R-wave Detection Using Continuous Wavelet Modulus Maxima

I Romero Legarreta[1], PS Addison[1,2], N Grubb[4],
GR Clegg[3], CE Robertson[3], KAA Fox[4], JN Watson[2]

[1] Faculty of Engineering and Computing, Napier University, Edinburgh, UK,
[2] Cardiodigital, Elvingston, UK, [3] Department of Emergency Medicine, Royal Infirmary of Edinburgh, Edinburgh, UK, [4] Department of Cardiology, Royal Infirmary of Edinburgh, Edinburgh, UK

Abstract

Modulus maxima derived from the continuous wavelet transform offers an enhanced time-frequency analysis technique for ECG signal analysis. Features within the ECG can be shown to correspond to various morphologies in the Continuous Modulus Maxima domain. This domain has an easy interpretation and offers a good tool for the automatic characterization of the different components observed in the ECG in health and disease. As an application of these properties we have developed an R-Wave detector and tested it using patient signals recorded in the Coronary Care Unit of the Royal Infirmary of Edinburgh (attaining a Sensitivity of 99.53% and a Positive Predictive Value of 99.73%) and with the MIT/BIH database (attaining a Sensitivity of 99.7% and a Positive Predictive Value of 99.68%).

1. Introduction

The surface electrocardiogram is a crucial diagnostic instrument in many areas of modern medicine. Analysis of the ECG has become an important area of research, in particular where advanced signal processing techniques can yield useful and timely information which is otherwise inaccessible, e.g. the interpretation of ventricular fibrillation during cardiac resuscitation. Traditionally, analytical tools extracting time-frequency information have been based around the Fourier Transform (for example [1], [2]). More recently, the continuous wavelet transform has been used successfully in the processing of ECG signals, and offers significant advantages – in particular the preservation of location specific features [3], [4], [5].

QRS complex or R wave detectors are extremely useful tools for the analysis of ECG signals. They are used for finding the fiducial points for averaging methods and to calculate the RR time series in Heart Rate Variability techniques. They also useful for automatically calculating some very important heart function parameters such as the R-R interval length and heart rate.

There are currently a number of QRS detection algorithms available which use a variety of signal analysis methods. The most common of these are based on signal matched filters or time-frequency decomposition methods. Other less common methods have also been proposed including include neural networks, genetic algorithms, syntactic methods, etc. See, for example, Köhler et al [6] who have performed an analysis of the most important QRS complex detectors currently in existence. Recently, wavelet-based QRS detection methods have been suggested by a variety of groups including Li et al [7] and Kadambe et al [8]. Li et al propose a method based on finding the modulus maxima larger than a threshold obtained with the preprocesing of some initial beats. The threshold is updated during the process to obtain a better performance. This method has a post-processing phase in which redundant R Waves or Noise peaks are removed. This method achieves a good performance with a sensitivity of 99.90% and positive prediction value of 99.94% achieved with the MIT/BIH database. Kadambe et al use the Dyadic Wavelet Transform. The authors describe an algorithm which finds the local maxima of two consecutive Dyadic Wavelet scales and compare them to classify local maxima produced by R waves and those due to noise. This method obtains a Sensitivity of 96.84% and Positive Prediction of 95.20% from four 30 minute tapes from the AHA database.

We present here an enhanced method for QRS detection based on Continuous Modulus Maxima that offers a performance comparable with the best of existing methods proposed in the literature. The beat detector algorithm is an offshoot from our main study of using modulus maxima methods to characterise beat morphologies. Our method is simple and robust. It does not require pre-filtering and is robust against interference signals such as EMG noise or movement artefact. Note also that our technique can be employed in the detection of other features within the ECG such as P and T Waves.

2. Theory

A. Wavelet Transform

The wavelet transform of a continuous time signal, *x(t)*, is defined as:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{1}$$

where $\psi^*(t)$ is the complex conjugate of the wavelet function $\psi(t)$, a is the dilation parameter of the wavelet and b is the location parameter of the wavelet. In order to be classified as a wavelet, a function it must satisfy certain mathematical criteria. These are:

1 – A wavelet must have finite energy: i.e.:
$$E = \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \tag{2}$$

2 - If $\hat{\psi}(f)$ is the Fourier transform of $\psi(t)$, i.e.:
$$\hat{\psi}(\omega) = \int_{-\infty}^{\infty} \psi(t) e^{-i(\omega)t} dt \tag{3}$$
then the following condition must hold:
$$C_g = \int_0^{\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < \infty \tag{4}$$

This implies that the wavelet has no zero frequency component, i.e. $\hat{\psi}(0) = 0$, or, to put it another way, it must have a zero mean. Equation 4 is known as the *admissibility condition* and C_g is called the *admissibility constant*. The value of C_g depends on the chosen wavelet.

3 - For complex (or analytic) wavelets, the Fourier transform must both be real and vanish for negative frequencies.

The contribution to the signal energy at the specific a scale and b location is given by the two-dimensional wavelet energy density function known as the scalogram:

$$E(a,b) = |T(a,b)|^2 \tag{5}$$

The total energy in the signal may be found from its wavelet transform as follows:

$$E = \frac{1}{C_g} \int_{-\infty}^{+\infty}\int_{0}^{\infty} \frac{1}{a^2} |T(a,b)|^2 \, da\,db \qquad \left[= \int_{-\infty}^{+\infty} x(t)^2 dt \right] \tag{6}$$

The contribution to the total energy distribution contained within the signal at a specific a scale is given by

$$E(a) = \int_{-\infty}^{+\infty} |T(a,b)|^2 db \tag{7}$$

In practice a fine discretisation of the continuous wavelet transform is computed where usually the b location is discretised at the sampling interval and the a scale is discretised logarithmically. The a scale discretisation is often taken as integer powers of 2, however, however, we use a finer resolution in our method where the a scale discretisation is in fractional powers of two. The discretised continuous wavelet transform (CWT) is made distinct from the discrete wavelet transform (DWT) in the literature. In its basic form, the DWT employs a dyadic grid (integer power of two scaling in a and b) and orthonormal wavelet basis functions and exhibits zero redundancy. (Actually, the transform integral remains continuous for the DWT but is determined only on a discretised grid of a scales and b locations. And, in practice, the input signal is treated as an initial wavelet approximation to the underlying continuous signal from which, using a multiresolution algorithm, the wavelet transform and inverse transform can be computed discretely, quickly and without loss of signal information.). Our method, i.e. using a high resolution in wavelet space as described above, allows individual maxima to be followed accurately across scales, something that is often very difficult with discrete orthogonal or dyadic stationary wavelet transforms incorporating integer power of two scale discretisation. Further background information concerning continuous wavelets and their modulus maxima can be found in references [9] and [10]

B. Modulus Maxima

Wavelet *modulus maxima* are defined as

$$\frac{d\,|T(a,b)|^2}{db} = 0 \tag{8}$$

and are used for locating and characterising singularities in the signal. (Note that equation 8 also includes inflection points with zero gradient. These can be easily removed when implementing the modulus maxima method in practice.). Although relatively new, continuous modulus maxima-based methods in have recently been used by our group to analyse some engineering and medical signals [11], [12].

In this study we employ the second derivative of a Gaussian function, defined as

$$\psi(t) = (1-t^2)e^{-\frac{t^2}{2}} \tag{9}$$

This wavelet, known as the Mexican hat, has been used in practice for a number of data analysis tasks in engineering including: the morphological characterisation of engineering surfaces, the interrogation of laser-induced ultrasonic signals and the analysis of turbulent flows.

3. A new beat detector algorithm

Using the continuous Modulus Maxima, a new R wave have is proposed.

The algorithm is described as follows:

1. Compute the Continuous Wavelet Transform in the frequency interval 15 to 18hz (scales 5 and 6 for Mexican hat and f_s=360 Hz). A mask is applied to avoid edge effects.
2. Compute the squared modulus maxima the Wavelet Transform. Ignore those maxima lines below the preset threshold. We chose a threshold of 30% of the maximum value of the modulus maxima coefficients.
3. The remaining modulus maxima are taken as possible R wave points. Between all the modulus maxima found within an interval of 0.25 sec the point with the maximum coefficient value is selected as the R wave point.

Examples of the beat detection algorithm are shown in figure 1.

4. Results

The algorithm has been tested with our own collected data acquired by our group from the Royal Infirmary of Edinburgh [13] and has also been compared against results obtained from the MIT database. Below we summarize the results obtained using our beat detection algorithm.

A Validation with continuous CCU data

We have collected all the ECG signals from a five bed Coronary Care Unit (CCU) at the Royal Infirmary of Edinburgh continuously over the period of a year [13]. Protocols were formulated for data collection and archiving of the collected signals. The data collected was archived over the one-year period requiring approximately 3 GB of storage per week for a signal sample rate of 500Hz. The technology is now available to perform this task in a compact, easily accessible form at a reasonably affordable price. Archiving the whole ECG time series for each patient allows an analysis of the signal using a variety of techniques. Our particular interest is in the pre-VF signal. It will also serve as a useful data resource to be revisited in the future for other studies where other types of analyses could be applied to other parts of the patient's ECG history. Our beat detection algorithm was tested with 10 hours taken at random from the whole database. A performance of 99.53% sensitivity and 99.73% positive predictive value was achieved.

B Validation with MIT/BIH database

We compared our results with the MIT/BIH database. The algorithm was implemented using MatLab version 6.0 running on a Pentium IV computer with 1.6 GHz of clock speed. Each signal of the MIT database contains approximately a half hour of ECG data. The calculation time for each MIT signal took approximately 25 seconds. However, we report a sensitivity of 99.7% and a positive predictivity of 99.68% with this data set.

5. Conclusions

It can be seen that the Continuous Modulus Maxima technique offers a high accuracy in QRS detection. The algorithm proposed offers a sensitivity of 99.53% and a positive predictive value of 99.73% with real signals obtained from the CCU unit at the Royal Infirmary of Edinburgh and a sensitivity of 99.7% and a positive predictive value of 99.68% with the MIT/BIH database. These results are comparable with the best of alternate others methods proposed in the literature. The computation time is not very high because it incorporates an efficient frequency interval, which contains the most significant part of the temporal-spectral energy distribution. Our method does not require signal pre-processing and yet is able to cope with the significant breathing and skeletal muscle artefact seen in our clinically relevant 'real-world' test data.

The most important problem now is the necessity of finding more precisely the R Wave point. Modulus maxima lines follow a wandering path across frequency scales determined by the morphology associated with the ECG signal features. Hence, the algorithm, as described in this paper, will sometimes 'locate' the R wave at a point offset from the R wave peak. One possible remedy for finding the R wave peak location is to follow the modulus maxima line up the highest frequencies. However, this method is problematic in that an algorithm to track the modulus maxima line often confuses the high frequency noise with the high frequency part of the R wave maxima line. Another alternative to finding the exact location of the QRS peak is by switching back to the time domain and following the signal from the detection point to the peak.

The technique, which can also be employed in the detection of other pertinent ECG features, has been developed during the first stage of our study to use enhanced time-frequency methods for ECG signal analysis.

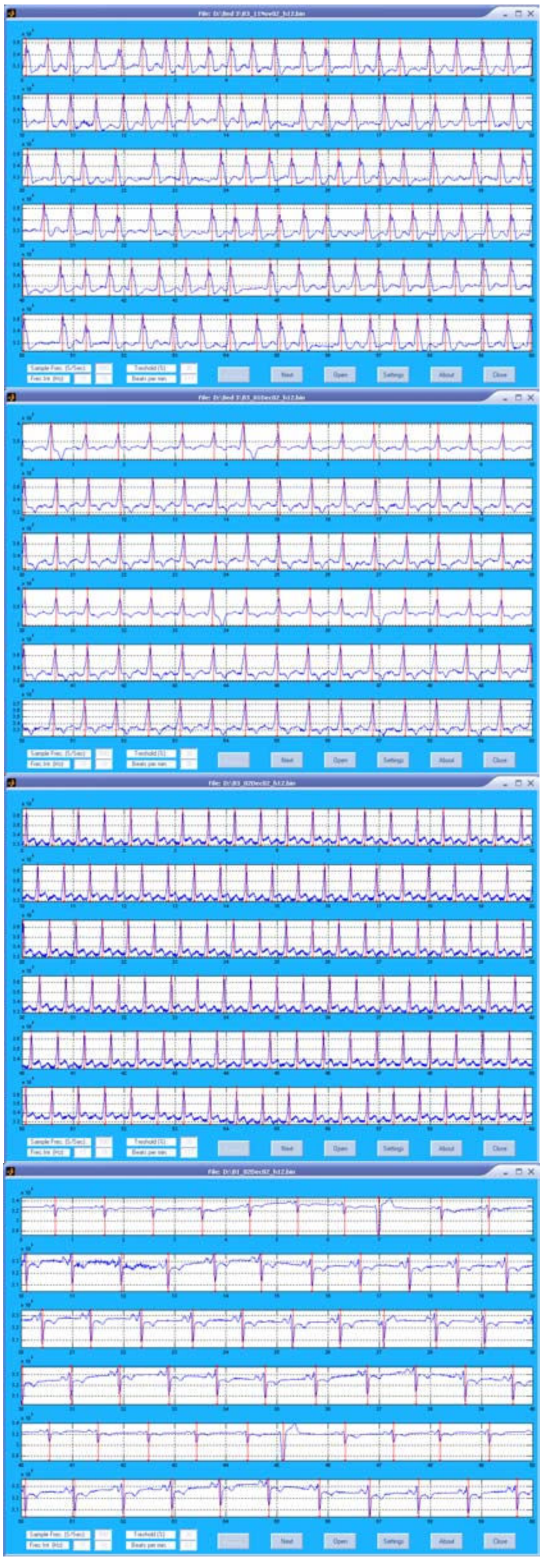

Fig. 1. Four screen shots of the R Wave detection algorithm operating on 1 minute ECG segments with a variety of beat morphologies

References

[1] Romero I, Serrano L, Ayesta U. ECG Frequency Domain Features Extraction: A New Characteristic for Arrhythmias Classification. Conference of the IEEE Engineering in Medicine and Biology Society 2001.

[2] Ayesta U, Serrano L, Romero I. Complexity Measure Revisited: A New Algorithm for Classifying Cardiac Arrhythmias. Conference of the IEEE Engineering in Medicine and Biology Society 2001

[3] Addison PS, Watson JN, Clegg G, Holzer M, Sterz F, Robertson C. Evaluating Arrhythmias in ECG Signals using Wavelet Transforms. IEEE Engineering in Medicine and Biology 2000;19:383-392.

[4] Addison PS, Watson JN., Clegg G, Steen PA, Robertson C. Finding Coordinated atrial activity during ventricular fibrillation using wavelet decomposition. IEEE Engineering in Medicine and Biology 2002;21:58-65.

[5] Addison PS, Watson JN, Clegg G, Holzer M, Sterz F, Robertson C. A Novel Wavelet Transform based Analysis Reveals Hidden Structure in Ventricular Fibrillation. Resuscitation 2000;43:121-127.

[6] Köhler BU, Hennig C, Orglmeister R. The principles of software QRS detection. IEEE Engineering in Medicine and Biology 2002;21:42-57.

[7] Li C, Zheng C, Tai C, Detection of ECG characteristic points using wavelet transforms. IEEE Transactions on Biomedical Engineering 1995;42:21-28.

[8] Kadambe S, Murray R, Boudreaux-Bartels GF. Wavelet transform-based QRS complex detector. IEEE Transactions on Biomedical Engineering 1999;46:838-848.

[9] Addison PS. The Illustrated Wavelet Transform Handbook: Applications in Science, Engineering, Medicine and Finance. Institute of Physics Publishing, Bristol, 2002.

[10] Addison PS, Watson JN, Feng T. Low-Oscillation Complex Wavelets. Journal of Sound and Vibration 2002;254:733-762.

[11] Watson JN, Addison PS. Spectral-Temporal Filtering of NDT Data using Wavelet Transform Modulus Maxima. Mechanics Research Communications 2002;29:99-106.

[12] Watson JN, Addison PS, Grubb N, Clegg G, Robertson C, Fox KAA. Wavelet-Based Filtering for the Clinical Evaluation of Atrial Fibrillation. Conference of the IEEE Engineering in Medicine and Biology Society 2001.

[13] Romero Legarreta I, Watson JN, Addison PS, Grubb N, Clegg G, Robertson C, Fox KAA. Time-frequency analysis of the ECG preceding ventricular fibrillation from a continuously collected CCU signal. European Medical and Biological Engineering Conference 2002.

Address for correspondence.

Iñaki Romero Legarreta
Faculty of Engineering and Computing
Napier University
10, Colinton Road
Edinburgh EH10 5DT, UK
inaki@napier.ac.uk