Lightweight signal analysis for R-Peak detection

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Abstract. The electrocardiogram signal is considered very important in clinical practice in order to assess the cardiac status of patients. In this paper, a computer aided detection system for R peak localizations is indicated. A four stage architecture is implemented which is able to differentiate R waves from peaked T and P waves with an high degree of accuracy. The performance of the algorithm is tested using ECG waveform records from the MIT-BITH Arrhythmia database. A sensitivity of 96 % and a positive prediction of 99% are achieved.

Keywords: ECG, QRS, Hilbert transform, wavelet transform, computer aided detection (CADe), R-Peak

1 Introduction

Signal processing technique has a large number of uses in medical environments where it is a difficult task the differentiation between real pathological signs and false alarms because of noise and imperfect signals [1]. Modern signal processing techniques can improve existing investigation processes for diagnostic, treatment evaluation, and research applications even in presence of corrupted and weak signals. Therefore, Computer-aided detection (CADe) systems have become one of the major research subjects in medical signal and imaging [2-5]. The fusion of technology and medical science thus produces significant innovations that greatly contribute to human health and to people quality of life. In particular CADe systems are important in detecting abnormalities related to heart function in presence of signals corrupted by noise, artifacts and so on [6]. The electrical activity of the heart is represented by the Electrocardiogram (ECG) signal which shows the regular contraction and relaxation of heart muscle. It is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. Therefore its analysis is adopted to detect heart abnormalities. The ECG is a non-invasive technique whose useful information are indicated by the ECG shape such as intervals and amplitudes of the signal [7]. Due to the non-stationary behaviour of biological signals, disease indicators may be present all the time or may occur at random during certain irregular intervals of the day. Therefore, the

D. Impedovo and G. Pirlo (Eds.), Workshop on Artificial Intelligence with Application in Health, Bari, Italy, November 14, 2017.

study of ECG pattern by analysts may have to be carried out over several hours with an high probability of missing vital information. The implementation of a procedure for the detection of ECG key points (such as the P wave, the QRS complex and the T wave) is a difficult task because of the time varying behaviour of human body and consequently all processing methods should change their state during measurement. Moreover, noise contaminations, due to baseline drifts changes, motion artefacts and muscular noise, is frequently encountered [7, 8]. The QRS detection is one of the most important task in ECG signal analysis systems. In fact after the QRS identification, the heart rate may be calculated and other parameters can be examined to avoid and to prevent serious pathologies such as ischemia.

In this paper an improved signal processing technique able to detect R peaks in ECG signals for heart rate evaluation, is presented. Its variability is linked to various disorders such as obstructive sleep apnea syndrome, congestive heart failure [8, 9]. The implemented method adopts the Hilbert transform envelope and a thresholding technique for the detection of zones inside the ECG signal which could contain a peak. Experimental results show the method validity and its high sensitivity and predictivity parameters. In section II a briefly description of ECG technique is presented while section III describes the adopted methods. Section IV makes an in depth presentation of the implemented CADe system and in section V the system performance are evaluated. Moreover, some conclusions are drawn out.

2 ECG technique

ECG signal is the representation of the heart muscle electrical activity over time. It supplies physicians with useful information and represents an important part of the cardiac patient assessment.

A single normal cycle of ECG represents successive atrial depolarization/repolarization and ventricular depolarization/repolarization which occur in every heartbeat. In fig.1 an example of the ECG shape is indicated [9].

The P wave is the first upward pulse of the ECG signal and is generated when the atria contract to pump blood into the ventricles. The PR interval, which is a short period where no electrical activity is seen, is due to a physiological delay; in fact the atrioventricular node slows the electrical depolarization before it proceeds to ventricles. The successive pulse, the QRS complex, is formed when ventricles contract to pump out blood. The next S-T segment represents the early stage of ventricular repolarization and under normal conditions is isoelectric (constant potential). A marked displacement of the S-T segment signifies coronary artery disease. The ventricular repolarization forms the T wave and the cardiac muscle is prepared for the next cycle of the ECG. Therefore, the Q-T interval reflects the total duration of ventricular systole. A long QT interval can be associated with heart failure, ischaemic heart disease, bradycardia, some electrolyte disorders (i.e. hypocalcaemia) and can be consequence of different drugs taking.

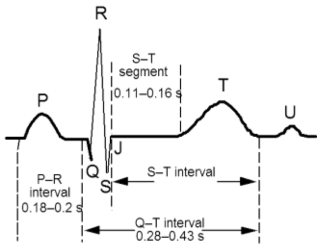

Fig. 1 ECG characteristic shape

3 Proposed Method

3.1 Hilbert transform

The Hilbert transform $x_H(t)$ of a real function x(t) is defined as [10]:

$$x_H(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} x(\tau)\frac{1}{t-\tau}d\tau = x(t) \times \frac{1}{\pi t} \quad (1)$$

Therefore, $x_H(t)$ is both a time dependent function and a linear function of x(t). In fact, it is obtained from x(t) applying the convolution with $(\pi t)^{-1}$. Equation (1) shows that $x_H(t)$ is obtained by filtering the signal x(t) through a linear time-invariant filter with impulse response equal to $(\pi t)^{-1}$. Because of the integrand has a singularity and the limits of integration are finite, the Hilbert transform is properly defined as the Cauchy principal value of the integral in (1), whenever this value exists.

Considering the frequency domain and applying the Fourier transform it results:

$$F\{x_H(t)\} = -j\ sgn\ F\{x(t)\} \quad (2)$$

where

$$sng\ F\{x(t)\} = \begin{cases} +1 & f > 0 \\ 0 & f = 0 \\ -1 & f < 0 \end{cases}$$

Therefore, the Hilbert transform shifts all positive frequency components by -90° and all negative frequency components by +90° while the amplitude of F[x(t)] remains constant. Thus it is found that: x(t) and $x_H(t)$ are orthogonal and $x_H(t)$ represents the harmonic conjugate of x(t). The function x(t) and its transform $x_H(t)$ are related to each other and they together create an analytic signal that is expressed as:

$$z(t) = x(t) + jx_H(t) \quad (3)$$

The envelope of z(t) is:

$$B(t) = \sqrt{x^2(t) + x_H^2(t)} \quad (4)$$

It is evident that B(t) and x(t) have common tangents and the same values in the points where $x_H(t)$ is zero. Therefore, B(t) have the same slope and magnitude of x(t) at its local maxima.

3.2 Wavelet transform

Wavelet transform is a suitable tool for studying non-stationary signals. In fact, both the property of time-frequency localization (which allows us to obtain a signal at a particular time and frequency or to extract features at various locations in space) and the multirate filtering option (which permits the differentiation of signals with different frequencies) make the wavelet transform an effective tool in signal processing analysis. It decomposes the signal into several components with various scales or resolutions. Therefore, it can identify useful information for R point detection and discard signal bands which provide scant contribution to the study [11].

Since wavelet functions are compact, wavelet coefficients only measure the variations around a small region of data array. This feature makes wavelet analysis particularly useful for signal processing; the "localized" nature of the wavelet transform allows us to pick out features in analyzed data with ease such as spikes (i.e. noise or discontinuities), discrete objects, edges of objects, and so forth. Moreover, wavelet coefficients at one location are not affected by coefficients at other locations in data under study. As the aim of this paper is the implementation of a fast algorithm, a non-redundant wavelet decomposition has been chosen. Moreover, as the temporal ECG shape is an important parameter, the wavelet to be adopted should be a symmetrical function to avoid the introduction of non-linear phase shift.

3.3 Block Diagram

The proposed system is composed of four stages (fig.2).

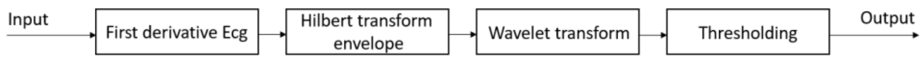

Fig.2 The block diagram of the implemented method

The first stage is the pre-processing phase in which the ECG signal is derived. This is done for preparing the signal for Hilbert envelope computation. The second stage performs the Hilbert transform envelope of the first derivative of ECG waveform. This envelope represents an enhancement of the signal that can be used for the peak detection [12] (fig.3,4).

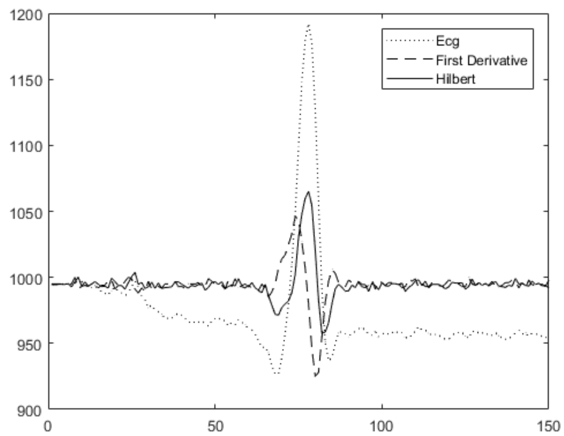

Fig.3 Details of processed signal at stage 1, 2

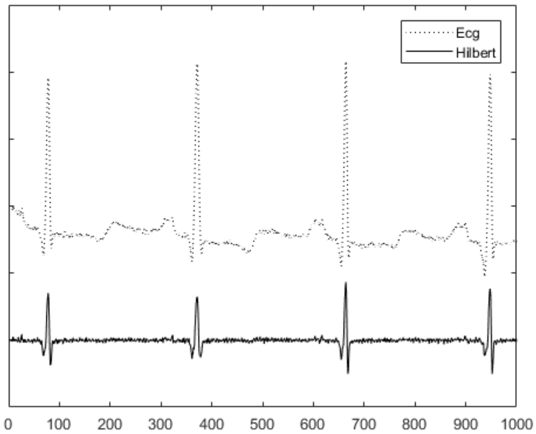

Fig.4 Overview of the signal at the output of stage 2 compared to the original signal

In order to guarantee an accurate detection of R peaks, a third stage is necessary. In this step, the method decomposes the output signal of the second stage into six dyadic scales (fig.5). After validation tests, wavelet bior 3.3 has been used. According to the power spectra of the input signal of the third stage, the larger contribute of the signal is located in scales 3 and 4. The implemented method adopts both an evolution of the classical Mallat decomposition, called a' trous algorithm and equivalent parallel filter banks. A hard threshold is adopted for singularity selection over the scales 3 and 4.

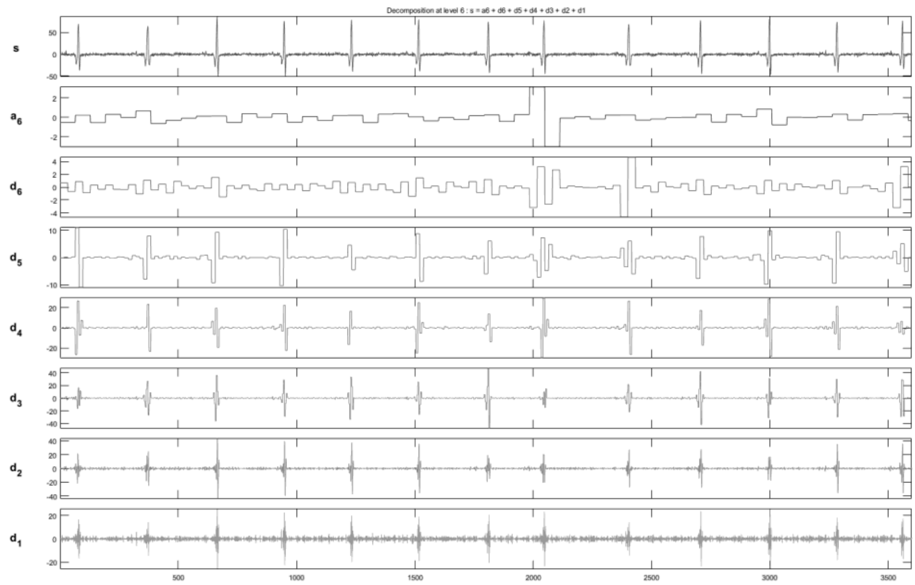

Fig.5 Decomposition of Hilbert signal over six dyadic scales

4 Simulation Results

For the performance evaluation of the method, sensitivity and positive prediction are taken into account. The Sensitivity (Se) is defined as the probability of detecting a R point when a R point exists really; the positive prediction (+P) represents the probability of detecting a R point among the detected ECG peaks. They are computed adopting the following expressions:

Sensitivity: $$Se = \frac{TP}{TP+FN} \quad (5)$$

Positive Prediction: $$^{+}P = \frac{TP}{TP+FP} \quad (6)$$

where

- TP (the number of true positives) is the number of correct identifications of R points present in the signal under test;
- FN (the number of false negatives) is the number of R points present in the signal that the algorithm is not able to detect;
- FP (the number of false positive) is the number of R points detected by the algorithm but actually in the signal.

The proposed algorithm is tested on the ECG signals taken from the first channel of the MIT-BIH arrhythmia database [13]

In fig.6 are shown the system performance related to the threshold value adopted in the last stage. The threshold value is a percentage of the peak maximum value in the dyadic scales.

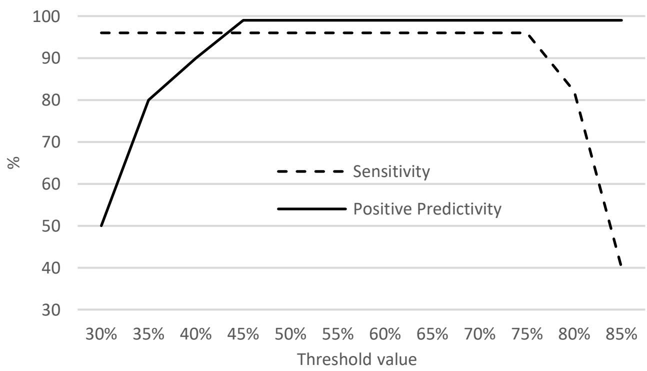

Fig.6 Se and P vs. threshold values

The algorithm gives Se and $^{+}$P parameters of about 96% and 99% for a threshold value in the range [45% ÷ 70%] of R* denoting with R* the R point average value in the related dyadic scales.

5 Conclusion

Real time ECG signal processing is an important diagnostic procedure for the monitoring of heart functional status. The proposed CADe system, makes the localization of R peaks possible even if noisy signals and peaked T and P waves are present. The Hilbert transform envelope and a multiscale analysis is performed for ECG enhancement and R points localization. The parallel behavior of the implemented method optimizes the procedure computational time and makes it suitable for a hardware implementation.

ACKNOWLEDGMENT

The work has been developed within the framework of Masvis's Internal Research Project, task titled: "Analisi di segnali mono e bidimensionali".

References

1. Rizzi M., D'Aloia M., Guaragnella C., Castagnolo B., Health Care Improvement: Comparative Analysis of Two CAD Systems in Mammographic Screening, IEEE Trans. Syst., Man, Cybern. A, Syst., Humans 42, 1385-1395 (2012)
2. Pirlo G., Diaz M., Ferrer M.A., Impedovo D., Occhionero F., Zurlo U., Early Diagnosis of Neurodegenerative Diseases by Handwritten Signature Analysis, LNCS 9281, 290-297 (2015)
3. Rizzi M., D'Aloia M., Computer Aided System for Breast Cancer Diagnosis, Biomed. Eng-App. Bas C. 26,1450033 (2014)
4. Impedovo D., Pirlo G., Mangini F.M., Barbuzzi D., Rollo A., Balestrucci A., Impedovo S., Sarcinella L., O'Reilly C., Plamondon R., Writing Generation Model for Health Care Neuromuscular System Investigation, Springer Int. Publishing, 137-148 (2014)
5. Rizzi M., D'Aloia M., Cice G, Computer aided evaluation (CAE) of morphologic changes in pigmented skin lesions, Lect. Notes Comput. Sc. (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 9281, 250-257 (2015)
6. Rizzi M., D'Aloia M., Castagnolo B., Semiconductor detectors and principles of radiation-matter interaction. Journal of Applied Sciences 10, 3141-3155 (2010)
7. Bohui Z., Yongsheng D., Kuangrong H, A novel automatic detection system for ECG arrhythmias using maximum margin clustering with immune evolutionary algorithm, Computational and Mathematical Methods in Medicine 2013, 453402 (2013)
8. Pentel T., ANS and heart rate variability in normal sleep and sleep disorders, Sleep Medicine 8, 44-45 (2007)
9. Rizzi M., D'Aloia M., Castagnolo B., ECG-QRS detection method adopting wavelet parallel filter banks, 7th WSEAS Int. Conf. on Wavelet Analysis & Multirate Systems (WAMUS'07), Arcachon (France), Oct. 13-15, 2007, pp.158-163
10. Kschischang F.R., The Hilbert Transform, Department of Electrical and Computer Engineering, University of Toronto, http://www.comm.toronto.edu/frank/papers/hilbert.pdf
11. Rizzi M., D'Aloia M., Castagnolo B., A New Method for ICG Characteristic Point Detection. 1st International Conference on Bio-inspired Systems and Signal Processing (BIOSIGNALS 2008), Funchal, Madeira (Portugal), 28-31 Jan., pp. 244- 249, (2008)
12. Wilson J.D., Govindan R.B., Hatton J.O., Lowery C.L, Preissl H., Integrated approach for fetal QRS detection, IEEE Trans. on Bio-Med. Eng., vol. 55, Sep. 2008, pp. 2190-7
13. MIT-BIH Arrhythmia Database https://www.physionet.org/physiobank/database/mitdb/