Parameter Optimization of a Wavelet-Based Electrocardiogram Delineator with an Evolutionary Algorithm

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Abstract

A recurrent problem encountered in many algorithms proposed to detect and segment ECG waves is the adjustment of the numerous parameters used. This work presents a method to optimize these parameters with an Evolutionary Algorithm (EA). The signal processing chain contains a filter to remove baseline wandering, a QRS detector (Pan & Tompkins) and a wave segmentation step based on the Wavelet-Transform (WT). The EA adjusts the parameters of the segmentation step in order to minimize the result of a cost function which measures how close the detector is from characteristic points annotated by a cardiologist. Results obtained with the QTDB are compared with other approaches of wave segmentation for which thresholds have been experimentally defined. EAs have shown to be an effective method to solve this complex problem of multiobjective optimization.

1. Introduction

Main ECG waves (P, T waves and the QRS complex) are important sources of information to evaluate cardiac pathologies. Automatic ECG wave delineators supply fundamental features, which can be used by the cardiologist to formulate hypotheses on the underlying physiological phenomena, and are particularly convenient for long-term monitoring or the analysis of Holter recordings. Performing a reliable detection is a challenging task, partly due to the fact that: *i)* the ECG can present a low signal-to-noise ratio (SNR), *ii)* numerous morphologies exist, even for healthy subjects, *iii)* there is no universal definition of where the boundaries of each wave are located (specially for T-waves). In the last decade, different WT-based ECG delineators have been proposed, providing interesting results compared to other approaches [1, 2, 3, 4]. Indeed, this multi-scale approach, which permits to attenuate noise at rough scales and then to refine the candidate wave positions with the help of finer scales, usually provides a robust detection. However, a typical WT-based delineator for ECG waves requires more than 15 parameters (time windows where these waves are searched for, threshold definitions for slopes and wave amplitudes...). Since these algorithms work in the time-scale domain, *a priori* information, like candidate wave positions, is difficult to use and setting the value of all these parameters is not straightforward. In general, the parameters of these algorithms are experimentally defined in order to produce:

- a low probability of wave detection error
- a small detection jitter with respect to cardiologist annotations, particularly for specific points such as Pon, Ppeak, Poff, QRSon, QRSoff, Tpeak and Toff.

In this work, we present an optimization scheme, based on an EA, and apply it to find the set of parameters that maximize the performance of a WT-based ECG wave delineator, with respect to the above-mentioned criteria. The first section of this paper describes the method, with details on the signal processing chain that carries out the detection and a presentation of the optimization process. The second section provides results obtained with the QTDB [5]. The last section gives some concluding remarks.

2. Method

2.1. Detection algorithm

The processing chain of the ECG wave delineator can be decomposed into three stages. The first stage makes use of a filter to remove baseline drift [6]. In the second stage, a sequence of *N* QRS detection instants $\tau_i, i = 1, ..., N$ is obtained, by applying the Pan & Tompkins algorithm [7]. Finally, the third stage performs wave segmentation with a WT method, based on the work of Martinez et al [2]. This work is focused on the optimization of this third stage, which employs 30 parameters, and is the crucial part of the segmentation algorithm. A synthetic description of this stage is presented below.

The temporal support of each individual beat i, $B_i(n)$ is obtained from the studied ECG lead *X(n)* by applying a fixed-width window $B_i(n) = X(\tau_i - 360ms, ..., \tau_i + 900ms)$. A wavelet decomposition is performed on each segment B_i, with a set of low pass and high pass filters implemented in a filter bank. It is a typical dyadic decomposition, excepted that the signal is not subsampled after

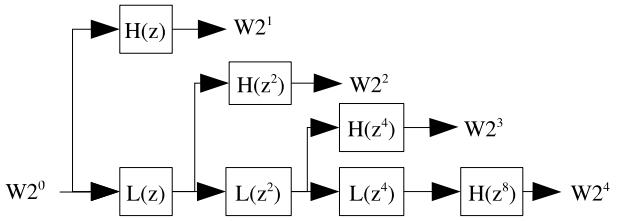

Figure 1. Filter bank, $W2^k$ are the output of the filter at scales 2^k (k = 1 to 4), $W2^0$ is the original beat.

each high pass/low pass filter, to preserve a good temporal resolution. A schematic diagram of this filter bank implementation is presented in figure 1. The mother wavelet is a quadratic wavelet and can be identified as the derivative of a Gaussian. This wavelet proved to be useful to characterize ECG beats and has already been applied in [1, 2].

Waves are detected from the WT decomposition in the following order: R, S, Q, T, P. Detection of the P, Q, S and T waves roughly follow the same process:

- Temporal support definition: time windows are defined and referenced either from the R wave (for P, Q and S waves) or from the S wave (for the T wave). Time windows for P-wave and T-wave detection depend on the previous RR interval (thresholds P_RR and T_RR). T1X/P1X are the left bounds of these windows and T2X/P2X are the right bounds. X is the index that changes in function of the RR. R1 and R2 define the temporal support for the R wave.
- Detection of WT maxima (only for P and T wave): the detection of all maxima, exceeding a given threshold $\epsilon_{(P,T)}$ is performed inside the defined temporal support of scale 4. These thresholds are proportional to the power at scale 4. If there are no maxima exceeding $\epsilon_{(P,T)}$, it is considered that the wave cannot be detected.
- Slope analysis: significant slopes for each wave are detected. The amplitude of the slope has to be higher than a threshold $\gamma_{QRSpre,QRSpost,T,P}$, proportional to the maximum slope in the corresponding time window.
- Onset, offset and peak detection: wave onset and offset are detected with respect to a threshold $\xi_{(QRSon,QRSend,Ton,Tend,Pon,Pend)}$, relative to the amplitude of the first or last significant slope. Peaks are defined at the instant of zero-crossing, found in the lower scale between the slopes associated with wave onset and offset.

The two first scales, $W2^1$ and $W2^2$, which have a quite high frequency content, are used to detect S and Q waves as well as QRSon and QRSoff ($W2^1$ for S and Q peaks and $W2^2$ for significant slopes, QRSon and QRSoff). The highest scale, $W2^4$ is used to delimit the P and T waves (Pon, Poff, Toff) whereas their peaks are found on $W2^3$.

Figure 2 shows an example of T-wave segmentation for

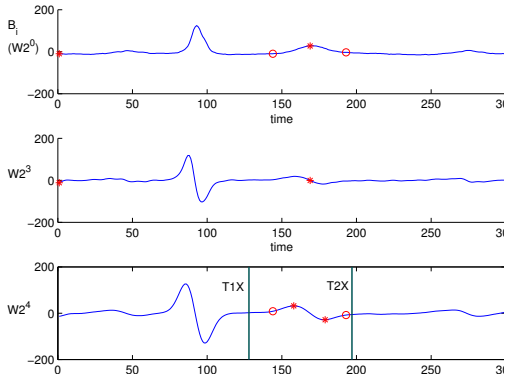

Figure 2. T wave detection and scales $W2^0$, $W2^3$, $W2^4$

a sinus beat. The upper panel presents the segment to be analyzed B_i=$W2^0$, the middle and lower panels show the scales used for T-wave segmentation, $W2^3$ and $W2^4$, respectively. Vertical lines on $W2^4$ represent the temporal support defined to start T wave segmentation. The stars on $W2^4$ are the detected significant slopes and the star at $W2^3$ is the zero-crossing corresponding to Tpeak.

The performance of this approach depends heavily on the correct definition of thresholds ϵ, γ, ξ for each wave and on the definition of the temporal search windows. All these parameters are presented in Table 1. The next section describes a method based on an evolutionary algorithm to optimize these parameters.

2.2. Parameter optimization method

The objective here is to adjust the parameters of the detection algorithm so that detected peaks and wave boundaries are nearly the same as those manually annotated by cardiologists and stored in a database. This optimization can be performed by defining an error function that takes into account both wave detection performance and the detection jitter for each characteristic point (Pon, Poff, Ton, etc.). Standard gradient-based methods cannot be used in this context, mainly because of the presence of threshold-comparisons that will lead to discontinuous error functions. Stochastic search methods, such as evolutionary algorithms, are particularly adapted to this problem.

EAs are optimization techniques, inspired on the theories of evolution and natural selection, which can be employed to find an optimal configuration for a given system within specific constraints [8]. In these algorithms, each individual of a population is characterized by a set of parameters to be optimized (or chromosome). An initial population is created, usually from a set of random chromosomes, and this population will evolve, improving its global performance, by means of an iterative process. During this process, each individual is evaluated by means of a fitness function, representing how its chromosome con-

figuration can be a good solution for the given problem. A new generation is produced by applying mutation and crossover operators, with probabilities p_m and p_c respectively, on selected individuals presenting high fitness values.

Two independent EAs are sequentially applied in this work. The first one, named EA1, jointly optimizes the parameters for the detection of Pon, Ppeak, Poff, QRSon, R and QRSoff. Parameters for Tpeak and Toff are optimized with a second EA noted EA2. Such a partitioning permits to reduce the dimension of the search space and is possible because the detection of the T-wave will be optimal only if the detection of the S-wave is previously optimized. In all EA, the best individual of the last generation has been retained as the optimal solution. Details of these EAs are the following:

• *individual coding*: individuals are coded with real-valued chromosomes. Values for each parameter were bounded to a meaningful interval: time windows are defined from possible extrem position and duration of each wave whereas boundaries of other thresholds are determined by largely increasing (upper bound) and decreasing (lower bounds) parameters from [2]. These intervals are employed by the EA during the construction of the initial population and the application of genetic operators.

• *cost function*: we are interested in the optimal set of parameters that jointly minimizes the probability of detection error ($Perr_p = \sqrt{Pfa_p^2 + (1 - Pd_p)^2}$) and the detection jitter, for each characteristic point p. This kind of multiobjective optimization is a complex task and can be approached as a single-objective problem, where the cost function is a weighted average of different criteria. In this work, the EA has been defined to minimize such a weighted cost function, defined as:

$$O = \sum_p \left(\frac{Perr_p}{a_p} + \frac{\varepsilon_p}{b_p} + \frac{\sigma_p}{c_p}\right)$$

where ε_p is the mean difference between detected and annotated instants (detection jitter) for point p. $\sigma_p = \frac{\sum_r (N_r \sigma_p^r)}{\sum_r N_r}$ is the global standard deviation, calculated as the mean of the standard deviation of the detection jitter for each record (σ_p^r) which are weighted according to their number of beats (N_r).

a_p, b_p and c_p are weighting factors setting the relative importance of each criterion. These weights are defined from results published by [2] and [9], in order to provide similar weights to each criteria.

• *selection method and genetic operators*: the ranking selection method was used in this work. Standard genetic operators for real-valued chromosomes were used (arithmetic and heuristic crossover, uniform mutation).

Individuals are composed of 19 parameters for the first EA (P and QRS delineation optimization) and 11 parameters for the second one (T-wave delineation optimization). Both EAs are trained over 80 generations, with 60 individuals and probability p_c is set to 0.7. In order to obtain more reliable and stable solutions, p_m has been adapted through the evolutionary process, being high during the first generations (to ensure a wider individual distribution on the search space) and quite low at the end (to assure the converge to a minima), as proposed in [10].

Table 1. Optimal parameters

EA1				EA2	
P11	299	γ_{QRSpre}	0.057	ϵ_T	0.13
P12	237	$\gamma_{QRSpost}$	0.079	γ_T	0.13
P21	96.5	$\xi_{QRSonpos}$	0.12	ξ_{Ton}	0.43
P22	94	$\xi_{QRSonneg}$	0.065	ξ_{Tend}	0.43
R1	127	$\xi_{QRSendpos}$	0.18	T11	140
R2	173	$\xi_{QRSendpos}$	0.46	T21	540
P_RR	616	QRS_Qlim	67	T12	152
ϵ_P	0.18	QRS_Slim	87	T22	0.53
γ_P	0.46			T23	444
$\xi_P on$	0.47			T_RR1	849
$\xi_P end$	0.73			T_RR2	1320

Temporal parameters are in ms, other parameters have no unit.

3. Results

The QTDB (physionet) contains 105 records with around 30 annotated beats per record [5]. These records have been acquired from healthy subjects and patients presenting different pathologies. There are two ECG channels per record and the sampling rate is 250 Hz. In this work, all available records have been divided into three equal portions, called subrecords. Two datasets are created from available subrecords: a training set, consisting of two thirds of the subrecords, selected randomly from the database, and a test set, with the rest of the data.

Table 1 presents the optimal parameters obtained after the application of both optimization stages (EA1 and EA2) on the training set. These parameters have been used to evaluate the performance of the detector on the test set, by using the evaluation framework proposed by Jané [11]. Results obtained with the optimal parameter set are compared to those achieved by [2] and [9]. Mean error (m) and standard deviation (s) are computed and averaged over all the records of the test set with a weight corresponding to the number of beats per record. These results are presented in table 2. As we disposed of two channels and cardiologists used a combination of both to detect only one position, we chose for each point the channel providing less error. Sensibility and predictivity are also computed (table 3).

Table 2. Delineation Comparison with the test set

Method	Criteria	Pon	Ppeak	Poff	QRSon	QRSoff	Tpeak	Toff
This work	m±s (ms)	1.9±11.8	1.4±9	3.1±10.1	0.3±6.6	-1.9±8.3	0±14.3	3.5±24
Martinez [2]	m±s (ms)	2.0±14.8	3.6±13.2	1.9±12.8	4.6±7.7	0.8±8.7	0.2±13.9	-1.6±18.1
LPD [9]	m±s (ms)	14.0±13.3	4.8±10.6	-0.1±12.3	-3.6±8.6	-1.1±8.3	7.2±14.3	13.5±27

Table 3. Detection Comparison

Method	Criteria	Pon	Ppeak	Poff	QRSon	QRSoff	Tpeak	Toff
This work	Se (%)	98,79	98.39	98.58	100	100	98.77	97.09
	P+ (%)	99.23	98.88	98.88	98.10	98.48	97.9	98.47
Martinez [2]	Se (%)	98.87	98.87	98.75	99.97	99.97	99.77	99.77
	P+ (%)	91.03	91.03	91.03	N/A	N/A	97.79	97.79
LPD [9]	Se (%)	97.7	97.7	97.7	99.92	99.92	99.0	99.0
	P+ (%)	91.17	91.17	91.17	N/A	N/A	97.74	97.71

Results in table 2 show that the jitter observed with the proposed algorithm is often lower than the jitter obtained by [2] and [9]. For three characteristic points (Pon, Ppeak, QRSon) out of seven, both the mean error and the standard deviation are lower than the other algorithms. The standard deviation is only higher for Tpeak and Toff when compared to [2] and higher for QRSoff when compared to [9]. Errors in QRSoff detection revealed to be mostly due to beats presenting bundle branch block, leading to undetected S-waves. Results about the sensibility and specifity reported in table 3 show that our algorithm perform well compared to other algorithms: all beats were detected with the Pan & Tompkins detector whereas a few beats are not detected with the other algorithms.

4. Discussion and conclusions

The optimal definition of the set of parameters required in complex signal-processing algorithms can be a complicated problem. In this work, we have proposed a method to obtain such an optimal set of parameters, based on an EA. It has been employed to tune all the parameters of a WT-based ECG delineators by minimizing the jitter error and the probability of false detection for each detected point. Even if the comparison of the results can be difficult because our test data was one third of the QTDB instead of the whole database for other methods, it can be noticed that our algorithm achieved better results for most of the points evaluated, showing that our parameters are well set. Finally, altough records of the QTDB offer a wide panel of beat morphologies, and thus should avoid problems of generalization, it would be interesting to evaluate this algorithm on other standard ECG databases.

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