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Spatially adaptive soft truncation based on the hierarchical correlation map and with the establishment of the threshold value based on local statistics

C. DUMITRESCU*

Department Telematics and Electronics for Transports, National University of Science and Technology POLITEHNICA Bucharest, 313 Splaiul Independentei 060042, Bucharest, Romania, Energy & Eco Concept SRL

Most images have non-stationary properties, so they contain smooth regions and regions with abrupt transitions. These regions with different characteristics can be well highlighted in the wavelet domain. The wavelet decomposition of an image contains high and low energy areas (or coefficients with high and low absolute values). Maintaining the idea of point-wise thresholding and exploiting the interband dependence by determining a map of accounts using the concept of hierarchical correlation, in this article we propose and develop a new spatial adaptive filter that allows point-wise thresholding and exploits the interband dependence by determining a map of accounts using the concept of hierarchical correlation, being more efficient in terms of computational effort than the adaptive spatial filtering of wavelet coefficients with contextual modeling. The proposed algorithm was tested on different images, and from the analysis of the obtained data it appears that the effect of the threshold value used to obtain the contour map from the hierarchical correlation map does not depend on the processed image (as in the case of optimal threshold values in the case of soft truncation), but only on the dispersion of the disturbing noise.

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1. Introduction

Researchers in the field of applied sciences and engineers working with data obtained from observations made on the environment know that there are no signals unaffected by noise. Under ideal conditions, the noise can reach insignificant levels compared to the useful signal level, so in many practical applications it is not necessary to process to remove the noise. However, ideal conditions cannot always be ensured, so that in other practical situations the useful signal is degraded by noise to an extent that may affect the interpretation of the experimental data. In such a case, however, there is the problem of eliminating or at least reducing noise from the input data, so that the interpretation of the results obtained after processing is as good as possible both in terms of PSNR and in terms of contour preservation.

For many authors [1, 2], noise reduction is synonymous with smoothing input data (low-pass filtering), which, in the case of signals containing transitions, leads to loss of information. Therefore, noise reduction involves its removal in the conditions of preserving as accurately as possible the abrupt variations in the signal, variations that often have a high informational content. Noise reduction in signals can be performed both in the primary domain of the signal and in a transformed domain. The traditional domain for signal processing in the transformed domain is the Fourier domain, and the filter considered ideal for reducing signal noise is the Wiener filter.

Advanced and efficient methods for reducing signal noise, based on Bayesian estimators, use statistical signal modelling based on a priori information. However, the "true" signal model is often not available in practice. In this case, Bayesian estimators cannot be used, methods based on nonparametric estimators being an extremely attractive alternative. Donoho and Johnstone [3] have shown that such estimators, despite their simplicity, perform almost ideal performances considering a wide variety of error functions when unknown functions belong to overly broad classes of signals that resemble signals belonging to the Besov classes, as in the case of more signals and images from nature. Such estimators can be implemented using the wavelet domain. The simplest and at the same time the first method of reducing the noise in the wavelet domain, called the hard truncation of the wavelet coefficients, is similar to the compression process with losses in the wavelet domain. The use of multiscale transformations, such as wavelet transformations, has led to significant advances in signal representation, compression, restoration, analysis, and synthesis. The fundamental reason for these advances is that the statistics of most signals in nature (voice, image), when decomposed using such bases, are substantially simplified.

However, choosing a base adapted to the statistical properties of the signal is a problem. The traditional solution is the Principal Components Analysis, in which a linear transformation is chosen to diagonalize the autocorrelation matrix of the input data.

The best-known description of image statistics is that their Fourier spectrum decreases by a power law. Together with the invariance condition at translation, this would suggest that the Fourier transform is an approximate representation of the principal component analysis. For example, the classic solution to the problem of noise removal is the Wiener filter, which is obtained by modelling the coefficients in the Fourier range as uncorrelated and respecting a Gaussian distribution [4]. However, the use of bases other than Fourier allows the description of images by higher order statistics than the second order, while in the case of Gaussian additive white noise the statistical moments higher than two order are zero. This allows the design of effective methods to reduce Gaussian additive white noise in images. In [5] propose a method of soft reduction of wavelet coefficients that uses different threshold values not only depending on the scale and orientation as in [6] but adapted to the local statistics of signal in the wavelet domain. Such a spatially adapted threshold selection strategy is sometimes necessary because the use of a uniform threshold for an entire subband is not good enough. The essence of a threshold value is that it must be large enough to reduce noise, but small enough to be able to store the details in the signal. However, when the noise coefficients happen to be higher than the signal coefficients, the two mentioned goals cannot be achieved using the same threshold value [7, 8]. Spatially adaptive filters in the wavelet domain aim to achieve the best possible noise reduction performance while preserving the contours as faithfully as possible. Spatially adaptive filters in the wavelet domain are more efficient both due to the property of concentrating the signal energy in a small number of coefficients, a property common to many orthonormal transforms, and the interscale correlation, specific to wavelet transforms. The ability of the wavelet transform to adapt to local variations of the signal and noise leads to a faster and more accurate adaptation of the filtering parameters depending on the local characteristics of the signal.

2. Experimental

Most images have non-stationary properties, so they contain smooth regions and regions with steep transitions. These regions with different characteristics can be well highlighted in the wavelet domain. The wavelet decomposition of an image contains areas of high and low energy (or coefficients with high and low absolute values). High energy areas in the wavelet domain correspond to characteristics with abrupt signal variations such as contours or texture. Low energy areas correspond to smooth areas. When noise is added, it tends to increase, on average, the absolute values of the wavelet coefficients. We expect that especially in the smooth regions the dominant coefficients will be determined by the noise, the noise being more visible in these regions and therefore these coefficients must be removed. In regions characterized by steep variations, the coefficients possess most of the energy due to the signal, and a smaller part due to the noise (which is not very visible in these regions). Therefore, these coefficients can be retained unchanged or slightly reduced their absolute values, thus ensuring the preservation of most of the details, especially the most important. It is possible, in this way, to establish a strategy for adapting the threshold used for the soft truncation of the wavelet coefficients according to the energy of the considered area.

In the field of image compression, it is accepted that, for a large class of images, the wavelet coefficients corresponding to each subband can be very well represented by a probability function with generalized Gaussian distribution [9]. The context modeling technique allows the modeling of each wavelet coefficient as a random variable with a generalized Gaussian distribution, with variable parameters. By determining the distribution parameters for each wavelet coefficient separately, it is possible to establish, in the case of each coefficient, an optimal threshold value. Maintaining the idea of punctually establishing the threshold value and exploiting interband dependence by determining a map of accounts using the concept of hierarchical correlation, we propose a new spatial adaptive filter, more efficient in terms of computational effort than described in the previous paragraph and which, according to Table 1, leads to better results. The proposed algorithm has 3 stages. In the first stage, the threshold values for each coefficient, necessary for the soft truncation of the wavelet coefficients, are determined based on the local statistics. The difference from the method set out in the previous paragraph is primarily in simplifying the determination of the local dispersion of the signal. For this we give up the selection of the coefficients used to determine the signal dispersion based on the random variable z, considering all wavelet coefficients contained in each window, but which has much smaller dimensions and we give up the use of the parent coefficient to evaluate local dispersion (from Table 2 shows that this coefficient contributes less than 5.5% to the determination of the local signal dispersion).

In this case, the local dispersion corresponding to the coefficient $w(i, j)$ will be given by:

$$\hat{\sigma}_x^2(i,j) = max(\sigma_s^2 - \sigma^2, 0) \qquad (1)$$

where:

$$\sigma_s^2(i,j) = \frac{1}{M} \sum_{k,l \in B(i,j)} w^2(k,l) \qquad (2)$$

$B(i, j)$ being the set of indices of the coefficients in the current window, and M is the number of coefficients contained in the window.

The current threshold value will be given by:

$$\hat{\lambda}(i,j) = \frac{\sigma^2}{\hat{\sigma}_x(i,j)} \quad (3)$$

Also, in this stage is determined the contour map based on the hierarchical correlation corresponding to the degraded image.

In the second stage, all the wavelet coefficients of the detail subbands are subjected to a soft truncation operation, determining the coefficients:

$$w_s(i,j) = \eta_s\left(w(i,j), \hat{\lambda}_{i,j}\right) \quad (4)$$

η_s being the soft truncation operator with threshold.

In the third stage, a correction is made on the coefficients $w_s(i,j)$ obtained in the second stage, depending on the contour map. Thus, the coefficients that were established as belonging to a contour are estimated by the arithmetic mean between the initial value and the value obtained in the second processing stage, the rest of the coefficients remaining unchanged:

$$\hat{w}(i,j) = \begin{cases} \frac{w_s(i,j)+w(i,j)}{2}, if\ (i,j) \in on\ contour \\ w_s(i,j),\ otherwise \end{cases} \quad (5)$$

We call this correction switched based on the hierarchical correlation map. Another possibility of correction on the coefficients $w_s(i,j)$ according to the hierarchical correlation map, this time a continuous one, which we propose is given by:

$$\hat{w}(i,j) = \rho\left(i/_2, j/_2\right) w(i,j) + \left(1 - \rho\left(i/_2, j/_2\right)\right) w_s(i,j) \quad (6)$$

where $\rho(k,l)$ it represents the normed value of the hierarchical correlation corresponding to the coordinate coefficient (k,l).

Table 1 compares the results obtained in the case of processing subbands of details corresponding to the first scale of a wavelet transformation by the method described in [10] (adaptive soft truncation with contextual modeling) and presented in the previous paragraph and applying the first step of the proposed method.

3. Results and discussions

As can be seen from the data presented in Table 1, even in the case of applying only the first two steps of the proposed algorithm, better results are obtained both in terms of PSNR and in terms of contour conservation. Regarding the proposed method, it can be found that as the window size increases, the results are weaker both in terms of PSNR and in terms of coefficient *C*. This can be justified by the fact that those signal-induced wavelet coefficients are grouped, and once with the increase of the window their influence on the local dispersion decreases, this approaching the dispersion of the noise.

Table 1. Comparative results obtained by adaptive soft truncation with contextual modeling and applying the first two steps of the method proposed in this paragraph, in the case of processing only the subbands of details corresponding to the first scale of a wavelet transformation. The side of the analysis window is 2L + 1

	By adaptive soft truncation with contextual modeling (Chang)		By applying the simplified algorithm, based on local statistics	
L	*PSNR (dB)*	*C (%)*	*PSNR (dB)*	*C (%)*
3	28.98	64.74	**30.00**	**67.14**
5	28.99	65.31	**29.99**	**67.08**
10	29.02	64.74	**29.90**	**66.82**
20	29.21	63.85	**29.81**	**65.73**
50	29.31	64.53	**29.76**	**66.20**

A first parameter of the proposed algorithm is the length of the window. The effect of this parameter, as well as the number of wavelet decomposition levels used on the image quality obtained after the second processing step is presented in Table 2, compared to the results obtained by soft truncation with optimal threshold values. A third parameter that influences the performance of the algorithm is the threshold value used to obtain the contour map from the hierarchical correlation map, the effect of which, on the whole filtering process, is presented in Table 3.

Table 2. Dependence of the results obtained in the first stage of the proposed algorithm, depending on the number of wavelet decomposition levels (n), the length of the analysis window (2L + 1). The results obtained by soft truncation with optimal threshold values on the same images are also presented

Image	σ	Initial		Soft truncation with optimal threshold values		Soft truncation with local statistics n=3, L=3		Soft truncation with local statistics n=3, L=5		Soft truncation with local statistics n=3, L=7		Soft truncation with local statistics n=4, L=3		Soft truncation with local statistics n=4, L=5	
		PSNR (dB)	C (%)	PSNR (dB)	C (%)	PSNR (dB)	C (%)	PSNR (dB)	C (%)	PSNR (dB)	C (%)	PSNR (dB)	C (%)	PSNR (dB)	C (%)
Lena	0.05	26.00	63.93	29.74	61.96	**30.27**	**65.84**	30.18	65.51	30.08	65.75	**30.27**	65.67	30.18	65.48
	0.1	20.06	**48.10**	26.13	44.65	**26.59**	46.74	26.57	45.66	26.49	46.38	26.01	**46.78**	**26.59**	45.80
Bridge	0.05	26.09	**63.59**	27.49	62.67	**27.65**	62.56	**27.63**	62.74	**27.65**	62.76	**27.65**	62.36	**27.65**	**62.86**
	0.1	29.13	**48.07**	23.38	**44.76**	23.45	43.75	23.48	44.03	**23.49**	43.87	23.45	43.99	23.48	43.96
House	0.05	26.05	65.47	31.17	62.89	31.72	66.93	31.57	66.59	**31.42**	66.93	**31.73**	**67.03**	31.58	66.51
	0.1	**20.13**	49.04	27.56	51.59	**28.07**	**53.78**	27.98	52.55	27.80	52.66	28.12	**53.78**	28.02	52.81
Boat	0.05	26.03	64.03	30.44	62.72	**30.87**	65.06	30.74	64.75	30.66	**65.22**	**30.87**	65.00	30.75	64.92
	0.1	20.04	47.09	26.83	46.12	27.10	49.53	27.08	48.16	27.00	47.75	**27.14**	**49.92**	27.11	49.22
Peppers	0.05	**26.04**	**63.50**	30.08	60.78	**30.44**	62.36	30.32	63.44	30.22	**63.36**	30.43	62.40	30.32	63.40
	0.1	20.16	**50.08**	26.51	48.65	26.78	49.28	26.73	49.28	26.66	48.47	**26.79**	**49.30**	26.74	49.12

Table 3. Dependence on the threshold value used to obtain the contour map from the hierarchical correlation map, in the case of the proposed method. Results obtained by using the ideal, real and filtered hierarchical correlation map are presented

Threshold value	$\sigma = 0.05$					
	Image initial		PSNR= 26.07 db		C = 64.61 %	
	The second stage processing		PSNR= 30.88 db		C = 64.29 %	
	Ideal contour map		Real contour map		Filtered contour map	
	PSNR (db)	C (%)	PSNR (db)	C (%)	PSNR (db)	C (%)
0.050	30.93	65.17	30.29	64.38	30.39	65.03
0.075	30.94	64.87	30.68	64.90	30.79	64.98
0.100	30.93	64.90	30.82	65.12	30.84	64.75
0.150	30.90	64.66	30.86	64.27	30.86	64.30
0.175	30.89	64.59	30.87	64.58	30.87	64.32
0.200	30.88	64.51	30.87	64.45	30.87	64.41
0.225	30.88	64.38	30.87	64.32	30.87	64.38
0.250	30.88	64.43	30.87	64.40	30.87	64.30

The effect of the number of wavelet decomposition levels on the final results is presented in Table 4.

It can be observed that in all the considered cases, better results are obtained in PSNR terms than in the case of soft truncation with optimal threshold values, in many cases obtaining even higher C coefficients than the initial ones, ie an improvement of the contours.

Considering an ideal contour map, determined on the basis of the image not degraded by noise, the simulations show (Table 3) that by the proposed method an improvement of the contours can be obtained, expressed by higher values of the coefficient *C*, provided that the noise reduction is not affected, which is expressed by constant PSNR values. In the real case, only the noise-degraded image is available, the contour map being determined based on it.

Table 4. Dependence of the results obtained by applying the filtering algorithm proposed in this paragraph, depending on the number of wavelet decomposition levels. The test images were 256 × 256 pixels and were degraded with white Gaussian additive noise

IMAGE	Initial Values	Stage processing	Number of wavelet decomposition levels N = 3	
			PSNR (dB)	***C*** (%)
Lena	$\sigma = 0.05$ **PSNR=*26.00 dB*** ***C*=65.84 %**	after the second stage	30.27	65.84
		using correlation map	30.19	66.09
		with filtered correlation map	30.22	65.98
	$\sigma = 0.1$ **PSNR=*20.06 dB*** *C*=48.10 %	after the second stage	26.59	46.74
		using correlation map	26.29	48.17
		with filtered correlation map	26.50	48.20
Bridge	$\sigma = 0.05$ **PSNR=*26.03 dB*** *C*=62.96 %	after the second stage	27.59	61.26
		using correlation map	27.54	62.83
		with filtered correlation map	27.56	62.49
	$\sigma = 0.1$ **PSNR=*20.19 dB*** *C*=47.44 %	after the second stage	23.48	44.66
		using correlation map	23.38	44.82
		with filtered correlation map	23.46	44.49
Aerial	$\sigma = 0.05$ **PSNR=*26.06 dB*** *C*=70.14 %	after the second stage	28.15	68.36
		using correlation map	28.10	69.55
		with filtered correlation map	28.13	***69.39***
	$\sigma = 0.1$ **PSNR=*20.15 dB*** *C*=54.39 %	after the second stage	24.21	49.91
		using correlation map	24.07	52.75
		with filtered correlation map	24.17	52.02
Boat	$\sigma = 0.05$ **PSNR=*26.03 dB*** *C*=64.53 %	after the second stage	30.88	64.61
		using correlation map	30.80	65.22
		with filtered correlation map	30.84	64.75
	$\sigma = 0.1$ **PSNR=*20.07 dB*** *C*=47.50 %	after the second stage	27.07	47.54
		using correlation map	26.72	48.84
		with filtered correlation map	26.96	48.16

As can be seen, false contour points appear in this case, resulting in a smaller amount of noise removed. Therefore, on the hierarchical correlation map, before determining the contours, we proceed to process it with a median-hybrid filter. As can be seen from the data in Table 3, this filtering operation leads to images characterized by PSNR values closer to those of the images obtained after the first two processing steps of the proposed algorithm, in the conditions under which an improvement of the contours takes place.

The proposed algorithm was tested on different images with dimensions of 256 × 256 pixels and 512 × 512 pixels, under conditions of their degradation with white noise and Gaussian dispersion additive. The results are presented in Table 3.

The analysis of the data presented in Table 3 shows that the effect of the threshold value used to obtain the contour map from the hierarchical correlation map does not depend on the processed image (as in the case of optimal threshold values in the case of soft truncation), but only on dispersion. disturbing noise. Thus, for a noise dispersion the optimal value is between 0.1 and 0.15, and for, between 0.15 and 0.175.

I approached this algorithm in invariant translation form in two ways:

- A) by fully applying the proposed algorithm in invariant form to translation, ie by mediating the results obtained by applying all three processing steps on the cyclic displacements of the input image;
- B) by partially applying the proposed algorithm (only steps 1 and 2) in the invariant form to the translation and performing the correction according to the contour map only on the result thus obtained.

Table 5. Application of the proposed algorithm in invariant approach to displacement, in the two approaches proposed. There were 4 circular trips. The test images were 256 × 256 pixels and were degraded with white Gaussian additive noise

Image	σ	Initial		Integral application of the algorithm in invariant form to translation	
		PSNR (dB)	***C*** (%)	**PSNR** (dB)	***C*** (%)
Drone	0.05	26.00	63.94	31.07	**66.70**
	0.1	20.08	47.64	27.55	**50.77**
PC	0.05	26.07	63.73	28.08	**63.89**
	0.1	20.17	***48.02***	24.17	46.44
Compo-nents	0.05	26.01	69.43	29.00	**70.50**
	0.1	20.10	53.90	25.27	**56.47**
Car	0.05	26.03	64.12	31.97	**67.28**
	0.1	20.03	47.58	28.19	**51.26**
People	0.05	26.05	65.47	32.68	**68.70**
	0.1	20.13	55.13	29.16	**56.95**

It is observed from the data presented in Table 5, that the invariant translation approach of the proposed algorithm leads to good results both in terms of PSNR and in terms of contour conservation. Only in one of the cases presented in Table 5 the initial image has a higher *C* coefficient than the processed image, otherwise the processed images have a higher *C* coefficient. This means that with the removal of the noise, an improvement of the contours is obtained.

The integral application of the proposed algorithm on the circular displacements of the input image.

The proposed algorithm leads both in the invariant approach to translation and in the simple one to good results both in terms of PSNR and of the *C* coefficient, as well as visually, as can be seen in Figs. 1, 2 and 3.

Table 6 compares the two correction methods based on the hierarchical correlation map. It can be seen that in the case of continuous type correction, better results are obtained in terms of PSNR than in the case of switched type correction, especially for higher noise levels. However, this is done at the cost of poor preservation of the contours in the image, which is highlighted by lower values of the *C* coefficient.

Table 6. Comparison between the correction methods based on the hierarchical correlation map. The test images are 256 × 256 pixels and have been degraded with white Gaussian additive noise

Imagine	σ	Initial		Switched type correction	
		PSNR (dB)	***C*** (%)	**PSNR** (dB)	***C*** (%)
Drone	0.05	26.00	63.94	30.19	66.38
	0.1	20.06	48.10	25.47	48.55
PC	0.05	26.03	62.96	27.54	62.74
	0.1	20.19	47.44	23.17	46.32
Components	0.05	26.05	65.47	31.66	67.55
	0.1	20.14	50.96	26.49	55.08
Car	0.05	26.24	66.29	30.73	65.94
	0.1	20.45	51.59	25.86	51.28
People	0.05	26.03	64.03	30.80	65.84
	0.1	20.00	45.78	25.63	48.92

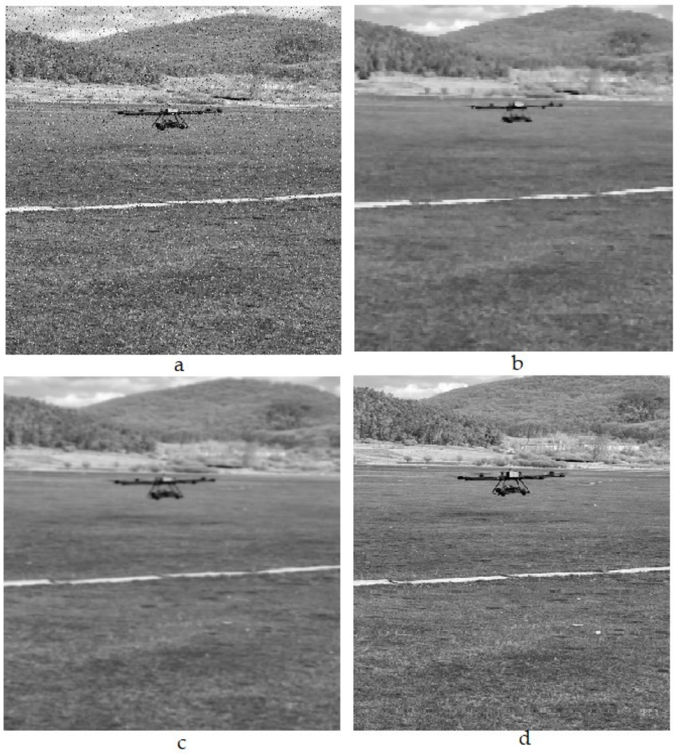

Fig. 1. Images processed by the invariant approach to translation of the proposed algorithm in the two cases considered. 16 circular trips were considered. a. Drone image, 256 × 256 pixels, degraded with Gaussian additive white noise, PSNR = 26.03 dB, C = 57.42%; b. Image obtained by mediating the images resulting from moving the input image and processing according to the first two stages of the proposed algorithm, PSNR = 30.25 dB, C = 59.89%; c. Image obtained by applying the third stage of the proposed algorithm (correction depending on the contour map) on the image from point b, PSNR = 30.11 dB, C = 61.15%; d. Image obtained by applying the invariant integral to translation of the proposed algorithm, PSNR = 30.21 dB, C = 60.95%

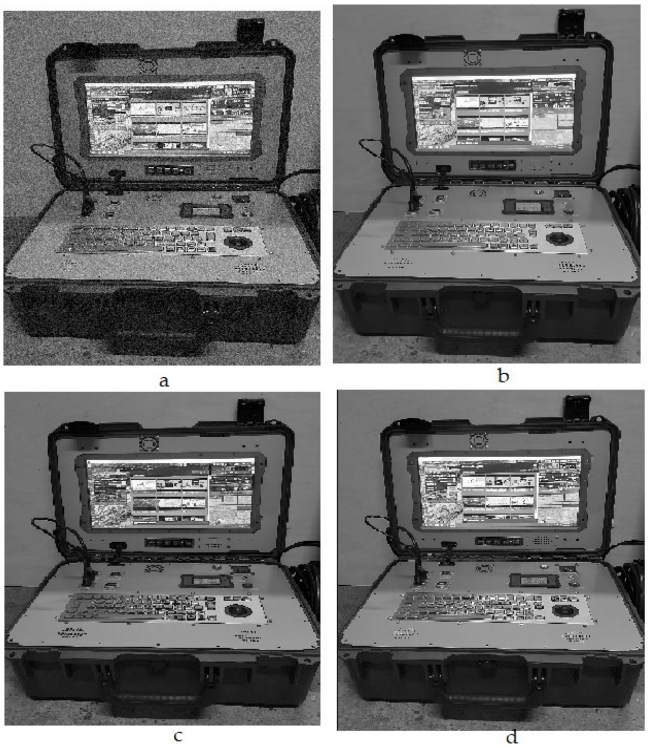

Fig. 2. Images processed by the invariant approach to translation of the proposed algorithm in the two cases considered. 16 circular trips were considered. a. PC image, 256 × 256 pixels, degraded with Gaussian additive white noise, PSNR = 26.06 dB, C = 63.94%; b. Image obtained by mediating the images resulting from moving the input image and processing according to the first two stages of the proposed algorithm, PSNR = 31.60 dB, C = 65.12%; c. Image obtained by applying the third stage of the proposed algorithm (correction depending on the contour map) on the image from point b, PSNR = 31.38 dB, C = 64.88%; d. Image obtained by the integral invariant application to translation of the proposed algorithm (case A), PSNR = 31.53 dB, C = 65.29%

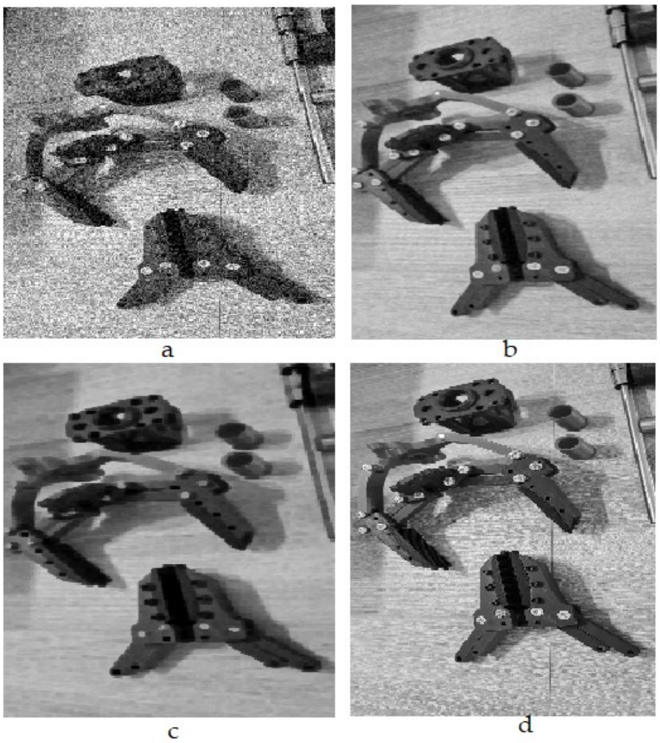

Fig. 3. Images processed by the invariant approach to translation of the proposed algorithm in the two cases considered. 64 circular trips were considered. a. Components image, 256 × 256 pixels, degraded with Gaussian additive white noise, PSNR = 21.07 dB, C = 58.35%; b. Image obtained by mediating the images resulting from moving the input image and processing according to the first two stages of the proposed algorithm, PSNR = 23.91 dB, C = 60.05%; c. Image obtained by applying the third stage of the proposed algorithm (correction depending on the contour map) on the image from point b, PSNR = 24.00 dB, C = 61.53%; d. Image obtained by applying the invariant integral to translation of the proposed algorithm (case A), PSNR = 24.14 dB, C = 62.56%

4. Conclusions

We can say that now, the most used noise reduction algorithms are those that use the wavelet domain, this being due both to their efficiency and simplicity, as well as to a strong theoretical foundation.

This article addresses the issue of spatially selectable wavelet filters. The interest in such filters is determined by the fact that much of the existing information in the images is provided by contours, and most of the noise removal methods cause them to fade. Such filters can be designed starting from the finding that near the contours the noise is less noticeable than in the smooth regions, thus being possible to change the filter parameters depending on the level of activity of the processed region. In this case, at the cost of removing a smaller amount of noise in the regions containing contours, they can be better preserved. There is thus a compromise between the amount of noise removed and the quality of preserving the contours in the image.

Also, in the article, a novelty filter is proposed. The method uses soft truncation of the coefficients, but this time the threshold value is calculated for each coefficient based on local statistics in the wavelet domain. On the wavelet coefficients thus obtained, a correction is made according to a contour map determined based on a hierarchical correlation map.

Two correction variants were tested: a switched correction, in which case either the truncated coefficient is chosen, or the average between the truncated coefficient and the unprocessed one, depending on whether or not the respective coefficient belongs to a contour and a continuous correction, in which case a weighted sum of the two wavelet coefficients is performed, the values of the weights being calculated based on the hierarchical correlation coefficient. In the second case, images are obtained with higher values of PSNR, especially in conditions of higher noise level, but which have more blurred contours.

Both variants use noise dispersion as a parameter, but the switched version also needs a parameter, namely the threshold value to obtain the contour map from the hierarchical correlation map. Obtaining images in which the contours are best preserved is done primarily in conditions of increasing computational complexity, and there is a decrease in the amount of noise removed from the image.

We can say that the wavelet domain offers us the possibility to implement efficient noise reduction algorithms in terms of the amount of noise removed and which ensures a good conservation of contours; obtaining good performances under both aspects is done with the price of increasing the complexity of calculation.

The performance obtained by using the noise reduction algorithm presented in this article differs from image to image. In the case of some of the tested images, the performance obtained using the implemented algorithms is significantly lower than the performance obtained using the same algorithms but applied to other tested images.

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*Corresponding author: catalin.dumitrescu@upb.ro