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Oil Spills Detection from SAR Images Using Wavelets

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ABSTRACT

Oil spills detection is an actual environmental problem. Oil spills can occur during ships' oil and/or fuel leakage or in great catastrophes. Small leaks are hardly detectable. Early detection and monitoring of greater spills can be useful in damage suppression and control. A new oil spill detection algorithm is presented in the paper. The algorithm is based on wavelet analysis of the radar image and the data fusion of VTS data, which should correlate to the image processing results to obtain the validated detection. The proposed algorithm exploits both the approximation and the details of the wavelet decomposition.

Keywords: Image processing, Ecology, Oil spill, Data fusion, VTS.

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1. INTRODUCTION

Oil spill detection on sea/ocean surface has been considered in many references due to the increased interest in monitoring and/or prevention of environmental accidents. The typical approach is the usage of SAR (Synthetic Aperture Radar) images obtained by ships, coast or satellites (Akkartal and Sunar, 2008; Likoka *et al*., 2015; Brekke and Solberg, 2005; Salberg *et al*., 2014; Santillan and Paringit, 2011; ElZaart and Ghosn, 2013; Ramakrishnan and Majumdar, 2013; Fana *et al*., 2015). SAR can be seen as an active sensor in the microwave range which cannot be influenced by any weather conditions (Kwon and Li, 2012). The SAR antenna records backscattered pulses, which are processed by SAR processor to produce a SAR image. When analyzing SAR data, the SAR image is commonly analyzed instead of EMW (Electro-Magnetic Wave) raw data. Hence, the problem of SAR data interpretation is resolved as an image analysis problem. The area of image processing and analysis is very wide and advancing. Satellite surveillance is effective for coverage of large surfaces with little cost, like oceans. It is inevitable for monitoring large oil spills. Further advantages of SAR over optical sensing are the ability to function at any weather and time of day or night at lower cost than alternatives, such as airborne ocean surveillance. Image processing/analysis is not all-mighty and its result is the detection of possible, not actual oil spills. Some other quality should be added to differentiate between possible (lookalikes) and actual oil spills. Data fusion is proposed in various forms to obtain such additional quality. In this paper, data fusion of VTS ship tracking and image data processing is proposed, because Adriatic Sea (our zone of interest) is narrow and small.

Repeated ecological accidents call for the development of methods for fast and reliable detection of oil spills on large sea surfaces. There are many different researches and approaches to this issue. Several of them are mentioned in the second section.

The dangers of oil spills are more evident in narrow seas and straits. We are especially interested in an example of such a sea – the Adriatic Sea, as a part of the Mediterranean, in which there is tanker traffic and exploitation of gas from rigs. Furthermore, great plans from several governments exist for further exploitation of oil and gas, increasing the probability of accidents. The detection and monitoring of oil spills in narrow seas is important as well.

This paper is organized as follows. The second section overview some researches in this field. The third gives the mathematical background. The fourth section describes the proposed algorithm. Results are presented in the fifth section. Finally, conclusions are given.

2. LITERATURE OVERVIEW

Results in (Marghany, 2001) show that texture analysis can be promising for automatic oil spill detection by SAR data. The classification of segmented structures was further considered in (Karantzalos and Argialas, 2008). The properties of such structures were extracted in real-time. Automatic segmentation was covered by (Arvelyna *et al*., 2001; Keramitsoglou *et al*., 2002; Saleh, 2004). Different approaches were used in various references. Fuzzy logic was used in i.e. (Ramakrishnan and Majumdar, 2013). Wavelets for noise reduction were used in (Amirmazlaghani *et al*., 2009). RADARSAT and ENVISAT SAR images were used in (Solberg *et al*., 2004). A training sequence of 60 to 100 frames was used. Results for suspicious areas are very encouraging. However, there are problems with distinguishing oil spills from seaweed agglomerates, especially in the Baltic. Basically, algorithms incorporate three main parts: detection of dark spots, feature extraction and classification. Adaptive threshold is used for the first part in (Solberg *et al*., 2004). Classification features are calculated in the second stage. Finally, the third stage is the classification of every spot (low to high reliability of spill detection).

Morphological SAR image analysis was used in (Gasull *et al*., 2002) to detect oil spills. The goal was to segment oil spills without prior knowledge. Final confirmation is obtained by cross-correlation with the ship's movement. Reference (Lia and Zhangab, 2014) dealt with morphological characteristics of the oil spills in other to detect it correctly.

Publicly available software image was enhanced to obtain better oil spill detection results in (Vyas *et al*., 2015). Fuzzy solution for oil spill classification was presented in (Keramitsoglou *et al*., 2006). The probabilistic approach to distinguishing oil spills from lookalikes is presented in (Shu *et al*., 2010). The manner of distinguishing dark pixels caused by oil spills from background dark pixels is proposed. Texture entropy algorithm was presented in (Bhogle and Patil, 2012), which is an improvement of the Mahalanobis classification (Marghany and Hashim, 2011).

Wavelet transform (WT) spectrum was considered in (Dongmei *et al*., 2015). It was used to classify thickness of the oil spill film at the 5^{th} level of decomposition by the db4 (Daubechies wavelet of 4^{th} order) kernel.

One of literature approaches in oil spill detection (Logman *et al*., 2017) is to combine a simple averaging method and the Discrete Wavelet Transform (DWT). DWT is used to check the frequency discrepancy effect between the SAR images.

More complex is a method presented in (Osman *et al*., 2017), where cross-correlation and the Fast Fourier Transform (FFT) are used to estimate oil flow in deep waters.

Fast connection of the oil spill and the sourced ship is presented in (Lupidi *et al*., 2017). The authors developed wavelet correlator, but in ship detection part of the algorithm, not in part of oil spills detection.

(Song *et al*., 2017) used RADARSAT-2 SAR images as a dataset for creation of optimized wavelet neural networks (WNN). As the neuron function, Morlet wavelet was used. There were no explanation why this wavelet and the WNN is compared only to un-optimized WNN with the same wavelet.

Hyperspectral characteristics of the oil-polluted sea ice was explored in (Liu *et al*., 2018), where the 5^{th} level of the decomposition of the DWT was used. The wavelet family was also db4.

(Huang *et al*., 2018) used wavelet packages to extract coefficients of the significance. Then, NN was used to perform pattern recognition – oil spill detection.

3. MATHEMATICAL BACKGROUND

WT is an integral transform, which can be defined as in definition 2.1 (Mallat, 2009; Jansen and Oonincx, 2005; Christopher and Walnut, 2006).

Definition 2.1. Let $\psi(t) \in \mathbf{L}_2(\mathbf{R})$ be the wavelet in the time domain and $\Psi(\omega)$ the same wavelet in the frequency domain. If and only if exists the integral:

$$CWT_f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right)dt = \langle \psi_{a,b}(t), f(t) \rangle \quad (1)$$

the following rules apply:

1° $\int \psi(t)dt = \Psi(\omega = 0) = 0$ (2)

2° Translated (which is presented with parameter b) and scaled (which is presented with parameter a) function of $\psi(t)$ is described as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \cdot \psi\left(\frac{t-b}{a}\right) \quad (3)$$

where a, b $\in$ **R** and a $\neq$ 0. Function $\psi(t)$ is called mother wavelet, and $\psi\left(\frac{t-b}{a}\right)$ is dilated version of mother wavelet at given scale a. In practical applications, scale parameter is always $a \leq 1$.

3° Normalization rules apply: $\left\|\psi_{a,b}(t)\right\| = \left\|\psi(t)\right\|$, and

$$4° \left\|\psi(t)\right\|^2 = \int_{-\infty}^{+\infty} \left|\psi(t)\right|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left|\Psi(\omega)\right|^2 d\omega = 1 \quad (4)$$

Then the CWT satisfies the sufficient and necessary conditions and it is called Continuous Wavelet Transform (CWT) (Kingsbury and Magarey, 1997; Vujović *et al.*, 2012; Chandrasekhar *et al.*, 2014).

4. PROPOSED ALGORITHM

The proposed algorithm exploits WT characteristics to detect oil spills. However, since oil spills resemble many other dark-tone phenomena, the algorithm cannot be claimed to detect oil spills exclusively and nothing else. Therefore, data fusion is included to differentiate between lookalikes and actual oil spills. The proposed algorithm's flowchart is shown in Fig. 1. The algorithm can be explained in four steps:

Step 1: Input is a satellite radar image. This image is inverted and the inverted image is used as the second input. Both inputs are decomposed by DWT. In the experiments, we used Daubechies wavelet (Matlab designation db10).

Step 2: Thresholds are calculated. For the approximation of the inverted original image, the threshold is set to about 80 to 90% of the maximum coefficients value (threshold T_1). To obtain detail coefficients of the original image, the thresholds are set to about 1% of the maximum of the details of the original image (threshold T_2).

Step 3: Approximation coefficients are thresholded in such a way that coefficients below the threshold are discarded. This generates the candidates' mask of approximation coefficients. Both sets of detail coefficients are thresholded (details of the original and the inverted image) with the same threshold. Candidates' mask of detail coefficients is obtained if detail coefficients of the original and the inverted image are both bellow the calculated threshold (step 2). Candidates' masks (for approximation and details) are denoised using morphological closing operation. The morphological closing operation is a dilation followed by an erosion, using the same structuring element for both operations.

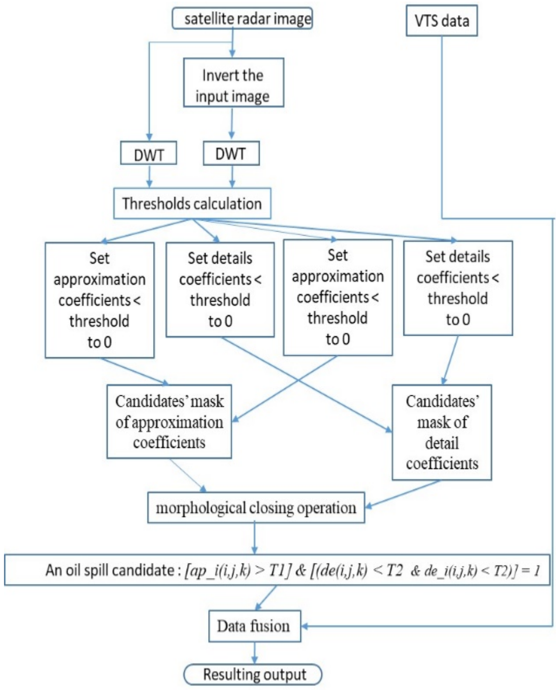


Figure 1. Flowchart of the proposed algorithm

Grey-scale erosion is not used, because thresholding produces a binary image. Binary erosion of A by B is denoted as A – B and defined as a set of operations, where a set of pixel locations z is obtained by overlapping foreground pixels in A with a structuring element:

$$A - B = \{z | (B_z \subseteq A)\} \quad (5)$$

The binary dilatation of A by B, denoted by $A \oplus B$, is defined as a set of operations:

$$A \oplus B = \{z | \left(\hat{B}\right)_z \cap A \neq \varnothing\}, \quad (6)$$

where $\hat{B}$ is the reflection of the structuring element B. It is a set of pixel locations z, where the reflected se overlaps with foreground pixels in A when translated to z (Matlab help – imclose, 2012).

An oil spill candidate is identified if the logical expression is truth:

$$[ap\_i(i,j,k) > T1] \ \& \ [(de(i,j,k) < T2 \ \& \ de\_i(i,j,k) < T2)] = 1 \qquad (7)$$

where ap_i denotes approximation coefficients of the inverted image, and de and de_i the detail coefficients of the original and the inverted image.

Step 4: Data fusion is the last step. In order to validate that an oil spill candidate is actually a spill, and not some other dark-color phenomenon, data fusion must be applied. The VTS data is correlated with possible oil spills obtained by image processing (step 3). If the correlation of the candidate for oil spill with possible sources (ships, rags, etc.) is high, than it is an oil spill, and actions to protect the environment, reduce damage and save lives should be taken. If the correlation is low, than it is some other phenomenon and no action should be taken.

5. RESULTS

Dataset is obtained by RADARSAT-2. Figure 2 shows an example of the original (input to the proposed algorithm) image. There are many dark areas which could be oil spills.

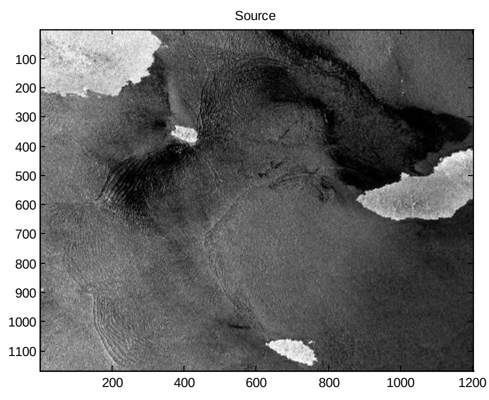
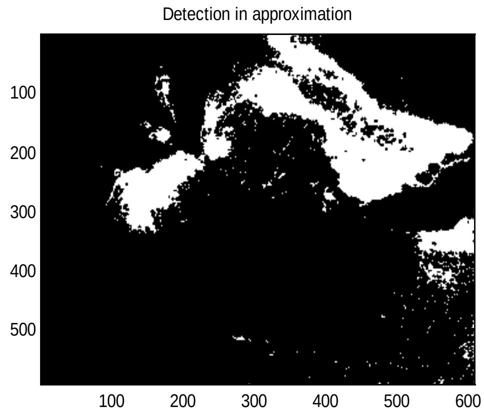
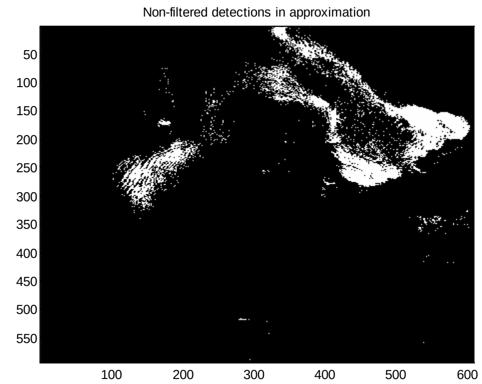


Figure 2. An example of the source image imported in Matlab software package

Figure 3.a illustrates the detection of possible oil spills in the approximation coefficients of the WT. White are areas of possible oil spill locations. The figure is obtained by the application of the morphological filter (see step 3 in the proposed algorithm). Figure 3.b shows the same, but without the application of the morphological filter. The morphological filter can be concluded to give a more compact mask of possible oil spills.



a)

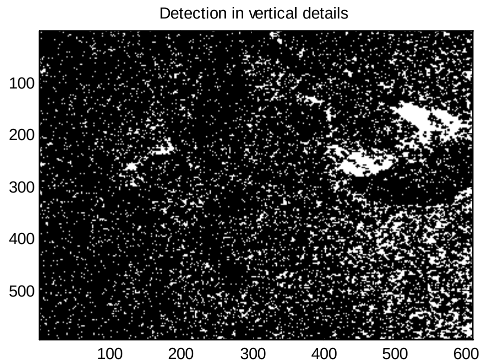


b)

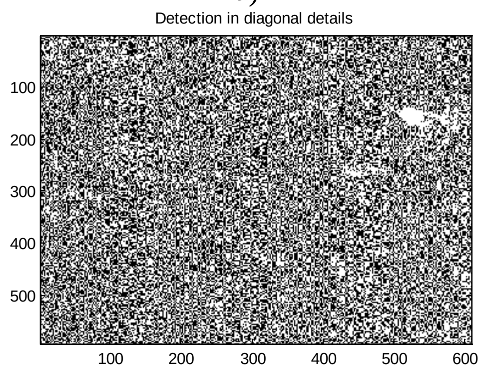
Figure 3. Example of the results:
a) detection of possible oil spills in the approximation coefficients of the WT,
b) non-filtered approximation coefficients of the WT

Figure 4.a shows vertical detail WT coefficients, which are too noisy to be useful. The first instinct is to decrease the noise threshold. However, since it is already at about 1%, there is no realistic change.

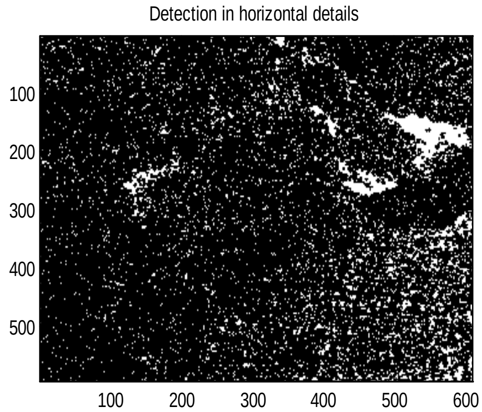
Diagonal details (Fig. 4.b) are even worse. Static noise is too great to be denoised. Horizontal details (Fig. 4.d) also contain great noise, but after morphological filtering (Fig. 4.c), it is reduced to a meaningful image. Finally, Figure 5 shows the result of (7).



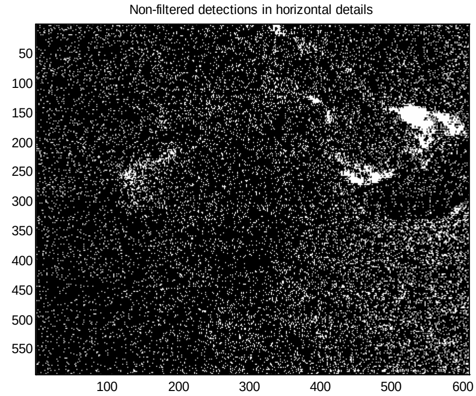
a)



b)



c)



d)

Figure 4. Example of the results: a) vertical details coefficients of WT, b) diagonal details coefficients of WT, c) horizontal details coefficients of WT filtrated with morphological operations, d) horizontal details coefficients of WT filtrated without filtering

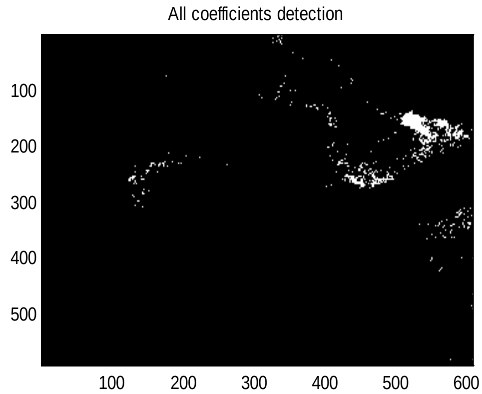


Figure 5. Fused detection for all coefficients with proposed logical relation

6. CONCLUSIONS

A new algorithm for oil spill detection is presented in the paper. The algorithm exploits approximation coefficients and detail coefficients. In order to obtain better results, inverted image is first formed. Approximation coefficients of the inverted image are thresholded to extract white areas. Details of the original and the inverted image are thresholded with the same threshold. If equation (7) is satisfied, possible oil spill is detected. Validation is proposed to be performed with data from the

VTS, which must correlate the oil spill with a possible source. Although, these results are promising, further research should be performed to obtain more reliable conclusions about the usefulness of the proposed algorithm in real situations. Further work should include establishing of ground-truth data for testing of various algorithms in the field.

Step 4 of the proposed algorithm is vital to final classification of look-alikes. Namely, big dark regions could be many things, i.e. algal blooms, wind shadows, result of image acquisition (depending on polarization), dirt from ships carried by ocean/sea currents, etc. However, the proposed algorithm differs from others, because different levels of data are fused. The first data is low-processed image data, and the second highly-processed information. So, it can be said that step 4 is like differential diagnostics.

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