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# Background Noise Elimination from Heart Rate and Electrocardiogram Data Using the Undecimated Wavelet Transform

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*Abstract* - The study done to remove noise from heart rhythm and ECG readings is described in this article. the goal is to acquire signals with clarity and dependability so that a professional can subsequently interpret them. The Undecimated Wavelet Transform (UWT) is the foundation of this work[1]. The Wavelet filter D6 (Daubechies) was used in order to obtain a better identification of the collected signal, mainly because its scaling function is closely connected to the ECG's form and fits the application's restrictions extremely well [2].

The processed signals were acquired using an amplifying board of bioelectrical signals (front-end board) and a NI PCI-6221 data acquisition board with a sampling frequency of 200 Hz. The ECG signals are obtained through the implant of electrodes connected to a channel of the frontend board. The cardiac rhythm is then obtained using an optic dactilar sensor connected to an independent channel of the ECG signal. The amplifying board was designed and developed for researching purposes on the telemedicine and signal processing area. The application to denoise the ECG signal was developed by Lab View® and is capable of graphically showing the data before and after it's processed.

**Keywords:** reduction of background noise, wavelet transform, electrocardiogram.

## INTRODUCTION

We can eliminate the noise from the ECG data that would otherwise skew the results by filtering them. These pollution sources can be categorized into the following types:Electrode noise caused by contact and line interference The electrical connection between the board and the electrodes Regardless of the cause, the noise significantly taints the ECG signal, making analysis difficult. WHILE GETTING AN ECG SIGNAL MAY BE EASY, IT'S MUCH HARDER TO GET A RELIABLE ECG SIGNAL THAT A PHYSICIAN CAN USE FOR CLINIC ANALYSIS. This explains the importance of signal processing tasks including manipulation and filtering. IDENTIFYING VARIOUS ARRHYTHMIAS (INCLUDING TACHYCARDIA, BRADYCARDIA, AND VARIATIONS IN HEART RATE) AND OTHER MYOCARDIAL ABNORMALITIES IS MADE EASY WITH THE USE OF THE PQRST COMPLEX.

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# I. 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 ortho normal 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 is the scaling function, the two-scale relation states that the scaling function, 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 down sampling and up sampling of the signal. As we can see in equations (3) and (4), a factor of 2 exists that allows us to do the down sampling or the up sampling, besides that the sum of the outputs is exactly the same as the input signal.

**Signal Decomposition.**

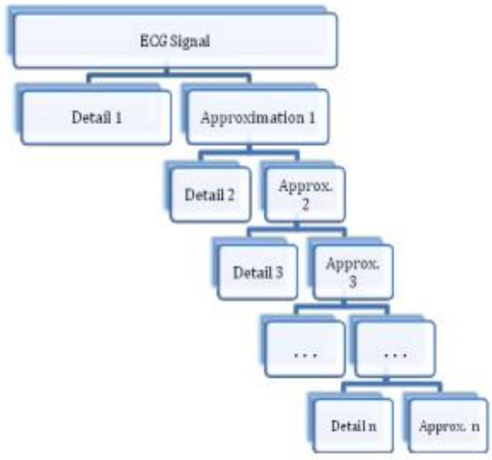


Fig. 1. Decomposition signal tree with its Approximation Coefficients (low pass filter) and the Detail Coefficients (high pass filter).

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).

## B. *The Stationary Wavelet Transform.*

Where as 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 signals ( ), it is given by

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

$$\upsilon = 2^k, k \in \mathbb{Z}, \tau \in \mathbb{R} \quad (5)$$

Where are the UWT coefficients on scale and shift, and is the complex conjugation of the mother wavelet. Actually the UWT transform

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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 down samples the detail and approximation coefficients in each decomposition level, the UWT transform does not incorporate downs ampling operations. The UWT transform up samples 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.

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. Signal Acquisition

The signal it's acquired using a bioelectrical signal amplification board that passes the data to a data acquisition board NI PCI-6221 and stores all the information in a data base. Figure 2 shows the system diagram.

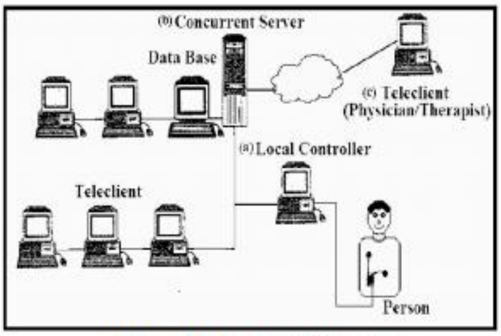


Figure 2 Telemonitoring System

Using the tools for digital signal processing of LabView 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. This software 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.

*D. 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. Lab View 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 board, which shows noise that eliminated.

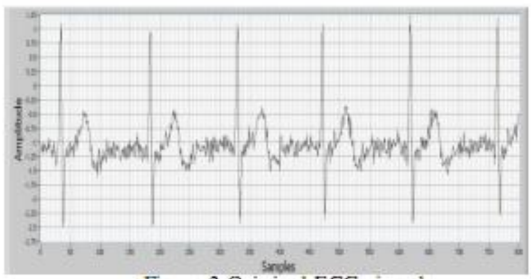

Figure 3 Original ECG signal
(Sampling Freq. 200Hz.)

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.

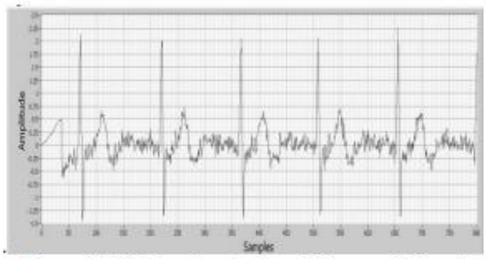


Figure 4 ECG signal applying a high pass Kaiser filter (Sampling Freq. 200Hz.)

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.

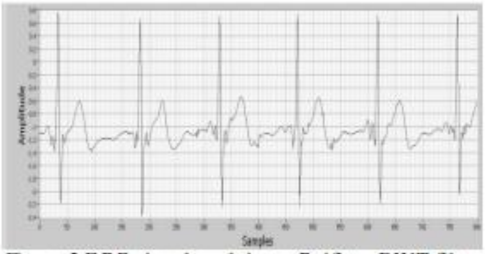


Figure 5 ECG signal applying a Coiflet - DWT filter (Sampling Freq. 200Hz.)

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

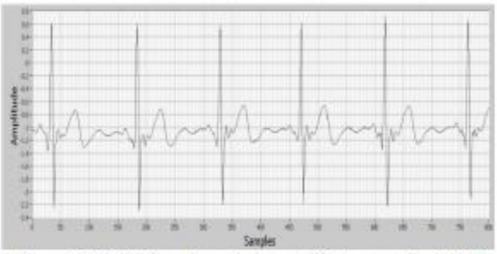


Figure 6 ECG signal applying a Biortogonal - UWT filter (Sampling Freq. 200Hz.)

Figure 7 shows the application of Daubechies UWT Wavelet filter where it is observed that the iso electric line of the ECG signals is straight.

## II. 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.

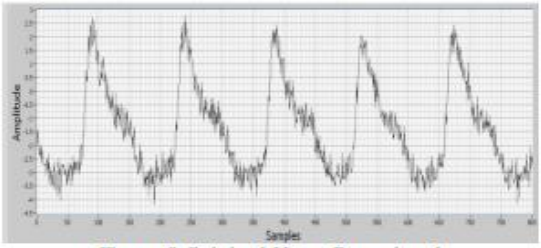


Figure 8 Original Heart Rate signal (Sampling Freq. 200Hz.)

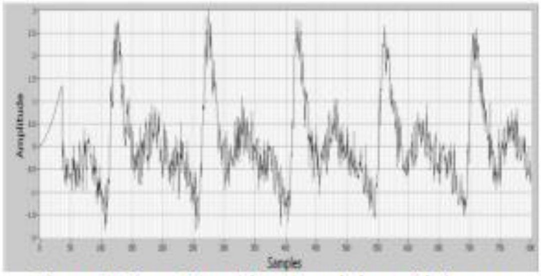


Figure 9 Heart Rate Signal applying a high pass filter (Sampling Freq. 200Hz.)

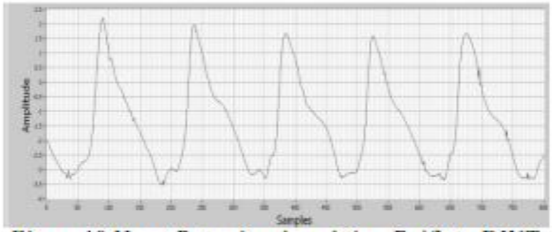


Figure 10 Heart Rate signal applying Coiflet - DWT filter (Sampling Freq. 200Hz.)

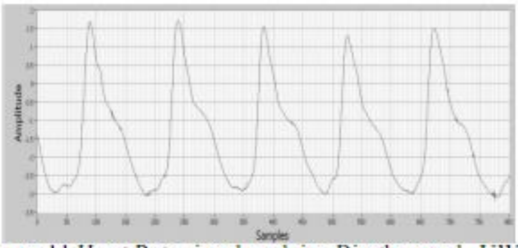


Figure 11 Heart Rate signal applying Biorthogonal - UWT filter (Sampling Freq. 200Hz.)

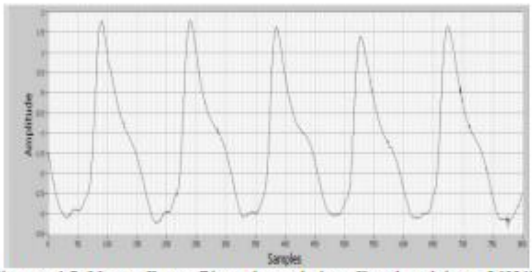


Figure 12 Heart Rate Signal applying Daubechies - UWT filter (Sampling Freq. 200Hz.)

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## III. CONCLUSIONS

IV. As a biomedical signal processor, our goal in this work was to provide an alternate method for filtering the ECG and heart rate data, making them more interpretable and potentially useful in other fields of study. In order to ensure the correctness of each wave it contains, obtaining an appropriate electrocardiogram (ECG) signal is a key job for telemedicine applications. In reality, determining a correct heart rate, various forms of arrhythmias like bradycardia, and fluctuations in the heart rate also requires proper detection and identification of each component of it, in addition to processing. The outcomes of this study that used wavelets proved that they are a reliable method for handling non-stationary data, such bioelectrical signals. It is feasible to conclude that applications such as noise reduction and signal filtering for bioelectrical signals get the best results when using Wavelets based on studies performed using data matching to the ECG signal and heart rate. These processes were carried out "Offline" since they begin with data acquisition, continue with data storage in a database, and conclude with data extraction into a text file for processing. When compared to the DWT Wavelet transform, the UWT Wavelet yields superior results. They used a bioelectrical signal amplifying board to collect data from a variety of samples, which they then entered into a database for analysis. FUTURE WORK

In this study, we provide a method for improving the accuracy of a bioelectrical signal obtained from superficial electrodes connected to a person by reducing noise using Wavelet transform. Bioelectrical signal processing and noise reduction for telemedicine applications is an area that will be addressed in future research. We also want to include a fuzzy logic-based AI subsystem into our concept so that we may create an automated decision-making process that can use the processed data to categorize or anticipate potential heart illnesses.

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