Noise Cancellation on ECG and Heart Rate Signals Using the Undecimated Wavelet Transform

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***Abstract*—This paper presents a new approach to eliminate the noise found in ECG signals due to artifacts and cardiac rhythm. This work is carried out using the Undecimated Wavelet Transform (UWT)[1]. [2]. The signals were acquired using an MATLAB SIMULATION of bioelectrical The ECG signals are obtained through the implant of electrodes connected to a channel of the front- end board. The cardiac rhythm is then obtained using an optic dactilar sensor connected to an independent channel of the ECG signal. In order to get a better identification of the acquired signal the Wavelet filter D6 (Daubechies) was chosen, primarily because its scaling function is closely related to the shape of the ECG, fitting very well with the applications constraints The processed signals were further analyzed using SIMULATION using MATLAB. The application to denoise the ECG signals was developed by MATLAB 2008Rb and is capable of graphically representing the data before and after it's processed.**

Keywords:* *noise cancelation, wavelet transform, Wavelet filter D6, ECG.

I. INTRODUCTION

Filtering ECG signals helps us eliminate those signals that contaminate our reading. These contaminating agents can be classified in the following categories:

- Line interference
- Noise by contact in the electrode
- Electrical coupling of the electrodes and the board

The noise, whatever the source is, significantly contaminates the ECG signal and therefore makes its analysis difficult.

Obtaining an ECG signal could be an easy task, but obtaining a **reliable** ECG signal to provide a clinic analysis by a specialist is a more complicated task, This is why manipulating and filtering a signal is a complex task.

The advantage of effectively filtering the ECG signals is to determine in a clear and simple way the PQRST complex, that helps the specialist identify different types of arrhythmias, like the tachycardia or the bradycardia and variations in the heart rate; as well as determine other types of abnormalities in the myocardium [3].

The Wavelet Transform is a mathematical tool also known as a mathematical microscope. It has the Short Window Fourier Transform (STFT) as its antecedent. Its main characteristic is the Multi Resolution Analysis (MRA), different scales and resolutions, constituting an adapted way for the analysis of non-stationary signals, as the bioelectrical signals are [4].

Given a signal f(x), we wish to produce an estimation judged as a quite faithful representation of f '(x). The problem of de noising, is that the coefficients must be noise free. This noise could be due to any number of sources the environment. [5].

The purpose for applying a filter is to reduce the noise level in the signal and simultaneously preventing a loss in the signal's wave fidelity which could deform it.

To remove the noise level in the signal using Wavelets, it must be selected among those similar to ECG waveforms, like the ones developed by Daubechies, Coiflets, or Biortogonals. In this research, all the above waveforms were tried out but only the Daubechies was selected.

Subsequent to the selection of the Wavelet, the de noise process involves a smoothed stage by a threshold, using the minimax principle [12].

II. PROBLEM DEFINITION

A. The Discrete Wavelet Transform.

The most popular wavelet transform algorithm is the discrete wavelet transform (DWT), which uses the set of *dyadic* scales (i.e. those based on powers of two) and translates from the mother wavelet to form an orthonormal basis for signal analysis [1].

To implement the discrete wavelet transform, we need to use a discrete filter bank and make use of the equation scale to two.

$$\varphi(2^j t) = \sum_k h_{j+1}(k)\varphi(2^{j+1}t - k) \quad (1)$$

Where $\varphi(2^j t)$ is the scaling function, the two-scale relation states that the scaling function $\varphi(2^j t)$, at a certain scale can be expressed in terms of translated scaling functions at the next smaller scale. Where J indicate the resolution level associated to the frequency, k indicates the localization and t is the translation variable.

The first scaling function replaced a set of wavelets and therefore we can also express the wavelets in this set in terms of translated scaling functions at the next scale. More specifically we can write for the wavelet transform at level *j*:

$$\psi(2^j t) = \sum_k g_{j+1}(k)\varphi(2^{j+1}t - k) \quad (2)$$

This is the two-scale relation between the scaling function and the wavelet transform.

Manipulating these two equations, and keeping in mind that the inner product can also be written as integration, we arrive at the next result:

$$\lambda_{j-1}(k) = \sum_m h(m-2k)\lambda_j(m) \quad (3)$$

$$\gamma_{j-1}(k) = \sum_m g(m-2k)\gamma_j(m) \quad (4)$$

These two equations state that the scaling function coefficients (h) and the Wavelet function (g) on a certain scale can be found by calculating a weighted sum of the scaling function coefficients from the previous scale.

Now that we have implemented the wavelet transform, as an iterated digital filter bank it's possible now to speak of the *discrete wavelet transform* or *DWT*. Thanks to this we can do the downsampling and upsampling of the signal.

As we can see in equations (3) and (4), a factor of 2 exists that allows us to do the downsampling or the upsampling, besides that the sum of the outputs is exactly the same as the input signal.

Signal Decomposition.

The decomposition of the signal is an iterative process as it can be observed in the wavelet and scaling function, where the signal is divided to obtain a better resolution in the time- frequency domain.

The process begins creating two symmetrical filters of a mother wavelet function (2) and a scaling function (1) that provide a orthogonal basis dividing the signal in its frequency spectrum, generating low and high frequency signals in each of these iterations, the low frequency components are the "approximation coefficients" obtained by the low pass filter, whereas the components of high frequency are the "Detail Coefficients" obtained by the high pass filter (see figure 1).

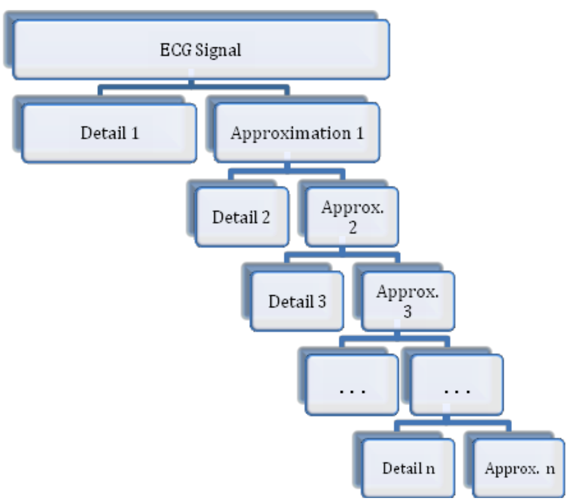

Figure 1. Decomposition signal tree with its Approximation Coefficients (low pass filter) and the Detail Coefficients (high pass filter).

B. The Stationary Wavelet Transform.

Whereas the discrete Wavelet transform has a suitable implementation in applications like data compression where compact signal description is required [5], the obtained results were not the optimal for our signal filter noise reduction application to analyze the signal; this is mainly due to the loss of the invariant translation property of the Discrete Wavelet Transform, but the variation of this parameter is allowed, this take us to the Undecimated Wavelet Transform (UWT), for a signal $s \in L^2(\mathbb{R})$, it is given by:

$$\omega_v(\tau) = \frac{1}{\sqrt{v}} \int_{-\infty}^{+\infty} s(t)\psi * \left(\frac{t-\tau}{v}\right) dt$$

$$v = 2^k, k \in \mathbb{Z}, \tau \in \mathbb{R}$$

(5) Where $\omega_{\upsilon}(\tau)$ are the UWT coefficients on scale υ and shift τ, and Ψ* is the complex conjugation of the mother wavelet. Actually the UWT transform can be calculated in N log N using fast filter banks algorithms [1].

The Wavelet function selection depends on the application or the application for which it's going to be used. Selecting a Wavelet function that looks like the signal that will be processed is the most convenient selection. Daubechies 6 (D6) from Daubechies family is similar in shape to the QRS complex and its energy spectrum is concentrated around low frequencies [7].

Unlike the DWT transform, which downsamples the detail and approximation coefficients in each decomposition level, the UWT transform does not incorporate downsampling operations. The UWT transform upsamples the low and high pass filter coefficients in each level. The resolution of the UWT transform coefficients decreases with the increase in the decomposition levels.

C. Characteristics.

Now we will describe the unique characteristics of the UWT transform comparing with the DWT.

1. Invariant Translation Characteristic

Unlike the DWT transform, the UWT has the property of invariant translation, or shift invariant property. For example we can use this property if we wanted to detect some discontinuity on the signal in case it is out of phase or with some displacement [9].

2. Better Capacity to reduce noise

Reducing noise with UWT transform allows for better balance between smoothness and exactitude than the DWT transform.

3. Better peak detection

Peaks often represent important information about a signal. We can use the UWT transform to identify peaks in a signal contaminated with noise.

III. METHODOLOGY

In the first phase it's the selection of the mathematic tool that is going to be used to attain our objective which is noise reduction.

Using the tools for digital signal processing of MATLAB it was realized the processing of the ECG and cardiac rhythm file obtained from the database.

The tool for the analysis of the different filters was implemented under a friendly interface to handle it in a very efficient way.

The MATLAB tool allows us to represent the ECG or heart rate signal in two windows. The first window shows the signal before processing and in the second window the signal just filters. This feature allows the user to compare both signals.

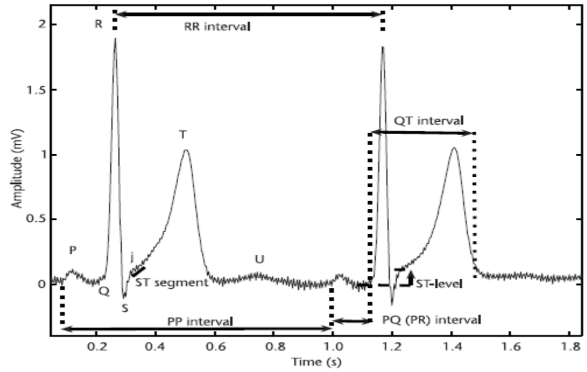

Figure 2. Standard fiducial points in the ECG (P, Q, R, S, T, and U)

Figure2 shows Standard fiducial points in the ECG (P, Q, R, S, T, and U) respectively typical normal values for these standard clinical ECG features in healthy adult males in sinus rhythm, together with their upper and lower limits of normality. Note that these figures are given for a particular heart rate. It should also be noted that the heart rate is calculated as the number of P-QRS-T complexes per minute, but is often calculated over shorter segments of 15 and sometimes 30 seconds. In terms of modeling we can think of this heart rate as our operating point around which the local inter beat interval rises and falls. Of course, we can calculate a heart rate over any scale, up to a single beat. In the latter case, the heart rate is termed the instantaneous (or beat-to-beat) heart rate,

Denoising procedure

- Apply the UWT transform to the contaminated signal to obtain the UWT coefficients of the signal. The noise in the signal usually corresponds to small value coefficients.
- Select an appropriate threshold for the UWT transform coefficients, to adjust these coefficients to values near zero. MATLAB provides methods to automatically select the threshold level. The reduction limit of the noise level with this method is of 3 dB. In order to reach better performance eliminating the noise of the signal, we can select a threshold manually.
- Rebuild the signal with the UWT inverse transform

Figure 3 shows the corresponding ECG signal obtained from the bioelectrical amplifying signal obtained from MATLAB simulation , which shows noise that need to be eliminated.

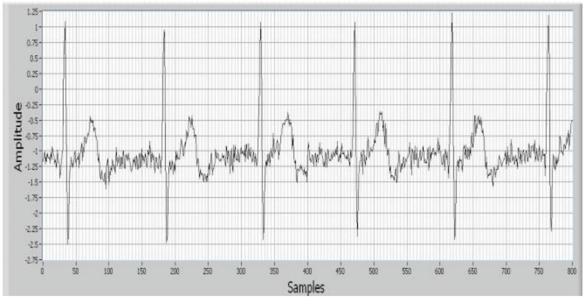

Figure 3 Original ECG signal
(Sampling Freq. 200Hz.)

In figure 4 a High pass Kaiser filter was applied to the signal, the result of applying this filter was a right shift of the signal, due to its begins to filter the signal in zero, but the noise was not eliminated reason why this filter is inefficient.

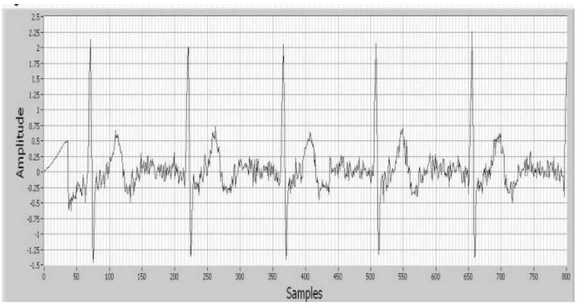

Figure 4 ECG signal applying a high pass Kaiser filter (Sampling Freq. 200Hz.)

Figure 5 shows the ECG signal applying the Coiflet - DWT wavelet filter, where we can observe a well know improvement in clarity of the complex P,Q,S y T, although also small peaks can be observed right before beginning the QRS wave.

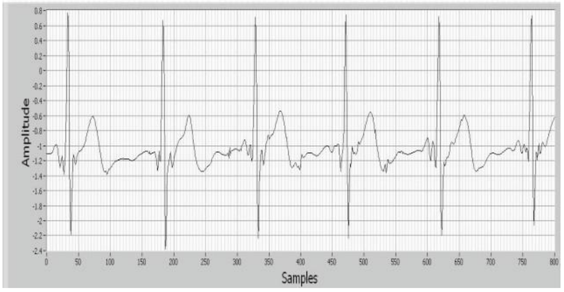

Figure 5 ECG signal applying a Coiflet - DWT filter (Sampling Freq. 200Hz.)

In figure 6 a Biortogonal - UWT Wavelet filter has been applied where the T wave is smoother and QRS wave peak has been eliminated.

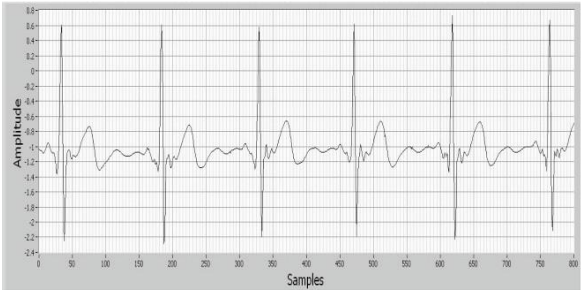

Figure 6 ECG signal applying a Biortogonal - UWT filter (Sampling Freq. 200Hz.)

Figure 7 shows the application of Daubechies UWT Wavelet filter where it is observed that the isoelectric line of the ECG signal is straight.

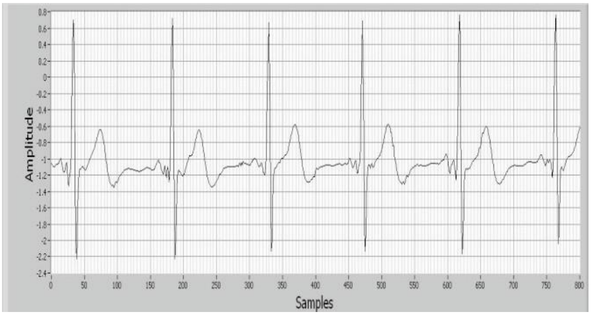

Figure 7 ECG signal applying Daubechies UWT filter (Sampling Freq. 200Hz.)

IV. RESULTS

Figures 9, 10, 11 and 12 show the same filters applied to the Heart Rate signal, where we can also see that the best result between smoothness and efficiency is the Daubechies - UWT wavelet filter.

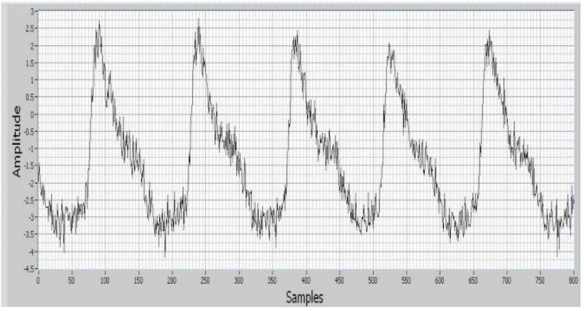

Figure 8 Original Heart Rate signal (Sampling Freq. 200Hz.)

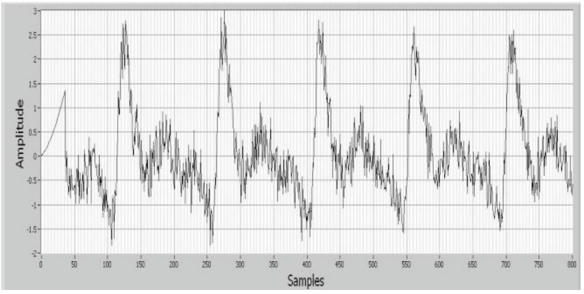

Figure 9 Heart Rate Signal applying a high pass filter (Sampling Freq. 200Hz.)

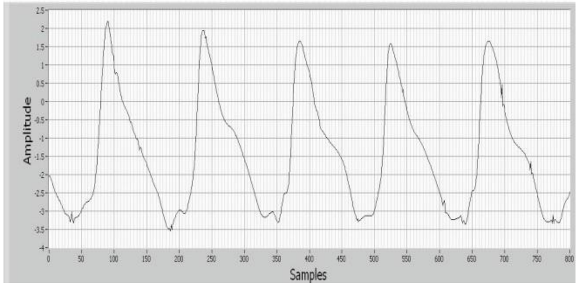

Figure 10 Heart Rate signal applying Coiflet - DWT filter (Sampling Freq. 200Hz.)

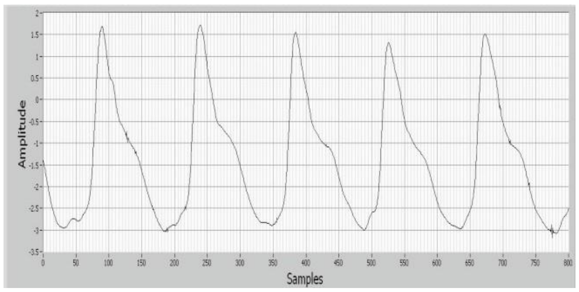

Figure 11 Heart Rate signal applying Biorthogonal - UWT filter (Sampling Freq. 200Hz.)

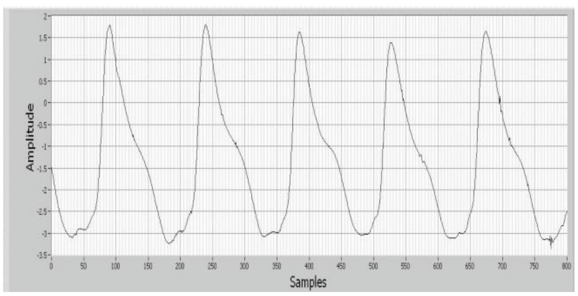

Figure 12 Heart Rate Signal applying Daubechies - UWT filter (Sampling Freq. 200Hz.)

V. CONCLUSIONS

In this work we have tried to present an alternative to filter the ECG signal and Heart Rate and thus obtain signals easier to interpret, that serves as a biomedical signal processing and that can be applied in other areas of research.

Obtaining a suitable ECG signal for telemedicine applications is a fundamental task in order to have accuracy of every wave that it is formed of. In fact besides processing, it is necessary to detect it with accuracy and to identify each feature of it in order to determine an accurate heart rate, different types of arrhythmias like the bradycardia and variations in the heart rate, as well.

The obtained results in this work using wavelet demonstrated to us that they are and accurate tool for processing non-stationary signals such as the bioelectrical signals are.

With base on the experiments carried out to the information corresponding to the ECG signal and heart rate and, the obtained results, it is possible to determine that the use of Wavelets in applications like noise reduction and signal filtering for bioelectrical signal have optimal results. These procedures were realized "Offline" since the information is first acquired, later it is stored in a database and finally the information is extracted in a text file for its processing.

UWT Wavelet show better results in contrast with the DWT Wavelet transform. Different samples for their analysis were taken that were acquired by using the bioelectrical signal MATLAB SIMULATION and stored signals in a data base, to be processed latter on.

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