Reduction of the speckle noise in echocardiographic images by a cubic spline filter

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ABSTRACT
One of the main problems to resolve in the processing of biomedical images is the reduction of noise. The problem is specially important if the noise has a multiplicative nature (speckle noise), for instance if the object of analysis is an ultrasonic image. In this report we carry out a review of techniques which can be used to reduce this type of noise on four-chamber view B-mode echocardiographic images in an appropriated way. Different ways of nonlinear filtering, adaptive techniques based on the statistical ordering and a cubic spline interpolation will be shown as suitable techniques for this objective but regarding quantitative and qualitative results we have obtained, we can confirm that a cubic spline filter is the most suitable filter that we have reviewed.

KEY WORDS
Ultrasound Speckle Noise, Adaptive Filters, Cubic Spline, Medical Imaging

1. Introduction

The processing and treatment of the ultrasonic image has become one of the themes which has drawn the attention of researchers in the study of diagnostic systems based on the analysis of images for a long time, mainly due to the non-ionizing nature of the ultrasonic radiation and the consequent reduction of risks for both the patient and the medical professional. In this sense, it can be confirmed that some aspects of the techniques used in the analysis of images have been strongly influenced by the development of solutions to typical problems in this biomedical domain such as recognition of areas in the image with anatomical meaning and tracking of their non-rigid movement.

One of the main problems associated with the enhancement of the echocardiographic image is the speckle noise. This type of noise, which is coherent with the nature of the ultrasound, is one of the main sources of impoverishment in the resolution and lack of ability to detect the objects of the image, which makes up the content of the clinical information. Images containing multiplicative noise have the characteistic that the brighter the area the noisier it is. A starting condition in any scheme oriented to the reduction of this type of noise is that the designed procedure must not imply a loss of contrast in the most significant features of the image [1, 2, 3]. The primary goal of speckle filtering ought to be the reduction of speckle noise without sacrificing the information content to enhace the diagnostic value of the image and for future segmentation or tracking of non-rigid anatomical structures.

Our aim with this paper is to show a comparative study of different reduction techniques based on the use of filtering schemes. The set of actions over the image has been tested on real four-chamber view B-mode echocardiograms of different patients elected randomly. The quality of images is relatively poor. The images are plagued by low image intensity contrast, dropouts in the image in which structures exhibit apparents gaps, or dissappear temporaly in some frames of a sequence. The noise-smoothing performances of the various filter are compared by means of the mean square errors (MSE) measuring suppression of noise and a parameter β evaluating the performance of edge preservation. The results shows that the spline filter allows a high order of smoothness and of approximation on the image. In addition, the computational load is less as compared with other discussed techniques, since most of them can require several iterations to smooth noise.

The body of this paper is organized in four sections. Section 2 introduces the speckle noise nature as the starting point to show the techniques of reduction which are reviewed and commented in section 3. The next section shows the results obtained after the application of these techniques on the echocardiographic images, and the achieved results are presented. The last section summarizes the achieved conclusions in this study.

2. Speckle noise

A system of images is named as *coherent* when the system is subjected to the action of a coherent illumination, that is, when the source points of the luminous radiation have relations of fixed phase and, though their phases fluctuate randomly, they do it in a synchronized way in order to keep a fixed relative phase. In this class of systems, and because of fluctuation of the source points in tune, the relations of the fixed phase allow to establish patterns of both destructive and constructive interferences. When a coherent ultrasonic radiation is reflected on a surface which has the same size as the radiant wave length, the interference of the waves produces a noise called speckle, whose nature is different from the so called additive noise [4, 5, 6].

In the free space, the intensity of the speckle noise can be considered as the infinite sum of independent, identical phasors with amplitude and random phase. This yields a representation of its complex amplitude as:

$$a(x,y) = a_R(x,y) + j a_I(x,y) \tag{1}$$

where a_R and a_I are independent Gaussian random variables, which have zero mean and variance σ_a^2. The intensity field is the square phasor module, that is:

$$s = s(x,y) = |a(x,y)|^2 = a_R^2 + a_I^2 \tag{2}$$

The intensity of noise, ξ, presents a function with a density of probability, P_s, of exponential type, with a parameter $\lambda = \frac{1}{\sigma^2}$:

$$P_s(\xi) = \begin{cases} \frac{1}{\sigma^2} exp(\frac{-\xi}{\sigma^2}), & \xi \geq 0 \\ 0, & \text{on any other case} \end{cases} \tag{3}$$

This distribution has a variance $\sigma^2 = 2\sigma_a^2$ and the same mean as the previous value. A white noise with this kind of statistical values receives the name of *fully developed speckle*.

When a plain object with complex amplitude distribution either reflectance or transmittance, $g(x,y)$, is imaged by a coherent lineal system with impulse response $K(x,y;x',y')$, the intensity of the observed image can be written as:

$$v(x,y) = \left| \iint_{-\infty}^{\infty} K(x,y;x',y') g(x',y') e^{j\Phi(x',y')}\, dx'\, dy' \right|^2 + \eta(x,y) \tag{4}$$

where $\eta(x,y)$ is the additive noise and $\Phi(x,y)$ represents the distortion in the phase due to scattering of the reflection. If the impulse response falls down quickly outside a region $R_{\text{cell}}(x,y)$, called *resolution cell*, and $g(x,y)$ approximates to a constant in that region, then:

$$\begin{aligned} v(x,y) &\simeq |g(x,y)|^2 |a(x,y)|^2 + \eta(x,y) \\ &= u(x,y)s(x,y) + \eta(x,y) \end{aligned} \tag{5}$$

The function $u(x,y)$ represents the object intensity distribution (reflectance or transmittance) and $s(x,y)$ corresponds to the speckle noise intensity distribution. The equation (5) shows the multiplicative nature of this type of noise.

3. Echocardiographic image filtering: speckle noise reduction

3.1 Nonlinear filter

Digital image noise appears to high frequencies of the spectrum but speckle is caused by scattered reflections produced by features that are small with respect to the wavelength. These multiple small reflections results from a roughs scattering surface with fine scattering structures. In the frequency domain, speckle exhibts a low pass characteristic. The use of nonlinear filters has been proposed in the literature as an attempt to eliminate noise but keeping the details of the image. Among these filters, the most effective ones are based on the statistical ordering of the data collected from the image [7, 8].

The median filter is the maximum likelihood estimate (MLE) for the Laplacian distribution. Studies about statistical ordering have not finished at the median, other different *L*-estimators have been tested such as: the maximum and minimum values, the rank, the average point or the extreme deviation. In general terms, all these nonlinear filters can be optimized for any specific type of noise, and sometimes even of signal.

Summing up, nonlinear filters work satisfactorily in those cases where the statistics of the image does not vary among regions, but they do not work so much appropriately in those cases where the density of the noise probability varies from region to region. In these cases, the most effective choice is the design of some adaptive filter [9].

3.2 Adaptive order statistic filters

Adaptive filters, among others, can be used particularly for the additive noise suppression:

$$x_{ij} = s_{ij} + n_{ij} \tag{6}$$

where s_{ij} is the estimation of denoise signal, n_{ij} is the noise and x_{ij} is the observable signal to filter. Some authors try to simplify the statistic of speckle noise through of a similar approximation. The following signal-dependent noise model can be used for the signal with speckle noise:

$$x_{ij} = s_{ij} + \sqrt{s_{ij}} n_{ij} \tag{7}$$

the reason for this approximation is that the different signal processing stages inside the scanner (logarithmic compression, low-pass filtering, interpolation) modify the statistics of the original signal [10].

According to this model of speckle noise, the speckle noise can be suppress using adaptive filters because the speckle noise is an additive noise. So, the *minimal mean square error* (MMSE) estimator is defined as:

$$\hat{s}_{ij} = \left(1 - \frac{\sigma_n^2}{\sigma_x^2}\right) x_{ij} + \frac{\sigma_n^2}{\sigma_x^2} \hat{m}_x \tag{8}$$

where σ_n, σ_x, $\hat{m}_x$ are local estimations of the standard deviation of the noise, the signal and the signal mean respectively. Its adaptability is easily understandable. In homogeneous regions of the image, the standard deviation of the noise is approximately the same as the standard deviation of the signal. For that, in these regions, the MMSE filter only estimates the signal as a local mean, $\hat{s}_{ij} \simeq \hat{m}_x$. In those regions which contain a edge, the standard deviation of the signal is much higher than that of the noise, that is, $\sigma_x >> \sigma_n$, so, in these regions any type of filtering ($\hat{s}_{ij} = x_{ij}$) is not developed. The *Double Window-Modified Trimmed Mean* (DW-MTM) adaptive filter uses the median as an estimator of the local mean and calculates a new local mean using only those pixels which are located in a small range of grey levels around the median. This reduces the noise in an effective way because it eliminates the extremes in the calculation of the mean estimation. The DW-MTM filter's work is easily understandable like the MMSE. Set a pixel located into the image, then a median filtering acts on it in a region of a certain size. The median value calculated in this operation is used in order to estimate the mean value of the local area. Afterwards, a bigger window centered in the pixel is used to calculate the mean of, being used only those pixels which are into a certain range. Those which do not belong to that given range, that is, the most extreme pixels in their grey levels, are scrapped. The modulator value of the size of the range, c, is function of the standard deviation of the noise ($c = k\sigma_n$). The range chosen for k (typically between 1.5 and 2.5) is based on the assumption that the Gaussian noise statistics implies that variations of grey level peak by peak have to stay in the range $\pm 2\sigma_n$. As k decreases, the filter makes a worse filtering of the Gaussian noise.

Finally, another type of adaptive filtering would consist in filtering the image in a combined way, that is, using a different type of filtering in those areas with edges that ones without edges. Such a filter, which is sensitive to the impulsive noise, is named *adaptive window edge detection* (AWED). It works as follows: The filter initially starts with a 5×5 or 7×7 window. The local image histogram in the filter window is calculated and examinated. If impulses are detected, they are rejected and the local images standard desviation is calculated without these pixels. If the local standard desviation is enough low, an homogeneous image region is assumed and the moving average filter (mean filter) is used. On the other hand, if the local standard desviation is large an edge region is declared. If the window size is 3×3 the median filter is used for image filtering, but if the window size is greater than 3×3, the window is reduced and the whole procedure is repeated.

4. Cubic spline interpolation for noise reduction

The use of curve or surface approximation techniques seems to be an interesting alternative to more conventional adaptive methods that have a notorious computational load. A polynomial local interpolation uses a finite number of neighbour points to obtain any interpolated values, $f(x)$, that in general do not have continuous first or higher derivatives. However, there are situations where the continuity of derivative is an unappealable concern, for instance when the interpolation function must provoke a fitting like a low pass filter on data. Perhaps, the most popular function which accomplishes this request is the cubic spline. This function produces interpolated data that are continuous through the second derivative, more stable than polynomials, with less possibility of oscillation between the tabulated points and thus, more unsensitive to outliers.

If an one-dimensional spline is applied an one-dimensional array of points, the technique can be extended to arrays in more than one dimension. Generally, this is made by a sequence of one-dimensional interpolations. In order to interpolate one functional value, m one-dimensional splines along the rows of the picture are performed. Instead of precomputing and storing all derivative information, the algorithm precomputes and stores only one second derivatives auxiliary table, in only one direction . Then the algorithm needs only to do spline evaluations (not constructions) for the m row splines. Recall that a spline construction is a process of order N, while a spline evaluation is only of order $logN$, and that is just to find the place in the table.

The use of cubic splines can go beyond simple interpolation and their main advantage can be to provide a convenient pass between the discrete and continuous signal domains. Other concerning applications are signal differentiation which is particularly relevant in the context of edge detection, discrete algorithms for the convolution of continuous signal and, data compression and noise reduction. In this last sense, the discrete cubic spline of order 0 corresponds to a moving average filter of size m that can be implemented recursively using a standard update procedure [11, 12]. Summing up, this procedure allows a superficial fitting of the echocardiographic image and subsequently a noise reduction keeping the high frequency features of the image for further processing. This technique samples the values of the echocardiographic image for each row of the image and for each four pixels; then the algorithm calculates the fitting curve for each interval and replaces the intermediate data for interpolated values. In the same way, the procedure could be iterated for the columns. Clearly, this technique is a data reduction method but can be considered as a noise reduction procedure too.

5. Experimental results

The source of ultrasound echocardiograms was recorded on a SVHS (or *Separated Video Home System*) videocassette. The records was obtained from real patient echocardiographs. In the first stage of processing it was necessary to sample digitally the video images. So a videocassette SHARP VC-D815, a frame grabber DT-3851, a personal computer were used and a special software of acquisition was implemented. Finally, we must point out that all the experiences were developed in a SUN SPARCstation 20 with 64 MBytes of RAM memory and Solaris 2.5 as operative system.

In such a particular domain, four-chamber view B-mode echocardiographic images, it is essential to establish the relative validity of the techniques revised in the previous section, and tuning them for this specific type of image. In this sense, we have applied different sets of actions on 25 sequences of echocardiograms (echotrainning set) of several patients trying different procedures to reduce the speckle noise without impoverishing the other features of high frequency in the image. The echotraining dataset permits us tuning of different parameters and estimations for the filters. Later, we tested and checked our filtering techniques over a new set of 15 test sequences (echotest set) of different patients without modifying the tuning parameters.

We have submited to the action of different types of adaptive filters based on the statistic ordering to test images. This type of filtering almost covers positively our expectations in improving the *signal to noise ratio* (SNR) of the image. The performance of the MMSE adaptive filter depends clearly on the choice of the local measures both the mean and the standard deviation of the signal, as well as the standard deviation of the noise. In our case, we have used several types of estimations for the standard deviation of the noise, being $\sigma_n = 50$ which that offered the best results. In the case of DW-MTM filter we have adopted a value $K = 1.5$ and a standard deviation $\sigma_n = 65$. These values are used in order to calculate the parameter c, as we have previously pointed out , and it is extremely important to limit the calculation of the mean value of a 5×5 window. In the case of AWED filter, we firstly use a 7×7 window to calculate the histogram, having previously eliminated those pixels whose gray level exceeds 20% the local mean. For the rest of pixels we use a edge detector (a Sobel mask) in order to decide the existence of a edge. This choice is taken when some pixel appears with a value higher than 20% of the mean obtained after passing the Sobel mask. If a border is detected, the window reduces 2 pixels its size and the process is repeated again. If any edge is not detected, a mean filtering is performed according to the window size in which the process is running.

The simply matching of the output images yielded by the application of filtering techniques over the original echocardiographic image cannot show the relative goodness of each technique due to their relative low contrast. Therefore, it has to use alternative displaying procedures which emphasize the effect of the filtering application on the echocardiograms, first passing two edge detectors (Sobel and DRF [13]) over the original and filtered image and second matching differents profiles of original image versus filtered image. In Figure 1, we show the effect of the adaptive filters based on order statistics for the profiles of the echocardiograms and in Figure 2 and 3 the pass of edge detectors.

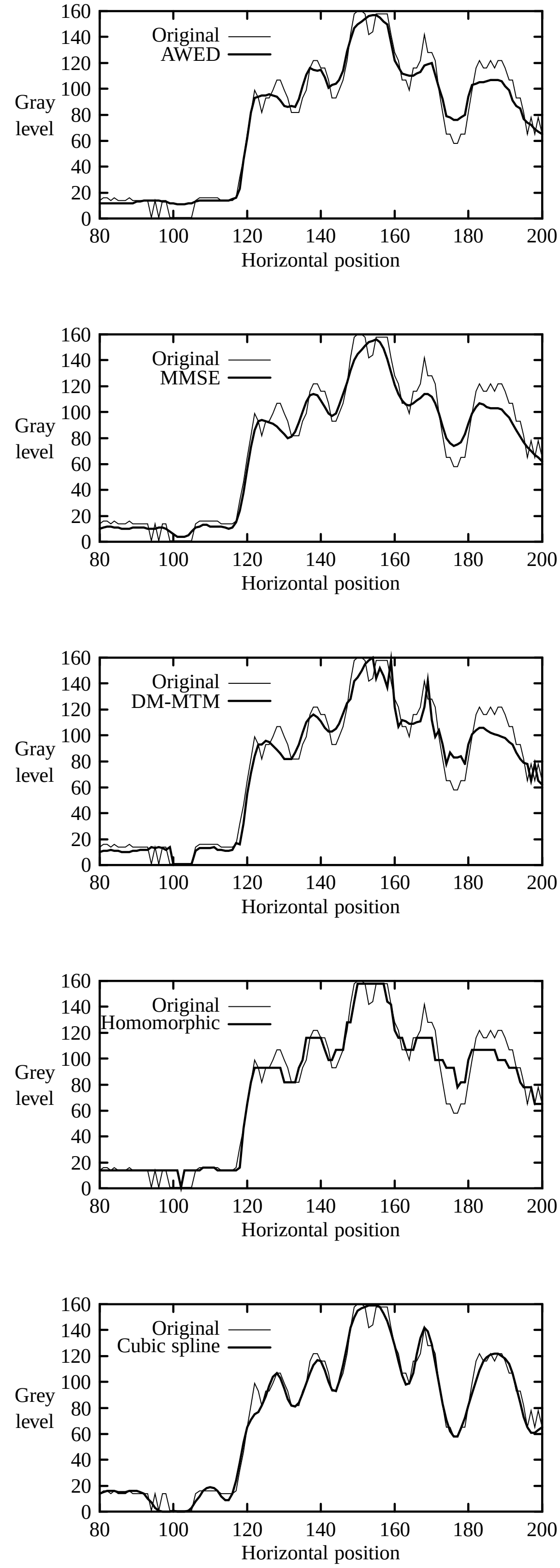
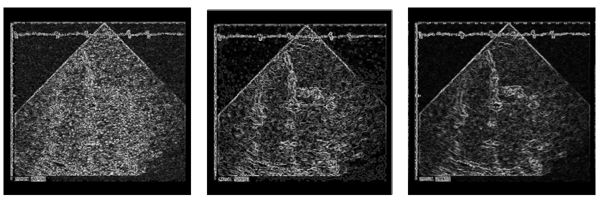
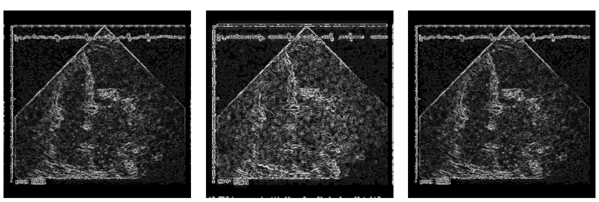


Figure 1. Filter comparison

In regard to the cubic spline (Figure 1(e)), the features of this functions allow to improve the quality of the image, what can be apparently observed via visual inspection, and hardly affecting the most interesting features of the image. The effect yielded on noisy profiles of the original signal, as it is shown in Figure 1(e), is the best effect of the whole set of techniques, keeping the information of all the border. The image utility obtained for further stages of zones delimitation seems evident. The interpolation on the image carried out by the spline produces a suppression of noise without attenuating the edge amplitude. An important fact is the reduction in the contrast of edges performed in all cases of adaptive filtering, but that contrast of edges has not been reduced in the case of cubic spline fitting as it is showed in Figure 1.



(b) Original (c) AWED (d) MMSE



(e) DW-MTM (f) Homomorphic (g) Cubic Spline

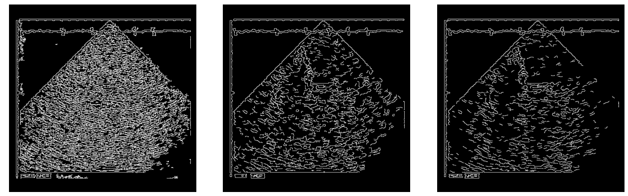
Figure 2. Edge detection by means of Sobel operator on different filtering echocardiographic images (Echotest-9).

Finally, it is necessary some type of quantitative evaluation that shows how the different algorithms can suppress noise while the edges and other important features are preserved. In this sense, we have used the mean square errors (MSE's) of the processed images like measurement of goodness for the estimation. The MSE is just one of different measures that we can use to calibrate speckle noise suppression, so it cannot reflect the performance of edge preservation. In order to evaluate the performance of edge preservation, a parameter β is proposed as [14].

$$\beta = \frac{\Gamma(\Delta s - \bar{\Delta} s, \Delta \hat{s} - \bar{\Delta} \hat{s})}{\sqrt{\Gamma(\Delta s - \bar{\Delta} s, \Delta s - \bar{\Delta} s) \cdot \Gamma(\Delta \hat{s} - \bar{\Delta} \hat{s}, \Delta \hat{s} - \bar{\Delta} \hat{s})}} \tag{9}$$

$$\Gamma(t_i, t_2) = \sum_{(i,j) \in \text{Image}} t_1(i,j) \cdot t_2(i,j) \tag{10}$$

where Δs and $\Delta \hat{s}$ are the high-pass filtered version of s and $\hat{s}$, original signal and signal estimation respectively, and $\bar{\Delta} s$ and $\bar{\Delta} \hat{s}$ the version without filtering. A better effect of edges preservation is produced by filters with high β. The values of β and MSE for each method are shown in Table 1.



(a) Original (b) AWED (c) MMSE

(d) DW-MTM (e) Homomorphic (f) Cubic Spline

Figure 3. Edge detection by means of DRF operator on different filtering echocardiographic images (Echotest-9).

6. Conclusions

We can comment the relative success of some of the argued techniques in a more detailed observation. Quantitative results demonstrate that non-linear filters can reduce the SNR of the images with speckle noise, but they are less effective when the statistic of the image varies region by region, as it happens in our case. Under these conditions, the adaptive implementations are more effective but, on the other hand, they are excessively dependent on the estimation of the statistical parameters where they are based and, as the algorithmic adaptability improves, they become more expensive computationally (for instance, AWED takes about 1 minute in a workstation Sparc20 to process a 512×512 image) and they do not preserve the edges and other important features of the image in a efficient way. It is difficult for the adaptive techniques to tradeoff between speckle suppression and detail preservation. Homomorphic filter can be used with a similar ratio of performance with less computational load.

Finally, an alternative noise reduction technique can be performed by the fitting of a spline surface on the image. This procedure allows a high order of smoothness (MSE) because it demands itself continuity in the higher order derivatives and of approximation on the image (β) like it is shown in the obtained results. In particular, MSE and β values can be checked in the image profiles fitting.

Table 1. MSE and β values for different methods

Processing Methods	Mean		set 1-5		set 6-10		set 11-15	
	MSE	β	MSE	β	MSE	β	MSE	β
MMSE	80.69	1.266	78.57	1.250	81.23	1.255	82.27	1.293
DW-MTM	67.65	1.298	66.98	1.301	67.03	1.290	68.94	1.303
AWED	41.19	1.345	42.20	1.423	42.03	1.302	39.34	1.310
Homomorphic	81.69	1.315	81.50	1.401	81.49	1.375	82.08	1.169
Spline	55.86	1.618	54.27	1.615	55.90	1.623	57.41	1.616

In addition, this technique disposes of a computational load better than the adaptive techniques in about half minute of computational time. The cubic spline filter is used in a pre-processing stage in a system based on DSP processor for tracking of endocardial wall [15, 16, 17].

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