HEART BEAT DETECTION USING WAVELET TRANSFORM

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ABSTRACT

This paper proposes an algorithm based on the first Gaussian derivative wavelet transform, able to detect heart beats (QRS complex) in ambulatory electrocardiogram recordings. The use of wavelet transform increases noise robustness, since the combination of two wavelet scales reduces the possibility of false beat detection. We have planned to implement this algorithm in an FPGA, which will be placed in a portable device aiming at performing patient monitoring and alarm generation associated to risk events.

1. INTRODUCTION

The ECG analysis is widely used to diagnose cardiac diseases, which are one of the main causes of mortality worldwide. The development of more precise and robust methods for automatic analysis of ECG signal has become more and more important, as more clinically useful information can be obtained from this data, especially in long-term ambulatory ECG recordings [2].

In this context, this work proposes an algorithm of real-time beat detection and heart rate calculation, using only two scales of filtering based on wavelet transform. This algorithm has been conceived for latter implementation in an FPGA in order to be integrated in a portable device of ambulatory ECG.

2. MATERIALS AND METHODS

2.1. WAVELET TRANSFORM

The wavelet transform represents a signal in the time-scale domain, where each scale is result of one band-pass filtering. The frequency bands depend on the value of the scale and the chosen wavelet function. The one used in this work is the first derivative of the gaussian function.

$$\psi(t) = \frac{1}{\sqrt{2\pi}}\left(1-t^2\right) e^{\left(-\frac{t^2}{2}\right)} \qquad (1)$$

where t is the time and $\psi(t)$ is the mother wavelet with zero mean. From the mother wavelet, the wavelets scales become [6]

$$\overline{\psi}_a(t) = \frac{1}{\sqrt{a}}\psi^*\left(\frac{-t}{a}\right) \qquad (2),$$

where $\overline{\psi}_a(t)$ represents the dilatation of the wavelet for a scale factor a, being a>0. Thus, the wavelet transform is

$$Wf(a,t) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-\tau}{a}\right)dt \qquad (3),$$

that represents the convolution of an $f(t)$ signal with the wavelet function in the a scale. For small values of a, the wavelet transform becomes more sensitive for high frequency components of the signal [6], while for large values of 'a' the components of low frequency are enhanced after the transformation.

In view of the behavior of the first derivative of the gaussian function (see equation (1)), it is expected that the QRS complexes can be seen after the filtering like pairs of maximums and, where the maximum point of beat (the QRS peak) corresponds to the crossing at zero.

2.2 DETECTION ALGORITHM

The detection algorithm, written in C language, analyzes the signal processed by the wavelet transform in two different scales (a = 2^1 and 2^3), where the QRS peak detection is done first in each scale separately, and then the individual results are combined using a intersection strategy of the detections in each scale.

The algorithm starts by performing an important stage of parameter initialization, where it searches for the five highest positive and negative peaks in the first six seconds of the signal in each scale in order to estimate the thresholds. Then, 30% of the average of the selected peaks is used as the initial positive and negative thresholds.

In the next stage, the algorithm analyzes the signal in blocks of 1000 samples, looking for those samples that exceed the threshold, saving in memory only the minimum or maximum points. When the distance betwen pairs of maximums and minimums are less than 150 ms, they are considered as beats. All this procedure is carried out independently for each scale of filtering, and only later it is done the intersection between the scales to confirm the detections, analyzing the distance between the just detected beat from one scale and the last beat detected in the other scale. If that distance is less than 300 ms, it is concluded that there was a concordance in the results.

The thresholds are constantly brought up to date in order to adapt to the fluctuations of ECG signal. In this way, for each five maximums detected in a scale, their

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average is calculated, and this value is multiplied by a constant, originating a new value of detection threshold. The constants used are: 34% for positive thresholds and 30% for negative thresholds. It is important to observe that the use of different constants is one originality of this work in relation to [1,2,3,4,5,6], which significantly increased system performance.

Moreover, it has also been added to the thresholds an indicative factor of the level of noise of the signal, which corresponds to 10% of the average of the positive and negative samples between consecutive beats. Thus, the larger is the noise that exists in the signal, the greater will be the positive and negative averages. In this way, the detection thresholds are less sensitive to noise, preventing, consequently, incorrect detections.

In some situations, the detection threshold can be too high or the signal level may fall too fast, resulting in false negative beats. For this reason, when 200% of the average distance betwen two beats are processed without a new detection, a new search is done in 2^3 scale (of greater energy) from the last detected beat, with the threshold reduced by half. It is important to remark that all constants involved have been empirically determined aiming at improving performance.

2.3. FPGA

The FPGA (*Field Programmable Gate Array*) is an integrated circuit configurable by software and used to implement digital logic circuits, like processors, interfaces, controllers and decoders. Basically, it consists of one strong condensed arrangement of identical blocks of small circuits, composed by some logical gates and flip-flops, with some interface signals. The connections between the blocks are easily programmable using a simple protocol [8].

Once the capacity of those devices grows, the number of possible use also grows, making the FPGA implementation more complex. To solve this problem, the FPGAs are programmed by hardware description language (HDL), where the most important one is the VHDL (Very High Design Language). This language has had a fast growth since its creation and has been used for many engineers in the world to implement different kinds of logic circuits.

In this context, due to the great availability of FPGA kits in the market and its low cost and high performance in signal processing applications, we have decided to implement our beat detection algorithm in such device. To attend to the specifications of memory, our choice was the *Spartan-3 (XC3S200)* model, from *Xilinx*, which has an internal memory divided in two columns, each one with six blocks of 16 Kbits [7], only two blocks of 1K x 16bit were needed, since the analysis requires memory space for 1000 samples for each wavelet scale.

3. RESULTS

For the validation of the beat detection algorithm written in C language, the MIT-BIH database was used. This database is composed by recordings of 30 minutes each, containing two ECG channels, sampled at a rate of 360 Hz. All recordings have annotations done by cardiologists that located and classified all the beats. Eight recordings were selected to compose our test set. The detection results are shown in Table 1, where *Se* indicates the sensibility (percentage of true beats detected) and *PP*, the positive predictive value (probability of the detected beat really exist).

Archive	Se	PP
100	99.87 %	100.00 %
101	99.89 %	99.95 %
102	100.00 %	100.00 %
103	100.00 %	100.00 %
104	99.33 %	99.73 %
105	98.44 %	97.35 %
106	99.31 %	100.00 %
107	99.72 %	99.12 %
Total	**99.54 %**	**99.45 %**

Table 1: Results obtained in some archives tested.

4. CONCLUSIONS

In this work, it was shown an algorithm for QRS complex detection that uses two wavelet transform scales. It presents some advantages in relation to other systems [2,3,4,5,6] since it uses only two wavelet scales, reducing the computational cost and presenting a comparable performance to other similar systems [3].

This system is being translated to the VHDL language for FPGA implementation in view of its utilization in a portable device for ambulatorial ECG signal monitoring.

5. REFERENCES

[1] P. Hamilton, "Open Source ECG Analysis", In Computers in Cardiology, vol. 29, Somerville, USA, pag. 101 - 104, 2002.

[2] J.P. Martinez, R. Almeida, S. Olmos, A.P. Rocha e P. Laguna, "A wavelet-besed ECG delineator: Evaluation on Standart Databases", IEEE Transactions on Biomedical Engineering, vol. 51, nº 4, 2004.

[3] J.S. Sahambi, S.N. Tandon, R.K.P. Bhatt, "Using Wavelet transforms for ECG Characterization", IEEE Engineering in Medicine and Biology, 0739-5175/97, 1997.

[4] R.V. Andreão, B. Dorizzi, P.C. Cortes, J.C.M. Mota, "Efficient ECG multi-level wavelet classification through neural network dimensionality reduction", In Proc. IEEE Workshop on Neural Network for Signal Processing, Martigny, Suisse, pp. 395-404, 2002.

[5] C. Li, C. Zheng and C. Tai, "Detection of ECG characteristic points using wavelet transforms", IEEE Transactions on Biomedical Engineering, vol. 42, nº 1, pag. 21 - 27, 1995.

[6] S. Mallat, "A Wavelet Tour of Signal Processing", Academic Press, 1998.

[7] http://www.xilinx.com/bvdocs/appnotes/xapp463.pdf em 01/06/06.

[8] http://www.mzeditora.com.br/artigos/fpga_fam.htm em 01/06/06.