Continuously Tested and Used QRS Detection Algorithm: Free Access to the MATLAB Code

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Abstract: *Each ECG analysis begins with the detection of the QRS complex, which is the most distinguishable wave for initial investigation. Long ago we published an algorithm for ventricular beats (VB) detection in single ECG lead. The classification of normal QRS complexes is based on the slope, the amplitude and the width of the ECG waves. Other criteria recognize ventricular ectopic beats (EB) by presence of biphasic beats and separate premature EB from the already detected QRS complexes. The aim of this paper is to place the MATLAB program of our algorithm at disposal to the readers (supplementary MATLAB codes) looking forward to more successful ECG investigations.*

Keywords: *Ventricular beat detection, QRS detection, Ectopic beat detection.*

Introduction

Each automated as well as manual ECG analysis comprises the next main stages: onset and offset detection of the waveforms; measurement of their amplitudes, widths, intervals and interrelationships; comparison between the extracted values and statistically created datasets of criteria to classify the found ECG morphology as normal or pathological heart activity. To be successful, the ECG analysis begins with the detection of the QRS complex, which is the most distinguishable wave for initial investigation.

One of the first software algorithms for QRS detection has been published by Caceres and Dreifus in the early 1970 [9]. The differentiated ECG signal was divided into short intervals where the absolute maximums higher than a dynamic threshold were assumed to belong to QRS complexes. Nowadays the number of the elaborated, tested and reported QRS algorithms is enormous that proves implicitly the impossibility to build an ideal QRS detector covering all the variety of shapes encountered in practice.

Generally, each QRS detection algorithm includes two parts: preprocessing and decision rule. The preprocessing is aimed to suppress the disturbances accompanying the ECG signals acquisition, such as power line interference (PLI), drift, tremor and artefacts due to bad electrode-to-skin contact (Nenova and Iliev [20], Bhoi et al. [8], Razavi and Mohammadi [22]). Here the processing parameters are selected rather to enhance the difference between the QRS complex and the other waveforms than to keep the informative ECG features.

The decision rules are highly varied. The commonly used algorithms interpret features extracted from first or second derivative of the ECG signal (Köhler et al. [17], Arzeno et al. [5]). As an example, Hamilton and Tompkins [14] reported a first derivative based squaring function

for QRS detection. The last two decades have been proposed algorithms designed by filter banks (Alfonso et al. [2]), wavelet transforms (Sumathi and Sanavullah [25], Sasikala and Wahidabanu [24], Benali et al. [6]); artificial networks (Abibullaev and Seo [1]); Hilbert transform (Benitez et al. [7]; Sahoo [23]); feature extraction (Paoletti and Marchesi [21], Harikumar and Shivappriya [15]).

Kohler et al. [17] investigate the QRS complexes counting the number of high amplitude zero crossings per segment in ECG signals, which are preliminary subjected to linear phase band pass filtration to suppress the P- and T-waves together with the noise oscillations around the zero line.

Kim and Shin [16] developed algorithm based on some spatiotemporal characteristic. The power spectrum components of the ECG signal are currently assessed and the maximum energy level within the 5÷25 Hz frequency band during a short time interval is accepted to belong to QRS complex.

The Christov's QRS detector [10] takes in consideration signals from one or more simultaneously recorded channels. The signals are differentiated and their absolute values are summed and compare to threshold with three components: adaptive slew-rate, correction depending on the presence of high-frequency noise and criterion supporting the detection of low amplitude QRS complexes. In another study [11] Christov reports new modifications of the combined threshold method. The test carried out with the AHA database recordings impresses with the obtained very high statistical indices.

Actually, the QRS detection represents a special case of ventricular beat (VB) recognition (Christov [10]), which is followed by discrimination between normal sinus beats (NB) and ectopic beats (EB) (Millet et al. [18], Dotsinsky and Stoyanov [13], Tanev [27]). This process is the first step of both morphological and rhythm analysis. Epochs of sinus QRS complexes are investigated for assessment of the heart rate variation (HRV). The EB are divided in different types according to their shape and/or time of occurrence that is used further for rhythm disorders discovery.

Tanev [27] describes very fast off-line procedure for accurate QRS detection in long term ECG Holter recordings, followed by classification of the complexes in normal and ectopic beats. The analysis of a 24 hour epoch needs no more than 7-8 min.

The efficiency of VB detection algorithms is usually tested with ECG signals taken from internationally recognized databases, e.g., the AHA database, the MIT-BIH arrhythmia database, the diagnostic PhysioNet database, etc. Generally, the performance of the algorithms is assessed by calculating the true positive (TP), the true negative (TN), the false positive (FP) and the false negative (FN) detections within the examined recording. Then some indices are evaluated, for example the sensitivity Se = TP/(TP+FN) and the specificity Sp = TN/(TN+FP), (Altman and Bland [4]); the positive and negative predictive values PPV = TP/(TP+FP) and NPV = TN/(TN+FN), thus giving objective rating of the algorithms accuracy.

As a rule, the TP, TN, FP and FN values are obtained by counting the coincidences between the recognized and the annotated beats inside the used database. Because of the enormous data array they have to be checked automatically.

The annotations have varying positions towards the complexes, e.g., in the AHA database they are mostly near to the onset of the R wave. Suppappola and Sun [26] advised the users to define themselves the interval that includes the ventricular beats or to set default borders at 10 ms before and 140 ms after the annotated locations. Dotsinsky and Stoyanov [13], as well as Christov [10] use specially designed software, which inserts windows surrounding the marked complexes by 60 ms. The algorithm published by Tanev [27] allows deviation of ±30 ms between the classified beats and the corresponding annotations.

Most of the published methods for QRS detection demonstrate very high performance values typically more than 95%.

There are numerous papers with extremely scientific contributions. Usually the theoretical approaches are perfectly carried out, the details are correctly revealed, and the results obtained are convincingly illustrated by tables and figures. However, a few of the reported studies may be easily implemented in similar investigations since usually no programs or extracted parts of them are available to the readers.

Long ago we published an algorithm for VB detection in single ECG lead (Dotsinsky and Stoyanov [13]). The normal QRS classification is based on the slope, the amplitude and the width of the ECG waves. Other criteria recognize ventricular EB by presence of biphasic beats and separate premature EB from already detected QRS complexes. Finally, sinus beats (NB) and all ectopic beats (EB) are discriminated in two categories. The algorithm was tested in MATLAB environment by the entire AHA [3] and MIT-BIH [19] databases demonstrating 99.04% sensitivity and 99.62% specificity, but more important is that it was shared with closed friends thus proving high efficiency in practice.

Aim of the this paper

We would like to place the MATLAB program (used version 7.0.0.19920 (R14)) of our algorithm at disposal to the readers looking forward to more successful ECG investigations.

Brief description of the algorithm

Preprocessing

Comb filter with first zero at 50 Hz (60 Hz) is applied to eliminate the power-line interference, followed by low-pas filtration with cut-off approximately at 40 Hz. The baseline drift is suppressed using first order high-pass filter with cut-off at 2 Hz.

QRS detection

The algorithm for ventricular beat detection (Dotsinsky and Stoyanov [13]) improves previously developed method for QRS detection (Dotsinsky [12]). Two identical in sign differences between the ongoing sample S_i and the adjacent samples S_{i-n} and S_{i+n} are currently calculated, where n is usually equal to the number of samples within the interference period. The positions of the ongoing samples S_i either coincide with or are very near to peaks of the investigated ECG signal. The absolute *SUM* of the differences

$$SUM = \left|2S_i - S_{i-n} - S_{i+n}\right| \quad \text{for} \quad sign(S_i - S_{i-n}) = sign(S_i - S_{i+n})$$

is compared to appropriate adaptive threshold *AT*. QRS candidates are marked each time when *SUM* > *AT*. Fig. 1 shows three QT intervals with difficult for detection QRS complexes.

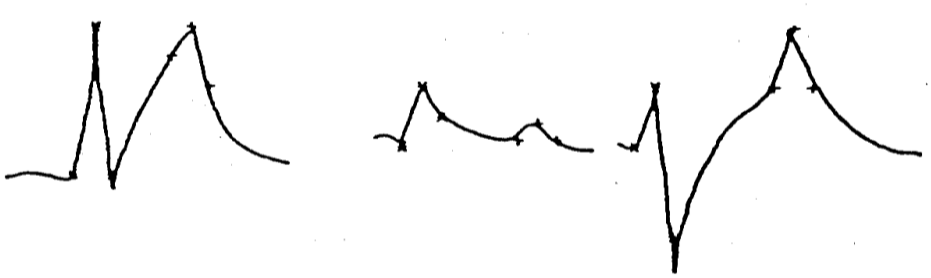

Fig. 1 Discrimination between different in shape QRS complexes and their T-waves

Nevertheless, the different *SUM* values ensure efficient discrimination between QRS and T-waves. For better illustration of the principle based on high amplitude, steep edges and sharp peak evaluation, the wave peaks are assumed to coincide with samples. Another sample distribution over the QRS complex can be seen in Fig. 2a.

The initial value of *AT* is set to 0.2 mV (Dotsinsky and Stoyanov [13]). Except for occurrence of very low peak amplitude, the threshold after each QRS detection becomes equal to 0.7 *SUM*. It does not change for 200 ms to skip high-amplitude T-waves, decreasing further linearly in accordance with different laws until and after the end of the first second.

A true beat candidate is expected to appear after a delay called *DIST* that is related to the expected QT interval duration of the ongoing RR interval. Each beat candidate located to the latest detected QRS complex nearer than *DIST* is ignored if its *SUM* is less than that of the latest complex. Otherwise, the latest complex is discarded assuming it is a lower amplitude component of the new candidate.

Further, the maximum value V_{max} inside the interval of 120 ms around the candidate is found. Its position is entered in buffer *normal beats* if $V_{max} > 80$ μV and the number of zero crossings $N < 8$. The first requirement allows the detection of low amplitude QRS complexes; the second one is aimed to suppress electromyographic artifacts and other high frequency disturbances.

Ectopic beats detection

Another algorithm branch investigates ventricular EBs. It is activated 120 ms after each detected QRS complex looking for biphasic wave consisting of three consecutive crossing of thresholds with alternative polarity $W_1 \div W_3$. Then the peaks A_1 and A_2 inside the thresholds are located and their amplitudes as well as the intervals W_1-W_2 and A_1-A_2 (see Fig. 2b) are checked for conformity with several criteria for EB identification. They are additionally aimed to cope with either previously detected QRS complexes with low amplitude or encountered EBs with sharp peak, after which the signal remains long time near to the zero line.

If the criteria are not met, W_1 is discarded, while W_2 and W_3 are marked as W_1 and W_2. They form the next two waves together with a new crossing W_3. This cycle is repeated until EB is detected. Its position is saved in buffer *ectopic beats*. Besides, it is entered in buffer s*uspicious beats* for additional analysis. The reason is that two consecutive VBs may occur at distance shorter than *DIST* in case of long RR intervals, which include burst of EBs or EB followed by compensatory pause.

Analogously, deviations of the QRS width and/or its maximum peak-to-peak amplitude may erroneously classify normal QRS complex as ectopic beat. That is why other algorithm branch compares the parameters of the currently detected QRS complexes with the corresponding parameters of a template *QRSe* created during the first 12 detected beats to distribute the

suspicious or erroneous beats in the true buffers. Among the used parameters are the maximum positive and negative amplitudes, their peak-to-peak amplitudes and the number of zero crossings.

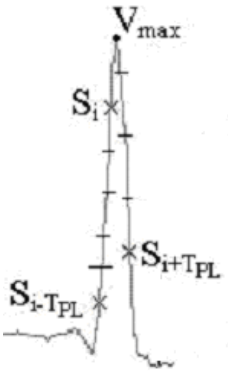

Fig. 2a. Discovery of typical QRS complex

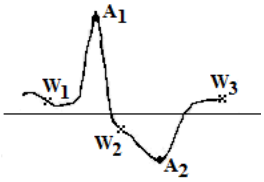

Fig. 2b. Investigation of ectopic beats

MATLAB codes

Two MATLAB codes for VB detection are available in compressed format at
http://www.biomed.bas.bg/bioautomation/2019/vol_23.1/files/23.1_06.zip
together with associated ECG signals.

They are structured in two directories: *version1* and *version2*. You can download every one of them and run the corresponding *VB1.m* or *VB2.m* code from archive 23.1_06.zip:
Free access to QRS detection code/version1/VB1.m
Free access to QRS detection code/version2/VB2.m

Our original MATLAB program discussed in the publication (Dotsinsky and Stoyanov [13]) was adapted to work with all ECG recordings from AHA and MIT-BIH databases, representing a lot of files of many Mbytes that have to be open in a complicated manner, specifically for the MIT-BIH database.

Therefore we compiled the file *VB1.m* to operate with several selected recordings, which are quite enough to discover the algorithm potential. The file execution starts with question about the database to be used. A click on the button *AHA* gives access to 8 recordings. Four recordings are available if the reader chooses the button *MIT-BIH* but not before selecting one of the two channels replying to a second question. The code entitled *%epoch length* (enclosed inside 174th and 186th lines) defines either the entire ECG file or its selected part to be opened, analyzed and displayed. The results are shown in sequence of figures, which include two curves, the non-used lead and the original processed and analyzed lead together with the marked normal and ectopic beats. In a lot of cases the correct recognition may be visually confirmed by the accompanying lead.

Below are presented results of ventricular beat detection obtained with *VB1.m*. Figs. 3 and 4 show the recognized normal QRS complexes and ectopic beats in epochs taken from the recordings AHA A7006D1 and MIT-BIH 212D2. Please, pay attention to the signal displayed in Fig. 4, where all QRS complexes are correctly detected regardless of the abrupt waveform change after the 251th s.

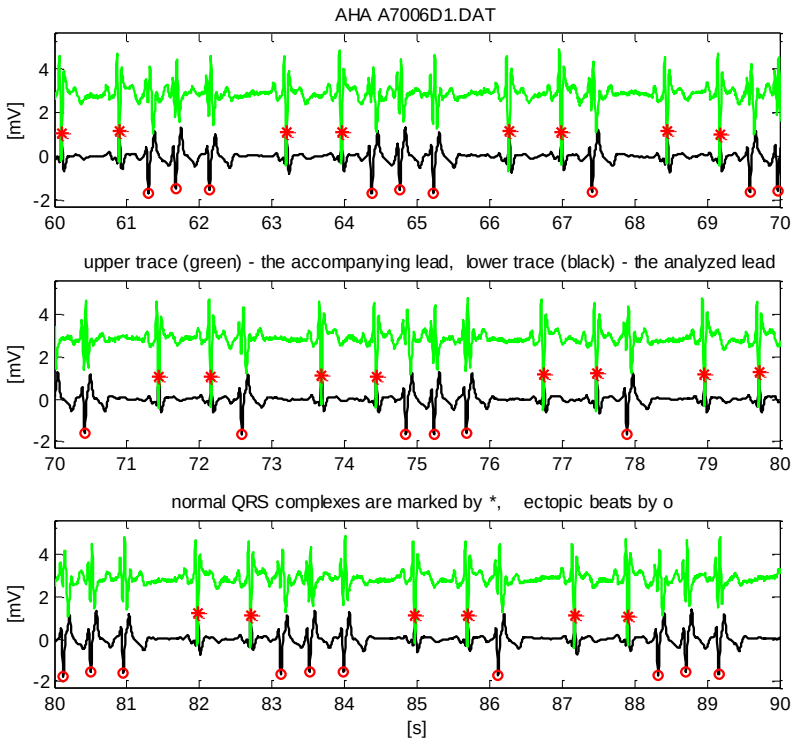

Fig. 3

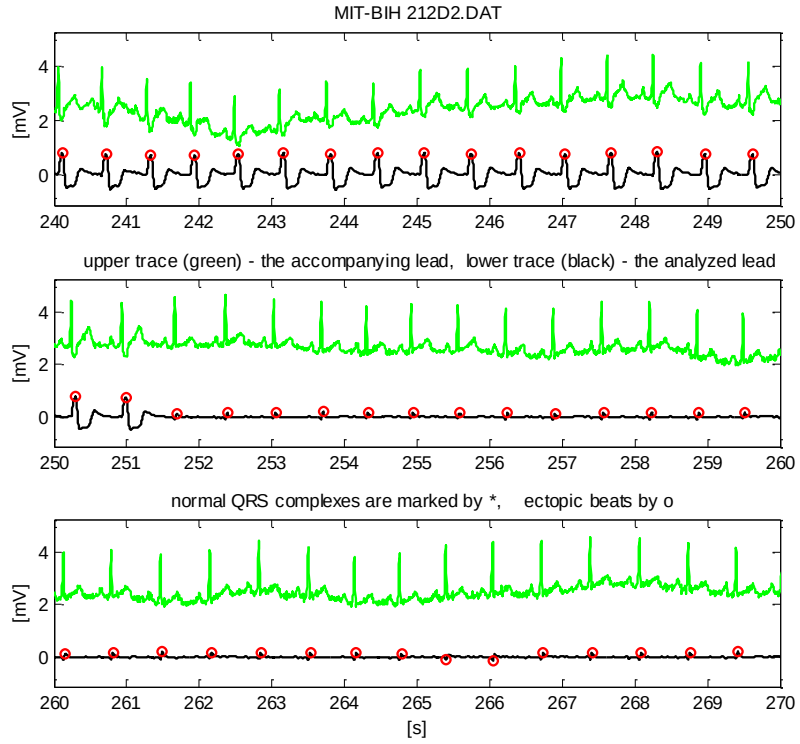

Fig. 4

The second file *VB2.m* simplifies the algorithm implementation working with the AHA/AHA6003d1 and MIT-BIH/203d1 recordings, which are preliminary opened and secondary saved in a format suitable for analysis of reader's files. Here the *%epoch length* definition is inside 98th and 110th lines. The results of the investigated signals are demonstrated in Figs. 5 and 6.

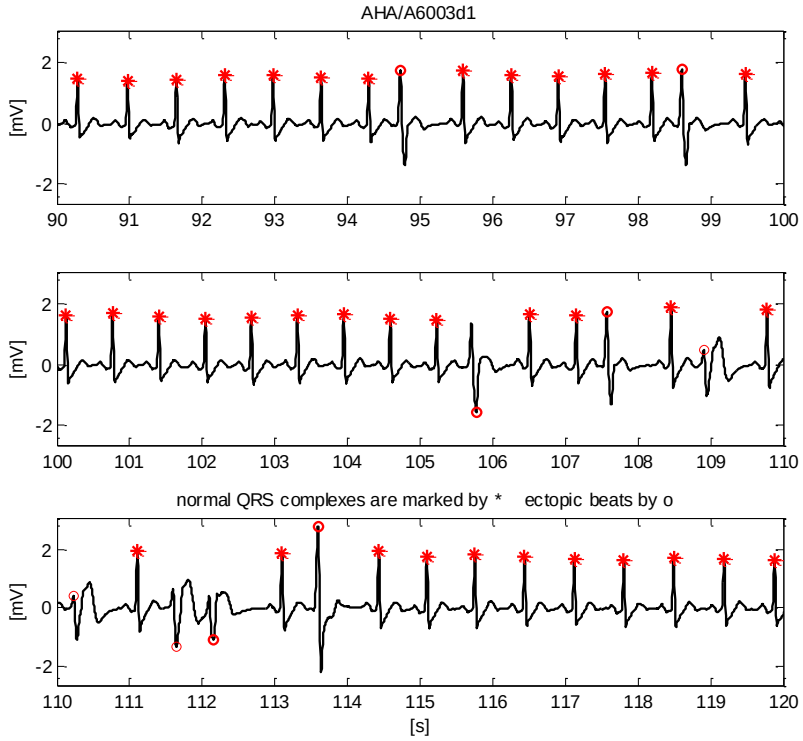

Fig. 5

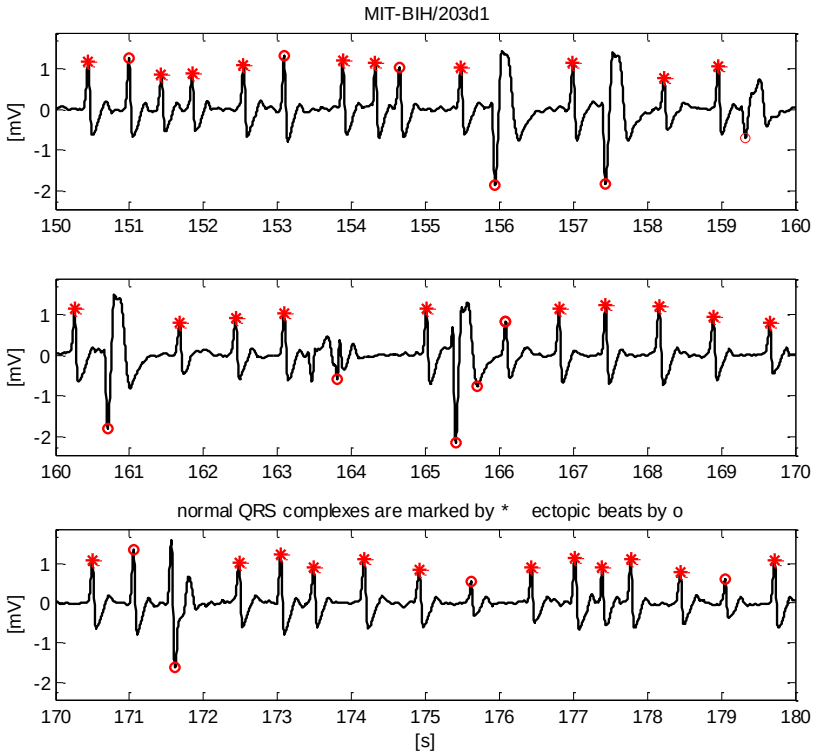

Fig. 6

More detail can be found in the attached MATLAB codes provided with comments.

Conclusion

We hope this paper may support the investigators in developing of complex ECG signal analyses. The shared algorithm was tested with the entire AHA and MIT-BIH databases demonstrating 99.04% sensitivity and 99.62% specificity.

The number of the attached to the first *VB1.m* version recordings is limited to save the space. Still, we think they demonstrate quite enough the algorithm power, although the discrimination between normal and ectopic beats can be improved. The reader can easily add other recordings from the mentioned databases if necessary. The presence of the accompanying leads may confirm the detection and classification considerations.

The two recorders attached to the second *VB2.m* version simplify the opening of files saved in a wide accepted mode.

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