Wavelet Domain RM L-Filter for Image Denoising

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Abstract. In this paper we present the wavelet domain RM L-filter for the removal of impulsive and speckle noise in image processing applications. The proposed filter uses the robust RM-estimator in the filtering scheme of L-filter in the wavelet domain. Extensive simulation results have demonstrated that the proposed filter consistently outperforms the RM L-filter in the spatial domain by balancing the tradeoff between noise suppression and detail preservation.

1 Introduction

Noise suppression in digital images is a classical problem to the signal-processing community [1,2]. The corruption of images by noise is common during its acquisition or transmission. The aim of denoising is to remove the noise while keeping the signal features as much as possible. Traditional algorithms based on order statistics perform image denoising in the pixel domain [1-4].

In recent years, wavelet transform-based image denoising algorithms show a remarkable success [5-10]. For many image-processing applications, e.g. medical imagery, astronomical imagery, and remote-sensing imagery, the image denoising methods based on the overcomplete expansion of the wavelet transform show significant improvement in MSE than in the case of critically sampled wavelet transform [10].

In this paper we present the capability features of the wavelet domain RM L-filter for the removal of impulsive and speckle noise in image processing applications. The proposed filter uses the robust RM-estimator [11,12] with the Tukey biweight influence function [13] in the filtering scheme of *L*-filter [1] in the wavelet domain. Extensive simulation results have demonstrated that the proposed filter consistently outperforms the RM L-filter in spatial domain by balancing the tradeoff between noise suppression and detail preservation.

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2 Proposed Wavelet Domain Filter

In recent works [11,12] we proposed the RM L-filters for image processing applications. We demonstrated that the RM L-filters consistently outperform other filters by balancing the tradeoff between noise suppression and detail preservation.

In this paper, we propose to use RM L-filter in the wavelet domain. Figure 1 shows a block diagram of proposed Wavelet domain Rank M-type L (WDRML) filter.

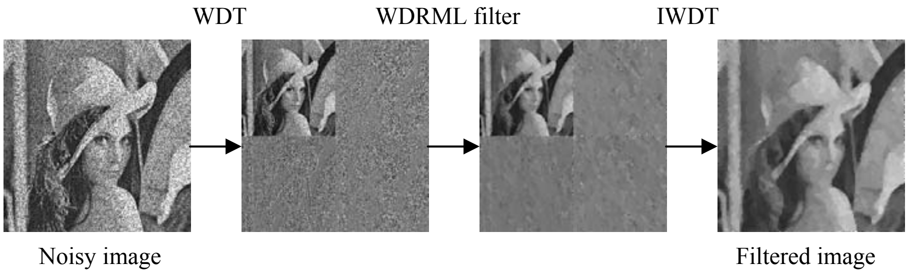

Fig. 1. Block diagram of proposed Wavelet domain Rank Median (WDRML) filter.

The WDRML filter is obtained by the combination of *L*-filter [1] and the RM-estimator [11,12] in the wavelet domain. The RM L-filter in the spatial domain can be writing as [11,12]

$$\theta_{RM\text{-}L} = \frac{\mathrm{MED}\{a_i \cdot [X_i \cdot \psi(X_i - \mathrm{MED}\{\vec{X}\})]\}}{a_{\mathrm{MED}}} \tag{1}$$

where $X_i \cdot \psi(X_i - MED\{\vec{X}\})$ are the selected pixels in accordance with the influence function in a sliding filter window, a_i are the weighted coefficients used into the proposed filter, and a_{MED} is the median of coefficients, and the influence function used here is the Tukey biweight [13],

$$\psi_{bi(r)}(X) = \begin{cases} X^2(r^2 - X^2), & |X| \le r \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The weighted coefficients of the RM L-filter were found using the uniform distribution function [1,2,13]. The coefficients are calculated by each sliding filter window due that the influence function selects whose pixels are used and then compute the weighted coefficients according with the number of pixels used into the filtering window. The RM L-filter is used in the wavelet domain by means of use the Daubechie wavelets [5,6]. Finally, we apply the proposed filter in the images of approaches and details obtained in the process of wavelet decomposition.

3 Results

We obtained from the simulation experiments the properties of proposed Wavelet Domain Rank M-type L (WDRML) filter and we compared it with its version in the spatial domain (RM L filter).

The criteria used to compare the performance of filters were the peak signal-to-noise ratio (PSNR) to evaluate the performance of noise suppression [1,2],

$$\mathrm{PSNR} = 10 \cdot \log\left[\frac{(255)^2}{\mathrm{MSE}}\right], \mathrm{dB} \tag{3}$$

and the mean absolute error (MAE) for evaluation of fine detail preservation [1,2],

$$\mathrm{MAE} = \frac{1}{M_0 N_0}\sum_{i=0}^{M_0-1}\sum_{j=0}^{N_0-1}\left|e(i,j) - \hat{e}(i,j)\right| \tag{4}$$

where $\mathrm{MSE} = \frac{1}{M_0 N_0}\sum_{i=0}^{M_0-1}\sum_{j=0}^{N_0-1}\left[e(i,j) - \hat{e}(i,j)\right]^2$ is the *mean square error*, $e(i,j)$ is the original image, $\hat{e}(i,j)$ is the restored image, and $M_0 \mathrm{x} N_0$ is the image size. In our experiments a 3x3 filter window is applied.

To determine the noise suppression properties of proposed filter the 256x256 standard test grayscale image "Lena" was corrupted by speckle noise. Table 1 shows the performance results in terms of PSNR in dB and MAE for the image "Lena" degraded with 0.1 of variance of speckle noise and free of noise by use the proposed filter in approaches (A) and details (D) with the wavelets db1, db2, db3, and db4 with one (1) and two (2) levels of decomposition. From this table one can see that the proposed WDRML filter provides better speckle noise suppression and detail preservation in comparison with the RM L-filter in the spatial domain in the most of cases.

Table 2 presents the performance results for the image "Mandrill" is degraded with 0.05 of variance of speckle noise and when is free of noise. This Table shows that the proposed WDRML filter provides better results in comparison with the RM L-filter in the spatial domain.

In Table 3 we show the performance results in the case of 5% of impulsive noise in the images "Lena" and "Peppers". From this Table one can see that the proposed filter has poor performance in comparison with the RM L-filter.

Table 1. Performance results in the image "Lena" obtained by the use of proposed filter.

Filters	Free noise		σ^2=0.1	
	PSNR	MAE	PSNR	MAE
RM L	29.62	3.78	22.95	13.24
WDRML (db1,A,1)	27.84	5.09	23.35	12.24
WDRML (db1,D,1)	31.46	3.24	20.53	18.78
WDRML (db2,A,1)	27.90	5.11	23.60	12.15
WDRML (db2,D,1)	32.26	3.05	20.69	18.00
WDRML (db3,A,1)	27.92	5.24	24.02	11.77
WDRML (db3,D,1)	32.70	2.97	20.79	17.99
WDRML (db4,A,1)	27.87	5.27	24.33	11.28
WDRML (db4,D,1)	33.00	2.92	20.90	18.11
WDRML (db1,A,2)	24.83	8.32	22.46	13.57
WDRML (db1,D,2)	27.48	5.73	22.66	13.93
WDRML (db2,A,2)	25.40	7.61	22.94	12.85
WDRML (db2,D,2)	28.37	5.34	23.21	13.15
WDRML (db3,A,2)	25.24	7.89	23.14	12.59
WDRML (db3,D,2)	28.39	5.42	23.49	12.90
WDRML (db4,A,2)	25.06	8.21	23.38	12.47
WDRML (db4,D,2)	28.29	5.46	23.69	12.73

Table 2. Performance results in the image "Mandrill" obtained by the use of proposed filter.

Filters	Free noise		σ^2=0.05	
	PSNR	MAE	PSNR	MAE
RM L	23.22	10.38	21.31	15.42
WDRML (db1,A,1)	21.30	15.49	20.75	17.58
WDRML (db1,D,1)	23.63	11.49	21.60	16.24
WDRML (db2,A,1)	21.34	15.52	20.75	17.55
WDRML (db2,D,1)	24.56	10.36	22.15	15.17
WDRML (db3,A,1)	21.33	15.53	20.77	17.52
WDRML (db3,D,1)	25.53	9.31	22.66	14.37
WDRML (db4,A,1)	21.25	15.70	20.77	17.52
WDRML (db4,D,1)	26.06	8.81	22.96	13.89
WDRML (db1,A,2)	19.98	19.01	19.69	20.37
WDRML (db1,D,2)	21.69	14.69	21.11	16.78
WDRML (db2,A,2)	19.92	19.50	19.62	20.58
WDRML (db2,D,2)	21.79	15.01	21.20	16.77
WDRML (db3,A,2)	20.00	19.26	19.71	20.30
WDRML (db3,D,2)	21.94	14.74	21.31	16.59
WDRML (db4,A,2)	19.96	19.40	19.66	20.49
WDRML (db4,D,2)	22.28	14.06	21.64	15.84

From the experimental results presented in this paper we can say that the proposed WDRML filter can be suppress the speckle noise effectively but in the case of impulsive noise it has poor performance.

One can improve the performance of proposed filter for speckle noise suppression if we use up to five levels of decomposition in the wavelet analysis. In the case of impulsive noise we can improve the noise suppression by use an impulsive detector [11,12]

Table 3. Performance results in the images "Lena" and "Peppers" obtained by the use of proposed filter.

Filters	"Lena"		"Peppers"	
	PSNR	MAE	PSNR	MAE
RM L	28.29	5.76	29.03	5.21
WDRML (db1,A,1)	25.95	7.20	25.06	8.02
WDRML (db1,D,1)	23.28	10.37	23.18	10.12
WDRML (db2,A,1)	25.89	8.01	25.34	8.46
WDRML (db2,D,1)	23.57	10.74	23.43	10.63
WDRML (db3,A,1)	25.84	8.33	24.83	8.97
WDRML (db3,D,1)	23.60	11.11	23.62	10.81
WDRML (db4,A,1)	25.88	8.25	24.17	9.18
WDRML (db4,D,1)	23.65	11.06	23.78	10.61
WDRML (db1,A,2)	23.89	10.47	21.69	13.29
WDRML (db1,D,2)	24.81	9.74	23.59	10.62
WDRML (db2,A,2)	24.12	10.15	21.75	13.43
WDRML (db2,D,2)	25.45	9.38	24.51	10.21
WDRML (db3,A,2)	24.00	10.52	21.58	13.84
WDRML (db3,D,2)	25.61	9.37	25.02	10.03
WDRML (db4,A,2)	24.15	10.64	21.42	14.12
WDRML (db4,D,2)	25.58	9.51	24.71	10.34

Figure 2 presents the visual results to apply the proposed filter with one and two decomposition levels in the image "Lena", and in Figure 3 shows the processed images in the case of use the image "Peppers".

From Figures 2 and 3, one can see that the proposed filter outperforms the RM L-filter in the case of speckle noise but in the case of impulsive noise has poor performance. In the case when the images are free of noise the proposed filter can conserve the properties of detail preservation better in comparison with the RM L-filter.

4 Conclusions

We adapt the RM L-filter to work in the wavelet domain. The proposed WDRML filter has better properties of speckle noise suppression and detail preservation in comparison with the RM L-filter. It is expected that the performance of noise suppression and detail preservation can be increased if we use up to five decomposition levels in the proposed filter. Therefore we will use other influences functions and distribution function in the filtering scheme of proposed filter.

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Fig. 2. Visual results in the image Lena, a) Original image, b) Degraded image with 20% of impulsive noise, c) Degraded image with 0.1 of variance of speckle noise, d) Restored image of a) with RM L-filter, e) Restored image of b) with RM L-filter, f) Restored image of c) with RM L-filter, g) Restored image of a) with WDRML filter (db4, D,1), h) Restored image of b) with WDRML filter (db1, A, 1), i) Restored image of c) with WDRML filter (db1, A, 1). j) Restored image of a) with WDRML filter (db3, D,2), k) Restored image of b) with WDRML filter (db3, A, 2), l) Restored image of c) with WDRML filter (db4, A, 2).

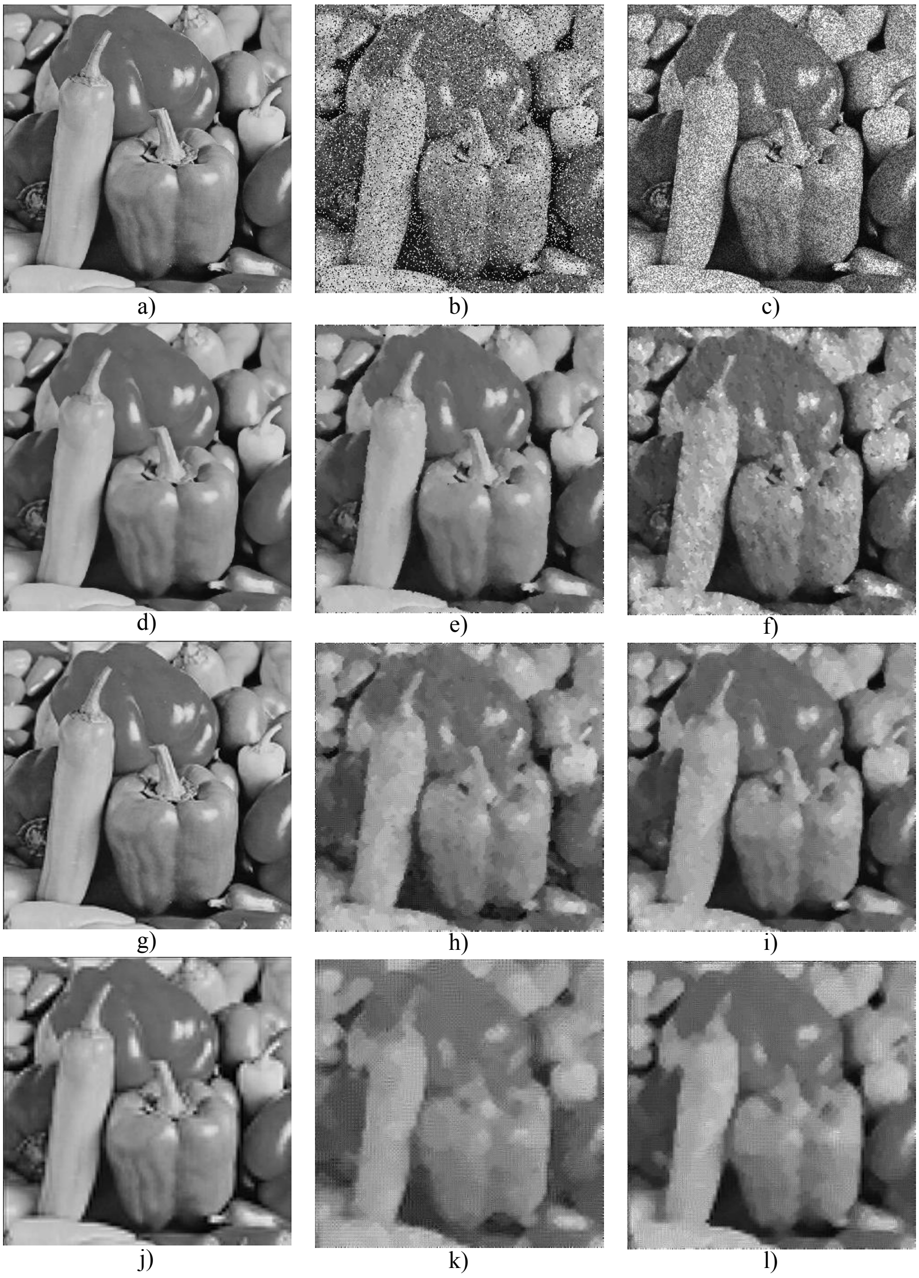

Fig. 3. Visual results in the image Peppers, a) Original image, b) Degraded image with 20% of impulsive noise, c) Degraded image with 0.1 of variance of speckle noise, d) Restored image of a) with RM L-filter, e) Restored image of b) with RM L-filter, f) Restored image of c) with RM L-filter, g) Restored image of a) with WDRML filter (db4, D,1), h) Restored image of b) with WDRML filter (db2, A, 1), i) Restored image of c) with WDRML filter (db2, A, 1), j) Restored image of a) with WDRML filter (db4, D, 2), k) Restored image of b) with WDRML filter (db2, A, 2), l) Restored image of c) with WDRML filter (db2, A, 2).

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