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EVALUATE THE QUALITY OF PROCESSED IMAGES IN TERMS OF NOISE REDUCTION AND CONTOUR PRESERVATION

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Rezumat. *Wavelet-urile sunt un interesant obiect de studiu al matematicii şi, de asemenea, un folositor instrument de lucru în multe aplicaţii cum ar fi compresia de imagini, îmbunătăţirea raportului semnal/zgomot, analiza numerică, în domenii ale ştiinţei cum ar fi statistica, fizica şi chiar geologia. Pentru aplicaţii cum ar fi compresia de date, analiza de semnale, reducerea zgomotului, estimarea statistică sau detecţia, metoda de procesare a coeficienţilor wavelet diferă de la caz la caz. De asemenea, cele mai utile proprietăţi ale transformării wavelet diferă de la aplicaţie la aplicaţie. In acest articol introducem un nou filtru cu statistica locala bazat pe transformate wavelet pentru a imbunatatii calitatea imaginilor, introducem o măsură pentru evaluarea cantitativă a conservării contururilor în urma prelucrării şi descriem o metodă pentru determinarea dispersiei zgomotului din imagini.*

Abstract. *Wavelets are an interesting object of study of mathematics and a useful working tool in many applications such as image compression, signal / noise improvement, numerical analysis, in fields of science such as statistics, physics and even geology. For applications such as data compression, signal analysis, noise reduction, statistical estimation or detection, the method of processing wavelet coefficients differs from case to case. Also, the most useful properties of wavelet transformation differ from application to application. In this article we introduce a new filter with local statistics based on wavelet transforms to improve image quality, we introduce a measure for the quantitative evaluation of contour preservation after processing and describe a method for determining the noise dispersion in images.*

Keywords: wavelet, image processing, noise reduction, image contour preservation

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1. Introduction

The fidelity of an image subjected to digital processing, such as a compression-decompression process or a noise reduction algorithm, can be evaluated based on two types of criteria: objective and subjective, sometimes the two types of criteria being considered together. Subjective criteria are the best tool for evaluating an image when the image obtained at the end of the processing is interpreted by man.

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The objective criteria are based on the difference, pixel by pixel, between theoriginal and the reconstructed image and ensure a good approximation of the image quality perceived by a human observer. There is also the possibility that in evaluating the fidelity of a remade image, the pixel-by-pixel differences (the difference between the two images in the Fourier domain or another transformed domain can also be used) are weighted according to the sensitivity of the human visual system. Evaluating the fidelity of images by methods based on objective criteria is easier to do, consisting only of performing calculations based on the two images, being possible to perform even during processing**.** Assessing the fidelity of images processed by subjective methods is much more difficult to perform, usually involving human observers.

2. Related works

The motivation for this choice is two fold: the elegance of this application and the professional concerns. This double motivation determined us, in addition to going through a large number of papers on this topic, to proceed to the implementation and testing, using the MATLAB programming environment, of a large number of noise reduction algorithms among those presented in the literature. specialized, which were compared with the results obtained with the algorithm proposed by us. Of course, the article does not provide an exhaustive overview of wavelet noise reduction methods. For example, we studied the methods for noise reduction developed by Mallat and Zhang [1] or S. Sardy P. Tseng and AG Bruce [2], [3] by using overcomplete representations, those of HA Chipman, ED Kolaczyk and RM McCulloch [4] on the use of adaptive Bayesian wavelet estimators for noise reduction, or those proposed by M. Crouse, R. Nowak and R. Baraniuk [5] on the statistical processing of wavelet signals using hidden Markov chains [6]. From the many applications of wavelet transformations [7–9] in the field of digital signal processing, we have chosen, as the title of the article shows, noise reduction in the wavelet field [10-13]. The article is structured around the method of noise reduction by soft truncation of wavelet coefficients, a method proposed and theoretically substantiated, which obtains better results than the previously mentioned methods of noise reduction in the wavelet domain.

3. Research methodology and Results achieved

In the case of image compression, the problem is posed by objective methods, so based on a calculation scheme that uses the two images, original and processed to evaluate the distortions introduced and the loss of information [14]. In the case of noise reduction algorithms, the problem is to evaluate the amount of noise removed, the distortions introduced and the loss of information [15].

One such measure can be the mean square error between the pixel values in the original image and those in the remade image:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x(i,j) - \hat{x}(i,j)\right)^2 \quad (1)$$

M and N being the image size, $x(i,j)$the pixel intensities in the original image, and $\hat{x}(i,j)$ the pixel intensities in the remade image.

Another measure of the similarity between the two images is the ratio between the peak value of the signal and the mean square error, defined by:

$$PSNR = 10\, log_{10}\frac{\left(2^k - 1\right)^2}{MSE} \quad (2)$$

where k is the number of bits with which the pixel intensity is quantized.

PSNR is a widely used metric both in the evaluation of image compression algorithms and in the evaluation of image noise reduction algorithms.
Quantitative evaluation of the quality of images processed based on MSE or other derived metrics such as SNR or PSNR does not provide sufficient information on the preservation of image contours. Thus, images with the same PSNR may have different visual qualities. Such examples are shown in figures 1 and 2.

If the PSNR can be used to evaluate the amount of noise removed from the image, instead for the quantitative evaluation of images processed in terms of preserving contours this metric is not sufficiently suggestive. Therefore, for the purpose of quantitative evaluation of images and in this aspect, we introduce the coefficient C defined by:

$$C = \frac{N_c}{N_0} \quad (3)$$

Where N_c it represents the number of common pixels, determined as belonging to the contours in both the original and the processed image, and N_0 is the total number of pixels determined as belonging to the contours in the original image.

From the visual analysis of the images presented in figures 1 and 2 the images with a higher C coefficient have a better visual quality.

We thus obtain a way to quantitatively evaluate the conservation of contours in an image. In this article we will use, in the quantitative evaluation of processed images, especially PSNR, this being a very common metric both in the field of image compression and noise reduction, but we will also use the second metric, then we will have to compare two images with the same PSNR.

For this reason, in order to gain more sensitivity in performing the comparison, we will perform the determination of contours in order to calculate the *C* coefficient using Canny's algorithm, an algorithm that is more sensitive to noise compared to other contour detection algorithms available in MATLAB, as can be seen from the data presented in table 1.

In fact, what we want by introducing this metric is to have, in order to characterize the processed images and implicitly the tested algorithms, a double evaluation: how much noise has been removed and how well the contours have been preserved, both aspects being important in image noise reduction algorithms. We can define, depending on the PSNR and the coefficient *C*, a merit factor of the processed image, expressed by:

$$F_{merit} = PSNR(dB) + 100 \cdot C \quad (4)$$

If we proceed to optimize the parameters of a filter considering as a criterion the maximization of the merit factor, we obtain results slightly different from those obtained by maximizing the PSNR [16]. Such examples are shown in figures 3 and 4.

Table 1. Dependence of the C coefficient as a function of the white Gaussian noise level superimposed over a test image, in case of using for its calculation several methods for determining the contours available in the MATLAB programming environment.

σ	***Canny***	***Prewitt***	***Sobel***	***Roberts***
0.01	87.24 %	92.21 %	95.93 %	94.14 %
0.02	78.61 %	92.04 %	92.06 %	88.80 %
0.03	69.55 %	87.96 %	87.96 %	82.77 %
0.04	63.77 %	83.42 %	83.89 %	75.38 %
0.05	62.24 %	79.13 %	78.34 %	70.63 %

The filter with local statistics proposed by us, is a spatial adaptive filter that works in the primary domain of the signal, in the spatial domain in the case of images, by changing the working parameters according to the local statistics of the signal. Thus, this filter with local statistics can level the noise in the smooth regions of the image, leaving fine details, such as lines or text, unchanged. This filter uses small analysis windows of the order of 3 x 3, 5 x 5 or 7 x 7 pixels [17].

The average and dispersion are estimated in each window:

$$\bar{x}(i,j) = \frac{1}{(2M+1)^2} \sum_{k=i-M}^{i+M} \sum_{l=j-M}^{j+M} x(k,l) \quad (5)$$

$$\sigma_x^2(i,j) = \frac{1}{(2M+1)^2} \sum_{k=i-M}^{i+M} \sum_{l=j-M}^{j+M} \left(x(k,l) - \bar{x}(i,j)\right)^2 \quad (6)$$

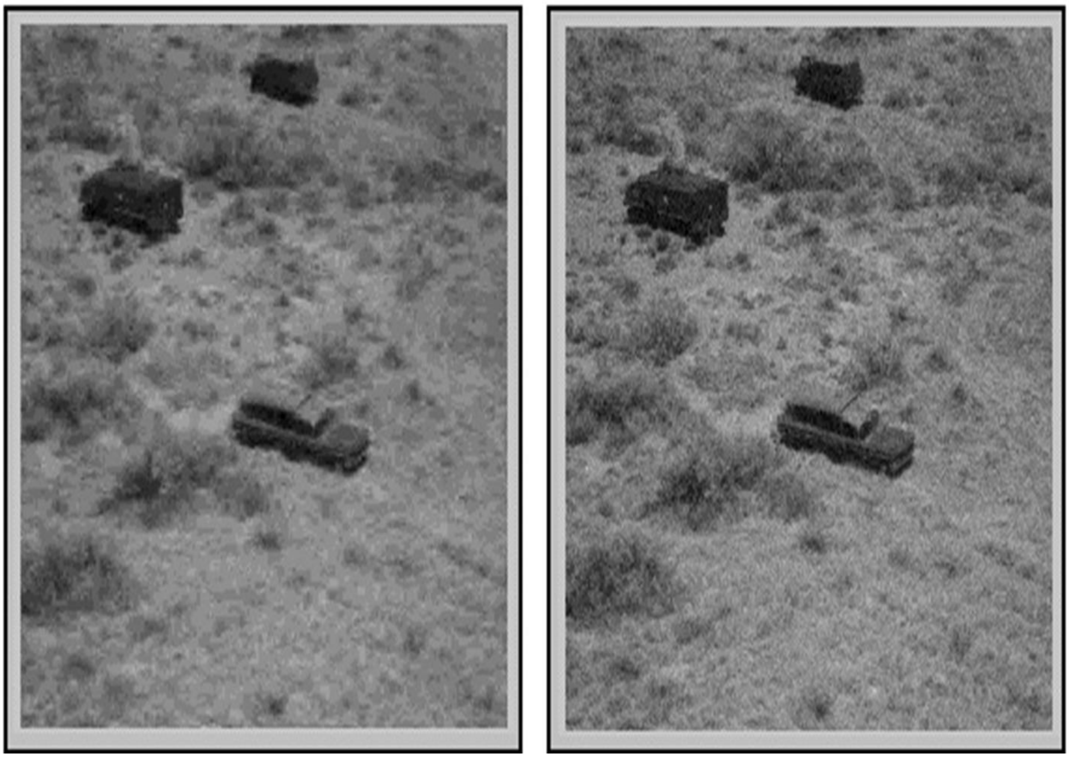
$2M + 1$ being the length of the analysis window.
In regions where the signal is not active, the filter has an average output value ($\bar{x}$). When activity is detected (lines and contours for example), the filter lets the signal pass almost unchanged, which is done by:

$$\hat{x}(i,j) = \beta x(i,j) + (1-\beta)\bar{x}(i,j) \quad (7)$$

The parameter β has values between 0 (smooth regions) and 1 (for regions with high signal activity).
In the case of additive noise, the formula is used:

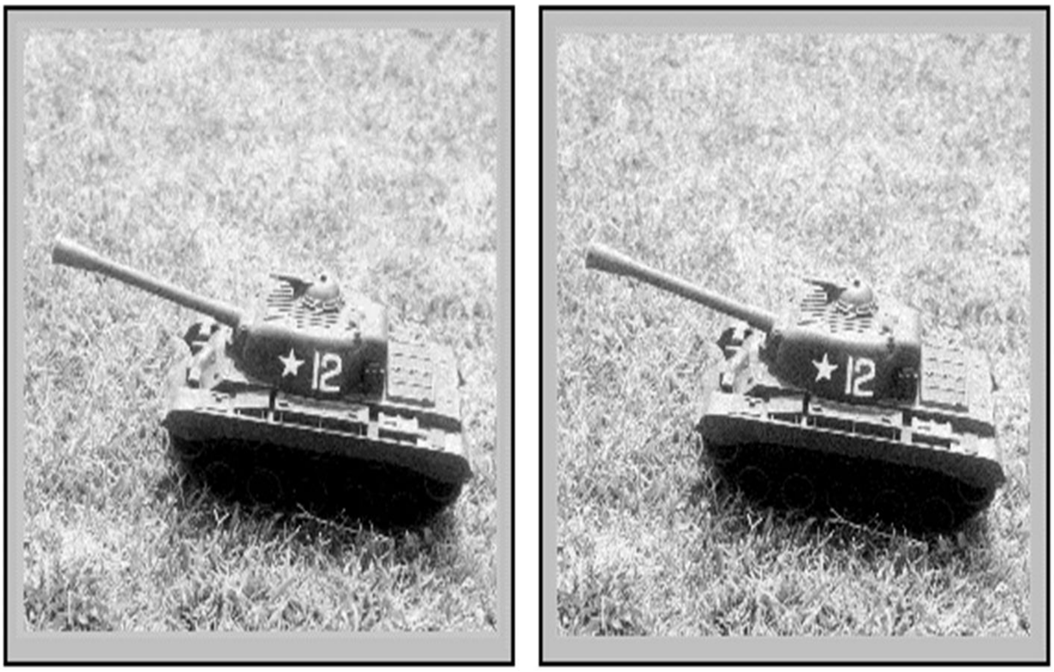
$$\beta = max\left(\frac{\sigma_x^2(i,j) - \sigma_n^2}{\sigma_n^2}, 0\right) \quad (8)$$

where σ_n^2 is an estimate of noise dispersion.



a) *b)*

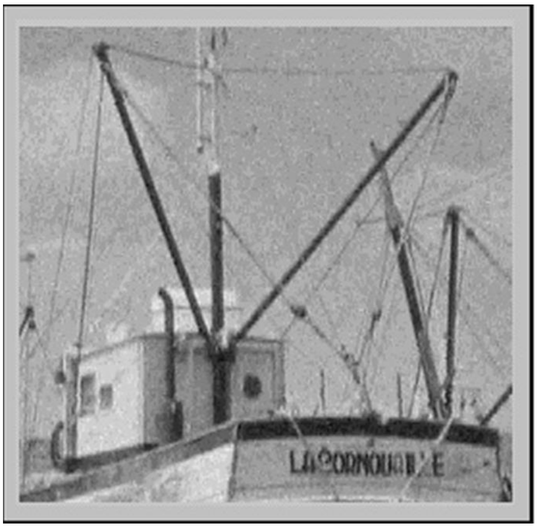
Figure 1. The two images, *a* and *b*, have the same PSNR¬, but in terms of visual quality they differ. Image *b* has clearer contours, which is highlighted by the higher value of the coefficient C; image *a* is characterized by PSNR = 29.98 dB and C = 43.73%, and image *b* by PSNR = 29.98 dB and C = 54.21%.



a) *b)*

Figure 2. The two images, *a* and *b*, have the same PSNR¬, but in terms of visual quality they differ. Image *b* has clearer contours, which is highlighted by the higher value of the coefficient C; image *a* is characterized by PSNR = 31.31 dB and C = 70.22%, and image *b* by PSNR = 31.31 dB and C = 71.48%.

a) ***b)***



c***)*** ***d)***

Figure 3. Optimization of threshold values in the case of software truncation using as a criterion the maximization of PSNR and the maximization of the merit factor.

a. Original image, Boat, 256 x 256 pixels.

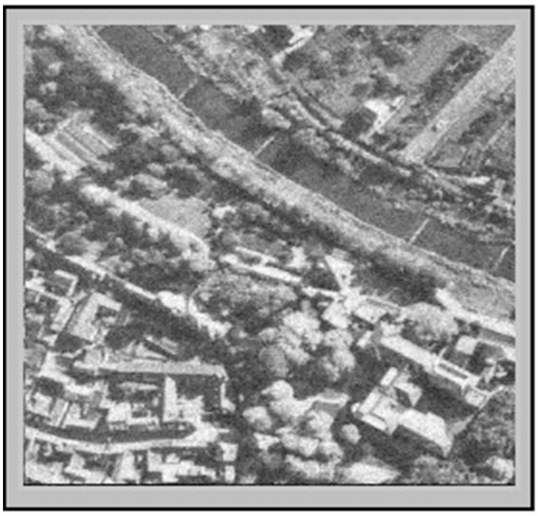
b. Degraded image with Gaussian additive white noise, PSNR = 26.03 dB, C = 63.69%, Fmerit = 89.72.

c. Image obtained by soft truncation of wavelet coefficients with threshold values established by maximizing the merit factor, PSNR = 30.10 dB, C = 64.27%, Fmerit = 94.37.

d. Image obtained by soft truncation of wavelet coefficients with threshold values established by maximizing the PSNR, PSNR = 30.39 dB, C = 62.42%, Fmerit = 92.80.

a)

b)



c)

d)

Figure 4. Optimization of threshold values in the case of software truncation using as a criterion the maximization of PSNR and the maximization of the merit factor.

a. Original image, Aerial, 256 x 256 pixels;

b. Image degraded with white Gaussian additive noise,, PSNR = 26.10 dB, C = 70.28%, Fmerit = 96.38;

c. Image obtained by soft truncation of wavelet coefficients with threshold values established by maximizing the merit factor, PSNR = 27.70 dB, C = 71.18%, Fmerit = 98.89;

d. Image obtained by soft truncation of wavelet coefficients with threshold values established by maximizing the PSNR, PSNR = 27.17 dB, C = 69.65%, Fmerit = 97.82.

Conclusions

This article introduces a quantitative measure for assessing the preservation of contours in processed images, based on the contour detector proposed by Canny, and proposes a method for determining the noise dispersion in images. The measure introduced for the quantitative evaluation of contour conservation, which we called the C coefficient, is used to separate images characterized by the same PSNR values. The need to introduce this measure arose mainly from the need to characterize adaptive-spatial filtering algorithms, whose purpose is to reduce noise in images while keeping the details as accurate as possible.

In the case of most Gaussian additive white noise reduction algorithms, the dispersion value is an important parameter. Estimating it as accurately as possible will allow obtaining optimal results considering both the amount of noise removed from the image and the quality of contour preservation. Estimating the dispersion by values lower than the correct one leads to the removal of a smaller amount of noise, and the estimation by higher values generates the blurring of the contours. From the simulations performed, we found that the robust estimators proposed in the literature introduce an image-dependent error. Therefore, the method proposed by us in this article for determining the dispersion brings a correction, depending on the processed image, so as to minimize the risk of reducing a smaller amount of noise than that which would be removed knowing the correct value of the dispersion. The simulations performed using this method of determining the noise dispersion show that in the case of all considered test images, no less noise is reduced than would be reduced knowing the correct value of the dispersion and an insignificant contour degradation is introduced.

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