SONAR Images Despeckling Using a Bayesian Approach in the Wavelet Domain

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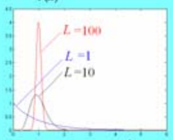
During acquisition, the SONAR images are corrupted by multiplicative noise (speckle). The aim of an image denoising algorithm is then to reduce the noise level, while preserving the image features. There is a great diversity of wavelet based estimators used like denoising systems. The corresponding denoising methods have three steps: the computation of the forward Wavelet Transform (WT); the filtering of the wavelet coefficients; and the computation of the inverse wavelet transform of the result obtained. We have associated the Dual Tree Complex Wavelet Transform (DT-CWT) with a variant of a maximum a posteriori bishrink filter because its explicit input-output relation permits a sensitivity analysis. The bishrink filter has a high sensitivity with some parameters, especially in the homogeneous regions. The main idea is to reduce this sensitivity by diversification. In this respect the regions with different homogeneity degrees are identified and in each of them the WT of the acquired image is filtered using a number of different variants of bishrink filters in accordance with its homogeneity. The SONAR images are a particular case of Synthetic Aperture Radar (SAR) images. The speckle that perturbs the SAR images is a white noise distributed following a law Gamma, which parameter is the number of views, *L*. Its mean is unitary and its variance equals 1/*L*.

SAR Images

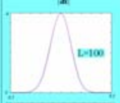
$$p_{X_\Gamma}(x)=\frac{L^L}{\Gamma(L)}\cdot x^{L-1}\cdot e^{-Lx}\quad \text{for}\quad x\ge 0$$



$$\mu=1\qquad \sigma^2=\frac{1}{L}$$

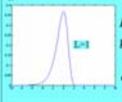
Particular case: $L=1$ $\Gamma\rightarrow\chi^2$

SONAR Images



$$\mu=\sum_{k=1}^{L-1}\frac{1}{k}-\gamma-\ln L$$

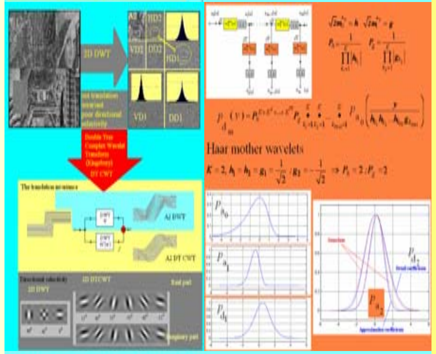
$$\sigma^2=\frac{\pi^2}{6}-\sum_{k=1}^{L-1}\frac{1}{k^2}$$



$$p_{\log-\chi^2}(y)=e^y e^{-e^y}$$

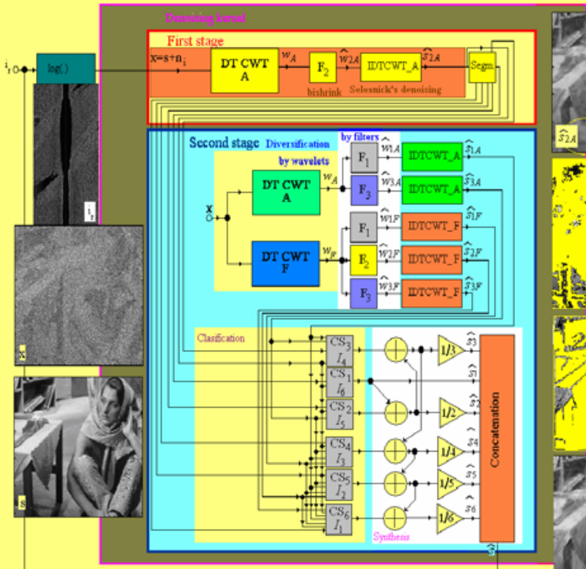
$$\mu_{\log-\chi^2}=-\gamma$$

$$\sigma^2_{\log-\chi^2}=\frac{\pi^2}{6}$$



Donoho's denoising method

1. A Wavelet Transform (WT) of the signal x is computed. The result is the signal $y_i = y + n_y$
2. A filtering is applied in the wavelet domain (to the detail coefficients) obtaining the signal y_{ip}
3. Taking the inverse WT (IWT) of the signal y_{ip}, the denoised version of the signal s, $\hat{s}$, is obtained.



For the denoising kernel, a two stage algorithm is conceived. In the first stage the denoising procedure based on the association of a DT-CWT and the genuine bishrink filter is applied. The standard deviation of each pixel of the resulted image is computed obtaining the pilot image. This image is segmented in six classes following the values of its pixels. The coordinates of the pixels corresponding at each class are identified and the six masks are generated.

mean extraction

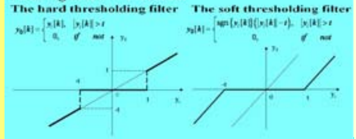
mean correction

In the second stage of the proposed algorithm the acquired image is processed once again using the pilot image already obtained. The solution proposed for the second stage is based on the enhancement of the diversity of the estimation. In this paper are proposed three diversification mechanisms. The first one supposes the utilization of two different mother wavelets. The others are based on the utilization of two different variants of bishrink filter, named in the following: adaptive bishrink filter with global estimation of local variance F_1 and mixed bishrink filter, F_3. Using these diversification mechanisms and the genuine bishrink filter six estimates, called in the following partial results, are obtained. The final estimate is obtained by the fusion of the six partial results. Using the six masks obtained at the end of the first stage we identify in each partial result the six corresponding classes. Each one contains only the pixels with the coordinates specified by the corresponding mask.

Filtering in the WT domain

The hard thresholding filter

The soft thresholding filter



MAP filters

$$x[k]=s[k]+n[k]$$

$$y_i[k]=WT\{s[k]\}+WT\{n[k]\}=y[k]+n_y[k]$$

$$\hat{y}=\arg\max_y\{p_{y/y_i}(y/y_i)\}=\arg\max_y\{p_{n_y}(y_i-y)p_y(y)\}$$

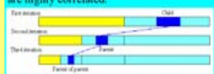
$$\hat{y}=\arg\max_y\{\ln(p_{n_y}(y_i-y))+\ln(p_y(y))\}$$

If y and n_y are Gaussian distributed then the MAP filter is a zero order Wiener filter.

If y is distributed following a Laplace pdf and n_y following a Gauss pdf then the MAP filter is a soft-thresholding filter.

The bishrink filter

The details coefficients of two successive iterations of the WT are highly correlated.



For the estimation of the parameters of a detail coefficient (mean, variance) its parent and its neighbors (at the same iteration) can be used.

Let ${}^1y_i$ be the considered detail coefficient and ${}^2y_i$ its parent. $\mathbf{y}_i=\mathbf{y}+\mathbf{n}_y$

where: $\mathbf{y}_i=({}^1y_i,{}^2y_i);\mathbf{y}=({}^1y,{}^2y);\mathbf{n}_y=({}^1n_y,{}^2n_y)$

$$\hat{\mathbf{y}}(\mathbf{y}_i)=\arg\max_{\mathbf{y}}\{\ln(p_{\mathbf{n}_y}(\mathbf{y}_i-\mathbf{y})\cdot p_{\mathbf{y}}(\mathbf{y}))\}$$

$$p_{\mathbf{n}_y}(\mathbf{n}_y)=\frac{1}{\sqrt{2\pi\sigma_n}}\cdot e^{-\frac{({}^1n_y)^2+({}^2n_y)^2}{2\sigma_n^2}}\qquad p_{\mathbf{y}}(\mathbf{y})=\frac{\sqrt{3}}{\sqrt{2\pi\sigma}}\cdot e^{-\frac{\sqrt{3}}{\sigma}\sqrt{({}^1y)^2+({}^2y)^2}}$$

$$\hat{{}^1y}=\frac{\left(\sqrt{({}^1y_i)^2+({}^2y_i)^2}-\frac{\sqrt{3}\hat{\sigma}_n^2}{\hat{\sigma}}\right)_+}{\sqrt{({}^1y_i)^2+({}^2y_i)^2}}\cdot{}^1y_i,\qquad \hat{\sigma}_n^2=\frac{median(|n_y|)}{0.6745},\ n_y\in DD1,$$

$$\hat{\sigma}^2[k]=\max\left(0,\hat{\sigma}^2_{{}^1y_i}[k]-\hat{\sigma}_n^2\right),\ \hat{\sigma}^2_{{}^1y_i}[k]=\frac{1}{(2P+1)}\sum_{l\in P_k}\left({}^1y_i[l]-\hat{m}_{{}^1y_i}[k]\right)^2,$$

$$\hat{m}_{{}^1y_i}[k]=\frac{1}{(2P+1)}\sum_{l\in P_k}{}^1y_i[l]$$

Experimental Results

Real Noise

Root Mean Squares

Noisy Image	Moving Averager	Median Filter 7	Lee's Filter 7-5-1	Kuan's Filter 9-5.5-1	Gamma Filter 5-1.5-1	Frost's Filter 5-1-1	Proposed
3655	571.7	569.8	807.5	732.8	559.5	566	90.6

	Noisy	[2]	[5]	[6]	[8]	[9]	Proposed
Lena				soft l.e			
$\sigma_n=10$	28.18	-	35.34	34.75	35.48	35.24	33.39
$\sigma_n=15$	24.65	-	33.67	33.03	33.90	33.46	33.68
$\sigma_n=20$	22.14	-	32.40	31.87	32.66	32.28	32.47
$\sigma_n=25$	20.17	-	31.40	30.89	31.69	31.21	31.49
$\sigma_n=30$	18.62	-	30.54	30.18	-	30.33	30.87
$\sigma_n=50$	14.15	-	28.27	-	28.48	-	28.50
$\sigma_n=100$	8.13	-	25.18	-	25.44	-	22.47
Boat				soft l.e			
$\sigma_n=10$	28.15	32.90	33.10	33.09	33.58	33.25	33.33
$\sigma_n=15$	24.62	30.85	31.36	31.44	31.70	31.32	31.45
$\sigma_n=20$	22.10	29.47	30.00	30.19	30.38	29.93	30.24
$\sigma_n=25$	20.17	28.44	29.06	29.21	29.37	28.88	29.32
$\sigma_n=30$	18.58	27.63	28.31	28.51	-	28.04	28.38
$\sigma_n=50$	24.74	25.58	26.01	-	26.38	-	26.12
$\sigma_n=100$	22.44	22.97	23.31	-	23.79	-	23.43
Barbara							
$\sigma_n=10$	28.13	32.18	33.53	-	34.03	33.46	33.78
$\sigma_n=15$	24.81	29.66	31.31	-	31.86	31.19	31.27
$\sigma_n=20$	22.11	27.98	29.88	-	30.32	29.53	30.07
$\sigma_n=25$	20.17	26.74	28.61	-	29.13	28.23	28.48
$\sigma_n=30$	18.62	25.83	27.65	-	-	27.17	27.87
$\sigma_n=50$	14.15	23.78	25.40	-	25.48	-	25.45
$\sigma_n=100$	8.13	21.76	22.54	-	22.61	-	22.69

Analysis of the denoising kernel

The PSNR values at the output of different denoising systems proposed in literature for different levels of AWGN input noise

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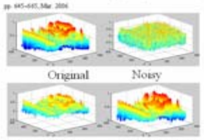
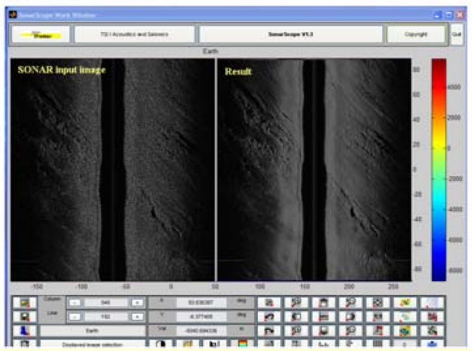


Real Images



CONCLUSION

This paper presents an effective image denoising kernel that optimizes the treatment of homogeneous zones of very noisy images. The diversity enhancement technique proposed can be used also for the improvement of other denoising systems.

The results of the proposed denoising kernel are competitive with the best wavelet - based results reported in literature, especially for very noisy images.

These results encouraged us to use the proposed kernel like the core of a SONAR images denoising system. We evaluated its results on both synthetic data and real SONAR images, validating the theoretical hypotheses used. Due to its performance the proposed denoising method was included in the tool box SONARSCOPE , recently conceived at IFREMER Brest, for the acquisition and treatment of SONAR images obtained by the specialists of this research center during the campaigns on the ocean.

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