SHIP DETECTION IN SAR IMAGERY BASED ON THE WAVELET TRANSFORM

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ABSTRACT

Satellite-based Synthetic Aperture Radar (SAR) provides a powerful vessel surveillance capability in front of time consuming traditional reconnaissance methods. Nevertheless, due to the presence of speckle and to the reduced dimensions of the targets compared to the sensor resolution, the automatic interpretation of SAR images is often complicated even though vessels undetected are sometimes visible by eye. Therefore, the main difficulties of automatic ship detection will be reviewed and the main drawbacks will be identified. As a result of this preliminary analysis, the application of wavelet tools is found to be a useful mathematical object for this purpose. So, according to the capabilities of the wavelet analysis, the objective is to provide other tools for a better understanding and further exploitation of satellite high resolution images. More specifically, a novel method for ship detection based on multiscale tools is proposed, justified and tested over simulated and real images.

1. INTRODUCTION

The objective of this paper is to provide an alternative reliable approach for ship detection in SAR images based on multiscale tools. First, the main drawbacks of this type of problem are overviewed and then the suitability of a multiscale analysis by means of the wavelet transform (WT) is justified. The basic theoretical principles of the WT are reviewed in section 3. The algorithm proposed is then presented in section 4 and tested on simulated and real RADARSAT and ENVISAT images (Section 5).

2. SHIP DETECTION IN SAR IMAGERY: MAIN DRAWBACKS

Since the dimensions and the shape of the signature of the target are, a priori, unknown and very diverse, conventional ship detection algorithms are conceived to discriminate a bright pattern on top of the sea clutter, according to an established decision rule expressed by a threshold [1]. But SAR sea images are highly heterogeneous (Fig. 1) and this fact affects to the viability of this approach.
It appears that multiresolution processing with wavelets might be a suitable tool for modeling the operation of the human vision [3], performing a localized statistical analysis at different scales.

In this section, some aspects of the WT will be briefly discussed. For a more exhaustive mathematical study, [4] may be consulted.

3.1. Wavelet theory basics

The WT proposes the study of a complex phenomenon dividing it into different simpler pieces. Mathematically, this means projecting it in a function space (1)

\[ \psi_j^{a'} = \sum_{n} f[m] \psi_j^{a'} \left[ m - n \right] \]  

being \( f \) the discrete signal, \( \psi_j \) a discrete wavelet basic function and \( a' \) the scale.

This is the same principle of the Fourier Transform, but the particularity of the WT is that the basic functions or atoms come from dilations and translations of a mother wavelet \( \psi \), localized in both time and frequency (2).

\[ \psi_j[n] = \frac{1}{\sqrt{a'}} \psi \left( \frac{n}{a'} \right) \]  

In order to obtain a complete representation, a scaling function \( \phi \), which is an aggregation of wavelets at scales larger than 1, is introduced (3). The modulus of its Fourier transform is defined by [4]

\[ \left| \hat{\phi}(\omega) \right|^2 = \int_{-\infty}^{+\infty} \left| \hat{\psi}(\xi) \right|^2 d\xi \]  

and the complex phase of \( \hat{\phi}(\omega) \) can be arbitrarily chosen. So the scalar product of the function \( f \) with the scaling function \( \phi \) will provide a low pass filtered version of \( f \).

In the time-frequency plane (Fig. 3), a wavelet atom is symbolically represented by a rectangle, so that the WT measures the energy content in it. The time and frequency spread are respectively proportional to \( a' \) and \( 1/a' \). When the scale varies, the height and width of the rectangle change but its area remains constant according to the Heisenberg uncertainty principle which states a compromise between the resolution in time and the resolution in frequency. By adjusting the term \( a' \), the WT permits the extraction of features at a given scale and so, as the human visual system, it allows focusing on structures with a “zooming” procedure [4].

In order to better analyze the effect of the WT at one iteration, it is interesting to notice that a wavelet is a zero average function (4)

\[ \int_{-\infty}^{+\infty} \psi(t) dt = 0. \]  

Yet, the WT measures the variation of \( f \) in a neighborhood of \( n \) whose size is proportional to the scale. That is why when the scale decreases to zero, the decay of the wavelet coefficients characterizes the regularity of \( f \) in a region [4]. Consequently, the WT can thus be applied to transient detection.

For 2D signals, a wavelet orthonormal basis is constructed by means of separable products of a scaling, \( \phi \), and a wavelet, \( \psi \), function which can be assimilated to low (L) and bandpass (H) filters respectively

\[ l[n] = \frac{1}{\sqrt{2}} \left[ \phi \left( \frac{\xi}{2} \right) \phi(t-n) \right] \]  

\[ h[n] = \frac{1}{\sqrt{2}} \left[ \psi \left( \frac{\xi}{2} \right) \phi(t-n) \right] \]
Three wavelets are then defined (HL, LH, HH), each of them extracting image details for a given orientation, while LL is a low pass filtered version of the original image (see Fig. 4).

![Fig. 4. Blocks diagram of the 2D wavelet transform algorithm.](image)

More specifically, the WT performs at each iteration a separation of the different frequency components of the original image, according to their orientation: coefficients of large amplitude in the different detail subbands correspond to horizontal, vertical and diagonal edges (Fig. 6).

![Fig. 5. Fragment of real RADARSAT image (256x256 px) presenting an easy detectable ship.](image)

![Fig. 6. Result of the application of the discrete WT by means of the dyadic pyramidal algorithm with Haar coefficients. Each detail subband enhances edges in a particular direction (HL: vertical edges; LH: horizontal edges; HH: diagonal edges).](image)

### 3.2. Intrascle dependencies between wavelet coefficients in the different subbands

As the WT can be considered as a projection in a function space, it should be expected to be a perfect whitener if the elements of the basis are orthogonal. In fact, the WT constitutes an effective decorrelator for a wide variety of random processes, but it is not a perfect whitener. As a result, the wavelet coefficients conserve some degree of correlation. More specifically, the primary features of the WT usually assume the decorrelation of the detail subbands. However, it has been shown that the WT is not able to remove the most local dependencies, due to the presence of regular or homogeneous spatial structures and patterns [5]. This fact can be observed in Figs. 5 and 6. Fig. 5 presents a SAR oceanic image with an easy noticeable vessel. Fig. 6 presents the four subbands resulting from the first application of the discrete WT to the image in Fig. 5. The presence of the ship, which can mathematically be approximated as a short pulse, with frequenciel components in every subband, is noticeable in the four subbands though its contour. More specifically, subband HL enhances vertical discontinuities, subband LH does the same for horizontal discontinuities and the subband HH sharpens diagonal frequencies.

The exploitation of this property seems to constitute a useful tool for the detection of isolated singularities and, in particular, for ship detection.

### 4. PROPOSED ALGORITHM

#### 4.1. Some preliminary considerations

As it has been previously analyzed, the WT extracts edges at different orientations. A spatially localized homogeneous pattern will thus be detectable in a noisy background through its contour. Moreover, the WT can focus on different features and this, both in space and frequency, adjusting the time – frequency window. Furthermore, by modifying the scale, morphological characteristics also participate in the WT representation. Thus, different kind of marine heterogeneities with similar intensity characteristics will appear at different locations in the time – frequency plane (Figs. 7 - 12). This operation enforces the idea that the consideration of space – frequency analysis contains information, useful to contribute to the discrimination of oceanic discontinuities and vessels. Moreover, this analysis is much less dependent on the intensity of the targets or, namely, on their contrast with the noisy background.
The observation of the images presented before suggests that the WT allows the discrimination of different targets with similar intensity characteristics. In particular, an extended target will have more energy at lower scales and the maxima caused by the presence of a discontinuity will vanish faster if the discontinuity is regular.

4.2. Principles of the proposed algorithm

Attending to these observations, a novel algorithm for ship detection is proposed which consists on spatially multiplying the four components obtained at each iteration of the WT (Fig. 13).

The algorithm is quite simple and not very computationally costly since only two operations are required at each iteration.
As a result of the application of the algorithm, a local singularity will result in a local maxima (in absolute value) in the wavelet subbands detecting the contour of regular structures. If the frontiers of the structure are close to each other (and they will become closer as the number of iterations increase), it will come a point when they will coincide summing up their amplitude.

In order to provide a better understanding of this approach, its effect on a simplified 1D model (Fig. 14) will be analyzed.

![Fig. 14. Simulated model of a vessel surrounded by sea clutter.](image)

The vessel is represented by a short pulse, \( p \), \( L \) samples long, \( p_i(m) = \sum_{i=1}^{L} \delta(m-i) \) whereas the sea clutter, \( n \) with mean amplitude \( \sigma \), follows a Rayleigh distribution (7)

\[
x[m] = p[m] + \sigma n[m] 
\]  

When applying the WT, the process is the same for each iteration and it is constituted by two steps. Firstly, original data pass through a filtering step and then they are downsampled. For a Haar wavelet [4], the expressions of the impulsional response for the lowpass and bandpass filters are

\[
h_L[m] = [0 \ 1 \ 1 \ 0]/\sqrt{2} \\
h_H[m] = [0 \ -1 \ 1 \ 0]/\sqrt{2}
\]  

The filtered signals, \( y_L \) and \( y_H \) can be expressed as

\[
y_L[m] = (p_i(m) + \sigma n[m]) \ast \frac{\delta[m-1] + \delta[m-2]}{\sqrt{2}} \\
y_H[m] = (p_i(m) + \sigma n[m]) \ast \frac{-\delta[m-1] + \delta[m-2]}{\sqrt{2}}
\]  

Defining \( n_L \) and \( n_H \) as low pass and bandpass filtered noise components respectively (10)

\[
n_L = \sigma n[m] \ast \frac{\delta[m-1] + \delta[m-2]}{\sqrt{2}} \\
n_H = \sigma n[m] \ast \frac{-\delta[m-1] + \delta[m-2]}{\sqrt{2}}
\]  

From (9), it can be deduced:

\[
y_L[m] = \frac{1}{\sqrt{2}} (p_L[m-1] + p_L[m-2]) + n_L \\
y_H[m] = \frac{1}{\sqrt{2}} (\delta[m-1] + \delta[m-(L+1)] + 2p_{L-1}[m-2]) + n_L \\
y_H[m] = \frac{1}{\sqrt{2}} (-p_L[m-1] + p_L[m-2]) + n_H \\
y_H[m] = \frac{1}{\sqrt{2}} (-\delta[m-1] + \delta[m-(L+1)]) + n_H
\]  

On the one hand, it can be seen from the equations in (11) that as the pulse in the approximation subband, \( y_L \), becomes shorter with the increase of the number of iterations, so does the distance between the frontiers of the contour of the ship, coming to a point where they coincide and sum up their amplitudes as illustrated in Fig. 15.

![Fig. 15. Four iterations of the DWT with Haar coefficients applied to a pulse in a noisy background and result of the proposed algorithm in 1D.](image)
As a consequence, the spatial product of the four subbands obtained after the application of the DWT will thus greatly enhance the presence of a localized isolated regular pattern and greatly reduce background noise, enlarging the contrast and thus facilitating the decision rules.

5. EXPERIMENTAL RESULTS

The performance of the proposed algorithm has been tested on simulated and real RADARSAT images.

5.1. Application to simulated images

The proposed method is first applied to simulated images with small and weak targets (Figs. 16 to 19). It has been assumed that the speckle in the simulated image follows a Rayleigh distribution. Two matrices containing two different random variables normal distributed with mean equal to zero and standard deviation equal to one have been generated and then added together. The isolated targets to detect are assumed to be constituted by a set of pixels with the same amplitude, placed in a noisy matrix.

As a result of the application of the proposed method to simulated images, the presence of vessels is greatly enhanced, whereas noise is drastically reduced.

5.2. Application to real RADARSAT and ENVISAT images

The algorithm is then tested over a set of real RADARSAT and ENVISAT oceanic images [6, 7] (acquired in ScanSar mode). Groundtruth data was available for these images through reported VMS positions.

In order to quantify the difficulty of performing a correct detection, a contrast parameter, called hereafter the significance is defined as:

$$\text{significance} = \frac{\text{peak of the target} - \text{background mean}}{\text{background standard deviation}}$$  (12)

The histogram of both the input and the output images is presented to provide a graphical interpretation of the effect of the proposed algorithm on contrast. The minimum and the maximum of the horizontal axis correspond respectively to the minimum and the maximum values of the image. Then, a vertical line marks the position of the minimum value for a threshold to perform a correct detection (the vessel is detected with no false alarms). As such, a higher threshold will still perform a correct detection but a lower one will produce false alarms.
From the observation of the histograms provided, it can be deduced that the adjustment of the threshold is greatly simplified after the application of the proposed algorithm, becoming thus less critical.

6. CONCLUSIONS

An alternative approach for ship detection in SAR imagery has been presented and justified. This approach is based on the properties of the WT and consists on the spatial multiplication of the four subbands obtained at each iteration of the discrete WT. As a result, the presence of a ship is enhanced, whereas noise is greatly reduced. This enlargement of the contrast is reached at the expense of a loss of resolution. Nevertheless, as the WT is an invertible process, with further processing, the original resolution can be recovered.

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7. REFERENCES


