A NOVEL APPROACH FOR THE DETECTION OF PUNTUAL ISOLATED TARGETS BY MEANS OF THE WAVELET TRANSFORM

Marivi Tello(1), Carlos Lopez-Martinez(2), Jordi J. Mallorqui(1)

(1) Dept. Teoria del Senyal i Comunicacions (TSC), Jordi Girona 1-3, 08034 Barcelona, marivi.tello@tsc.upc.edu, (2) Université de Rennes 1, CNRS UMR 6164 Rennes, France

ABSTRACT

The detection of an isolated localized structure in a noisy background, with no a priori information about its presence, nor its shape presents multiple drawbacks. Nevertheless, this problem is present in a great number of applications as, for instance, ship detection from satellite radar imagery. Conventional algorithms for ship detection are conceived to discriminate an exceptionally bright localized pattern according to an established decision rule, expressed by the determination of a threshold. But the adjustment of thresholds involved in the decision step is complicated and relies on the existence of a considerable contrast between the vessels and the surrounding sea clutter which is not always reached. Thus, a novel method, based on the intrascale dependencies between wavelet coefficients in the different subbands, is proposed, justified and successfully tested on simulated and real images.

1. INTRODUCTION

The objective of this paper is to present a novel approach for the automatic detection of localized isolated structures in a noisy background. This approach aims at facing the detection not only taking exclusively into account the intensity characteristics of the image but also studying its very localized statistical behaviour by means of the wavelet transform (WT). Particularly, this method takes advantage of the fact that the wavelet transform is not a perfect whitener.

2. WAVELET TOOLS

Automatic detection of localized isolated structures is difficult even if surprisingly, undetected, targets are sometimes visible by eye. The eye sees a texture over two fundamental properties: the orientation of its different elements and its frequency content, simultaneously performing over the observed scene a selective filtering in both time and frequency [1]. It appears that multiresolution processing with wavelets is a suitable tool for modeling the operation of the human vision [2]. In this section, some of the aspects of the WT will be very briefly discussed.

2.1. Multiresolution analysis with the wavelet transform

The WT proposes the study of a complex phenomenon, dividing it into different simpler pieces. Mathematically, this implies projecting it in a function space, in which it is located by measuring its degree of similarity with each basic function or atom, i.e:

\[ Wf[n, a'] = \sum_{n=0}^{N-1} f[m] \psi'_{m-n} \]  

where \( f \) is the discrete signal, \( \psi' \) is a discrete wavelet atom and \( a' \) is the scale. The atoms come from dilations and translations of a mother wavelet, localized in both time and frequency and consequently, the WT can focus on structures with a “zooming” procedure [3]. For 2D signals, a wavelet basis is constructed with separable products of a scaling \( \phi \) and a wavelet \( \psi \) function which can be assimilated to low (l) and bandpass (h) filters respectively. Three wavelets are then defined (HH, LH, HL), each of them extracting image details for a given orientation, while LL is a low pass filtered version of the original image, taken as the input for the next iteration.

2.2. Intrascale 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 and 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 regular or homogeneous spatial structures and patterns [4]. This can be observed in Figs. 1 and 2. Fig 1 presents a SAR oceanic image with an easy noticeable vessel.

Fig. 1. Fragment of real RADARSAT image (256x256 px) presenting an easy detectable ship.

Fig. 2. Result of the application of the discrete WT by means of the dyadic pyramidal algorithm with Haar coefficients.

Fig. 2 presents the four subbands resulting from the first application of the discrete WT to the image in Fig. 1. The presence of the ship, which can mathematically be approximated as a short pulse, with frequencial components in every subband, is noticeable in the four subbands, through its contour.

The exploitation of this property seems to constitute a promising tool for the detection of isolated singularities.

3. A NOVEL ALGORITHM FOR THE DETECTION OF ISOLATED TARGETS IN A NOISY BACKGROUND

These previous considerations lead to the proposed method which consists on spatially multiplying the four components obtained at each iteration of the WT (Fig.3).

A local singularity will result in 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.

On the contrary, due to sparsity of the WT, noise power will be reduced in the wavelet domain as a result of the projection. Furthermore, orthogonality between the wavelet subspaces ensures quasi-decorrelation of the noise, regarded as a random distributed variable, identically distributed within each scale and thus the correlation applied will produce much reduced values, attending to the poor probability of coincidence of related coefficients.

Fig. 3. Diagrams block of the proposed algorithm.

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.

4. EXPERIMENTAL RESULTS

4.1. Application to ship detection

The proposed algorithm has been applied to automatic ship detection in Synthetic Aperture Radar (SAR) imagery. Carrying out an effective control of fishing activities is essential to guarantee a sustainable exploitation of sea resources. Traditional reconnaissance methods such as planes or patrol vessels are quite time consuming and costly over the extended regulated areas. On the contrary, satellite-based SAR provides a powerful surveillance capability already confirmed. Nevertheless, automatic ship detection is still far from being perfect [5], mainly because SAR oceanic imagery is affected by speckle and marine discontinuity effects and because of the diversity of the vessels signature. In order to illustrate the principle of the proposed algorithm, the results on a simulated 1D model are justified below. The vessel is represented by a short pulse, \( p \), L samples long, 
\[
p_L(m) = \sum_{i=1}^{L} \delta(m-i)
\]
whereas the sea clutter, \( n \) with mean amplitude \( \sigma \), follows a Rayleigh distribution:
\[
x[m] = p_L[m] + \sigma n[m]
\]
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, 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:

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

(4)

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

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

(5)

From (4), it can be deduced:

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

(6)

As the pulse becomes shorter with the number of iterations, it comes a point when the two maxima (in absolute value) constructively combine simultaneously in both subbands (Fig. 4).

### 4.2. Simulated Images

The proposed algorithm is first tested on simulated images with small and weak targets (Fig. 5 and 7). 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. The isolated targets to detect are assumed to be constituted by a set of pixels with the same amplitude, placed in the noisy matrix.

![Fig. 5. (right) Simulated image (128x128 px.) presenting a small (3 px.) and weak target (4 times the mean of the background). (left) Result of the product of the wavelet subbands (no threshold applied).](image1)

![Fig. 6. Four subbands resulting from the first iteration of the application of the discrete wavelet transform.](image2)

![Fig. 7. Simulated image with a small target (5 px, 3 times the mean of the background) (left) and result of the application of](image3)
one iteration of the proposed algorithm (no threshold applied) (right).

After the application of the discrete WT to the image in Fig. 5, the target is visible in none of the subbands (Fig. 6), but the subsequent product operation enhances its presence while drastically removing background noise.

So, the WT is not a perfect whitening process. More precisely, the feature that is interesting here is that the decorrelation is not homogeneous since it is not identically performed over the different classes pixels corresponding to different localized statistical behaviors: the coefficients in the different wavelet subbands of a same scale corresponding to a noisy region present a considerably lower correlation than that of those reflecting the presence of a target through its contour.

4.3. Real images

The algorithm is then tested over a set of real RADARSAT and ENVISAT oceanic images [6] (Fig. 8 and 9). Groundtruth data was available for these images. In order to quantify the difficulty of performing a correct detection, a contrast parameter, called the significance is defined as:

$$\text{significance} = \frac{\text{peak of the target} - \text{background mean}}{\text{background standard deviation}}$$  \hspace{1cm} (7)

![Image](image1.png)

Fig. 8. Real SAR image (top left) and result of the algorithm (no threshold applied) (top right). The second row shows the histograms of the images and the location of the minimum threshold performing a correct detection with no false alarms.

![Image](image2.png)

Fig. 9. Real SAR image (top left) and result of the algorithm (no threshold applied) (top right). The second row show the histograms of the images and the location of the minimum threshold performing a correct detection with no false alarms.

6. CONCLUSIONS

A novel approach for the detection of localized regular structures in a noisy background has been proposed, based on the intrascale dependencies of the coefficients in the wavelet subbands. This method has been applied to ship detection in satellite SAR imagery and it appears to be a robust method for automatic ship detection purposes.

This work was supported by the Spanish MCYT and FEDER funds under project TIC2002-04451-C02-01 and the European Commission in the scope of IMPAST project (Q5RS-2001-02266).

7. REFERENCES