COMPARISON OF COMPONENT AND VECTOR FILTER PERFORMANCE WITH APPLICATION TO MULTICHANNEL AND COLOR IMAGE PROCESSING

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ABSTRACT

Several efficient component and vector filters applicable for processing multichannel and color images are compared quantitatively. The cases of Gaussian and mixed Gaussian and impulsive noise are considered. It is shown that in situations typical for practice the best results are provided by a vector double-window modified trimmed mean filter and by a modified sigma filter applied to each component.

1. INTRODUCTION

Many images, e.g., color images and multispectral remote sensing data, can be considered as multichannel data. It is an important and difficult task to remove noise from these images while preserving edges and fine details. This task becomes especially complicated when, besides additive or multiplicative Gaussian noise, also spikes are present. In this case only robust, mainly nonlinear, filters perform reasonably well.

There are two principal ways to filter the multichannel data [1]. First, the components can be processed separately. For instance, for RGB color images each color component (i.e., red, green, and blue) can be filtered separately. Second, it is possible to apply vector filters, which take into account the mutual correlation of the components.

Yet another problem is that, e.g., the performance of different filtering algorithms for color images also depends on the properties of the images [2]: the level of noise, the probability of spike occurrence, the object contrasts and shapes, etc. Moreover, there are no commonly accepted criteria for the analysis of the quality of the processing algorithms for color images.

In previous articles we have introduced several nonlinear filters, which perform well with grayscale images. In this paper we compare through experiments the suitability of some of those filters to the componentwise processing of color images. Moreover, we compare the performance of those selected (component) filters to the performance of vector filters.

2. STUDIED FILTERS

The studied component filters are the adaptive L_{pq}–filter (ALPQF) [3], the modified sigma filter (MSF) [4], and the iterative filtering procedures based on the sequential application of the FIR median hybrid filter to the output of the local statistic Lee (LEE+FIRMH) [5] or the adaptive L_{pq} (ALPQF+FIRMH) [6] filter. (The L_{pq}–filter is a nonlinear filter, whose output is based only on the *p*th and *q*th order statistics.)

The examined vector filters contain basic filters like the vector median filter (VMF) [1], the vector L_{pq}-filter (VLPQF) [7], the vector α-trimmed mean filter (VATMF) [7], and adaptive vector filters based on hard switching between the vector L_{pq}–filter and vector median filter (VLPQF+VMF) or between the vector α-trimmed mean filter and vector median filter (VATMF+VMF) [7]. In addition, the performance of the filters was compared to the performance of the vector double window modified trimmed mean (DW MTM) filter, which has been shown to be one of the best vector filtering algorithms [8].

3. TEST CASE

The comparison tests were done using both artificial test image (see Fig. 1a) and real RGB color images, e.g., the image “Mandrill” in Fig. 2a. To simplify the visual inspection, the contrast and brightness of the images in Fig. 1 are enhanced. Moreover, due to technical limitations all images are in grayscale in the printed version of this paper. For test purposes the test images were corrupted (each component separately) by mixed noise, which contained spikes with different probabilities and additive Gaussian noise with zero mean and different variances (an example is presented in Fig. 1b). For spikes the “salt and pepper” model was used.

As can be seen, the artificial test image contains objects of various shapes, dimensions, and contrasts with respect to the surrounding background. Thus, it is possible to achieve good estimates for the performance of the filtering algorithms. Also, it is possible to analyze visually the peculiarities of the output images.

The size of the scanning window was 5x5 for the component filters. For the vector filters both the 3x3 and the 5x5 scanning windows were used. The norms used for the vector filtering were the L_1 norm and the Euclidean L_2^2 norm. In addition, the adaptation procedure of the adaptive componentwise filters was suited for the case of additive noise.

For the quantitative characterization of the filter efficiency we used several commonly accepted criteria including such that take into account, e.g., the mutual correlation of the image components. These criteria were calculated for the entire test image, for its homogeneous regions (background), and for the locally active areas of the image, i.e., edges, details, and their neighborhoods. Besides the traditional criteria like the MAE, the RMSE [7], and the correlation coefficient (*Corr*) [7], some typical criteria for the analysis of the vector filter performance were

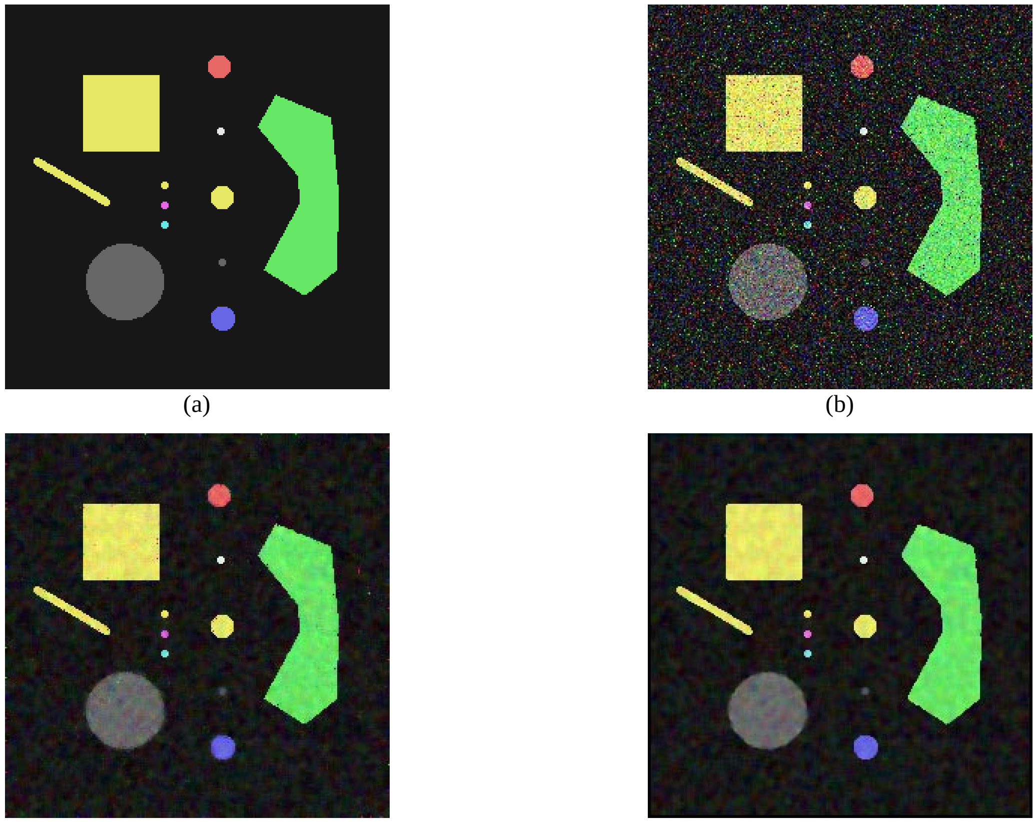


Figure 1. (a) Artificial RGB color test image; (b) the test image corrupted (for every component) by additive Gaussian noise with σ^2=100 and impulsive “salt and pepper” noise (P_i=0.03); (c) the output of the 5x5 MSF; (d) the output of the 5x5 vector DW MTM filter.

MAE in $L^*a^*b^*$ space ($E_{L^*a^*b^*}$) [10], and the V-distance (V_d) defined by

$$V_d = \sqrt{\frac{1}{|G|}\sum_{i\in G}\frac{\left\|\boldsymbol{I}_i - \hat{\boldsymbol{I}}_i\right\|^2}{\left\|\boldsymbol{I}_i\right\|\cdot\left\|\hat{\boldsymbol{I}}_i\right\|}}\,, \qquad (1)$$

where $\boldsymbol{I}_i$ and $\hat{\boldsymbol{I}}_i$ are the ith samples (vectors) of the noise-free and the filtered signal, respectively, $\|\cdot\|$ is the Euclidean norm, and $|G|$ is the size of the sample set G. The possible division by zero must naturally be taken care of in the V-distance calculation. In the tests reported in this paper we have used instead of zero the value one, which is the minimal nonzero value.

Together these criteria describe the performance of the filtering algorithms from different points of view. For example, the RMSE is more sensitive to spike influence than the MAE is and, conversely, the MAE is more sensitive to edge/detail distortions. Among the considered criteria, the $E_{L^*a^*b^*}$ criterion reflects most the human perception. The MCRE criterion, on the other hand, evaluates chromaticity (color preservation) error and does not take into account error in the intensities. Finally, the V-distance takes into account both the intensity error and the color error (angle between “color vectors”) between the output image and the noise-free image. Thus, it combines the advantages of the RMSE and the MCRE.

4. EXPERIMENTAL RESULTS

Some of the experimental results are presented in Tables 1-4. In the reported tests the variance σ^2 of the Gaussian noise was 25 and 100 and the probability P_i for the total occurrence of spikes was 0.0 and 0.03. The probability for both the positive and negative impulses was equal. The size of the scanning window was 5x5 except for the adaptive vector filters, for which the size of the scanning window of the latter operation was 3x3, and the vector DW MTM filter, for which the size of the scanning window of the first operation was 3x3.

The trimming in the VATMF as well as the selection of the order statistic used in the vector L_{pq}–filter was done by omitting 9 most distant samples. The order statistics used in the componentwise L_{pq}–filters were 6 and 20. The trimming parameter in the vector DW MTM filter was chosen so that with Gaussian noise on the average 5.45 per cent of the samples would be omitted in the homogeneous areas of the image.

Filter type	Norm	MAE	RMSE	*Corr*	MCRE	$E_{L^*a^*b^*}$	V_d
No filtering (= original error)		4.000	5.011	0.9861	0.096	14.693	0.232
Vector median (VMF)	L_2^2	1.718	2.859	0.9954	0.036	5.764	0.107
	L_1	1.639	2.612	0.9961	0.037	5.704	0.101
Vector L_{pq} (VLPQF)	L_2^2	1.707	3.303	0.9938	0.033	5.325	0.111
	L_1	1.792	3.338	0.9937	0.035	5.724	0.114
Vector α-trimmed mean (VATMF)	L_2^2	1.148	2.175	0.9973	0.025	3.928	0.076
	L_1	1.154	2.154	0.9974	0.025	4.011	0.076
Adaptive vector L_{pq} + vector median	L_2^2, L_2^2	1.434	2.019	0.9977	0.032	5.068	0.086
(VLPQF+VMF)	L_1, L_1	1.525	2.056	0.9977	0.035	5.380	0.089
Adaptive vector α-trimmed mean + vector median	L_2^2, L_2^2	1.092	1.653	0.9985	0.025	3.966	0.069
(VATMF+VMF)	L_1, L_1	1.108	1.613	0.9985	0.026	4.050	0.068
	L_2^2, L_1	1.072	1.570	0.9986	0.025	3.916	0.066
Iterative Lee + FIR median hybrid (LEE+FIRMH)		1.185	1.706	0.9984	0.028	4.341	0.073
Adaptive L_{pq} (ALPQF)		1.037	1.549	0.9987	0.023	3.670	0.066
Iter. ALPQF + FIR med. hyb. (ALPQF + FIRMH)		0.974	1.474	0.9988	0.022	3.485	0.062
Modified sigma (MSF)		0.906	1.263	0.9991	0.022	3.456	0.057
Vector DW MTM	L_2^2	0.820	1.214	0.9992	0.020	3.143	0.053

Table 1. Results from the filtering of the artificial test image corrupted only by additive Gaussian noise (σ^2=25).

Filter type	Norm	MAE	RMSE	*Corr*	MCRE	$E_{L^*a^*b^*}$	V_d
No filtering (= original error)		7.930	9.836	0.9497	0.200	30.418	0.454
Vector median (VMF)	L_2^2	3.226	4.526	0.9884	0.069	10.953	0.184
	L_1	3.208	4.339	0.9894	0.072	11.252	0.185
Vector L_{pq} (VLPQF)	L_2^2	3.039	4.492	0.9887	0.063	9.961	0.175
	L_1	3.256	4.642	0.9879	0.070	10.977	0.186
Vector α-trimmed mean (VATMF)	L_2^2	2.223	3.253	0.9940	0.046	7.612	0.131
	L_1	2.262	3.256	0.9940	0.051	7.867	0.133
Adaptive vector L_{pq} + vector median	L_2^2, L_2^2	2.841	3.836	0.9918	0.063	9.864	0.163
(VLPQF+VMF)	L_1, L_1	3.060	3.967	0.9913	0.070	10.763	0.175
Adaptive vector α-trimmed mean + vector median	L_2^2, L_2^2	2.220	3.170	0.9943	0.050	7.827	0.132
(VATMF+VMF)	L_1, L_1	2.240	3.052	0.9947	0.052	8.018	0.132
	L_2^2, L_1	2.180	2.998	0.9949	0.050	7.751	0.128
Iterative Lee + FIR median hybrid (LEE+FIRMH)		2.261	3.099	0.9946	0.052	8.011	0.133
Adaptive L_{pq} (ALPQF)		2.049	3.077	0.9947	0.047	7.348	0.127
Iter. ALPQF + FIR med. hyb. (ALPQF + FIRMH)		1.922	2.888	0.9953	0.044	6.865	0.118
Modified sigma (MSF)		1.826	2.458	0.9966	0.042	6.558	0.107
Vector DW MTM	L_2^2	1.635	2.181	0.9973	0.038	5.894	0.097

Table 2. Results from the filtering of the artificial test image corrupted only by additive Gaussian noise (σ^2=100).

It should be noted here that all parameters except the correlation are to be minimized. The *Corr* is to be as close to unit as possible. In addition, we can see from Tables 1-4 that the V_d criterion is in coherence with the other error criteria. Thus, it is an appropriate criterion for the filter performance characterization.

Tables 1 and 2 contain the error values for the entire artificial test image in cases of only Gaussian noise. As can be seen, the α-trimmed mean filter is clearly the best non-adaptive vector filter. In fact, it was in practice the only non-adaptive vector filter that could produce better results than the worst considered adaptive vector filter. Moreover, the vector α-trimmed mean filter usually performed better than the adaptive vector filters based on the combination of the VLPQF and the VMF but worse than the adaptive vector filters based on the combination of VATMF and the VMF. Finally, the vector DW MTM filter produced the best results according to all used quantitative criteria.

When componentwise filtering was applied the best results were obtained using the modified sigma filter. Also, the iterative procedure based on the ALPQF and the FIR median hybrid filter produced good results. Moreover, these two filters, as well as the adaptive L_{pq}-filter, performed better than all tested vector filters, excluding the vector DW MTM filter, which was the best also when compared to component filters.

Although the L_2^2 norm is theoretically optimal for Gaussian noise we can see that in some cases the results are better with the L_1 norm. The reason for this is that the L_1 norm leads to

Filter type	Norm	MAE	RMSE	*Corr*	MCRE	$E_{L^*a^*b^*}$	V_d
No filtering (= original error)		7.703	28.725	0.7471	0.134	23.905	0.558
Vector median (VMF)	L_2^2	3.639	5.323	0.9862	0.072	11.824	0.211
	L_1	1.692	2.731	0.9958	0.038	5.893	0.105
Vector L_{pq} (VLPQF)	L_2^2	2.560	4.259	0.9902	0.048	7.960	0.154
	L_1	1.952	3.627	0.9926	0.038	6.191	0.124
Vector α-trimmed mean (VATMF)	L_2^2	1.510	2.725	0.9959	0.030	4.926	0.100
	L_1	1.217	2.297	0.9970	0.026	4.136	0.080
Adaptive vector L_{pq} + vector median	L_2^2, L_2^2	2.298	3.718	0.9929	0.048	7.713	0.143
(VLPQF+VMF)	L_1, L_1	1.632	2.270	0.9971	0.037	5.761	0.097
Adaptive vector α-trimmed mean + vector median	L_2^2, L_2^2	1.478	3.009	0.9951	0.031	5.009	0.105
(VATMF+VMF)	L_1, L_1	1.124	1.751	0.9983	0.026	4.111	0.071
	L_2^2, L_1	1.349	1.978	0.9979	0.031	4.820	0.082
Iterative Lee + FIR median hybrid (LEE+FIRMH)		2.490	7.454	0.9704	0.056	9.012	0.206
Adaptive L_{pq} (ALPQF)		1.128	2.045	0.9977	0.026	4.023	0.077
Iter. ALPQF + FIR med. hyb. (ALPQF + FIRMH)		1.056	1.892	0.9980	0.024	3.800	0.072
Modified sigma (MSF)		1.038	2.111	0.9975	0.027	4.077	0.075
Vector DW MTM	L_2^2	0.888	1.496	0.9987	0.022	3.394	0.059

Table 3. Results from the filtering of the artificial test image corrupted by additive Gaussian noise (σ^2=25) and impulsive noise (P_i=0.03).

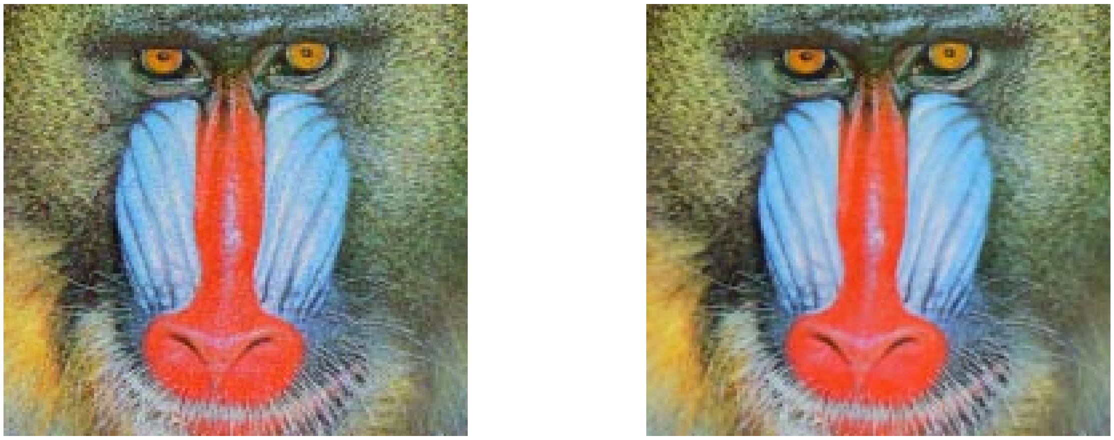
Filter type	Norm	MAE	RMSE	*Corr*	MCRE	$E_{L^*a^*b^*}$	V_d
No filtering (= original error)		8.136	29.364	0.8322	0.118	22.528	0.513
Vector median (VMF)	L_2^2	5.747	9.591	0.9741	0.063	12.736	0.300
	L_1	2.963	6.061	0.9894	0.036	6.802	0.174
Vector L_{pq} (VLPQF)	L_2^2	6.252	10.175	0.9696	0.050	11.586	0.301
	L_1	5.298	9.398	0.9743	0.048	10.619	0.267
Vector α-trimmed mean (VATMF)	L_2^2	3.436	6.743	0.9868	0.029	6.511	0.210
	L_1	2.656	5.736	0.9907	0.025	5.289	0.155
Adaptive vector L_{pq} + vector median	L_2^2, L_2^2	3.866	8.015	0.9822	0.049	9.326	0.244
(VLPQF+VMF)	L_1, L_1	2.385	3.945	0.9955	0.039	6.712	0.133
Adaptive vector α-trimmed mean + vector median	L_2^2, L_2^2	3.139	7.759	0.9831	0.037	7.229	0.231
(VATMF+VMF)	L_1, L_1	1.803	3.574	0.9963	0.029	5.057	0.113
	L_2^2, L_1	1.974	3.672	0.9961	0.032	5.536	0.119
Iterative Lee + FIR median hybrid (LEE+FIRMH)		3.689	9.245	0.9760	0.064	11.194	0.230
Adaptive L_{pq} (ALPQF)		2.535	5.015	0.9928	0.043	7.389	0.160
Iter. ALPQF + FIR med. hyb. (ALPQF + FIRMH)		2.305	4.589	0.9939	0.040	6.850	0.149
Modified sigma (MSF)		1.350	3.537	0.9964	0.028	4.502	0.090
Vector DW MTM	L_2^2	1.174	3.079	0.9973	0.021	3.638	0.088

Table 4. Results from the filtering of the locally active areas of the artificial test image corrupted by additive Gaussian noise (σ^2=25) and impulsive noise (P_i=0.03).

better edge/detail preservation and to a more robust filter than the L_2^2 norm (see, e.g., [1, 7]). Naturally, this kind of properties are important for image enhancement.

The results for the mixed noise (presented in Tables 3 and 4) are, in general, coherent to results presented in Tables 1 and 2. For instance, the vector DW MTM filter remains superior. There are, however, also some differences due to the fact that the robustness of the filters starts to play an important role. The most interesting change is that now both the combination of the VATMF and the VMF utilizing the L_1 norm and the iterative combination of the ALPQF and the FIRMH filter outperformed the MSF in the entire image according to most criteria. However, the MSF was still better in the locally active areas of the image, i.e., the MSF has better edge/detail preservation ability. Another interesting change is that now the iterative combination of the Lee and the FIRMH filter was among the worst of the studied filters.

The results in the homogeneous regions of the test image are coherent to those presented here. For example, the RMSE values for the homogeneous regions of the test image are 4.525, 1.960, 1.644, 1.366, 7.202, 1.192, 1.861, and 1.159 for VMF with L_2^2 and L_1 norms, VATMF+VMF with L_2^2, L_2^2 and L_1, L_1 norms, LEE+FIRMH, ALPQF+FIRMH, MSF, and vector DW



(a) (b)

Figure 2. Real RGB color image "Mandrill": (a) corrupted (for every component) by additive Gaussian noise with σ^2=100 and impulsive "salt and pepper" noise (P_i=0.03); (b) the output of the 5x5 MSF.

MTM filter, respectively. As can be seen, the robustness of the MSF and, especially, the iterative combination of the Lee and the FIRMH filter is rather poor. The adaptive combination of the VATMF and the VMF with L_1-norm, on the other hand, gives rather good results also in the case of spike presence.

The visual evaluation of the test images confirms the conclusions drawn above. As can be seen from Fig. 1c, the modified sigma filter provides very good edge preservation but fails to remove all of the spikes. The output of the vector DW MTM filter in Fig. 1d also seems to be a good trade-off between the detail preservation and spike removal.

A noisy "Mandrill" corrupted by Gaussian and impulsive noise is shown in Fig. 2a. As can be seen from Fig. 2b, the modified sigma filter produces now visually good quality. It is interesting that in this case the best detail-preserving component filters (the modified sigma filter and the iterative combination of the Lee and the FIRMH filter) outperform the vector DW MTM filter according to all quantitative criteria. For example, the RMSEs of the MSF, the iterative LEE+FIRMH, and the vector DW MTM filter are 12.0, 12.8, and 19.0, respectively. The large number of small details in the image "Mandrill" explains this fact as the vector DW MTM filter smears those details heavily.

5. SUMMARY

In this paper the performance of several recently introduced nonlinear filters was studied in the context of color image processing. It was shown through experiments that some of the component filters performed so well that they outperformed all but one of the studied vector filters. Moreover, with the modified sigma filter the results were even so promising that it motivates us to design next a modified vector sigma filter based on the approach similar to that one used in the modification of the scalar valued sigma filter.

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