3D Rank Median L-Filters to Process Video Sequences

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Abstract. This paper presents the Rank Median L-Filters to suppress speckle noise in the 3D ultrasound sequences. The proposed technique uses the Rank M-type (RM) estimator and this one is adapted to 3D video processing applications. The real-time implementation of the proposed algorithm is realized by means of use of the DSP TMS320C6711. Therefore, the results from known 3D techniques are compared with the proposed one to demonstrate its performance in terms of noise suppression, detail preservation, and processing time.

1 Introduction

The 3D ultrasound imaging has been considered as one of the most powerful techniques for medical diagnosis and it is often prefer over other medical imaging modalities due it is noninvasive, portable, and versatile [1-3]. It does not use ionizing radiations, and is relatively low-cost. One of the areas where research in this field has addressed is the fundamental problem of speckle noise influence, which is a major limitation on image quality in ultrasound imaging [1, 2].

Imaging speckle is a phenomenon that occurs when a coherent source and a non-coherent detector are used to interrogate a medium, which is rough on the scale of the wavelength. Speckle noise occurs especially in images of the liver and kidney whose underlying structures are too small to be resolved using long ultrasound wavelength. The presence of speckle noise affects the human interpretation of the images as well the accuracy of computer-assisted diagnostic techniques. As a result, speckle filtering is a critical pre-processing step for feature extraction, analysis, and recognition from medical imagery measurements [1, 2].

In this paper, we present the capability and real-time processing features of the robust RM-L (Rank M-type L) filters [4] for the removal of speckle noise in 3D ultrasound images. An experimental system was used to capture 3D ultrasound images. The Texas Instruments DSP TMS320C6711 was used to implement the algorithm and to obtain the processing time [5, 6]. Different configurations of sweeping cubes (voxels) were used to obtain a balance between the processing time and quality of the res-

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toration of the 3D images [7, 8]. Extensive simulation results have demonstrated that the proposed filter can consistently outperforms other filters by balancing the tradeoff between noise suppression, detail preservation, and processing time.

2 The Speckle Noise

A general model for ultrasound speckle noise can be written as [2],

$$x(i,j)=S(i,j)\eta_m(i,j)+\eta_a(i,j) \tag{1}$$

where $x(i,j)$ is a noisy observation (i.e., the recorded ultrasound image) of the two-dimensional (2D) function $S(i,j)$ (i.e., the noise-free image that has to be recovered), $\eta_m(i,j)$ and $\eta_a(i,j)$ are the corrupting multiplicative and additive speckle noise components, respectively, and i and j are variables of spatial locations that belong to 2D space of all real numbers $(i,j)\in\Re^2$.

Generally, the effect of the additive component (such as sensor noise) of the speckle in ultrasound images is less significant than the effect of the multiplicative component (coherent interference). Thus, ignoring the term $\eta_a(i,j)$, one can rewrite (1) as [2]

$$x(i,j)=S(i,j)\eta_m(i,j) \tag{2}$$

To transform the multiplicative noise model into additive one, we apply the logarithm function on both sides of (2) [2]

$$\begin{aligned}\log x(i,j)&=\log S(i,j)+\log\eta_m(i,j)\\ x^l(i,j)&=S^l(i,j)\eta_m^l(i,j)\end{aligned} \tag{3}$$

where $\eta_m^l(x,y)$ is approximated as additive white noise. We assume here that the speckle pattern has a white Gaussian noise model.

3 3D Rank M-type L-Filters

In recent works [9, 10], we proposed the combined RM (Rank M-type) –estimators for applications in image noise suppression. These estimators use the *M*-estimator combined with the *R*-estimator, such as the median, Wilcoxon or Ansari-Bradley-Siegel-Tukey estimator. We demonstrated that the robust properties of the RM-estimators exceed the robust properties of the base *R*- and *M*- estimators for the speckle noise suppression [9]. The RM-estimator used in the proposed 3D filtering scheme is presented as [9, 10]:

$$\theta_{\mathrm{medM}}=\mathrm{MED}\{X_p\tilde{\psi}(X_p-\mathrm{MED}\{\mathbf{X}\}),\ p=1,\ldots,N\} \tag{4}$$

where θ_{MedM} is the Median M-type estimator, X_p are data samples, $p = 1,\ldots,N$, $\tilde{\varphi}$ is the normalized function ψ: $\psi(X) = X\tilde{\varphi}(X)$, and $\vec{\mathrm{X}}$ is the primary data sample.

The RM L-filter has been designed by use the combined RM-estimator (4) [9, 10] to increase the robustness of the *L*-filter [11]. The detail description of such a filtering scheme is presented in [4], and in here we proposed its modifications for 3D imaging purposes. So, the 3D RM-L (Rank M-type L) filter is defined in the following way:

$$\theta_{RM\text{-}L}(i,j,k) = \frac{\mathrm{MED}\{a_p[X_p\psi(X_p - \mathrm{MED}\{\vec{\mathrm{X}}\})]\}}{a_{\mathrm{MED}}} \tag{5}$$

where $X_p \cdot \psi(X_p - \mathrm{MED}\{\vec{\mathrm{X}}\})$ are the selected pixels in accordance with the influence function into a rectangular 3D grid of voxels, $a_p = \int_{p-1/n}^{p/n} h(\lambda)d\lambda \Big/ \int_0^1 h(\lambda)d\lambda$ are the weighted coefficients where $h(\lambda)$ is a probability density function [11], a_{MED} is the median of coefficients a_p, the filtering 3D grid size is $N_1 \times N_2 \times N_3$, $N_p = (2L+1)^2$ and $l_p, m_p, n_p = -L,\ldots,L$, and X_p is the input data sample from the $x(i,j,k)$ of the 3D image contaminated by noise in the rectangular 3D grid where i and j are the 2D spatial axes and k is the time axis (or third dimension). We use the Tukey biweight [12] influence function $\psi_{\mathrm{bi}(r)}(X) = \begin{cases} X^2(r^2 - X^2), |X| \le r \\ 0, |X| > r \end{cases}$ in the proposed 3D RM-L filter.

To improve the properties of impulsive noise suppression of the proposed filter we introduced an impulsive detector, this detector chooses that voxel is or not filtered. The impulsive detector is defined as [13]:

$$[(rank(X_{ijk}) \le s) \vee (rank(X_{ijk}) \ge N_p - s)] \wedge |X_{ijk} - \mathrm{MED}(\vec{\mathrm{X}})| \ge U_2 \tag{6}$$

where X_{ijk} is the central voxel in the 3D grid, $s>0$ and $U_2 \ge 0$ are thresholds.

The weighted coefficients of the 3D RM L-filter were found using the exponential, Laplacian, and Uniform distribution functions [11, 12]. We note that 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 of *L*-filter according with the number of pixels used into the filtering window.

The parameters that characterize the 3D RM L-filter were found after numerous simulations by means of use a 3x3x3 grid (i.e., $N_1 \times N_2 \times N_3 = 27$, $l,m,n = -1,\ldots,1$, and $N_p = (2L+1)^2 = 9$). The idea was to find the parameters values when the criteria PSNR and MAE should be optimum. The optimal parameters of proposed filters are: $s=3$ and $U_2=15$ for the impulsive detector, and $r=15$ for Tukey influence function. 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 ±(5-10)%, it is due that we propose to fix the parameters to can realize the real-time implementation of the 3D RM L-filters.

4 Experimental Results

The described 3D RM L-filter with Tukey biweight influence function and different distribution functions has been evaluated, and its performance has been compared with different nonlinear 2D filters which were adapted to 3D. The filters used as comparative ones were the *modified α-Trimmed Mean* [7, 14], *Ranked-Order* (RO) [15], *Multistage Median* (MSM1 to MSM6) [16], *Comparison and Selection* (CS) [15], *MaxMed* [17], *Selection Average* (SelAve) [15], *Selection Median* (SelMed) [15], *Lower-Upper-Middle* (LUM, LUM Sharp, and LUM Smooth) [18], and *Rank M-type K-nearest Neigbour* (RM-KNN) [3] filters. These filters were computed according with their references and were adapted to 3D imaging. Several experiments were realized to investigate the performances of the different techniques in 3D imaging.

The criteria used to compare the performance of noise suppression of different filters was the *peak signal to noise ratio* (PSNR) [19, 20],

$$\mathrm{PSNR} = 10 \cdot \log\left[\frac{(255)^2}{\mathrm{MSE}}\right], \mathrm{dB} \tag{7}$$

and for the evaluation of fine detail preservation the *mean absolute error* (MAE) was used [19, 20],

$$\mathrm{MAE} = \frac{1}{N_1 N_2 N_3} \sum_{i=0}^{N_1-1} \sum_{j=0}^{N_2-1} \sum_{k=0}^{N_3-1} \left| S(i,j,k) - \hat{f}(i,j,k) \right| \tag{8}$$

where $\mathrm{MSE} = \frac{1}{N_1 N_2 N_3} \sum_{i=0}^{N_1-1} \sum_{j=0}^{N_2-1} \sum_{k=0}^{N_3-1} \left[S(i,j,k) - \hat{f}(i,j,k) \right]^2$ is the *mean square error*, $S(i,j,k)$ is the original free noise 3D image, $\hat{f}(i,j,k)$ is the restored 3D image, and N_1, N_2, N_3 are the sizes of the 3D image.

The experimental ultrasound system used here works in the following way: the microcontroller Microchip PIC 16F84 sends a sign to the motor, so that of a step, sequentially the microcontroller sends a signals to the capture card to acquire the image in the BMP file image format from the ultrasound equipment of General Electric Comp, and in that moment stores it into the computer memory. The rail is the reference point, so, this allows calculating the measure of the explored human organ. There is a distance of 0.069 cm between each captured 2D image. The rail helps obtaining the longitudinal distance and other measures of the ultrasound images (height and width) of the explored organ. Using the presented system it is possible to reconstruct the human organ as an object into 3D space with their real measures. The coordinate z represents each an image 2D of the sweeping in the 3D space, and the coordinates x and y represent the height and width of the 2D image, respectively. Having the 3D image, one can carry out courts in the planes yz, xy, or xz. The proposed ultrasound system is depicted in Figure 1.

The runtime analysis of the 3D RM L-filters and other concerned filters were implemented by using the Texas Instruments DSP TMS320C6711 [5]. This DSP has a performance of up to 900 MFLOPS at a clock rate of 150 MHz [5]. The filtering algorithms were implemented in C language using the BORLANDC 3.1 for all routines, data structure processing and low level I/O operations. Then, we compiled and executed these programs in the DSP TMS320C6711 applying the Code Composer Studio 2.0 [6]. The processing time in seconds includes the time to acquisition, processing, and storing data.

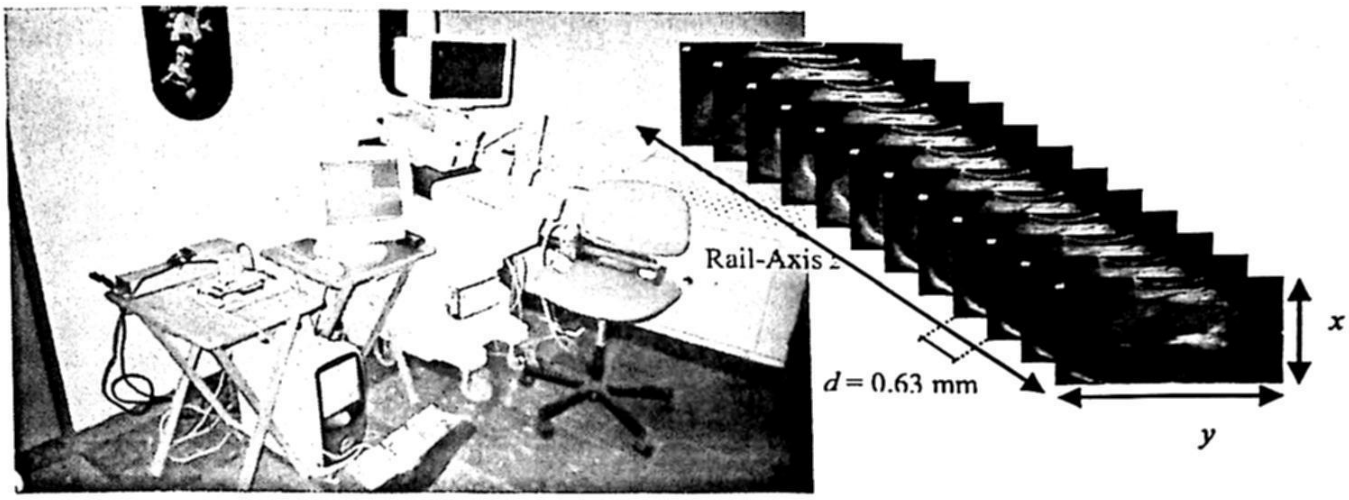

Figure 1. The proposed ultrasound system used to capture the 3D images

The experiment 1 was realized by degraded an ultrasound sequence of 640x480 pixels with 90 frames (3D image of 640x480x90 voxels) with 0.05 and 0.1 of variance of speckle noise added to the natural speckle noise of the sequence. The performance results are depicted in Table 1 by use a frame from xy plane of the sequence. From this table one can see that the 3D RM L-filters provide the best results in comparison to other filters proposed as comparative.

Figure 2 exhibits the visual results of restored images obtained by the use of different filters according to Table 1. In this Figure we observe that the proposed filters provide the better results in speckle noise suppression and detail preservation in comparison with other filters proposed in the literature.

In the experiment 2 we used different voxels cube configurations to provide better noise suppression [7 8]. Figure 3 presents nine configurations of voxels used in the proposed 3D filtering algorithm. It is obvious that by use of less voxels in the different cube configurations the processing time can be decreased. In this experiment the ultrasound sequence was degraded with 20% of impulsive noise. Then, we implemented different cube configurations in the α-Trimmed Mean, MM-KNN, and RM L filters.

Table 2 presents the performance results of different filters in the case of use different cube configurations in the xy plane of the sequence. We observe from this Table that the MM-KNN and α-Trimmed Mean filters provide better results in terms of PSNR in comparison with the RM L-filter but in the MAE performance the proposed filter provides the better results. About the time to process the algorithms, the proposed RM L-filter has less processing time in comparison with the MM-KNN filter.

Figure 4 shows the visual results obtained by RM L-Filter with the use of different cube configurations in a frame of ultrasound sequence degraded with 20% of impulsive noise according with Table 2. From Figure 4 we observe that the restored images appear to have a good subjective quality.

From the results presented in this paper we notice that the proposed filters can suppress the speckle noise with detail preservation better than other filters proposed in the literature. In the case of impulsive noise suppression the proposed filters have good performance in comparison with other filters.

Finally, the processing time of RM L-filters is acceptable to process 3D images in real time applications because the proposed filters can process QCIF video format with standard film velocity for computer vision systems.

Table 1. Performance results in a frame of ultrasound sequence degraded with speckle noise.

3-D Filters	Speckle noise variance			
	0.05		0.1	
	PSNR	MAE	PSNR	MAE
CS	15.435	32.875	13.843	39.778
LUM Smooth	17.915	25.142	15.440	33.823
LUM Sharp	15.625	30.927	14.444	36.425
LUM	15.518	31.427	14.379	36.748
MaxMed	18.562	24.206	15.919	32.913
MM-KNN CUT	21.554	15.199	18.949	20.995
MM-KNN HAMPEL	21.572	15.169	19.040	20.798
MM-KNN SINE	21.399	14.614	18.640	20.226
MM-KNN BERNOULLI	22.658	13.309	20.075	17.819
MM-KNN TUKEY	22.499	13.446	19.855	18.125
Modified α-Trimmed Mean	20.418	15.124	19.095	18.663
MSM1	20.568	17.624	18.061	23.684
MSM2	20.484	17.789	18.038	23.725
MSM3	22.421	14.206	20.261	18.456
MSM4	21.697	15.401	19.348	20.351
MSM5	19.554	20.207	16.964	27.444
MSM6	22.083	14.688	19.744	19.374
Ranked Order	21.587	14.520	19.802	18.179
SelAve	21.182	17.647	19.192	22.814
SelMed	20.836	15.750	19.013	20.094
RM-L TUKEY UNIFORM	29.876	5.016	28.6175	5.7429
RM-L TUKEY LAPLACIAN	28.797	5.646	28.188	6.0194
RM-L TUKEY EXPONENTIAL	28.034	6.261	26.299	7.6657

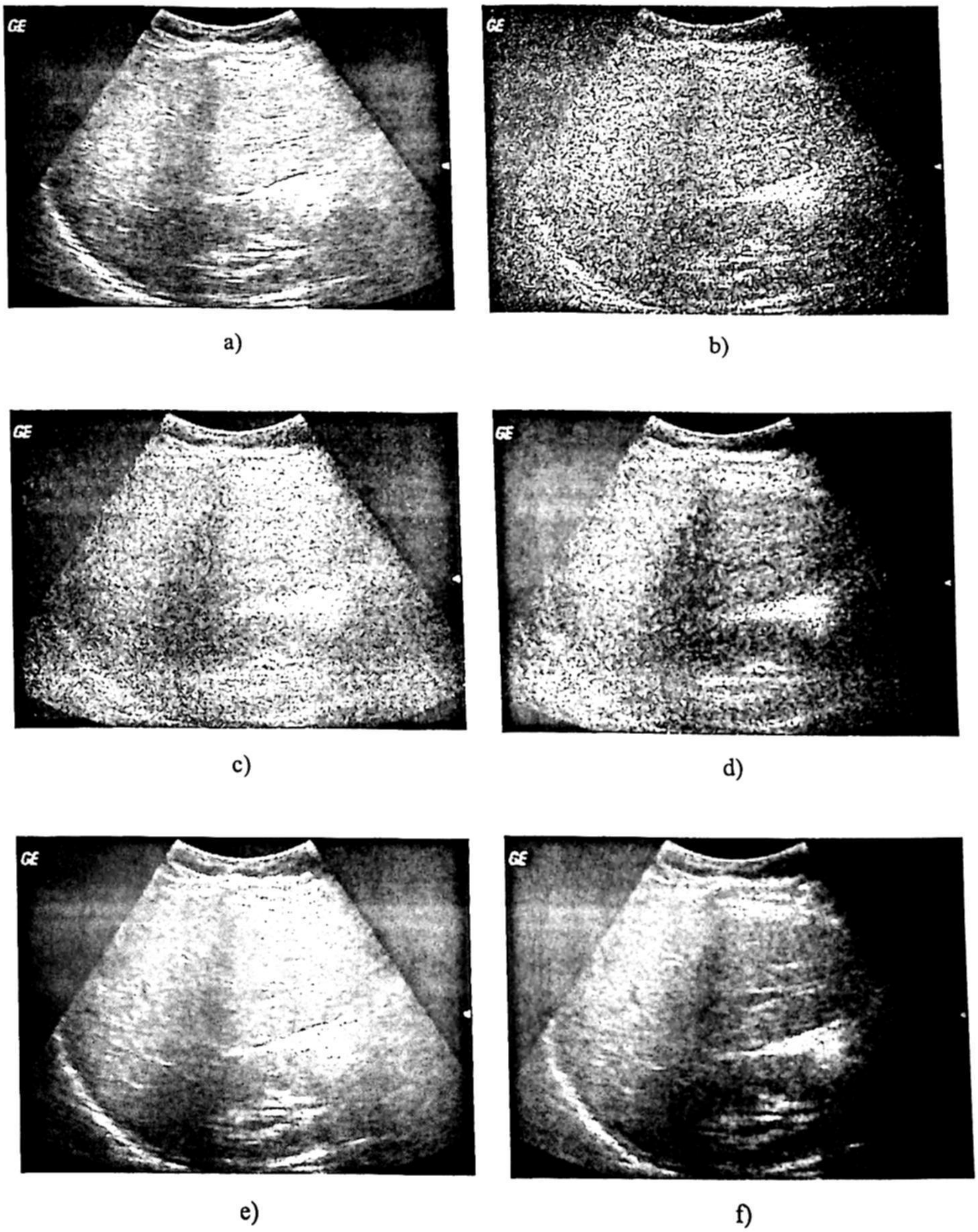

Figure 2. Visual results in a frame of ultrasound sequence. a) original frame, b) frame degraded by 0.05 of variance of speckle noise, c) restored frame by MSM3 filter, d) restored frame by MM-KNN (Bernoulli) filter, e) restored frame by RM L-filter (Uniform), f) restored frame by RM-L filter (Laplacian).

Table 2. Performance results by use different cube configurations in a frame of ultrasound sequence degraded with impulsive noise.

Voxel Configuration on different filters	20% of impulsive noise								
	MM-KNN filter			Modified α-trimmed mean filter			RM L-filter Uniform		
	PSNR	MAE	Time	PSNR	MAE	Time	PSNR	MAE	Time
a	28.408	4.538	1.6425	26.315	6.979	0.6398	26.831	5.812	1.1485
b	29.410	4.415	1.9082	28.236	5.687	0.7127	27.670	5.003	1.1627
c	28.768	5.284	4.8228	28.748	5.486	0.8267	27.572	5.062	2.3251
d	28.855	5.156	5.1989	28.876	5.348	0.8269	28.295	4.305	2.3247
e	28.709	5.289	4.8159	28.680	5.494	0.8267	27.532	5.104	2.3289
f	28.683	5.297	4.8297	28.658	5.502	0.8268	27.541	5.114	2.3254
g	28.431	5.233	10.0552	28.295	5.684	1.3775	28.068	4.548	3.4934
h	28.192	5.384	10.0775	28.037	5.851	1.3769	27.438	5.211	3.4993
i	27.919	5.136	20.6575	25.745	7.764	2.1716	27.768	4.848	4.7732

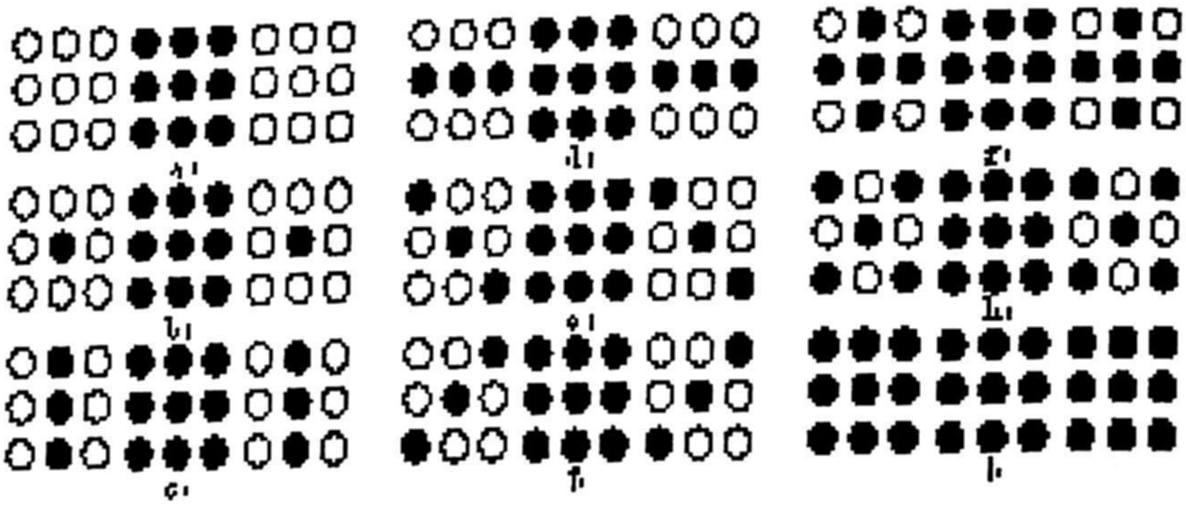

Figure 3. Different configurations of processing cube.

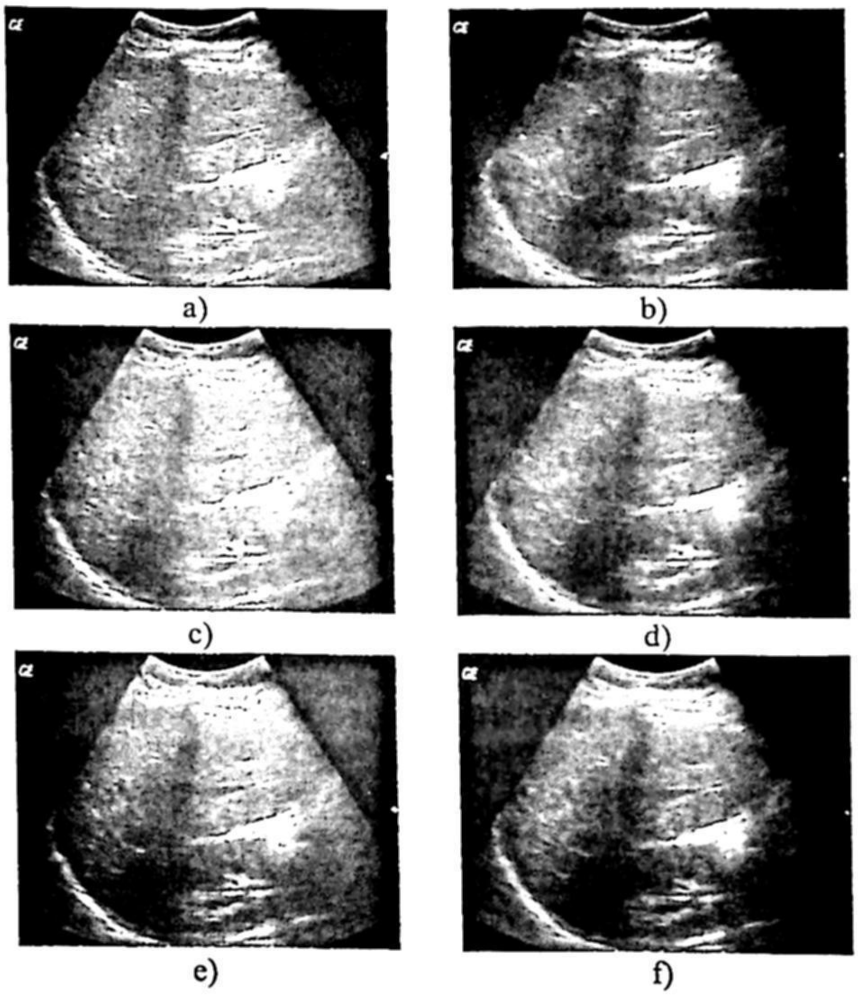

Figure 4. Visual results obtained by RM L-Filter with the use of different cube configurations in a frame of ultrasound sequence degraded with 20 % of impulsive noise. a) original frame, b) restored frame by b cube, c) restored frame by d cube, d) re-stored frame by f cube, e) restored frame by g cube, f) restored frame by i cube.

5 Conclusions

We present the real-time implementation of the 3D RM L-filter for suppression of speckle noise with good detail preservation by means of use of DSP TMS320C6711. The simulation results have demonstrated that the proposed filter consistently outperforms other filters by balancing the tradeoff between speckle noise suppression, detail preservation, and processing time. The proposed filter potentially provides a real-time solution to quality video transmission. The use of the linear combinations of order statistics with the RM-estimator provide to proposed 3D RM L-filter better performance in terms of speckle noise in comparison with the 3D RM-KNN filtering algorithm. Therefore, we realized simulation results in the case of impulsive noise and we notice that the proposed filter provide good results in comparison with different filters.

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