Assessment of Wiener Method Applied to Filtering of Bio-Ultrasonic Signals

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Abstract. Ultrasound has a varied field of applications, especially in the evaluation of biological tissues providing important information of the analyzed structures. Whether in one dimensional signals or images, in Ultrasound is common to find noise in them. The Linear FIR Wiener method proposed in this work is used to denoise the bio-ultrasonic signals simulated considering a wide range of white noise. Evaluation parameters such as SNR and FFT were used to assess the denoising method effectiveness applied to different levels of noise. Results showed consistent decreased noise, and a SNR enhancement.

Keywords: Wiener filtering, signal processing, ultrasound, SNR, FFT.

1 Introduction

Ultrasound is widely used as a noninvasive technique for obtaining structural information of materials, especially in biological tissues. The main modalities used are A-scan, a single dimension signal showing echoes in a timeline; and B-scan, a series of A-scan signals forming an image [1].

As in any other acquisition system, in ultrasound is common to find along with the desired signal, unwanted components that make it hard to analyze or process the signal, those components are commonly known as noise [2]. The noise can vary from signal to signal, even when obtained under similar conditions and its origin may be diverse like from electromagnetic interference, a power line interference acoustic noise, etc. For ultrasound signals and images, the most common kind of noise found is structural noise, generated by the interference of several echoes originated in small structures inside the analyzed material. For A-scan evaluations, that kind of noise is known as back scattering and as speckles in the case of B-Scan evaluations [1, 2].

The methods of filtering ultrasound signals are varied, from non-adaptive FIR an IIR filters, wavelet transform [1, 3], denoising method based on matching pursuit [4] and several forms of Wiener filtering. [5, 6] In this article the filtering method applied is a linear FIR Wiener method, looking to eliminate most of the white noise present in ultrasound signals, and to evaluate the effectiveness considering different levels of

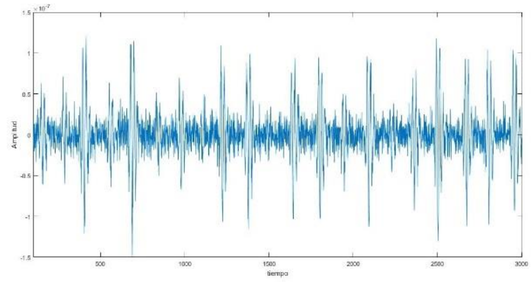

Fig. 1. Simulated signal with an SNR of 5.93dB.

noise. One of the advantages of working with Wiener Filter is that it is not required to know the frequency components of the desired signal and of the noise, such as in traditional techniques e.g. Butterworth or Chebyshev filters. In Wiener filtering the signal and the noise are considered stochastics processes, therefore the solution is obtained using statistical analysis, estimating the best filter response [7].

2 Methodology

2.1. Simulation of Data

The simulation of the ultrasound signal from biological tissue, used in this work, is made by the superposition of single echoes. These echoes are generated by the interaction of an ultrasonic emitted pulse and the tissue characterized by the presence of dispersive behavior. These structures can be associated with cells, blood vessels and any tissue with dispersive properties.

Using the model described in [8], biological tissues can be described as a series of scatterers separated by as distance “d”. When the pulse mentioned above travels through this path of scatterers the result is several single echoes from each scatterer, which summed, depending on the distance each echo travels, can be described accordingly to:

$$x(t) = \sum_{m=1}^{n} A_k S_k \left(t - \left(\frac{2p_k}{v}\right)\right), \quad (1)$$

where A_k is the echo amplitude caused by the k^{th} reflector, S_k (.) is the shape of that echo caused by the k^{th} reflector, t is time, p_k is the position vector of the k^{th} reflector and v is the speed of sound.

In this case, the ultrasonic pulse mentioned before is modeled accordingly to:

$$u(t) = -te^{-4\sigma^2 t^2} \sin(2\pi f_c t), \quad (2)$$

where σ is the bandwidth, and f_c is the central frequency of the transducer.

The white noise was calculated by an algorithm based on the signal power. These noises were calculated to obtain an SNR between 1 dB and 120 dB and then added to the simulated signals. 120 signals with different levels of noise were obtained to be processed using the wiener filter. In Fig. 1, an example of simulated signal with an SNR=5.93dB is shown.

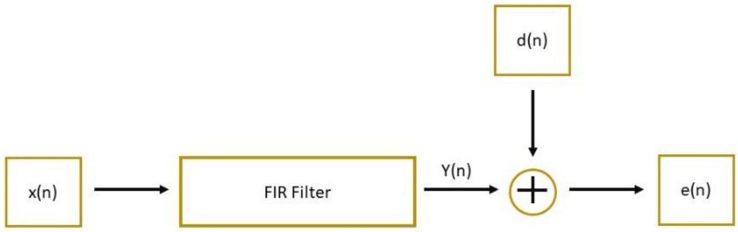

Fig. 2. Diagram representing the working of the Wiener filter.

2.2. Wiener Filter

Wiener filtering uses properties of a signal that is considered to have the characteristics desired in the data to be processed, and the properties of the noise added to the signal, considering both as linear and stochastic processes [7, 9].

Considering a finite impulse response (FIR) filter, where *x(n)* is the signal corrupted with noise, and G_k are the coefficients of the filter, the output *y(n)* of the filter can be defined as:

$$y(n) = \sum_{k=0}^{N} G_k \, x(n-k). \tag{3}$$

The objective of the Wiener algorithm is to find the most adequate value to the coefficients to minimize the error between the desired signal *d(n)* and the filtered signal *y(n)* [9]. In Fig. 1 a diagram explaining that logic can be observed.

Calculating the optimal coefficients is achieved through the Wiener-Hopf equation, obtained according to [7]. This equation involves the autocorrelation, *r*, of the input signal, and the cross correlation, *p*, of the desired and the input signals [7]:

$$\sum_{j=0}^{a} G_k \, r(i-k) = p(-k). \tag{4}$$

Expressed in vectorial terms we have:

$$\begin{bmatrix} r(0) & r(1) & \dots & r(N-1) \\ r(1) & r(0) & \dots & r(N-2) \\ \vdots & \vdots & \ddots & \vdots \\ r(N-1) & r(N-2) & \dots & r(0) \end{bmatrix} \begin{bmatrix} G_0 \\ G_1 \\ \vdots \\ G_{N-1} \end{bmatrix} = \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{N-1} \end{bmatrix}. \tag{5}$$

2.3. Data Analysis

Two parameters are used to analyze the results. The first is the Fast Fourier Transform (FFT), which is applied to the signals prior and post filtering, and then compared.

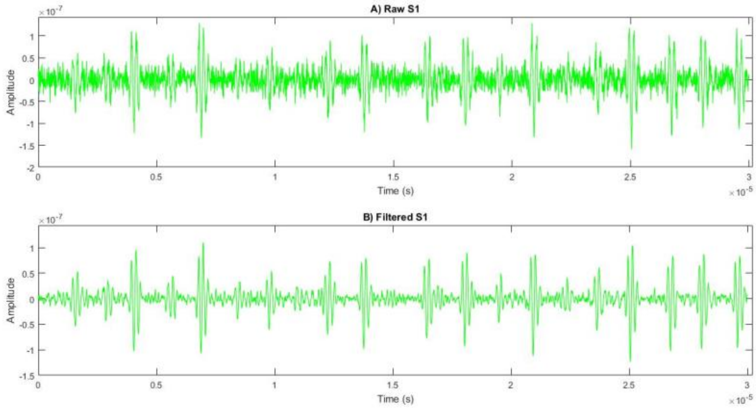

Fig. 3. (a) Original bio-ultrasonic signal, (b)Bio-ultrasonic filtered signal.

The second parameter is the signal to noise ratio (SNR), which in a similar way to the FFT is obtained prior filtering and post filtering and later the data is compared. The SNR was calculated according to:

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right), \tag{6}$$

where P_{signal} and P_{noise} are the energy of the signal and the noise, respectively and were obtained following the equation:

$$P = \frac{\sum_{i=0}^{N-1}(X_i)^2}{N}, \tag{7}$$

where P is the energy, N is the number of samples in the signal and X_i is the i-th sample of the signal.

3 Results and Discussion

From the 120 simulated bio-ultrasonic signals, those corresponding to a SNR between 1 and 119 dB were filtered using the Wiener method, the signal with the SNR of 120dB was used as the desired signal, here the result data of 1 of those signals is shown. Fig. 3 shows the data of the signal before and after filtering. Fig. 4 shows the FFT of the signals in Fig. 3.

Averaging the FFT Amplitudes and comparing them between the cases before and after the filtering, result in a reduction of the average energy of 53% for S-1, a 40% for S-5, 24% for S-10 and 2% for S-25. Meanwhile, for S-49, S-73, and S-97 the reduction is close to 0%, an indicator that the level of noise in those signals is minimal which allows to suppose that the applied Wiener Filter does not affect the frequency band of interest and performs an efficient elimination of components mainly in the undesired frequencies band. This aspect is relevant in the conditioning stage of the bio-ultrasonic signals.

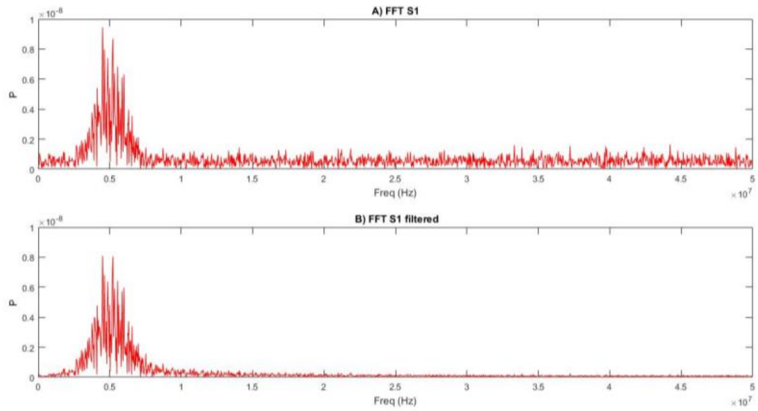

Fig. 4. a) FFT of the original bio-ultrasonic signal, b) FFT of the bio-ultrasonic filtered signal.

Table 1. Energy reduction in the FFT for the signals in different frequency intervals.

Signal	Overall	0-10MHz	10MHz-50MHz
S-1	53%	14.9%	80%
S-5	40%	5.1%	74%
S-10	24%	1.2%	65%
S-25	2%	0%	30%
S-49	0%	0%	0%
S-73	0%	0%	0%
S-97	0%	0%	0%

Table 2. SNR parameter results before and after filtering of the signal.

Signal number	Initial SNR	Final SNR
S-1	3.8403	9.8757
S-5	8.1045	13.3407
S-10	13.1333	17.1846
S-25	28.0637	29.6697
S-49	52.0623	52.0480
S-73	75.9167	75.7463
S-97	100.0126	99,8557

Now making the same analysis but separating the frequency bands, the results show that for S-1dB from 0 to 10Mhz the reduction of energy in FFT is 14.9% and for the rest of the spectrum is 80%.

Similar results are found for S-5, S-10, and S-25. For S-49, S-73, and S-97 the changes are minimal for the same reasons explained before. Results in detail are shown in Table 1.

Regarding the second parameter, the signal to noise ratio, it was obtained before and after filtering the signals. The SNR data can be found in Table 2. If we compare SNR results these show that for the first three signals, the increase of the SNR is considerable. For the S-1 the increase is 157%, for the S-5 is 64.6% and for S-10 is 30.84%.

Meanwhile for S-25 the increase is merely 5%, and in the rest of signals the SNR practically stays the same, showing that the applied filter is more efficient for small to medium values of SNR than for large values.

Comparing the results obtained with those of methods such as denoising based on wavelet frames[3] and on matching pursuit[4], a similar behavior is found regarding the SNR improvements: To a higher SNR, the improvement is worse than those with lower SNR.

Regarding the numerical improvement of the SNR, results show similar improvements to denoising with wavelet methods, for example: for a signal with an original SNR of 5dB, the Wiener filter shows a 5dB improvement while in [3], depending on the order of the wavelet SNR improvements vary from 4 to 6dB; for a signal with an original SNR of 10dB the Wiener Filter shows an improvement of 4dB while the wavelets show improvements from 2 to 5 dB for that same original SNR.

Making the same comparison showed above for the matching pursuit method[4] it is clear that the method in [4] provides better SNR improvements since for a 4dB original SNR level it shows an 8dB improvement while the Wiener filter shows an improvement of 6dB. Other example is that for a 10dB original SNR, [4] shows a 7dB improvement while the Wiener filter shows a 6dB improvement.

Although there are better results found with other more complex methods, it is important to highlight that the Wiener Filter still provides good results while being a less complex method. And when compared with other more traditional methods of filtering Wiener Filter still provides the advantage that it is not required to know the frequency components of the desired signal and of the noise, such as in Butterworth or Chebyshev filters.

4 Conclusions

There are some important conclusions to be drawn from these results, the first one is the Wiener Filtering technique used in this article observed good results when applied to eliminate the white noise in simulated ultrasound signals. The results showed that the filter eliminates a considerable amount of the frequency components corresponding to the noise, leaving those components where the ultrasound signal information is.

The second is that in those signals where from the beginning there were not much noise, the signal obtained after filtering remains practically the same, which was also confirmed from the analysis of the FFT.

The third is that though the increase in SNR percentage is considerable for the signals with a higher level of noise, it still is nowhere near the SNR of the signals with lower level of noise. Thus, for those signals with the higher level of noise it is possible that not all the noise was filtered.

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