Photogrammetrie • Fernerkundung • Geoinformation 5/2007, S. 327–336, 9 figs., 1 tab.

Fractal Algorithm for Oil Spill Detection from RADARSAT-1 SAR Data

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Keywords: Oil spill, look-alikes, RARARSAT-1 SAR, fractal algorithm

Summary: This paper introduces a new approach for modification of the formula of the fractal box counting dimension which is based on the utilization of the probability distribution formula in the fractal box count. The purpose of this method is to use it for the discrimination of oil spill areas from the surrounding features e. g., sea surface and look-alikes in RADARSAT-1 SAR data. The result shows that the new formula of the fractal box counting dimension is able to discriminate between oil spills and look-alike areas.

Zusammenfassung: *Ein fraktaler Algorithmus zur Detektion von Ölverschmutzungen aus RADARSAT-1 SAR Daten.* Dieses Papier stellt einen neuen Ansatz für die Modifikation der Formel der fraktalen ,,Box Counting" Dimension vor, der auf der Nutzung der Wahrscheinlichkeits-Verteilungs-Formel beim fraktalen ,,Box Count" basiert. Die Methode wird eingesetzt, um Flächen mit Ölverschmutzungen von umgebenden Objektarten, wie z. B. der Meeresoberfläche und ähnlich aussehenden Objekten in RADARSAT-1 SAR Daten zu unterscheiden. Das Ergebnis zeigt, dass die neue Formel für die fraktale ,,Box Counting" Dimension zwischen Ölverschmutzungen und ähnlich aussehenden Flächen unterscheiden kann.

1 Introduction

Synthetic aperture radar (SAR) has been recognized as a powerful tool for oil spill detection. Several algorithms have been introduced for the automatic detection of oil spills in SAR images. These algorithms have involved three steps: (i) dark spot detection, (ii) dark spot feature extraction, and (iii) dark spot classifications. Various classification algorithms for oil spill detection have been utilized, including pattern recognition algorithms (FUKUNAGA 1990), spatial frequency spectrum gradient (LOMBARDINI et al. 1989, TRIVERO et al. 1998) and fuzzy and neural networks techniques (MOHAMED et al. 1999, CALABRESI et al. 1999). However, oil spills detection over SAR images is not at all an easy task. Other physical phenomena can also generate dark patches and SAR images are affected by multiplicative noise known as speckle. In this context, dark patches not related to oil spill are known as look-alikes. They can be due to low wind speed areas, internal waves, biogenic films, grease ice, wind front areas, areas sheltered by land, rain cells, current shear zones, and up-welling zones (LOMBARDINI et al. 1989, TRIVERO et al. 1998, CALABRESI et al. 1999). However, the presence of a high number of oil spill look-alikes could be possible in SAR imagery with a low wind speed of less than 3 ms^{-1} (TRIVERO et al. 1998). Detection of oil spill look-alike features in SAR scenes can be obtained by power-to-mean ratio values which is used to adjust the threshold (SOLBERG & VOLDEN 1997, KANNA et al. 2003 and NIRCHIO et al. 2005).

A new approach has been introduced by MAGED (2001) to detect thin and linear slicks

1432-8364/07/2007/0327 $ 2.50

by using the Lee algorithm (Touzi 2002). Maged & van Genderen (2001) reported that the Lee algorithm operates well to determine linear slick features. Recently, Huang et al. (2005) explored the segmentation of oil slicks using a partial differential equation (PDE)-based level set method with ERS-2 SAR data. They concluded that the level set method allows an extraction of smooth and ideal boundaries rather than a number of zigzag edges. However, this method failed to distinguish between oil slicks and dark spot areas that were located close to the coastline due to low wind speed. In fact this method produced automatic snake contours around the presence of any dark spot areas in SAR imagery. Furthermore, Maged & van Genderen (2001) introduced a new approach by using texture algorithms for the automatic detection of oil spills in a RADARSAT-1 SAR image. However, computing the texture features from a co-occurrence matrix may become critical due to the multiplicative noise impacts (Tricot 1993). Different approaches to texture identification have been introduced that involve exploiting the fractal algorithm which can be estimated from a specific multi-resolution representation of the SAR images. The main question that can be raised is how the fractal algorithm can be used to discriminate between oil spills and look-alikes in RADARSAT-1 SAR data.

2 Fractal Analysis and SAR Data

According to Pentland (1984) and Redondo (1996) fractal geometry can be used on occasion to discriminate between different textures. A fractal refers to entities, especially sets of pixels, which display a degree of self-similarity at different scales. Self-similarity is the foundation for fractal analysis and is defined as a property of a curve or surface where each part is indistinguishable from the whole, or where the form of the curve or surface is invariant with respect to scales, meaning that the curve or surface is made of copies of itself at reduced scale and enlarged scales.

The most well known procedures that have been proposed for estimating the fractal dimension of SAR images are box counting, fractal Brownian motion (Falconer 1990, Gade & Redondo 1999 and Benelli & Garzelli 1999) and fractal interpolation function system dimension of images (Aiazzi et al. 2001). Initially, Falconer (1990) introduced the fractional Brownian motion model with SAR image intensity variation, which has shown promise in the SAR data textures. In fact, both the sea surface and its backscattered signal in the SAR data can be modeled as fractals (Wornell & Oppenheim 1992, Maragos & Sun 1993, Benelli & Garzelli 1999, Aiazzi et al. 2001). By contrast, Gade & Redondo (1999) found that a box counting fractal dimension model provided excellent discrimination between oil spills and look-alikes, although the backscatter information, which could allow a first robust localization of the oil spills, had not been considered. Furthermore, Benelli & Garzelli (1999) used a multi-resolution algorithm which was based on fractal geometry for texture analysis. They found that the sea surface is characterized by an approximately steady value of fractal dimension, while the oil spills have a different average fractal dimension compared to look-alikes.

This work has hypothesized that the dark spot areas (oil slick or look-alike pixels) and its surrounding backscattered environment-

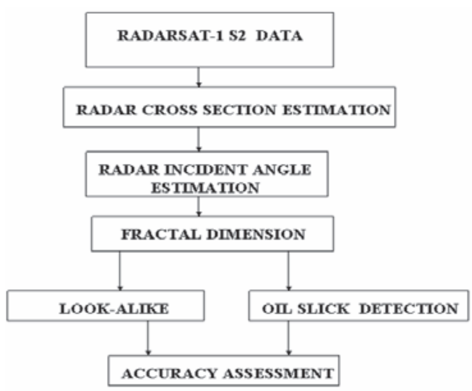

Fig. 1: Block diagram of fractal dimension algorithm.

al signals in the SAR data can be modeled as fractals. In this context, a box-counting fractal estimator can be used as a semiautomatic tool to discriminate between oil spills, look-alikes and surrounding sea surface waters. In addition, the utilization of a probability density formula in the box-counting equation can improve the accuracy of discrimination between oil slick pixels and surrounding feature pixels such as ocean surface and look-alikes. The procedures which have been used to discriminate oil spills from the surrounding sea surface environment are shown in Fig. 1.

3 Data Characteristics

The SAR data acquired in this study were from the RADARSAT-1 Standard 2 beam mode (S2) image. According to Hashim et al. (2006), an oil spill occurred on 20 December 1999 along the coastal water of the Malacca Straits. The RADARSAT-1 SAR is a C-band instrument with a variable acquisition swath, presenting a large variety of possible incidence angles, swath widths, and resolutions (RADARSAT INTERNATIONAL 2006). It is argued that oil slicks can be detected with a contrast as small as 4 dB (Kotova et al. 1998, Farahiday et al. 1998, and Lu et al. 2000). This suggests that a large part of the RADARSAT-1 swath could be useful for oil slick detection. Recently, Ivanov et al. (2002) reported that the RADARSAT-1 SAR, in its ScanSAR Narrow mode with swath width that exceeds 300 km, is an attractive tool for marine oil pollution detection. They showed that the entire ScanSAR image can be used for oil slick detection, at least for suitable wind conditions. The standard 2 beam mode is C-band and has a lower signal-to noise ratio due to its HH polarization with wavelength of 5.6 cm and frequency of 5.3 GHz. The RADARSAT-1 SAR standard 2 beam data has spatial resolution of 12.5 m $\times$ 12.5 m and the swath area of 110 km $\times$ 100 km. The incidence angle is between 23.7° and 31.0° (RADARSAT INTERNATIONAL 2006).

4 Methodology – Fractal Algorithm for the Oil Spill Identification

The oil slick detection tool uses fractal algorithms to detect the self-similar characteristics of RADARSAT-1 SAR image intensity variations. A box-counting algorithm introduced by Benelli & Garzelli (1999) was used in this study. The box counting algorithm was used to divide a convoluted line of slick (cf. Fig. 2), which was embedded in the image plane (i, j), into smaller boxes. This was done by dividing the initial length of the convoluted line at backscatter level β_s by the recurrence level of the iteration (Lu et al. 2000). We define a decreasing sequence of backscattering β_s tending from β_s, the largest value, to less than or equal to zero. The fractal dimension $D(\beta_s)$ as a function of the RADARSAT-1 SAR image backscattering amplitude β_s is given by:

$$D(\beta_s) = D_B = \lim_{s \to \infty} \frac{\log M(\beta_s)}{-\log(\beta_s)} \tag{1}$$

where, $M(\beta_s)$ denotes the number of boxes which are needed to cover the various slick areas with different backscatter intensity β_s in the RADARSAT-1 SAR image and the subscript s indicates the backscatter amplitude variation and its unit is dB. The number of boxes was calculated from the fractal dimension algorithm having side length l_s, and needed to cover a fractal profile, varies as β_s^{-D}, where D is the fractal dimension that is to be estimated. If the profile being sampled is a fractal object, then $M(\beta_s)$ should be proportional to β_s^{-D}, i. e., the following relation, which was adopted from Milan et al. (1993), should be satisfied:

$$M(\beta_s) = C\beta_s^{-D} \tag{2}$$

where C is a positive constant derived from a linear regression analysis between $\log M(\beta_s)$ and $\log(\beta_s)$. For different box sizes β_s, a number of points was produced in the log-log plane. The dimension $D(\beta_s)$ = DB can be estimated from a linear regression of these points (Milan et al. 1993).

In practice it is difficult to compute $D(\beta_s)$using equation (1) due to the discrete

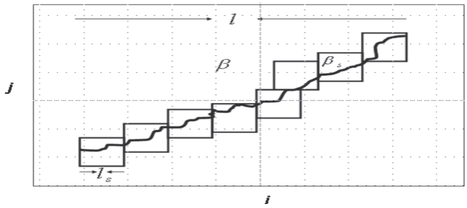

Fig. 2: Box counting technique for estimating fractal dimension from RADARSAT-1 SAR image.

RADARSAT-1 SAR images surfaces, and so approximations to this relationship are employed. First, the RADARSAT-1 SAR intensity image is treated as a two-dimensional matrix $(\beta \times \beta)$. This $\beta \times \beta$ intensity image matrix has been divided into overlapping or abutted windows of size $l_s \times l_s$. For each window, there is a column of accumulated boxes, each box with size of $l_s^2 \times l$. The backscatter values (β_0) are stored at each intersection of the column i and row j of the various slick areas. Then l is calculated by using the differential box counting proposed by Sarkar & Chaudhuri (1994)

$$\left[\frac{\beta_s}{l}\right] = \left[\frac{\beta}{l_s}\right] \tag{3}$$

Let the minimum and maximum (β_s) in the (i,j) window fall in boxes numbered n and m. The total number of boxes needed to cover the various slick pixels in the RADARSAT-1 SAR image with the box size $l_s^2 \times l$ is:

$$M(\beta_s) = \sum_{i,j}^{l} n(\beta_0) - m(\beta_s) + 1 \tag{4}$$

Let $P[M(\beta_s), l_s]$ be the probability of the total number of box $M(\beta_s)$ with box sizes l_s. This probability should be directly proportional to the number of boxes $\sum_{i,j}^{l} n(\beta_0) - m(\beta_s) + 1$ spanned on the (i,j) windows. By using equation (4) the expected number of boxes with size l_s which is needed to cover the slick pixels can be calculated using the following formula:

$$M(\beta_s) = \sum_{i,j} \frac{1}{n} P[M(\beta_s), l_s] \tag{5}$$

According to Fiscella et al. (2000), the probability distribution of the dark area belonging to slick pixels can be calculated using the formula below:

$$P[M(\beta_s)] = [1 + \Pi_n q_n(M(\beta_s))/p_n(M(\beta_s))] \tag{6}$$

Let $n = \sum_{i,j}^{l} n(\beta_0) - m(\beta_s) + 1$, q and p are the probability distribution functions for look-alike and oil spill pixel areas, respectively. From equations (5), (6) and (1) one can get a new formula for estimating the fractal dimension D_B

$$D(\beta_s) = D_B$$

$$= \lim_{s \to \infty} \frac{\log \sum_{i,j} n^{-1} [1 + \Pi_n q_n(M(\beta_s))/p_n(M(\beta_s))]}{-\log(\beta_s)} \tag{7}$$

In practice, the limit of M going to zero cannot be taken as it does not produce a texture image for oil spills or look-alikes in SAR data. Using fractal dimensions to quantize texture for segmentation, we may divide the slick's pixel areas into overlapping sub-images. Each sub-image is centered on the pixel of interest. We then estimate the fractal dimension $D(\beta_s)$ within each sub-image, and assign the fractal dimension value to the central pixel of each sub-image. This will produce a texture image that may be used as an additional feature in slick pixel classification.

5 Results and Discussion

The RADARSAT-1 SAR Standard 2 beam mode (S2) image has been selected for testing the proposed fractal algorithm. The RADARSAT-1 SAR image detail of Fig. 3 contains a confirmed oil-slick which occurred near the west coast of Peninsular Malaysia on 20 December 1999 (Hashim et al. 2006). Fig. 4 shows the variation of the average backscatter intensity along the azimuth di-

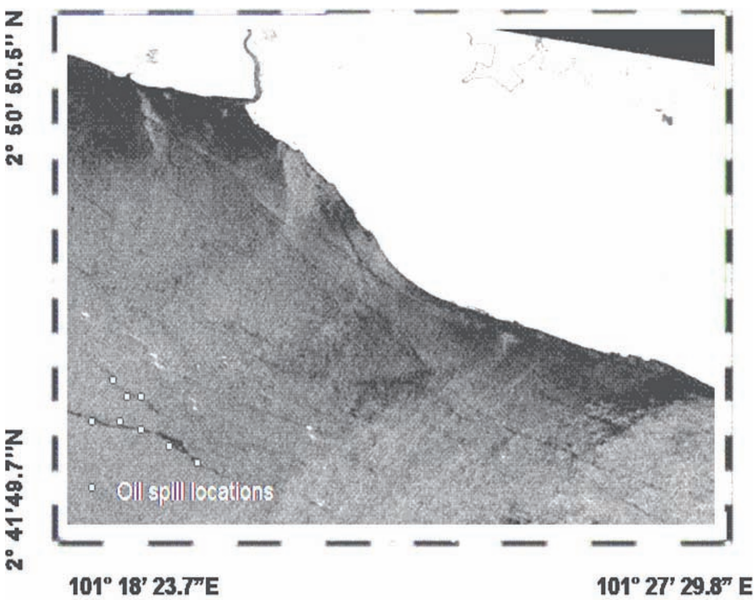

Fig. 3: Locations of oil slick are shown by small circles.

rection in the oil-covered area as function of incidence angle for RADARSAT-1 SAR. The backscattered intensity is damped by −10 dB to −18 dB, which is above the RADARSAT-1 noise floor value of nominally −20 dB. The RADARSAT-1 image covered an area located in between 101° 01′ 01.01″ E to 101° 17′ 11.5″ E and 2° 25′ 38.6″ N to 2° 34′ 23.5″ N. This result of backscatter variation across oil spill locations agrees with the study of MAGED & MAZLAN (2005).

The proposed method for estimation of the fractal dimension has been applied to the single look complex (SLC) RADAR-

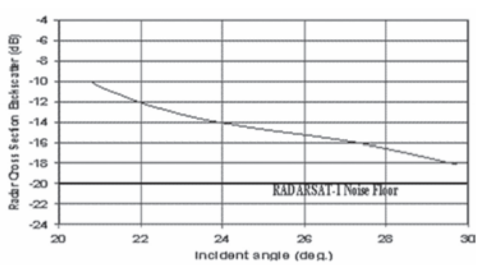

Fig. 4: Radar cross section backscatter along oil slick locations.

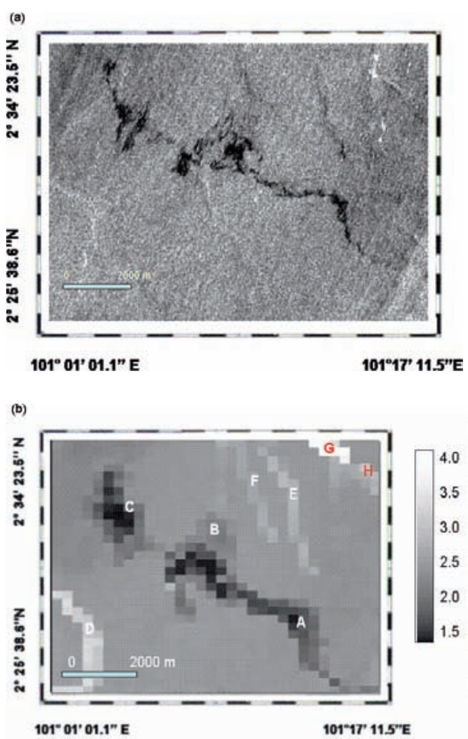

Fig. 5: (a) RADARSAT-1 SAR texture feature of oil spill and (b) fractal map.

SAT-1 SAR standard 2 beam (S2) data by using a 10 × 10 block at full resolution (cf. Fig. 5). Fig. 5b shows the resulting fractal map. The fractal dimension map shows good discrimination between different textures on the RADARSAT-1 SAR image. The resulting fractal dimension map appears to correlate well with image texture regions (cf. Figs. 5a & 5b). The oil slick pixels are dominated by lower fractal values than look-alikes and surrounding environment (cf. Fig. 5b). It is interesting to find that the region of oil slick has fractal values between 1.5 and 2.3 which might suggest the spreading of the oil spill. As well as the fractal dimension value increases, the oil spill becomes more thin which can be noticed in areas of (A to C). In fact, a thick oil spill dampens small scale waves and reduces the roughness of the sea surface compared to a thin oil spill, so that there is no Bragg resonance (Bern et al. 1993). In this context, the fractal dimension is a function of sea surface level intensities over the RADARSAT-1 SAR image which expresses the self similarity (Benelli & Garzelli 1999). The fractal dimension values of look-alikes are between 2.6 and 2.8 which can be seen in the areas F and E. The highest fractal dimension values of 3.4 and 4.0 in the areas D and G represents the occurrence of shear current flow and the presence of a ship, respectively (Tab. 1). It is interesting to discover that the fractal dimension algorithm based probability is able to extract ship wake information in area H with a value of 3.6. This suggests that the corresponding value of fractal dimension for different categories allows a multi-fractal characterization of the different features in a RADARSAT-1 SAR image. These results confirm the study of Maged & Mazlan (2005).

Tab. 1: Fractal dimension with different classes.

Areas	Fractal Dimension
Oil spill	
A	1.5
B	2.3
C	1.9
Shear current	
D	3.4
Look-alikes	
E	2.8
F	2.6
Ship	
G	4.0
H	3.6

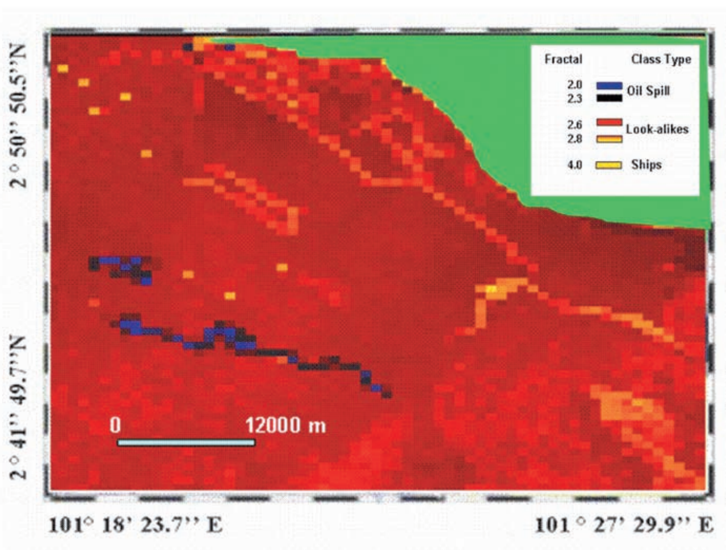

Fig. 6: Density Slicing map of fractal algorithm.

The density slicing of the fractal map for the large scale area of Fig. 3 shows that the low wind zone areas are observed close to the coastline with a fractal value of 2.6 (cf. Fig. 6). The look-alikes occupy narrow areas which are observed parallel to the coastline with a fractal value of 2.8. The wide distribution of dark zone pixels represents the natural slick in low wind areas (Henschel et al., 1997) which is aligned with what could be a current shear or convergence zone. This result confirms the output result of Fig. 5b. By contrast with natural slicks and low wind areas the oil slicks are located away from the coastline with fractal values between 2.0 and 2.3 which agrees with Fig. 5b. The density slicing map (cf. Fig. 6) confirms the result of oil spill spreading which was shown in Fig. 5b.

The comparison between oil slick fractal dimension curve and surrounding environment condition curves was extracted from density slicing map (cf. Fig. 6) is shown in Fig. 7. The maximum fractal value of 4.0 is observed for a group of ships with normalized backscatter value of 0.9. This suggests that the strong amplitude of variation in a RADARSAT-1 SAR image can be mapped as fractal discontinuities and small details are easily detected, *e.g.* ships. This result confirms the study of Maged & Mazlan (2005). Furthermore, it is apparent that the oil spill areas have a-symmetric curve with maximum fractal dimension peak value of 2.6 and normalized RADARSAT-1 SAR backscatter value of 0.03 (cf. Fig. 7). It is also found that the sea surface is dominated by a wide steady peak of fractal dimension (cf. Fig. 7), which is 2.7, while the oil spill has substantially different values of fractal dimension, which range between 1.9 and 2.6 (cf. Fig. 7). In fact, the sea surface is considered as a non-fractal object. According to Falconer (1990), the slope measure of non-fractal objects corresponds to the complexity of the objects, with the natural implication that the sea surface would have a steady value (cf. Fig. 7). By contrast, the look-alike tends to have a normal distribution curve with fractal dimension peak of 2.8 and the normalized backscatter is between 0.15 and 0.55; this is distinguishable from the oil slick and the surrounding rough sea (cf. Fig. 7). There appears to be a reduction in the maximum fractal dimension of the oil slick compared to that of the look-alike. This could be due to the short spatial extent of the oil spill. It can also be seen that there is quite large overlap of the oil-spill curve and the see-roughness curve (cf. Fig. 7). This could be attributed to high surface wind speed which induced sea surface roughness in the RADARSAT-1 SAR image along the surrounding area of the oil slicks and look-alike areas. This made large overlap between the fractal results for oil spills and the surrounding sea surface (Bertacca et al. 2005). Nevertheless, the receiver-operator-characteristics (ROC) Curve in Fig. 8 indicates significant difference in the discrimination between oil spill and sea surface roughness pixels. In terms of ROC area, this evidence is shown by area difference of 0.25 and p value less than 0.005

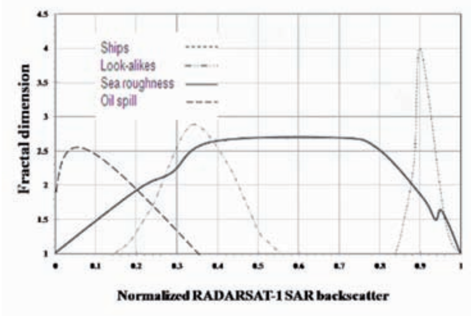

Fig. 7: Fractal dimension curve for different features.

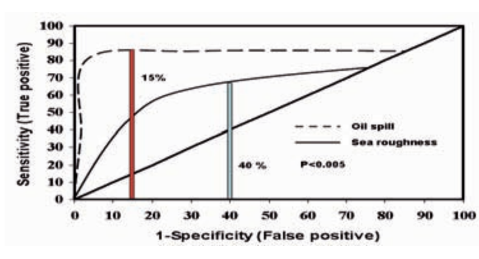

Fig. 8: Receiver-Operator-Characteristics (ROC) Curve for oil spill and sea roughness.

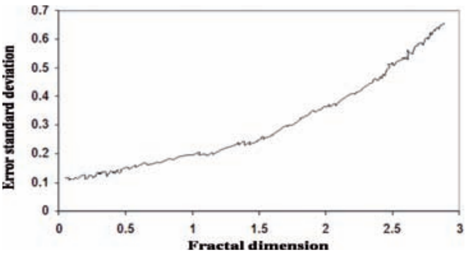

Fig. 9: Accuracy assessment of fractal dimension performance.

which confirms the study of HANLEY & NCNEIL (1983).

Fig. 9 shows an exponential relationship between fractal dimension and standard deviation of the estimation error for fractal dimension. The maximum error standard deviation is 0.68 which corresponds to the fractal dimension value of 2.9. This could be attributed to the fact that the fractal dimension can be viewed as a measure of the scale of the self-similarity of the object. In a statistical fractal set, the interference looks statistically similar if the scale is reduced, which is similar to the result of BERTACCA et al. (2005). This suggests that fractal analysis is a good method to discriminate regions of oil slick from surrounding water features. The use of fractal dimension based on the probability distribution function (PDF) improves the discrimination between oil spill, look-alikes, sea roughness and low wind zones. In fact, involving the PDF formula in the fractal dimension map directly relates the textures at different scales to fractal dimensions. In addition, this modification of the fractal equation reduces the problems of speckle and sea clutter and assists in the accurate classification of different textures over SAR images.

6 Conclusions

The utilization of RADARSAT-1 SAR imagery for oil slick detection has been implemented by using a fractal dimension algorithm as an automatic tool to discriminate between an oil slick and other surface features such as slick look-alikes and variability of surface roughness. The oil spill has characteristic values of fractal dimension, which ranged between 1.5 and 2.6. The sea surface roughness has a steady value of fractal dimension which is 2.7. In terms of ROC area, there is evidence to conclude that oil spill and sea surface roughness are perfectly discriminated. The interesting result is that the low wind area was characterised by the highest value of fractal dimension which is 2.9. It can be said that the new approach of the fractal box counting dimension algorithm can be used as an automatic tool for oil spill, and look-alike detections.

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Manuskript eingereicht: Mai 2007
Angenommen: Juni 2007