes.” They can be generated by other phenomena such as organic films, grease ice, wind front areas, areas sheltered by land, rain cells, internal waves, and upwelling zones. Manual inspection is still being used in SAR oil spill detection since it is relatively more adaptive and easy to implement. However, its accuracy largely depends on the experience of the interpreter (5). Besides, it is time-consuming and not suitable for large-scale and all-day monitoring. Therefore, automatic or semi-automatic techniques for accurate and efficient oil spill mapping need to be developed (14, 15).

Neural networks have been largely investigated and recognized as robust tools for oil spill classification. Del Frate et al. (16) proposed a semi-automatic detection of oil spill by neural network of which the input is a vector describing the features of an oil spill candidate. It was proved that the neural network could correctly discriminate oil spill and look-alikes over a set of independent examples. Topouzelis et al. (17) adopted neural networks in both dark formation detection and oil spill classification. In the experiment 94% of the dark formations segmentation and 89% accuracy of classification were obtained, respectively. Topouzelis et al. (18) also carried out a detailed examination of robustness of the combinations derived from 25 commonly used features. They found that a combination of 10 features yields the most accurate results. Hashim et al. (19) compared three algorithms for oil spill classification including co-occurrence textures, post-supervised classification, and neural network. Quantitative study on standard deviation of the estimated error shows that artificial neural network (ANN) has the largest accuracy among all these methods.

Although neural network has shown its advantage in oil spill monitoring based on SAR images, it is time-consuming. Besides, the probability of misclassification does not always decrease as the number of features increases, especially when sample data are insufficient. This phenomenon is known as “the curse of dimensionality” (20). To solve the problem of small-size sample machine learning, Statistical Learning Theory (SLT) was proposed. Based on SLT, support vector machine (SVM) was developed according to structural risk minimization principle and Vapnik-Chervonenkis dimension principle. SVM has the ability of achieving highly accurate classification based on limited samples. It has been applied in the classification of remote sensing data and has given a lot of promising results. Inglada (21) used a supervised learning approach based on SVMs for the detection and recognition of man-made objects in high-resolution optical remote sensing images. Chi et al. (22) introduced and tested an alternative implementation technique for SVM in the classification problem of hyperspectral remote sensing data with small-size training sample set. Chakraborty et al. (23) presented a semi-supervised SVM that uses self-training approach to fix the problem of pixel classification of remote sensing images. Several Chinese scholars employed SVM for oil spill monitoring applications on both pixel level (24) and feature level (25, 26) recently. All these examples tend to prove that SVM has the potential to be designed as an excellent classifier for oil spill detection: given a small number of samples, it can obtain relatively high classification accuracy in a short processing time.

In this paper, a new oil spill detection algorithm has been proposed. Dual-threshold segmentation and intensity estimation were implemented to lower the false alarm rate while maintaining the boundary of oil spills to the largest extent. In the classification phase, an SVM was built based on SAR data, sample and then its performance on oil slicks classification was tested in another SAR image received after three days.

2. Methodology

SAR oil spill detection usually starts from the extraction of dark spot areas over the sea surface. It has been proved that the existence of oil spill has an impact on the scattering of electro-magnetic wave, mainly due to its dump due to the short gravity waves and capillary waves, and hence alter the roughness of the sea surface. As a result, the Bragg scattering in these areas is weakened. On SAR image, this phenomenon is usually observed as dark spot areas. However, due to its imaging mechanism, there are lots of other phenomena that may result in dark spots in the SAR image due to suppressing of the radar backscatter from the sea surface. Dark spots caused by these factors are called look-alikes. In order to distinguish real oil spills from look-alikes, morphological characteristics are always used.

2.1. Dark spot detection

Intensity of pixels in backscatter images reflects the roughness of the surface being observed. Oil spill covered region has relative low intensity compared with the sea background and coastal areas. Most oil spill detection methods are based on intensity to highlight the region of oil spill and look-alikes from sea background.

In the detection of dark spots, overall threshold is usually used due to its convenience and high efficiency. However, in SAR images, the grayscale range of oil spill and sea background always has an intersection. Simply picking one overall threshold in the segmentation will either lead to losing of some detail of dark region or failing to suppress the interference of speckle noise from sea background. In this paper, two thresholds were used in the segmentation of dark spots and background, both
of which were obtained by histogram analysis of the data sample. The low-threshold segmentation result has relatively low false alarm rate, which can be used in the classification of oil spill and look-alikes based on morphological analysis. And the high-threshold segmentation result keeps the boundary of dark spots well, and hence it can best indicate the shape of the detected oil spill.

2.2. Oil spill classification based on SVM

Oil spills are caused by a variety of reasons. Hence, they have various morphological characteristics. For regions like Hong Kong and its vicinity, most observed oil slicks are small ones caused by deliberate discharges and illegal tank or engine washing operations. Based on previous researches (9, 10) and study for the data sample (27), two morphological characteristics that can best distinguish oil spill and look-alikes for the data-set were determined—complexity (C) and the ratio (R) between the length (in pixels) and width of the dark patches, which are the same as those of an ellipse that has the same normalized second central moments as the dark region. These characteristics will not change with rotation and scaling of the target region.

Complexity (C) can be calculated by:

\[ C = P^2/A \]  

where \( P \) stands for perimeter and \( A \) stands for area of the dark spot region. Since mineral hydrocarbons have larger tension force compared with seawater, a small amount of oil (common types) usually has more regular and smooth boundaries. Generally speaking, the higher the \( C \) of the dark spot, the lower the possibility of real oil spill.

The ratio \( R \) is calculated by the length (in pixels) and width of the ellipse that has the same normalized second central moments as the dark region, which describes the shape of the dark spot region. Most ships discharge waste oil while moving, so these oil slicks usually lie along their trajectory. Moreover, under the influence of wind field and current, oil spill will usually get stretched and bent. Hence, the shape of the oil spill is usually thinner (having lower \( R \)) compared with look-alikes. In other words, the higher the \( R \) of the dark spot, the lower the possibility of real oil spill.

In this paper, linear SVM is used as the classifier of oil spill and look-alikes. Linear separable samples can be expressed as \((x, y)\), where \( x \) stands for characteristics and \( y \in \{-1, 1\} \) is the class label of the sample. The hyperplane separating the two kinds of samples is \( w \cdot x + b = 0 \). Therefore, the classification function is:

\[ g(x) = w \cdot x + b \]  

where \( g(x) \) can be normalized to satisfy \( |g(x)| \geq 1 \) for all samples. Hence, the distance between the nearest point to the hyperplane is \( 1/|w| \). The objective of the learning phase of SVM is to find lines or curves that can maximize the geometrical margin between classes in the feature space, which is equivalent to maximize:

\[
\min_{s.t.} \frac{1}{||w||} \quad y_i(w \cdot x_i + b) \geq 1
\]  

As for this paper, morphological characteristics \( C \) and \( R \) are extracted from the dilated low-level segmentation result. Together with their relative categories, oil spill or look-alikes, features were used as the training input of the classifier. Then, the SVM is used to generate a model that will represent these training samples of different class as points in space. Using specific algorithms (22), parallel lines separating different class that has the largest gap are determined. Samples on the margin of the gap are called the support vectors. A centerline having the same distance to these two parallel lines is then obtained as the classification line. In the classification phase, characteristics of dark spots are mapped into the same feature space and predictions of oil spill or look-alikes are done based on which side of the line they would fall on.

2.3. Progress of the algorithm

The flowchart of traditional oil spill detection algorithm and dual-threshold algorithm used in this paper can be seen in Figure 1, respectively. In the experiment, SAR data were first processed using Basic Envisat SAR Toolbox (BEST, version 4.2.2) and Environment for Visualisation Images (ENVI, version 4.7) to generate backscatter images and extract the region of interest. Then, the images being studied were smoothed to reduce the interference of speckle noise. Two thresholds were used in the segmentation of dark spots.

Spatial density threshold segmentation was implemented on both high- and low-level segmentation results, respectively. It has been proved to be capable of reducing false alarm rate and enhancing the separability between dark spots and clean the sea background (9). Gauss kernel was used in intensity estimation. The intensity estimator \( g \) of a pixel \((x, y)\) in the SAR image was computed by the pixels around it:

\[ g(x, y, t) = \frac{1}{n^2 \pi t} \sum_{i=1}^{n^2} e^{-(x-x_i)^2+(y-y_i)^2/2t} \]  

where \( t \) is the deviation of the Gauss function and \( n \) stands for the size of the sample window.

For low-threshold result, a region dilation operation is implemented so as to connect the separated dark spots which may belong to the same oil film. Then, morphological parameters such as complexity \( C \) and width to length ratio \( R \) were extracted. Based on these parameters, dark spots were classified by the SVM built based on the training data acquired before. For high-threshold result, dark spots too small or too close to the seashore were excluded.
Finally the results were obtained by fusing the results of both the two levels of segmentations:

\[
C_{ij} = \begin{cases} 
1 & \text{if } C_{\text{low}}(ij) = 1 \text{ and } C_{\text{high}}(ij) = 1 \\
0 & \text{otherwise}
\end{cases}
\]  

(5)

where \(C_{\text{low}}\) and \(C_{\text{high}}\) stand for the result of the two levels, respectively, and \(C\) is the final detection result.

3. Experiments and results

At 10:13 am, 19 May 2010, the ground station of the Institute of Space and Earth Information Science, CUHK, detected oil slicks from the received ENVISAT ASAR image. The oil slicks were about 5 km from the coast, covering approximately 17 km². Oil films were lying along the main ship route, which was probably due to deliberate oil discharges from ships. Seventy-two hours later, oil spills were also detected in the SAR image received at 10:18 am, 22 May 2010 near Shangwei’s coast. Although, with evaporation and the joint effect of ocean currents and wind field, the shape and area of the oil slicks largely alternated, they were recognized as the same oil slicks detected three days before. The oil slicks had floated about 81 km during the three days. Both the drift velocity and direction were in accordance with the observed wind and current field data (6).

In this paper, the SAR image received on 19 May was first analyzed. Based on low-threshold segmentation, features extracted from oil spills were used to build an SVM. Then, dark patches were detected in the SAR image of 22 May which were automatically classified and the oil slicks were detected by a dual-threshold algorithm.

Figure 2(a) shows the VV polarization ENVISAT 1B Swath Width SAR image received on 19 May which covers the coastal area of Hong Kong and its vicinity. A series of long dark patches were detected 5 km to the south of Hong Kong Island. Based on artificial analysis concerning texture information and prior knowledge, such as the distance between the dark patch to the coastal line and ships, they were interpreted as oil slicks. For convenience, a smaller area containing oil spills (inside the block) was studied (Figure 2(b)).

The intensity image was firstly calibrated by BEST. Backscatter coefficient image was obtained through a series of processing including amplitude to power conversion and backscatter image generation. All the intensity values of pixels in the image were scaled to digital numbers [0, 255]. Then, a smooth operation was implemented to reduce the interference of speckle noise.

In the histogram analysis of typical oil slick and sea background it was found that the grayscale of most of the oil slick region was below 60 (Figure 3(a)), while that of most of the sea background was above 50 (Figure 3(b)). Therefore, the high and low thresholds for this data-set were set to 50 and 60, respectively.

Figure 4 shows the low-threshold segmentation result, in which pixels below 50 were regarded as probable dark spots, and given the Boolean value of 1. Others were regarded as background, and given the value of 0. Then, a Gauss kernel was used to carry out intensity estimation on the binary image. The window size of the Gauss kernel was 7 × 7 and the standard
deviation was 1. According to the experiments, the optimized intensity segmentation threshold was 0.4. Then, region growth was implemented on the segmentation result, with a disk of 9 pixels radius (Figure 5).

Based on human experiences and investigation reports, oil spills are distinguished from look-alikes artificially. The dilated dark spots indicating oil spills are classified as group 1 (Figure 6), others are classified as group 0. Morphological characteristics including C and R of all the dark spots were extracted, forming a two-dimension vector. Together with the group information, an SVM was constructed based on linear kernel. The

Figure 2. ENVISAT ASAR image received at 10:13 am, 19 May 2010, Hong Kong coastal region.

Figure 3. Histogram of unified grayscale value of different study areas.

Figure 4. Result of low-threshold segmentation.

Figure 5. Result of region growth.
feature space of the grouped training data-set was plotted, shown in Figure 7.

Figure 8 shows the VV polarization ENVISAT 1B Swath Width SAR image of Shanwei’s coast at 10:18 am, 21 May 2010. The oil slicks in this image were thinner in shape and separated into relatively small pieces. Dual-threshold oil spill detection algorithm was implemented on this image based on the constructed SVM. A series of operations were also conducted on the image: low-threshold segmentation result was obtained (Figure 9), intensity estimation based on Gauss kernel was implemented, and the dark spot region was dilated (Figure 10). Features of $C$ and $R$ were then extracted, forming a test data-set. Based on the SVM constructed before, the dilated dark spots were classified. The grouped vectors were plotted as shown in Figure 11. The dark spots in this SAR image, which are likely oil slicks, are shown in Figure 12.

High-threshold segmentation was then implemented; pixels whose unified grayscale was below 60 were regarded as probable dark spots, and given the value of 1, while others were regarded as background, and given the value of 0 (Figure 13). After intensity estimation, the extremely small dark spots or those too close to the seashore were excluded. Then, the result was fused with the

Figure 6. Dilated dark spots containing oil spills.

Figure 7. Feature space of the constructed SVM.

Figure 8. SAR images near Shanwei’s coast at 10:18 am, 21 May 2010.

Figure 9. Result of low-threshold segmentation.

Figure 10. Result of high-threshold segmentation.
classified dark regions obtained from low-threshold segmentation, forming the final detection result. The detection result was finally integrated with the original SAR image as shown in Figure 14.

The performance of SVM classification was also compared with characteristic possibility function (CPF) (27) and ANN-based methods. The CPF was built by assuming that the characteristics obey Gauss distribution and the threshold for classification was set experimentally. The feed-forward network used tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. It has a typical three-layer structure with eight hidden neurons, which is sufficient for this classification problem. In the experiment, the SVM-based method outperformed other methods in the limitation of both type I error (missing oil spill) and type II error (misclassifying look-alike as oil spill), and the results are listed Table 1.

4. Discussion and conclusions

In this paper, a new approach to automatically detect oil spill from SAR images has been presented. A dual-threshold segmentation was implemented on SAR backscatter images to extract information from different grayscale levels. In the classification phase, a linear SVM was firstly built according to the training data-set.
Table 1. Performance comparison between SVM-, CPF-, and ANN-based classification.

| Method | Type I error | Type II error | Training sample | Testing sample |
|--------|--------------|---------------|-----------------|----------------|
| SVM    | 1            | 3             | 36              | 28             |
| CPF    | 2            | 5             | 36              | 28             |
| ANN    | 1            | 4             | 36              | 28             |

Then, the constructed SVM was used to distinguish probable oil slicks and look-alikes based on morphological characteristics extracted from the dilated low-threshold segmentation result. Final detection result was obtained by fusing the classification result of both low-and high-threshold segmentations.

Experiments were carried out on two SAR images received in three days consecutively by the ground station of remote sensing satellite, CUHK. The first image received on 19 May was treated as training data sample. Oil spill and look-alikes were artificially classified and morphological features were extracted to build an SVM. The second image obtained three days later was used to examine the performance of the proposed algorithm. Experimental results illustrate that the new procedure is able to effectively detect oil spills, including small-size ones in coastal regions based on prior morphological characteristics. In the comparison with CPF-based method, the SVM method outperformed in both type I and type II errors. And in the comparison with ANN-based method, lower false alarm rate was obtained. This is because the SVM has better classification capability when training samples are insufficient. And if there are increased number of samples, the proposed method will require shorter training time compared with ANN-based method. Hence, the advantage of SVM in achieving optimum classification based on limited training samples was preliminarily proved. This technique can be used to trace spills in the consecutive days after an accident happens or to carry on maritime monitoring giving prior knowledge such as shape or texture information of the oil spills which are likely to occur in the target region. More SAR images after oil spills accidents will be studied in the future to further convince the accuracy and stability of this method, hoping it will help the alarming, clean-up and damage estimation of oil spill accidents.

Further study will focus on the optimization of the SVM. If there are more training samples, the parameters in the construction of the SVM such as slack variable and penalty parameter can be optimized by a cross-validation procedure. The performance of different kernel functions used in the SVM also needs to be studied based on a variety of data-sets. Besides, complimentary information such as wind speed obtained by spaceborne scatterometers can also be considered to enhance the stability of the algorithm.

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