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Digitals filters in heart sound analysis

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Abstract

Valvular pathologies introduce significant changes in the morphology of the phonocardiogram signal. Heart murmurs are often the first signs of these changes, and are usually found during auscultation in primary health care. Eliminate those breaths to isolate normal heart sounds gives considerable diagnostic support term. This article highlights the importance of the choice of digital filter in the phonocardiogram signal analysis. Indeed, on the basis of the results that IIR (Infinite Impulse Response) filters take the advantage of being more useful in filtering PCG signal including the separation of heart sounds (S1 and S2), heart murmurs and clicks. They still seem more likely to be used if we want to conduct filtering murmurs without too distorted S1 and S2 sounds because they always have the smaller error. The FIR (finite Impulse Response) filters represented by the frequency sampling technique affects the morphology of internal components much more, and this is confirmed by a larger error between the original signal and the synthesized signal.

1. Introduction

Under normal conditions, the heart provides two major audible sounds (S1 and S2) for each cardiac cycle. Two other sounds (S3 and S4), with lower amplitude than S1 or S2 [1], appear occasionally in the cardiac cycle by the effect of disease or age.

The sound S1correspondent to the beginning of the ventricular systole is due to the closure of the atrioventricular valves. This sound is composed of four components including two major internal; the mitral component (M1) associated with the closing of the valve mitral and the component tricuspid (T1) associated with the closing of the valve tricuspid. The sound S2, marking the end of the ventricular systole and signify the beginning of diastole [2] is composed for its two main components: the aortic component (A2) for the closure of the aortic valve and the pulmonary component (P2) corresponding to the closure of the pulmonary valve. Valvular pathologies induce considerable modifications on the morphology of the PCG signal [3].

These changes affect the heart sounds S1 and S2 by making changes in terms of duration and amplitude. On the other hand, systolic and diastolic murmurs of different shapes can be added to signal PCG to build a track resulting from a given disease.

The application of digital filters on phonocardiogram signals provides an overview of the behavior of these to the output of digital filters.

The aim of this work is to apply different methods of digital filtering on the PCG signals with the objective aim to make possible discrimination between heart sounds, systolic and diastolic murmurs and clicks.

2. Digital Filter Design

2.1. Basic Concepts of Digital Filtering

Digital filtering has specific characteristics that we need to pay special attention to [4]. The analog input PCG signal must satisfy certain requirements. Furthermore, on converting an output digital PCG signal into analog form, it is necessary to perform additional signal processing in order to obtain the appropriate result. Figure 1 shows the block diagram of digital filtering process.

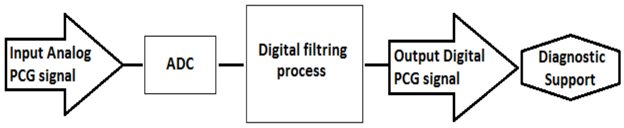

Figure 1. *Digital filtering.*

2.2. Types of Digital Filters

Filters can be classified in several different groups, depending on what criteria are used for classification. The two major types of digital filters are finite impulse response digital filters (FIR filters) and infinite impulse response digital filters (IIR). If we know the filter response, we can calculate the filters amplitude and phase behavior. In General a filter gives us a certain response to a given input signal. In a digital system a signal consists of samples and each sample in the signal is a pulse. Therefore it is quite easy to calculate the filter response. With the known IIR filters, we had an input and received a (theoretically) infinite number of output pulses. With the FIR filters described here, we get a finite number of response pulses. FIR filter gives us some advantages over IIR filter which we will describe later [5].

2.2.1. IIR Filter

IIR stands for Infinite Impulse Response. As mentioned above we get an output response with (theoretically) infinite samples. The rational system function in the z-plane is:

$$\mathrm{H(z)} = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=1}^{N} a_k z^{-k}} \tag{1}$$

Where a_k and b_k are the filter coefficients, M the number of zeros and N the number of poles. From this system function we get the corresponding time domain difference equation:

$$\mathrm{y[n]} = a_1.\mathrm{y[n-1]} + a_2.\mathrm{y[n-2]} + \ldots + a_k.\mathrm{y[n-k]} + b_0.\mathrm{x[n]} + b_1.\mathrm{x[n-1]} + \ldots + b_k.\mathrm{x[n-k]} \tag{2}$$

We can see that the output of the IIR filter depends on previous input and output samples. One problem with IIR filters is that they don't have a linear phase-characteristic, so they should be used in applications where linearity is not a big issue. Due to the fact that IIR filters have zeros and poles, a poorly designed filter could get unstable if the zeros and poles lie outside the unit circle [5].

2.2.2. FIR Filter

The problem of IIR filters is that they are not stable in every case. Therefore our idea is to reduce the system function to the nominator which means, there are no poles anymore and so the system is always stable. This is because there is no possibility the system function will be infinity [6].

So the causal (realizable) FIR systems the system function has only zeros, except for poles with z = 0 and therefore all coefficients a_k in equation 1 are zero and we get:

$$\mathrm{H[z]} = \sum_{k=0}^{M} b_k z^{-k} \tag{3}$$

and the corresponding time-domain difference equation :

$$\mathrm{y[n]} = \sum_{k=0}^{M} b_k \mathrm{x[n-k]} \tag{4}$$

Where y[n] is the output signal of the filter at instant n, x[n] is the input signal at instant n, b_k the filter coefficient (the impulse response from 0 to N instants), N(number of samples in the pulse response). We can see that the output no longer depends on previous output samples, only on previous input samples. The output can be recognized as the discrete convolution of x[n] with the impulse response:

$$\mathrm{h[n]} = \begin{cases} b_n & n = 0,1,\ldots M \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

We can see now, that the because of the fact, that the output only depends on the previous input samples, we get a finite impulse response from our filter. Therefore this filter is called Finite Impulse Response Filter (FIR). Because of the fact, that we have a finite impulse response, we can easier get a linear phase-characteristic because we can easily make the coefficient sequence symmetric around the center coefficient. FIR filters are generally designed to be linear-phase, so they should be used in applications where a linear phase characteristic is required. We obtain linear phase characteristic by making the coefficient sequence symmetric around the center coefficient. That means the first coefficient is the same as the last, the second is the same as the second to last etc. The only problem with FIR filters is that we require more memory than with IIR filters, because FIR filters are not recursive and therefore they need more coefficients than IIR filters. This also leads to a longer computation delay.

The FIR direct form is called tapped delay line structure because of the chain of delay elements at the top of the diagram (figure2).

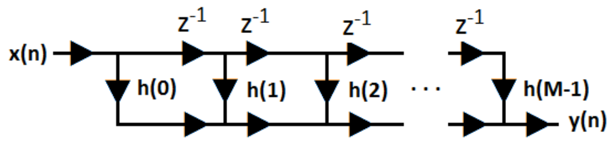

Figure 2. *Tapped delay line structure - input is weighted by the coefficients [6].*

3. Application of IIR Filters

The main methods of synthesis IIR filters proceed by discretization of an analog filter. The procedure for synthesis of an IIR digital filter can be summarized in the following block diagram:

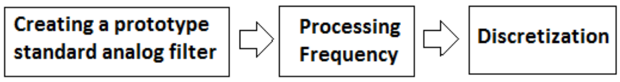

Figure 3. *Block diagram for the synthesis of an IIR digital filter.*

The objective is to obtain the transfer function H(z) of a digital filter which has the same frequency response as an analog reference filter H(p), ie the same template. In practice, we use this method coupled with a method of synthesis of analog filters that will be seen also in electronic (Butterworth, Chebyshev, Bessel, Elliptic ...). To match the best analog and digital domains this method aims. In fact, because of the sampling conditions (Shannon / Nyquist), it will be possible to match the two domains in a fraction of the useful field.

For example, the figure above (Figure 4.a) is an analog low-pass 3rd order (normalized cutoff frequencies 0.02 Hz) filter obtained by synthesis Butterworth method in Matlab. It may be noted that the frequency response is not limited because it is also very large for the frequency values. On the other hand, we note the existence of a quantity of -3 dB for low frequencies (equivalent to 0.02 Hz). The frequency response of an equivalent digital filter may be of the following form (Figure 4.b).

This filter was obtained by using the bilinear transformation from the analog filter equations obtained above and with a sampling frequency Fe = 11025Hz (pulse 314.1593 rad / sec): Since it is not possible to exactly match the frequency response of the analog filter (on $[0,+\infty[$) and digital (on [0, Fe / 2]), the bilinear transformation object will at best matching for both responses.

It is proposed to filter PCG signal (healthy subjects) embedded in white Gaussian noise. Noise is defined as unwanted signal mingling additively or otherwise signal there will be the original PCG signal. The most common model of noise measurement of physical quantities is the Gaussian (white noise) it is a random noise whose samples are uncorrelated.

The average error (ε_{moy}) is a considered parameters for the most distinction between the application of different digital filters also to distinguish the degree of severity between different pathology studied [7].

The average error calculated is the difference between the original signal (signal of a normal unprocessed case) and the synthesis signal (signal after filtering). The error will be calculated each time is given by the following expression:

$$\varepsilon_{moy} = \frac{\sum_{i=1}^{N} |S_{0i} - S_{ri}|}{N} \quad (6)$$

With S_0 is the original signal; S_{0i} is the sample of S_0; S_r is the synthesis signal and S_{ri} is the sample of S_r.

3.1. Results and Discussion

The following figure shows the different results after applying Butterworth filter types (N = 3), Elliptical (N = 5), Bessel (N = 3) on a noisy PCG signal with a cut-off frequency W0 = 62.8319 (empirical choice).

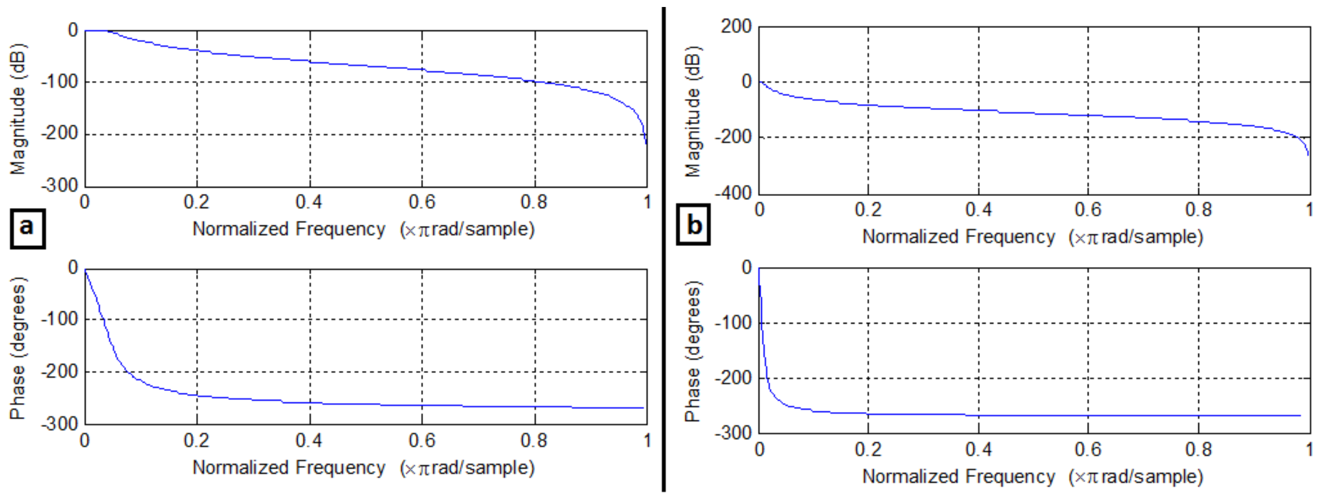

Figure 4. *a) Frequency response of the Butterworth filter order N = 3. b) Frequency response of a filter from the bilinear transformation.*

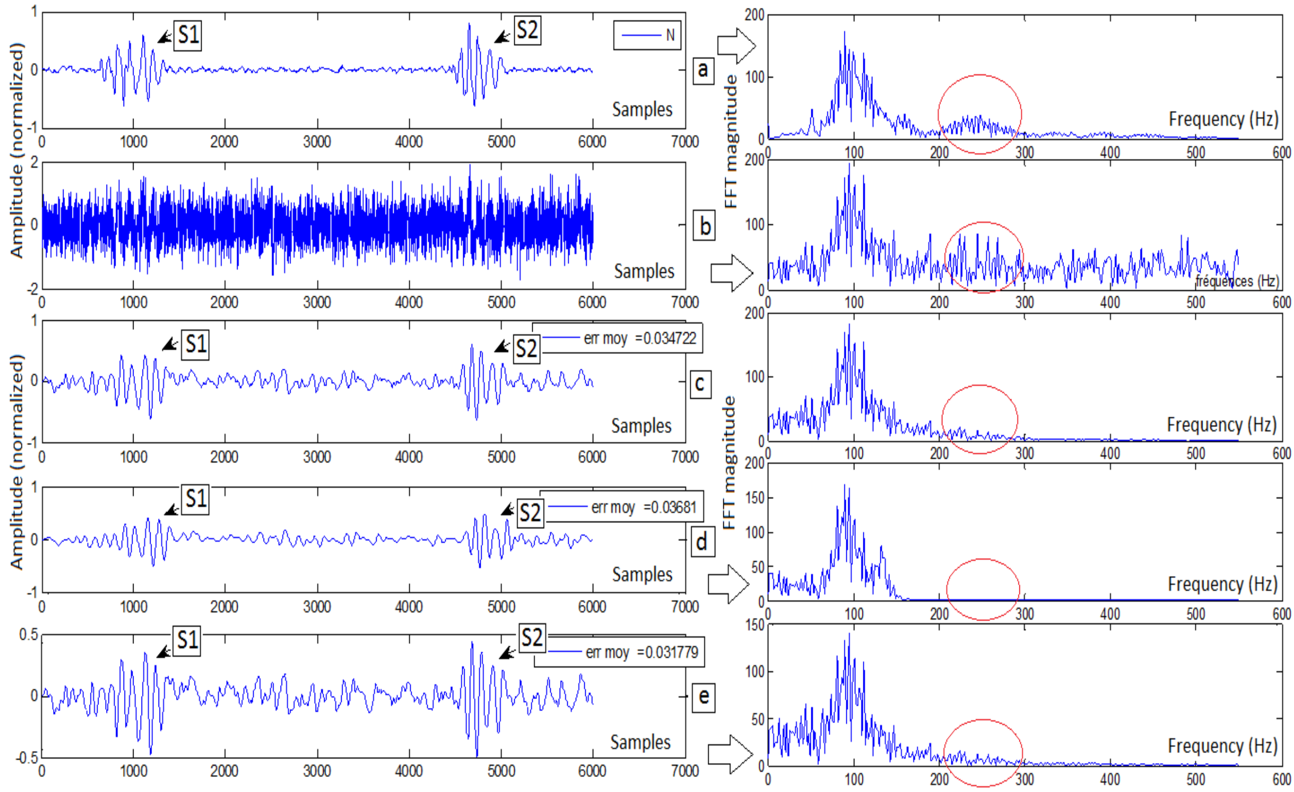

Figure 5. *Normal PCG signal filtered and its frequency spectrum (FFT): a) PCG signal (N), b) Original noisy signal (white Gaussian noise), c) Filtered signal (with Butterworth filter), d) Filtered signal (with Elliptical filter), e) Filtered signal (with Bessel filter).*

According to the figure 5 we notice the presence of S1 and S2 heart sounds because they are low frequency (<200 Hz) and the frequency transformation type is low pass.

Gaussian noise reduction indicates that these filters retain some form of heart sounds is their amplitude or width, except for the case of the figure (d) of or notice slight amplitude attenuation. So we can found that the Butterworth and Bessel filters are most effective for reducing white noise relative to the Elliptical filter.

Indeed, the average error calculated (ε_{moy}) (figure 5) can be seen that the decrease in this value is relatively good shape retention of the PCG signal. We also note that the Bessel filter gives the most reduced error compared to Butterworth and Elliptical filters value.

The spectrum of a signal in the frequency domain represents the set of frequency components that make up this signal [8]. The spectra of the figure 5 represent composed signals of a frequency band around 150 Hz to 180 Hz. These spectra are obtained by the Fast Fourier Transform (FFT). A white noise (figure 5.b) has a spread over the entire frequency band spectrum, so that the original signal (figure 5.a) is concentrated around the frequency. Lower than 180 Hz appear in the three spectra corresponds to three different filters, Butterworth and Bessel filters attenuate the amplitude of the high frequency of the noisy signal (Figure (b)) and gives a spectrum similar to that of the original signal. On the other hand the Elliptical filter removes high frequencies from 180 Hz which implies a loss of information in the filtered signal (figure 5.d).

It can be concluded that the Bilinear transformation coupled with the synthesis analog filter [9] applied to the PCG signal (Normal case) provides good filtering results. The Butterworth and the Bessel filters coupled with the Bilinear transformation take advantage of the best filters relative to Elliptic filter.

The work above, we were able to find and choose the two types of filters "Butterworth" and "Bessel" in the synthesis of IIR filters as the most suitable for filtering PCG signals.

3.2. Separation of Heart Sounds (S1 and S2), Heart Murmurs and Clicks

The separation of sounds and murmurs is based on the frequency behavior of the PCG signal [Sounds S1 and S2 (low frequency), murmurs and click (high frequency)] [10] [11]. For this synthesis IIR filter used to select only low frequencies or high frequencies. The following figure shows the application filters "Butterworth" and "Bessel" on pathological PCG signals (PAS (with Systolic murmurs), ES (with Clicks) and AR (with Diastolic murmurs)) for heart sounds (S1 and S2) separation; the frequency transformation (Low pass) is used.

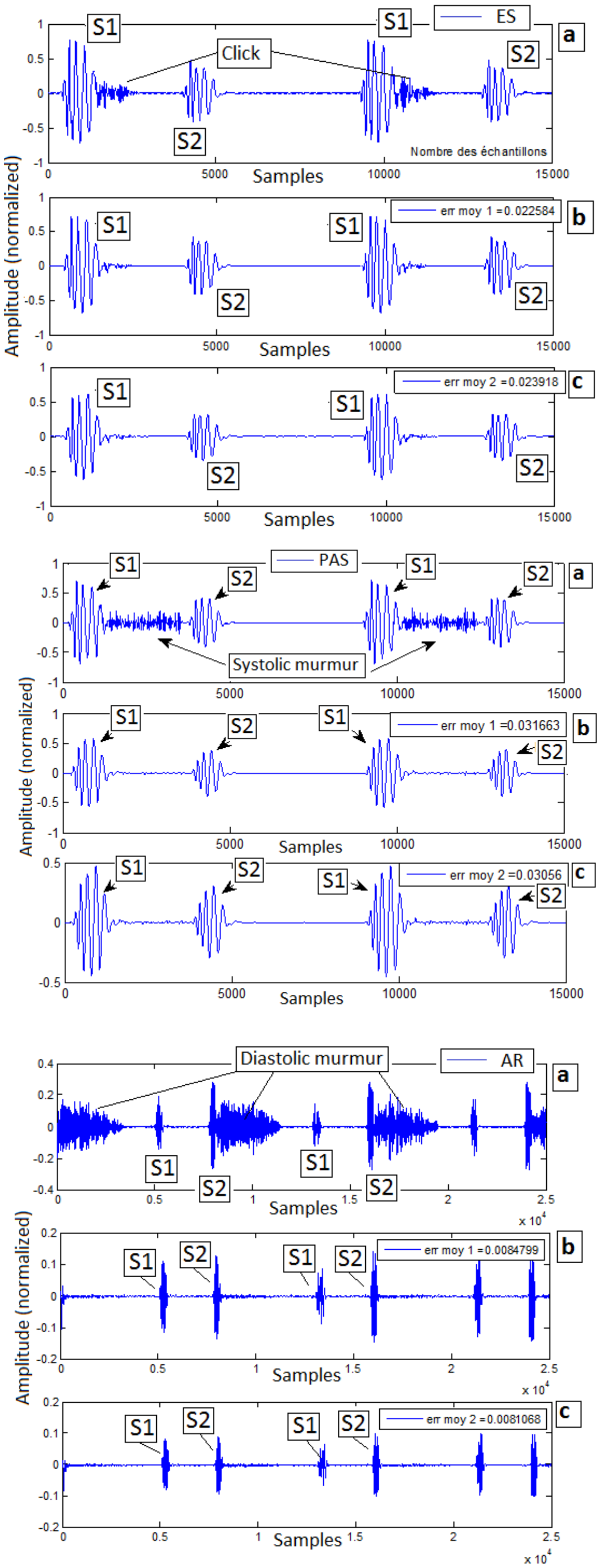

Figure 6. *Separation of heart sounds S1 and S2 of pathological PCG signals (PAS (Systolic murmurs), ES (Clicks) and AR (Diastolic murmurs)). a) PCG signals, b) filtered signal (Butterworth filter), c) filtered signal (Bessel filter).*

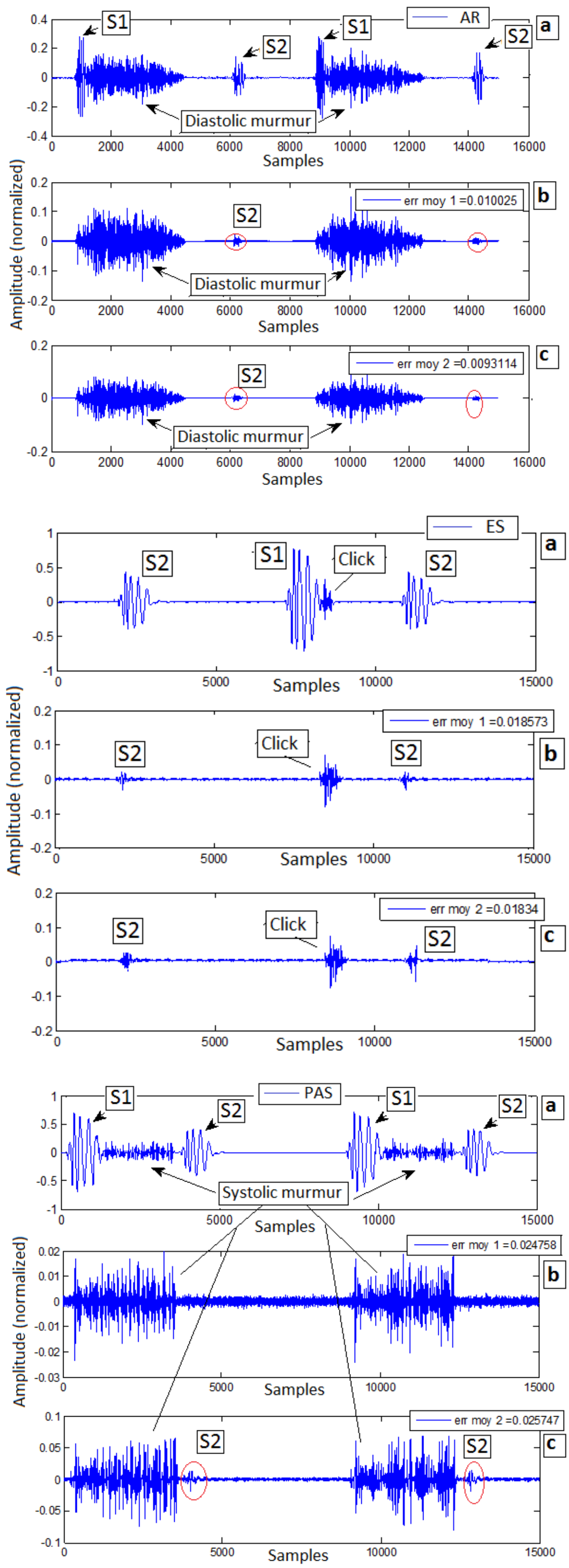

Figure 7. *Separation of heart murmurs (systolic and diastolic) and clicks of pathological PCG signals (PAS (Systolic murmurs), ES (Clicks) and AR (Diastolic murmurs)): a) PCG signals, b) filtered signal (Butterworth filter), c) filtered signal (Bessel filter).*

The separation of heart murmurs (systolic or diastolic) and clicks requires the use of the frequency transformation (High pass). Figure 7 shows the application filters "Butterworth" and "Bessel".

The application of "Butterworth" and "Bessel" filters to filter heart murmurs and clicks doesn't give very good results compared to filtering heart sounds (S1 and S2), there are still frequencies S2 (figure 7).

4. Application of Fir Filters

The synthesis of the FIR filters is the major step for attaching the coefficient values of the impulse response. These samples, called the filter coefficients are obtained by trying to get as close as possible to an ideal frequency response. Many methods exist and it is difficult to make an exhaustive inventory. However, several families were identified either by their simplicity or their performance in terms of approximation of the ideal filter.

The first method we present is undoubtedly best known for its properties and for simplicity. Commonly known method of the window, it corresponds to a weighting of the truncated impulse response of a filter arising directly from an ideal template frequency. We present in the next part of many weights to meet the compromise attenuation in the stop and fast decay of the transition band [9].

4.1. Sampling Frequency Method

The inverse Discrete Fourier Transform is used. This is to say that one "sampled" the desired response in the frequency domain; one obtains N points of this frequency response which is matched to the N points obtained by equivalent time response inverse DFT (IDFT).

It is proposed to realize a low-pass filter RIF match the template defined by the following parameters:

- Maximum attenuation in the pass band: A_{max} =3 dB (ou A_{max} =0.7079),
- Minimum attenuation in the stop band: A_{min} =40 dB (ou A_{min} =0.01),
- Cutoff frequency Fc =180 Hz, Offset frequency Fs = 200 Hz.

$$Bt = Fs - Fc \qquad (7)$$

$$a = \frac{A_{max} - A_{min}}{Bt} \qquad (8)$$

$$Fc1 = \frac{[0-(1-A_{max})]}{a} + Fc \qquad (9)$$

$$Fs1 = A_{min}/\mathrm{a} + \mathrm{Fs}) \,; \qquad (10)$$

Compared to the template set that we realized we define the desired track by which the characteristic points are filter:

$$f = \frac{\left[0 \ \mathrm{Fc1} \ \mathrm{Fc} \ \mathrm{Fs} \ \mathrm{Fs1} \frac{\mathrm{Fe}}{2}\right]}{\frac{\mathrm{Fe}}{2}} \qquad (11)$$

$$m = [1 \ 1 \ A_{max} \ A_{min} 0 \ 0] \qquad (12)$$

We note that when increasing the order of the filter frequency response of the filter will be ideal (figure 8).

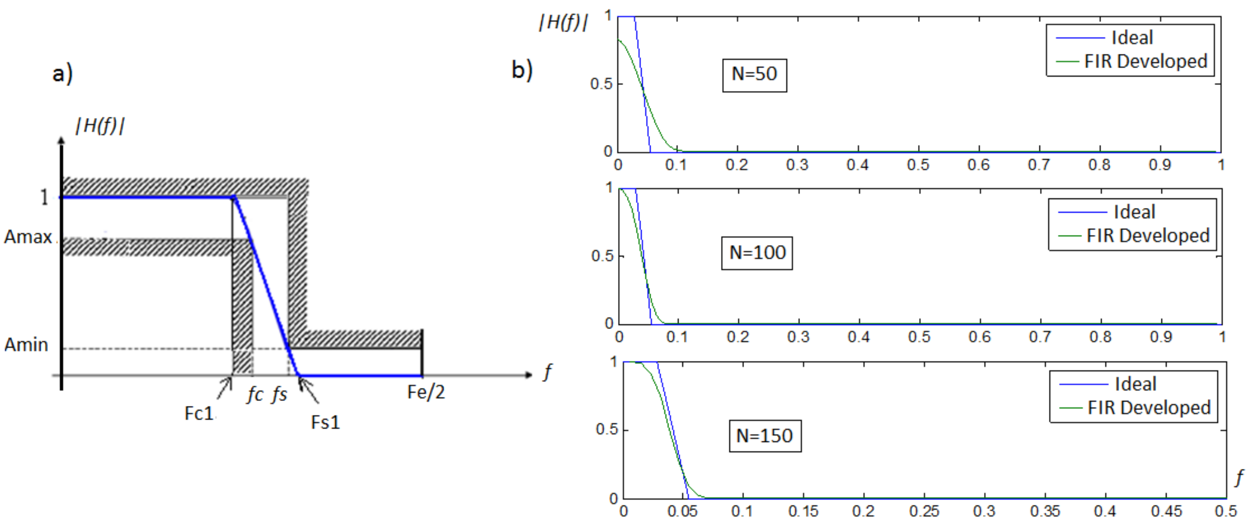

Figure 8. Frequency responses of RIF (low-pass) filter developed: a) Template low-pass filter type RIF used. b) Comparison of frequency responses for different orders of filter (N = 50, 100, 150).

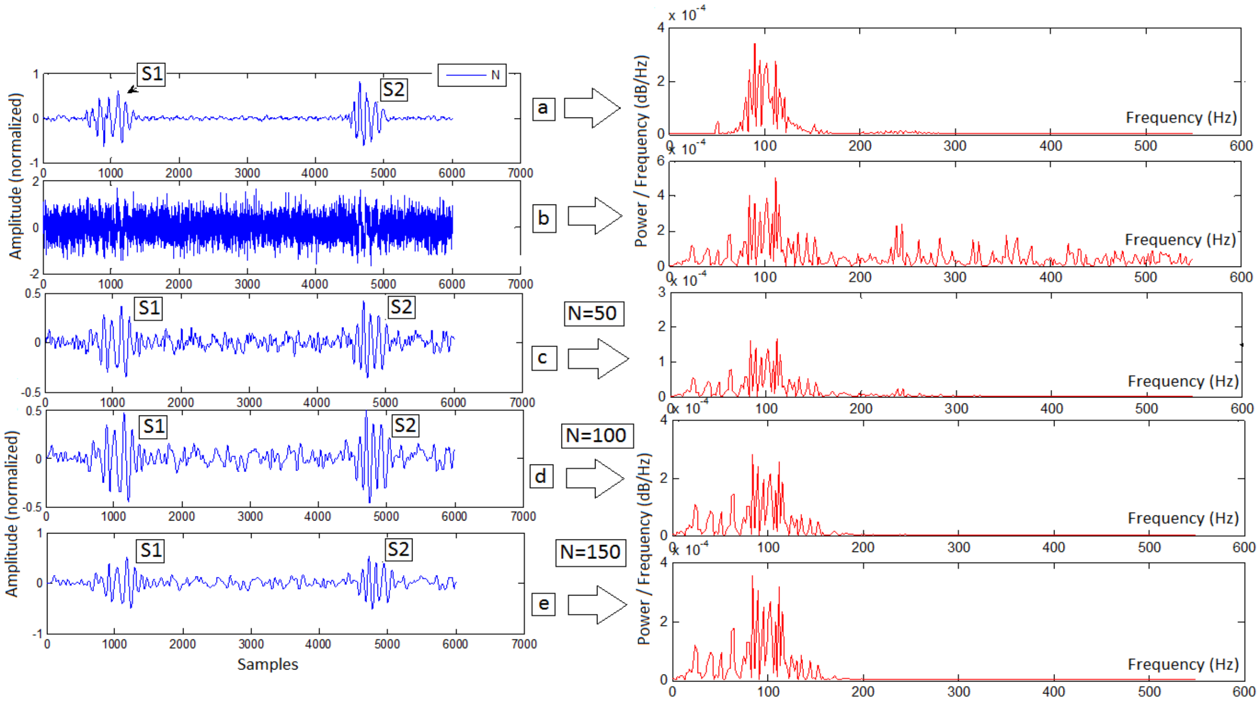

Figure 9. *The power spectral density (PSD) through the Welch method of Normal PCG signal: a) PCG signal (N), b) Original noisy signal (white Gaussian noise), c) Filtered signal (N=50), d) Filtered signal (N=100), e) Filtered signal (N=150).*

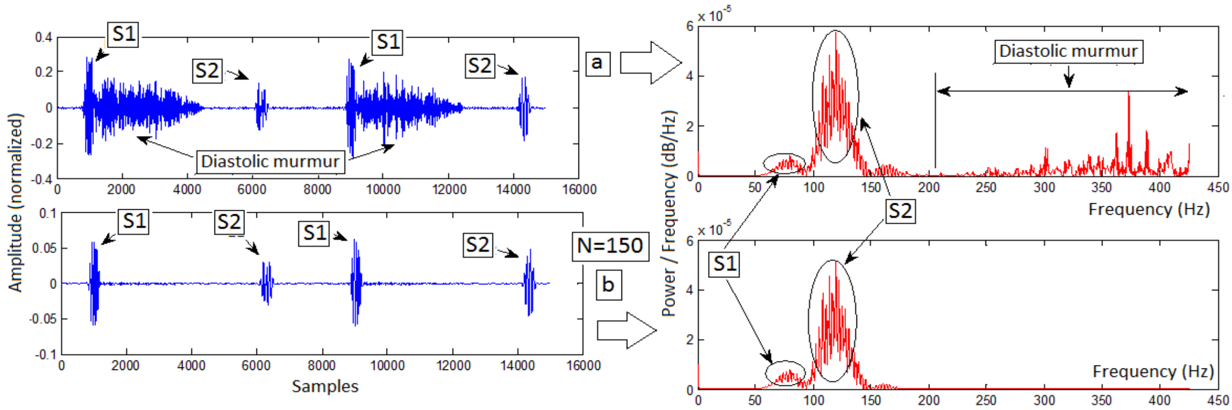

Figure 10. *The power spectral density (PSD) through the Welch method of pathological PCG signal (AR): a) PCG signal (AR), b) Filtered signal (N=150).*

So we are going to apply filter on noisy PCG signals by a Gaussian white noise and will increase the filter order, the results are shown in the figure 9

This figure shows the different results after filtering PCG signal (healthy subjects) contaminated by a Gaussian white noise with a variation of the filter order (N = 50, 100 and 150). From figure 9 the results are very close which requires other methods (frequency response and power spectral density) to determine the best order of the filter.

When the signal is not stationary (PCG signal of the case), one can analyze the frequency content of the signal from the spectrogram. This is to calculate the power spectral density by considering successive segments of the PCG signal. This tool then gives a two-dimensional representation of the PCG signal (frequency, energy). This quantity is represented by varying the amplitude of the spectrum according to the frequency values as shown in the right portion of figure 9.

The power spectral density obtained using Welch method shown in figure 9 can evaluate the power spectrum. High power corresponds to low frequencies (<200 Hz) of the original signal (Fig. 9a) was to be retained by the filter and the power of high frequency (> 200 Hz) corresponds to the Gaussian noise (Figure 9 b) was to figure.9.d and e completely removed in that of figure9.c. We can conclude that an order equal to '150 'gives more performance filter when applied directly to pathological PCG signals. The frequency sampling method treats the PCG noisy signal point by point and this gives a very remarkable result.

In this part of the frequency sampling method will be applied directly to the pathological PCG signals to separate heart sounds (S1 and S2). But the problem here is that for each pathological PCG signal noise superimposed and heart murmurs have different frequency content, which requires changing the order of the filter when filtering for each PCG signal and the results will be satisfactory. The figure 10 shows an example of application in pathological PCG signals.

The power spectral density obtained using the Welch method (figure 10) shown in the first 800 lines shows that the filter eliminates the high frequency portion (> 200 Hz) corresponds to the heart murmurs, the other the filter retains the low frequency part (> 200 Hz) corresponds to the heart sounds.

4.2. Windowing Method

The windowing method is applied to a healthy subject noisy PCG signal by a Gaussian white noise with a degradation of information in relation to noise. Note the presence of heart sounds (S1 and S2) after filtering (figure 11. c, d and e) with a gradual reduction of Gaussian noise proportional to the increase of the filter order (N) and the width of the window (N +1) Hamming used.

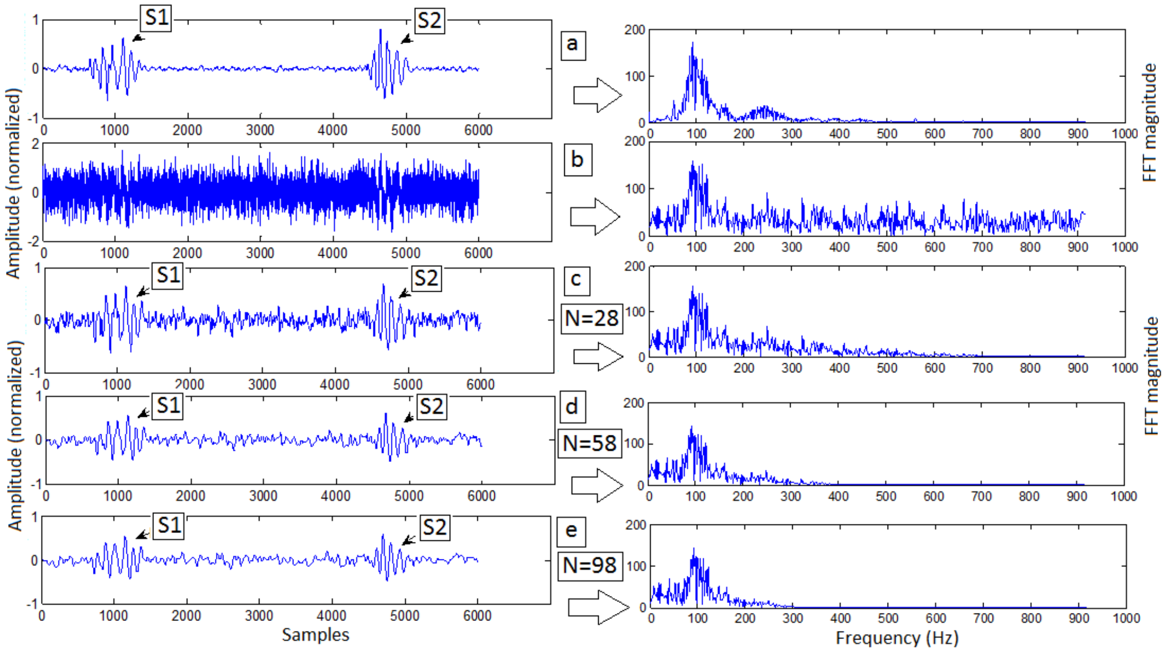

Figure 11. *PCG signal filtered and its frequency spectrum (FFT): a) PCG signal (N), b) Original noisy signal (white Gaussian noise), c) Filtered signal (N=28), d) Filtered signal (N=58), e) Filtered signal (N=98).*

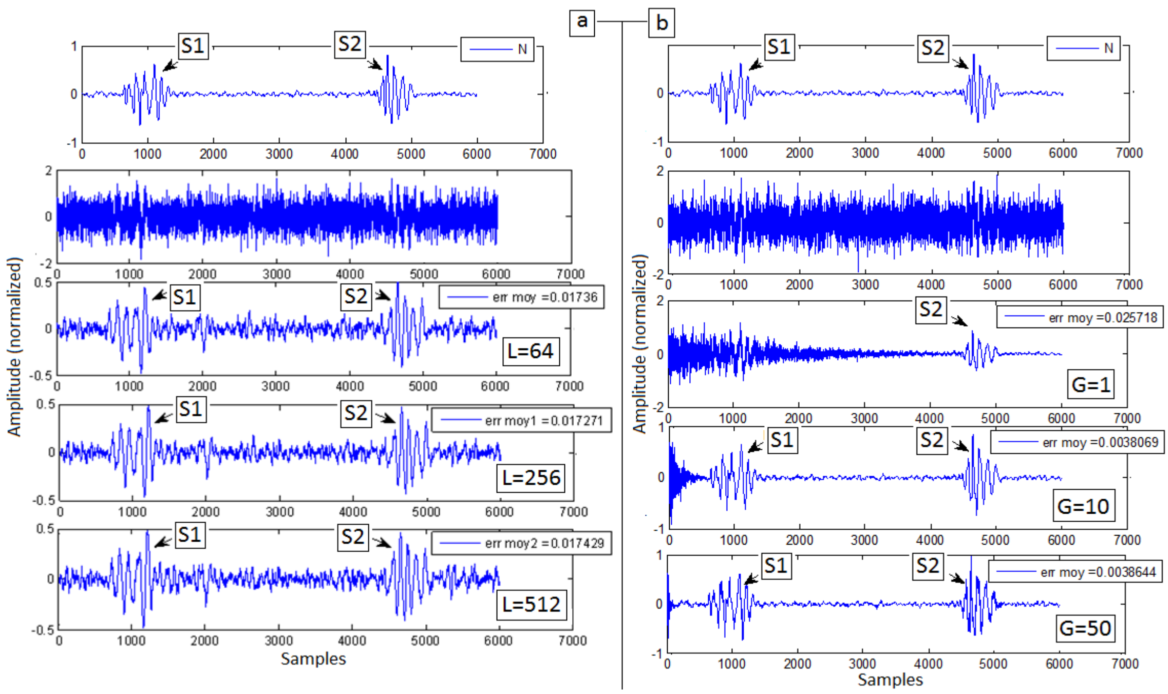

Figure 12. *Adaptive filtering of PCG signal (N) contaminated by a Gaussian white noise: a) Optimal filtering Method (Wiener-Hopf approach) (for L=64, 256 and 512). b) Least Mean Square algorithm Method (for G=1,10 and 50).*

The spectra shown in figure 11 obtained by the fast Fourier transform (FFT) shows the effectiveness of the windowing method in PCG signal filtering and the removal of white Gaussian noise. From Figure 11.c, d and e we notice the absence of the spectrum from 700 Hz (Figure 11.c) from 400 Hz (figure 11.d) and from 300 Hz (Figure 11.e). So we can say that the filter order (N = 98) is the most efficient in filtering the PCG signal. Determination of coefficients by the windowing method provides very remarkable results viewpoints temporal and spectral, when filtering PCG signal.

4.3. Adaptive Filtering Method

4.3.1. Optimal Filtering (Wiener-Hopf Approach)

When the PCG signal is embedded in noise, the approach of the optimal filter produces a band pass filter with a peak at the frequency of the original PCG signal [12]. Figure 12. Shows the results obtained after filtering the Normal noisy PCG signal by a Gaussian white noise with the Wiener-Hopf approach. In effect, heart sounds (S1 and S2) are shown but has a deformation of the morphology at the S1, for the three value of L (64, 256 and 512).

4.3.2. Least Mean Square Algorithm (LMS Algorithm)

The aim of this section is the application of the LMS algorithm (Least Mean Square) at PCG signal affected by a Gaussian white noise for adaptive noise cancellation. Whenever you increase convergence of the gain G to select the most effective filter as shown in Figure 12.b

The cancellation of the Gaussian white noise is done gradually according to (figure 12.b). We note that the heart sound S1 does not appear well (figure 12.c), by against a gain = 10 (figure 12. d) makes the filter faster, which eliminates the Gaussian noise on the signal and minimize average error (the smaller value: ε_{moy}= 38,06.10-4). Although the speed of convergence is very fast if the gain is 50 (figure 12.e) we note that the PCG signal is not completely filtered. So we can say that the most efficient gain is one that is equal to 10. We can confirm the results obtained by a non-parametric and parametric spectral analysis of signals processed.

4.4. Results and Discussion

In this section we filter pathological PCG signals by eliminating heart murmurs using different methods for synthesizing a digital filter to isolate the heart sounds (S1 and S2). The separation of heart sounds and murmurs based on the frequency behavior of the PCG signal for the synthesis of IIR filter used to select only low frequencies or high frequencies. The methods of synthesis of FIR filter: frequency sampling method and determination coefficients method require changing the type of filter to be a high-pass filter. The results of this application are as shown in the figure 13. The first three methods (IIR filter, sampling frequency method and windowing method) completely eliminate systolic murmurs with a greater average value of error; thereby isolating the heart sounds (S1 and S2).

The Wiener-Hopf approach was minimized heart murmurs (figure 13.e) much better than the LMS filter, and it does not retain the shape of the heart sounds (figure 13. f). We can confirm these results with the power spectral density as represented in fig.13. The power spectral density obtained using the Welch method shown in the first '800 ' lines shows that the filter eliminates the high frequency portion (> 200 Hz) corresponds to the heart murmurs , the other Apart from the filter retains the energy of the original signal. The frequencies represented in the interval [50-180Hz] which is very large powers' matching the heart sounds S1 and S2. High frequencies (> 200 Hz) the power is reduced systolic murmurs are matching to. The power spectral density corresponds to figures 13. b, c and d shows that the first three methods are more effective at eliminating systolic murmurs against by the other two methods (Wiener-Hopf and LMS approach) do not completely eliminate fig13. e, f.

Noise superimposed (murmurs and click) are considered high frequencies which requires the use of a filter high-pass applications in different synthesis techniques, in this way heart sounds (S1 and S2) will be eliminated in order to isolate the noise superimposed (figure 14).

The average error, which measures the difference between the filtered signal and the original signal, gives a special appreciation (figure 15). Calculates the average error of each filter is used to classify PCG signals that form groups (Normal PCG signals, PCG signals with murmurs and PCG signals with clicks). A good filtering results in a good separation of the frequencies [13]. Intact morphology of heart sounds or murmurs. IIR filters represented by the Bessel and Butterworth filter give very good results in the separation of heart sounds and murmurs. It is noted that it has a smaller error with respect to the variation given by the variation Elliptic filter. FIR filters represented by the Sampling frequency method also gives very good results with a variation of error reduced compared to other methods (windowing method, Wiener-Hopf approach and adaptive filter (LMS)).

Digital filters we used to filter the phonocardiogram signal to separate heart sounds (S1and S2), clicks and heart murmurs. Thus they retain the morphology of the PCG signal in terms of amplitude and duration of heart sounds during the elimination breaths superimposed. Changing the frequency content of heart sounds due to the pathology of PCG signal filtered at the disposal of heart murmurs will introduced a change in the form of sound (S1 and S2) (noticed in several cases (ES , AS and AR)) remain constant but the period .

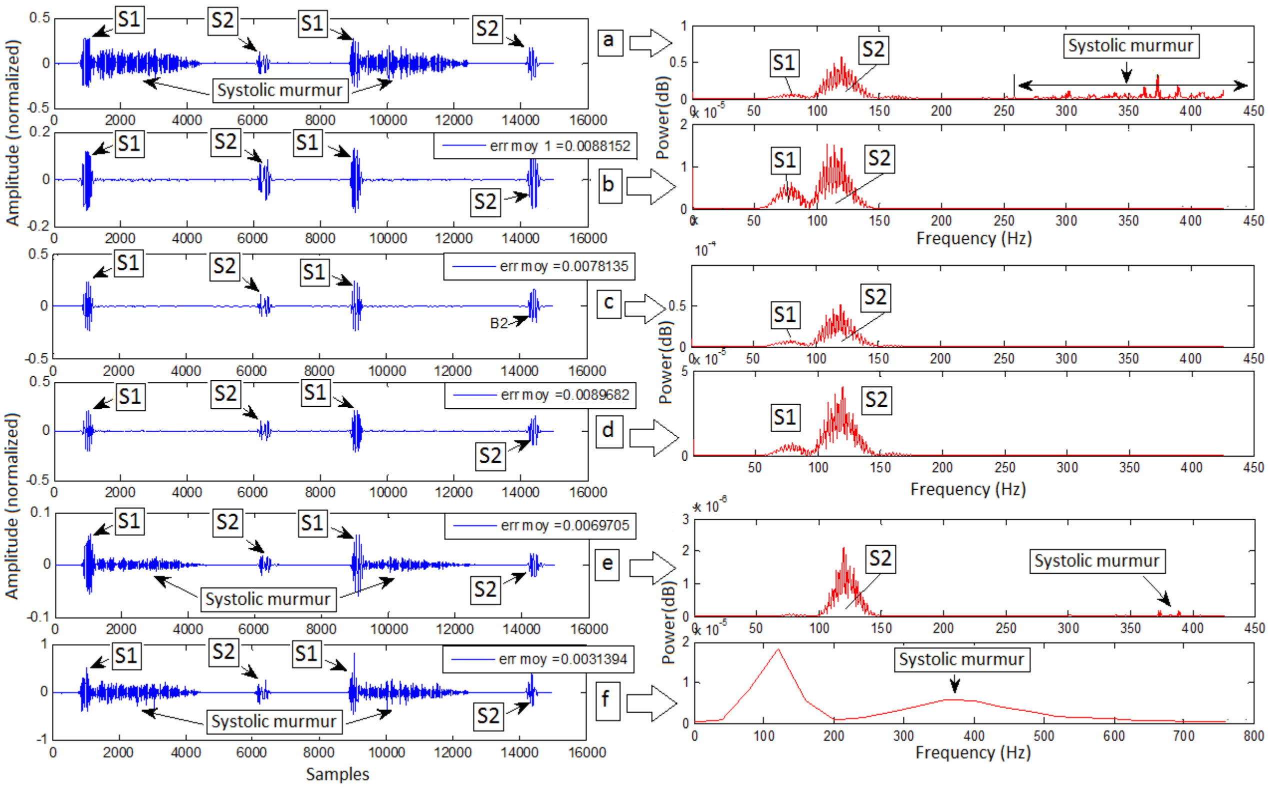

Figure 13. *The Power Spectral Density (PSD) through the Welch method applied to the pathological PCG signal (AR): a) PCG signal (AR), b) filtered signal (IIR filter), c) filtered signal (method of sampling frequency), d) filtered signal (windowing method), e) filtered signal (Wiener-Hopf approach), f) filtered signal (adaptive filter (LMS)).*

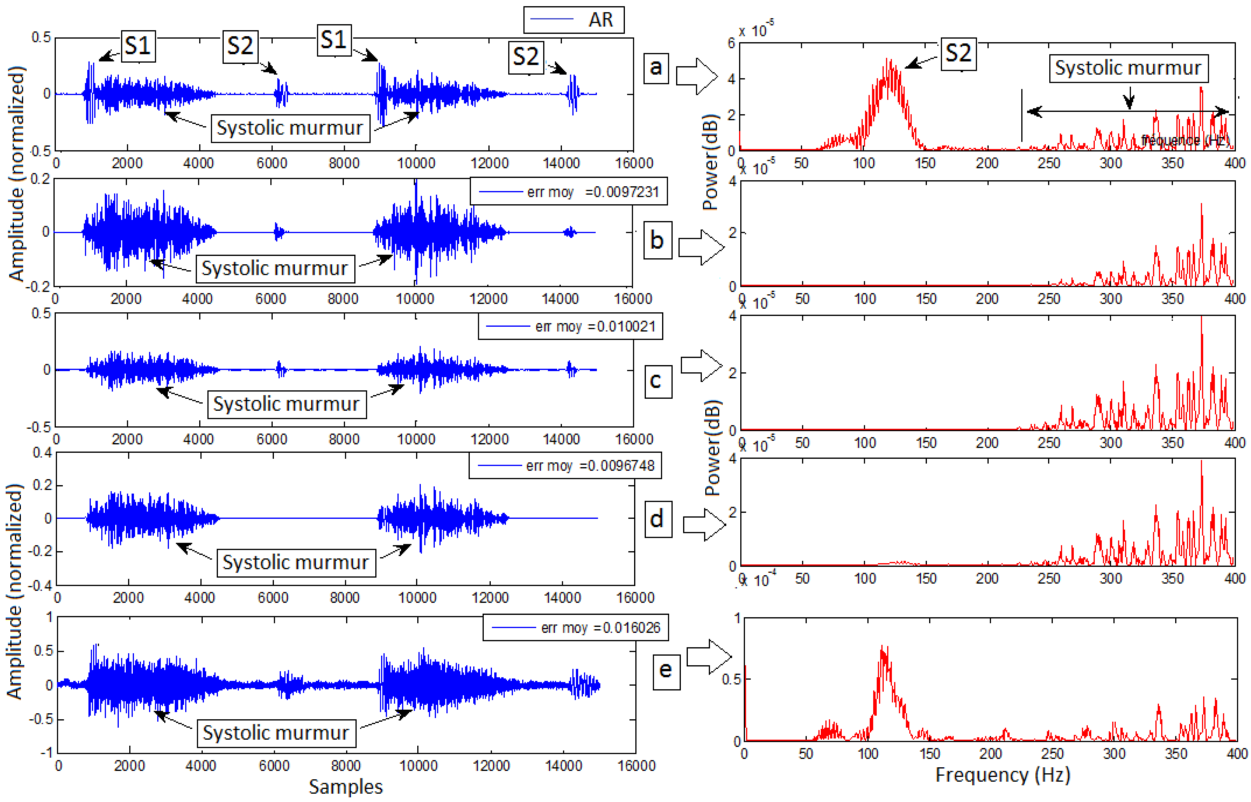

Figure 14. *The Power Spectral Density (PSD) through the Welch method applied to the pathological PCG signal (AR): a) PCG signal (AR), b) filtered signal (IIR filter), c) filtered signal (method of sampling frequency), d) filtered signal (windowing method), e) filtered signal (Wiener-Hopf approach), f) filtered signal (adaptive filter (LMS)).*

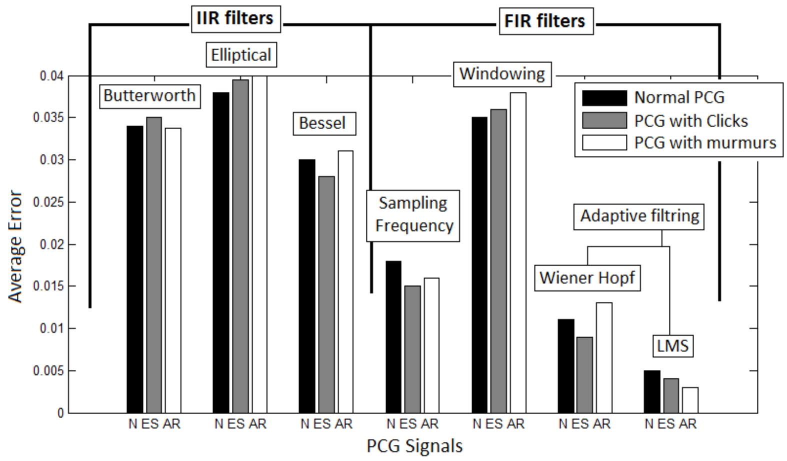

Figure 15. *The average error calculated for different filters applied to PCG signals (N, ES and AR).*

The choice of the cutoff frequency and the filter order is very important to have a complete separation of the heart sounds (S1 and S2) or heart murmurs [14] [15]. The average error according to the measurements appears to be a very important consideration in the classification of PCG signals parameter. Indeed, it proved on the basis of these results that the variation of this parameter is very sensitive to the importance of blasts present in a PCG signal, confirming the regularity and reliability of this parameter in such a test.

5. Conclusion

The digital filters are digital systems linear time invariant, used to modify the distribution of frequency components of a signal according to given specifications. Their success is due to their properties and reliability in signal processing. Methods of digital filter used is based on the modification of the frequency distribution of each treaty PCG signal, heart sounds (S1 and S2) are considered low frequency and noise superimposed (murmurs and clicks) considered high frequencies. Filters IIR take the advantage of being more useful in filtering PCG signals including the separation of heart sounds, murmurs and clicks. The FIR filter represented by the frequency sampling technique that based on Discrete Fourier Transform (DFT) and the determination of coefficients by the method for windowing gives satisfactory results when filtering the PCG signal. Filters we have cited are defined using templates specific type filter low-pass and high-pass. Adaptive filtering approach represented by the Wiener-Hopf and LMS algorithm adaptive cancellation of broadband noise added to the signal PCG reduced band, but still insufficient in eliminating heart sound disease. Spectral analysis represented by both parametric and non-parametric methods used to evaluate the power spectrum when there is a better adaptation to determine the frequencies of the internal heart sounds components S1 and S2 , which are located on a narrow range (30 to 300Hz).

Declaration of Interest

The authors state no conflict of interest.

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