

# Analysis of SAR Images using New Image Classification Methods

B. Malakonda Reddy, Md. Zia Ur Rahman

**Abstract:** Oil spills are carrying out by the marine echo system and these are originated from scientific and political concern since they are seriously affecting the coastal echo system and fragile marine. Oil spills can be detected from the satellite images with more potential by covering the larger areas. While getting satellite images they cover very limited area and require large aperture antennas. But with small aperture and large captured areas Synthetic Aperture Radar (SAR) descriptions are extensively worn in favor of oil spill discovery. In SAR image the oil spill regions can be detected with oil film backscattering. In this process dark patches are formed which are affecting the detection correctness of oil spills. In this occupation oil drop regions are detecting using dual threshold segmentation. In dual threshold segmentation image is partitioned based on histogram analysis. The proposed method illustrates the helpfulness of technique in noticing plus classifying the oil spills.

**Index Terms:** Synthetic-Aperture-Radar(S/A/R), oil spills, thresholding, segmentation

## I. INTRODUCTION

Marine oil spills are basically reasons by the misfortunes such as drilling platform accidents, ship collisions, oil pipe line cracking and deliberate discharges [1]. It has one of the significant concerns of environmental things [2]. Now there are quite a lot of techniques on behalf of monitoring oil spills which comprise air surveillance, ship pathway as well as satellite distant sensing [3]. Among all these satellites remote intelligence has large reporting variety, which is most appropriate in support of large size maritime ministering[4]. At present SAR is the popular one and it has all weather observation capability [5][6].

To capture the reflecting signals from the targets, an active sensor SAR is used. By wind and short gravity, the oil spills suppressing the back scattering of sea with damping the capillary waves stimulation, by this observation of the dark regions on the image can possible. However mostly the SAR images suffers from speckle sound which disgrace the excellent particulars along with edges description and restrictions the difference declaration. A lot of work that would be done on segmentation of dark regions that represents the oil spills from sea background. A lot of threshold

algorithms [7] [8] are used for this segmentation. Solberg et al. [9] introduce that the threshold is to be  $n$  and it is beneath the mean charge of the affecting window. Li et al. has used the space density approach for separate the dim spots also

background [10]. Migliaccio et al. implements the spill detection process over SAR image supported on physical model [11]. Huang et al. carried out the level set methods for oil spill detection. However, these level set methods are performing well for detection of oil spills these are time consuming process [12]. Li et al. made up a representation based on hydrodynamic reproduction to observe the oil spill from a moving point. Tang et.al. [13] investigated the consequence of oil spills on ecological scheme. So automatic and semi- automatic techniques are needed to detect the oil spills [14] [15]. Del Frate et al. introduced the semi-routine methods intended for oil spill discovery [16]. A neural network is the robust tool for oil spill discovery. Topouzelis et al. also stated regarding dark arrangement detection as well as oil spill organization using neural network. [17]. The three algorithms in favor of classification of oil spills including neural network, post supervised classification and co-occurrence textures proposed by the Hashim et.al. [18] even the neural networks having the advantages in oil spill monitoring these are time consuming. Chakraborty et al. [19] introduces the semi supervised SVM for rectifying the problem of classification of pixels in remote sensing images. The main goal of segmentation is extract out all the area of oil spill. Dark spot detection and segmentation generally done by threshold methods [20]. K-means algorithm [21] is a process of cluster investigation which performs divider with  $n$  explanations hooked on  $k$  clusters in which every observation feels right to the group which is having the adjoining mean.

Fuzzy C-Means algorithm [22] [23] (FCM algorithm) is used to perform the segmentation in SAR image. This method is simple and standard deviation and mean values are obtained from DN value (Digital Number or Data Number or Brightness Value) of image. Threshold value is also obtained from histogram of DN values.

In this paper another oil slick perceived calculation has proposed. In the discovery of dim spots, in general limit is normally utilized because of its comfort and high proficiency. Be that as it may, in SAR pictures, at whatever point the grayscale scope of oil slick and ocean foundation dependably has a convergence, with one in general limit in the division, it is beyond the realm of imagination to expect to stifle the impedance of spot commotion from ocean foundation and there is an opportunity to misfortune a few subtleties of dull district. Double limit calculation is utilized to bring down the bogus caution rate while dealing with the limit of oil slick to substantial degree.

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## II. PROGRESS OF THE PROPOSED METHOD



The processing steps for existing and proposed dual threshold algorithms are shown in Fig.1. The images are initially processed with low pass filter to decrease the meddling of the speckle sound and the segmentation of oil spills is performed by final threshold which is determined from two thresholds. The two thresholds which are the lower and higher achieved with the help of semi-automated and fuzzy logics respectively. With dual threshold the false alarm rate will be reduced effectively and the oil spills regions extracting fine details.

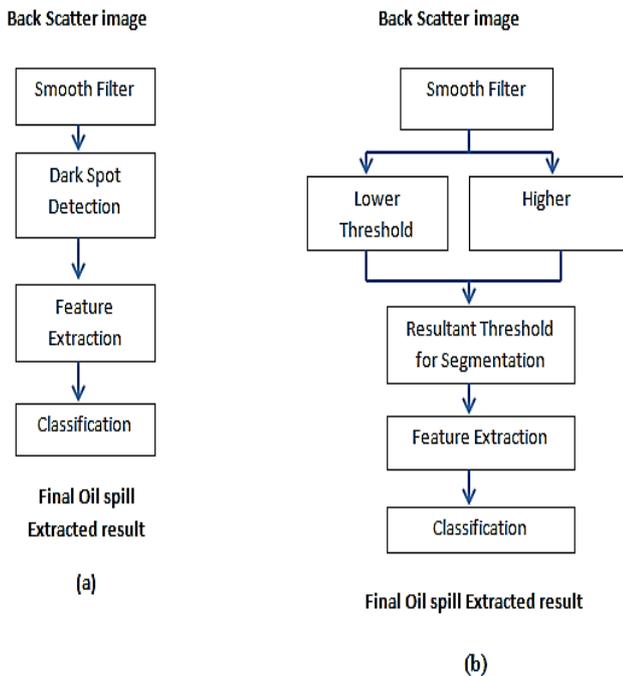


Figure 1: Flow diagram for (a). Traditional method and (b). Proposed method

Here the segmentation is comprising in three steps. Initially segmented using global thresholding is utilized. The next step is segmenting its gradient image by global threshold method. Third division is uniting the primary as well as subsequent step for last segmentation of image.

In the new proposed process of segmentation, the initial step is computing the threshold value from original image. A new threshold technique is projected in this manuscript to make better segmentation based on previous study [25]. Original image histogram is calculated and transforms it to Fourier space. The main term of Fourier change contains DC esteem (The zero-recurrence coefficient,  $F(0, 0)$ , is regularly called the "DC component") and second term contains sketchiest worldwide estimations of histogram dispersion. On the off chance that the picture contains the articles and the dark sizes of their back ground are Gaussian disseminated then the second term of Fourier change is scrappy overlay of two Gaussian dispersions. The pinnacle of worldwide variety is existed between these two Gaussian conveyances. The pinnacle of this worldwide variety is distinguished naturally and it is utilized as a kind of perspective limit to make the division of unique picture. The edge estimation technique contains the accompanying advances.

Step 1: Initially rearrange the image gray scales within the time  $[0,255]$  also calculate its normalize histogram,  $H(n)$

$$H(n = i) = \frac{N_i}{N_j}; i = 0,1,2,3 \dots 255 \quad (1)$$

$N_i$  is the frequency of gray scale  $i$  plus  $N_j$  is the greatest frequency which occurs at  $j$  with in the interval  $[0, 255]$

Step 2:

Using the DFT the transform of  $H(n)$  is given by

$$F(k) = \sum_{n=0}^{255} H(n)e^{-j\frac{2\pi kn}{255}}, k = 0, 1, 2 \dots 255 \quad (2)$$

Step 3:

After completing the second step eliminate the all the other components other than first and second low frequency parts using following equation

$$\tilde{F}(k) = \begin{cases} F(k), k = 0,1 \\ F(k), k = 254, 255(3) \\ 0, k = 2,3 \dots 253 \end{cases}$$

Step 4:

Smooth the histogram based on,

$$\tilde{H}(x) = \frac{1}{255} \sum_{k=0}^{255} \tilde{F}(k) e^{j\frac{2\pi kn}{255}}, n = 0,1,2 \dots 255 \quad (4)$$

Step 5:

Each point on  $\tilde{H}(x)$  has  $\Pi$  grades. One is on gone moreover another individual is on right. These are computed by fitting a line representation through several adjacent positions on every surface. Here we choose 15 main efficient points in support of histogram choice since 0 to 255. This is mathematically can be written as,

$$y_n = ax_n + b \quad (5)$$

$$[a, b]^T = (P^T P)^{-1} P^T Y \quad (6)$$

$$\text{Where } P = \begin{bmatrix} x_0 & 1 \\ x_1 & 1 \\ \vdots & \vdots \\ x_{14} & 1 \end{bmatrix} \quad (7)$$

$$Y = [y_0, y_1 \dots y_{14}]^T \quad (8)$$

The two slopes at a point  $n, a_1(n)$  and  $a_2(n)$  are computed beginning Eq.(6)

Step 6:

Calculate the slope dissimilarity  $sd(n)$  at a point  $n$

$$sd(n) = a_2(n) - a_1(n), n=15,16 \dots 240$$

In the slope distinction allocation, the positions can be found using the condition,

$$sd(n) - sd(n - 1) = 0$$

Here we get the valleys and peaks with greatest local variations. Let it would be  $p_1$  and  $p_2$ . We select the lower threshold  $T_l$  in between  $p_1$  and  $p_2$  valleys.

Step 7:

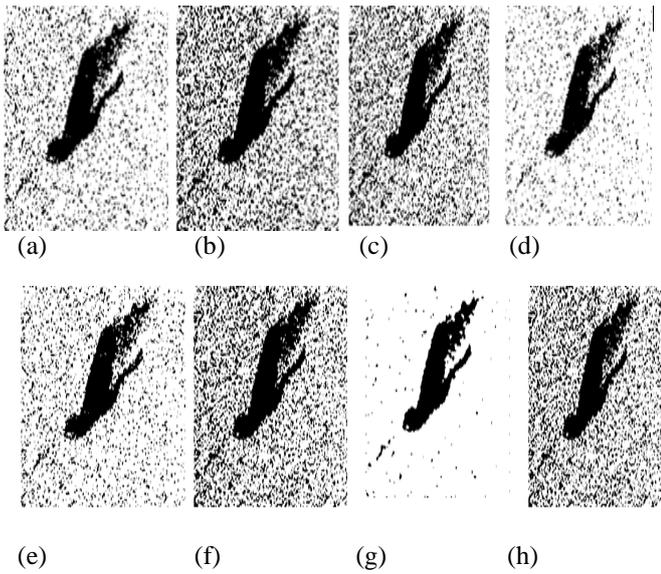
The higher value of threshold  $T_h$  is founded from the Fuzzy entropy based multilevel thresholding optimized with differential evolution approach [33]. Finally, the resultant threshold  $T_R$  value is emerged from

$$T_R = \frac{T_l + T_h}{2}$$

The smoothed original image  $I$  is binarized as

$$B_I = \begin{cases} 1, I \geq T_R \\ 0, I < T_R \end{cases}$$

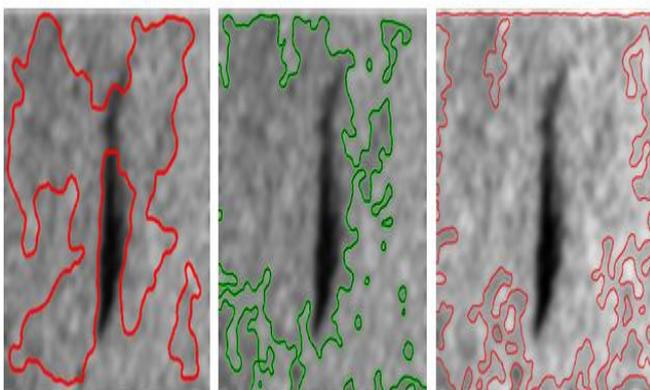




**Figure 2:** (a) Expectation Maximization Segmentation method (b) K means method (c) iterative selection method [22] (d) Maximum entropy method [18] (e) cross entropy method [24] (f) fuzzy c-means technique [20] (g) new fuzzy thresholding system [23] (h) Otsu technique [21] based AEP

### III. RESULTS AND DISCUSSION

For these experiments, we have taken several real time images were taken from ERS-I IM (Image Mode) VV polarized image in east of Indian coastal near Krishna-Godavari Delta is to be analyzed to detect the oil spills. We initially evaluated the several residential existed methods among popular Otsu process moreover fuzzy entropy methods. Fig 2(a) represents segmented image using maximum expectation method, Fig 2(b) represents K-means algorithm output, in this output noise is not eliminated effectively. Fig(c) shows output of iterative selection method [26], Fig(d) shows maximum entropy method results, Fig(e) represents cross entropy method [28] output and Fig(f) represents fuzzy c-means method [27] output in segmentation of SAR image for detecting and extraction of the dark spots of oil spill images. Disadvantage of FCM is that for noisy images, it will not consider the spatial information which makes it sensitive to noise & other image artifacts. Fig 2(g) is the new fuzzy thresholding method which makes better extraction of dark region boundary than Standard Otsu method shown in Fig 2(h). Among these new fuzzy threshold methods perform the good extraction of the oil spill dark regions from blurred images due to speckle noise.

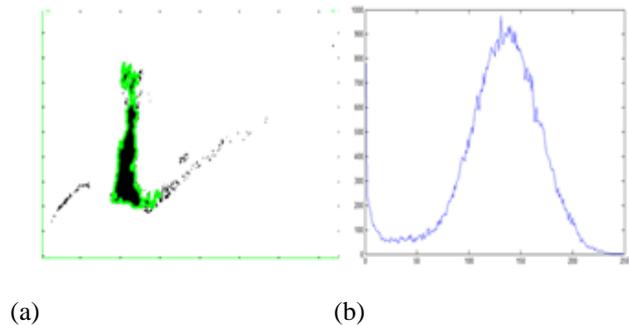


(a) (b) (c)

Figure 3: (a) DRLS method (b) Active contours without edges (c) Localizing region based active contours.

Here the performance of extraction of regions by active contour methods [29]-[30] has shown in Fig 3. Fig. 3(a) demonstrates the DRLS-based bend development process. Since the evoked Oil spill locales are discretionary shapes which are not giving accurate shape. The Fig.3 (b) demonstrates the yield which has the shapes both with and without angle, for example protests with smooth limits or even with intermittent limits. Fig.3(c) gives the examination of neighborhood areas enables the division strategy to precisely isolate required locale from whatever is left of the district notwithstanding its slim structure and the nearness of adjacent structures of comparable intensity. As it can be seen that dynamic form techniques are stops unfortunately without spreading at the edges of dull locales and these neglects to recognize the oil slick locales in SAR picture. The pictures are should be combine before applying to dynamic form techniques as a result of expansive number of dim spots makes complex to remove the areas.

For the calculation of semi- automated limit determination process the carmine line speaks to the first histogram conveyance and green line for likelihood of smoothed histogram appropriation. Nearby pinnacles of slant distinction conveyance are spoken to with blue line which regularly more noteworthy than zero and red line demonstrates the neighborhood pinnacles of the slant contrast circulation which is under zeros typically invert to the more prominent. The blue cross relates to blue pinnacles and signifies the pinnacles of histogram conveyance. Valleys of histogram spoke to with red circles relates to red pinnacles. The blue bullet in Fig. 4(b) represents the lower threshold ( $T_l$ ) value which makes the segmentation as in case 3 is 25. The segmentation performed by this threshold values is shown in Fig.4(c) which is under segmentation. Majority of the oil spill dark region is not covered by this threshold value. Another threshold ( $T_h$ ) value is to be taken from mean of optimized differential evolved fuzzy parameters which is peak value of distribution function is 215.5 shown in Fig.4(d). The segmentation performed by this threshold gives the over segmentation results shown in Fig.4(e). Finally mean of these two thresholds considered as reference threshold for make segmentation which has extracted the major part of the oil spill efficiently shown in Fig.4(f).



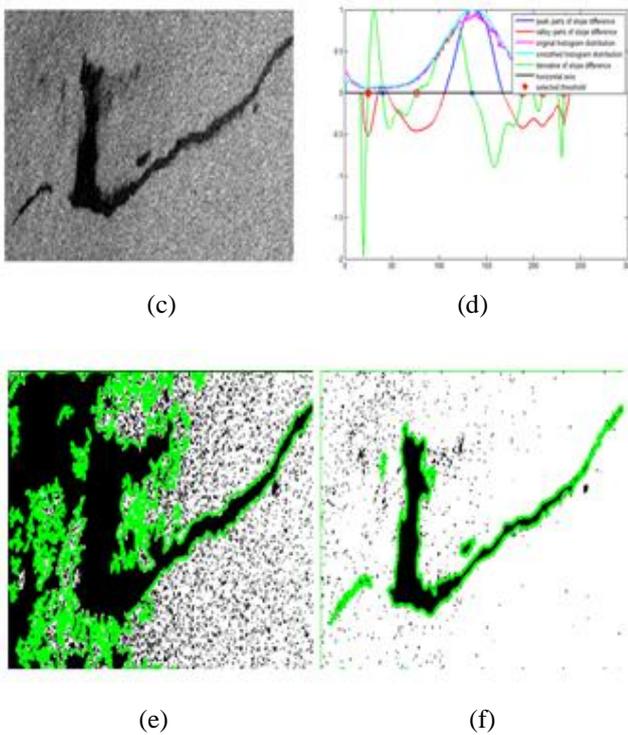


Figure 4: (a) original image (b) low threshold selection (c) under segmented using low threshold (d) high threshold selection (e) over segmented image (f) proposed segmented image The blue bullet in Fig. 4(b) represents the lower threshold ( $T_l$ ) value which makes the segmentation as in case 3 is 25. The segmentation performed by this threshold values is shown in Fig.4(c) which is under segmentation. Majority of the oil spill dark region is not covered by this threshold value. Another threshold ( $T_h$ ) value is to be taken from mean of optimized differential evolved fuzzy parameters which is peak value of distribution function is 215.5 shown in Fig.4(d). The segmentation performed by this threshold gives the over segmentation results shown in Fig.4(e). Finally mean of these two thresholds considered as reference threshold for make segmentation which has extracted the major part of the oil spill efficiently shown in Fig.4(f).

IV. CONCLUSION

In this document a new advance is anticipated for automatic discovery of oil spills starting SAR images. A robust double threshold segmentation is proposed for SAR backscatter descriptions to take out the regions from gray scale images. The final detection of the regions is obtained by processing of lower and higher threshold values. The efficiency of extraction has been compared with many states of art segmentation methods that give the less false alarm rate.

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