A NEW METHOD FOR ICG CHARACTERISTIC POINT DETECTION

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Abstract: Impedance Cardiography is a cost-effective, non-invasive technique particularly useful in measuring cardiac functions. It evaluates systolic time intervals and stroke volume measuring thorax bioimpedance. In this paper, adopting the time-frequency analysis method, a new design has been developed to study the first derivative of impedance cardiography signal. The application of parallel wavelet filter banks has been investigated and a new method for ICG signal characteristic point detection has been developed. Test results show the improvement of the method in sensitivity and the feasibility of an easy implementation by design tools. Moreover, the algorithm noise immunity has been investigated.

1 INTRODUCTION

Impedance Cardiography (ICG) is a technique to study cardiac functions through measurements of the thorax electrical impedance. It has been widely adopted because it is noninvasive, easy to use and suitable for long-term and continuous monitoring of hemodynamic function (Jensen, 1995). Moreover, the ICG signal can be correlated with other significant signals (i.e. ECG) to generate alarm in critical situations.

In the past difficulties associated in ICG signal processing have been motion artefacts, muscle noise, pacemakers, etc. The most recent ICG devices have shown improved accuracy. Therefore the ICG has established a role in the management of outpatients with hypertension, heart failure and other chronic diseases (Treister, 2005). The use of ICG in therapeutic decision making regarding patients with critical diseases is primarily based on its ability to identify presence or absence of hemodynamic abnormalities. For these reasons many researches have been developed both to study physiological mechanisms for understanding origin and meaning of ICG signals and to improve effectiveness and applicability of ICG diagnostic test adopting advanced signal processing techniques (Wang, 1995).

Many efforts have been done to implement automatic detection of reference points in biological signal. However, existing peak detection algorithms are difficult to automate for generic use because either they rely on a number of parameters that need to be customized for a particular application of the algorithm or they use reference informations that is highly specialized for a particular application.

Most of the proposed methods make use of filtering technique (band pass filtering and temporal filtering) (Leski, 1992), (Pan, 1984), or adaptive thresholding technique (Sun, 1992), (Suppappola, 1994). All the previous techniques exhibit limitations when real signal are adopted (Sun, 2005). In fact, the first drawback of filtering-based approach is that frequency variations in the signal under test (due to different causes such as, for instance, cardiac frequency changes) may adversely affect the method performance. For instance, the frequency band of some biological signal, such as ECG, differs for different subjects and can change for the same subject due to particular events. The second problem in the filter based algorithms is the frequency band overlapping of noise and some biological signals. Therefore, the choice of a suitable bandwidth is a trade off between noise and high frequency details while the duration of the sliding window is a trade off between false and missed detections.

Whereas, the main problem of the thresholding techniques is their sensitivity to baseline variations and signal intensity. This high noise sensitivity can

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be a problem for some types of signals having low signal to noise (S/N) ratio.

An extensive overview of various algorithms for peak detection in ECG signals can be found in (Kohler, 2002) which includes approaches based on neural networks, adaptative filters, Hidden Markov models and Hilbert transform, too.

The purpose of this paper is to introduce an improved signal processing technique able to provide an easy implementation in design tools. It adopts the wavelet transform for ICG waveform characteristic point detection. Moreover, for parallel computing and for implementation by design tool, parallel filter banks have used in the adopted technique. Experimental results show the method validity and its high sensitivity parameter. In fact, sensitivity reliable results with minimum interferences from noise and artifact have been obtained.

2 ICG TECHNIQUE

Impedance cardiography is the study of cardiac function by means of thorax electrical impedance measurements. High frequency (20-100KHz), low intensity current (1-5mA rms) is injected through the thorax by some electrodes and the impedance change is sensed by measuring a voltage across other electrodes. No risk of physiological effects have been found because various tissues of human body are not excitable at this frequency and at this low current level (Patterson, 1989). The impedance variation can be used for diagnostic information and for the stroke volume (SV) estimation by using blood flow appropriate model. The term SV indicates the amount of blood pumped by the heart left ventricle in one contraction.

Figure 1 shows a typical impedance waveform obtained from electrodes in which the characteristic points are indicated.

Pulsating blood flow through the thoracic aorta causes shifts in the thoracic impedance as a function of changes in blood volume. This oscillating component of the total thoracic impedance can be expressed as its derivative (dZ/dt). Measurements of the changes in the thoracic impedance (dZ/dt waveform) during the cardiac cycle are used to calculate SV. This can be done in several ways (Kubicek, 1974), (Sramek, 1982), (Bernstein, 1986). Generally all the equations take into account position and value of C-point related to B-point and X-point.

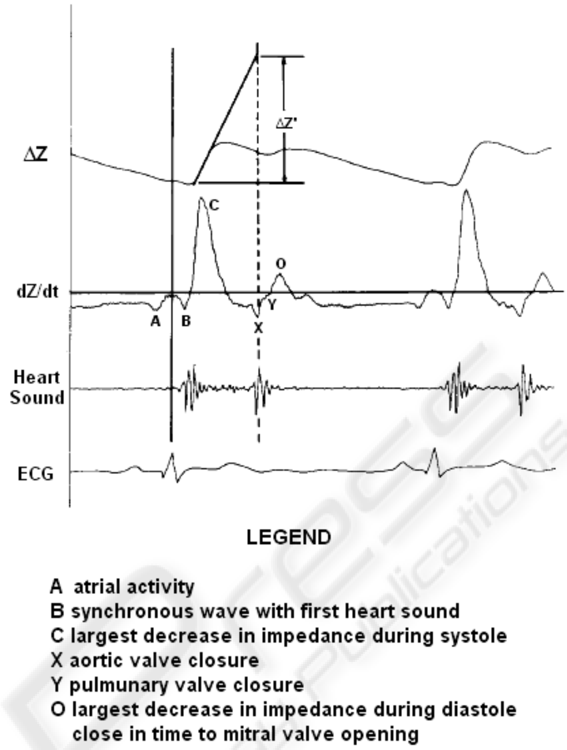

Figure 1: Typical impedance waveforms from the thorax of a human subject.

3 WAVELET TRANSFORM

Wavelet transform provides temporal and spectral information simultaneously, so it is suited for determining characteristic points of non stationary and fast transient signals, such as ICG signals. This feature is suitable to distinguish the ICG signal from noise and interferences.

The wavelet method decomposes a time variant signal into several components having various scales or resolutions. A suitable time and frequency limited wavelet is chosen as the "*mother*". Scaling and shifting the mother wavelet, a family of functions called "*daughter*" wavelet is generated. For small value of the scale factor, the wavelet is constructed in the time domain and gives information about fine details of signals. Therefore a global view of the signal is obtained by the scale factor large value. The wavelet transform of a time signal at any scale is the convolution of the signal and a time-scaled daughter wavelet.

There are essentially two types of wavelet decompositions: the redundant ones (continuous wavelet transform (CWT)), and the nonredundant ones (orthogonal, semi-orthogonal, or biorthogonal wavelet bases) (Unser, 1996). The first type is preferable for feature extraction because it provides for a description that is truly shift-invariant. The second type is preferable for data reduction, or when the orthogonality of the representation is an important factor. However, the choice between these types of decompositions has to take into account computational considerations, too. A decomposition in terms of wavelet bases using Mallat fast algorithm is typically orders of magnitude faster than a redundant analysis, even if the fastest available algorithms are used (Rioul, 1992), (Unser, 1994).

As the aim of this paper is the implementation of a fast parallelized algorithm, a nonredundant wavelet decompositions has been chosen. To determine the best wavelet function to be used, the ICG signal properties have been studied, such as the shape and the time localization of events. Temporal signal shape is an important parameter, so orthogonal wavelets are unsuitable to be used. In fact they are unable to provide symmetry in the time domain and they introduce non-linear phase shift. The signal shape is maintained if the phase shift is linear. Thus the wavelet to be adopted should be a symmetrical function (Dinh, 2001). Spline wavelets have properties satisfying the previous requirements. The higher order of the Spline wavelet results in the sharper frequency response of the equivalent FIR filter, that is always desirable. But the FIR equivalent filter of the higher order Spline wavelet has longer coefficient series leading to more computational time consumption. Therefore, the cubic spline wavelet is assumed to have an order high enough for this application.

Traditional wavelet theory (Cohen, 1996) considers a decomposition algorithm with an iterative structure (in particular an asymmetrical tree structure) that does not efficiently merge with the novel computational techniques, such as parallel processing, concurrent programming and design tools. In this study the a' trous and the Mallat algorithms for parallelized filter bank design have been used (Yang Li, 2005). The algorithm generates a set of parallelized perfect-reconstruction filter banks for an arbitrary number of end-nodes of a traditional tree structure (Koh, 2003).

4 PEAK DETECTOR METHOD

The method presented in this section processes the first derivate of the impedance signal and allows to determine the time domain absolute position of C Peak (figure 1).

ICG signal (figure 2) is sampled at a frequency of 250 Hz. The input hardware stores sequentially all the sample in a high speed frame which is then processed in real time by the system.

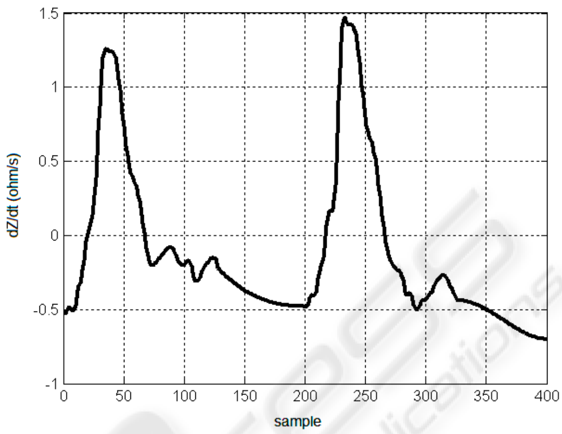

Figure 2: ICG signal.

In figure 3 the algorithm model is represented. The starting signal is indicated with 'ICG Signal', while the results with:

- 'C_point_Number' that evaluates the number of peaks presents in the processed frame;
- C_Indices' whose aim is the determination of the position of samples which corresponds to peaks

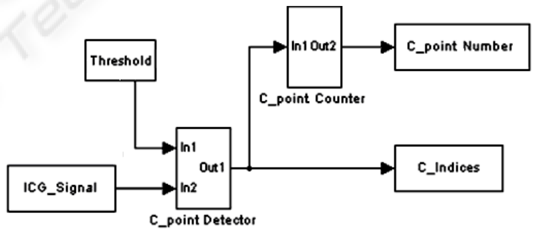

Figure 3: Algorithm model realized with the software tool MATLAB Simulink®.

The 'C_point Detector' subsytem (figure 4) determines the ICG signal peaks.

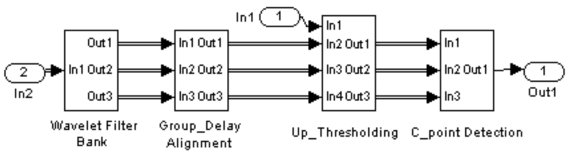

Figure 4: 'C point detector' subsystem model.

It uses an evolution of the classical Mallat decomposition, called a' trous algorithm. The a' trous algorithm for non-ortogonal wavelet uses a filter bank structure as the Mallat algorithm (Mallat, 1989), but differs only for the filters design. It has been demonstrated that after the application of wavelet filters for j-times, the precision of a' trous algorithm is 2j time higher then the Mallat algorithm (Table 1) (Shensa, 1992).

Table 1: Precision of Mallat algorithm and a' trous algorithm varying decomposition level

Algorithm	Precision level 1	Precision level 2	…	Precision level j
Mallat	1/512	1/256	…	2^j/1024
a' trous	1/1024	1/1024	…	1/1024

For the tree structure of the algorithm, the previous structure is not suitable for parallel computing and for implementation in design tools. To overcome this limit equivalent parallel filter banks have been used. As it is known, the output signal realignment is necessary only to put just the delay introduced by each filter (figure 5).

A cubic spline wavelet (wavelet 'bior3.3') has been chosen because it makes possible the perfect signal reconstruction (figure 6).

For ICG signal processing, six dyadic scales have been used to decompose the signal (figure 7).

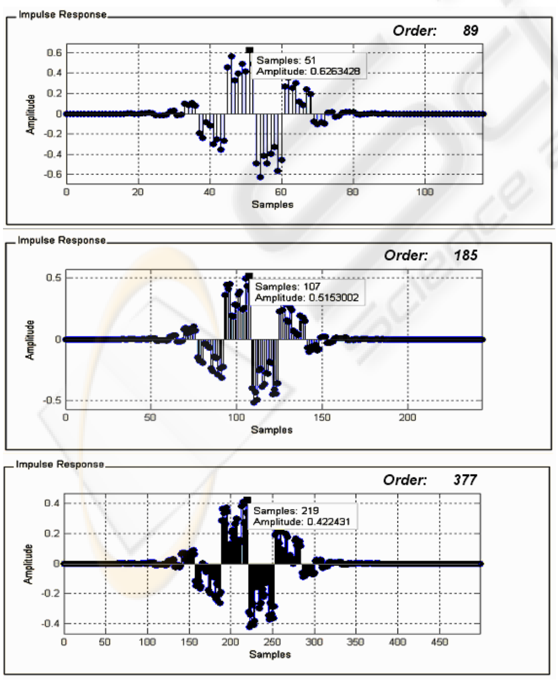

Figure 5: Pulse response of FIR filters equivalent to levels 4, 5, 6.

With a soft treesholding technique applied to level 1, 2, 3, the noise has been reduced and then the signal reconstructed in the time domain.

To localize characteristic points inside signal, detail levels 4, 5, 6 have been considered because they contain the highest number of C signal frequencies.

In respect to each singularity in ICG signal, a point of maximum value in detail coefficient signal is present. The proposed method searches local maximum points in the positive region of scale 4, scale 5 and scale 6 using a thresholding technique. Various tests have indicated the local maximum in the lower scale as the best points for the real signal peak localization

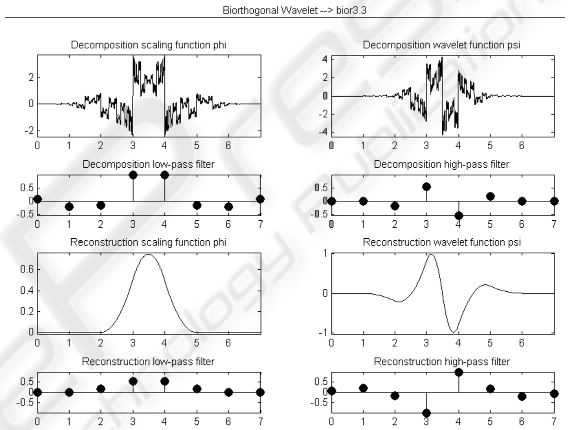

Figure 6: Wavelet 'bior3.3'.

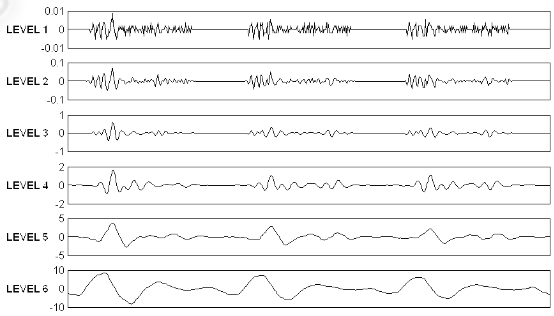

Figure 7: Decomposition of ICG signal over six scales.

5 RESULTS AND DISCUSSION

Real ICG signal (fig.8) has been tested with good results. Moreover the test has been repeated adding Gaussian noise with zero average and variable variance. In this situation the algorithm noise immunity has been evaluated.

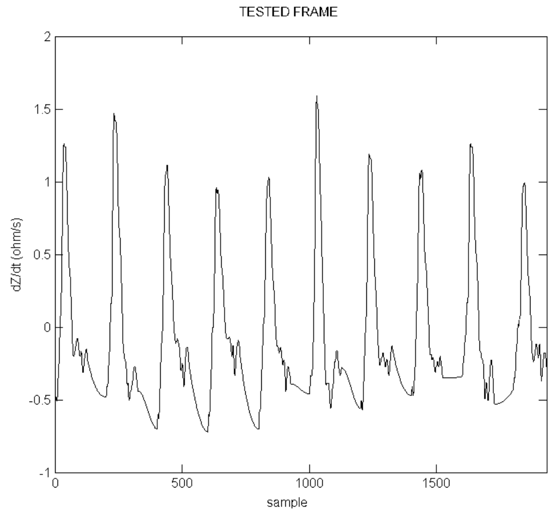

Figure 8: Frame tested.

The software detection algorithms for medical applications requires the evaluation of the detection performance according to ANSI/AAMI standard. Two parameters are used to evaluate algorithms:

Sensitivity:

$$Se = \frac{TP}{TP + FN} \quad (1)$$

Positive Prediction:

$$P = \frac{TP}{TP + Fp} \quad (2)$$

where:

- TP is the number of true positive detections;
- FN (the number of false negatives) is the number of C points present in the signal that the algorithm is not able to detect;
- FP (the number of false positives) is the number of C points detected by the algorithm but really not present in the signal.

Tested Frame presents C-peak value fluctuations in the range [1÷1.5Ω/s]. Other local maximum points are all in the negative region. Algorithm has individuated the 50% of the maximum value of the wavelet in each windowed segment of data as the optimal threshold value.

The obtained sensitivity parameter is very satisfactory and appears quite independent from noise (figure 9). Predictivity is fairly good but decreases as noise increases (figure 10).

Anyway it is to be noted that very heavy noise conditions have been chosen to test the algorithm noise immunity. An additional Gaussian noise signal with v=0.1$(\Omega/s)^2$ corrupts heavily the ICG signal; in particular the noise, besides changing the ICG signal shape, introduces many false peaks while cancels a minor number of true peaks.

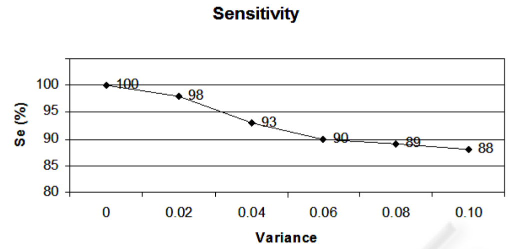

Figure 9: Sensitivity.

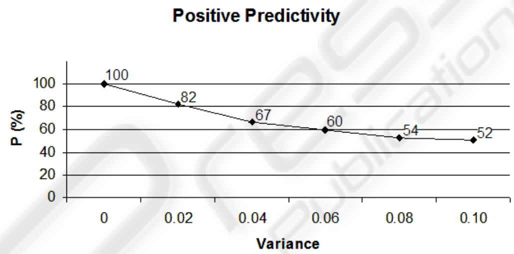

Figure 10: Positive Predictivity.

6 CONCLUSIONS

The real-time C-point detection algorithm presented in this paper has demonstrated to have high sensitivity.

The method computational time has been optimized adopting a parallel procedure to analyze the ICG signal. Therefore the realized procedure is suited to be implemented in real applications. Practical performance is to be improved for positive predictivity that appears to be sensible to noise level. Moreover, the absence of standard and validated ICG data bases, such as those used for ECG signals, makes the algorithm efficiency evaluation difficult and provides results poorly reproducible and comparable.

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