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Real-Time Image Processing Using the Rank M-type L-Filter

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1. Abstract

In this paper we present the capability and real-time processing features of a new type of L-filter for the removal of mixtures of impulsive and speckle noise in real-time image processing applications. The proposed filter uses the robust RM-estimator in the filtering scheme of *L*-filter. Extensive simulation results have demonstrated that the proposed filter consistently outperforms other filters by balancing the tradeoff between noise suppression and detail preservation. The criteria used to compare the performance of various filters were the PSNR, MAE, and processing time. The real-time implementation of proposed algorithm was realized on the DSP TMS320C6701. The processing time of proposed filter includes the time of data acquisition, processing and store data. We found that the processing time values of proposed filter depend of the image to process and do not practically vary for different mixtures of noise; these values depend also of the calculation of influence functions, parameters of the proposed filter, and different distribution functions used to calculate the coefficients of the new type of *L*-filter.

Key words: *L*-filter, RM-estimators.

2. Resumen (Procesamiento de imágenes en tiempo real usando el filtro L de rango tipo M)

En este artículo, se presentan las características de capacidad y procesamiento en tiempo real de un nuevo tipo de filtro *L* para la supresión de mezclas de ruido impulsivo y multiplicativo en aplicaciones de procesamiento de imágenes en tiempo real. El filtro propuesto usa el estimador robusto RM en el esquema de filtrado del filtro *L*. Extensivos resultados de simulación demuestran que el filtro propuesto consistentemente mejora el desempeño de otros filtros balanceando su capacidad de desempeño entre supresión de ruido y preservación de detalles. Los criterios usados para comparar el desempeño de varios filtros fueron el PSNR, MAE y tiempo de procesamiento. La implementación en tiempo real del algoritmo propuesto fue realizada en el DSP TMS320C6701. El tiempo de procesamiento del filtro propuesto incluye el tiempo de adquisición, procesamiento y almacenamiento. Se encontró que el tiempo de procesamiento depende de la imagen a procesar y prácticamente no varía para diferentes mezclas de ruido; estos valores también dependen del cálculo de las funciones de influencia, de los parámetros del filtro propuesto y de las diferentes funciones de distribución usadas para calcular los coeficientes del nuevo tipo de filtro *L*.

Palabras clave: filtro *L*, estimadores RM.

3. Introduction

Many different classes of filters have been proposed to remove the noise from digital images [1-4]. They are classified into several categories depending on specific applications. Linear filters are efficient for Gaussian noise removal but often distort edges and have poor performance against impulsive noise [1,2]. Nonlinear filters are designed to suppress noise of different nature; they can remove impulsive noise and guarantee detail preservation [1-5]. They have proven to be exceptionally useful in many image restoration applications. Because of their robust properties, some of these filters have been used when the images are corrupted by non-Gaussian noise [5]. Different nonlinear filters are based on the order statistics [1,2]. They use the concept of data ordering [6]. Among them are the L-filters whose outputs are defined as linear combinations of order statistics [1,6]. Some examples of L-filters are the Combination (C-L) filter [7], the normalized least mean squares L (NLMS-L) filter [8], and the Sampled-Function Weighted Order (SFWO) filter [9].

Recently, we presented the Rank M-type K-Nearest Neighbor (RM-KNN) filters [10,11] for the removal of impulsive and speckle noise in image processing applications. These filters are based in the combination of the KNN filter [2] and the RM-estimator [10,11]. The use of KNN algorithm provides good detail preservation. The RM-estimator utilizes the combination of the R-estimator and the M-estimator with different influence functions to improve the noise suppression and detail preservation [11].

In this paper, we present a new class of *L*-filter. The proposed filtering scheme uses the RM-estimator into the *L*-filter according with the RM-KNN filtering approach [10,11]. The use of the RM-estimator with different influence functions [1,6,11] in the *L*-filter improves the properties of noise suppression and detail preservation in comparison with other classes of *L*-filters. We also introduce the use of an impulsive noise detector [12] to improve the properties of noise suppression and detail preservation in the proposed filtering scheme. Additionally, we use the exponential, Laplacian, and uniform distribution functions [1,6] to calculate the coefficients of the new *L*-filter. Extensive simulations in different images with different impulsive noise percentages and variances of speckle noise were realized. The criteria used to compare the restoration performance of various filters were the peak signal-to-noise ratio (PSNR) for the evaluation of noise suppression and the mean absolute error (MAE) for quantification of edges and fine detail preservation [1-5]. To evaluate the processing time of various filters we present the implementation of them by means of use of the Texas Instruments DSP TMS320C6701 [13] to demonstrate that they can potentially provide a real-time solution to quality the video transmission.

4. RM-estimators

The *R*-estimators form a class of nonparametric robust estimators based on rank calculations [1,2,6,11].

The median estimator is the best estimator when any a priori information about data X_i distribution shape and its moments is unavailable [2]

$$\hat{\theta}_{med} = \{ X_{(N+1/2)} \quad \text{for odd } N \} \tag{1}$$

if the probability density function is a symmetrical one, the Wilcoxon test of signed ranks is asymptotically the most powerful one and it determines the Wilcoxon order statistics estimator [2]

$$\hat{\theta}_{Wil} = \underset{i \leq j}{\text{MED}} \{ {}^1/_2 (X_{(i)} + X_{(j)}) \} \tag{2}$$

where $X(k)$ is the element with rank k, N is the size of sample, and $1 \leq k \leq N$.

Huber proposed the *M*-estimators as a generalization of maximum likelihood estimators (MLE) [1,2,6,11].

The *M*-estimator can be calculated in the following way [11]:

$$\hat{\theta}^{(q)} = \frac{\sum_{i=1}^{N} w((X_i - \hat{\theta}^{(q-1)})/S_0) X_i}{\sum_{i=1}^{N} w((X_i - \hat{\theta}^{(q-1)})/S_0)} \tag{3}$$

where $\hat{\theta}^{(q)}$ is the *M*-estimate of the sample location parameter θ on a step q, X_i is the input data sample, and $(X_i - \hat{\theta}^{(q-1)})/S_0$ is the argument of $w(\cdot)$; $\hat{\theta}^{(0)} = \text{MED}\{X_N\}$ is the median of primary data, $S_0 = \text{MED}\ \{|X_i - \hat{\theta}^{(0)}|\} = \text{MAD}\ (X_N)$ is a scale estimate, MAD is the median of the absolute deviations from the median [2,6], and X_N is the primary data sample.

The equation (3) can be simplified to such a one-step estimator [11]:

$$\theta_{\mathbf{M}} = \frac{\sum_{i=1}^{N} X_i \tilde{\psi}(X_i - \text{MED}\{X_N\})}{\sum_{i=1}^{N} 1_{[-r,r]} \tilde{\psi}'(X_i - \text{MED}\{X_N\})} \tag{4}$$

where $\tilde{\psi}$ is the normalized influence function ψ: $\psi(X) = X\tilde{\psi}(X)$.

It is evident that (4) represents the arithmetic average of

$$\sum_{i=1}^{n} \psi(X_i - \text{MED}\{X_N\}),$$

which is evaluated on the interval $[-r,r]$, where the parameter r is connected with restrictions on the range of $\psi[X]$ [11].

The lowered *M*-estimates are used to derive the function $\tilde{\psi}(X)$ to cut the outliers off the primary sample. Table 1 shows the influence functions used in the *M*-estimator (4) [6,11].

The proposal for enhancement the robust properties of *M*-estimators by using the *R*-estimators consists of the

Tabla 1. Influence functions used in the *M*-estimator.

Influence function	Formulae
Simple cut	$\psi_{cut(r)}(X)=\begin{cases}X, & \lvert X\rvert\le r\\ 0, & \text{otherwise}\end{cases}$
Andrew's sine	$\psi_{sin(r)}(X)=\begin{cases}\sin(X/r), & \lvert X\rvert\le r\pi\\ 0, & \text{otherwise}\end{cases}$
Tukey biweight	$\psi_{bi(r)}(X)=\begin{cases}X^2(r^2-X^2), & \lvert X\rvert\le r\\ 0, & \text{otherwise}\end{cases}$
Hampel's three part redescending	$\psi_{\alpha,\beta,r}(X)=\begin{cases}X, & 0\le\lvert X\rvert\le\alpha\\ \alpha\cdot\text{sgn}(X), & \alpha\le\lvert X\rvert\le\beta\\ \alpha\dfrac{r-\lvert X\rvert}{r-\beta}, & \beta<\lvert X\rvert\le r\\ 0, & \text{otherwise}\end{cases}$

application of the procedure similar to the median average instead of arithmetic one [11], the iterative MM (Median *M*-type) -estimator that is derived from (3) [11],

$$\theta_{MM}=\text{MED}\{X_i\,\psi(X_i-\theta^{(q-1)})\} \tag{5}$$

and the non-iterative MM-estimator [11],

$$\theta_{MM}=\text{MED}\{X_i\,\psi(X_i-\theta)\} \tag{6}$$

in the same way, the iterative WM (Wilcoxon *M*-type) -estimator is given by,

$$\theta^{(q)}_{WM}=\underset{i\le j}{\text{MED}}\{{}^1/_2[X_i\tilde{\psi}(X_i-\theta^{(q-1)})+X_j\tilde{\psi}(X_j-\theta^{(q-1)})]\} \tag{7}$$

and the non-iterative WM-estimator,

$$\theta^{(q)}_{WM}=\underset{i\le j}{\text{MED}}\{{}^1/_2[X_i\tilde{\psi}(X_i-\theta)+X_j\tilde{\psi}(X_j-\theta)]\} \tag{8}$$

where X_k is the input data sample and $k = 1, 2,\ldots,N$, ψ is the normalized influence function ψ : $\psi(X) = X\psi(X)$, $\theta^{(0)} = \theta =$ MED $\{X_N\}$ is the initial estimate, and X_N is the primary data sample.

The estimators (5-8) are called the combined RM-estimators [10,11]. The *R*-estimator provides good properties of impulsive noise suppression and the *M*-estimator uses different influence functions to provide better robustness. So, it is expected that the performances of combined RM-estimators can be better in comparison with original *R*- and *M*- estimators [11]

5. Proposed Rank M-Type L-Filter

We propose to use the RM-estimators into the linear combinations of order statistics defined by the *L*-filter. The proposed RM L (Rank *M*-Type *L*) -filter employs the idea of the RM-KNN algorithm [10,11].

The following representation of the *L*-filter is often used [1]

$$\theta_L=\sum_{i=1}^{N}a_i\cdot X_{(i)} \tag{9}$$

where $X_{(i)}$, $i = 1,\ldots,N$ is the ordered data sample and a_i, $i = 1,\ldots,N$ are the weighted coefficients of filter whose are calculated in the following form [1]

$$a_i=\frac{\int_{i-1/N}^{i/N}h(\lambda)d\lambda}{\int_0^1 h(\lambda)d\lambda} \tag{10}$$

where $h(\lambda)$ is a probability density function.

To introduce the RM-estimator in the scheme of *L*-filter, we should be to present the ordered data sample of *L*-filter as function of an influence function. For this reason, the *L*-filter is writing as [14,15]:

$$\theta_L=\sum_{i=1}^{N}a_i\cdot\psi(X_i)X_i \tag{11}$$

and

$$\psi(X_i)=\begin{cases}1 & i\le(2L+1)^2\\ 0 & \text{otherwise}\end{cases} \tag{12}$$

where $\psi(X_i)$ is the influence function used in the *L*-filter, $\psi(X_i)\cdot X_i$ is the ordered data sample according with the eq. (9), and $(2L+1)^2$ is the filtering window size.

Then, the new filter can be obtained by the combination of *L*-filter (11) and the RM-estimators (6) and (8) [14,15].

The Median M-type L (MM L) -filter can be writing as [14,15],

$$\theta_{MM\text{-}L}=\frac{\text{MED}\{a_i[X_i\psi(X_i-\text{MED}\{\vec{X}\})]\}}{a_{MED}} \tag{13}$$

and the Wilcoxon M-type L (WM L) -filter,

$$\theta_{\text{WM-L}} = \frac{\text{MED}\{{}^1/_2[a_i X_i \psi(X_i - \text{MED}\{\vec{X}\}) + a_j X_j \psi(X_j - \text{MED}\{\vec{X}\})]\}}{a_{\text{MED}}} \quad (14)$$

where $X_k\psi(X_k - \text{MED}\{\vec{X}\})$ are the selected pixels in accordance with the influence function in a sliding filter window, a_k are the weighted coefficients used into the RM L-filters, and a_{MED} is the median of coefficients a_k used as an scale constant.

To improve the properties of impulsive noise suppression of the proposed filters we introduce an impulsive detector, this detector chooses that pixel is or not filtered. The impulsive detector used here is defined as [12]:

$$[(rank(X_{ij}) \le s) \vee (rank(X_{ij}) \le N - s)] \wedge (|X_{ij} - \text{MED}\{\vec{X}\}| \ge U_2) \quad (15)$$

where X_{ij} is the central pixel in the filtering window, $s>0$ and $U_2 \ge 0$ are thresholds, N is the length of the data, and $\text{MED}\{\vec{X}\}$ is the median of pixels into the filtering window.

The weighted coefficients of the RM L-filter were found using the distribution functions shown in table 2 [1,6]. We note that the coefficients ak are calculated by each sliding filter window due that the influence function $\psi(U)$ selects whose pixels are used and then computes the weighted coefficients of proposed RM L-filter according with the number of pixels used into the filtering window. Table 3 presents the weighted coefficients used in the RM L-filter for different distribution functions.

6. Experimental results

We obtained from the simulation experiments the properties of the proposed filter and compared it with other classes of L-filters and based median filters proposed in the literature. We used the Adaptive Center Weighted Median (ACWM) [16], the Rank-Ordered Mean (ROM) [17], the Normalized Least Mean Squares L (NLMS-L) [8], Modified Frost (MFrost) [18], and the Sampled-Function Weighted Order (SFWO) [9] filters to compare our approach. These filters were computed according with their references. The criteria used to compare the performance of various filters were,

the *peak signal-to-noise ratio* (PSNR) to evaluate the performance of noise suppression [1-5],

$$\text{PSNR} = 10 \cdot \log\left[\frac{(255)^2}{\text{MSE}}\right], \text{ dB} \quad (16)$$

Tabla 2. Distribution functions used in the RM L-filter.

Distribution function	Formulae
Exponential	$f(x) = {}^1/_2\, e^{-\lvert x \rvert}$
Laplacian	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-m)^2}{2\sigma^2}}$
Uniform	$f(x) = \begin{cases} 0, & x \le a \\ \frac{1}{b-a}, & a \le x \le b \\ 0, & x > b \end{cases}$

and the *mean absolute error* (MAE) for evaluation of fine detail preservation [1-5],

$$\text{MAE} = \frac{1}{M_0 N_0} \sum_{i=0}^{M_0-1} \sum_{j=0}^{N_0-1} |e(i,j) - \hat{e}(i,j)| \quad (17)$$

where

$$\text{MSE} = \frac{1}{M_0 N_0} \sum_{i=0}^{M_0-1} \sum_{j=0}^{N_0-1} [e(i,j) - \hat{e}(i,j)]^2$$

is the mean square error, $e(i,j)$ is the original image, $\hat{e}(i,j)$ is the restored image, and $M_0 \text{x} N_0$ is the image size. In our experiments a 3x3 filter window is applied.

The runtime analysis of the MM L-filter and other concerned filters were conducted for different images and video sequences by using Texas Instruments DSP TMS320C6701 [13]. The TMS320C6701 device is based on the high-performance, advanced very long instruction word (VLIW) architecture, making this DSP an excellent choice for multichannel and multifunction applications. With a performance of up to 1 GFLOPS at a clock rate of 167 MHz, the 'C6701 offers cost effective solutions to high performance DSP programming challenges [13]. The 'C6701 has a complete set of development tools which includes: a C compiler, an assembly optimizer to simplify programming and scheduling, and a Windows debugger interface for visibility into source code execution [13].

The 320x320 standard test grayscale image "Peppers" was corrupted by impulsive and speckle noise. Table 4 shows the performance results in terms of peak signal-to-noise ratio (PSNR in dB) and mean absolute error (MAE) for the image

Table 3. Weighted coefficients for different distribution functions used in the RM L-filter.

Distribution Functions	weighted coefficients								
Exponential	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
1	1.0000								
2	0.6224	0.3775							
3	0.4484	0.3213	0.2302						
4	0.3499	0.2725	0.2122	0.1652					
5	0.2867	0.2347	0.1922	0.1573	0.1288				
6	0.2428	0.2055	0.1740	0.1473	0.1246	0.1055			
7	0.2105	0.1825	0.1582	0.1371	0.1189	0.1030	0.0893		
8	0.1858	0.1640	0.1447	0.1277	0.1127	0.0994	0.0878	0.0774	
9	0.1663	0.1488	0.1332	0.1192	0.1066	0.0954	0.0854	0.0764	0.0683
Laplacian (m=0, σ^2=2)	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
1	1.0000								
2	0.5308	0.4691							
3	0.3579	0.3387	0.3032						
4	0.2695	0.2613	0.2455	0.2235					
5	0.2160	0.2117	0.2035	0.1916	0.1769				
6	0.1802	0.1777	0.1728	0.1658	0.1568	0.1463			
7	0.1545	0.1530	0.1499	0.1454	0.1396	0.1326	0.1247		
8	0.1353	0.1342	0.1321	0.1291	0.1251	0.1203	0.1148	0.1087	
9	0.1203	0.1195	0.1181	0.1159	0.1131	0.1096	0.1056	0.1012	0.0963
Uniform ($a < b$)	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
1	1.0000								
2	0.5000	0.5000							
3	0.3333	0.3333	0.3333						
4	0.2500	0.2500	0.2500	0.2500					
5	0.2000	0.2000	0.2000	0.2000	0.2000				
6	0.1666	0.1666	0.1666	0.1666	0.1666	0.1666			
7	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428		
8	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	
9	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111

"Peppers" degraded with 20% of impulsive noise and 0.1 of variance of multiplicative noise by use the proposed MM L-filter with the simple (S), Andrew´s sine (A), Tukey biweight (T), and Hampel´s three part redescending (H) influence functions, and with the exponential (E), Laplacian (L), and Uniform (U) distribution functions and, with (D) and without (ND) impulsive detector.

From Table 4, one can see that the proposed MM L-filter provides better noise suppression and detail preservation in comparison with other filters proposed in the literature in the most of the cases. Figure 1 exhibits the processed images for test image "Peppers" explaining the impulsive noise suppression. The restored images by proposed filter appear to have a good subjective quality.

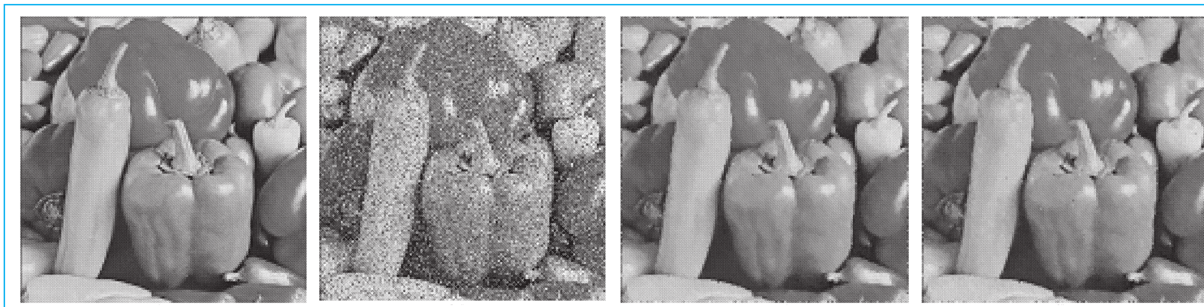
The processing time (in seconds) of various filters includes the time of acquisition, processing and store data. From the processing time results of the Table 4 we conclude that the processing time of proposed filters are less than other filters proposed as comparative. We can see that the proposed filters take less processing time when we use the impulsive detector. We also observe that the processing time results of all filters almost do not vary but in the fifth or sixth significant number these values are changing. The processing time of ROM filter does not include the time to obtain the weighted coefficients used in its filtering scheme.

Table 5 presents the performance results for the 256x256 standard test grayscale image "Lena" degraded with 5% and 20% of impulsive noise, and 0.05 and 0.1 of variance of speckle noise by use different filters. From this table we observe that the proposed filter provides better performance results in comparison with other filters in the most of the cases. Figure 2 exhibits the visual results for the image "Lena" in the case of impulsive degradation according with the performance results of the Table 5. From Figure 2 one can see that the best results in terms of noise suppression and detail preservation are obtained when we use the proposed MM L-filter.

Table 4. Performance results in the image "Peppers" obtained by the use of different filters.

Filters	20% of impulsive noise			σ^2=0.1 of speckle noise		
	PSNR	MAE	TIME	PSNR	MAE	TIME
ACWM filter	26.015	8.442	0.2533	17.718	26.209	0.2535
ROM filter	25.822	8.709	0.1084	17.414	27.466	0.1085
NLMS-L filter	20.851	18.171	0.2169	18.463	17.672	0.2168
SFWO filter (E)	21.254	15.437	0.1544	24.190	10.594	0.1544
SFWO filter (L)	23.227	9.804	0.1544	19.882	19.186	0.1543
SFWO filter (U)	13.672	43.757	0.1543	21.944	13.775	0.1544
MM L-filter (S, E, ND)	24.305	9.825	0.1095	18.642	23.166	0.1096
MM L-filter (S, L, ND)	25.231	8.557	0.1096	21.343	16.439	0.1097
MM L-filter (S, U, ND)	26.202	6.457	0.1096	23.133	12.619	0.1096
MM L-filter (A, E, ND)	23.961	10.385	0.1149	18.426	24.096	0.1149
MM L-filter (A, L, ND)	25.177	8.625	0.1149	21.264	16.706	0.1149
MM L-filter (A, U, ND)	26.196	6.476	0.1150	23.125	12.629	0.1149
MM L-filter (T, E, ND)	23.075	12.125	0.1130	18.305	24.380	0.1131
MM L-filter (T, L, ND)	25.115	8.750	0.1130	21.091	17.101	0.1130
MM L-filter (T, U, ND)	26.196	6.476	0.1130	23.125	12.629	0.1130
MM L-filter (H, E, ND)	24.676	9.126	0.1105	20.528	18.046	0.1106
MM L-filter (H, L, ND)	25.473	7.907	0.1105	21.492	16.187	0.1106
MM L-filter (H, U, ND)	26.231	6.379	0.1105	23.157	12.620	0.1106
MM L-filter (S, E, D)	25.369	7.908	0.0970	19.809	19.885	0.0972
MM L-filter (S, L, D)	25.927	7.255	0.0971	21.883	15.278	0.0972
MM L-filter (S, U, D)	26.508	6.045	0.0971	23.142	12.596	0.0972
MM L-filter (A, E, D)	25.279	8.226	0.1016	19.670	20.257	0.1020
MM L-filter (A, L, D)	25.898	7.328	0.1017	21.006	16.923	0.1020
MM L-filter (A, U, D)	26.508	6.045	0.1018	23.142	12.596	0.1019
MM L-filter (T, E, D)	24.945	8.957	0.0986	19.680	20.115	0.0988
MM L-filter (T, L, D)	25.882	7.341	0.0985	21.828	15.465	0.0989
MM L-filter (T, U, D)	26.508	6.045	0.0986	23.142	12.596	0.0988
MM L-filter (H, E, D)	25.487	7.818	0.0978	20.904	17.224	0.0979
MM L-filter (H, L, D)	26.037	7.030	0.0979	21.918	15.910	0.0979
MM L-filter (H, U, D)	26.516	6.031	0.0979	23.152	12.586	0.0979

The optimal parameters of proposed filter are: s=3 and U_2=15 for the impulsive detector, r=25, α=0.16r, and β=0.8r for Hampel influence function, and r=35 and r=15 for Andrew and Tukey influence functions, respectively [14,15]. The times can change when we use other values for the parameters, increasing or decreasing the times but the PSNR and MAE values change within the range of ±5%, it is due that we propose to fix the parameters to can realize the real-time implementation of proposed filters.



a) b) c) d)

Fig. 1. Visual results in image "Peppers", a) Original image "Peppers", b) Image degraded with 20% of impulsive noise, c) Restored image with the MM L- filter, (A, G, ND), d) Restored image with the MM L-filter (A, G, D).

Table 5. Performance results in the image "Lena" obtained by the use of different filters

Filters	20% of impulsive noise						σ^2=0.1 of speckle noise					
	5%			20%			0.05			0.1		
	PSNR	MAE	TIME	PSNR	MAE	TIME	PSNR	MAE	TIME	PSNR	MAE	TIME
ACWM	27.73	7.35	0.2299	25.56	8.75	0.2299	19.96	20.34	0.2299	17.73	26.42	0.2299
ROM	27.49	7.64	0.0750	25.20	9.11	0.0750	22.82	20.96	0.0750	21.67	15.78	0.0750
MFrost	23.87	12.69	0.1004	21.62	15.80	0.1004	24.56	10.99	0.1004	22.52	12.82	0.1004
NLMS-L	24.24	11.57	0.1835	22.03	12.83	0.1835	21.59	21.54	0.1835	20.45	14.68	0.1835
SFWO (L)	25.25	8.03	0.1310	23.01	10.24	0.1310	23.48	11.79	0.1310	22.07	14.20	0.1311
MM L (S, E, ND)	25.99	7.97	0.0762	23.65	10.86	0.0762	20.30	19.14	0.0762	18.45	24.02	0.0762
MM L (S, L, ND)	27.08	7.47	0.0762	24.79	9.11	0.0762	22.89	14.00	0.0762	21.14	17.19	0.0762
MM L (S, U, ND)	28.05	6.12	0.0762	25.59	7.38	0.0762	24.64	10.89	0.0762	22.84	13.48	0.0762
MM L (A, E, ND)	25.28	8.33	0.0815	23.16	11.21	0.0815	19.98	20.08	0.0815	18.27	24.95	0.0815
MM L (A, L, ND)	27.01	7.61	0.0815	24.68	9.33	0.0815	22.78	14.21	0.0815	21.05	17.46	0.0815
MM L (A, U, ND)	28.03	6.13	0.0815	25.59	7.40	0.0815	24.61	10.92	0.0815	22.82	13.49	0.0815
MM L(T, E, ND)	24.33	9.91	0.0796	22.68	12.74	0.0796	19.74	20.64	0.0796	18.23	24.45	0.0796
MM L (T, L, ND)	26.93	7.62	0.0796	24.69	9.33	0.0796	22.63	14.44	0.0796	20.92	17.67	0.0796
MM L (T, U, ND)	28.29	5.76	0.0796	25.74	7.05	0.0796	24.79	10.63	0.0796	22.95	13.24	0.0796
MM L (S, E, D)	27.10	7.00	0.0637	24.64	8.79	0.0637	21.19	16.98	0.0638	19.24	21.62	0.0638
MM L (S, L, D)	28.06	6.36	0.0637	24.97	8.05	0.0637	23.02	13.63	0.0637	21.16	17.04	0.0638
MM L (S, U, D)	28.73	5.64	0.0637	25.47	7.02	0.0637	24.54	11.01	0.0638	22.68	13.71	0.0638
MM L (A, E, D)	26.94	7.05	0.0684	24.56	8.83	0.0684	21.06	17.30	0.0684	19.09	22.08	0.0686
MM L (A, L, D)	28.62	6.01	0.0684	24.40	7.85	0.0684	23.38	13.10	0.0685	21.57	16.21	0.0685
MM L (A, U, D)	29.10	5.51	0.0684	25.94	6.96	0.0683	24.60	11.00	0.0684	22.70	13.87	0.0685
MM L(T, E, D)	26.80	7.42	0.0652	24.39	9.25	0.0652	20.84	17.74	0.0653	18.89	22.37	0.0654
MM L (T, L, D)	28.59	6.04	0.0652	25.44	7.19	0.0652	23.40	13.03	0.0652	21.60	16.15	0.0654
MM L (T, U, D)	29.23	5.34	0.0651	26.06	6.71	0.0652	24.63	10.96	0.0652	22.72	13.82	0.0654

The main problem in the implementation of different filters was the computational complexity. All filters presented here use the data ordering in their filtering schemes, for the reason, we use the Huang's algorithm to calculate the median of data sample [19]. This algorithm requires only $2m$ comparisons per output point, whereas the quicksort algorithm requires $O(2m^2 \log m)$ comparisons. Thus the running median algorithm is much faster than the quicksort used in the median filtering. In general, the ACWM filter computes four 3x3 median filters, the ROM filter needs to calculate one 3x3 median algorithm but it uses training data, the NLMS-L filter computes one 3x3 median filter but it calculates the weighted coefficients in each filtering window by using the LMS algorithm, the SFWO filter computes one 5x5 median algorithm, and the proposed MM-L filter requires to compute one 3x3 median algorithm but the advantage is that the number of elements used in this scheme depends of the influence functions.

We also process real video sequences to demonstrate that the proposed method potentially can provide a real-time solution to quality video transmission. In the case of this test we use one frame of the video sequences "Carphone" and "Miss America" that were corrupted by mixed noise of 20% of impulsive noise and 0.1 of variance of speckle noise. The PSNR, MAE, and processing time performances are depicted in Table 6. The visual results of the processing frames in the case of a frame of video sequence "Carphone" are displayed in Figure 3 according with Table 6. Figure 4 presents the restore frames in the case of use a frame of video sequence "Miss America".

From the simulation results from the Table 6 we observe that the best results are obtained when we use the proposed MM L-filters. From the processing time results we observe that the time (in seconds) of proposed filters is less that the time of other filters proposed as comparative. From the results of Table 6 and Figures 3 and 4, we say that the proposed method can process a QCIF video sequence suppressing the mixed noise and providing the detail preservation in real-time applications. Finally, the propose method can suppress between 8-10 images of 320x320 pixels, or 11-14 images of 256x256 pixels, or 28-35 frames in QCIF format per second by use different schemes in the proposed method.

We observe that the use of the proposed filters in image processing applications provide good results in terms of

Fig. 2. Visual results in the image "Lena", a) Original image "Lena", b) Image degraded with 20% of impulsive noise, c) Restored image with the ACWM filter, d) Restored image with the ROM filter, e) Restored image with the MFrost filter, f) Restored image with the N-LMS L filter, g) Restored image with the SFWO filter, h) Restored image with the MM L- filter (T, U, ND), i) Restored image with the MM L-filter (T, U, D).

PSNR and MAE performances. To demonstrate the performance of the proposed filtering scheme we apply it for filtering of the SAR images, which naturally have speckle noise. The results of such a filtering are presented in the Figure 5 in the case of the SAR image "Pentagon". It is possible to see analyzing the filtering images that speckle noise can be efficiently suppressed, while the sharpness and fine feature are preserved using the proposed MM L-filter in comparison with other filters proposed in the references.

7. Conclusions

We present the real-time implementation of a new type of *L*-filter for suppression of mixtures of impulsive and speckle noise with good detail preservation by means of use of DSP TMS320C6701. The robust RM L-filters were designed with different influence functions for image processing applications. Extensive simulation results have

Fig. 3. Visual results in a frame of video sequence "Carphone", a) Original frame of "Carphone", b) Frame degraded with mixed noise of 20% of impulsive noise and 0.1 of variance of speckle noise, c) Restored frame with the ACWM filter, d) Restored frame with the ROM filter, e) Restored frame with the N-LMS L filter, f) Restored frame with the SFWO filter (E), g) Restored frame with the proponed filter, (S, G, ND), h) Restored frame with the proposed filter (S, L, ND), i) Restored frame with the proposed filter (T, G, D).

Table 6. Performance results in a frame of video sequences "Carphone" and "Miss America" degraded with 20% of impulsive noise and 0.1 of variance of speckle noise by the use of different filters.

Filters	20% of impulsive noise			σ^2=0.1 of speckle noise		
	PSNR	MAE	TIME	PSNR	MAE	TIME
ACWM	18.3725	22.8943	0.092032	21.1231	17.6730	0.092157
ROM	18.1743	23.7223	0.028475	20.1886	20.0677	0.027865
MFrost	20.0880	18.7353	0.039904	23.1864	14.5833	0.039572
NLMS-L	14.8404	39.8522	0.073282	17.1494	30.7522	0.073328
SFWO (E)	19.5451	19.9642	0.068836	22.1166	18.4721	0.068872
MM L (S, E, ND)	18.8798	20.4191	0.031900	21.5452	15.0880	0.032047
MM L (S, L, ND)	20.4120	16.1230	0.031912	24.1252	9.1169	0.032040
MM L (S, U, ND)	20.8869	15.1964	0.031901	24.5764	8.4784	0.032045
MM L (A, E, ND)	18.7851	20.5979	0.034322	21.7132	14.6400	0.034758
MM L (A, L, ND)	20.1754	16.7244	0.034325	23.3368	11.3958	0.034745
MM L (A, U, ND)	20.8739	15.1766	0.034321	24.5887	8.3699	0.034746
MM L (T, E, ND)	18.7267	20.8123	0.033245	21.8969	13.8547	0.033461
MM L (T, L, ND)	20.2732	16.4404	0.033254	23.8234	10.0028	0.033460
MM L (T, U, ND)	20.9571	14.9662	0.033253	24.7151	8.1187	0.033467
MM L (S, E, D)	19.6140	18.6373	0.026531	22.3189	13.4343	0.026748
MM L (S, L, D)	20.8262	15.4113	0.026541	24.1749	9.3143	0.026752
MM L (S, U, D)	21.1347	14.8667	0.026539	24.5214	8.5751	0.026752
MM L (A, E, D)	19.5839	18.4999	0.028911	22.4798	12.5679	0.029994
MM L (A, L, D)	20.7565	15.5679	0.028910	24.1335	9.3982	0.029990
MM L (A, U, D)	21.1309	14.8691	0.028911	24.5237	8.5375	0.029987
MM L (T, E, D)	19.5138	18.6947	0.027147	22.4313	12.6873	0.027289
MM L (T, L, D)	20.7843	15.5185	0.027154	23.9603	9.9071	0.027299
MM L (T, U, D)	21.1308	14.8694	0.027147	24.5236	8.5236	0.027294

demonstrated that the proposed filters consistently outperform other filters by balancing the tradeoff between noise suppression and detail preservation. The proposed filters potentially provide a real-time solution to quality video transmission. In the case of 176x144 QCIF video format the proposed filtering technique can preserve the edges and small-size details and remove the noise practically with standard film velocity for computer vision systems.

Fig. 4. Visual results in a frame of video sequence "Miss America", a) Original frame of "Miss America", b) Frame degraded with mixed noise of 20% of impulsive noise and 0.1 of variance of speckle noise, c) Restored frame with the ACWM filter, d) Restored frame with the ROM filter, e) Restored frame with the MFrost filter, f) Restored frame with the N-LMS L filter, g) Restored frame with the SFWO filter (E), h) Restored frame with the MM L-filter (A, U, ND), i) Restored frame with the MM L-filter (A, U, D).

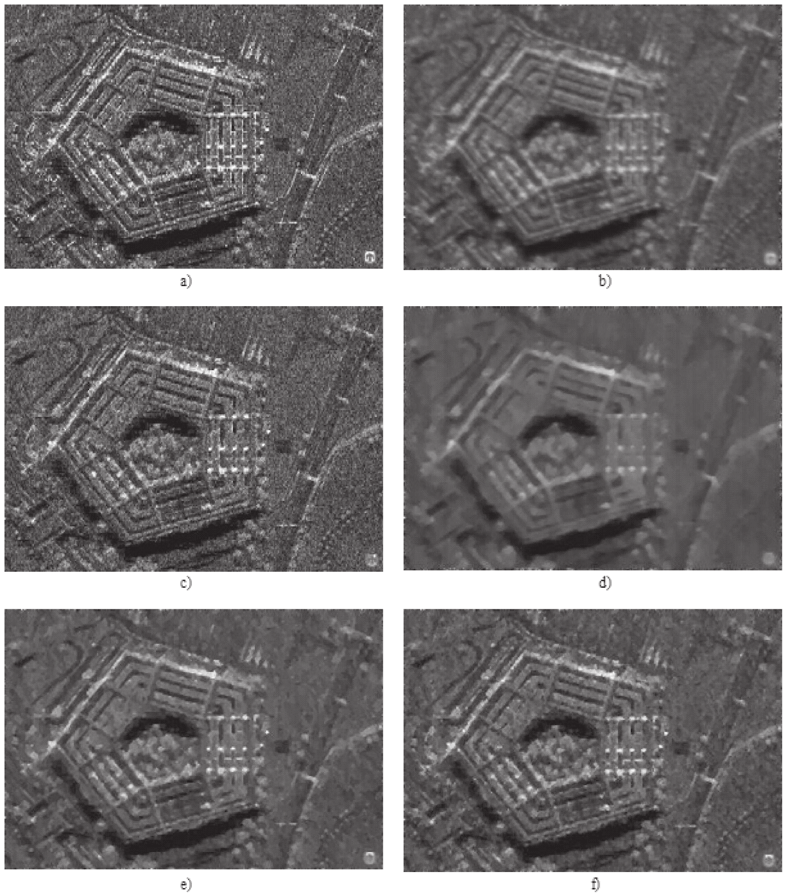


Fig. 5. Comparative results of despeckled SAR image. a) Original image "Pentagon", resolution 1m, source Sandia National Lab., b) Despeckled image with MFrost filter, c) Despeckled image with the ROM filter, d) Despeckled image with the SFWO filter (E), e) Despeckled image with the MM L-filter (S, U, ND), f) Despeckled image with the MM L-filter (S, U, D).

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