A New Method for Denoising SONAR Images

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***Abstract*—The SONAR images are perturbed by a multiplicative noise called speckle, due to the coherent nature of the scattering phenomenon. The use of speckle reduction filters is necessary to optimize the images exploitation procedures. This paper presents a new speckle reduction method in the wavelets domain using a novel Bayesian-based algorithm, which tends to reduce the speckle, preserving the structural features (like the discontinuities) and textural information of the scene. First, the different wavelet transforms are investigated and arguments to select the Dual Tree Complex Wavelet Transform are presented. Next, accurate models for the subband decompositions of SONAR images, that permit the construction of Maximum A Posteriori filters, with closed-form input-output relations, are investigated. A blind speckle-suppression method that performs a non-linear operation on the data is obtained. Finally, some simulation examples prove the performances of the proposed denoising method. These performances are compared with the results obtained applying state-of-the-art speckle reduction techniques.**

I. INTRODUCTION

The SONAR systems exploits techniques developed in the radar field and the capabilities of the high resolution imagery in a great number of applications such: marine geology, commercial fishing, offshore oil prospecting and drilling, cable and pipeline laying and maintenance and underwater warfare, [1]. Using an important number of transducers, operating at sound or ultrasound frequencies, the SONAR systems generate high-resolution images. The user can observe, analyzing such an image, some regions. This observation process is perturbed by the speckle noise. This noise is a result of the coherent addition of the backscatter waves generated by the elementary targets contained in every resolution cell. The speckle reduction filters are very important in the preprocessing phase to increase the detection or classification performances. Such a filter must realize a great speckle reduction in the regions where the reflectivity is constant and the preservation of the details of the scene in the other regions. There is a great diversity of estimators used like speckle reduction filters. The SONAR images represent a particular case of SAR images. Some classical estimators, used to denoise SAR images are, [2]:

- The Kuan filter (least mean square error linear estimator),
- The Frost filter (Wiener filter adapted to multiplicative noise).

Between the modern estimators can be found:

- The marginal MAP filter (for the maximization of the a posteriori probability), [3],
- The multiresolution MAP filter (a combination between a marginal MAP filter and a multiscale transform), [3].

A new estimators category uses the wavelets theory, [3], [4], [5], [6]. The corresponding denoising methods have three steps:

1. The computation of the forward wavelet transform, WT,
2. The filtering of the result obtained,
3. The computation of the inverse wavelet transform of the result obtained, IWT.

The good performances of those methods are explained by the great decorrelation capacity of wavelets. The scene power is concentrated into a reduced number of wavelet transform coefficients and the noise power is distributed uniformly into all the wavelet transform coefficients. Some comparisons between the application of the classical speckle reduction filters and the application of the denoising methods based on wavelets, in the case of SAR images, were proved the superiority of this last category of methods, [6-7]. Numerous WTs can be used to operate these treatments. There are two kinds of WTs: redundant and non-redundant. The first wavelet transform used in denoising applications was the Discrete Wavelet Transform, DWT. This transform is most commonly used in its maximally decimated form (Mallat's dyadic filter tree), [8-9]. The DWT is an orthogonal (non-redundant) wavelet transform. It was also used in [5-6]. It has three main disadvantages, [10]: lack of shift invariance, lack of symmetry of the mother wavelets and poor directional selectivity. The first disadvantage can be reduced using the Cycle Spinning, [11]. This solution is used in [6]. The second disadvantage can be eliminated using complex WT, [12] or biorthogonal WT, [13]. But in the last case the orthogonality is lost. Unfortunately, the influence of the third disadvantage cannot be reduced. The non-decimated form of the DWT is named Undecimated WT, UWT. This is a very redundant WT, having also the last two disadvantages already mentioned. The UWT was already used for the denoising of SAR images, [3,5]. For these reasons, in the following, the Dual Tree Complex Wavelet Transform, DT CWT, [10,14], will be used. This is a redundant WT, with a redundancy of 4. Its architecture is based on two trees, each implementing a DWT, [15]. The second DWT represents the Hilbert transform of the first one, increasing in this way the directional selectivity and realizing the shift invariance. All the WTs have two parameters: the mother wavelets, MW and the primary resolution, PR, (number of iterations). The importance of their selection is highlighted in [16]. This influence is more important in the case of the DWT or of the UWT, being very small in the case of the DT CWT. Numerous filter types can be used in the WT domain: the

Wiener filter, that minimizes the mean square estimation error, the hard-thresholding filter, [17], that realizes a very simple treatment, the soft-thresholding filter, [17, 7, 4], that minimizes the Min-Max estimation error, the marginal MAP filter, [3], or the bishrink filter, [14]. Some variants of those filters were used in [4-7]. In [3] and [6] two special types of MAP filters were used. Unfortunately, these filters have not closed-form input-output relations. Their application requires the use of numerical methods. This paper proposes a new denoising method for SONAR images based on the combination of the DT CWT with a variant of the bishrink filter. This variant has a closed-form input-output relation. The second section presents the architecture of the proposed denoising system. The aim of the third section is the presentation of some simulation results. These performances are compared with the results of state-of-the-art speckle reduction techniques.

II. THE DENOISING METHOD

The SONAR images are perturbed by a multiplicative noise of speckle type,

$$i_r(\tau_1,\tau_2) = i_o(\tau_1,\tau_2)\cdot n_r(\tau_1,\tau_2). \qquad (1)$$

When the speckle is fully developed the hypothesis of the independence of the random processes i_o and n_r can be adopted, [3,6]. The architecture of the denoising system proposed is presented in figure 1. The WT is applied after the transformation of the multiplicative noise into an additive one. The coefficients of this transform are filtered using the variants of the bishrink filter, proposed in this paper. At the system output, after the computation of the IWT, the logarithm inversion and the mean compensation, the estimation of the useful image, $\widehat{i_o}$, is measured. A statistical analysis of this denoising system is presented in [18], for the case when the WT used is the DWT or the DEDWT.

For the simulations presented in this paper we have chosen the DT CWT. A very good MAP filter, that takes into account the correlation between two wavelet coefficients, situated at the same geometric position into two adjacent scales, is the bishrink filter [14]. For the denoising method proposed in this paper we have used this filter with a minor modification. We have called this variant composed bishrink filter. There is an important correlation between a wavelet coefficient at a given scale and the same coefficient situated in the same position at the next scale (named the parent of the considered coefficient). This correlation can be exploited to construct adaptive filters acting at a given scale and using for the estimation of their parameters information obtained at the next scale. Using the parent and child wavelet coefficient of the input signal it is possible to estimate the child coefficients of the WT of the useful part of the input signal, with the aid of a bishrink filter. Let ${}^1y_i$ be the considered detail coefficient and ${}^2y_i$ its parent. We have noted with y_i the WT of the logarithm of i_r and with n_y the WT of the logarithm of n_r. The statistical parameters of the child coefficients can be determined using their parent coefficients and the neighbor child coefficients, located in a window with dimensions 7x7, centered on the current child coefficient. It can be written:

$$\mathbf{y}_i = \mathbf{y} + \mathbf{n}_y. \qquad (2)$$

where:

$$\mathbf{y}_i = \left({}^1y_i, {}^2y_i\right); \mathbf{y} = \left({}^1y, {}^2y\right); \mathbf{n}_y = \left({}^1n_y, {}^2n_y\right). \qquad (3)$$

The MAP estimation of **y**, realized using the observation $\mathbf{y}_i$, is given by:

$$\hat{\mathbf{y}}(\mathbf{y}_i) = \underset{\mathbf{y}}{\arg\max}\left\{\ln\left(f_{\mathbf{n}_y}(\mathbf{y}_i - \mathbf{y})\cdot f_{\mathbf{y}}(\mathbf{y})\right)\right\}. \qquad (4)$$

In the following, we will consider that the DWT of the noise is distributed following a zero mean Gaussian:

$$f_{\mathbf{n}_y}(\mathbf{n}_y) = \frac{1}{\sqrt{2\pi}\sigma_n}\cdot e^{-\frac{\left({}^1n_y\right)^2 + \left({}^2n_y\right)^2}{2\sigma_n^2}}. \qquad (5)$$

Concerning the model of the DWT of the useful component, in the case of the composed bishrink filter, for the first two iterations, a Laplace distribution will be considered (like in the case of the bishrink filter):

$$f_{\mathbf{y}}(\mathbf{y}) = \frac{\sqrt{3}}{\sqrt{2\pi}\sigma}\cdot e^{-\frac{\sqrt{3}}{\sigma}\cdot\sqrt{\left({}^1y\right)^2 + \left({}^2y\right)^2}}. \qquad (6)$$

and for the other iterations, a Gaussian distribution will be considered:

$$f_{\mathbf{y}}(\mathbf{y}) = \frac{1}{\sqrt{2\pi\,{}^1\sigma\,{}^2\sigma}}\cdot e^{-\frac{\left({}^1y\right)^2 + \left({}^2y\right)^2}{2\,{}^1\sigma\,{}^2\sigma}}. \qquad (7)$$

(like in the case of the zero order Wiener filter). For the models in (5) and (6) the solution of the maximization problem in (4) is:

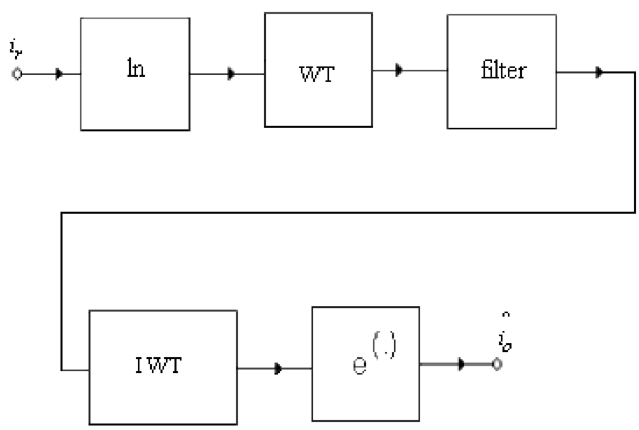

Figure 1. The architecture of the denoising system.

$$\widehat{{}^1y} = \frac{\left(\sqrt{\left({}^1y_i\right)^2 + \left({}^2y_i\right)^2} - \frac{\sqrt{3}\widehat{\sigma_n}^2}{\widehat{\sigma}}\right)_+}{\sqrt{\left({}^1y_i\right)^2 + \left({}^2y_i\right)^2}} \cdot {}^1y_i . \tag{8}$$

where:

$$\widehat{\sigma}^2 = \widehat{{}^1\sigma} \cdot \widehat{{}^2\sigma}. \tag{9}$$

and:

$$(g)_+ = \begin{cases} g, & g > 0 \\ 0, & if \quad not \end{cases}. \tag{10}$$

and for the models in (5) and (7) the solution of the maximization problem in (4) is:

$$\widehat{{}^1y} = \frac{\widehat{{}^1\sigma} \cdot \widehat{{}^2\sigma}}{\widehat{{}^1\sigma} \cdot \widehat{{}^2\sigma} + \widehat{\sigma_n}^2} \cdot {}^1y_i. \tag{11}$$

So, the input-output relations of the composed bishrink filter are (8) and (11). The noise variance is estimated using the details obtained after the first iteration and the variances $\widehat{{}^1\sigma}$ and $\widehat{{}^2\sigma}$ are estimated in moving windows centered on the current child and parent coefficients. First the means are estimated in each window and second the variances. But, applying the statistical analysis reported in [18], a different estimation of the local variance of the child coefficients can be obtained:

$$\widehat{{}^1\sigma_d} = \frac{\widehat{{}^2\sigma}}{\sqrt{2}}. \tag{12}$$

To profit of these two estimations of the local variances, obtained at two successive scales, it can be written:

$$\widehat{\widehat{{}^1\sigma}} = \frac{\widehat{{}^1\sigma} + \frac{\widehat{{}^2\sigma}}{\sqrt{2}}}{2}. \tag{13}$$

This estimation will be used in (8) and (11), substituting $\widehat{{}^1\sigma}$, for the input-output relations of the composed bishrink filter.

III. Simulation Results

A comparison between the results of different speckle reduction methods is presented in the following table. The image Lena was perturbed with a multiplicative Rayleigh noise, obtaining the input image. The mean square error is of 3635. This image was treated using: a running averager, a median filter, the Lee's filter, the Kuan's filter, the Gamma filter, the Frost's filter and the proposed denoising method. The mean square errors obtained after the treatments are presented in the table I.

TABLE I. A comparation of seven speckle reduction methods.

Noisy Image	**Averager 5**	**Median 7**	**Lee 7-5**	**Kuan 9-5.5**	**Gamma 5-1.5**	**Frost 5-1**	**Proposed**
3635	***571.7***	***569.8***	***807.5***	***732.8***	***595.5***	***566***	***372.7***

The first parameter of each filter represents its window size. The second represents, the so-called, filter's parameter. These quantities were selected to minimize the mean square error of the result for the considered image. All the parameters of the proposed denoising method are selected automatically. Finally, a real image was treated. The original SONAR image is presented in figure 2. It can be seen that the speckle is fully developed. The result obtained, using the proposed denoising method, is presented in figure 3. Analyzing the two images it can be observed the fact that the noise was practically entirely removed and the fact that the details of the useful part of the input image (textures or edges) were not affected by the treatment proposed. An objective measure of the performances of a denoising method for SONAR images is the enhancement of the equivalent number of looks, ENL. This is a measure of the performances obtained in homogenous zones. For the image in figure 2 the ENL value, computed into a homogenous zone, localized in the bottom left corner, is of 31.26. For the image in figure 3 the ENL value, computed into the same homogenous zone, is of 105.8.

IV. Conclusion

A new denoising method for the processing of SONAR images was proposed. It is based on the use of the DT CWT and of an original variant of bishrink filter. This method combines image multiscale analysis and classical techniques of adaptive filtering. It permits to retain coefficients produced by significant structures present in the useful part of the input image and suppress those produced by the speckle noise. For the first two iterations of the DT CWT, the pdf of the wavelet coefficients correspond to heavy-tailed distributions. We have approximated those distributions with a Laplace pdf. For the following iterations these pdf can be considered Gaussians. Using these hypotheses a MAP filter with closed-form input output relation was derived. Its parameters are locally estimated. In this estimation process a very important property of the WTs, the correlation between wavelet coefficients at the same position and successive scales, is exploited. Because two different estimations of the local variance of the child wavelet details of the useful component of the input image are at our disposal, they are combined to increase the precision of this estimation. An adaptive mean correction method was also applied. We evaluated the results on both synthetic data and real SONAR images, validating the theoretical hypotheses used. Further improvements could be obtained if a better WT and a 3D bishrink filter would be used. The latter avenue is currently under investigation and results will be reported soon.

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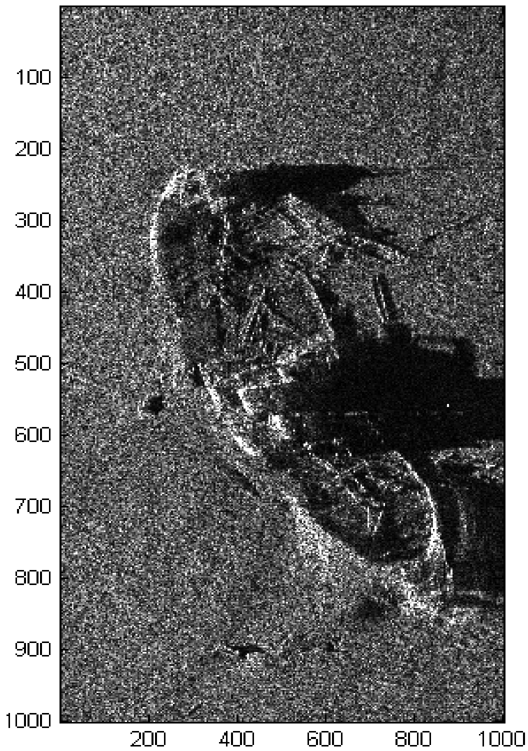

Figure 2. The original image. Thanks to GESMA France.

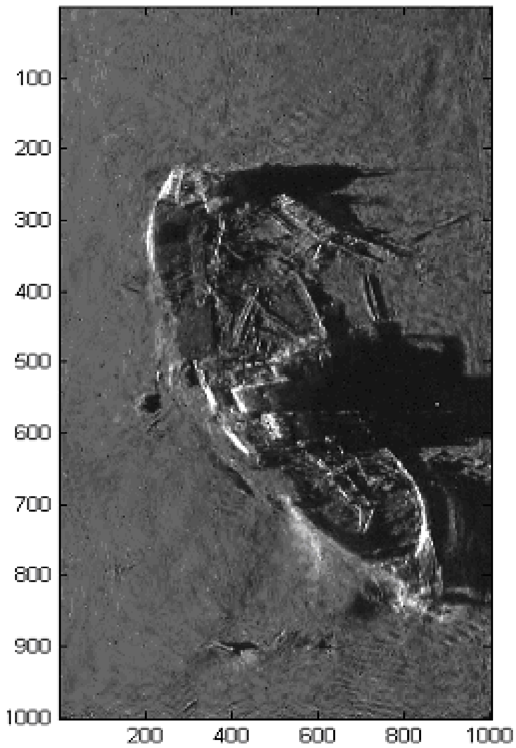

Figure 3. The result obtained.