Robust detection of ECG waves

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Abstract

In this paper we present an overview of a new method for ECG wave detection and labelling. It is based on a wavelet transform of the ECG signal, but expands upon previous approaches by including both multi-lead and multi-scale treatment of the input signal. This unique property allows for a very robust operation with relatively simple processing.

Our ECG wave detector is designed to be robust against changes in sampling rate, recording noise and missing leads. Our current implementation is developed and tested on standard 12 lead ECGs sampled with a sampling rate of 500 Hz and 10 second segments. We work in the wavelet domain by applying dyadic discrete wavelet transforms to each lead separately. This representation is merged into a single signal, which is processed uniformly and independently of the initial number of leads.

1. Introduction

Cardiovascular diseases are the major cause of mortality in developed countries. Therefore, early and reliable diagnosis of malfunction in the human heart is crucial in medical practice. Electrocardiogram (ECG) is a graphical representation of a depolarisation wave spreading through the heart, hence it is a very powerful and common method of analysis and diagnosis of cardiac diseases. Independently of the details of ECG registration, each cardiac cycle contains evidence of major successive stages: depolarisation of atria, depolarisation of the ventricles, and their repolarization, represented by P wave, QRS complex and T wave, respectively. The shape of the waves, their relation to the *orientation* of measurement, and their repetitiveness, all enclose important parts of the information needed for clinical diagnosis [1].

Unfortunately, ECG is often registered under time pressure in an ER environment where a cardiologist is not always immediately available, and untrained doctors may easily misinterpret the results. Therefore, there is ongoing research aiming at supporting doctors in the process of diagnosis. Such support might be double-pronged: automatic delineation of single waves, providing measurements and features to simplify and speed up the process of diagnosis [2], and/or fully automated recognition of pathological patterns in the ECG signal [3].

This study aims at developing an ECG wave detector that can support doctors in the evaluation of heart function. It separates cardiac cycles and delineates specific waves (P, QRS, T) in each cardiac cycle of the incoming ECG signal, in an automated and robust manner.

2. Methods

Automatic measurement/feature extraction from ECG signals has been investigated for many years, and different techniques have been proposed. An overview of algorithms for QRS detection can be found in [4]. One of the most popular techniques in use is the wavelet transform. Wavelets break down the signal into elementary multi-resolution components localised in time. A correlation between singularities of the signal and wavelet transform modulus maxima across various scales is well documented [5], and it is used by many researchers in detection and delineation of ECG singularities [6–9].

The majority of algorithms use a single-lead, multi-scale approach based on the analysis of pairs of local minima and maxima and their zero-crossing of wavelet coefficients in different scales [2, 10–12]. A smaller number of works concentrate on multi-lead ECG signal analysis [13].

Following the insights from the above mentioned works, we use a combined multi-lead and multi-scale approach. The representation of the signal which is used for wave detection is obtained by combining wavelet coefficients at different scales obtained from a wavelet transform of ECG signal from all available leads.

The algorithm for wave detection consists of two steps. Firstly, it localises the QRS complexes. Secondly, the QRS complexes are removed from the data, and then the algorithm looks for P- and T-waves in the modified signal. Both steps of the algorithm are based on processing of the signal in the wavelet domain in a very similar manner.
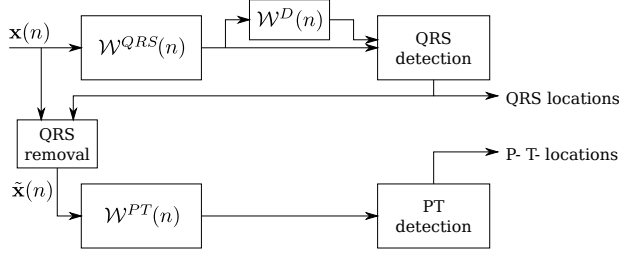
Figure 1. Overview of the algorithm for QRS-complex, and P-, T-wave detection.

Figure 2. Original wavelet signal $\mathcal{W}^{\mathcal{QRS}}(n)$ and its corresponding dilated form $\mathcal{W}^{\mathcal{D}}(n)$

2.1. Wavelet Domain

The representation of an ECG signal in the wavelet domain is obtained by applying dyadic discrete wavelet transform of bi-orthonormal quadratic splines on each of the leads $x_l(n)$ separately.

The process of expressing the signal in the wavelet domain is performed twice in exactly the same way, albeit at different scales (see figure 1). At first we operate on the original multi-lead vector signal $x_l(n)$ (obtaining the QRS delineation), then we operate on the residual signal $\tilde{x}_l(n)$ obtained after the QRS is removed from the original (obtaining P- and T waves).

The ECG signal of each lead is decomposed into two dyadic scales s_1 and s_2. The wavelet coefficients $W_s x_l(n)$ of ECG signal $x_l(n)$ at chosen scales s_1 and s_2 are summed up for each lead:

$$W x_l(n) = W_{s_1} x_l(n) + W_{s_2} x_l(n) \tag{1}$$

Next, this multi-scale sum of wavelet coefficients for each lead is normalised, squared and summed up, giving a single vector of multi-lead multi-scale wavelet transform representation of ECG signal:

$$\mathcal{W}(n) = \sum_{l \in L} \left[\frac{W x_l(n)}{\max_{n=1}^{N} \| W x_l(n) \|} \right]^2 \tag{2}$$

Thanks to the normalisation of the coefficients for each lead separately, we give the same significance to frequency response in all leads. We will refer to this final signal as *wavelet signal*, and depending on the chosen s_1, s_2 scales denote $\mathcal{W}^{QRS}(n)$ or $\mathcal{W}^{PT}(n)$. The same procedure can easily be followed for a single lead-signal ($L = \{1\}$), or any multi-lead ECG data (e.g. for 3-, 6- or 12-lead ECG).

In the above presented procedure we lose the information about the sign of wavelet coefficients and position of zero-crossing between modulus maxima. Although the exact morphology of ECG waves (QRS complex, P-, ad T-wave) is different for various medical conditions, yet it is not important for their automated localization in the signal. What is needed for this task are the positions where the
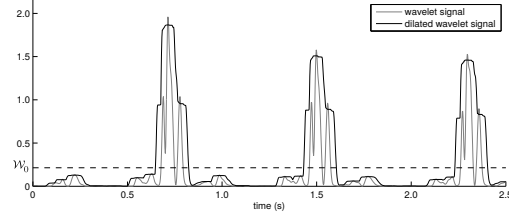
absolute values of wavelet coefficients are the largest, as these places represent the biggest changes in the ECG signal at a given frequency. Our approach actually enhances the amplitude of these maxima making them amenable for detection by a simple threshold operation.

2.2. Algorithm

The process flow of the wave detection algorithm is presented in figure 1. The input vector signal $x(n)$ is transformed into the wavelet domain signal $\mathcal{W}^{QRS}(n)$ (used for QRS detection). Next, all of the detected QRS complexes are removed from the input signal, and this new data ($\tilde{x}_l(n)$) is again converted into wavelet domain $\mathcal{W}^{PT}(n)$ (used for P-, and T-waves detection). In both detection stages, the waves are localised in three steps: coarse localisation, verification, and fine onset and offset detection.

QRS complex: Coarse localisation of QRS complexes is obtained by applying a threshold rule on the dilated wavelet signal $\mathcal{W}^{D}(n)$ (see figure 2). The threshold $\mathcal{W}_0$ is automatically determined on the basis of the (cumulative) distribution of the normalised amplitudes of this signal.

Verification of a probable QRS localisation is based on checking if the threshold dilated wavelet signal in the selected area fulfils the following three straightforward requirements for being a well defined QRS complex: (i) minimal duration, (ii) significance of intensity, and (iii) temporal distance consistency.

Precise detection of the onset and offset of QRS complex is done also by applying a threshold rule to the original wavelet signal $\mathcal{W}^{QRS}(n)$. However, in this case, the threshold is simply chosen to be 2% of the maximum value of the wavelet signal within each record (th_{ON}). Both the beginning and the end points of the coarse localisation of each QRS complex is monitored independently and if the corresponding wavelet signal values are above the threshold, the QRS localisation interval is expanded. Conversely, the QRS localisation interval is shrunk if the wavelet signal is below this threshold (see figure 3).

P-, and T-waves: Detection of P-, and T-waves starts with the removal of QRS complexes detected in the previous step. The ECG signal without QRS complexes $\tilde{x}(n)$
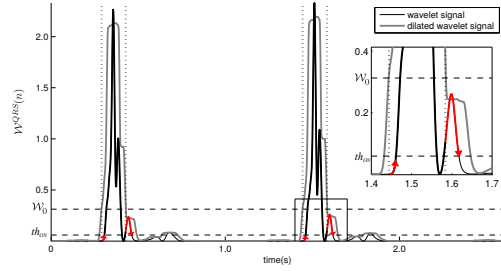
Figure 3. Example of process of onset & offset detection. Detected QRS complexes are depicted in bold line while the red line represents the changes in QRS selection after applying the threshold rule. The levels of thresholds $\mathcal{W}_0$ (applied in coarse detection) and th_{ON} (applied in fine onset & offset detection) are represented by dashed lines.

is, again, transformed into wavelet domain $\mathcal{W}^{PT}(n)$. Similarly to the QRS detection, we start by applying a threshold to the $\mathcal{W}^{PT}(n)$. For this operation, the threshold operation is done at 40% of the wavelet signal normalised as follows:

$$\overline{\mathcal{W}^{\mathcal{PT}}}(n) = \frac{\mathcal{W}^{\mathcal{PT}}(n)}{\sigma(\mathcal{W}^{\mathcal{PT}}(n))} \qquad (3)$$

For every local maxima found within the threshold window, we process the wavelet signal around its location in order to establish whether this maximum is in fact a part of a meaningful wave. This is done by constructing a sign-change preserving transformation of the wavelet signal and locating the intervals connecting local minima with the currently processed maximum. Such coarse regions of interest are then collated together.

Verification of probable P-, and T-waves localisation depends on the number of local maxima found in the analysed region of interest. In general, localisations with small single maxima are discarded. Those with two maxima are left without any changes, and the rest is processed further. The new range for wave localisation is redefined as the span between the first and the last significant local maxima and if it still contains more than four local maxima, the range will be split in two.

The fine onset and offset detection of P- and T- waves is done in a similar way to the operation presented for the QRS complex. The initial interval is expanded until the signal reaches an automatically determined threshold, or local minimum. In contrast to the QRS detection, the onset and offset thresholds are evaluated separately (th_{ON}^{PT} and th_{OFF}^{PT} in figure 4).

After finishing the algorithm for P-, and T-waves detection, the process of beat allocation is performed. In case no P- or T-wave was detected by the algorithm, the above wave detection algorithm is run once more, but the original maximum marking threshold is reduced four-fold to 10%
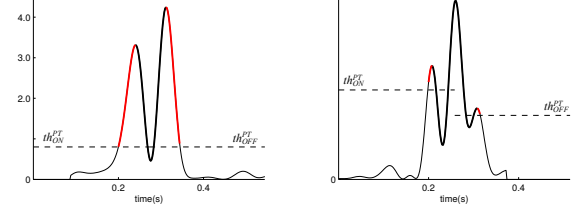

Figure 4. P-, T-wave onset and offset detection: on the left side strong and clean wave case, on the right side weak wave with sharp edges

of the maximum value of the normalised signal.

Cardiac cycles: After delineation of the ECG signal, the detected waves are grouped into cardiac cycles. For each QRS complex, the closest P-, and T-waves are assigned. Then, cardiac cycles are grouped according to the shape of their constituent waves. Once, the grouping is achieved, the onset and offset values of waves are adjusted and the median cardiac cycle for each beat type is calculated. All fundamental features, durations of waves and intervals are calculated on the base of the median beat.

3. Results

The performance of our ECG wave detector is presented on a set of 181 pathological, 12-lead ECGs. For each ECG, the algorithm provides durations of QRS complexes, P-waves, PR intervals, and QTc intervals for the main beat type. The algorithm measures also RR interval providing it in the form of heart rate. The computed heart rate and wave durations were compared to manual measurements provided by cardiologists.

3.1. Dataset

The ECGs used in our study were selected from a database of 1390 ECGs obtained from the patients admitted to the cardiology service of Hospital Clínic in Barcelona between years 2011-2012. All ECGs available in the database were diagnosed and manually measured by cardiologists from the hospital. The report provided by the cardiologists contained rhythm description with heart rate, diagnosis, and in case of abnormal ECG signals, the description of abnormal features and measurements.

The main criteria in the selection of patients to our study was availability of at least one of the desired measures (QRS complex, P-wave, PR and QTc intervals). However, we discarded patients with pacemaker rhythm and atrial fibrillation. Because of the specification of our database, manual measurements are available only for abnormal durations, and therefore all examined durations are pathological.

Table 1 contains the statistical information (number, range, mean value and standard deviation) of manual measurements available for a given type duration.

Table 1. Statistical information of examined data.

	number	range	mean	std
HR	181	35 – 120	71.8	14.1
QRS	134	105 – 206	150.9	21.2
P	41	125 – 180	142.4	13.7
PR	79	90 – 466	237.7	48.6
QTc	11	450 – 525	484.1	24.2

3.2. Performance

Table 2 contains performance results (maximum absolute error, and mean absolute error) for our algorithm, as compared against manual measures provided by a cardiologists. Additionally, we provide as a benchmark the results from the commercially available software (HES® – Hanover ECG System, Corscience, Germany).

It is worth to mention, that the commercial software failed to provide results for 5 out of 181 examined ECGs (one had missing V1-V6 leads, and HES® software needs them to work correctly, and four failed with error suggesting some problems with QRS-T interpretation). Those ECGs were not taken into account when calculating error for HES software. Additionally, in 5 other cases the software did not locate the P-wave at all.

Table 2. Summary of absolute performance (expressed in ms) of the presented algorithm and HES® software.

	algorithm		HES®	
	max error	mean error	max error	mean error
HR	32	2.4±3.2	12	2.3±1.9
QRS	32	9.7±6.6	74	12.1±10.5
P	82	24.1±20.0	180	21.2±31.4
PR	157	15.7±19.5	466	42.1±80.5
QTc	50	28.5±15.4	41	16.36±12.6

4. Conclusions

In this paper we presented a new method for ECG measurement extraction. The algorithm presented compared well with the results obtained from commercially available software. It proved to be very robust against unreliable input data, with no apparent accuracy loss. It presented only few systematic errors which will be addressed in further developments (especially in case of QTc). Due to its ro-

bustness the algorithm looks promising for the application in the less than ideal conditions of ER environment.

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