QRS Detection Optimization in Stress Test Recordings Using Evolutionary Algorithms

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Abstract

QRS detection in exercise stress test recordings remains a challenging task, because they are highly non-stationary and contaminated with noises, such as large baseline wander and muscular noise, among others. The aim of this work is to find an optimal set of parameters for QRS detection in very noisy ECG signals, such as those acquired during stress tests. Parameter optimization was addressed by an evolutionary algorithm. A training database was created using 48 ECG recordings with reference QRS complexes. Each ECG recording is artificially contaminated with 3 types of real noise. A cost function combining the detection error probability, the mean detection jitter, and its standard deviation was defined, in order to obtain a quantitative performance evaluation of the detector. Evaluation was performed on an exercise stress test database composed of 54 real ECG recordings, with annotated QRS. The detector was configured with default parameter values, and also with the optimal values obtained from the evolutionary algorithm. The QRS detector with its optimized parameters showed a mean improvement of 4.6% compared to its performance with the default parameters. Furthermore, the use of optimized parameters led to at least the same performance than the initial parameters for all records, and the improvement was higher (up to 19.36 %) in noisy records, demonstrating the advantages of the optimized parameters in noisy environments.

1. Introduction

Extraction of the heart rate variability (HRV) during exercise remains today as an open problem in the field of cardiovascular signal processing. During exercise, it is particularly difficult to obtain a reliable and robust QRS detection, due to the highly non-stationary nature of the acquired signals and the significant levels of noise observed in this context.

Although a number of QRS detectors have been proposed in the literature, most of them have been tuned for operation on rest ECG recordings, with limited noise. In this paper, we will apply one such wavelet-based QRS detector [1], which is characterized by a great number of parameters (thresholds, time windows...) that have to be specifically tuned for it to perform correctly on exercise stress recordings. It is not an easy task to manually tune all these parameters, therefore, an optimization methodology, integrating an evolutionary algorithm (EA), based on the approach proposed in [2] is applied in this work.

EAs are optimization techniques, inspired on the theories of evolution and natural selection. They can be used to find the optimal configuration to a system within specific constraints [3]. They have already been applied in several biomedical applications to estimate a large set of parameters and have provided quite good results [2, 4, 5].

The main objective of this work is thus to enhance the algorithm in [1] regarding the robust QRS detection in very noisy ECG recordings, applicable to stress testing. Baseline wander, muscle artifact, and electrode motion artifact will be taken into account in the optimization of the detector parameters.

2. Methods and materials

2.1. Database

Training database

A training database was created using the MIT-BIH Arrhythmia Database, which contains 48 half-hour-length ECG recordings with annotated QRS complexes. The first lead of each ECG recording is artificially contaminated with 3 types of real noise recordings, leading to 144 noisy ECG recordings. A sample of this noisy database can be found online named MIT-BIH Noise Stress Test Database [6, 7]. The noise recordings were made using physically active volunteers and standard ECG recorders, leads, and electrodes; the electrodes were placed on the limbs in positions in which the subjects' ECGs were not visible. The three noise records were assembled from the recordings by selecting intervals that contained predominantly baseline wander, muscle artifact, and electrode motion artifact. The signal to noise ratio during the noisy segments of these records were as low as -6 dB.

Figure 1 shows an example of this database: the original ECG recording, and after the contamination of each noise recording.

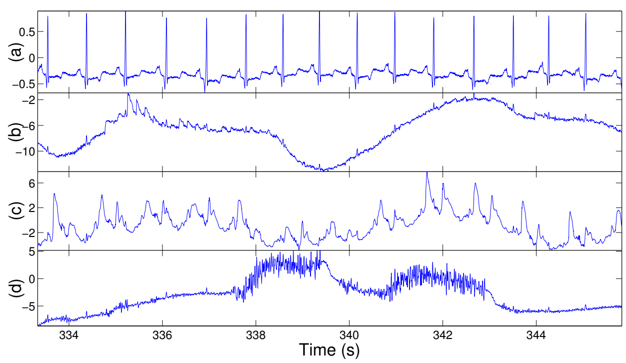

Figure 1. Original ECG signal (a), and the same recording contaminated with baseline wander (b), electrode motion artifact (c) and muscle artifact (d), measured in mV.

Evaluation database

Evaluation was performed on an exercise stress test database composed of 54 real ECG recordings, which were continuously recorded throughout exercise (ergocycle) phase at a 1000 Hz rate (Cardionics, Webster, Texas) at the University Hospital of Rennes, France. The QRS complexes were detected using the Pan & Tompkins algorithm [8] and each detection was manually verified by a trained operator with a dedicated interface.

2.2. Parameters to optimize

The QRS detection is based on wavelet decomposition of the ECG signal [1]. This detector uses several parameters, mainly thresholds and temporal windows to detect QRS complexes and find the boundaries of the different waves in the ECG signal. For QRS detection, these are the parameters which are going to be optimized:

- Refractory period (*refper*): This parameter prevents a QRS detection within that period, restricting the minimum beat duration to a physiologically based value.
- Length of the analysis window (*nsamp*): ECG segment length to be analyzed at a time, in which some parameters are locally calculated or adjusted.
- T wave related thresholds (*thres1*, *thres2*): These parameters try to avoid misdetections related to the peaky T wave.

2.3. Evolutionary algorithm

Parameter optimization was addressed by an evolutionary algorithm [2]. These optimization algorithms are particularly adapted to problems involving cost functions that are not differentiable and presenting multiple local minima.

An initial population is created, consisting of 100 individuals. Each individual is represented as a different set of values for the parameters which are going to be optimized, being one of them the default ones. A cost function combining a global detection error criterium (C_{err}), the mean detection jitter (ϵ), and its standard deviation (σ) was defined, in order to obtain a quantitative performance evaluation of the detector using the training database. This fitness is measured as:

$$fitness = \frac{C_{err}}{a} + \frac{\epsilon}{b} + \frac{\sigma}{c} \tag{1}$$

where a, b and c are normalization coefficients which are obtained as the mean value of each criteria in the initial population. The detection error criterium is defined as:

$$C_{err} = \sqrt{(1 - Se)^2 + (1 - PPV)^2} \tag{2}$$

being Se and PPV the sensitivity and positive predictive value respectively, which represent the proportion of actual QRS complexes which are correctly identified as such (Se) and the proportion of detection marks which actually correspond to QRS complexes (PPV). A TP is considered when a beat is detected within a 50 ms window centered in the reference QRS complex.

In each iteration of the algorithm, the best individuals are selected using a function based on the normalized geometric distribution. It is assigned a probability of selection P_j to each individual j based on its fitness value. A series of N random numbers is generated and compared against the cumulative probability P_j. The appropriate individual i is selected and copied into the new population if $P_{i-1} < U(0, 1) \leq P_i$.

Then, a number of arithmetic, heuristic and simple crossovers are applied, with a crossover probability of 0.3, 0.5 and 0.2 respectively, which create two new individuals combining the information of two existing ones. Mutations also happen: multi non-uniform, non-uniform and uniform mutations, with a mutation probability of 0.025, 0.1 and 0.025 respectively, which change every (multi) or one parameter from one existing individual.

The individual which present the best performance is established as the optimal set of parameters.

2.4. Evaluation of the optimal set of parameters

The evaluation database is used to compare the detector performance using both the default and optimal parameter values, using the reference annotations as described in section 2.1. The fitness value will be used to qualitative measure the detector performance in both scenarios, as described in equation (1). The improvement of the performance is evaluated for every recording individually, and globally with the whole database.

3. Results

The evolution of the parameters *refper*, *nsamp*, *thres1* and *thres2* is shown in Figure 2 (mean and standard deviation) for 23 iterations. It shows the default (D) and the optimized (O) values for each parameter, as well as partial results in iterations 1, 5, 10, 15, 20, 23. Parameters *nsamp* and *refper* are measured in seconds.

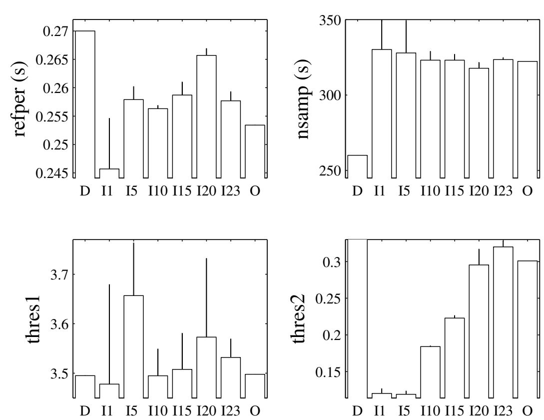

Figure 2. Evolution of the parameters *refper*, *nsamp*, *thres1* and *thres2*. First and last column represent the default and optimal parameters respectively. Also the mean and standard deviation in iterations 1, 5, 10, 15, 20 and 23 are represented.

The QRS detector showed a global improvement of 4.6%, when comparing the mean fitness value from all the recordings using the optimal and default parameters. Furthermore, when analyzing each record individually, the use of optimized parameters led to at least the equivalent performance than the initial parameters for all records, and the improvement was higher (up to 19.36 %) in noisy records. It is important to remark that the performance is not lowered in standard resting condition.

The fitness value combines a global detection error criterium, the mean detection jitter, and its standard deviation. In Table 1, these values for the default and optimal parameters are shown. The error criterium is the most improved (it presents a decrease of 6%), while the standard deviation of the detection jitter is the least improved (only 1%).

	Default set	Optimal set
C_{err}	0.3084	0.2902
ϵ (ms)	6.13	5.87
σ (ms)	9.89	9.78

Table 1. Values of C_{err}, ϵ and σ when using the default and optimal parameters.

Figure 3 shows an ECG segment from the evaluation database. Among the detections obtained with the default parameters (+) there are several errors in the noisy area, which are corrected when using the optimal parameters (x). The reference marks (o) are in the top of the figure.

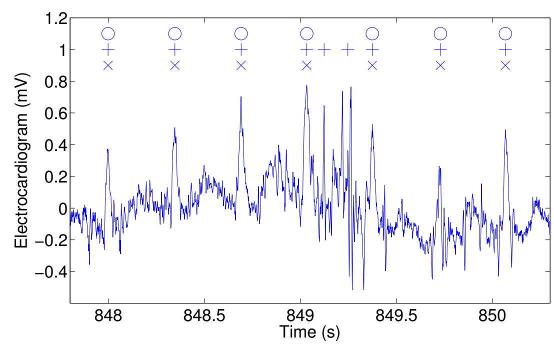

Figure 3. Example of an ECG segment with the reference annotations (o), the marks obtained with the default parameters (+) and the ones obtained with the optimal parameters (x).

4. Discussion

As it is shown in Figure 2, the parameter *nsamp* converges towards an optimal value within few iterations, which is stable through the optimization process and presents the minimal dispersion on the final iteration, suggesting that the obtained optimal value is robust and that this parameter is particularly sensitive for detection performance. Furthermore, the obtained optimal parameter for *nsamp* is quite different from the default one (a difference larger than a minute). Parameters *refper* and *thres2* show slower convergence and relatively low dispersions. Concerning parameter *thres1*, it presents significant oscillations and high dispersion values, that indicate that this parameter is less sensitive than the others for this particular detection algorithm. The optimal value for this parameter is very close to the default one. It is to note, though, that the optimal parameter set is obtained from a nonlinear and complex function of these parameters, making difficult any further analytical analysis on parameter evolution. Results from Figure 2 suggest that an additional gain could be obtained if the EA is applied for more generations.

The obtained global detection performance improvement of 4.6% may seem low, and thus a revision of the chosen parameters is proposed. The parameter *nsamp*, which represents the number of samples which are analyzed, is important for the detector: since the ECG signals are too long, they are divided into segments for detection, and several thresholds related to the signal to noise ratio (SNR) in that interval are determined. This parameter can lead to miss some QRS complexes if there is an abrupt change of SNR in the selected segment. Therefore, the length of these intervals makes sense to be introduced as a parameter to be optimized.

However, the other parameters are more suited to be optimized with an exercise stress test database. The algorithm is trained with a database containing significant noise levels of various natures (baseline wander, muscle artifact, and electrode motion artifact). While exercise stress recordings, like the evaluation database, commonly have these different kinds of noise, they also present other characteristics such as abrupt changes in the heart rate and changes in wave morphology, which were not taken into account into the optimization process. In particular, the refractory period should be trained with a database presenting such changes in heart rate. These aspects are limitations of the current results and may be improved in further works. Nonetheless, as stated above, the obtained optimal parameter set provides detections performances that are at least equal to that obtained with the non-optimized parameters, with performance improvements of more than 10% on very nosy records.

5. Conclusion

This study uses an evolutionary algorithm to optimize the input parameters for a QRS detector in very noisy recordings. Problems such as the ECG morphology and the high level of noise during these tests lead to wrong detections. The input parameters of the QRS detector have been optimized by an evolutionary algorithm, which is trained with a database consisting of ECG signals contaminated with 3 types of noise, commonly found in exercise stress test recordings, such as baseline wander, electrode motion artifact and muscle artifact. After parameter optimization, the detector performance shows a global improvement. The results are, at least, the same than using the default parameters, but significantly higher in the noisier recordings. This demonstrates the advantages of the optimized parameters in noisy environments.

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