Digital processing of a ECG using a DSP: Wavelet approach[1]

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Abstract. This work presents the digital processing of an electrocardiogram with the object of extracting useful information for its comprehension. The Wavelet technique is used for this porpouse. In order to perform the test a digital signal processor (DSP) TMS320C6711 Texas Instruments, was used.

Key words: Digital Processing, Electrocardiogram, Wavelets, DSP.

1 Introduction

Electrocardiogram (ECG) is a graphical register of the electrical potentials produced by cardiac tissue, which ones are located between a frequency range from 1 to 100 Hz. And the synchronization mechanism is shown on figure 1.

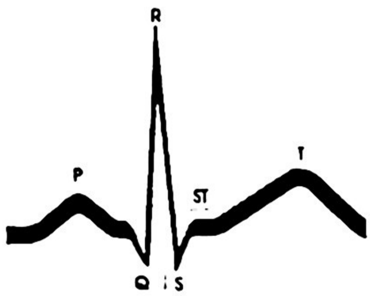

Fig. 1. Electrocardiogram elemental signal.

The bents presents in the drawing of an ECG represent different states of the heart during a beat. The *P wave* and the *QRS complex* indicates contraction of the atriums and ventricles respectively, the *ST segment* indicate the time that transcurse since a ventricle contraction ends to a starting rest period previous to the ventricles start to

[1] Supported by PROMEP with project number 103.5/03/1130

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contract themselves for the next beat, and finally the *T wave* indicate the rest period of the ventricles.

The microelectrical signal analysis has been strongly used to determine different kinds of medical malaises and diseases such as muscular fatigue, cardiac disfunctions, etc. Y thanks to the advance of this area, actually it is possible to realize medical diagnostics.

The most used methods for the study of microelectrical signals are those that make use of Fourier Transform, but this ones have certain limitations, e. g. The fact that are only appropriated for stationary signals, which means that are not adapted in the signal analysis with transitory components in time, such as microelectrical signals.

Recently, time-scale methods (based on the Wavelet Transform) were proposed in an effort to superate the limitations of the traditionals time-frequency based ones. This kind of methods act as a math microscope that can be used to observ diferent components by only adjusting the wavelet focus [12].

This allows component discover of short duration in a signal. Between this methods are the generalizations of the Wavelet Transform, the banks or Wavelets paquets (WP) that allows a better adapted analysis of a signal.

Wavelet Transform actually is beeing used in an important manner in several medical applications [1], besides that new techniques that allows an adecuation in front of several applications cases are continuously introduced. Inside medical applications where Wavelet Transform is used as analysis technique, are:

- Echocardiogram generated data compression.
- Magnetic resonances.
- Electrocardiograms.
- Others.

The work is organized in the following way. Section 2 presents the math tools used to realize the digital processing of the signal of the ECG, section 3 shows the filter design used in the noise elimination from the signal to study, section 4 shows the results obtained in real time, and finally on section 5 are located the accomplished conclusions from results shown during work development.

2 Wavelet Transfrom (WT)

Wavelet theory provides a unified framework for a number of techniques which had been developed independently for various signal processing applications. For example, multiresolution: used in computer vision, subband coding: developed for speech and image compression, and wavelets series expansion, developed in applied mathematics, have been recently recognized as different views of a single theory [12]. In particular, the Wavelet Transform (WT) is of interest for the analysis of non-stationary signals, because it provides an alternative to the classical Short-Time

Fourier Transform (STFT). The basic difference is as follows. In contrast to the STFT, which uses a single analysis window, the WT uses short windows at high frequencies and long windows at low frequencies, as one is in the figure 3.

2.1 What Is a Wavelet?

The term Wavelet means little wave. In the most general context, a wavelet is a function with special properties and that satisfies the main (time domain) conditions:

1. it has a small concentrated burst of finite energy in the time domain; and
2. it exhibits some oscillation in time.

In addition a wavelet have a limited duration and average value equal to zero, it is possible to be seen in figure 2.

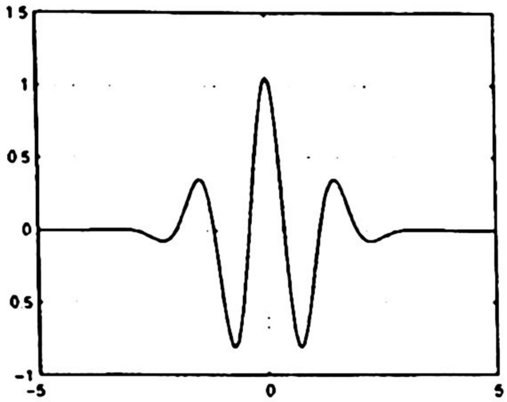

Fig. 2. Example of Wavelet.

2.2 Continuous Wavelet Transform

When a function *f(t)* is scaled:

$$f(t) \rightarrow f(at);\ \text{donde}\ a > 0$$

for the constant a > 1 the function is contracted, and expanded if a < 1, using this basic idea of calculus, next the formal definition of the *Wavelet Continuous Transform* is showed.

Definition 1

$$CWT_f(\tau; \alpha) = \frac{1}{\sqrt{\alpha}} \int f(t)\psi(\frac{t-\tau}{\alpha})dt \qquad (1)$$

In this part a function $\psi(\tau,\alpha)$ is generated, this function depends of the parameters τ and α, where both are used to transfer and to climb respectively.
Changing t by αt in (1), yields

$$CWT_f(\tau,\alpha) = \sqrt{\alpha}\int f(\alpha t)\psi(t - \frac{\tau}{\alpha})dt \quad (2)$$

The interpretation of (2) is that as the scale grows, an increasingly contracted version of the signal is seen through a constant length filter. From (1) and (2) is possible to be concluded that the Wavelet Transform is the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet ψ. Multiplying each coefficient by the correct scaled and shifted wavelet we obtain wavelets that compose the original signal. The process implied in the Transformed Wavelet is in figure 3.

It's important to understand that the scale is related to the size of the signal, while resolution is linked to the amount of detail present in the signal.

For many signals, the low-frequency content is the most important part, like EKG's. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance.

In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale and high-frequency components.

2.3 Discrete Wavelet Transform (DWT)

In general, discrete wavelet transforms are generated by samplings (in the time-scale plane) of a corresponding continuous wavelet transform. Such a discrete wavelet transform is specified by the choice of items:

1. a time-scale sampling set(a countable set of points), and

2. an analyzing wavelet, in this case was used the Daubechies wavelet.

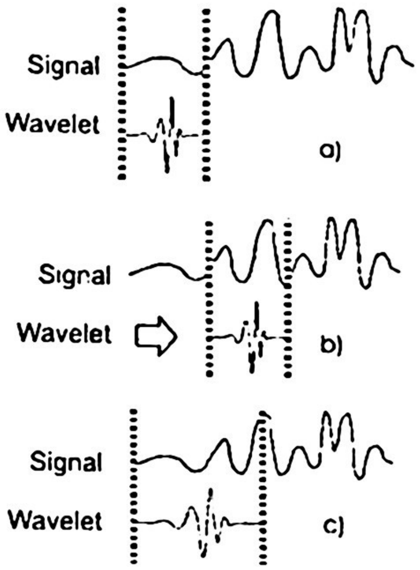

Fig. 3. Wavelet Transform a) Contraction $\alpha > 1$ b) Shifting with parameter τ c) expansion $\alpha < 1$.

Daubechies Wavelet. This family includes the Haar wavelet, written db1, the simplest wavelet imaginable and certainly the earliest. The names of the Daubechies family wavelets are written *db*N, where N is the order, and *db* the "surname" of the wavelet. In (3) one can see the definition of the family.

$$\psi = 2^{j/2}\varphi(2^j x - k) \quad j, k \epsilon Z \tag{3}$$

In (3), 2^j is the scaling factor and *k* the function's localization or the shifting factor; figure 4 is the graphic representation of the Daubechies wavelet.

In the discrete time case, two methods broadly used in the digital implementation were developed, these methods are:

- Subband coding.
- Pyramidal coding or multiresolution signal analisys.

2.4 Subband Codding

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. And for this reason the Subband coding schema choose scales and positions based on powers of two – so called dyadic scales and positions–.

An efficient way to implement this scheme using filters was developed in 1988 by Mallat [13]. The Mallat algorithm is in fact a classical scheme known in the signal processing community as a two channel subband coder. This filtering algorithm yields a fast wavelet transform.

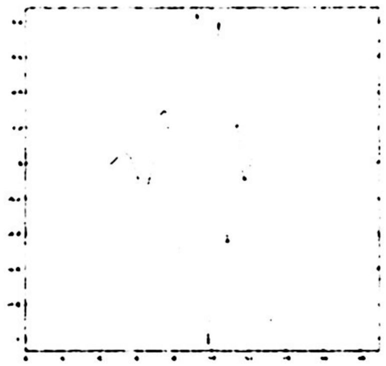

Fig. 4. Example of Daubechies Wavelet

The filtering process, at its most basic level, is showed in the figure 5. The original signal, S, passes through two complementary filters and emerges as two signals A y D. Unfortunately, if we actually perform this operation on a real digital signal, we wind up with twice as much data as we started with.

However, exists a more subtle way to perform the decomposition using wavelets. The Downsamplig allows keep only one point out of two to get the complete information. So are produce two sequences called cA and cD figure 6.

Example. To gain a better appreciation of this process, in the figure 7 our signal will be a pure sinusoid with highfrequency noise added to it, by means of the filtering process with downsampling an approach the natural form of the signal and the components in high frequency (noise) are observed as well as the reduction in the amount of data.

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the Wavelet Decomposition Tree showed in the figure 8.

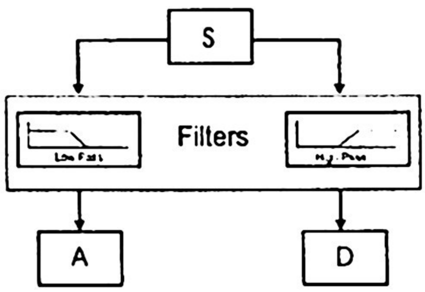

Fig. 5. Filtering Process.

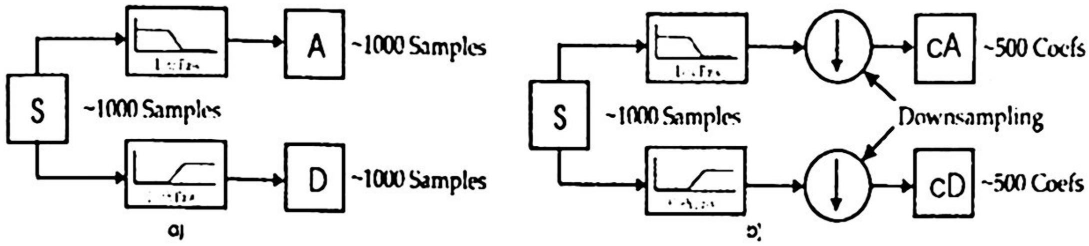

Fig. 6. a) Process without downsampling b) Process which includes downsampling.

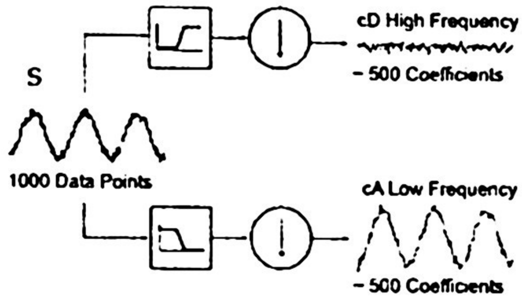

Fig. 7. Example of filtering process with downsampling.

2.5 Pyramidal Codding

This scheme was introduced by Burt and Adelson [15] and was recognized by the wavelet community to have a strong connection to multiresolution analysis, It consists of deriving a low-resolution version of the original, then predicting the original based on the coarse version, and finally taking the difference between the original and the prediction (figure 9). At the reconstruction, the prediction is added back to the difference, guaranteeing perfect reconstruction.

Obviously, the scheme can be iterated, decomposing the coarse version repeatedly, to obtain a coarse version at level J plus J detailed versions.

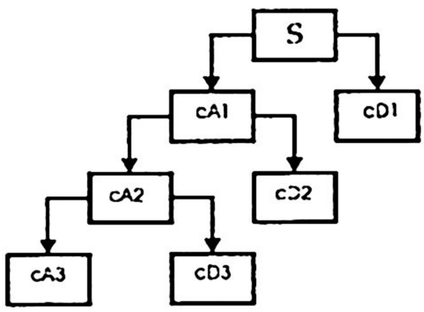

Fig. 8. Wavelet Decomposition Tree.

3 Filters Design

The processing of the ECG signals, was made in two steps, first of them consisted in filtrate stage with the intention of eliminating the possible presence of noise in the signal. The later stage consisted of applying the Transformed Discreet Wavelet to the filtered signal using the Tree of Wavelet Decomposition like analysis scheme, wavelet of analysis was the wavelet of Daubechies 10.

For the case of the signal of an Electrocardiogram, the rank of frequencies in where is the information of importance for its study is located between 1 and 100 Hz.

It is so the designed filter is a low pass Butterworth with cut frequency of 100 Hertz, in the equation (4) is observed the function of transference in s of the filter, in addition in the equation (5) its corresponding function of transference in z can be seen.

$$H(s) = \frac{248050000}{s^3 + 1256.6s^2 + 789570s + 248050000} \tag{4}$$

$$H(z) = \frac{0.17843z^3 + 0.53529z^2 + 0.53529z + 0.17843}{z^3 + 0.084523z^2 + 0.33522z + 0.0076958} \tag{5}$$

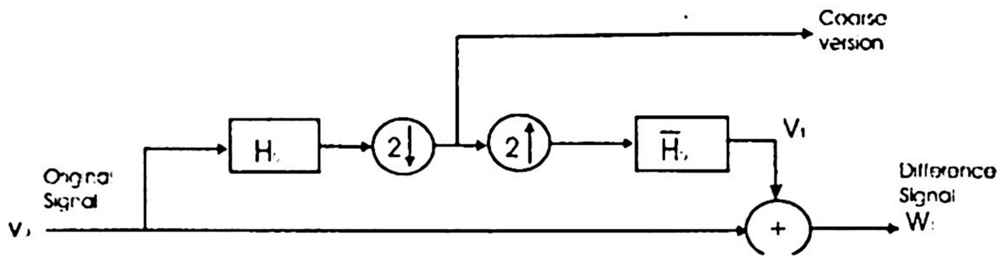

Fig. 9. Pyramid Scheme involving a coarse lowpass approximation and a difference between the coarse approximation and the original.

Finally the frequency response by Bodes Diagram of the filter is observed in figure 10. This filter was designed with commands that MATLAB has for that purpose. The used code is the following one:

```
% -- Analog Filter
[NumB,DenB] = butter(3,2*pi*[100],'s');
Bode(NumB,DenB);
% -- Digital Filter
Fs = 300; % -- Sampling frequency
[NumBd,DenBd] = bilinear(NumB,DenB,Fs);
```

4 Experimental results

For the real time implementation of this algorithms was used a DSP of the family of TMS320C67x devices [14], which permitted to process the data of an ECG that previously was obtained from the PhysioNet's network database[3].

The test results made to the filter with the signal of an Electrocardiogram to which has added him noise, is in figure 11.

For the Analysis schema was determined by empirical tests made in simulation to arrive at a decomposition level equal to four (4); the electrocardiograms are produced by the cardiac synchronization mechanism figure 1, that is tried to be located in this process.

The final result produced by the analysis schema is showed in figure 12, which consists in the ECG signal and the last two branches of decomposition tree. The figure 12.a corresponds to the signal previously filtered of the ECG; the figure 12.b talks about to the approach of this signal to a level 4, in this figure can be observed which is the natural shape of the signal, the part corresponding to the low frequencies (in great scales).

On the other hand the figure 11.c corresponds to the details of the signal (also at a level 4), information in high frequencies, in this part are forms of the signal that are not appreciable at simple view (in short scales).

5 Conclusions

The digital signal processing is a scientific field that can be explored from different perspectives, in this article has been presented a modern technology of digital processing used indifferently in images and signals. Also the algorithm of the Transformed Wavelet has been implemented on a DSP TMS320C6711 for the processing of the signal of an Electrocardiogram.

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[3] www.physionet.org

When taking advantage of the multiresolution capacity of this transformed was extracted information of the signal that can be of utility in other applications.

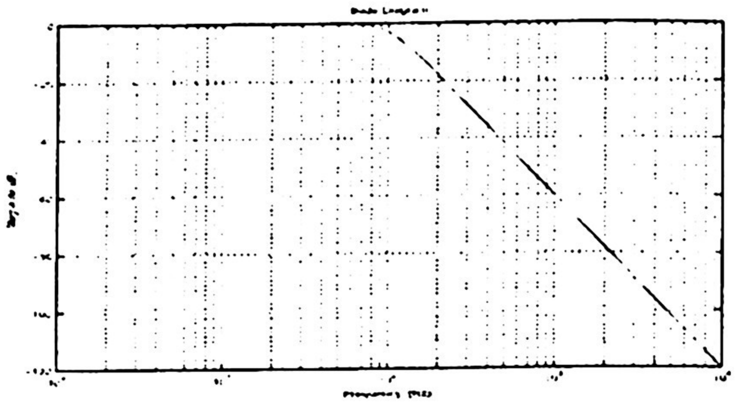

Fig. 10. Bode's diagram for low pass Butterworth filter, with cut frequency w_c = 100 Hz.

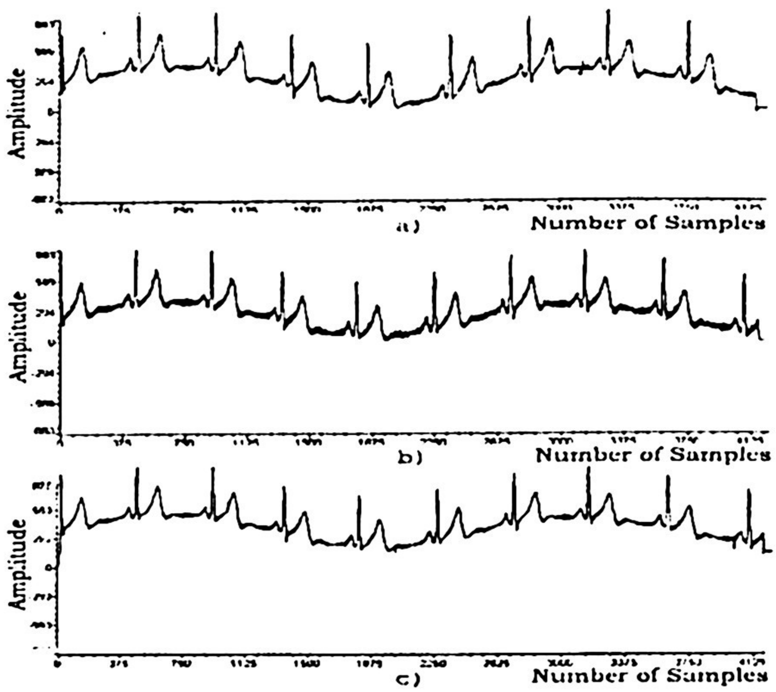

Fig. 11. a) ECG signal, b) ECG signal with noise, c) ECG signal filtered with the Buttertworth low pass filter.

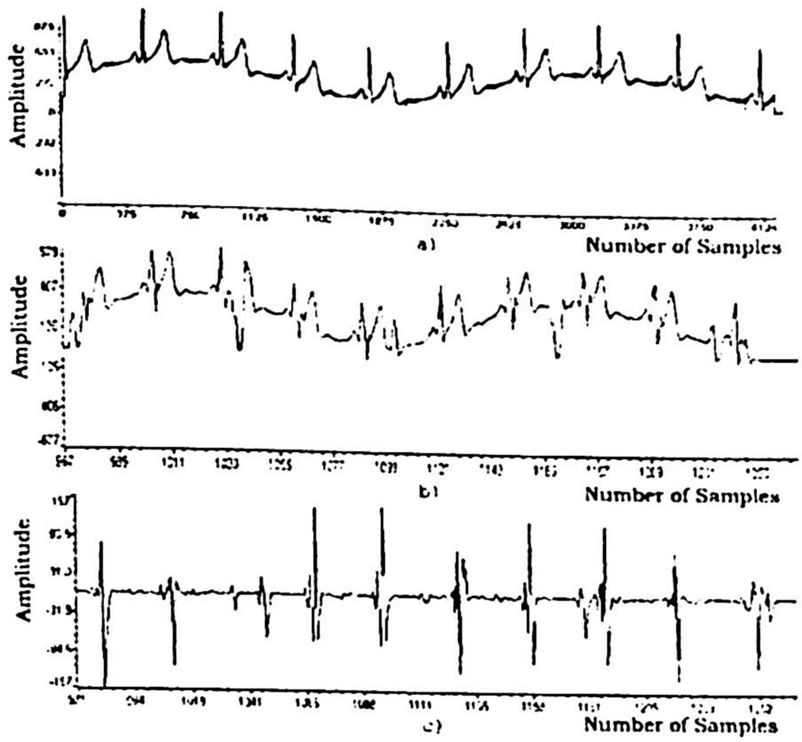

Fig. 12. a) ECG filtered signal, b) Approach of the ECG signal to a level 4 with the Wavelet of Daubechies 10, c) Derivate at a level 4.

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