On Speckle Noise Reduction In Medical Ultrasound Images

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Abstract: In general, one of the main problems to be solved in the processing of biomedical images is the noise reduction. The problem is particularly important if the noise has a multiplicative nature (speckle). We present a review of techniques that can be used to reduce this kind of noise in ultrasound images. That techniques have been used on B-mode echocardiograms with four-chamber view, selecting and tuning the most appropriate in this application. Procedures for non-linear filtering, adaptive techniques based on order statistics and certain types of interpolation are shown as the most suitable for this end in view of the results.

Key–Words: Speckle noise, filtering, adaptive filters, image processing, biomedical image

1 Introduction

Ultrasonic processing images has become one of the issues that have received more attention from researchers in the field of diagnostic systems based on image analysis, primarily due to the nature of non-ionizing radiation and subsequent risk reduction for both the patient and the physician. In this sense, it can be argued that certain aspects of image analysis techniques have been strongly driven by the development of solutions to typical problems in this domain, for example the recognition of meaningfully anatomical areas in the image and the tracking of their non-rigid motion. One of the major problems associated echocardiographic image enhacement is the so-called "speckle" noise. This type of coherent noise, inherent in the nature of noise, is a major sources of degradation in the resolution and the detectability of objects compose the image, masking the contents of the clinical information.

A condition for any scheme aimed at reducing this type of noise is that the procedure does not involve a loss in contrast the most significant features of the image and, ultimately allow us the analysis proposed.This paper presents a comparative study of different techniques of noise reduction, from classical filtering schemes to more sophisticated techniques as Savitzky-Golay or interpolation by B-splines. The battery of actions on the image have been tested on B-mode echocardiographic images with four-chamber view.

The body of the paper is organized into four sections. In section 2 introduces the nature of the speckle noise as a starting point for the reduction techniques, which are reviewed and discussed in section 3. In following section, different techniques are applied in echocardiographic images then present the results. The final section summarizes the conclusions obtained in this study.

2 Nature of speckle noise

In the statistical representation of the image, each pixel is considered a random variable. This random dot matrix can be defined adequately by a probability distribution. In free space, the intensity of speckle noise can be considered as an infinite sum of independent and identical fasor with random phase and amplitude. This produces a representation of its complex amplitude as:

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

where a_R and a_I are independent Gaussian random variables with mean zero and variance σ_a^2. The field of intensity is simply the square of the fasor module, i.e.:

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

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

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

This distribution has a variance $\sigma^2 = 2\sigma_a^2$ and with mean equal to previous value. A white noise with this type of speckle statistics is called totally developed. We can obtain the expression of the speckle noise from the characteristics of the object under observation and the system used for this. Indeed, when a plane object with a distribution of complex amplitude of reflectance or transmittance, $g(x, y)$, is viewed through a coherent linear system with impulse response $K(x, y, x', y')$, the intensity of the image can be described as the integral:

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

where $\eta(x, y)$ is the additive noise and $\Phi(x, y)$ represents the distortion in the phase due to the dispersion of the reflection. If the impulse response decays rapidly outside a region $R_{\text{cell}}(x, y)$, called the resolution cell, and $g(x, y)$ approaches a constant in this 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 distribution of object intensity (reflectance or transmittance) y $s(x, y)$ corresponds to the distribution of intensity of speckle noise. The random field $a(x, y)$ is Gaussian, and its function auto-correlation is supported on a region twice the size that R_{cell}. The equation 5 shows the nature of this type of multiplicative noise.

3 Comparing and analyzing of traditional filtering methods

The use of nonlinear filters has been proposed in the literature as an attempt to eliminate noise but keeping the details of the image [7]. Among these filters, the most effective ones are based on the statistical ordering of the data collected from the image [1, 2].

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 [4]. The behavior of these filters depends in a natural way on the determination of certain statistical values taken from both the signal and the noise, and we are dealing with special attention in the next section.

So, the *minimal mean square error* (MMSE) estimator is defined as [7]:

$$\hat{s}_{ij} = \left(1 - \frac{\sigma_n^2}{\sigma_x^2}\right) x_{ij} + \frac{\sigma_n^2}{\sigma_x^2} \hat{m}_x \tag{6}$$

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. Logically, since any type of noise filtering is not developed in these regions with edges, the MMSE filter will be not able to properly filtering images if these ones contain noise.

The *Double Window-Modified Trimmed Mean* (DW-MTM) adaptive filter [7] tries to solve the problems of the impulsive noise that the MMSE filtering cannot resolve. In order to obtain this, the 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

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range $\pm 2\sigma_n$. As k decreases, the filter makes a worse filtering of the Gaussian noise.

There is a filter, which is sensitive to the impulsive noise, which is named *adaptive window edge detection* (AWED) [7]. 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.

The adaptive filter SAM (Signal Adaptive Median filter) is based on the fact that a uniform region of the image contains very little high frequency information. This information can be found mainly in regions with presence of edges and impulses. The SAM filter first separates the original image in low and high frecuency components. Subsequently, in the homogeneous regions of the image only the low frequency components be used as output filter; whereas those regions where the presence of edges is detected in the image, both components such as high frequency and low frecuency be used as output filter.

Some filters such as AWED (Adaptive Edge Detection Window) filter or SAM (Signal Adaptive Median) filter are characterized by changing the window size depending on the filtering characteristics of the region of the image that is filtering. Lee filter [5], however, uses a window of fixed size, such 3×3, centered on the pixel to be filtered. Within this window are calculated statistical parameters such as local mean and standard deviation for determining appropriate weight factors to soften the image. The multiplicative speckle noise model is approximated to a linear model. Crimmins geometric filter is a nonlinear filter because from the standpoint of the value of the filtered pixel is not a linear combination of the values of neighbor pixels. This algorithm uses a nonlinear technique for reducing noise, the intensity of each pixel in an image is compared with 8 pixels of its neighborhood and, based on the relative values, increases or decreases the value of the pixel so that becomes the representative of the pixels around it. There are other filters to reduce speckle noise often referenced in the bibliography. We can list the Sigma filter, Frost filter, the Kuan filter and the Gamma-MAP filter[3].

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 [6]. Conceptually, an interpolation process has two stages: fitting an interpolating function to the data points provided and evaluating that interpolating function at any point x between tabulated points.

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.

The Savitzky-Golay filter, also called least squares DISPO (Digital Poynomial Smoothing) filter is a special low pass filter suitable for smoothing data. The measurement of a variable that varies slowly at the same time is contaminated by random noise [9]. To eliminate this noise, a useful solution is to use a spatial filter that replaces each pixel of the image by a linear combination of itself and some nearby pixel.

Suppose an image where the value of each pixel is defined by a function $f \equiv f_i(t_i)$ where $t_i \equiv t_0 + \delta i$ e $i = ... - 2, -1, 0, 1, 2....$ The Savitzky-Golay filter replaces each value of f_i by a linear combination of the form:

$$g_i = \sum_{n=-n_L}^{n_R} c_n \cdot f_{(i+n)} \tag{7}$$

where n_L represents the number of pixels used to the left of the pixel at position i and n_R represents the number of pixels used to the right of the pixel at position i. If we set $n_L = n_R$, a mean filter calculates g_i as the average of pixels between $f_{i-n_L} - f_{i-n_R}$ and the coefficient would given by the formula:

$$c_n = \frac{1}{(n_L + n_R + 1)} \tag{8}$$

The mean filter preserves the moments of order 0 and order 1, but no higher moments. The idea is to find Savitzky-Golay coefficients c_n which preserve the higher moments, this will replace the constant (c_n) by a quadratic or cubic polynomial. For each f_i is adjusted by a least squares polynomial to $n_L + n_R + 1$ equidistant points and then g_i is obtained as the value of the polynomial at position i. The value of the polynomial is not used in another point. As we move to position $i + 1$ is realized just another least squares to obtain a new polynomial, and so on.

4 Experimental results

This section discusses the results obtained by applying some of the filters previously described in this paper to a series of echocardiographic images, taken as a sample. The study was carried out on a series of echocardiografic images obtained in the Cardiology Unit of the Hospital Nuestra Señora del Rosell from Cartagena. Image size was 256×256 pixels, black and white, using a gray scale of 256 levels. On this set of echocardiografic images we have applied different filtering techniques, widely used in digital image processing. Specifically, in addition to the basic filters mean and median, adaptive filters, MMSE filter, DWMTM filter, AWED filter and SAM filter have been used. Our study has been completed with a series of filters that are considered of special interest such as Lee filter, geometric (Crimmins) filter, and filter developed from the algorithm developed by Savitzky-Golay and those based on the use of splines.

In Figure 1 along with the original image, we show the result of the filtered images using filters exposed in Section 2. Beginning the analysis with basic filters, such as mean and median filter, as expected we observe that the mean filter, due to the smoothing effect it generates, provides an image less sharp than the original. Moreover, if we increase the size of the mask filter, the degree of smoothing is increased, blurring the edges and details. By contrast, the median filter provides a clearer picture in which there is an enhancement of the edges in the image.

Among the adaptive filters, AWED and SAM filters provide an result image less sharp than the rest of results of adaptive filters and, of course, that the original. Especially the filter SAM provides an image with the edges very blurred. By contrast, the MMSE and DWMTM filter present a clearer image, achieving an enhancement of the edges, while the MMSE filter for the emergence of a few outliers pixeles diminish the quality of the final image. It is also interesting to note the similarity between the image obtained by applying the DWMTM filter and by applying the median filter, this is because the DWMTM filter not used, in the calculation of the average, those pixels that are not in a certain range of values around the median which are considered outliers, and the average values will be close to the median value.

Lee filter presents an output very similar to that obtained with the mean filter and as the mean filter, the use of large windows in the filtering process produces some loss of detail. The geometric filter significantly reduces the sharpness of the filtered image, whose quality is comparable to that obtained with SAM filter. In addition it should be noted that this loss of quality is compounded in the case of the geometric filter with increasing the number of iterations. Finally, both Savitzky-Golay filter and based on the spline interpolation present an image of higher quality visually, softening slightly while retaining the details in the image.

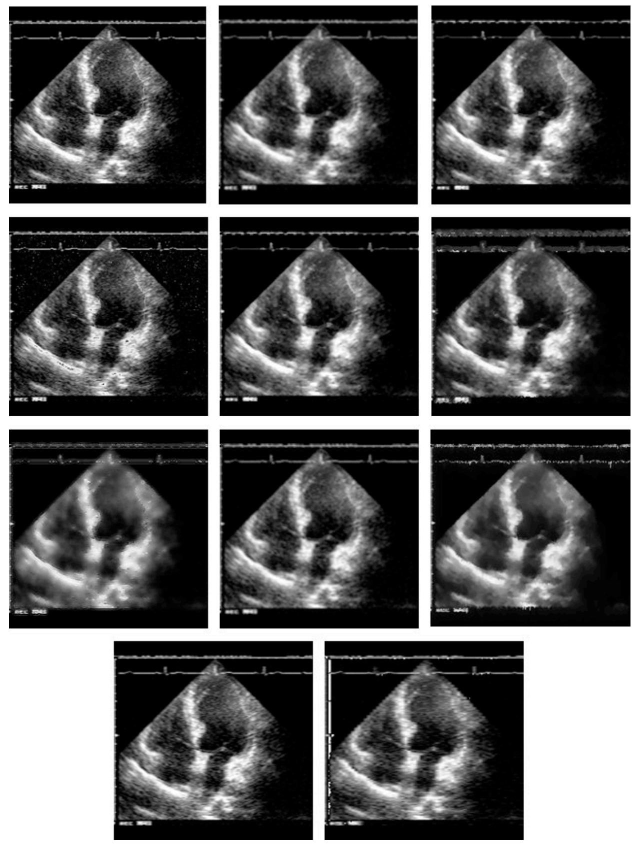

Figure 1: Output images obtained by applying a set of implemented filters on a test image: from left to right and top to bottom; image original, mean filter, median filter, MMSE filter, DWMTM filter, AWED filter, Sam filter, Lee filter, geometric filter, Savitzky-Golay filter and Bi-cubic Spline filter

The evolution of the methods used to obtain medical images have allowed to provide more clinical information. Therefore, it appears necessary to obtain quantitative data more than just a subjective observation because this subjetive analysis will not allow to extract all the major information, especially when a large number of images is analyzed or when the images are frames in a dynamic process of analysis in the time. Therefore, to make a quantitative assessment of the different techniques of filtering described in this work as criteria has been used the calculation of: the mean square error (MSE), the signal to noise

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ratio (SNR family) and parameters that can help to determine effectiveness of the preservation of edges in the filtering process (β parameter). Some of these parameters are traditionally used to measure noise, the mean square error or MSE, the square root of mean square error or RMSE, the signal noise ratio or SNR, and peak signal to noise ratio or PSNR. The use of such quantitative measures presents major advantages like easy-to-calculate, they are globally accepted and their objectivity because they not are linked to perceptions of an observer. They are particularly useful when comparing a set images with a reference image such as in this study. Therefore, these measures we will allow to evaluate in a quantitative assessment, with objective data, the goodness of a filter in connection with the elimination of noise.

The interpretation of the data obtained is based on a small value of MSE due to filtering of original image provides better noise reduction in output image. Similarly, small values of RMSE indicate better filtering of noise, while by contrast high values of SNR and PSNR, expressed normally in logarithmic scale and using as unit the decibel (dB), show an increased efficacy of filtering in the reduction of noise. Table 1 present the mean values obtained for different filtering techniques on each set of test images (5 set of 10 images). Analyzing the results, we note that the Savitzky-Golay and MMSE filter are those with smaller values of MSE and RMSE and higher values of SNR and PSNR. Therefore, according to parameters, Savitzky-Golay and MMSE filter provide a better reduction of noise. By against , AWED and Spline filters provide higher values of MSE and SNR and lower values of RMSE and PSNR indicating less reduction of noise. The other filters show very similar results. The parameters described so far, MSE, RMSE, SNR and PSNR allow us to assess the effectiveness of the filter efficiency in reduction of noise, but do not provide information on other aspects of the image, such as maintaining the information of edges. We have used the calculation of a parameter, β. β is given by the equation which it assess the filtering effectiveness in the preservation of the edges of the image [8]:

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

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

where Δs y $\Delta \hat{s}$ are the high-pass filtered version of s and $\hat{s}$, original signal and signal estimation (median) respectively, and $\bar{\Delta} s$ and $\bar{\Delta} \hat{s}$ the version without filtering. The better effect of preservation of edges are produced by filters with larger values of β.

The Table 1 shows the values of β obtained using the five set of test images, the last column shows the processing time obtained for the different filters. These data have been graphically represented in Figure, joining with a line the values obtained for different images for a particular filter for better graphic interpretation.

Analyzing the results with the images tested, we noted that the Savitzky-Golay filter has the highest value of β for all filters. Then, the highest value of β is shown by DWMTM, median and MMSE filter. Instead, Spline and geometric filter have a lower value of β for all filters. Finally, we tried to compare the filters analyzed from another point of view as is the computational load. A simple way of evaluating the computational load is by measuring the processing time. The results are not far from our expectations. The more complex algorithms are the most computational load. Observing the data, it appears that the AWED and SAM filter have a process time high unlike other filters. That is because it includes an edge detection algorithm. In our case, the filter uses a Sobel edge detector. In the case of geometric filter, it has a fairly complex algorithm and therefore it has a great impact on processing load. On the other hand, this complex algorithm has not successful in filtering or retaining edges. You can also observe that an increase in the size of the mask (e.g., mean, median and MMSE filter) increases the processing time. Nevertheless, the processing time is not a particularly important parameter to select a filter in clinic diagnostic applications when the processing on the image can be performed off-line. In brief, we can say that the more complex algorithms are more computational load bear.

5 Conclusions

The Lee and mean filter present very similar values for all parameters analyzed. This is because the estimation of the coefficient of noise variation has tilted the output filter to a mean filter. The geometric filter has a poor result in noise reduction. Neither the geometric filter highlights for its results in the elimination of noise. In short, the more processing time used in this filter due to a more complex algorithm, it does not provide better results. Finally, the spline filter has not good results as it depends excessively on the situation of control points, so we consider that this filter is more suitable for detection of contours than for noise reduction. Among the implemented adaptive filters, the MMSE filter performs a better preserving of edges and removing of noise than other filters. Although this filter leaves in homogeneous zones in the image some remanent noise that deteriorates its quality. The filter

Filter	β					average				
	Test1	Test2	Test3	Test4	Test5	MSE	RMSE	SNR	PSNR	T(s)
Mean	1,21688	1,18206	1,19343	1,18387	1,17537	288	16,97	11,13	23,53	3
Median	1,21949	1,20423	1,21171	1,20070	1,19413	359	18,94	10	22,58	3
MMSE	1,20266	1,19416	1,19453	1,19183	1,19179	101	10,04	15,79	28,09	3
DWMTM	1,21842	1,20698	1,21365	1,20289	1,19682	363	19,05	10	22,53	10
AWED	1,21915	1,18545	1,19316	1,18522	1,18054	495	22,24	8,45	21,18	170
SAM	1,22065	1,16320	1,16813	1,16291	1,15766	402	20,04	9,54	22,09	44
Lee	1,21524	1,18209	1,19381	1,18406	1,17564	306	17,49	10,79	23,27	3
Geom	1,19349	1,15907	1,16682	1,15988	1,15204	392	19,79	9,54	22,20	153
S-Golay	1,22567	1,21430	1,22267	1,21177	1,20717	29	5,38	21,20	33,5	4
Spline	1,20939	1,13688	1,14736	1,13801	1,12270	571	23,89	7,78	20,56	< 1

Table 1: β values for each set of images and average values for MSE, RMSE, SNR, PSNR and calculation time for different filtering techniques.

DWMTM presents good results in terms of preservation of edges and therefore the picture is clearer than for other adaptive filters. Either way, we obtain values similar to that of other filters in noise reduction. The DWMTM filter has average results both in terms of noise reduction as in conservation edge. SAM and AWED filter soften the image too so causes a loss of detail in the image and a high computational cost. In general, the main problem of the adaptive filters is its dependence on the estimation of statistical parameters. In the case of AWED and SAM filter both are dependent of threshold chosen for the edge detection. Analyzing the results, we conclude that the best results are obtained with the Savitzky-Golay filter. From a qualitative visual observation of the resulting images show that this filter achieves soften the original image without removing its significant details, i.e., the edges of the image. The quantitative results also support these conclusions, as the Savitzky-Golay filter is the one that presents a lower MSE and therefore the best noise reduction, and provides the highest values for β. So, this filter combines the noise reduction and the edge preservation of the image, and with a relatively low computational load.

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