Title: Genetic Design of Optimum Linear and Non-linear QRS Detectors

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Abstract

This paper describes an approach to the design of optimum QRS detectors. We report on detectors including a linear or non-linear polynomial filter, which enhances and rectifies the QRS complex, and a simple, adaptive maxima detector. The parameters of the filter and the detector, and the samples to be processed are selected by a genetic algorithm which minimizes the detection errors made on a set of reference ECG signals. Three different architectures and the experimental results achieved on the MIT-BIH Arrhythmia Database are described.

I. Introduction

During the last twenty years, QRS detection has been one of the most frequently addressed tasks in ECG-signal processing [1], [2], [3], [4], [5], [6]. The typical structure of a QRS detector emerging from the various solutions reported in literature consists of two cascaded blocks: a module which enhances the QRS complex and a module which performs the actual detection.

The parameters of the second module are usually optimized to maximize the number of correct detections or similar performance criteria. However, as performance is a non-continuous function of such parameters, optimization can be obtained only with a trial-and-error procedure or with a regular sampling of the parameter space. Usually, this optimization strategy cannot be adopted for the first module because of the larger dimension of the parameter space. Actually, in most recent detectors the first module is designed, tuned, or trained with respect to other criteria, such as the signal-to-noise ratio or the RMS error with respect to a reference output [1], [4], [6]. No method has been reported in which both modules have been jointly optimized.

In this paper, we propose a new class of optimum QRS detectors which efficiently face noise, artifacts and variability of ECG morphology by exploiting non-linear processing and/or sub-sampling, and by making the enhancement and detection modules cooperate at their best. The modules are designed using genetic algorithms, which allow for an effective search of the optimum parameters in both discrete and continuous spaces.

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II. Genetic Algorithms

Genetic algorithms (GAs) are optimization and search procedures inspired by genetics and the process of natural selection in which the individuals of a population which are fitter with respect to the environment tend to survive and reproduce longer than the others [7], [8]. GAs simulate, in a rather simplified way, the processes outlined above to get better and better solutions (individuals) for a problem. In order to score each individual and determine how many offspring it will issue, an explicit fitness function is assigned which defines a performance surface in the search space of the optimization problem.

In our experiments we have used GAucsd, a public-domain software package that implements the basic GA [9].

III. Method

The first module of our detectors is a polynomial filter which enhances and rectifies the QRS complex. In order to accomplish maximum efficiency, the filter operates on a very small number of input samples that can be selected by the GA. The second module is a simple, adaptive maxima detector with spurious-peak removal.

The parameters of the filter and the detector are optimized according to a performance criterion related to the number of correct detections on a set of reference ECG signals extracted from the MIT-BIH Arrhythmia Database (MBAD) [10].

A. The Polynomial Filter

In polynomial filters, the output signal y_i at time i is the value taken by a polynomial of order M of a set of N input samples $\{x_{i-d_1}, x_{i-d_2}, \cdots, x_{i-d_N}\}$:

$$y_i = \underbrace{\sum_{k_1=0}^{M} \sum_{k_2=0}^{M} \cdots \sum_{k_N=0}^{M}}_{\sum k_j \leq M} a_{k_1 k_2 \cdots k_N} \, x_{i-d_1}^{k_1} x_{i-d_2}^{k_2} \cdots x_{i-d_N}^{k_N}, \tag{1}$$

where d_j's are delays with respect to time i.

B. The Maxima Detector

We have adopted a simple algorithm which detects the maxima of the filter output. To avoid false detections in the presence of noise, QRS-like artifacts and multi-spike filter responses, only the maxima that have an amplitude greater than a threshold Y and which do not fall within a refractory period of C samples after the last QRS are detected. To cope with the variability of the ECG signal, we have used an adaption scheme in which Y, initially set to a constant value Y_{start}, spontaneously decreases exponentially towards 0. This ensures that the detection process will start even in the presence of ECG signals with a very small amplitude. However, after each detection the threshold is moved towards a target value represented by a predefined percentage γ of the amplitude of the last detected peak of the filtered signal.

We can write:

$$\begin{cases} Y_0 = Y_{start} \\ Y_i = g((1-\alpha)Y_{i-1} - \beta z_{i-1}(Y_{i-1} - \gamma y_{i-1})) \end{cases}$$

where $g(x) = \max\{Y_{min}, \min[Y_{max}, x]\}$ is a clipping function which makes the adaption scheme more robust by keeping the threshold within the predefined range $[Y_{min}, Y_{max}]$, α is the decay rate, and β is a parameter which controls the speed with which Y_i moves towards the target value γy_{i-1}.

C. Genetic Design

The design of such a QRS detector requires the definition of the characteristics of the polynomial filter as well as the selection of its coefficients and the parameters of the maxima detector. Some of these variables are set by the human designer, the others are chosen by a genetic algorithm.

The order of the polynomial and the number of input samples affect the number of operations per sample: to get maximum efficiency, only low-order polynomials and a very limited number of input samples should be considered. However, using a small number of samples does not necessarily mean that the filter will work on a short tract of the ECG signal, as the delays $d_1, \cdots, d_N$ can be selected by the GA.

In general, the coefficients $a_{k_1 k_2 \cdots k_N}$ of the polynomial filter and the parameters of the detector should always undergo genetic optimization, except $a_{0 \cdots 0}$, which should be set to zero, as it is not independent from such parameters.

Once the parameters which undergo genetic optimization have been selected, it is necessary to define a proper fitness function. This should be a decreasing function of the number of wrong detections (or false positives, FP) and of missed detections (or false negatives, FN) produced when processing a set of reference ECG signals (training set). We have adopted the following fitness function:

$$f = f_{max} - (FP^2 + FN^2)$$

where f_{max} is a constant such that $f \geq 0$ for any set of parameters. This form of f has the advantage of favouring solutions in which FP and FN are not only minimum but also balanced.

IV. Experimental Results

We have considered three classes of filters for QRS enhancement: one for which many design strategies and instances exist (FIR filters with consecutive taps), one for which only a few design methods and instances exist (FIR filter with selected samples), and one for which no other optimization strategy and example has been proposed in literature (quadratic filters with selected samples). To show the increasing power of the three architectures we have kept the number of degrees of freedom (parameters) of each filter approximately constant while reducing the quantity of information in input.

The filters and the maxima detectors that were obtained should be considered the actual experimental results of this paper. However, we have tested our QRS detectors on the 48 records of the MBAD in order to

TABLE I

PARAMETERS OF THE OPTIMUM QRS DETECTOR BASED ON A QUASI-LINEAR FILTER WITH CONSECUTIVE SAMPLES.

Filter		*Detector*	
Parameter	Value	Parameter	Value
$a_{1000000000}$	-7.13024	C	25 (208 ms)
$a_{0100000000}$	-7.94744	α	0.00216
$a_{0010000000}$	3.04609	β	0.50137
$a_{0001000000}$	4.77475	γ	0.93127
$a_{0000100000}$	9.22591	Y_{start}	9.80099
$a_{0000010000}$	7.31803	Y_{min}	5.16208
$a_{0000001000}$	9.37990	Y_{max}	13.24999
$a_{0000000100}$	-8.26923		
$a_{0000000010}$	-9.57643		
$a_{0000000001}$	-0.62212		

assess their performance and compare them to other QRS detectors. To reduce the computation involved in the genetic design and in the tests, the sampling frequency of the records of the database (360Hz) was lowered to 120Hz.

The training set for the evaluation of the fitness function was obtained by randomly picking 10 10-second tracts of the ECG from the first channel of each of the 48 30-minute records of the database. Thus, the training set contained 5981 beats out of the about 110,000 of the whole database.

A. Quasi-Linear Filters with Consecutive Samples

The choice $M = 1$ in Equation 1 leads to a linear FIR filter. This kind of filter cannot produce a positive peak both in the presence of the positive R waves of normal QRSs (in Holter ECG signals) and the negative R waves of some anomalous QRS complexes. Thus, in this experiment, we adopted the *quasi-linear filter* obtained by taking the absolute value of the output of the linear filter.

In order to obtain high efficiency the number of input samples was fixed to $N = 10$, so that only 10 multiplications and 9 additions per sample are required.

Table I shows the optimum filter and detector found by the genetic algorithm. (The parameters shown in the table refer to an input signal expressed in millivolts.)

The second column of the table represents the impulse response of the filter before rectification. Interestingly, despite the large absolute value of the coefficients, the sum $a_{10\ldots0} + \cdots + a_{0\ldots01}$ is quite small (≈ 0.2), so that the filter tends to suppress low frequency components. Actually, the optimum filter is, on a broad approximation, a band-pass filter with cut-off frequencies of about 10Hz and 20Hz.

The QRS detector was tested on the first channel of the 48 records included in the MBAD. Table II illustrates the results obtained on each record expressed as: number of errors E, number of false positives FP, number of false negatives FN, sensitivity S and positive predictivity PP. The global results are also summarized in Table III.

TABLE II

PERFORMANCE OF THE OPTIMUM QRS DETECTOR BASED ON A QUASI-LINEAR FILTER WITH CONSECUTIVE SAMPLES ON THE MIT-BIH ARRHYTHMIA DATABASE (109963 QRS COMPLEXES).

Record	E	FP	FN	S (%)	PP (%)
100, 102, 103, 115, 117, 122, 123, 124, 212, 219, 220, 223, 231	0–1	0–1	0–1	99.96–100.00	99.93-100.00
101, 106, 107, 109, 111, 112, 119, 121, 202, 205, 209, 213, 214, 215, 217, 221, 230, 232, 233, 234	2–8	0–8	0–6	99.72–100.00	99.73–100.00
222	14	4	10	99.60	99.84
114	15	1	14	99.25	99.95
200	20	18	2	99.92	99.31
116	23	4	19	99.21	99.83
118	26	26	0	100.00	98.87
228	28	25	3	99.85	98.80
210	31	9	22	99.17	99.66
208	33	15	18	99.39	99.49
113	34	33	1	99.94	98.19
201	45	0	45	97.71	100.00
203	62	50	12	99.60	98.34
104	64	64	0	100.00	97.21
105	91	86	5	99.81	96.76
108	168	143	25	98.58	92.40
207	243	17	226	90.31	99.20
Total	986	545	441	99.60	99.51

TABLE III

SUMMARY OF THE PERFORMANCE OF THREE GENETICALLY DESIGNED AND TWO REFERENCE QRS DETECTORS ON THE MIT-BIH ARRHYTHMIA DATABASE.

Detector	E	FP	FN	S(%)	PP(%)
Lin. /w consecutive taps	986	545	441	99.60	99.51
Lin. /w selected taps	993	394	599	99.46	99.64
Quad. /w selected taps	1097	422	675	99.39	99.62
Okada's	3660	1822	1848	98.32	98.34
Engelse and Zeelenberg's	3515	1772	1743	98.42	98.39

TABLE IV

PARAMETERS OF THE OPTIMUM QRS DETECTOR BASED ON A QUASI-LINEAR FILTER WITH SELECTED SAMPLES.

Filter		*Detector*	
Parameter	Value	Parameter	Value
a_{10000}	-9.44797	C	31 (258 ms)
a_{01000}	8.94211	α	0.00336
a_{00100}	0.79523	β	0.39331
a_{00010}	-0.53695	γ	0.87430
a_{00001}	0.50358	Y_{start}	5.35688
d_1	1 (8 ms)	Y_{min}	3.56577
d_2	4 (33 ms)	Y_{max}	11.57131
d_3	5 (42 ms)		
d_4	10 (83 ms)		
d_5	14 (117 ms)		

Some observations can be made on these results. First, it should be noted that $E \leq 1$ on more than one fourth of the records and $E \leq 8$ on more than two thirds. Such records are real Holter recordings of subjects presenting different rhythm alterations. The sensitivity and positive predictivity of the detector on such records are typically over 99.8%. As noise and alterations increase, the performances of the detector decrease smoothly. Detection performances degrade only in the presence of records containing very high noise or long episodes of flutter or fibrillation such as records 104, 105, 108, 203, and 207 which the annotators of the MBAD themselves consider extremely difficult even for humans.

B. Quasi-Linear Filters with Selected Samples

This type of filter has the same structure as the one described in the previous section the only difference being that also the delays $d_1, d_2, \cdots, d_N$ undergo genetic optimization.

In order to avoid multiple selections of the same sample, we use the following set of equivalent parameters: $\{d_1, \Delta d_2, \Delta d_3, \cdots, \Delta d_N\}$. The delay of each sample (apart from the first one) is then given by:

$$d_i = d_{i-1} + \Delta d_i + 1.$$

The addition of these new degrees of freedom allows the GA to discover more powerful filters. To show this and to further decrease the computation load we decided to use filters with $N = 5$ taps only. With this choice, only 5 multiplications and 4 additions per sample are required.

Table IV shows the parameters of the optimum QRS detector found by the GA.

Also in this case, the optimum filter tends to suppress low frequency components. Actually, the filter has a basic derivative behavior due to the large opposite values of a_{10000} and a_{01000}. The delays d_1 and d_2 show that the GA has rediscovered the sub-sampling technique used in [11] for increasing the selectivity of FIR filters. In fact, due to the 1:3 sub-sampling, the basic spectrum $|f|$ of the derivative filter has been made approximately periodic with a period of 40Hz so as to present a large notch between 30 and 50Hz.

TABLE V

PARAMETERS OF THE OPTIMUM QRS DETECTOR BASED ON A QUADRATIC FILTER WITH SELECTED SAMPLES.

Filter		*Detector*	
Parameter	Value	Parameter	Value
a_{100}	5.81166	C	38 (317 ms)
a_{010}	-9.37731	α	0.00384
a_{001}	3.84030	β	0.23277
a_{200}	8.29333	γ	0.69024
a_{110}	-9.15624	Y_{start}	6.09388
a_{101}	-8.37377	Y_{min}	2.64001
a_{020}	9.51904	Y_{max}	13.12357
a_{011}	-9.97495		
a_{002}	4.79801		
d_1	0 (0 ms)		
d_2	5 (42 ms)		
d_3	8 (67 ms)		

The second row of Table III reports a summary of the results obtained on the MBAD.

C. Quadratic Filters with Selected Samples

The choice $M = 2$ in Equation 1 leads to quadratic filters. Such filters include a constant term, N linear terms and $(N + 1)N/2$ quadratic terms.

Using quadratic terms also the correlation between samples is taken into account. We decided to consider the extremely simple case of a quadratic filter with $N = 3$ taps and not to rectify the output of the filter.

This choice keeps the number of operations per sample quite small, as it requires only 9 multiplications and 8 additions per sample. As in the previous case , the choice of the appropriate values for the delays of the input samples was left to the GA.

Table V shows the parameters of the optimum QRS detector found by the GA.

The linear part of the filter has again a high-pass behavior. However, the large absolute values of the coefficients of the quadratic terms indicate that they are more important in determining the output of the filter. By analyzing the signs of such coefficients we see that the terms of form $x^2_{i-d_j}$ are always positive, while the terms of form $x_{i-d_j}x_{i-d_k}$ with $j \neq k$ are (usually) negative. The former are mainly responsible for the rectifying behavior of the filter. The latter prevent the former from making the filter "fire" in the presence of P or T waves and base-line drifts.

Table III (third row) reports a summary of the results obtained on the MBAD. Despite the reduced quantity of information available to this filter (just 30–60%) with respect to that fed into the quasi-linear filters described above, the total number of errors is only 11% greater thanks to the exploitation of the correlation between samples.

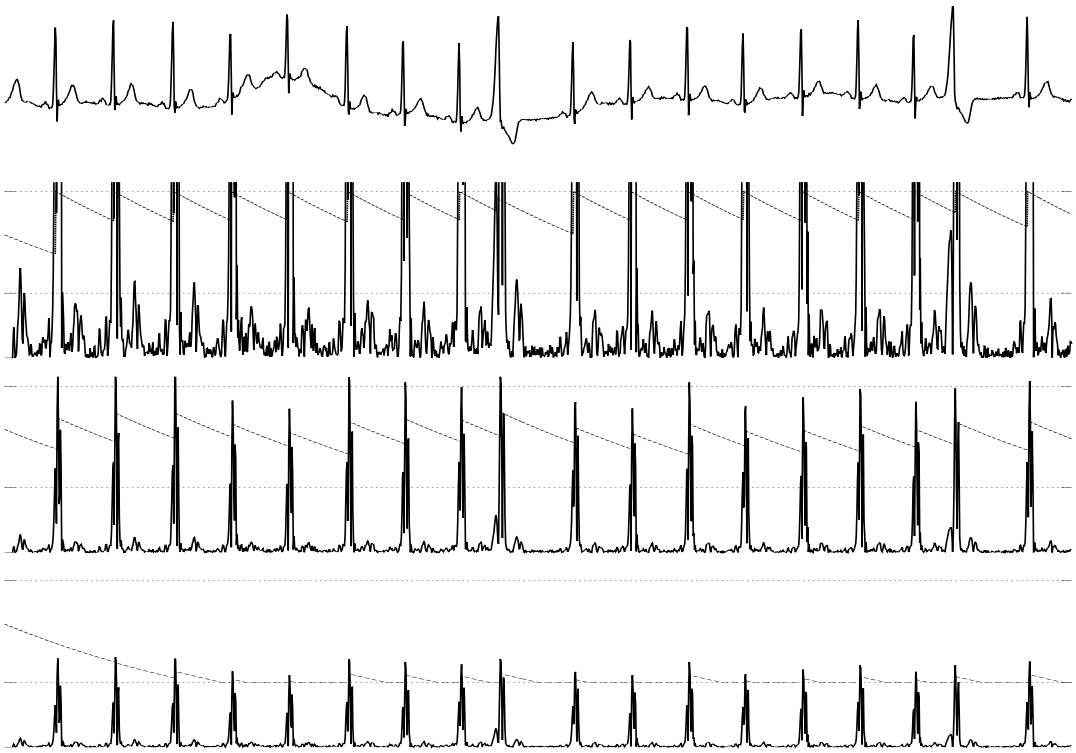

Fig. 1. A tract of ECG signal from record 116 (upper panel) and the output produced by the quasi-linear filter with consecutive samples along with the behavior of the threshold (dashed line) on (top to bottom) the original signal, amplitude reduced by a factor of 5, amplitude reduced by a factor of 10. The lower panels also include two dotted lines which represent the extrema Y_{max} and Y_{min} for the threshold.

D. Behavior of the Adaptive Maxima Detector

In order to illustrate threshold adaption mechanism, in Figure 1 we have reported a tract of the ECG signal from record 116 and the output produced by the quasi-linear filter with consecutive samples along with the behavior of the threshold in the following three cases: a) the input signal has the original amplitude, b) the amplitude has been reduced by a factor of 5, c) the amplitude has been reduced by a factor of 10.

It can be noted that in case a) the amplitude of the output signal is so large that the threshold is always clipped and wanders near the upper limit. However, no misdetection can occur as the noise on the output signal is almost always below the lower limit Y_{min}, while the minimum value of the threshold is more than twice such value (after the transient phase). In case b), the threshold never reaches the clipping limits and adapts constantly to follow the variations of the signal. In case c), the initial value of the threshold is too high for the small amplitude of the signal. However, the threshold quickly decreases so that only one QRS is lost.

TABLE VI

PERFORMANCE OF SOME QRS DETECTION ALGORITHMS ON DIFFERENT ECG DATABASES AS REPORTED IN LITERATURE.

Paper	Database	$S\%$	$PP\%$	Q
[12]	CSE	99.99	99.67	14292
[6]	CSE	99.38	99.48	14292
[2]	MIT-BIH[a]	99.76	99.56	116137 (?)
[13]	MIT-BIH[a]	99.69	99.77	109267
[4]	MIT-BIH[b]	99.84/99.09	99.61/98.59	2572/1763
[5]	AHA[c]	99.71	99.72	55689
[15]	other	99.96	99.94	4990

[a] Ventricular flutter excluded from record 207.
[b] Records 105 and 108.
[c] Records 1001–1010, 2001–2010.

E. Performance Comparison

Comparison of the performances of different QRS detectors is not easy as the detectors described in literature have been tested on different ECG databases, such as the CSE (Common Standard for Quantitative Electrocardiography) library [6], [12], the MBAD [2], [4], [13], the AHA (American Heart Association) database [5], or other ECG databases [1], [3], [14], [15].

The values of sensitivity and positive predictivity shown in Table VI have been reported in or can be deduced from the papers listed in the first column. However, the differences existing in the databases as to the number Q of QRS complexes, the ratio between normal and abnormal beats, and the intensity and frequency of artifacts make it difficult to perform a fair comparison on the basis of reported performances, only.

To provide a reference, we have implemented and tested on the MBAD the detector designed by Engelse and Zeelenberg [14] and the one described by Okada in [15] that, though simple and outperformed by many others, are very well known and have been shown to be among the most robust and reliable with respect to noise and artifacts [3]. In addition, complete and unambiguous details on their implementation are reported in the cited papers. Both detectors are ruled by parameters that were optimized to get the minimum number of errors E on the whole database. Table III (rows 5 and 6) provides a summary of the results obtained.

V. FINAL REMARKS

GAs have allowed us to optimize the parameters of the maxima detector and the coefficients of the filter according to a single criterion: minimizing the number of misdetections. While this objective function is commonly used in the optimization of detectors having few parameters, it has never been adopted in designing more complicated QRS enhancing filters or detectors.

The joint optimization of the two stages of our detectors has made them optimally adapted to each other. This has allowed for the discovery of parameters which yield robust and efficient QRS detectors even with

very simple layouts and only a few operations per sample.

In the second and third experiments we made the GA select the most adequate input samples to be processed. The equivalent performances obtained with the linear filter with selected samples and with the detector using consecutive samples show how the genetic design technique can identify and exploit the redundancies which are present in the input signal.

As concerns non-linear processing, the use of non-linear filters allowed us to exploit the correlations between the input samples. This yielded results which are comparable to those obtained with linear filters receiving 2 to 3 times more information.

Finally, the tests on the MBAD have also evidenced the light computation-load required by our detectors. The processing of a 30-minute record required no more than 1–2 seconds on an IBM RS-6000/320 computer. This would be 1,000–2,000 times the speed needed for real-time processing.

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