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Operational Texture Algorithms for Oil Spill Detection from RADARSAT Data

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Abstract: This paper presents work done to utilize texture algorithms in oil spill detection. Detection of oil spill from RADARSAT image using texture statistics derived from the conditional joint probability density functions of the grey level co-occurrence matrix. Texture algorithms are implemented to RADARSAT image without performing any type of filter. Texture algorithms are applied with window size of 7 × 7.

This study shows that, out put results are varied between a different algorithms. Contrast created a poorly image structure for oil spill detection. The entropy, energy and homogeneity perform good detection of oil spill compared to correlation and contrast algorithms. The combination of entropy, energy and homogeneity provided good improvement for oil spill detection. It can be concluded that texture algorithms such as entropy, energy and homogeneity could be used as automatic tool for oil spill detection.

Zusammenfassung: *Nutzung von Textur-Algorithmen für die Erkennung von Ölverschmutzungen mittels RADARSAT-Daten.* Diese Veröffentlichung präsentiert die Ergebnisse einer Forschungsarbeit über die Nutzung von Textur-Algorithmen für die Erkennung von Ölverschmutzungen. Die Erkennung von Ölverschmutzungen in Radarsat-Bildern mit Hilfe von Textur-Statistiken wurde von bedingten Wahrscheinlichkeitsdichtefunktionen, basierend auf einer Grauwert co-occurrence Matrix, abgeleitet. Die Textur-Algorithmen wurden ohne vorherige Filtervorgänge auf Radarbilder angewendet. Sie wurden mit Fenstergrößen von 7 × 7 eingesetzt.

Diese Studie zeigt, dass die Ergebnisse von verschiedenen Algorithmen unterschiedlich sind. Kontrast schafft minderwertige Bildstrukturen für Ölverschmutzungserkennungen. Entropie, Energie und Homogenität eignen sich sehr gut für diese Anwendung, verglichen mit Korrelation oder Kontrastalgorithmen. Eine Kombination von Entropie, Energie und Homogenität stellte eine Verbesserung für die Ölverschmutzungserkennung dar. Als Schlussfolgerung kann man sagen, dass Textur-Algorithmen wie Entropie, Energie und Homogenität als automatisierte Methode für die Erkennung von Ölverschmutzungen genutzt werden können.

Introduction

Synthetic aperture radar (SAR) images exhibit many interesting peculiarities, such as independence of meteorological conditions and possibility of evaluating dielectric and geometric properties of surface. Nevertheless, they are characterized by considerable speckle noise, which causes a granular aspect, even in homogenous areas. According to ULABY et al. (1986) different kinds of image objects can be investigated by using statistical classification approach. The statistical classification approach is represented in texture analysis. Texture analysis play vital role in radar data processing. According to LARRY et al. (1979) texture feature can be crucial for the segmentation of an image and can serve as the basis for classifying image parts. The radar image contains microtextures and macrotextures. Microtextures are represented only several pixels, while macrotextures are represented large pixel areas. The discrimination between both textures is

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function of spatial statistical variation. The spatial statistical variation will be function of pixel intensity. This approach has been documented by HARALICK et al. (1973). They proposed the spatial co-occurrence procedure in the derivation of textural features which characterize spatial variability in digital imagery. They assumed that the texture information on an image is contained the overall or average spatial relationship which the gray tones in the image have to one another. Those relationships are computed for four directions between neighboring image pixels within a specified window on the image.

SAR image intensity is created by point measurements of the backscattering coefficient. Backscattering coefficient is function of size interrelationships between the radar wavelength and the scattering points within a single pixel footprint. The image intensity described by variation of backscattering coefficient. Backscattering variation in radar image will create random variability in grey level over the spatial resolution. According to DAVID & LEDREW (1991) texture refers to spatial variation of backscattering.

Oil dampens the small waves (on the order of 3 cm) that provide radar reflection from the ocean surface. This causes dark blotches on the radar image compared to the surrounding pixels characteristics (WAHL 1993, WESITEEN et al. 1993, MICHAEL et al. 1997). According to ANNE et al. (1991) and BEENELLI & GARZELLI (1999) the presence of oil on water causes clutter suppression over the area of the spill, resulting in attenuation of the Bragg scale waves and reduced signal return to the sensor. On the image an oil spill will have a darker tone than the surrounding water. Wind shadows near land, regions of low wind speed, natural surfactants and grease ice can be mistaken for oil spills and ancillary or multi-temporal information is needed to discriminate the oil spill from other phenomena (HOVLAND et al. 1994).

It may be the variation of the gray level with oil spill pixels can be discriminated easily by applying texture analysis. The most commonly oil spill detection algorithms are based image classification such as maximum likelihood and fuzzy classification techniques (ANNE et al. 1999 and MOHD et al. 1999). These algorithms operate on per pixel basis only without taking into account the surrounding pixels. Texture analysis detect the gray level variation per pixels which are related to neighboring pixels. This will be useful to discriminate between oil spill areas from surrounding sea water. This because of the different texture features in image represented by a set of statistics for the occurrences of each grey level at different pixels and along different direction (HARALICK 1979).

This study will focus on the following two approaches: (i) that texture analysis can be discriminated oil spill area from the surrounding area. Texture analysis could be used to map the location of oil spill on the coastal water; and (ii) that the integration between texture analysis could be used as automatic tool for oil spill detection.

The main objective of this study is to examine texture analysis model in detection of oil spill. Several texture algorithms will be used to identify the suitable texture model for oil spill detection.

Methodology

RADARSAT Image

The RADARSAT data were acquired at 26 October 1997. This RADARSAT fine mode with Cvv band which covered the Malacca Straits between 102°16′ E to 103°48′ E and

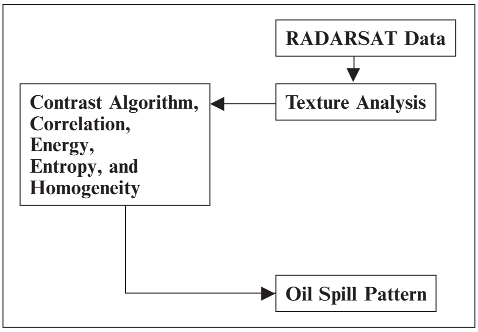

Fig. 1: Flowchart of Texture Algorithms for Oil Spill Detection.

1°16′N to 2°13′N. The processing of the RADARSAT fine mode image is shown in Fig. 1.

According to Mohd et al. (1999) oil spills occurred on 26 October 1997 due to collision between two ships, i. e. MT Orapin Global and MV Evoikos in Singapore. Mohd et al. (1999) reported that this collision caused 25 000 tones of crude oil to be spilled into the sea.

Oil Spill Detection by Textures Analysis

The main content of the present module is based on the co-occurrence matrices as one of the best approaches to texture analysis. The coherent nature of SAR can be determined from the variation of image intensity from pixel to pixel. This can be described by the fading statistics and can be represented as a fading random variable. The spatial variation in image intensity of every pixel that constitutes a target gives rise to intrinsic scene texture. This texture can be described in texture random variable. The texture methods are represented in the first order statistics of the fading and the texture random variables described their probability density functions (pdf). The second order fading and texture statistics describe the relationships between a pixel and its neighbors (Ulaby et al. 1986).

The measurement of textures is based on Haralick's (1979) method, which emphasized the use of statistics derived from a co-occurrence matrix. The aim of this method is to characterize the stochastic properties of the spatial distribution of gray level in an image. Furthermore, the co-occurrence matrix depends not only on the spatial relationships of gray level but also on regional intensity background variation within the image. Texture analysis can be based on criteria derived from these co-occurrence matrices. These criteria are energy, contrast, and correlation. Energy is an angular second moment i.e. an image homogenates which measure the more homogenous in image, contrast is a measure of local image variation and correlation is a measure of image linearity; linear directional structures result in large correlation values in this direction (Milan et al. 1993).

Texture analysis was calculated a specified texture measure for each pixel using gray level co-occurrence matrices. The output image might be used as one of several input features to the classification process. Texture analysis was done which no pre-filtering performed since these filtering programs average out a lot of the textural character of the image (Haralick 1979).

The texture of an image is related to texture statistics such as homogeneity, contrast, and entropy. These different statistics of texture are selected in order to get more feature information. The texture analysis depends on window size. In this study the window, size was 7×7 pixels and lines. According to Haralick (1979), Soren & Curtis (1996) the window size of 7×7 gives more details on an image. As the window, size is used for producing the co-occurrence matrix for each input pixel. Spatial parameter is specified the relationship for a pixel to its neighbor to define the direction and distance for texture analysis. The spatial relationship is considered for pixel and its neighbor. In this study, 0 and 1 selected the spatial that mean the texture algorithm considered the relationship between each pixel and one below it.

Texture features were computed by the following equations.

(i) Contrast:

$$\mathrm{Con} = \sum_i \sum_j (i-j)^2 p_{ij} \tag{1}$$

(ii) Entropy:

$$\mathrm{Ent} = \sum_i \sum_j p_{ij} \log p_{ij} \tag{2}$$

(iii) Energy:

$$\mathrm{Eng} = \sum_i \sum_j (p_{ij})^2 \tag{3}$$

(iv) Homogeneity:

$$\mathrm{Hom} = \sum_i \sum_j p_{ij} / \{1 + (i-j)\}^2 \tag{4}$$

(v) Correlation:

$$\text{Cor} = \{\sum_i \sum_j (ij)p_{ij} - \mu_x \mu_y\} \qquad (5)$$

where i and j are the pixels and lines in SAR image and P_{ij} is the marginal probability of gray-level co-occurrence matrix in the direction of the pixels and lines are the means and standard deviations of marginal probability through pixels and lines (ARAI 1991).

Result and Discussion

Fig. 2 shows that the raw data of RADARSAT with heavy oil pollution which represented with dark spots. These dark spots cover area with approximately 300 km along the coastal waters of Malacca Straits. Fig. 2b shows that the results of the RADARSAT image of texture analysis after averaging filter had performed. It is obvious that the output image was lost its spatial information. According to MAGED et al. (1996) the filters average out a lot of texture in an image. The out put result was destructive image (Fig. 2b).

Fig. 3 shows the texture analysis results without employing any filter. Fig. 3 shows the result of contrast texture analysis. It is obvious that the large area of oil spill is detected compared to smallest area. This result is poor compared to the raw data. The dark spots of oil spills are obvious clearly in raw data compared to contrast result. According to CONNERS & HARLOW (1980) contrast measures the amount of local variation in the image. It is high when the local region has a high contrast in the scale of spatial. It is obvious that contrast is function with large size of oil spill (Fig. 3). This is because of the fact that contrast reflects both the coarseness of the texture and the contrast of edge. This explains why large size of oil

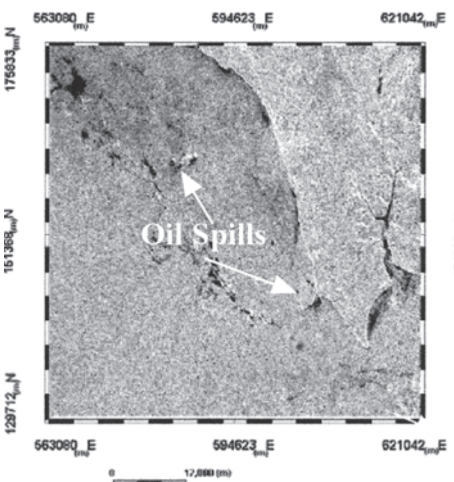

Fig. 3: Result of Contrast Analysis.

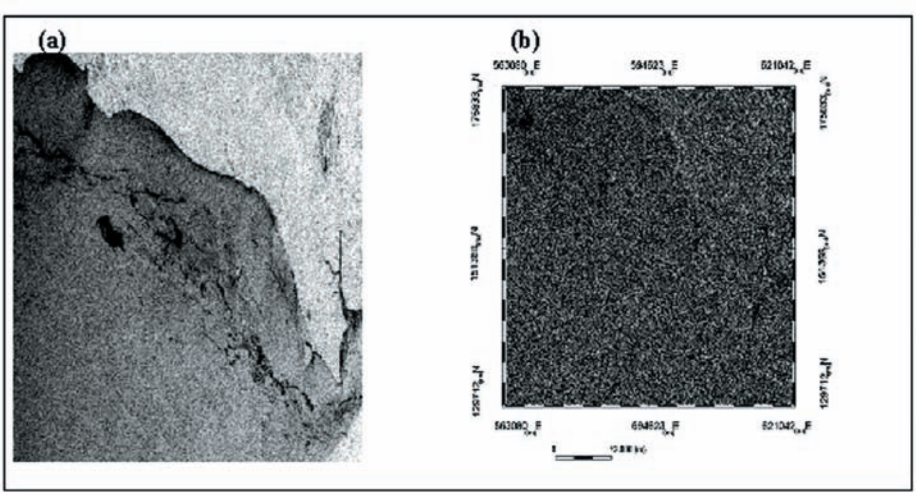

Fig. 2: (a) RADARSAT Raw Data and (b) Average Filter before Texture Analysis.

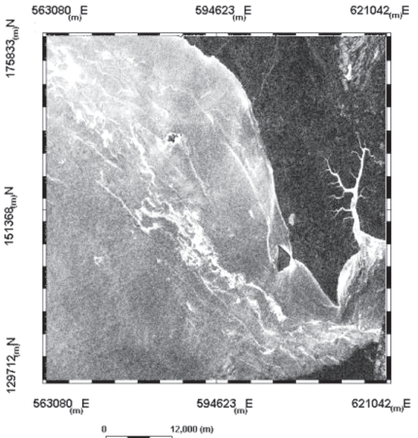

Fig. 4: Result of Correlation Analysis.

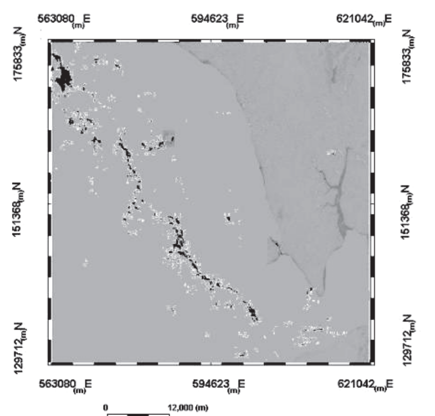

Fig. 6: Result of Energy Analysis.

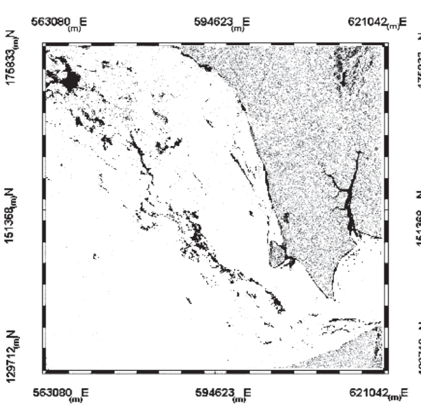

Fig. 5: Result of Entropy Analysis.

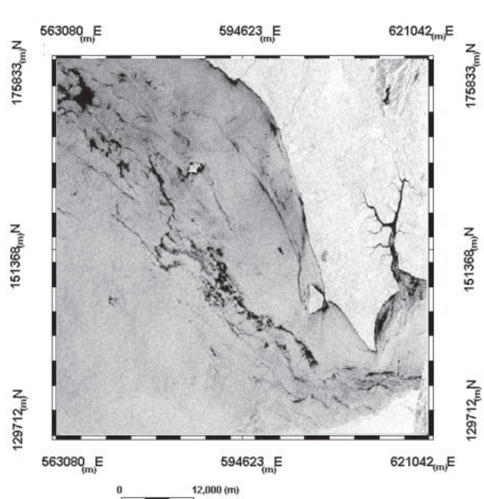

Fig. 7: Result of Homogeneity Analysis.

spills are detected in contrast image with sharp shoreline edge.

It is obvious that the correlation image signed the area of dark spots wit bright signatures (Fig. 4). This is because of fact that correlation measures the linear dependency of gray levels of neighbouring pixels. According to HARALICK (1979) when the scale of local texture is much larger than the distance of spatial, correlation is typically high. When the local texture has a scale similar to or smaller than spatial, there will be low correlation between pairs of pixels.

It is obvious that entropy, energy and homogeneity can distinguish between oil spill areas surrounding area compared to contrast and correlation (Figs. 5, 6 and 7). This is because of the fact that energy is measured the non-uniformity in the image. This could be used to distinguish between low backscattered value of oil spills and surrounding pixels area. Entropy used to separate be-

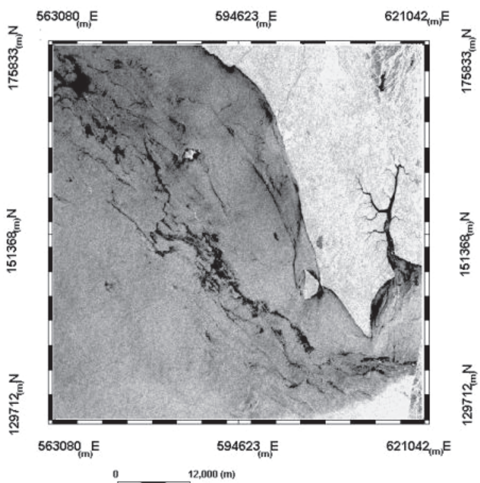

Fig. 8: Combination of Entropy, Energy and Homogeneity Algorithms.

tween oil spills layers and water and land. This could be attributed to that entropy is a measure of uniformity in the image.

In general, the entropy provided a grater improvement than correlation and contrast. The integration between entropy , homogeneity and energy provided a grater improvement than either the entropy or energy separately. The greatest improvement was achieved with the combination of the three algorithms (Fig. 8).

Fig. 9 shows that the percentage of oil spill detection is increased with combination of entropy, energy, homogeneity. This is because of the fact that energy is a measure of homogeneity. In relatively low gray level on oil spill areas, there will be low backscatter changes and hence, there will be large entries in the matrix off the diagonal. The energy value will be closed to its minimum in oil spill areas.

Entropy is a measure of variability or randomness because the concentration of backscatter changes in relatively few locations would be nonrandom essentially, the entropy measure will be low. It notice that these features measure the same characteristic texture and they are interpreted differently. Entropy measures the absolute variability in backscatter change over the selected window.

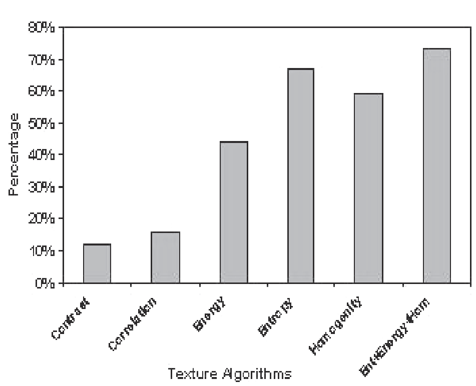

Fig. 9: Percentage Accuracy of Texture Algorithms for Oil Spill Detection.

Conclusions

It can be concluded that texture algorithms such as entropy, homogeneity, energy are good for automatic detection of oil spill. It is preferred to work with texture algorithms prior to any filtering operation. The integration between the entropy, homogeneity and energy provided a greatest improvement for oil spill detection. The contrast and correlation algorithms are not suitable for oil spill detection. Both algorithms can be work with large or surrounding oil spill area.

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