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ALGORITHMS USED FOR OIL SPILL MONITORING AND DETECTION USING SATELLITE IMAGES

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ABSTRACT- *Coastal zones are the most inhabited area of the world and it is affected by humans and natural disaster. In order to evaluate these changes an effective monitoring system for ocean zone must be place. In this research, comparing of algorithms take place which results in less time consuming, oil spill tracking, oil spill area, dark patches and spill patterns. It helps in regular monitoring and detection of oil spill in the sea. This approach helps to find out which algorithm is best suited for detection of oil spill with low time complexity. This work is carried out using ASAR RADARSAT-2 image, which is capture from Gulf of Mexico region. In conclusion, morphological closing techniques can be used as a good tool for monitoring and identifying the occurrence of oil spill.*

KEY WORDS- *Oil spill, Gulf of Mexico, pattern, tracking, ASAR RADARSAT-2.*

1. INTRODUCTION

Oil spill is one of the most important problem occurs in the world which become one of the biggest issue in marine life. So regular monitoring is important, which helps to solve problems based on oil spill. Extraction of oil from ocean is a fundamental work done for agencies to regular monitoring the sea. In this scenario satellite image play an important role for data acquisition. In ever year oil spill accident take place in history it was on the Gulf of Mexico in Deepwater Horizon on April, 20, 2010, with explosion in July 15, 2010. It effected on wildlife habitats and maritime spices. To overcome this problem radar image was used for regular monitoring which improves over all oil spill problems by various approaches. To survey oil spill SAR image provide various advantage for detection and tracking of oil spills. Several satellite SAR sensors are involved in the oil spill detection and survey. These data are from ERS-1/2, (Brekke and Solberg 2005) ENVISAT (Marghany 2013), ALOS, (Zhang et al. 2011, 2012), RADARSAT-1/2, (Zhang et al. 2012) and Terra SAR-X (Velotto et al. 2011) which have been globally used to identify and monitor the oil-spill. Recently, the multi polarimetric SAR high-resolution data have become a vital research area for oil spill detection (Skrunes et al. 2012; Shirvany et al. 2012). Topouzelis et al. (2007) has used neural networks in finding both oil-spill and dark patches detection. Experimental results shows, 89 % accuracy and 94 % dark patches segmentation but certain disadvantages like they cannot efficiently detect small and fresh spills. Skrunes et al. (2012), reports that there are several disadvantages associated with SAR sensors based oil spill detection. So they suggested using multi-polarization acquisition data, such as Terra SAR-X satellites and RADARSAT-2. Oil spill detection and monitoring using SAR technology, data are scarce job, because of barely discrimination between oil spill and other features of look-alike ,shadows, wind speed that appear patches in SAR data as Dark patches (Topouzelis 2008). The problems faced in oil spill automatic using SAR data, is achievements in past decades. Simultaneously, Frate et al. (2000) proposed semi-automatic oil spill detection by using neural network, in which a vector defining features of an oil-spill is used. Topouzelis et al. (2007, 2009) and Marghany, Hashim (2011) confirmed that neural network technique could give precise difference among look-alike and oil- spill in SAR data.

2. DATA ACQUIRED

RADARSAT-2 SAR data acquired by RADARSAT-2 operating with Scan SAR Narrow single mode beam on 27th April, 2010; 1st May 2010; and 3rdMay, 2010 are investigated for detection of oil spill in the Gulf of Mexico. The satellite armed with Synthetic Aperture Radar (SAR) with multiple modes of polarization, which includes fully polar metric mode of operation in which HH, VV and VH polarized data's were acquired (Maurizio et al. 2012). It has got highest resolution of 1 m in Spotlight beam mode (Ultra Fine mode of 3 m) with 100 m of positional accuracy. In the Scan SAR Wide Beam mode (WBM), the SAR has nominal width of 500 km and 100 m imaging resolution.

Sl. No	Beam mode	Place	Date	Nominal pixel spacing(m)	Resolution (m)	Incident angle	Polarization
1.	ENVISAT ASAR	Gulf Of Mexico	27 April 2010	25 x 25	79.9-37.7 x 60	20-55	HH
2.	ENVISAT ASAR	Gulf Of Mexico	1 May 2010	25 x 25	79.9-37.7 x 60	20-46	HH
3.	ENVISAT ASAR	Gulf Of Mexico	3 May 2010	25 x 25	79.9-37.7 x 60	25-50	HH

Table1. ENVISAT ASAR IMAGE

Figure1. Input images

3. MATERIAL AND METHODOLOGY

Here Different methodology is applied during each phases they are Processes of dark spot detection, oil spill/slick/look-alike and feature extraction classification.

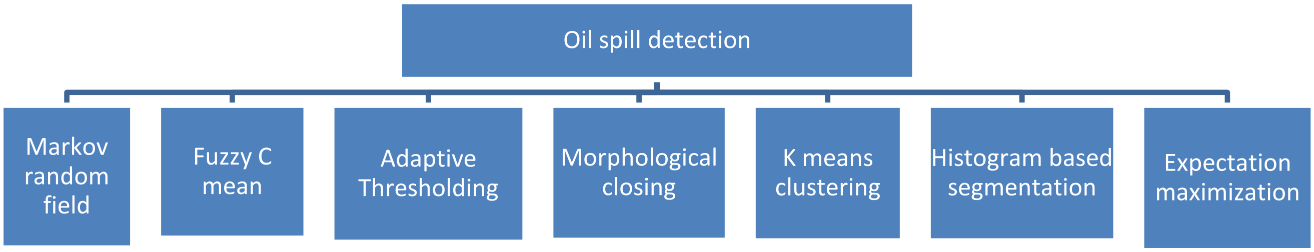


Figure2. Methodology

3.1 Markov random field

Markov random field technique provides mutual influences in given data, which helps to provide more clear detection on oil spills in images with objective function modification. With the help of modification process it helps in reducing speckle noise effect in radar images. It works together with membership function using neighborhood pixels. Steps are as follows- (1) initially two satellite image has to be taken, consider as $P_1 = \{P_1(I,h), 1 \leq I \leq M,\ 1 \leq h \leq N\}$ and $\{P_2(I,h), 1 \leq I \leq M,\ 1 \leq h \leq N\}$, where M x N. (2) in second step generate logarithmic and mean operator to cover over all area taken for monitoring it is denoted with $l = \frac{k_1}{f_1}$, $\quad mean = 1 - \min(\frac{k_1}{f_1}, \frac{k_2}{f_2})$, Where as, , f_1 &f_2, k_1 &k_2 are logarithmic and mean values. Here Mean produces difference images using information of pixels. Log value used to find out intensity for images and it covers larger area. Let us considered iteration x =1 with standard deviation σ_r^1 *and* mean μ_r^1 values. Now find out energy function E_{pq}^x with iteration 'x'. Now apply Gibbs expression, to find out prior probability (π_{pq}^c)

$$\pi_{pq}^c = \frac{\exp(-\mathrm{E}_{\mathrm{pq}}^{\mathrm{x}})}{\exp(-\mathrm{E}_{\mathrm{pq}}^{\mathrm{x}}) + \exp(-\mathrm{E}_{\mathrm{pq}}^{\mathrm{x}})}$$

Now (p_r^c) determine conditional probability then generate the distance matrix (d_{pq}^c) for the given input image.

$$p_r^c\left(\frac{y_j}{\mu_r^c, \sigma_r^c}\right) = \frac{1}{\sigma_r^c\sqrt{2\pi}} exp\left[-\frac{y_{j\,-}\,\pi_r^{c\,2}}{2(\sigma_r^c)^2}\right]$$

$$d_{pq}^c = -1n\left[p_r^c\left(\frac{y_j}{\mu_r^c, \sigma_r^c}\right)\right]$$

Now compute objective function- $d_{pq}^c = -1n\left[p_r^c\left(\frac{y_j}{\mu_r^c,\sigma_r^c}\right)\right]$,

$$\left|J_{pq}^c - J_{pq}^{c-1}\right| \leq \delta$$

Now determine Membership matrix $\{\mu_{pq}^{c+1}\}$

$$\mu_{pq}^{c+1} = \frac{\pi_{pq}^c \exp(-d_{pq}^c)}{\pi_{pq}^c \exp(-d_{pq}^c) + \pi_{pq}^c \exp(-d_{pq}^c)}$$

Update deviation and mean values σ_r^{c+1} and μ_r^{c+1} respectively, $c=c+1$

$$\mu_r^{c+1} = \frac{\sum_x(\mu_{pq}^c\, y_j)}{\sum_x(\mu_{pq}^c)}$$

$$\sigma_r^{c+1} = \sqrt{\frac{\sum_x\left[u_{pq}^c\ (y_j - \mu_r^{c+1})^2\right]}{\sum_x(u_{pq}^c)}}$$

3.2 Fuzzy c-Mean:

It is a clustering technique, which allows one object belongs to two or more object in clusters form. Similarly object or data will be placed in one place and other place. This method improves frequently using pattern recognition.
Minimization object function

$$J_x=\sum_{p=1}^{M}\sum_{q=1}^{b} u_{pq}^{n} \,||\, x_p - c_q||^2 \quad , 1\leq n<\infty$$

Whereas m, belongs to real number which is greater than 1, $u_{pq}$is a degree of membership, p is a dimensional measured data, $C_q$is a cluster center. || * || it denotes similarity between center and measured data.
In fuzzy c- mean clustering, with the help of iterative optimization objective function, fuzzy partitioning can be done, using update membership u_{pq} and center of cluster c_p.

$$u_{pq}=\frac{1}{\sum_{i=1}^{b}\left(\frac{||x_p-c_q||}{||x_p-c_i||}\right)^{\frac{2}{n-1}}} \qquad , c_{pq}=\frac{\sum_{p=1}^{M} u_{pq}^{n} x_p}{\sum_{q=1}^{M} u_{pq}^{n}}$$

Iteration stops when $max_{pq}\left[\!\left[u_{pq}^{(i+1)} - u_{pq}^{(i)}\right]\!\right]<$ Es

E denotes terminal point between 0 and 1 for k^th iteration; it also covers local minimum pointJ_x.

Following steps are

1. First initialize process U so it denoted as $[u_{pq}]$matrix, $u^{[0]}$
2. Now calculate center of vectors $c^{(i)}=[c_q]$ with $u^{(i)}$, $c_{pq}=\frac{\sum_{p=1}^{M} u_{pq}^{n} x_p}{\sum_{q=1}^{M} u_{pq}^{n}}$
3. Update the process by using $u^{(i)}$, $u^{(i+1)}$

Therefore $U_{pq}=\frac{1}{\sum_{i=1}^{b}\left(\frac{||x_p-c_q||}{||x_p-c_i||}\right)^{\frac{2}{n-1}}}$

If $\left[\!\left[u_{pq}^{(i+1)} - u_{pq}^{(i)}\right]\!\right]<$ E then stop the process for further operation otherwise return to step 2.

3.3 Adaptive Threshold

It helps to determine dark patches, bands and pattern for the given data set. Adaptive is important because radar contrast depends on condition of weather for detection of dark spot, look alike and surrounding water, which may change in investigation. In image threshold levels depends on angle incidence even in constant conditions in image. According to pre-determined rule threshold level should change. In mask operation mapping from one pixel to a new one's process take place, pixel modifies according to equation and are not dependent on neighborhood.

f(p,q)=F[g(p,q)], Where 'F' is input and output image with one to one mapping.

f(p,q)=(p+1,q),(p-1,q),(p,q+1),(p,q-1)

Adaptive help to produce segments with similar intensities, to determine boundaries and shape for the given images. It produces gray scale value with global and local image information.

$$\sigma_q^2 = n_1\,(\mu_1-\mu_2)^2 + n_2\,(\mu_1-\mu_2)^2$$

If denotes variance for the threshold silk smooth extracted using

(R)= $1-\frac{1}{(1-\sigma^2)}$, with standard deviation.

3.4 Morphological operation

Morphological operation is based on the structure analysis, in which some components are selected among all, which satisfy Gestalt principles such as (1) Proximity state that two objects are easier regard as a single object by a human being if those objects are close to each other. (2) Good continuation states that objects are easier regard as a single object if they can be continued from one to other. According to these principles criteria have been developed. If both analyzed components are lines then first group of criteria is applied. Based on this criteria proximity is state as minimum of Euclidean distances between starting and ending points of these lines and the excellent continuation is determined by checking orientation difference. If both objects are not lines then second group of criteria is applied. Relation of lines to non-lines then third group of criteria is applied. The analysis is done by two routines: In-level routine and inter level routine.

In-level routine: It Analyzes level N = {3, 2, 1} component to gain oil slick structure. Structure is consist element that satisfy proximity criteria and good continuation criteria. The oil slick structure is selected from each component of level N that calls the inter-level routine to group or cluster it with the structures levels from lower.

In Inter-level routine the component is given from a level N > 1, all component are search from level N-1 and component are find that satisfies criteria of Gestalt-based. Set current component, set level as N = N-1, then call Inter-level routine again, then stop the analysis when current level show N = 1or no components present to analyze. Analysis start for gray level mask from level 4. This level represents lowest backscatter area in radar images. If level 4 gray contain few pixel then merge level 4 and level 3 that represent dark areas of the Synthetic aperture radar fragments with slick correspond look-alikes areas. The levels N= {3, 2, 1} routine is run to find oil silk structure which correspond to less-dark areas of SAR image. Then this structure passed to subsequent analysis for inter-level routine analysis. Components are selected in stages of analysis are retained in the image and other considered as noise.

3.5 K-mean clustering:
K mean clustering is a vector quantization method used for oil spill detection. Here each element is partition into k clusters which belongs to nearest mean, act as prototypes for the cluster. It works on dividing data cell into voronoi cells. K mean cluster determine comparable spatial extent clusters. It classifies data which is new into existing clusters which called as centroid nearest classifier.

Let as consider set observations $(a_1, a_2, a_3, \ldots\ldots a_n)$ with D real vector dimensional. Here 'c' means clustering partition number of observation into c $\leq n$ sets which is denoted as S = $\{set_1, set_2, set_3 \ldots.\, set_k\}$, it will minimize sum of squares with cluster.

$\arg_S minimum \sum_{set=1}^{c} \sum_{a \in set_i} ||a - \mu_p||^2 = arg_{set} minimum \sum_{p=1}^{c} |set_p| vars_p$, μ_i is points mean of set_p which is similar to squared pairwise deviations in same cluster.

arg_{set} $\text{min}imum \sum_{p=1}^{c} \frac{1}{2|set_p|} \sum_{a,y \in set_p} ||x - y||^2$

similar features can be deleted by using formula $\sum_{a \in set_i} ||a - \mu_p\Big|^2 = \sum_{a \neq y \in set_p} (a - \mu_p\Big)(\mu_p - y)$, which shows number of total variance is constant between points in cluster.

Let as consider k mean initial set $n_1^{(1)}, \ldots\ldots\ldots n_k^{(1)}$, with assign observation in cluster, where mean has Euclidean distance

$set_p^{(i)} = \{a_p\big|\big|a_p - n_p^{(t)}\big|\big|^2 \leq \big|\big|a_p - n_j^{(t)}\big|\big|^2 \forall_j, 1 \leq j \leq c\}$, where a_p assigned one's and $s^{(t)}$ can be assigned to three or more cluster. In update step it calculates and observed new mean to be centroid in the new cluster.

3.6 Histogram based method
Histogram based analysis required one pass through pixel in satellite image. Histogram is computed according to all pixel and help to locate cluster in images. To measure image it can considered intensity and colour for input data. It helps in multiple frame adaptations in satellite image. Consider histogram based on pixel values$H_0, H_1, \ldots\ldots H_N$, here H_K define number of pixel with gray scale 'n' and 'k' which is maximum value of pixel. In first step guess has to be made

$\sum_{i=0}^{K} H_k \geq \frac{n^2}{2} > \sum_{i=0}^{k-1} H_k$, n^2 is number of pixels in n x n Images

In each category calculate pixel value of mean which is equal to or less than k.

Value less then and equal to denoted by $\mu_1 = \frac{\sum_{i=0}^{k} IH_i}{\sum_{i=0}^{k} H_i}$, if greater than 'k' it is given as $\mu_2 = \frac{\sum_{i=k+1}^{N} IH_i}{\sum_{k=i+1}^{N} H_i}$

Re-assign k between two mean as half way: $k = \frac{\mu_1+\mu_2}{2}$, Repeat above steps until k stop changing values

3.7 Expectation Maximization

Expectation maximization algorithm is used to determine maximum likelihood parameter of statistical model. It works as iterative model to find maximum posteriori (MAP) of parameters, which depends upon unobserved latent variable. For example it helps to find missing values exist on object which can be predicted using formula. Expectation maximization likelihood requires derivation of function with respect to unknown values of object with latent variables and parameters. It uses bit of misnomer. Its iteration increase data observation. It uses sequence converges of maximum estimator likelihood. It involved in liner maximizing function to drive expression of close form. It compute maximum priorities map to estimate Bayesian inference with object. It involves mean parameter and zero variance for same components for data points. Statistical modal generates 'i' set for observation data, the missing values 'x' and latent data set unobserved and 'θ' shows vector for unknown parameters with L(θ;i,x) = p(i, x / θ) likelihood function, maximum likelihood of parameters is defined with marginal likelihood for the given input data. L $(\theta; i) = p(i|\theta) = \int p(i, x/\theta)dz$, Sequence of event is denoted with 'x', it define object grows exponentially with length sequence and making sum calculation extremely hard. To estimate maximum likelihood it fallows two steps. First step is to find out expected value of function, with respect to 'x' conditional distribution under parameters $\theta^{(t)}$: $p(\theta|\theta^{(u)}) = E_{x|i,\theta^{(u)}}[\log L(\theta; i, x)]$, here maximization find the parameters for object $\theta^{(u+1)} = \arg\text{maximum}\, \theta(\theta|\theta^{(u)})$, $\theta^{(u)}$denotes initial estimates.

It uses 'x' for latent variable which denoted memberships in groups. 1. Observed data 'i' may be continuous or discrete, associated with vector observation. 2. Missing value 'x' is discrete, for fixed number of values in object. For per observed unit, it uses one latent variable. 3. Parameters works under continuous order, it follows two conditions- Parameters associated with data point and latent variables.

Function given: K(R, $\theta) = E_p[\log L(\theta; i, x)] + H(p)$, q is arbitrary probability distribution, H(p) is entropy distribution with F(p, $\theta) = -D_{kl}(R||p_{x|i}(|i;\theta|) + \log L(\theta; i); p_{x|i}(|i;\theta)$ is a conditional distribution of given data x, D_{kl} is kull back divergence, select q for maximization 'F', $q^{(u)} - \arg\text{maximum}\, R\, K(q, \theta^{(u)})$, select $\theta^{(u|1)} - \arg\, maximum\, \theta F(R^{(u)}, \theta)$.

Filtering and smoothing techniques

Filtering and smoothing technique used for minimum variance filtering and maximum likelihood calculations.

$$\sigma_x^w = \frac{1}{M}\sum_{i=1}^{M}(Z_i - \hat{p}_i)^2$$

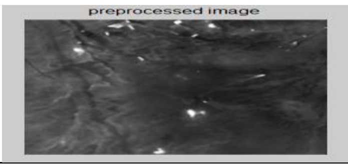
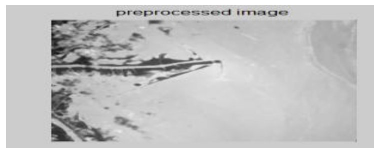
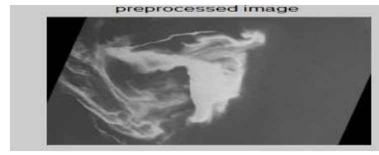
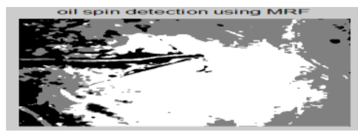
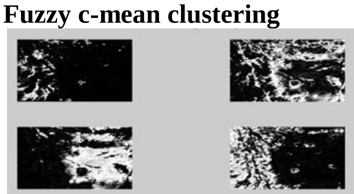
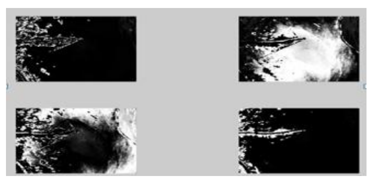
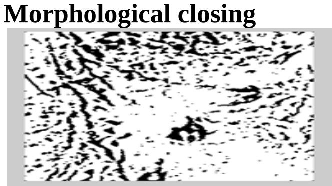
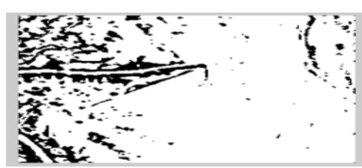
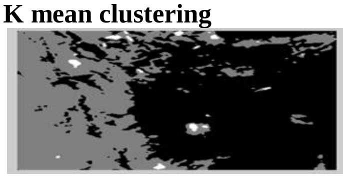
Where as $\hat{p}_k$ is scalar output value which is obtain by filtering and smoothing method.

$\sigma_x^w = \frac{1}{M}\sum_{i=1}^{M}(p_{i+1} - \hat{f}\hat{p}_i)^2$, $\hat{p}_k$ *and* $\hat{p}_{k+1}$is scalar values which is calculated using smoothing and filtering.

4. RESULTS AND DISCUSSION

Oil spill detection techniques were used which helps to regular monitoring and detection of oil spills in the ocean. This research work is carried out using SAR RADARSAT-2 image. This technique examined SAR image to find structure of the oil spill with levels of gray corresponding to less damp / most damped area of sea surface roughness. Radar images confirmed grey level mask containing structure of the slick in Gulf of Mexico. Oil spill happened on 27 April 2010 where crude oil spread in 49,500 km2 across 19,112 square miles in Gulf of Mexico. As we know oil spill is one of the biggest issue in marine environment. Here seven algorithms are applied to find out pattern, dark patches and tracking of oil spill with low time complexity in the given ENVISAT ASAR images. In this research different days images has been taken for regular monitor and observe occurrence of oil spill in ocean. For detection of oil spill incidence angle with HH polarization is suitable for research. According to HH polarization and incidence angles it helps to reduce noise which is created during bad weather conditions. For detection of spill ASAR width increase to 300km- 350km.Advance synthetic aperture radar provide high level of sensor images.Figure-3 indicates spills with patterns, dark patches, oil spill tracking and surrounding area of the images. To determine positive and negative pattern it compared with neighborhood pixels. In this paper after comparing seven algorithms, it define morphological closing techniques is more convenient and good for oil spill detection because in ASAR images it slowly varies gray level point based on image location and positions which help to monitor and detect oil spill region in fast way with low time complexity based on different weather condition.

Figure3. Oil spill Detection Results

		
Markov random field  Time taken for MRF 1.932765e+00 secs	 Time taken for MRF 1.764280e+00 secs	 Time taken for MRF 1.710396e+00 secs
Fuzzy c-mean clustering  Time taken for fuzzy c means 5.373666e+01 secs	 Time taken for fuzzy c means 5.373666e+01 secs	 Time taken for fuzzy c means 5.529804e+01 secs
Adaptive Thresholding  Time taken for 2.264546e-01 secs	 Time taken2.226974e-01 secs	 Time taken 2.470920e-01 secs
Morphological closing  Time taken 2.799448e-01 secs	 Time taken 2.790913e-01 secs	 Time taken 2.470920e-01 secs
K mean clustering  Time taken 5.442832e-01 secs	 Time taken 5.794191e-01 secs	 Time taken 5.312782e-01 secs

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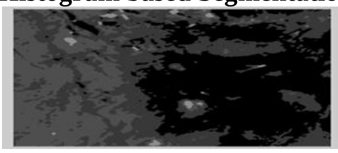
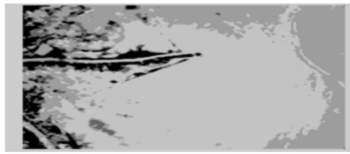
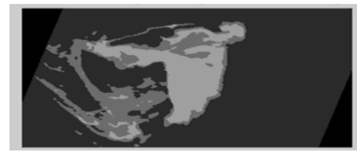

Time taken 6.324111e+00 secs</td><td>
Time taken 6.249907e+00 secs</td><td>
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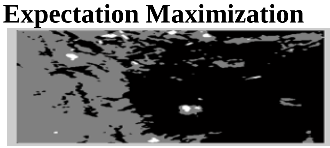
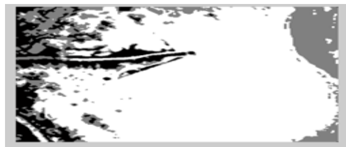

Time taken 2.767760e-01 secs</td><td>
Time taken 3.014248e-01 secs</td><td>
Time taken 2.558899e-01 secs</td></tr>
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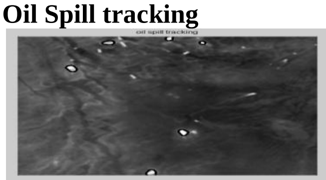
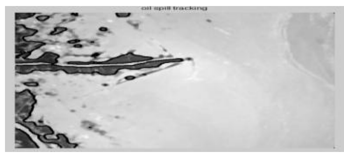
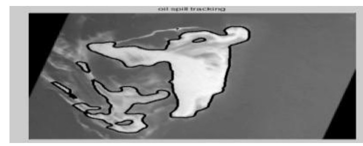
</td><td></td><td></td></tr>
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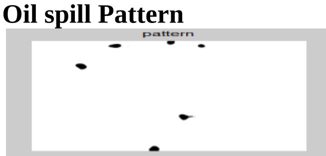</td><td></td><td></td></tr>
<tr><td>Dark patches

Area 3.561250e+02</td><td>
Area 6.009575e+04</td><td>
Area 1.209288e+04</td></tr>
</table>

Table2. Experimental Results for oil spill Detection Time

Techniques used	**Image 1**	**Image 2**	**Image 3**
Markov Random Field	1.932765e+00secs	1.764280e+00secs	1.710396e+00secs
Fuzzy c means	5.373666e+01secs	5.390935e+01secs	5.529804e+01secs
Adaptive thresholding	2.799448e-01secs	2.790913e-01secs	2.815672e-01secs
Morphological closing	2.264546e-01secs	2.226974e-01secs	2.470920e-01secs
K means clustering	5.442832e-01secs	5.794191e-01secs	5.312782e-01secs
Histogram based Segmentation	6.324111e+00secs	6.249907e+00secs	6.292125e+00secs
Expectation Maximization	2.767760e-01secs	3.014248e-01secs	2.558899e-01secs
Coverage Area (m^2)	3.561250e+02	6.009575e+04	1.209288e+04

CONCLUSION

Coastal zones are the most inhabited area of the world and it is affected by humans and natural disaster. In order to evaluate these changes an effective monitoring system for ocean zone must be place. In this research, comparing of algorithms take place which results in less time consuming, oil spill tracking, oil spill area, dark patches and spill patterns. It helps in regular monitoring and detection of oil spill in the sea. This approach helps to find out which algorithm is best suited for detection of oil spill with low time complexity. This work is carried out using ASAR RADARSAT-2 image, which is capture from Gulf of Mexico region. In conclusion, morphological closing techniques can be used as a good tool for monitoring and identifying the occurrence of oil spill.

REFERENCES

(1) Albert Osei, Edmund C Merem, Data to detect environmental degradation, Remote Sens., Applied plant and soil science 21, March 2010.

(2) TurgayCelik, unsupervised change detection for satellite image using Dual tree wavelet transform, IEEE transactions on geo science and remote sens. Vol-48, 3 March 2010.

(3) T.Nishidaid, H.Harahsheh, T.Onumad, monitoring and detection oil spill, Environmental Modeling and Software, Science Direct, March 2007.

(4) Istein Johansen, Mark Reed Oil spill modeling, science and technology Bulletin, vol. 5, pp 16, 1999.

(5) MagedMarghany, Detecting of oil spills in Gulf of Mexico using SAR Data, ISRS June 2016.

(6) K.Karantzalos and D.Argialas, level set segmentation oil spill tracking." International Journal of remote sensing (IJRS), Volume 29, November 2008.

(7) H.S. Solberg, Detection of oil spill, Elsevier, Science Direct, Remote Sensing of Environment, November 2004.

(8) M. Marghany, automatic reduction of oil spill from Satellite data. International symposium of the digital Earth IOP, July 2009.

(9) M. Marghany, Multi-Objective Evolutionary Algorithm for Oil Spill Detection, ICCSA,355-371, Springer 2014,

(10) M. Marghany , Automatic detecting oil Gulf of Mexico, Environment and Earth Science, June 2015, Springer.

(11) D. Camassa, Adalsteinsson, R. Harenberg, Z. McLaughlin, S. Lin, Subsurface trapping of oil plumes in stratification, Oil Spill Monitoring and Modeling the Deepwater Horizon, Geophysical Monograph Series, 2011. Camilla Brekke, Anne H.S. Solberg. November 2004,"Oil spill Detection by satellite remote sensing." Science Direct, Elsevier. Remote Sensing of Environment.

(12) Zhao J, Ghedira and Temini M, September 2014, Exploring the potential of optical remote sensing for oil spill detection in shallow coastal waters a case study in the Arabian Gulf, express 22:13755-13772.

(13) Van Genderen J and Marghany M, July 2009 Entropy automatic reduction of oil spill from RADARSAT-2 SAR Satellite data.International symposium of the digital Earth IOP conference10.1088/1755-1315/18/10/01 2051.