A SUPERVISED LEARNING APPROACH BASED ON THE CONTINUOUS WAVELET TRANSFORM FOR R SPIKE DETECTION IN ECG

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Keywords: Continuous wavelet transform, automatic ECG annotation, R spike detection, supervised learning.

Abstract: One of the most important tasks in automatic annotation of the ECG is the detection of the R spike. The wavelet transform is a widely used tool for R spike detection. The time-frequency decomposition is indeed a powerful tool to analyze non-stationary signals. Still, current methods use consecutive wavelet scales in an a priori restricted range and may therefore lack adaptivity. This paper introduces a supervised learning algorithm which learns the optimal scales for each dataset using the annotations provided by physicians on a small training set. For each record, this method allows a specific set of non consecutive scales to be selected, based on the record characteristics. The selected scales are then used on the original long-term ECG signal recording and a hard thresholding rule is applied on the derivative of the wavelet coefficients to label the R spikes. This algorithm has been tested on the MIT-BIH arrhythmia database and obtains an average sensitivity rate of 99.7% and average positive predictivity rate of 99.7%.

1 INTRODUCTION

In the framework of biomedical engineering, the analysis of the electrocardiogram (ECG) is one of the most widely studied topics. The easy recording and visual interpretation of the non-invasive electrocardiogram signal is a powerful way for medical professionals to extract important information about the clinical condition of their patients.

The ECG is a measure of the electrical activity associated with the heart. It is characterized by a time-variant cyclic occurrence of patterns with different frequency content (QRS complexes, P and T waves). The P wave corresponds to the contraction of the atria, the QRS complex to the contraction of the ventricles and the T wave to their repolarization. Because the ventricles contain more muscle mass than the atria, the QRS complex is more intensive than the P wave. The QRS wave is therefore the most representative feature of the ECG. Furthermore, once the QRS complex has been identified, other features of interest can be more easily detected.

Analyzing ECGs for a long time can lead to errors and misinterpretations. This is the reason why automatic feature extraction of the ECG signal can help physicians in their diagnosis for early detection of cardiac troubles. The feature extraction mainly consists in the automatic annotation of the different waves in the recording, the most important of them being the QRS. One of the main application of the QRS detection is the heart rate variability (HRV) analysis (Task Force of the European Society of Cardiology and The North American Society of Pacing and Electrophysiology, 1996). HRV measures have been proven successful in diagnosing cardiac abnormalities and neuropathies or evaluating the actions of the autonomic nervous system on the heart (Acharya et al., 2006). However, HRV measures heavily rely on the accuracy of the QRS feature detection on the digitalized ECG signal.

Automatic feature extraction and especially R spike detection is thus a milestone for ECG analysis. However, it is a difficult task in real situations: (1) The physiological variations due to the patient and its disease make the ECG a non-stationary signal. (2) Other ECG components such as the P or T wave looking like QRS complexes often lead to wrong detections. (3) There are many sources of noise that pol-

de Lannoy G., de Decker A. and Verleysen M. (2008).
A SUPERVISED LEARNING APPROACH BASED ON THE CONTINUOUS WAVELET TRANSFORM FOR R SPIKE DETECTION IN ECG.
In *Proceedings of the First International Conference on Bio-inspired Systems and Signal Processing*, pages 140-145
DOI: 10.5220/0001062501400145

lute the ECG signal such as power line interferences, muscular artifacts, poor electrode contacts and baseline wanderings due to respiration. These three problems highly compromise the detection of R spikes.

The detection of QRS complexes in the ECG has been conducted by many researchers in the past years. However, none of the current algorithms are able to automatically learn their parameters using pre-labeled beats provided by physicians. The aim of this paper is to introduce a new algorithm for R peak detection that does not blindly detect beats but learns and propagates the annotations provided by physicians on a small portion of the signal, which is often wanted in real situations. Our contribution consists in the design and experiment of a supervised learning algorithm for an optimal and automatic signal decomposition for further optimal R spike detection. The associated detection method by hard thresholding rule is also presented. The algorithm does not require any pre-processing of the signal and can also be adapted for the detection of other features such as the P or T wave.

The following of this paper is structured as follows. After this introduction, section 2 gives a brief literature review about the state of the art on ECG feature detection and especially the QRS detection. Section 3 provides a summary of the theory about the continuous wavelet transform used in this paper. Section 4 introduces the methodology followed by the algorithm and section 5 shows the experiments and results obtained on a real public database.

2 STATE OF THE ART

Due to the non-stationarity of the ECG signal, the physiological conditions and the presence of many artifacts, finding a robust and general algorithm for ECG feature detection is a tough task. A lot of work has been published in the literature about the detection of various interesting ECG features such as P waves, QRS waves, T waves, QT intervals or abnormal beats by numerous techniques (Addison, 2005; Sahambi et al., 2000; Senhadji et al., 1995). This paper focuses on R spike detection only.

For this purpose, several approaches using different signal processing methods have been reported previously: template matching (Dobbs et al., 1984), mathematical models (Pahlm and Sornmo, 1984), signal envelop (Nygards and Sornmo, 1983), matched filters (Koeleman et al., 1985), ECG slope criterion (Algra and Zeelenberg, 1987), dynamic time warping (Vullings et al., 1998), syntactic methods (Kohler et al., 2002), hidden Markov models (Clavier et al., 2002), beat detection by neural networks (Xue et al., 1992; Shyuand et al., 2004), adaptative thresholding (Madeiro et al., 2007; Christov, 2004), time-frequency decompositions by wavelet transforms (Addison, 2005), and geometrical approach (Surez et al., 2007).

Among all these methods, the time-frequency decompositions by wavelet transform (WT) seem the most intuitive tool for ECG analysis. The WT is naturally appropriate for analyzing non-stationary signals because it allows precise time-frequency representation of the signal with a low computational complexity. A lot of work has been published in past years on the use of the WT for QRS detection. In 1995, (Li et al., 1995) used an algorithm based on finding the maxima larger than a threshold obtained from the pre-processed initial beats. Later, (Kadambe et al., 1999) produced a method allocating a R peak at a point being the local maxima of several consecutive dyadic wavelet scales. In both these methods, a post-processing allowed to eliminate false R detections. Based on these two publications, a lot of other researches were published on the beat detection based on the WT (Shyuand et al., 2004; Fard et al., 2007; Martinez et al., 2004; Addison, 2005; Chen et al., 2005; Chen et al., 2006).

The main problem of the WT is that one has to choose the mother wavelet and the scales used to analyze the signal on an empirical basis. While the mother wavelet can easily be chosen based on its characteristics and ressemblance with a QRS wave, the ideal scale(s) at which the QRS are matched is harder to guess *a priori*. Current algorithms blindly search for QRS complexes in a limited number of consecutive scales selected in a range of *a priori* fixed scales. However, the shape of the QRS pattern can be varying between patients but also with time. One or several consecutive fixed wavelet scales may not be enough to match all complexes at once in a dataset. In this paper, we propose a new supervised learning algorithm based on the continuous wavelet transform that overcomes these issues. It only relies on the annotations provided by physicians on a small portion of the signal in order to select the optimal subset of non-consecutive scales for each dataset.

3 THEORY OF THE CONTINUOUS WAVELET TRANSFORM

The continous wavelet transform (CWT) is a tool which produces a time-frequency decomposition of a

signal $x(t)$ by the convolution of this signal with a so-called *wavelet function*.

A wavelet function $\psi(t)$ is a function with several properties. It must be a function of finite energy, that is

$$E = \int_{-\infty}^{+\infty} |\psi(t)|^2 dt < \infty, \quad (1)$$

and it must have a zero mean.

From a wavelet function, one can obtain a family of time-scale waveforms by translation and scaling

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (2)$$

where $a > 0$ represents the scale factor, b the translation and $a, b \in \mathbf{R}$. When $a = 1$ and $b = 0$, the wavelet is called the *mother wavelet*.

The *wavelet transform* of a function $x(t) \in L^2(\mathbf{R})$ is a projection of this function on the wavelet basis $\{\psi_{a,b}\}$:

$$T(a,b) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}(t)dt. \quad (3)$$

For each a, the wavelet coefficients $T(a,b)$ are signals (that depend on b) which represent the matching degree between wavelet $\psi_{a,b}(t)$ and the analyzed function $x(t)$.

The signal energy at a specific scale and position can be calculated as

$$E(a,b) = |T(a,b)|^2. \quad (4)$$

The two-dimensional wavelet energy density function is called the *scalogram*.

The CWT is a suitable tool for ECG analysis because of this time-frequency representation of the signal. With the multiscale feature of WTs, the QRS complex can be distinguished from high P or T waves, noise, baseline drift, and artifacts. The important time aspect of the non-stationary ECG signal is kept. Moreover, very efficient implementations of the algorithm exist and a low computational complexity is required, allowing real-time analysis. With the aim of a QRS detection, an appropriate mother wavelet must be chosen. It must match nicely with a QRS complex, in order to emphasizes these complexes and to filter the useless noise. For more details on the wavelet transform and on the standard wavelet functions available, the interested reader can consult (Mallat, 1999; Addison, 2005; Daubechies, 1992).

4 METHOD DESCRIPTION

4.1 General Description

The detection of R spikes is a tough task due to the complexity of the ECG signal. The aim of the algorithm introduced here is to automatically find the best subset of wavelet scales for optimal R detection. For each dataset, this subset is selected on a short training sample by a supervised learning procedure. The CWT at the selected scales is then computed on the complete dataset. Finally, R spikes are detected by a hard thresholding rule on the selected wavelet coefficients.

4.2 Training

The algorithm uses a supervised learning approach: it will use the labeled information that is provided and learn the best way to adapt to the problem. Here, the labeled information that is provided is the location of the R peaks in a training dataset.

Each dataset consists in a long-term ECG signal recording (for example 24 hours). With such long recording, the problem is that a manual extraction of the R peaks cannot be performed, as detailed in the Introduction. However, asking a specialist to annotate a small part of the signal by indicating the R peaks is perfectly feasible; this annotated part will consist in labeled segments of one minute each, taken at random locations over the entire dataset. Choosing random locations along the signal is a way to obtain a representative training set maximizing the probability to include all types of beats contained in the recordings. The CWT is then computed on the training set in a wide (therefore non restrictive) range of 50 fixed scales defined as $\{s_i\}$, $1 \leq i \leq 50$. The mother wavelet $\psi(t)$ that was used in our experiments is the mexican hat wavelet, for its similarity with the regular morphology of the QRS complex. It is defined as the second derivative of the gaussian probability density function:

$$\psi(t) = (1-t^2)e^{\frac{t^2}{2}}. \quad (5)$$

In order to select the appropriate scales among the wide range of wavelet scales, one needs a criterion. A natural criterion is the percentage of correct R peaks detection on the annotated parts of the signal using the coefficients of the wavelet transform at the trial scales in the set $\{s_i\}$. A *stepwise forward* method automatically selects the best subset $\{a_k\} \subset \{s_i\}$ of scales on the basis of the detection rate. It involves starting with an empty subset, trying out at each step the trial scales one by one and including them to the model if the detection rate is improved. The procedure stops when no scale left in $\{s_i\}$ can improve the detection rate. In addition, at each step, the scales previously selected in $\{a_k\}$ are individually challenged: if their removal does not decrease the detection rate, the scale is now useless and therefore removed from the model.

The set $\{a_k\}$ of scales coming from the selection is thus made of the scales giving the best R detection when combined together. The selected set of scales is then used for R spike detection on the complete original long-term recording. Figure 1 shows an original ECG segment and the coefficients of the first selected wavelet scale.

4.3 R Detection

The learning procedure extracted $\{a_k\} \subset \{s_i\}$, the best subset of scales on the training set. Note that the scales in the subset are not necessarily consecutive, which means that different QRS shapes can be matched at different scale levels. The CWT is computed on the whole signal at the scales $\{a_k\}$.

Because of the non-stationarity of the signal, a moving window of 5 seconds length with an overlap of one second is used to cut $T(a_k,b)$ into J parts, $1 \leq j \leq J$. For each a_k and b_j, the R spikes are detected on $T(a_k,b_j)$ by a hard thresholding rule, where index b_j scans the jth window. Let us define

$$D(a_k,b_j) = \left(\frac{d|T(a_k,b_j)|^2}{db_j}\right)^2. \quad (6)$$

A threshold $th(a_k,j)$ is estimated as the mean of $D(a_k,b_j)$. As $D(a_k,b_j)$ has sharp peaks in the slopes of the QRS complexes, the intervals $I(a_k,j)$ satisfying

$$D(a_k,b_j) > th(a_k,j) \quad (7)$$

belong to QRS complexes. The R spikes are then defined as the maxima of $|T(a_k,b_j)|^2$ in each of the $I(a_k,j)$ intervals. All the R spikes obtained at each scale k are then merged together.

4.4 Post-processing

A last step of post-processing makes sure that T waves or Q and S spikes have not been wrongly labeled as a R. If two or more R spikes were detected in a window smaller than 250ms (two heartbeats cannot physiologically happen in less than 250ms (Christov, 2004)), the algorithm keeps only the peak which has the highest value on the original ECG.

5 RESULTS AND VALIDATION

The learning of the model on the training set and the assessment of performances must be done using an annotated database. The public standard MIT-BIH arrhythmia database (Goldberger et al., 2000) was used in this work. It contains 48 half-hour recordings of annotated ECG with a sampling rate of 360Hz and 11-bit resolution over a 10-mV range. The recorded signals contain different wave types and only a robust algorithm can perform well on all datasets together. Some datasets include very few artifacts and clear R peaks, but others make the detection of the R spike more difficult because of (1) abnormal QRS shapes or P and T waves, (2) low signal-to-noise ratio, (3) heavy baseline drifts, (4) lots of non normal beats such as premature ventricular contraction, left bundle branch block beat, atrial premature contraction etc... Among the 48 available datasets, the four ones including paced beats were *a priori* rejected because they consist in a special case. After visual inspection of the data, datasets 207 and 208 were also rejected. The reason is that a representative training set of five times one minute would be hard to extract randomly as several minutes of these two datasets contain only non-labeled parts looking like a sinus wave.

The performances were assessed by evaluating two parameters as suggested in (Kohler et al., 2002). The sensitivity is measured as

$$\frac{TP}{TP+FN} \quad (8)$$

and the positive predictivity as

$$\frac{TP}{TP+FP}, \quad (9)$$

where TP is the number of true positive detections, FN the number of false negatives and FP the number of false positives. The error rate is also reported. It is computed by

$$\frac{FN+FP}{n_{QRS}}, \quad (10)$$

where n_{QRS} is the total number of QRS labeled in a dataset. On the database, the algorithm obtains an average sensitivity rate of 99.7% and average positive predictivity rate of 99.7%. The average error rate is below one percent. To our knowledge, only three R

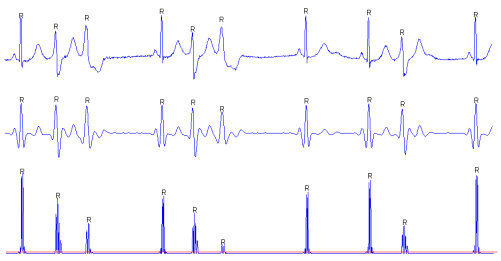

Figure 1: Example of an original ECG segment (upper plot), the first selected wavelet scale (middle plot) and its squared derivative (lower plot).

spike detectors based on WT reported in the literature obtained comparable results with a sensitivity and a positive predictivity of around 99.8% (Martinez et al., 2004; Li et al., 1995; Chen et al., 1997). Our algorithm achieves comparable performances without the need for a more advanced post-processing stage such as those used in these articles.

6 CONCLUSIONS

In this paper, a supervised learning algorithm for the automatic detection of R peaks in ECG is introduced. It uses the multiscale feature of the continuous wavelet transform (CWT) to emphasize the QRS complex over high P or T waves, noise, baseline drift and artifacts. The CWT keeps the important time aspect of the non-stationary ECG signal. Moreover, very efficient implementations of the CWT exist and a low computational complexity is required, allowing real-time analysis. This algorithm learns and propagates the annotations provided by a physician on a small annotated segment. For this purpose, the method selects the best subset of wavelet scales on a representative training set by a stepwise forward procedure. The forward procedure allows to select scales that are not necessarily consecutive and it does not a priori restrict the range of computed scales on an empirical basis. It allows a complete different set of scales to be selected for each ECG signal, based on its characteristics. The selected scales are then used on the original long-term ECG signal recording and a hard thresholding rule is applied on the derivative of the wavelet coefficients to label the R spikes. The method is robust and does not require any preprocessing stage. The selection procedure can be generalized in order to detect other ECG features such as the P and T wave.

Experiments on the public annotated MIT-BIH database lead to a sensitivity of 99.7% and a positive predictivity of 99.7% without the need of an advanced post-processing stage on the detected peaks. To our knowledge, only three R spike detectors based on WT reported in the literature obtained comparable results, while requiring a more complex post processing stage.

Further works will include: (1) The development of a more advanced thresholding rule that takes the peaks detected so far into account; (2) the use of a more advanced post-processing stage to eliminate wrong detections; (3) the design of an automatic selection of the best mother wavelet by the same learning methodology; (4) the generalization of the method for the detection of other ECG features such as P or T wave.

ACKNOWLEDGEMENTS

This work was partly supported by the Belgian “Région Wallonne” ADVENS convention 4994 project and by the Belgian “Région de Bruxelles-Capitale” BEATS project.

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