Adaptive Threshold QRS Detector with Best Channel Selection Based on a Noise Rating System

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Abstract

QRS detection performance can depend on the type of noise present in each lead involved in the overall processing. A common approach to QRS detection is based on a QRS enhanced signal obtained from the derivatives of the pre-filtered leads. However, the signal pre-filtering cannot be able to perform a complete noise rejection and the use of derivatives can enhance the noise as well. In many cases the noise occurs only on one lead and the addition of a noisy lead to the QRS enhanced signal decreases the overall detection performances of the QRS detector. For this reason the noise estimation on each channel, providing information for the channel inclusion or rejection in building the QRS enhanced signal, can improve the overall performances of the QRS detector.

The results have been evaluated on the 48 records of the MIT-BIH Arrhythmia Database where each ECG record is composed by 2 leads sampled at 360 Hz for a total duration of about 30 minutes. The annotated QRSs are 109494 in total. The results have been very satisfying on all the annotated QRSs and, with the inclusion of an automatic criterion for ventricular flutter detection, a sensitivity=99.76% and a positive predictive value=99.81% have been obtained.

1. Introduction

QRS detection in electrocardiograms (ECGs) is the basic step for any further processing. Usually the limited number of available leads can be an obstacle to the attainment of high performances for a QRS detection algorithm especially when there is a high noise in one or more of the available leads. Noise in ECGs can appear due to several different sources like poor contact between the electrode and the skin, patient movements or breathing, etc. All these different sources can produce different types of noise like a) baseline wandering, b) powerline interference, c) muscle artifacts, d) spikes, e) sudden baseline shifts. In several circumstances the noise can appear only in one or few leads, while the others have a good-quality signal. A common approach to time-based methods for QRS detection is through the QRS enhancement achieved in a QRS enhanced signal (QeS) based on the derivatives of pre-filtered leads. The contribution of the noisy channel to the QeS can strongly deteriorate the performances of the overall algorithm. Thus, the estimation of the noise level in each channel with a criterion for the best channel selection (excluding the noisy channels from the algorithm) can improve the total performances of the QRS detector.

In this paper the methods used for the QRS detection, noise estimation and best channel selection, and the results obtained on the entire MIT-BIH arrhythmia database are reported. Finally, further improvements are discussed in the final section.

2. Methods

Real data (surface ECGs) have been used from the MIT-BIH Arrhythmia Database [1] for a total of 48 records. The records are half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings are digitized at 360 Hz with 11-bit resolution over a 10 mV range. Each beat of each record has a reference annotation identifying the QRS position and type.

Several different techniques can be applied for QRS detection [2]. The selected approach belongs to the time-domain techniques and is derived from the simple QRS detector used in the Computers in Cardiology/PhysioNet challenge 2004 [3]. The first step consists in a signal pre-filtering using a moving-average linear filter in order to reduce the baseline wandering and the high-frequency noise, and to select the typical frequencies contained in the QRS complexes. Several different bands have been tested and the most appropriate results 5-15 Hz [4].

The QeS is built as the sum of the absolute derivatives of each pre-filtered channel. The filter for the generation of the derivatives has been chosen trying to reduce the effect of the high frequency residual noise. In practice a pass-band filter is used with a derivative behaviour in the band of interest.

An adaptive threshold is initially set up as 40% of the average QeS peaks in windows of 2 sec discharging the cases out of the 98% percentiles. The average QeS peak (QeSap) is continuously updated after each QRS detection using the QeS peak (QeSp) detected in the current QRS with the formula (n is the progressive number of the detected QRS):

If
QeSp(n) >= 1.5*QeSap(n-1)
Then
QeSap(n) = 0.97*QeSap(n-1) + 0.045*QeSap(n-1)
Else
QeSap(n) = 0.97*QeSap(n-1) + 0.03*QeSp(n)
End

The beginning of a QRS is detected when the QeS overcomes the threshold (0.4*QeSap(n-1)) while the end of the QRS is revealed when the QeS goes down to the threshold and remains down for a sufficient number of consecutive samples.

To avoid False Positives (FP) due to high T-waves detection, a dead-time zone of 200 msec is set up in order to reject any QRS detection too close to the previous one. Furthermore, the QRS detection threshold is artificially increased after detecting a QRS peak and linearly decreased, with the time-distance from the previous QRS, to its base value. The QeS and the detection threshold in an excerpt of record 100 are shown in Fig. 1.

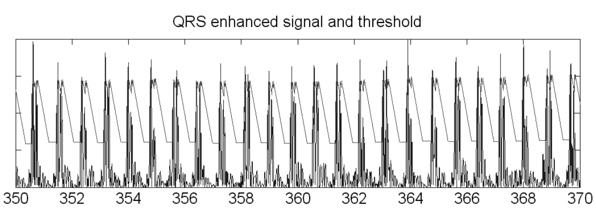

Figure 1. QeS and detection threshold for record 100 (on the abscissa there is the time expressed in seconds).

Using only the above algorithm the QRS detection results are good enough especially in recordings with low or medium content of noise. However, when the noise in one or both leads is high, the performances of the detector are significantly reduced.

It has been decided to take into account the impact of the noise in the QRS detection as already done in other studies [5], but with a different approach. In fact, it has been observed that, when the noise is present only in one channel, the exclusion of this noisy channel from the QeS improves the QRS detection results.

The noise level of each ECG lead is estimated with the following procedure. For each detected beat, the QRS average power is estimated as the square average of the samples in a 100 msec interval located around the detected R-peak. The T-P interval power is evaluated as the square average of the samples in an interval obtained by rough estimation of the end of T-wave and the onset of the following P-wave [6].

For each detected QRS a noise index (NI) is defined as the T-P interval average power divided by the QRS average power. The NI is quantized in three levels: NI<0.1 (low); 0.1<NI<0.2 (intermediate); NI>0.2 (high). The weights 0, 1, 2 are respectively assigned to each of these levels and, for any interval of an ECG, the Noise Score (NS) is estimated averaging the weights of the QRSs detected in that interval.

In Fig. 2, related to record 103, the diagrams with the NI for the detected QRSs with QeS_1+2 (QeS built with channels 1+2) are shown respectively for channel 1 and channel 2.

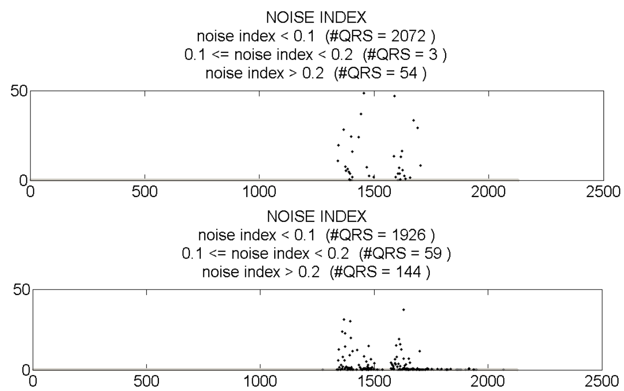

Figure 2. From top to bottom the NI in channel 1 and 2 of record 103 after QRS detection with QeS_1+2 (in the abscissa there is the #QRS). Around QRS #1500 it is evident an area (larger in channel 2) with high density of NI greater than 0.2.

The presence of high noise in channel 2 for the QRSs from #1270 to #1710 induces several False Positives (FP) and False Negatives (FN) in that interval, but the high noise is revealed by the NI that indicates 3 and 59 QRSs with intermediate noise and 54 and 144 QRSs with high noise respectively in channel 1 and 2.

In Fig. 3 an excerpt of record 103 from the area with high noise (identified in Fig. 2) shows how the noise is most contributed by channel 2.

If for building up the QeS in record 103 only channel 1 is used (QeS_1), then the NI for channel 1 is improved to a great extent as shown in Fig. 4.

Since the NI can be used as an indicator of the noise in the two different channels and of good QRS detection, the following algorithm has been implemented for the best channel selection.

The appearance of a number of consecutive noisy

QRSs (noise index greater than 0.1) determines the beginning of a Noisy Interval (No.In.), which ends once a few consecutive non-noisy QRSs appear. Based on the detected QRSs with QeS_1+2, the No.In. of channel 1 (No.In._1) and the No.In. of channel 2 (No.In._2) are calculated, and the total No.In. are evaluated as the union of No.In._1 and No.In._2. For each unified interval, the overlap percentages with channel 1 and channel 2 are calculated. For example, if a No.In. comes exclusively from channel 1, then the overlap percentage is 100% for channel 1 and 0% for channel 2.

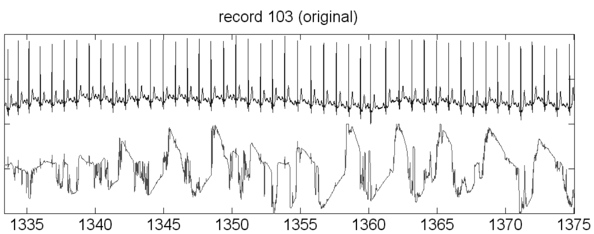

Figure 3. An excerpt of record 103 from the area with high noise identified in Fig. 2. It is evident how the noise is mostly contributed by channel 2.

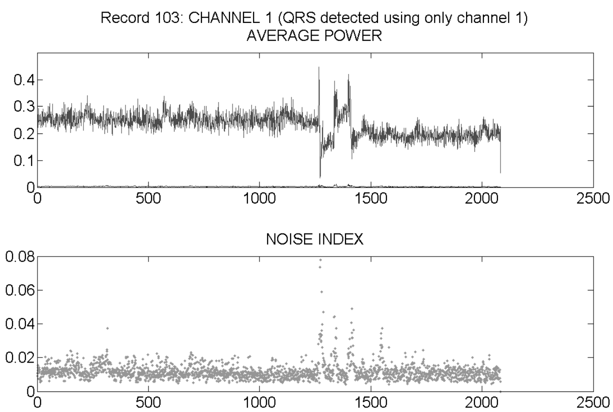

Figure 4. The (QRS and T-P interval) average power and NI in channel 1 of record 103 after QRS detection with QeS_1 (in the abscissa there is the #QRS). NI is always below 0.1.

For the record samples not belonging to any unified No.In., the QRS detection results with QeS_1+2 are used (best channel 1+2).

For the samples of each unified No.In., QRS detection with QeS_1 and QeS_2 are performed as well. Then, the following criterion is applied (j is the channel with the lowest overlap percentage and k is the other one):

1) If the NS (QeS_1+2) in channel j is 0, the QRS detection results with QeS_1+2 are used (best channel 1+2).
2) If the NS (QeS_j) in channel j is more than 0.75*NS (QeS_1+2) in the same channel, the QRS detection results with QeS_1+2 are used (best channel 1+2).
3) If the NS (QeS_j) in channel j is less than 0.75*NS (QeS_1+2) in channel j, the QRS detection results with QeS_j are used (best channel j) unless the NS (QeS_k) in channel k is less than the NS (QeS_j) in channel j and less than 0.1*NS (QeS_1+2) in channel k. In such case the QRS detection results with QeS_k are used (best channel k).

Furthermore, the database includes intervals with ventricular flutter waves that may be erroneously detected as QRSs increasing the number of FP. Although these VFL intervals might be manually excluded from the QRS detection evaluation, a first implementation of an automatic detection of the VFL intervals has been performed in order to obtain a fully automatic algorithm.

Similarly to ventricular fibrillation (VF) [7], the analysis of VFL can be performed with several different techniques. However, being the flutter waveforms almost sinusoidal, a frequency domain approach has been considered more appropriate.

The raw signals (both channels) are filtered with a moving average 1-30 Hz pass-band linear filter, with a Hamming window. Each pre-processed ECG signal of a record in the database (both channels of the record) is divided into periods of 5 seconds with a 50% overlap with the next one. Fourier transform of these intervals is computed and spectral characteristics as power peak amplitude and location are used to mark these 5-sec intervals as VFL or not. Each 5-sec interval marked as VFL is not considered in the QRS detection algorithm.

3. Results

In the overall database only record 207 contains VFL intervals. It has 6 VFL intervals for a total of about 142.5 seconds. The proposed algorithm for VFL interval identification has satisfying performance in all the records of the database resulting in no FP and only 12.5 seconds of FN intervals.

In Table 1 the results of the overall QRS detection algorithm, which includes noise estimation, best channel selection and VFL detection, are reported.

The total number of annotated beats results 109494, with 109288 TP. FN and FP are respectively 266 and 210. The sensitivity TP/(TP+FN) is 99.76% while the positive predictive value (PPV) TP/(TP+FP) is 99.81%. In 15 records a perfect detection without any FN and FP has been obtained. 12 records have more than 10 FP+FN and only 5 records more than 30 FP+FN.

4. Discussion and conclusions

The inclusion of best channel selection based on noise level and the VFL interval identification improves the performance of the original algorithm used in the Computers in Cardiology/PhysioNet challenge 2004 [7].

The obtained performances have also been compared with the ones of some published studies. The algorithm proposed in [3] provides a Sensitivity=99.76% and a PPV=99.80%, which are substantially the same of our developed algorithm, but the reported statistic results were obtained on a subset of the total annotated beats (about 91000 annotated QRSs). Similarly, the best results obtained by [4] are Sensitivity=99.74% and PPV=99.65%, a little lower than the ones obtained with our algorithm.

Table 1. The results in terms of annotated beats, detected beats, True Positive (TP), FP and FN for each record of the MIT-BIH Arrhythmia database.

Record	Annotat. beats (TP+FN)	Detect. beats (TP+FP)	True Positive (TP)	False Negative (FN)	False Positive (FP)
100	2273	2273	2273	0	0
101	1865	1867	1862	3	5
102	2187	2187	2184	3	3
103	2084	2094	2083	1	11
104	2229	2230	2222	7	8
105	2572	2592	2555	17	37
106	2027	2030	2027	0	3
107	2137	2134	2131	6	3
108	1763	1792	1758	5	34
109	2532	2530	2530	2	0
111	2124	2125	2124	0	1
112	2539	2539	2539	0	0
113	1795	1795	1795	0	0
114	1879	1879	1879	0	0
115	1953	1958	1951	2	7
116	2412	2396	2393	19	3
117	1535	1535	1535	0	0
118	2278	2279	2278	0	1
119	1987	1988	1987	0	1
121	1863	1863	1863	0	0
122	2476	2476	2476	0	0
123	1518	1518	1518	0	0
124	1619	1613	1609	10	4
200	2601	2598	2593	8	5
201	1963	1898	1898	65	0
202	2136	2134	2134	2	0
203	2980	2968	2947	33	21
205	2656	2649	2649	7	0
207	1860	1892	1852	8	40
208	2955	2947	2936	19	11
209	3005	3002	3000	5	2
210	2650	2631	2628	22	3
212	2748	2743	2743	5	0
213	3251	3250	3250	1	0
214	2262	2261	2259	3	2
215	3363	3361	3361	2	0
217	2208	2207	2206	2	1
219	2154	2154	2154	0	0
220	2048	2048	2048	0	0
221	2427	2427	2427	0	0
222	2483	2481	2480	3	1
223	2605	2605	2605	0	0
228	2053	2053	2052	1	1
230	2256	2256	2256	0	0
231	1571	1571	1571	0	0
232	1780	1782	1780	0	2
233	3079	3074	3074	5	0
234	2753	2753	2753	0	0

It has to be noticed that for the VFL detection algorithm further improvements can be applied in order to more precisely identify the start and the end of each VFL intervals instead of using multiples of 2.5 seconds and intervals with a length of 5 sec. Such approach should be able to reduce the number of false QRS detections with an increment in the total sensitivity. Furthermore, the developed criteria for the VFL detection algorithm could be further checked and improved on a specific annotated database like the Creighton University Ventricular Tachyarrhythmia Database.

Finally, it has to be mentioned that the implemented algorithm for noise detection and best channel selection can be easily extended to situations where the QeS is built with more than 2 leads.

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