Oil Spills Detection In SAR Images Using Nonlinear Fuzzy Filter

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Abstract

Oils spills broach high degree of pollution into the "blue" bodies which are considered fatal for the water ecosystem. So these oil spills need to be spotted at right time to prevent this disaster pursue. Many techniques are very actively inculcated for the same. Synchronous Aperture Radars (SAR) which is a space borne technique is primarily used for this purpose. Techniques which were used a way back beard its own hiders as follows: (1) the distinguishion between the look-alikes and the oil spills did not meet the satisfying accuracy, (2) the desired precision of clarity in the images were not obtained, (3) the oil territory were not detected to a accurate topology. So considering into the hurdles faced by the previously used techniques, we propose a novel system based on a fuzzy control filtering approach. It uses adaptively varying membership functions and incorporating fuzzy associative memory (FAM) with conventional multilevel median filter (MLMF) to detect the oil spills in SAR images. It also preserves object boundaries and structures, while removing noise effectively in the region of heterogeneous physical properties. This is an attempt to enhance spatial resolution and sensitivity of SAR images for better visualization and analysis. The system minimises the output mean squared error by tuning the shape of the membership function. A parabolic membership function is used, for the first time, to adaptively fine tune the reduction of noise level in the tomograms. The performance of the system is tested using oil spill SAR images. The system restores images corrupted with speckle noises of different levels. High impulse noise is effectively eliminated without significant loss in the sharpness of the image features. System performance is evaluated visually as well as by computing quantitative metrics such as standard deviation error (SDE), root mean square error (RMSE), normalized mean square error (NMSE) and peak signal to noise ratio (PSNR). Numerical measures show fuzzy filters to outperform the convincing performance that is superior to the conventional MLMF method. Among the two membership functions, the parabolic funcion is found to be more effective in noise removal.

Keywords: *SAR images, oil spill images, adaptive fuzzy filters, fuzzy control, noise reduction, feature detection, signal to noise ratio, root mean square error.*

1. Introduction

An emerging pathetic plight of aquatic flora and fauna is that they are prone to ample aquatic pollutions. These aquatic pollutions are primarily contributed by oil spills that come metamorphic [1]. Oil spills are caused by ships locomotives that when withers oil as they carry across the water bodies. Oil spills are also caused when rupture in oil pipes occurs across its cross section. Surveys show that annually, 48% of the oil pollutants in the oceans are fuels, 29% are crude oils and tanker accidents contribute only 5% to this pollution [2]. The major challenging task is to detect the presence of oil spills across the globe. Nowadays, many technical bodies serve this purpose. People face a number of challenges due to this problem and hence an attempt is made to have some remedial measures in this paper.

The technique of oil spill detection has its roots deep. Several years back a lot of techniques were adopted for the same. Initial era faced the advent of using Synchronous Aperture Radar (SAR) for the oil spill detection. It was a space borne technique where radars captured the images of the spills and an analysis of it were made to differentiate the oil spills with its “look-alikes”. The “look- alikes” includes natural slicks, grease ice, threshold pipelines and passing vessels that were visualized exactly like an oil spill on an homogenous background. Following SAR an air-borne technique called Side Looking Airborne Radar (SLAR) came into existence that beard its own disadvantages. After SLAR SeaWiFi’s were opted for that did not serve the purpose. Then came the Hyper Spectral Sensors that had many advantages of its own. The only disadvantage of these sensors was its limited size that accounted to only a 7.5*100 km on the orbit. The next technology incorporated a combination of IR and UV methodologies that yielded good reliability. Then Micro Wave Radars (MWR) beard quite a few advantages. Of the above mention techniques SAR proved to be the best bearing a number of advantages like : 1) independency of weather 2) can even sense good during nights and cloudy atmosphere 3) covers larger topography 4) high resolution and so on. Taking into account the proposed detection systems, our notion is to detect oil spills using SAR that incorporates Slide Stretching algorithm to provide better clarity and reliability.

The basic functionality of SAR included capturing of images by the radars on backscattering of rays by the water bodies. Oil usually absorbs heat during days and in nights they dissipate the heat into the water that they appear colder than waters at night. So even the thinnest layer of oil spilling can be detected. Firstly, the radars capture the images of the water bodies and then analyzed. Careful analysis of the image is done in the regions where dark spots are found.

Accurate estimate of quantitative information from oil spill images is of prime importance in further enhancing the potential of SAR images for various applications. Presence of noise limits the accuracy of pixel based parametric images. Noise reduction without the loss of image features such as the border of region of interest, to extract the diagnostically relevant image content, is a formidable task in SAR image processing. Attempts are made using both linear as well as nonlinear filters to enhance SNR of SAR image [1] .

Although noise suppression is achieved by these filters, signal distortion is introduced and the identification of features such as sharp corners as well as thin lines becomes ambiguous [3]. Variations of median filters such as the multistage filter [4], and the improved recursive median filtering (RMF) scheme given by [5],

$$y(n) = \mathrm{med}[y(n - m), y(n - m + 1), \ldots, y(n - 1), x(n), \ldots, x(n + m)] \quad (1)$$

lack the adaptability to differentiate the image information from that of the unwanted noise content [6].

By considering the classification of sharp features such as edges and the impulse noise as a fuzzy specification problem, fuzzy control logic has been used to enhance the performance of the multilevel median filter (MLMF) [7]. Fuzzy techniques can also manage the vagueness and ambiguity present in low SNR images. Adaptive systems based on fuzzy (or neural networks) with data driven adjustable parameters have emerged as attractive alternative [8, 9]. Nevertheless, their performance is sub-optimal under high noise level. As indicated earlier, the SAR images suffer from the inherent poor

SNR which is strongly influenced by the sea moisture [10] and surface roughness [11], and the difference in the surface roughness is sometimes useful in discerning objects on the surface of the sea. Hence the robustness of the adaptive system should be high enough to derive meaningful information [12].

In this paper, we propose an enhancement system based on fuzzy control algorithm, to improve its robustness to noise[13-16]. The improvement is formulated by fine tunning the membership functions to identify the grade of the brightness for each input pixel[17]. A new method for self tunning the shape and internal parameters is presented with the help of parabolic membership function. Each element is considered to be a fuzzy variable, and the membership functions identify the grade of brightness for each input pixel[18]. Two important features are presented: first, the filter estimates a fuzzy derivative in order to be less sensitive to local variations due to image structures such as edges; second, the membership functions are adapted accordingly to the noise level to perform "fuzzy smoothing"[19, 20]. Fuzzy rules applied to the proposed algorithm show improved performance even with increased noise levels. We have tested the system with Oil spill SAR images of our interest. Nevertheless, the fine tuning using the parabolic membership can be readily extended to other imaging modalities too.

2 Description of the system

The SAR image enhancement system is an improved approach that incorporates the fuzzy associative memory (FAM) in MLMF for efficient noise removal without significant image distortion. In the following, the detailsof the different modules of the integrated system are presented.

2.1 MLMF

The system design starts with an MLMF filter whose output is defined as,

$$Y(i, j) = median[Y_{max}(i, j); Y_{min}(i, j); S(i, j)] \quad (2)$$

where

$$Y_{max}(i, j) = Max[Z_n(i, j)] \text{ with } 1 <= n <= 4;$$
$$Y_{min}(i, j) = Min[Z_n(i, j)] \text{ with } 1 <= n <= 4. \quad (3)$$

and

$$Z_n(i, j) = median[S(.,.) \in W_n(i, j)\ 1 <= n <= 4 \quad (4)$$

for four subsets of window W. In Eqn 3, S(. , .) is a discrete image sequence with samples inside a square window (W) of size (2L+1) x (2L + 1), centered at (i, j). As outlined earlier, in most of the cases, the SAR images are corrupted with Speckle type of noise. Thin line details get burried inside the noisy images, S(i,j). Denoising the signal-dependent noise with the MLMF is not very effective in preserving fine details of the image. Combination of the filtering procedure with an adaptive technique can enhance the performance of MLMF. Adaptive filters based on fuzzy control logic have shown better performance than simple MLMF [16].

2.2 Fuzzification of MLMF

Fuzzy enhancement is based on gray level mapping into fuzzy plane, using a membership transformation function. The aim is to generate an image of higher quality than the original by giving a larger weight to the gray levels that are closer to the mean gray level of the image than to those that are farther from the mean. An image, I of size M X N, and of gray levels, L can be considered as an array of fuzzy singletons, each having a value of membership denoting its degree of brightness relative to a standard level. Fuzzy logic control (FLC) has the characteristic of representing human knowledge or experiences as fuzzy rules. However, in most of the existing FLCs, shapes and internal parameters of membership functions and fuzzy rules are determined and tuned by trial and error through operators. Therefore, it is necessary to design FLCs so that these elements can be optimized [17] and self-tuned for a particular solution. The modules of a fuzzy enhancement scheme is illustrated in For membership calculation, possibility distribution algorithm can be used to characterize the gray levels of the original image.

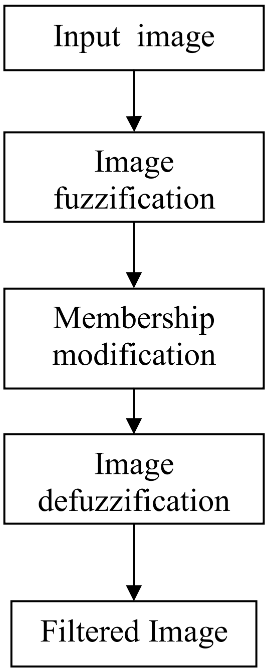

Figure 1. Modules of a fuzzy enhancement scheme

2.3 Fine tunning of membership function

Fuzzy rules applied to the proposed algorithm use fuzzy associative memory systems (FAM). This model is designed to approximate the relationship between input variables and known output variables. Very popular choices of membership functions are triangular and trapezoidal shapes because of their computational simplicity [18]. Main difference is that trapezoidal membership functions (as in Fig. 2A) are described by four parameters with the four breakpoints of the trapezium [19].

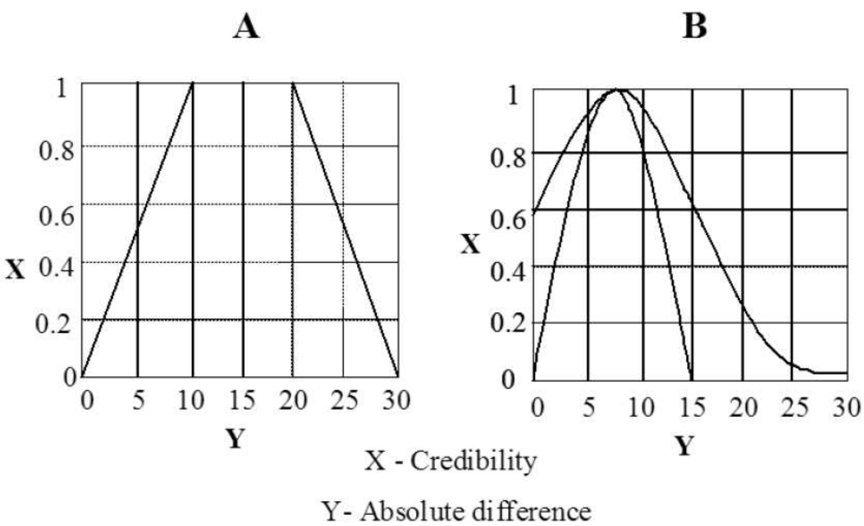

Figure 2: Membership function for credibility: A) Trapezoidal function B) Parabolic and bellshaped functions. X - Credibility, Y - Absolute difference.

The credibility value, using trapezoidal membership function was calculated as follows. Let the absolute difference between the median value Zs(i,j) and the other pixels in subset Ws(s = 1,2,3,4) be *4f* . Credibility, 'Cr'of Zs(i,j) is defined in general as,

$$Cr = \begin{cases} low & \text{if } 0 > 4f > 30\,; \\ high & \text{if } 10 < 4f < 20: \end{cases} \quad (5)$$

In between 0 and 10, and 20 and 30, following conditions were adopted for obtaining credibilityvalues.

$$Cr = \begin{cases} 0{:}2 \text{ if } 0 < \Delta f\, 2 <= 28 < \Delta f <= 30\,; \\ 0{:}4 \text{ if } 2 < \Delta f\, 4 <= 26 < \Delta f <= 28\,; \\ 0{:}6 \text{ if } 4 < \Delta f\ \ 6 <= 24 < \Delta f <= 26\,; \\ 0{:}8 \text{ if } 6 < \Delta f\ \ 8 <= 22 < \Delta f <= 24\,; \\ 1{:}0 \text{ if } 8 < \Delta f\, 10 <= 20 < \Delta f <= 22\,. \end{cases} \quad (6)$$

This relationship defines the linguistic variable difference as being small, medium, or large using the membership functions. The membership functions were defined in this way after analysis of the grey scale values of different image data sets, and the functions were adjusted by trial-and-error.Based on these conditions, the sum of credibility of Zs(i,j) (s=1,2,3,4) with respect to all the other pixels in the subset, Ws can be estimated.

Median with largest sum of fuzzy credibility values is important in the design of the proposed algorithm. Let $Yf1$ and $Yf2$ be the two medians with largest sum of credibility values among $Z1(i, j);Z2(i, j);Z3(i, j)$ and $Z4(i, j)$. Then the output can be defined as

$$Y(i, j) = med[(Ymin(i, j);\ Ymax(i, j);\ Yf1(i, j);\ Yf2(i, j);\ x(i; j)] \quad (7)$$

In some cases, $Yf1(i, j)$ and $Yf2(i, j)$ may coincide with $Ymin(i, j)$ and $Ymax(i, j)$. But in the presence of impulse noise, the probability is very low. When the noise level is high and the quality of the image is not satisfactory, the membership function needs further tuning.

The membership function is the crucial component of a fuzzy set. In this paper, we present a new method for self-tuning together the shape and internal parameters of membership functions. For better results, the credibility value can be obtained from more sophisticated choices such as parabolic function or bell shaped function (Fig. 2B) depending upon the requirement. For parabolic function, the credibility values are calculated using the standard parabolic equation, $f(x) = ax2 + bx$. The coefficient 'a' decides the shape and direction of the parabola. For adaptability of the algorithm, value of the coefficient (which is already negative for downward parabola) varies according to the local characteristics of the image.

3 Result and discussion

In this section, we test the proposed algorithm for SAR images. Additionally, we demonstrate the algorithm for oil spill detection in SAR images. In each case, we compare the results of the proposed algorithm with the multilevel median filter. We examine the root mean square error (RMSE), normalized mean square error (NMSE), standard deviation error (SDE) and peak signal to noise ratio (PSNR) to evaluate the performance of the algorithms. The real image examples show the usefulness of fuzzy control adaptive filter for SAR image processing applications to obtain accurate quantitative information.

3.1 Denoising

3.1.2 Oil spill detection

One of the major aims of the present system is to improve the quality of the image and hence facilitate the recognition of Oil spill in SAR images. Accurate interpretation may become difficult if noise levels are relatively high. In order to examine the oil spill identification as well as the noise suppression in SAR images by the proposed algorithm, image was used.

The noisy SAR images and their denoised output obtained from the conventional MLMF, and the adaptive fuzzy filters are shown in Fig.3. It can be readily seen that while the noise elimination by MLMF (Fig. 3A2, B2) is not very effective, both the fuzzy filters using both trapezoidal (Fig. 3A3, B3) and parabolic (Fig. 3A4, B4) membership functions efficiently adapt in removing the noise, and enable the recognition of the oil spill SAR images.

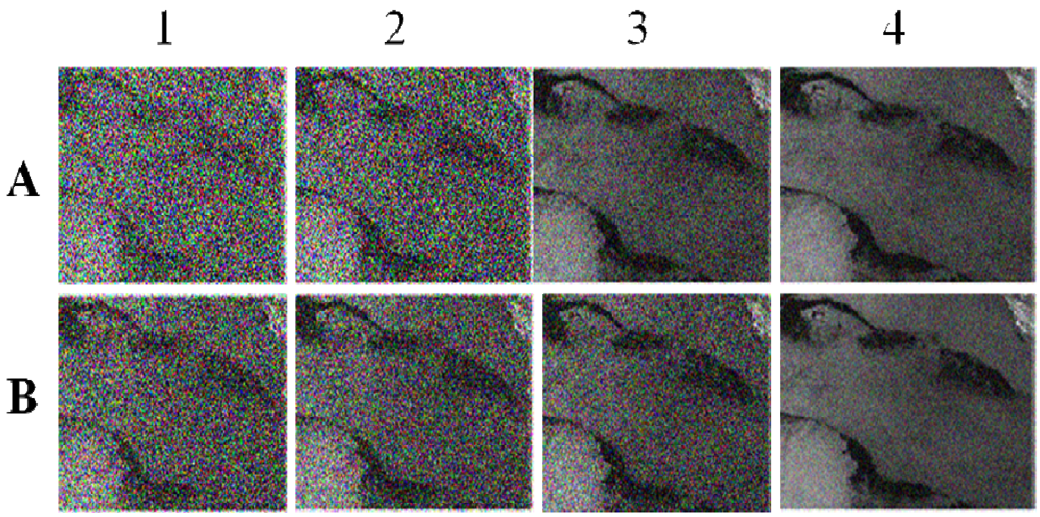

Figure 3: Application of fuzzy control approach to SAR images: image with 40% speckle noise (A1), 20% speckle (B1), forms the input to the system. Column two (A2, B2) corresponds to images in column 1 restored by MLMF. Column three (A3, B3) corresponds to images in column 1 restored by fuzzy control filter using trapezoidal member function. Column four (A4, B4) corresponds to images in column 1 restored by fuzzy control filter using parabolic member function.

The degree of confidence is more in the case of parabolic member function for the feature extraction.

4 Performance evaluation

Accurate identification of contours of oil spill plays an important role in SAR image processing. The quality of the enhanced image may be evaluated either by a subjective measurement or by a quantitative measurement. Subjective measurement is entirely based on human perception. Unfortunately, there is no good objective criterion or mathematical formula to mimic the human visual system in a realistic way. The goodness of an enhancement result depends on many factors such as homogeneity, spatial compactness, continuity, correspondence with psycho-visual perception etc. Therefore, a single measure is unlikely to capture all of them in a meaningful way. Such goodness should be evaluated by the usefulness that the image enhancement can provide in a particular application of interest. However, for quantitative evaluation, a common error measurement, RMSE and PSNR are widely employed [21]. RMSE is widely used as a metric to measure visual distortion and perceived image quality [21] and it is defined as,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[I(i) - I'(i)]^2}$$

Here, N is the total number of pixels in the image; I and I' are the 8-bit values of the ith pixel of the input and output images respectively. PSNR, measures the amount of useful data versus the amount of noise introduced into the image and it is given in dB by,

$$PSNR = 10 * log[\frac{Max(originalimage)^2}{MSE}]$$

These measures RMSE, and PSNR were for speckle noise of various levels (1%, 2%, 3%, 4%), and are listed in Table 1. Larger PSNR, and lower RMSE indicate better performance. Tables 1 shows that the fuzzy filter using parabolic membership function performs well even when the noise level is high.

Table 1: Quality measures computed for bladder region with speckle noise of different levels.

	1%	2%	3%	4%
Filter	MLMF/Trap/Parab	MLMF/Trap/Parab	MLMF/Trap/Parab	MLMF/Trape/Parab
PSNR	20.15/25.75/32.40	19.69/23.76/30.63	15.13/20.91/28.06	15.12/17.73/28.21
RMSE	0.41/0.37/0.09	0.57/0.38/0.22	0.60/0.48/0.26	0.62/0.49/0.31

5. Summary

Adaptive fuzzy filter controlled by using trapezoidal and parabolic membership functions for enhancement without loosing fine structure details is developed for the analysis of SAR images. . Local variations due to noise and image structures is distinguished by using fuzzy controlled membership functions. Additionally, the shape of the membership function is adapted according to the level of noise to preserve the image details. The feasibility of the proposed approach is validated by using oil spill images corrupted by speckle noise of different levels. Results are evaluated both by subjective and quantitative analysis. Numerical measures such as PSNR, RMSE, SDE and NMSE, show convincingly the better performance of fuzzy control approach over MLMF. The parabolic membership function shows superior performance, encouraging further work in the development of fuzzy filters for noise removal in SAR images. Results presented here show the comparison of performance of MLMF and fuzzy filter using trapezoidal and parabola membership functions for speckle noise reduction in one iteration. Clearly the fuzzy filters outperform the MLMF. Among the two fuzzy filters, it is evident that the filter controlled by parabolic membership function performs better.

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