Multispectral decomposition of synthetic aperture sonar images for speckle reduction

Jocelyn Chanussot\textsuperscript{a}, Alain Hétet\textsuperscript{b}, Gwendal Le Merrer, Elisa Tireau

\textsuperscript{a}Laboratoire des Images et des Signaux – LIS / ENSIEG – BP 46 – 38402 Saint Martin d’Hères, France
jocelyn.chanussot@lis.inpg.fr
\textsuperscript{b}Groupe d’Etudes Sous-Marines de l’Atlantique – DGA / DCE / GESMA – BP 42 - 29240 Brest Naval, France
hetet@gesma.fr

Summary

High resolution images provided by synthetic aperture sonar (SAS) sensors are of great interest, especially for the detection, location and classification of mines lying on the sea bottom. But these data obtained by an active imagery system are highly corrupted by a noise called the speckle. To reduce this noise and suppress the specular reflections it generates on the images, a first step consists in decomposing the initial broad-band image into different subband images (for instance three images with a narrower bandwidth). This is equivalent to the “multilook” mode used with synthetic aperture radar (SAR) systems. Then, different filters can be used. We present and test in this paper different classical image processing filters, some of them are classically used to filter SAR images.

1. Introduction

Over the past few years, synthetic aperture sonar (denoted SAS in the following) has been used in sea bottom imagery. One of the most promising tasks for SAS systems is the detection, location and classification of mines lying on the sea bottom, or even slightly buried in the sea ground. These data are highly corrupted by a multiplicative noise, called the speckle. The specular reflections generated by this noise can dramatically degrade the performances of automatic mines echoes detection algorithms by drastically increasing the false alarm rate. In this paper, we propose to enhance mines echoes and to reduce the speckle with image processing filters. The main idea is to use the broad bandwidth of the sonar.

In section 2, we briefly recall the principle of the synthetic aperture sonar.

In section 3, we present the spectral decomposition of the initial data. The broad bandwidth of the sonar is decomposed into three narrower bands. This gives three different images of the same scene, with a slightly degraded resolution (this technique is called “multilook”). These three subband images can be recombined to obtain a colour representation of the scene (each band respectively representing the red, the green and the blue component).

Then, in section 4, we present different solutions to reduce the speckle : the simple and direct incoherent summation of the different subband spectral components, or the application of different image processing filters (median filter, Lee’s filter) before summation.

2. Synthetic aperture Sonar

The real data processed and presented in this paper have been recorded during the IFSAS’99 experiment in collaboration between GESMA (Groupe d’Etudes Sous-Marines de l’Atlantique, France) and the DERA (Defense Evaluation and Research Agency, United Kingdom).
2.1. Active sonar

The active sonar is an active acoustic imagery system. It is composed of an emitter and a receiver. The emitter generates acoustic waves over a over a 64 kHz bandwidth centered at 150 kHz. The used pulses are 4ms chirps. The receiver, composed of different elements, is located at the same place. It records the emitted signal after its propagation in the sea, its reflection on the ground or on a target, and its back-propagation to the sensor.

The sonar can move on a rail and can therefore illuminate a wide part of the sea bottom. For a given position of the sonar on its rail, a specific region of the sea bottom is illuminated. The corresponding geometry with classical notations is presented on figure 1.

\[ \delta_c/2B \approx \frac{c}{2B} \]  
(Eq 1)

where \( c \) is the propagation speed in the sea.

For a given x sight, the azimuth resolution is given by:

\[ \delta_{az} \approx \frac{\lambda}{D} \]  
(Eq 2)

where D is the lateral dimension of the sonar. This resolution is low for low frequencies and for great x values. Therefore, after detection, a second sonar with increased performances is used for precise location and classification (most of the times based on the shadow of the mine).

2.2. Multisensor sonar antenna

To increase the value of D in Eq 2, and to improve the azimuth resolution, it is possible to use a wide antenna with several sensors and to perform a spatial processing called the beam-forming. The resolution turns to:

\[ \delta_{az} = \frac{\lambda}{L_a} \]  
(Eq 3)

where \( L_a \) is the length of the multi-elements array.

2.3. Synthetic aperture

Since building long antennas is quite a difficult technical task, another solution consists in using one single sensor and in letting it move along a rail to simulate the antenna. This corresponds to the classical synthetic aperture sonar system and this is illustrated on figure 2.

\[ \delta_{az} = \frac{\lambda}{L_a} \]  
(Eq 3)

where \( L_a \) is the length of the multi-elements array.

The next figure presents a zoom on a real SAS image. The hyperbolic shape generated by a strongly reflecting object (a mine) is clearly visible.

2.4. Synthetic aperture sonar

To obtain a useful and interpretable image, this hyperbolic echo has to be refocused (compensation of the different delays and stacking). This leads to the image presented on figure 4. It corresponds to
the echo of a sphere mine. It is constituted of several specific specular reflections. The elliptic shadow generated by the mine is also noticeable.

Figure 4 : reconstructed echo of a sphere mine

Note : since the sonar does not have a purely rectilinear movement, its trajectory has to be compensated. In our case, the motion compensation has been performed using the DPC algorithm (Displaced Phase Center, [7]). The relative moves of the sonar are estimated by computing the inter-correlation between successive signals.

3. Multispectral decompositioN

The multispectral technique is widely used in SAS and in SAR. It consists in considering several images of the same scene. These images can be obtained in different ways (multiple acquisitions, synthetic sub-antennas with an azimuth spatial filtering...).

In this paper, the original data are decomposed into several different spectral bands using several Hanning bandpass filters. The bandwidth is set to 20kHz. The original broad band is separated into 3 narrower bands : 120 - 140kHz ; 140 - 160kHz ; and 160 - 180kHz.

We obtain three different images of the same scene. But since the band is divided by 3, the range resolution is also degraded by a factor 3. Visually, these images look very similar to the original image. There is still a strong speckle noise on each image. But, assuming that for a given pixel the noise remaining on the different images is decorrelated, a combination of the 3 spectral components will enable an effective noise reduction without further degrading the resolution. This is explained in the next section.

4. Speckle reduction

4.1. Incoherent summation

The first idea to recombine the different spectral components is to compute the simple incoherent summation of the three images. This is illustrated on figure 5, and the result is presented on figure 6. This can be compared with figure 4 : the resolution is slightly degraded, but the noise has been reduced.

Figure 5 : Synopsis for the multilook processing

Figure 6 : result of the multilook processing

A quantitative evaluation of the method is presented in table 1. Three different regions have been selected in the image, corresponding to supposed homogeneous regions (shadow, regions without specific echoes). The variances are computed in each region. The multilook processing obtained by decomposing the original image into three subband images and by incoherently adding these images leads to a decrease of the variance by a factor three (almost). For a given pixel, assuming the noise on each component is decorrelated, the theoretical statistical limit is the number of images that are added (i.e. 3 in our case): we are very close to this limit. The noise is almost decorrelated.

A simple spatial filtering of the original image
would have given the same resolution degradation. But, since the noise is spatially not decorrelated, the noise reduction would have been smaller. This is an advantage of the multilook method we propose.

Table 1: Variance reduction with the multilook

<table>
<thead>
<tr>
<th>Region</th>
<th>Subband 120-140kHz</th>
<th>Incoherent summation</th>
<th>Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region 1</td>
<td>8.0 $\cdot$ 10^{-6}</td>
<td>2.7 $\cdot$ 10^{-6}</td>
<td>3</td>
</tr>
<tr>
<td>Region 2</td>
<td>6.4 $\cdot$ 10^{-6}</td>
<td>2.3 $\cdot$ 10^{-6}</td>
<td>2.8</td>
</tr>
<tr>
<td>Region 3</td>
<td>3.2 $\cdot$ 10^{-6}</td>
<td>1.3 $\cdot$ 10^{-6}</td>
<td>2.5</td>
</tr>
</tbody>
</table>

4.2. Median filter

To further improve the noise reduction, a solution consists in adding a denoising filter between the synthetic aperture and the incoherent summation. This is represented on figure 7 (note that a non linear rescaling of the range is also performed on visual purpose).

![Figure 7: Synopsis for further filtering](image)

The first spatial filter we used is the median filter. This is a classical non linear filter used in image processing to reduce noise with rather impulsive distribution [9]. For a given filtering window $W=\{x_i, i=1... N\}$, the filter output $Y$ is given by:

$$Y = \arg\min_{y} \sum_{i=1}^{N} |y - x_i|$$  \hspace{1cm} (Eq 4)

In our case, we used a rectangular filtering window of size 3x5. Figure 8 presents the obtained result. The noise reduction is stronger and the resolution is almost preserved (a linear filter would have further degraded the transitions and the echoes). The quantitative results in terms of variance reduction are presented in table 2.

![Figure 8: Result of the median filter + multilook](image)

4.3. Lee’s filter

We also tested a statistical filter derived from the SAR imagery: the Lee’s filter [4][5][6]. Assuming the speckle is a multiplicative noise with a unitary mean, the filter output is given by:

$$\hat{x} = \frac{x + k(z - \bar{x})}{\text{var}(x)\text{var}(v)+\text{var}(x)}$$  \hspace{1cm} (Eq 5)

where $z = x.v$ is the value of the noisy pixel ($v$ is the noise), $\bar{x} = \frac{\sum_x}{\sqrt{v}} = \bar{z}$ is the locally estimated mean of the signal and $\text{var}(x)=\frac{\text{var}(z)+\bar{z}^2}{\text{var}(v)+\bar{v}^2} - \bar{z}^2$ is the locally estimated variance of the signal.

Figure 9 presents the obtained result. The noise has been more efficiently removed and the echoes are still almost preserved. The quantitative results in terms of variance reduction are presented in table 2: the variance is better reduced with Lee’s filter than with the median filter.

Table 2: Variances reduction with other filters

<table>
<thead>
<tr>
<th>Region</th>
<th>Rescaled image</th>
<th>Median filter</th>
<th>Lee’s filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region 1</td>
<td>6.2 $\cdot$ 10^{-3}</td>
<td>5.4 $\cdot$ 10^{-3}</td>
<td>4.8 $\cdot$ 10^{-3}</td>
</tr>
<tr>
<td>Region 2</td>
<td>5.5 $\cdot$ 10^{-3}</td>
<td>5.1 $\cdot$ 10^{-3}</td>
<td>3.8 $\cdot$ 10^{-3}</td>
</tr>
<tr>
<td>Region 3</td>
<td>2.8 $\cdot$ 10^{-3}</td>
<td>2.2 $\cdot$ 10^{-3}</td>
<td>1.6 $\cdot$ 10^{-3}</td>
</tr>
</tbody>
</table>
5. Conclusions & perspectives

In this paper we discussed several techniques to reduce the speckle in SAS images. Methods derived from SAR imagery techniques lead to very promising results and other filters should be investigated [1][2][3][10][11]. The idea of decomposing the original image into several spectral subbands [12] enables to use the multilook technique and lead to a good noise reduction with. In the references section, we indicate some more papers dealing with the reduction of the speckle noise using image processing filters.

Acknowledgements

The authors would like to thank Sean CHAPMAN from Quinetics for operating the sonar during the 1999 IFSAS experiment in Brest.

References


