HIGHER ORDER STATISTICS FOR THE DETECTION OF UNDERWATER MINES IN SAS IMAGERY

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Synthetic Aperture Sonar (SAS) imagery is largely used in detection, location, and classification of underwater mines laying or buried in the sea bed. This paper proposes a detection method using Higher Order Statistics (HOS) on SAS images. The proposed method can be divided into two steps. Firstly, the HOS (Skewness and Kurtosis) are locally estimated using a square sliding computation window. In a second step, the results are focused by a matched filtering. This enables the precise location of the objects. This method is tested on real SAS data containing both underwater mines laying on the seabed and buried objects.

1. INTRODUCTION

The detection and classification of different types of underwater mines is a present crucial strategic task [1]. Thanks to their high resolution, the images provided by Synthetic Aperture Sonar (SAS) are of great interest for this purpose and have been increasingly used in seabed imagery. After the beam-forming, interesting information can be extracted from SAS images of the sea bed.

But these images are seriously corrupted by a speckle noise which gives a granular aspect to the image and disturbs its analysis. A plentiful literature deals with processing of sonar image to enhance information. Some of the methods use smoothing filters [2][3]. Other papers propose segmentation methods [4][5] based on a statistical model or using first and second order statistics. Higher Order Statistics (HOS) have been used as a powerful tool in various signal processing applications [6][7]. Nevertheless, they have very rarely been used to address sonar applications. To our knowledge, the only example is given by Aridgides et al. [8] who used HOS estimators (Skewness and Kurtosis) to extract features from side scan sonar images in order to classify sea mines by a fusion process.
In this paper, a detection method using third and fourth order statistics is proposed. It can be divided into two steps. In the first step, Kurtosis and Skewness are evaluated on a square window for each pixel of the image (section 2). The second step consists in focusing the result in order to obtain the correct location of the echoes of the detected objects (section 3). Finally, this method is tested on real data containing both underwater mines, or other objects, laying on the sea bed and buried in the seafloor (section 4).

2. HOS ESTIMATORS ON SAS IMAGES

2.1. Definition of the estimators

Among the plentiful choice of tools proposed by the Higher Order Statistics (HOS), the most famous estimators are Skewness (3rd order moment) and Kurtosis (4th order) [9]. If the \( r \)th order central moment of random samples \( X \) is noted \( \mu_{X(r)} \), the respective definitions of the Skewness and the Kurtosis estimated on \( X \) are given by:

\[
S_X = \frac{\mu_{X(3)}}{\mu_{X(2)}^{3/2}} \quad \text{and} \quad K_X = \frac{\mu_{X(4)}}{\mu_{X(2)}^{2}} - 3 \quad (1)
\]

Skewness gives a measure of symmetry of a random distribution, and Kurtosis measures whether the data are peaked or flat relative to a normal distribution. These estimators are null for a normal distribution.

2.2. Results on a synthetic image

To introduce the detection method used in this paper, it is tested on a simulated image (100x100) modelling a SAS image. It consists of a square (11x11) (Fig. 1-a), with an amplitude of 10, modelling the echo reflected by an object, surrounded by a noise. A Weibull law describes efficiently the amplitude \( R \) of the noise in a SAS image [5]. Therefore, the noise on the synthetic image is generated by a Weibull law described by the following probability density function:

\[
W_R(R) = \frac{\delta}{\alpha} \left( \frac{R}{\alpha} \right)^{\delta-1} \exp\left\{-\left(\frac{R}{\alpha}\right)^{\delta}\right\} ; \quad R \geq 0
\]

(2)

with \( \alpha = 0.25 \) (this ensures a realistic signal to noise ratio) and \( \delta = 1.65 \) (this value being estimated close to the parameter on real data).

Skewness and Kurtosis are then evaluated on a square window (11x11 here) for each pixel of the image (Fig. 2). The choice of the size of the estimation window is discussed later.

To explain the results obtained on Fig. 2, we consider \( p \) the proportion of the filtering window composed of deterministic pixels (i.e. belonging to the simulated echo) and \((1-p)\) the proportion of random values (Fig. 1-a). Considering \( \mu'_{E(r)} \), \( \mu'_{N(r)} \), and \( \mu'_{X(r)} \) the \( r \)th order non-central moments respectively computed on the “echo-part” of the filtering window, the “noise-part”, and the whole window, the following relation holds:

\[
\mu'_{X(r)} = p \mu'_{E(r)} + (1-p) \mu'_{N(r)}
\]

(3)
Moreover, considering $A$ the amplitude of the echo, the Weibull law describing the noise (equation 3), and $\Gamma$ being the Gamma function, we have:

$$
\mu_{E(r)} = A r \quad \text{and} \quad \mu_{N(r)} = \alpha \Gamma(1-r/\delta)
$$

(4)

If the moments of the noise are supposed to be negligible compared with the moments of the echo, and if we take into account the relationship between the central and non-central moments [9], approximations of Skewness and Kurtosis (equation 1) can be made by:

$$
S_X(p) \approx \frac{1-3p+2p^2}{p^{3/2}(1-p)^{1/2}} \quad \text{and} \quad K_X(p) \approx \frac{1-7p+12p^2-6p^3}{p(1-p)^2}
$$

(5)

The behaviour of these approximations versus parameter $p$ is shown on Fig. 1-b. An interesting property is the independence of these values from the amplitude of the echo.

From the results presented on Fig. 2, we can make the following observations:

- In the noisy background, the HOS estimators lead to small values. This corresponds to the low values of the statistical moments of the Weibull law (note that in this specific case, the approximations proposed in (5) do not hold anymore).
- Square structures can be seen around the echo. They are composed of pixels with high values, the highest being in the corners.

The size of these squares corresponds to the sum of the size of the echo and the size of the computation window. As can be seen on Fig. 1-b, the maximal values for the estimators are reached for the minimal values of parameter $p$. In our case, this corresponds to one single pixel of the echo included in the filtering window (i.e. the corner of the structure). If the number of deterministic pixels increases, the value of the estimators decreases, that justifies the shape of the square structures on the images end the decreasing values along the edges and inside the square. From (5), for low values of $p$, Skewness can be approximated by $\frac{1}{\sqrt{p}}$.
and Kurtosis by 1/p. This explains that for a 11x11 window, the highest value on the image of Skewness is close to 11 = √11×11 and 121 = 11x11 for Kurtosis (Fig. 2).

A critical case exists for Kurtosis. Indeed, when p goes above 0.5 (there are more deterministic pixels than pixels from the noisy background inside the filtering window), Kurtosis value increases with p (Fig. 1-b). The case of p = 1 is particular (infinite Kurtosis) and is put to its maximum value on the image. For Skewness, negative values appear for p > 0.5 (Fig. 2-a near the center of the square) as predicted by Fig. 1-b. A solution is to choose a high enough size to avoid these cases: for instance a size twice as big as the echo (Fig. 3-a) or more.

In the following, only the results obtained with Kurtosis will be considered, the behaviours of the two estimators being similar for p < 0.5.

3. FOCUSING OF THE RESULTS

3.1. Matched filtering approach

In this section, the second step of the detection method is described. It consists in focusing the detected squares to one point corresponding to the correct location of the sought element. In this subsection, a matched filtering approach is presented by performing a correlation of the Kurtosis image with a theoretical model of the result. To build this model, knowing approximately the size of the searched element and of the computation window, approximation made in (5) is used. For example, for the Kurtosis image obtained on the simulated image with a 21x21 window, the model built by this mean is similar to the result obtained on Fig. 3-a (with a size of 31x31). We can see on Fig. 3-b the result obtained by the correlation of the Kurtosis image (Fig. 3-a) by the model, which can be considered as a matched filtering. On the zoomed image (Fig. 3-c), the maximum value of the filtered result can be observed at the exact position of the center of the echo of the SAS image. A simple threshold of this last image then allows an easy detection and precise location of the object.

Given the size of the window, which is fixed before the Kurtosis image was built, the dimension of the echoes is not accurately known. To take this fact into account, a solution is to take, for the correlation, a model built with the normalised sum of several models, as described before, of different sizes. It is tested on a synthetic image with two echoes of different sizes, the size of the echoes being respectively 11x11 and 21x21. If a 41x41 model is chosen on the Kurtosis image obtained with a 21x21 window (Fig. 4-a), only the wider echo is correctly focused (Fig. 4-b). To solve this problem, a new model is built by summing 6 models of sizes between 31x31 and 41x41. This allows to have a relatively good detection of the two echoes (Fig. 4-c).

3.2. Correlation with a frame

In this subsection, a simpler process to focus the Kurtosis image is proposed. Instead of a correlation with a theoretical model, a correlation with a simple frame with well suited dimension is proposed. For example, the Kurtosis image of the synthetic image, with one single echo, built with a 21x21 computation window, is correlated with a 31x31 frame (zoomed on Fig. 3-d). Then, we can see that the maximum is slightly less visible than in the
result obtained with the matched filter (Fig. 3-c), but this process is simpler. In the case of several echoes of different sizes, a solution is to take a frame with a given “thickness”.

Fig.3: Kurtosis image obtained with a 21x21 window (a), result of the matched filtering (b), zoomed (c) and compared with a simple correlation with a frame (d).

Fig.4: Kurtosis image obtained on a synthetic image with two echoes by a 21x21 window (a), filtered with a simple 41x41 theoretical model (b) and with the sum of 6 models from 31x31 to 41x41 (c).

4. RESULTS ON REAL DATA

The proposed detection method has been tested on various real SAS data. These data have been provided by the DGA (Délegation Générale de l’Armement, France).

In this paper, the method is tested on a SAS image containing several buried, partially buried or not buried objects (underwater mines and rocks). This image represents a sea bed region of about 10m by 10m, with a resolution of about 10cm in both dimensions. On this image (Fig. 5-a), the echoes (see the numbered boxes) reflected by the objects are hardly visible apart from a partially buried cylindrical mine on the left (1). After having built the Kurtosis image with a 11x11 computation window, the result is filtered with the matched filter previously described using the sum of 4 simple theoretical models of dimensions between 11x11 and 17x17. The result (Fig. 5-b) is extremely promising: buried objects, that were badly visible on the SAS image, appear clearly on the resulting image (a buried mine (3) for example). Some false alarms appearing at the bottom are due to unidentified objects.

Fig.5: Real SAS image (dB scale) (a) and result obtained with the detection method (b).
5. CONCLUSION AND PERSPECTIVES

A detection method in SAS imagery, using higher order statistics has been proposed and studied in this paper. This detection uses the echoes reflected by the objects contained on the scene. The second step of the process focuses the result in order to obtain the exact location of the objects and the choice of the focus method (matched filtering or correlation with a frame) is a trade-off between the simplicity of the second method and the better visibility of the first. The robustness of the detection method can be underlined, the result being theoretically independent from the amplitude of the echoes.

The perspectives of this work include the recognition and classification of the detected objects. An other idea would be to use the segmentation results provided by other methods [5] to reduce the false alarm rate.

Note: This work was supported by the Groupe d’Etudes Sous-Marines de l’Atlantique (DGA/DCE/GESMA, France) under Grant 01-59-918.

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