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Remote Sensing in Earth Observation for Oil Spill Detection

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Abstract—Earth observation is the interdisciplinary scope of science and geography concerned with the physical, chemical and biological process on the surface of the earth which is monitored by different remote sensing techniques. Review of remote sensing in Earth Observation for oil spills is discussed. The spills across the world's water surface is increasing at an alarming rate which pose a threat to the aquatic and coastal ecosystem. This brings importance to accurately spot the place of oil spills. The discussion of different satellite remote sensing is done, keeping in mind that the emulation ratio of water to oil and other physical properties are the main response parameters. Camera helps in visual monitoring whereas the thermal properties of oil makes it detectable by the Infra-Red Sensor. Using reflectivity property of oil, Ultra Violet sensor can help in oil spill detection. Laser flurosenors also help in oil spill detection by absorbing UV light. Active microwave radar sensors have the upper hand of oil spill detection over larger area coverage, around the clock and across all weathers. Synthetic Aperture Radar (SAR) is one of the active microwave sensor which rules out the other remote sensing technique. SAR sensor methodology and algorithms in remote sensing have been discussed here.

Index Ter|ns-earth observation, remote sensing, oil spills, emolation, florosensors, SAR, algorithms

I. INTRODUCTION

Oil spills are very common phenomena across all the major shipping routes, all over the world. Oil spiJJs demand accurate location and extent of it. The importance of controlling oil spills is being taken into consideration as it destroys the aquatic ecosystem as well as coastal ecosystem as it hit the coast. This demands for precise location of oil spill and its extent to remove it. By use of modern engineering and technology, it is possible to meet the demands and the open oceans can be monitored for oil spills around the clock.

Remote sensing system for the oil spill is used for daily and routine monitoring, and it is different from the sensor which is used to detect oil in the coast or shoreline. A single sensor cannot satisfy all the needs as many functions are needed. General review on remote sensing in oil spill is already there, which generally shows specific sensors for different functions [1] [2] [3].

Oil spill monitoring and locating are still done by the same concept of image and video surveillance. Nowadays, remote sensing from satellites are gaining importance. Cameras deployed on the flying planes were used previously to detect the oil spill location, but photography is useful for documentation. Airborne monitoring is expensive and less effective because of limited coverage [4].

One of the physical properties of oil is that it absorbs radiations from sun and emits that as thermal energy. Infrared (IR) or Ultraviolet (UV) sensor are also used to monitor the oil spills on the surface of the earth distinguishing by the temperature and reflection respectively. IR sensor is unable to distinguish between very thin slick and water [5]. Even at night the thjck spill appears cooler, making it hard for IR sensor to locate a spill. Oil spills with the help of IR sensor is only possible under favorable conditions. As oil has higher reflectivity than water, so oil can be easily detected by UV sensor based on reflection of solar radiation. False alarms can be caused by UV sensors due to sun glints. Both UV and IR if used together can be a good combination but remains unusable at night.

Synthetic Aperture Radar (SAR) is a microwave sensor which captures two dimensional images by reconstructing the image from the microwaves reflected from the earth surface.

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SAR is cheaper and provides better coverage and resolution when compared to that of Side-Looking Airborne Radar (SLAR).

For automatic detection, new advancement on algorithms are being developed to prioritize the level of alarms depending on the slick. Artificial Intelligence has also stepped its foot into this. Implementation of Artificial Neural Network in data analysis will help to reduce a lot of pressure of operators at analysis centers.

We choose SAR sensor as our main remote sensor because it has many advantages compared to the others [6]. The detection of the oil spills along with the algorithms and methodology in SAR imagery is elaborated, based on wind conditions and other natural and artificial phenomenon.

11. SPACEBORNE SENSOR FOR OTL SPILL

From reflection, refraction, thermal conductivity, absorbance and difference in visual contrast between oil and water, each of this property brings a lot of importance in detection of oil spills. But these properties change with the surrounding atmospheric conditions. Some features are shown together [7] [8] [9].

A. Optical Sensing

Oil has a higher surface reflectance than water. It also reflects light over a wide spectral region. The spectrum of oil is flat but in presence of water it changes. Oil on water can be better viewed with polarized glasses but sun glitters have also come up when viewed. Even with night vision image it is possible to get visions but this process turned out to be costly [10] [11].

Discovery of charge coupled device detector brought a change to this optical detection as it was robust and could handle errors. Several scanners and detectors were developed in many countries evaluated [12). Fig. 1 & 2 shows a visible image by photography.

Sea-viewing Wide Field-of-view Sensor (SeaWiFi) is another kind of visible sensor which is compared with the SAR Images [13]. The major disadvantage of SeaWiFi is its spatial resolution which is lkm. Another instrument, Moderate-Resolution Imaging Spectre-radiometer (MODIS) which is deployed in NASA satellites Terra and Aqua also help in oil spill monitoring. Th.is instrument construct images based on the reflection of the solar radiations and thermal emissions. With multiple imagery, it is possible to discriminate between algae and oil spills but it fails to establish itself as one of the reliable oil spill remote sensor.

Hyperspectral images are captured by instruments called imaging spectrometers. The images contain a lot of data, but decoding them requires a lot of understanding on the properties of ground materials and how they relate to the measurements

Fig. 1. Astronaut photograph ISS024-E-9404 from July 23, 2010, was captured with a Nikon D2Xs digital camera using a 400 mm lens, and is provided by the ISS Crew Earth Observations experimentand Image Science & Analysis Laboratory,Johnson Space Center. [Source: NASA Website]

Fig. 2. Oil Offshore of Alabama and Florida's Western Panhandle. Image Credit: NASA MODIS Rapid Response Team [Source: NASA Website]

made by the hyperspectral sensor. The development of these complex sensors has involved the convergence of two related but distinct technologies: spectroscopy and the remote imaging of Earth [14]. As processing of these data are time consuming and computer intensive, there are a lot of developments going on in this field [15] [16].

B. Infra.red & Ultraviolet Sensing

Oil absorbs sun's radiation and emits it as thermal energy as long wave. Infrared (IR) sensor can be used to pick up these thermal differences [17]. Thinner the oil sheet, the cooler it is. So, it is impossible to detect very thin layer of oil from water and under unfavorable conditions [18]. Even at night, the IR sensors show oil spills but the contrast is not as good as it in daytime [19]. An image during daytime of oil spill using IR sensor is shown Fig. 3.

Ultraviolet (UV) sensors can be used to plot the location of oil slicks [I] as UV sensor can pick up the solar radiation at thin layers of oil. Bringing IR and UV sensors together can

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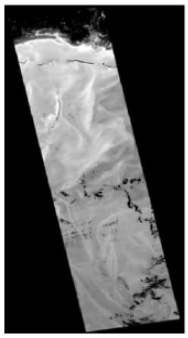

Fig. 3. An infrared image of the Gulf spilJ in 20l0. The black objects near the middle and lower portions of the image are oil. The black objects near the top are islands and shoreline. The oil slick is patchy as the sheen does not show up. This image is from the infrared sensor ASTER on the Terra satellite. [Source: NASA website]

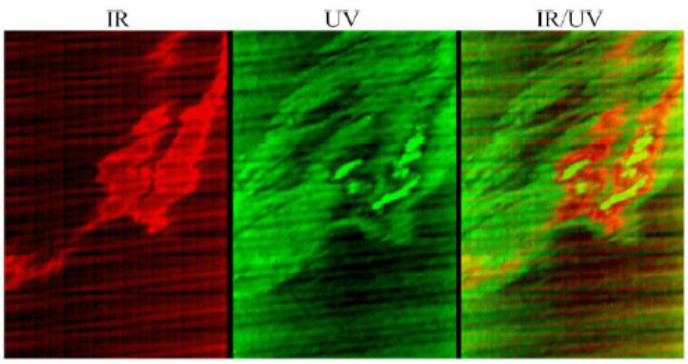

Fig. 4. IR, UV and combined artificial image from the UV/IR scanner. In the IR image (left) the contrast has been reversed so areas with higher brightness temperature (thick oil) appear darker, and areas with lower brightness temperature (thin oil) appear brighter. This is a common convention in thermal oil spill detection. Note how the combination of the images (right) allow a map of relative oil thickness to be obtained. The slanted stripes across the images are sensor noise and show a pattern typical of scanning sensors. [Source: Optimare GMBH]

produce a map of oil spills based on the thickness as shown in Fig 4. UV sensors may subject to false images of wind slicks or sun glints.

C. *Laser fiu.rosensors*

Laser flurosensors use the phenomenon of excitement of aromatic compounds in oil after absorbing ultraviolet ray. This excitement is removed by fluorescence emission in the visible region of the spectrum [20]. This property of fluorescence is an unique feature amongst the aromatic compounds. It proves the presence of oil. (see Fig. 5).

Most fluoresensors use the technique called gating which is opening the detectors just at the right time when the signal is reflected increasing the sensitivity. Some sensors can gate their detectors to look above the target surface or below them. Laser flurosensors have the potential to discriminate between

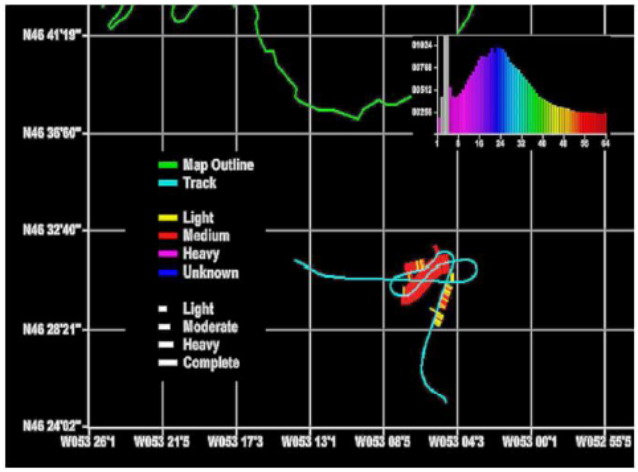

Fig. 5. Pan of ftuorosensor output. The bars a.long the mapped flight path shows the oil detections. The color of the bars shows the type of oil measured. The bar length shows the aerial coverage. Along the flight path the spectrum of the target is also displayed at each point [2].

oil and unoiled water borne weeds and detect oil on all major kind of shorelines. These sensors have shown a great use and are becoming an integral part of different sensing parts [21].

D. *Microwave Sensors*

Microwave sensors are the most important and the widely used sensor for oil spill detection and sensing. The passive sensors detect the oil spills by measuring the reflection of the surface from the space by the solar or other radiations. The emissivity factor of oil is 0.8 whereas that of water is 0.4. This difference helps to detect oil films on water surface by the microwave radiometer [22]. The passive radiometer can detect the thickness of the oil film. The demerits of passive radiometer includes interference of biogenic materials, less signal to noise ratio and difficulty to reach high spatial resolution which makes it less reliable. Considering accuracy and resolution, active sensors are preferred over passive sensors.

Microwave radars are the most commonly used and preferred remote sensing method for ocean pollution monitoring. This is because microwave radars can function alJ day and night, as well as through clouds and fog with wide coverage area.

There a.re ma.inly two types of active microwave sensors likely Synthetic Aperture Radar (SAR) and Side-Looking Airborne Radar (SLAR). The radar technology works on the principle of reflection of the microwave backscattering. The SLAR is relatively older and less expensive using antenna. to achieve high spatial resolution. SAR is more expensive and newer technology with great range and better resolution. Comparative study has shows SAR's superiority to SLAR [23].

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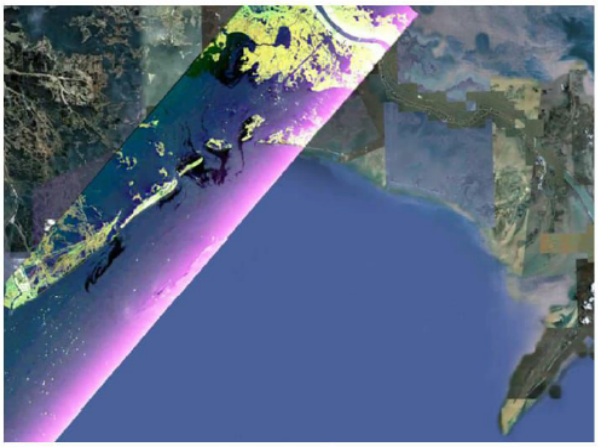

Fig. 6. NASA's Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) flew over the Gulf of Mexico to image the Deepwater Horizon oil spill.[Source: NASA website]

Several researchers have concluded that polarimetric SAR provides more powerful classification between spills and look-alikes, Even phase differences are used to detect oil and rule out from another phenomenon. Fig 6. shows an image from NASA's Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR).

In summary, SAR is still one of the most efficient superior satellite remote sensor for oil slicks identification. The SAR is very useful for sensing particularly at night and at cloudy weathers. Even small volumes of oil spills can cover a large area reducing the need of high spatial resolution which SAR can't offer. Even low resolution ERS-1 * images with a low resolution is good enough to detect oil spill of 100 meters. When ERS-1 images is filtered by a mean filter, better noise characteristics is available making the analysis easier. SAR do have some limitations. It might detect some false *oil* spills due to natural phenomenon. In addition to this, SAR can only operate at certain speed of wind. The importance of SAR in detecting oil spills is discussed elaborately in the next section.

III. DETECTION OF OIL SPILLS FROM THE SAR IMAGES

The dark spots or regions are due to damped Bragg waves on the ocean, reducing the backscatter coefficient of the radar. Fig. 7 are two samples of SAR images showing oil spills. Weathering process includes evaporation, dissolution, shifting, drifting, biodegrading, sedimentation, emulsification and photo-oxidation which are the main physicochemical properties and used to detect oil spills in SAR images. The light oils are evaporated quickly than heavy ones. Emulsification of oil also depends on the speed of wind and type of oil. Dispersion decides the lifetime of the spill and depends on the sea surroundings too.

•ERS-1 is the first European Remote Sensing Satellite

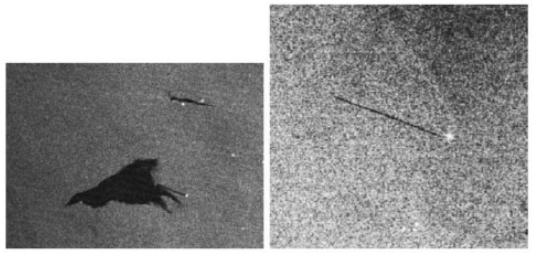

Fig. 7. Left: A subscene of a RADARSAT-1 ScanSAR Narrow (SCN) near range mode image containing two oil spill examples (classified as oil spill by manual inspection) on a homogeneous background. Right: A subscene of an ENVISAT ASAR WSM image containing a linear oil spill (classified as oil spill by manual inspection)[9].

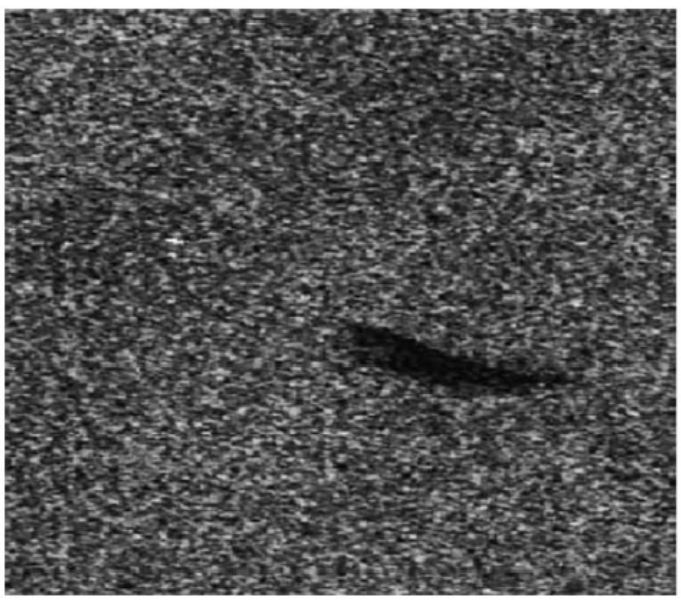

Fig. 8. RADARSAT-1 SCN near range mode subscene containing an oil slick look-alike detected as oil spill by Kongsberg Satellite Services AS (KSAT), QinetiQ and Norwegian Computing Center (NR)[9].

A. *Recognition of oil spills from other look-alikes*

The main problem is to discriminate the oil spills from look-alike which include natural phenomenon. Oil slicks dampen the Bragg waves on the surface of the water body in the range of 0.6 dB to 13 dB while the natural films range from 0.8 dB to 11 dB [24]. Look-alikes include grease ice, shear waves, wind speeds, internal waves etc. Oil spills are man-made associated with crude oil (types of oil) while the others fall into the category of natural phenomenon. Fig 8 shows a look-alike detected as oil spill by SAR image, verified by aircraft.

As there is no difference of radar cross section values for natural phenomenon and oil spills, this pose a major problem in oil spill detection and monitoring. Oil having higher viscosity tends to be more concentrated providing

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Wind speed (mis)	Slick signatures
0	No backscatter from the sea surface, hence no signature of oil slicks.
3	No impact from the wind on oil slicks. A high probability of oil slick look-alikes due to local wind variations.
3 to 7-10	Fewer false alarms from local low-wind areas. Oil slicks still visible and more homogeneous background.
>7–10	Only thick oil visible. Thinner oil slicks will be invisible due to a combination of oil spill dispersion. Thick oil can be visible with wind stronger than 10 mis.

Fig. 9. Visibility of slicks in SAR images [I0].

higher damping but still there is no one to one relationship to detect oil spills. A lot of modeling is done to distinguish oil slicks from natural phenomenon [25].

A lot of algorithms have been proposed based on multi-frequency and multi-polarization setups to discriminate oil spills from look-alikes to reduce false alarms [26] [27]. Different experiments were done by L-, C- and X-band multi-polarization SARs which concludes that discrimination is only possible under low wind speeds and small incidence angles. This paper focuses on single frequency and single polarization images.

In addition to this, there are different other kinds of pollution which might cause slicks which are also detected by SAR images. ERS-1 images show that diesel, run off water, drilling fluid from oil rigs are also detected as oil spills. A single SAR sensor is not enough to estimate the thickness of the oil spill as well as not capable of distinguishing between different pollutants, natural phenomenon and oil spills. Studies have been done based on Sea Empress oil spill to establish a correlation between reduction of backscatter and thickness of the oil [28]. *All* these things must be kept in mind while discriminating oil spills from look-alikes, along with different geographical and atmospherical parameters.

B. *Wind speeds*

SAR images have advantages over the visible sensors that it can acquire images all day and night even in foul weathers. However, the wind speed influences the backscatter heavily. Detailed information of wind speeds and their signatures are given in Fig 9. It is found that with higher wind speed around 10 *mis* oil spills are detectable in the SAR images. A wind speed of around 14 m/s is considered as the upper limit to detect spill in images but even the maximum wind speed to detect the spill depends on the spill's thickness and time since release [29] [30].

For oil spill detection algorithm, the wind speed is manually set after seeing the images. Wind speed can also be calculated by some external source and fed to the system for automatic methods. Estimations of wind speed can also be done by applying CMOD4 (wind vector calculation by C-band scatterometer) from the SAR images [31].

C. *Speckle noise*

When the resolution of the sensor is not sufficient to resolve individual scatters within a resolution cell that give rise to speckle noise. As large coverage area has a statistical distribution with large standard deviation so speckle noise become a vital problem. Barni et al. tested two types of filters, general noise reducing filters and adaptive filters. Better results were got using the later filter [41].

For oil spill applications, a filter should suppress speckle noise but still preserve small and thin oil spills.

IV. OIL SPILLS DETECTION METHODOLOGIES

Detection of oil spill can be broadly divided into two categories, suspected slick detection and verification of the slicks manually to assign different confidence level.

A. *Manual Inspection*

The operators are trained specially to detect oil spills. The external information like wind speed, wind direction, location of oil rigs, territory borders and coast lines are given to the operator to support the analysis. The images are went over manually to spot spills which is time consuming. *Oil* spills are then assigned to different confidence levels like high, medium and low. The determination of the confidence level is based on different contrast level of surroundings and there is always an uncertainty connected to it.

B. *Comparison. of manual detection to automatic detection*

Conceptual information is an important factor in classifying oil spills from look-alikes during manual inspection. The main challenge is to put all these expert knowledge together into the automatic system. A set of rules and knowledge about external conditions can be incorporated into a classifier based on multivariate probability distribution function.

A study based on comparison of KSAT's manual approach, NR's automatic algorithm and QinetiQ's semi automatic detection approach bas been performed [9]. Amongst 17 oil spills, KSAT detected 15, NR detected 14, and QinetiQ detected 12. KSAT operator uses 5-25 min to analyze a scene, NR's algorithm takes 5 min and QinetiQ used 20 min per scene in average. This proves that automatic approaches are feasible and quite accurate when the volume of SAR image data grows.

C. *Issues around automatic detection*

A number of issues comes up when developing a machine learning system for a spill detection. Firstly, less number of data as most SAR images acquired are without oil spills. Secondly, as oil spills appear in batches, dissimilarity is present between them resulting in imbalance training data set. Finally, the performance of the classifier which can possibly

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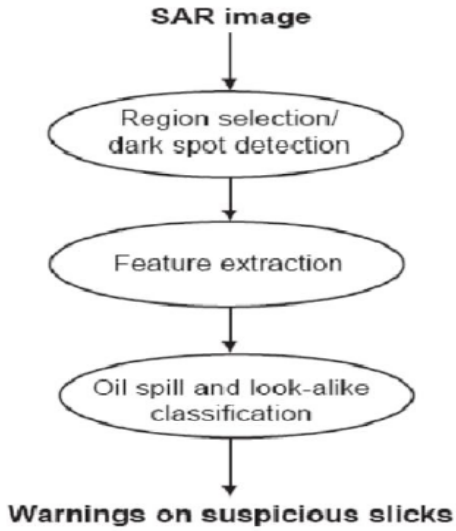

Fig. 10. Framework for oil spill detection algorithm [9]

decrease the number of alarms at the expense of missing genuine oil spills.

These conditions are kept in mind while designing an automatic system for oil detection.

V. AUTOMATING OJL SPILLS DETECTION

Algorithms for the detection of oil spill in SAR images have been discussed by several groups [32] [33]. Previously wind vector and its importance have been discussed and here two more steps namely wind direction estimation and wind speed calculation are added as per the findings of Salvatori et al (31]. Moreover, Solberg et al. estimated the manual wind. The framework includes SAR image calibration, land masking, speckle reduction and class signature databases. In Fig 10. shows core modules of oil spill detection and classification of algorithm which is discussed below.

A. Segmentation Techniques

Different types of segmentation techniques are used. Skoelv and Wahi postulated a segmentation technique for ERS-1 SAR images through an algorithm which is constructed in such a way that it finds bimodal histograms in NxN pixels of windows where N is equivalent to 25 pixels [34]. Later, several other groups came up with similar kind of methods for oil detection which are also effective. However, one of the major drawback of these algorithm is the absence of a classification step that cannot help to detect look-alikes. Besides, Solberg et al. describes an adaptive algorithm technique where the threshold for detection is kept, *k* dB below the mean value (35]. Later, Canny (36] came up with hysteresis thresholding for this purpose of detecting oil spill which is experimentally described by Kanaa et al. by means of searching in eight directions which followed a response of merging steps [37].

Moreover, Change et al. invented a detection method which is based on Difference of Gaussian (DoG) operators as well as Laplace of Gaussian (LoG) [38]. Here in this approach, LoG is applied on a 2X2 pixel reduced pyramid consist of three layers and the function of DoG is to locate the areas, Wavelet is used for the detection which is equivalent to the LoG for the previous methods and detection is observed by means of finding peaks in the wavelet transform spectra. Mercier et al. however examined the capillary waves and suggested another method to detect oil by means of local variations in the wavelet transform spectra [39]. A multi-resolution analysis followed by a Hidden Markov Chain (HMC) model 31·e tested for this method and the approach is examined on ERS PRI image system.

Besides, an algorithm namely QinetiQ's dai·k spot algorithm [40] relies on an method to locate dark areas which is called Constant False Alarm Rate (CFAR) algorithm. By adding the dark spots obtained through the algorithm and by using Hough transform the targets are detected. A special type of oil detection algorithm is conceptualized by Barni et al based on fuzzy clustering where the clustering is applied and a pyramid structure is used in order to locate the membership values [41]. Another method is proposed by Gasull et al. which uses a mathematical morphology for the segmentation of oil spill where opening and closing operations are combined [42]. This method is optimal for oil detection from oil tankers. For all the approaches described by different groups there exists a common goal behind every algorithm which is to successfully detect all types of slicks that can help in avoiding look-alikes,

B. Feature Extraction

Slick feature extraction is the next step through which the features of the clicks are computed from the thresholded dark spot image. In case of slick feature extraction each individual feature is defined by the following classes described next.

At first, geometric and shape features is described by Gasull et al (42] which is effective to detect pollutants reside in the sailing tankers. Next, Prate et al. obtained a feature that contains vital information for the classification [33]. Similar features are computed by Fiscella et al. which is termed as contextual features [31]. Another feature is named as spot contextual features where a database for pollution source is used as described by an algorithm from Espedal [43]. Later, it was found that improved classification results by adding up weather information with the context of the surroundings [44]. At last, texture is described to obtain the information regarding the spatial correlation among neighboring pixels. An early warning system that relies on the usage of texture is described [45].

The methods described above doesn't necessarily use same features but many of the features contain similar characteris-

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tics. The natural surfaces by using fractal texture [46] where fractal dimension is used for the observation of ocean radar signatures which is obtained [47]. All of the methods have tried to find out good feature which is extremely important but unfortunately it has not been established successfully through any method and the drawback is described [48].

C. *Methods of classification*

Classification methods are used in order to identify oil spills from the captured SAR image which also contains several similar dark patches. There is a method through which the probability for a dark patch to be oil spill can be identified [31]. The method proved to be extremely accurate with low failure rate, since 93% of the oil spills can help to identify spills successfully from the dark patches. Similarly, Solberg et al proposed a multivariate Gaussian density function through which the oil spill can be classified with high precision [44]. In the case, the accurate determination from oil spill is around 94% which is almost similar to previously proposed model. Moreover, advanced computational model such as artificial neural network has been used for oil detection as proposed by Frate et al [32]. Here both manual methods are used for the selection of dark areas and image fragmentation, and automatic approaches are used for feature extraction and oil spill classification. This method is also useful having a success rate of 82% with 18% of failure which is more compared to previously described methods. Hence, the above mentioned oil detection methods can accurately detect oil spill with a success rate in between 82%-94% which is decent for the detection. These methods are distinct in the sense that they use different data set as well as methodologies, segmentation and feature extraction. It is reported that the detection method with highest known accuracy for both classification and detection.

VI. CONCLUSION

The greatest challenges faced by the oil spill detection systems is distinguishing between oil spill and look-alikes. It is difficult to distinguish natural films from oil spills using SAR image alone when compared to low wind situations when spills can be identified by the side of the slick. In places like Baltic sea, algal blooms is popular in summers which calls for more information regarding algal blooms. KSAT manual approach is used to identify oil spills from satellite images. Currently, aerial surveillance is used only to prosecute the polluters.

Sensors which operate with wide swath mode having spatial resolution between 50 and 150m cover large ocean areas efficiently and are sufficient. Synthetic aperture radar is as of now the most reliable space borne sensor which is used for oil spill detection as it as wide coverage and all-day/all-weather detection capabilities.

There exist two types of oil spill detection systems - manual and automatic. There are three steps in automatic oil spill detection - dark spot detection, dark spot feature extraction, and dark spot classification The use of automatic spill detection depends on the number of images but in case of large areas it is more cost effective when compared to manual systems with high reliability and hence it is preferable over manual oil spill detection systems. Whenever a slick is identified as oil by automatic systems a manual check is also done and therefore in these cases inspection of couple of slicks is more efficient than inspecting the entire scene.

VII. FUTURE WORK

A lot of research can be done to find information on algal blooms. This can be done with the help of optical sensors. Oil spill systems must incorporate this information at any location irrespective of the time. Further research can be conducted to compare the performance of manual and automatic oil spill systems. Implementations of Artificial Intelligence in detection of oil spills and discriminate it from other look-alike is making easier. Deep Neural Network is also being implemented. By increasing the number of neural network layers the error of distinguish between oil spills and look-alikes reduces. Extensive research are made in this domain and it has a lot of future in it. In future SAR missions are planned for more sustainable operation. Japanese Advances Satellite and European Terra-SAR-L are L-band SAR which has increased wavelength. An imaging resolution of Im is provided by TerraSAR-X along with a ScanSAR mode with 16m resolution and lOOkm swath width. Also there is a need to replace ENVISAT ASAR with space borne C-band SAR to ensure that the quality of the oil spill detection services are sustained which can be assured as many other applications in the ocean use C-band SAR images. An integrated system which includes algal information, automatic algorithm, information about hotspots, wind and ship planes should be developed in future for increased performance and reliability.

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