Assessment of the Performance of the Adaptive Thresholding Algorithm for QRS Detection with the Use of AHA Database

Ivaylo Christov

Centre of Biomedical Engineering Prof. Ivan Daskalov – Bulgarian Academy of Sciences
105 Acad. G. Bonchev Str., Sofia 1113, Bulgaria
E-mail: Ivaylo.Christov@clbme.bas.bg
http://www.clbme.bas.bg/pwp/Ivaylo_Christov/

Received: December 4, 2006 **Accepted: February 6, 2006**

Published: Mart 27, 2007

Abstract: *Two modifications of an adaptive thresholding algorithm for heart beat detection have already been developed. The threshold combines three parameters: an adaptive slew-rate value, a second value which rises when high-frequency noise occurs, and a third one intended to avoid missing of low amplitude beats. The current study assesses the performance of a new modification of the combined adaptive thresholding method for heart beat detection with the use of AHA database. The results are: Mod. 1 Se=99.58 %, Sp=99.83 %; Mod. 2 Se=99.73 %, Sp=99.83 %; Mod. 3 Se=99.78 %, Sp=99.85 %. The statistical indices are higher than, or comparable to those, cited in the scientific literature.*

Keywords: *ECG, QRS detection, Heart beat detection and classification, Adaptive thresholding.*

Introduction

The QRS complexes and ventricular beats in an electrocardiogram represent the depolarization phenomenon of the ventricles and yield useful information about their behavior. Beat detection is a procedure preceding any kind of ECG processing and analysis. For morphological analysis this is the reference for detection of other ECG waves and parameter measurements. Rhythm analysis requires classification of QRS and other ventricular beat complexes as normal and abnormal. Real-time ventricular beat detection is essential for monitoring of patients in critical heart condition.

Correct beats recognition is impeded by power-line interference, electromyogram noise and baseline wander often presented in the ECG signal.

In long-term monitoring electrode impedance can increase considerably, resulting in very low signal-to-noise ratio, which can make detection practically impossible in a single lead. Therefore, usually two or three leads are used for monitoring [8].

Different methods for heart beat detection have been used: generic algorithms [10], hardware filter banks [1], heuristic algorithms [5], wavelet transforms [7] logical combination [8] of two different algorithms [6, 9] working in parallel, etc.

The large variety of QRS detection algorithms, and the continuous efforts for their enhancement, proves that universally acceptable solution has not been found yet. Difficulties arise mainly from the huge diversity of the QRS complex waveforms and the noise and artifacts accompanying the ECG signals.

In 2004 Christov suggested two modifications of a real-time QRS detection algorithm based on combined adaptive thresholding [3]. The algorithm operates with a complex lead combined of one, or any number of several primary leads. It has been tested with MIT Arrhythmia Database and the reported accuracy is among the best known: sensitivity *Se* = 99.69 % and specificity *Sp* = 99.65 % for Modification 1 and *Se* = 99.74 % and *Sp* = 99.65 % for Modification 2. At the end of 2006 the article was among the 5 most assessed articles for all the time of the Biomedical Engineering Online Journal (http://www.biomedical-engineering-online.com/mostviewedalltime).

The aim of this study is to assess the performance of a new modification of the combined adaptive thresholding method for heart beat detection with the use of AHA database.

Materials

The American Heart Association (AHA) database was considered. The data consist of 80 two-channel excerpts of analog ambulatory ECG recordings, digitized at 250 Hz sampling rate with 5 μV/bit resolution. The final thirty minutes of each recording are annotated beat-by-beat. The AHA recordings are divided into eight 'classes' of ten recordings each, according to the highest level of ventricular ectopy present:

- no ventricular ectopy (records 1001 through 1010);
- isolated unifocal PVCs (records 2001 through 2010);
- isolated multifocal PVCs (records 3001 through 3010);
- ventricular bi- and trigeminy (records 4001 through 4010);
- R-on-T PVCs (records 5001 through 5010);
- ventricular couplets (records 6001 through 6010);
- ventricular tachycardia (records 7001 through 7010);
- ventricular flutter/fibrillation (records 8001 through 8010).

Since flutter/fibrillation detection is not a subject of the current study, the last 10 recordings are not considered.

Methods

Two modifications of the combined adaptive thresholding algorithm for QRS detection have already been reported [3]. For reading expediency some parts of the method will be repeated in the current material.

The differentiated and summed signals from one or several $\boldsymbol{L}$ leads are compared to the absolute value of a threshold $\boldsymbol{MFR = M + F + R}$ – a combination of three independent adaptive thresholds, where:

✓ $\boldsymbol{M}$ – Steep-slope threshold;
✓ $\boldsymbol{F}$ – Integrating threshold for high-frequency signal components;
✓ $\boldsymbol{R}$ – Beat expectation threshold.

Two algorithms were developed:

Modification 1 detects at the current beat.

Modification 2 Pseudo-real-time detection with additional triggering of potentially missed heart beat in the last interval by RR interval analyses.

The algorithms are self-adjusting to the thresholds and weighting constants, regardless of resolution and sampling frequency used. They operate with any number L of ECG leads, self-synchronize to QRS or beat slopes and adapt to beat-to-beat intervals.

Preprocessing

- ✓ Moving averaging filter for power-line interference suppression: averages samples in one period of the power-line interference frequency with a first zero at this frequency.
- ✓ Moving averaging of samples in 28 ms interval for electromyogram noise suppression – a filter with first zero at about 35 Hz.
- ✓ Moving averaging of a complex lead (the sintesis is explained in the next section) in 40 ms intervals – a filter with first zero at about 25 Hz. It is suppressing the noise magnified by the differentiation procedure used in the process of the complex lead sintesis.

Complex lead

The algorithm operates with a complex lead Y of several primary leads L. A complex lead is obtained as:

$$Y(i)=\frac{1}{L}\sum_{j=1}^{L} abs\left(X_j(i+1)-X_j(i-1)\right), \tag{1}$$

where $X_j(i)$ is the amplitude value of the sample i in lead j, and $Y(i)$ is the current complex lead.

The above formula (except the normalizing coefficient 1/L and the absolute value) was initially adopted from the work of Bakardjian [2]. Operating with unsigned (absolute) values proved convenient when dealing with QRSs and extrasystoles having different, for example positive (in one lead) and negative (in the other lead) deflections.

Adaptive steep-slope threshold - M

- ✓ Initially $M = 0.6*max(Y)$ is set for the first 5s of the signal, where at least 2 QRS complexes should occur. A buffer with 5 steep-slope threshold values is preset:

  $MM = [M_1\ M_2\ M_3\ M_4\ M_5]$,

  where $M_1 \div M_5$ are equal to M.
- ✓ QRS or beat complex is detected if $Yi \geq MFR$,
- ✓ No detection is allowed 200 ms after the current one. In the interval **QRS÷QRS**$_{+200ms}$ a new value of M_5 is calculated:

  $newM_5 = 0.6*max(Yi)$

  The estimated $newM_5$ value can become quite high, if steep slope premature ventricular contraction or artifact appeared, and for that reason it is limited to $newM_5 = 1.1*M_5$ if $newM_5 > 1.5*M_5$.

  The MM buffer is refreshed excluding the oldest component, and including $M_5 = newM_5$. The steep-slope threshold M is calculated as an average value of MM.
- ✓ M is decreased in an interval 200 to 1200 ms following the last QRS detection at a low slope, reaching 60 % of its refreshed value at 1200 ms.
- ✓ After 1200 ms M remains unchanged.

The thresholds definitions are presented in more detail with the help of several examples. Two ECG leads are shown in Fig. 1a. Detected QRSs are marked with 'red O' on Lead 1. The summary lead and the steep-slope threshold are represented in Fig. 1b.

Adaptive integrating threshold – F

The integrating threshold $\boldsymbol{F}$ is intended to raise the combined threshold if electromyogram noise is accompanying the ECG, thus protecting the algorithm against 'erroneous beat detection'.

Initially $\boldsymbol{F}$ is the mean value of the pseudo-spatial velocity $\boldsymbol{Y}$ for 350 ms.

With every signal sample, $\boldsymbol{F}$ is updated adding the maximum of $\boldsymbol{Y}$ in the latest 50 ms of the 350 ms interval and subtracting $\boldsymbol{maxY}$ in the earliest 50 ms of the interval.

$$F = F + \left(max\left(Y_{\text{in latest 50ms in the 350ms interval}} \right) - max\left(Y_{\text{in latest 50ms in the 350ms interval}} \right) \right) / 150$$

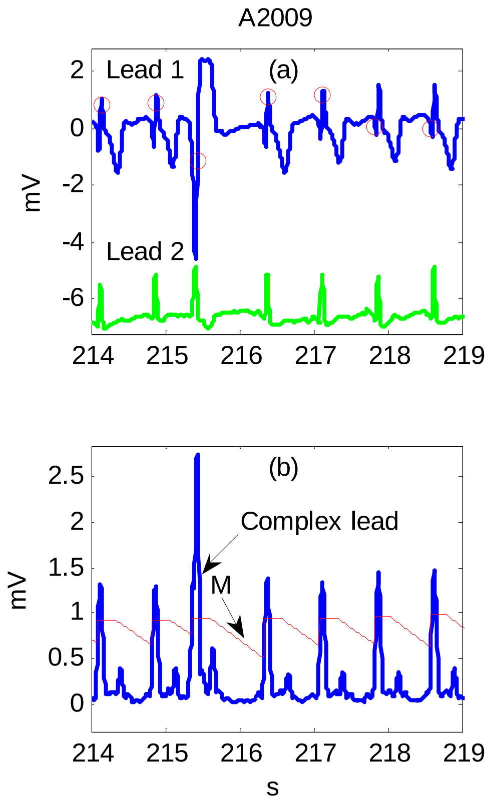

Fig. 1 Adaptive steep-slope threshold

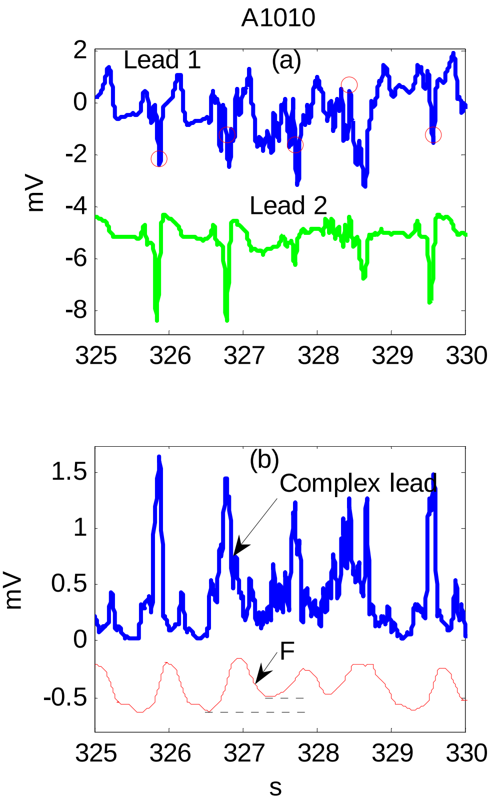

Fig. 2 Adaptive integrating threshold

The way $\boldsymbol{F}$ is updated means that not every sample in the interval is integrated, but just the envelope of the pseudo-spatial velocity $\boldsymbol{Y}$. The weight coefficient 1/150 is empirically derived.

Two ECG leads are shown in Fig. 2a. The pseudo-spatial velocity $\boldsymbol{Y}$ and the integrated threshold are presented in Fig. 2b. The correct detection is due to the rise of $\boldsymbol{F}$ (hence of $\boldsymbol{MFR}$) with about 0.2 mV. The beat complex is included in the integration process (note the high rise of ***F*** after any of the complexes), thus making almost impossible a close detection to the previous complex.

Adaptive beat expectation threshold – R

The beat expectation threshold ***R*** is intended to deal with heartbeats of normal amplitude followed by a beat with very small amplitude (and respectively with very small slew rate). This can be observed for example in cases of electrode artifacts. Conversely to the integrating threshold protecting against erroneous QRS detection, ***R*** is protecting against 'QRS misdetection'.

A buffer with the 5 last RR intervals is updated at any new QRS detection. ***Rm*** is the mean value of the buffer.

- ✓ ***R*** **=0 V** in the interval from the last detected QRS to 2/3 of the expected ***Rm***.
- ✓ In the interval **QRS +** ***Rm******2/3** to **QRS +** ***Rm***, ***R*** decreases 1.4 times slower then the decrease of the previously discussed steep slope threshold (***M*** in the 200-1200ms interval).
- ✓ After **QRS +** ***Rm*** the decrease of ***R*** is stopped.

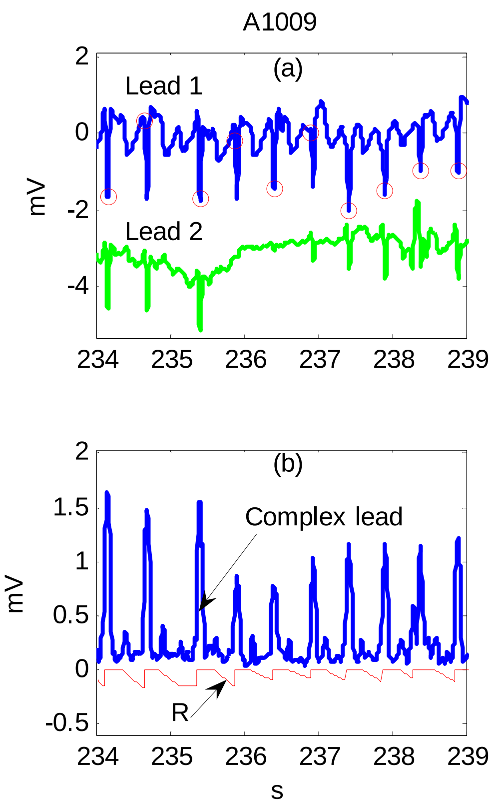

Fig. 3 Adaptive beat expectation threshold

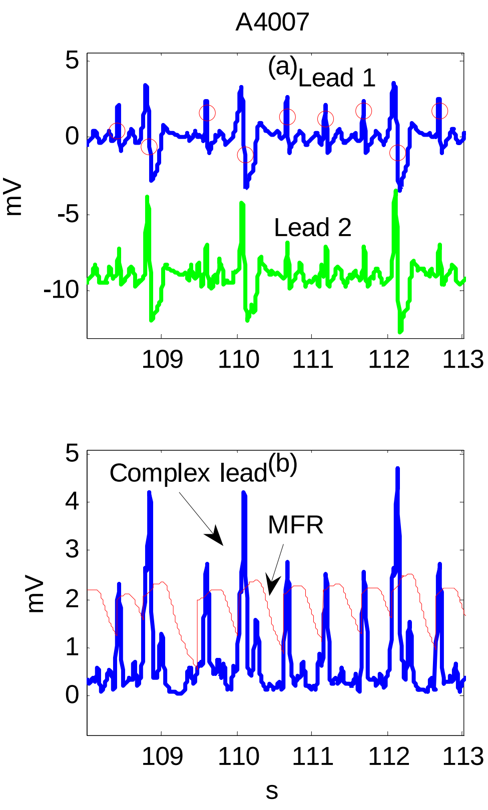

Fig. 4 Combined adaptive threshold

The time-course of the beat expectation threshold ***R*** is shown in Fig. 3. The decrease of ***R*** (respectively ***MFR***) with about 0.2 mV at the fourth QRS allows its detection, despite the lack of complex in Lead 2, which leads to a two-fold decrease of the summary lead amplitude ***Y*** (Fig. 3b).

Combined adaptive threshold – MFR

The combined adaptive threshold is a sum of the adaptive steep-slope threshold, adaptive integrating threshold and adaptive beat expectation thresholds. (Fig. 4)

$MFR = M + F + R$

Modification 2: Pseudo-real-time detection with additional triggering of eventually missed heart beat in the last detected RR interval

All previous considerations relate to Modification 1 (***Mod. 1***), which detects a beat at its occurrence. Additional checking for an eventually missed heartbeat is performed by Modification 2 (***Mod. 2***). Its function is explained by the signal in Fig. 5. The fourth complex at the 15.2 s in Fig. 5b should be missed due to the fact that, ***MFR*** is greater then the summary lead ***Y***.

Let's mark the previous RR interval with ***t1*** and the last – with ***t2*** (Fig. 5a).

If ***t1*** is not shortened, which is tested by logic OR of the 2 conditions ***t1*** > ***Rm*** OR ***Rm*** - ***t1*** < **0.12*Rm** AND in the same time ***t2*** is quite long to fulfill the condition **abs(*t2* - 2*Rm) < 0.5*Rm,** the interval is subjected to check for a missed complex.

A test is performed on each of the primary leads where a sharp peak is searched (defined as a product > 4 µV of two signal differences having one central and two lateral points 8 ms apart). If the test is passed, a second one is carried out for the amplitude of the summary lead at that point, which should be bigger then 1/3 of the mean value of the buffer ***MM***, in order to define this point as a missed QRS complex.

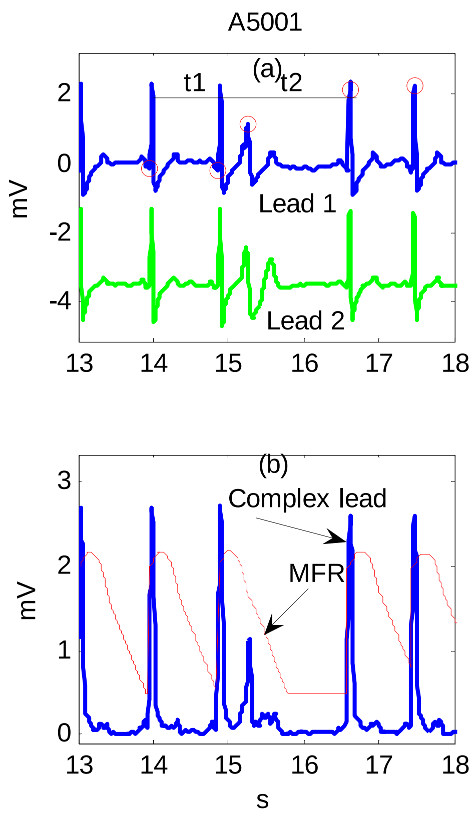

Fig. 5 Pseudo-real-time detection with additional triggering of eventually missed heart beat in the last RR interval.

Modification 3: Classification of the heart beats

Automatic classification of heart beats as: normal sinus rhythms (N), premature ventricular contractions (PVC), and premature supraventricular contractions (PSC) was published in 2004 [4]. The method is applied after reliable beat detection. Immediately after the detection PVC are separated from the normal beats in real-time by analysis of the shape variation. It is represented as absolute value of the difference between the area of the analyzed complex and the mean area of 5 previous normal complexes. The difference is compared to a threshold, which varies in accordance to the amplitude course of the analyzed complex. Beats exceeding the threshold are assumed to be PVC. PSC are discriminated from the normal beats in pseudo real-time, comparing the lengths of the adjoining RR intervals and the mean RR intervals.

The method was integrated as a feedback to the QRS detection algorithm (Fig. 6). It improved the performance of the adaptive beat expectation threshold ***R***, by not allowing RR intervals left and right-handed of a PVC or a PSC to form the mean value ***Rm*** of the 5 last RR intervals. Only RR intervals of normal complexes are allowed to form the ***Rm***

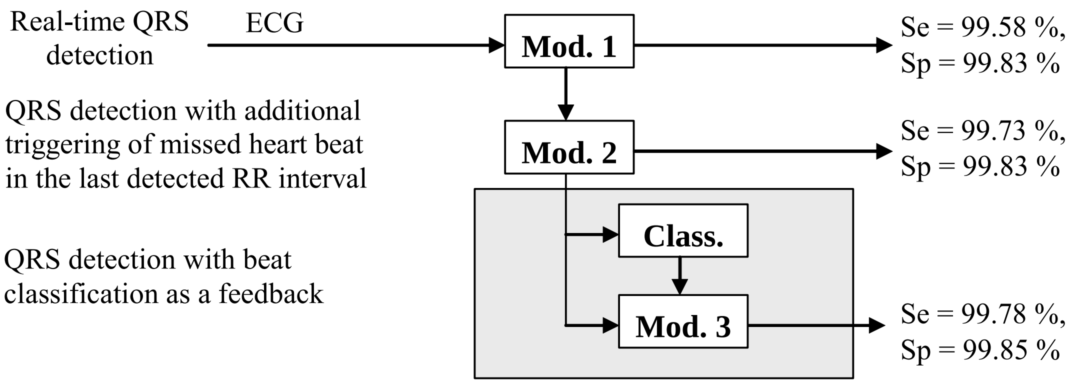

Fig. 6 Block diagram of the 3 modifications of the heart beat detection algorithm

Results

The processed files containing detection marks were automatically compared with the original AHA annotated beats by specially designed software given kindly to my disposal by the authors [5, 11]. It shows all cases where the annotation and detection marks differ of more than 60 ms and these occurrences can easily be observed and checked.

The results of the 3 modifications are presented in Table 1, where ***TP*** are the true detected beats, ***FP*** are the false beats detected by the algorithm, and ***FN*** are the missed by the algorithm beats. Of all 165641 annotated beats (‘unknown’ or ‘questionable’ were excluded from the study), true detected are 164942 for ***Mod. 1***, 165204 for ***Mod. 2***, and 165273 for ***Mod. 3***.

The commonly adopted statistical indices for assessment of the accuracy of the heart beat detection algorithms are sensitivity (***Se***) and specificity (***Sp***), calculated by:

$$Se = \frac{TP}{TP + FN} \tag{2}$$

$$Sp = \frac{TP}{TP + FP} \tag{3}$$

The results (presented also in Fig. 6) are:

Mod. 1: *Se* = 99.58 %, *Sp* = 99.83 %;
Mod. 2: *Se* = 99.73 %, *Sp* = 99.83 %;
Mod. 3: *Se* = 99.78 %, *Sp* = 99.85 %.

Table 1. Results of the 3 modifications of the algorithm obtained with the AHA database

AHA	Annotated beats	Modification 1			Modification 2			Modification 3		
		TP	FP	FN	TP	FP	FN	TP	FP	FN
1001	1623	1623	0	0	1623	0	0	1623	0	0
1002	2596	2596	0	0	2596	0	0	2596	0	0
1003	2180	2180	0	0	2180	0	0	2180	0	0
1004	2975	2975	0	0	2975	0	0	2975	0	0
1005	2554	2554	0	0	2554	0	0	2554	0	0
1006	2123	2123	0	0	2123	0	0	2123	0	0
1007	1536	1536	0	0	1536	0	0	1536	0	0
1008	2448	2448	0	0	2448	0	0	2448	0	0
1009	2583	2573	6	10	2574	6	9	2576	5	7
1010	1994	1985	26	9	1985	26	9	1989	24	5
2001	2876	2876	0	0	2876	0	0	2876	0	0
2002	2246	2246	0	0	2246	0	0	2246	0	0
2003	2414	2414	0	0	2414	0	0	2414	0	0
2004	3511	3487	21	24	3488	22	23	3494	18	17
2005	1628	1568	64	60	1568	63	60	1592	39	36
2006	1613	1613	0	0	1613	0	0	1613	0	0
2007	3288	3288	0	0	3288	0	0	3288	0	0
2008	2855	2855	0	0	2855	0	0	2855	0	0
2009	2415	2413	0	2	2413	0	2	2415	0	0
2010	2537	2537	0	0	2537	0	0	2537	0	0
3001	2177	2176	0	1	2176	0	1	2176	0	1
3002	2944	2944	0	0	2944	0	0	2944	0	0
3003	1950	1949	1	1	1949	1	1	1949	1	1
3004	1878	1871	4	7	1872	3	6	1872	5	6
3005	1784	1784	0	0	1784	0	0	1784	0	0
3006	3246	3246	0	0	3246	0	0	3246	0	0
3007	2325	2324	0	1	2324	0	1	2325	0	0
3008	2425	2425	0	0	2425	0	0	2425	0	0
3009	2585	2585	0	0	2585	0	0	2585	0	0
3010	2471	2463	0	8	2463	0	8	2462	1	9
4001	1933	1933	0	0	1933	0	0	1933	0	0
4002	2377	2373	1	4	2376	2	1	2377	1	0
4003	2582	2582	0	0	2582	0	0	2582	0	0
4004	2258	2258	0	0	2258	0	0	2258	0	0
4005	1452	1452	0	0	1452	0	0	1452	0	0
4006	1947	1946	0	1	1946	0	1	1947	0	0
4007	3520	3516	2	4	3515	4	5	3516	3	4
4008	1878	1877	2	1	1877	2	1	1877	2	1
4009	2372	2371	0	1	2371	0	1	2371	0	1
4010	2907	2907	0	0	2907	0	0	2907	0	0
5001	2257	2022	0	235	2168	0	89	2168	0	89
5002	2352	2351	0	1	2352	0	0	2352	0	0
5003	2374	2354	24	20	2354	22	20	2355	21	19
5004	2288	2288	0	0	2288	0	0	2288	0	0
5005	1806	1806	0	0	1806	0	0	1806	0	0
5006	2068	2064	4	4	2061	7	7	2061	7	7
5007	2924	2922	0	2	2922	0	2	2922	0	2
5008	1846	1846	0	0	1846	0	0	1846	0	0
5009	2165	2164	0	1	2164	0	1	2164	0	1
5010	2017	2015	2	2	2017	0	0	2017	0	0

Table 1. Continuation

6001	2501	2501	0	0	2501	0	0	2501	0	0
6002	1954	1954	0	0	1954	0	0	1954	0	0
6003	2699	2685	0	14	2694	0	5	2694	0	5
6004	2251	2249	0	2	2250	0	1	2250	0	1
6005	2295	2199	1	96	2273	1	22	2273	1	22
6006	2785	2690	115	95	2688	116	97	2699	110	86
6007	2045	2045	0	0	2045	0	0	2045	0	0
6008	2359	2359	0	0	2359	0	0	2359	0	0
6009	2501	2501	0	0	2501	0	0	2501	0	0
6010	3291	3259	3	32	3288	2	3	3288	2	3
7001	3164	3160	0	4	3160	0	4	3160	0	4
7002	2128	2128	0	0	2128	0	0	2128	0	0
7003	2533	2533	0	0	2533	0	0	2533	0	0
7004	1927	1927	0	0	1927	0	0	1927	0	0
7005	2438	2438	0	0	2438	0	0	2438	0	0
7006	3109	3073	0	36	3073	0	36	3089	0	20
7007	2341	2341	0	0	2341	0	0	2341	0	0
7008	1566	1566	0	0	1566	0	0	1566	0	0
7009	2897	2877	0	20	2877	0	20	2877	0	20
7010	1754	1753	0	1	1753	0	1	1753	0	1
Total:	**165641**	**164942**	**276**	**699**	**165204**	**277**	**437**	**165273**	**240**	**368**

Discussion

As it should be expected, the results are close to the obtained ones using the MIT-BIH database [3]. ***Mod. 2*** is having the same ***Sp*** as ***Mod. 1***, but improves the ***Se*** as a result of the decreased number of undetected beats. The change for the better of ***Se*** is expressed more in the current study (by 0.15 %), than in the published material (by 0.06%) [3]. This is due to the fact that special attention in collecting the AHA database is paid to patients, having the specific R-over-T premature ventricular contractions.

Mod. 3 improves ***Se*** of ***Mod. 2*** by 0.05% and ***Sp*** by 0.02%, due to the improved performance of the adaptive beat expectation threshold ***R***, not allowing RR intervals left and right-handed of a PVC or a PSC to form the mean value ***Rm*** of the 5 last RR intervals.

All modifications are confirming excellent performance when ECG signal in one of the channels gets to noisy or it is missing due to displacement of patient cables. This is illustrated in Fig. 7, (obtained with the program [5, 11]) where the noise in channel 1 is not an obstacle to the good functioning of the algorithm.

Conclusion

The proposed modifications for real-time and pseudo-real-time implementation are adaptive, independent of thresholds and constants values. They are self-synchronized to the QRS steep slope and the heart rhythm, regardless of the resolution and sampling frequency used. Due to the integration threshold, the algorithms are practically insensitive to electromyogram and similar high-frequency noise.

The algorithms can operate with one, two or more leads, using a combined lead signal derived from the sum of absolute values of the differentiated lead signals.

The statistical indices are higher than, or comparable to those, cited in the scientific literature.

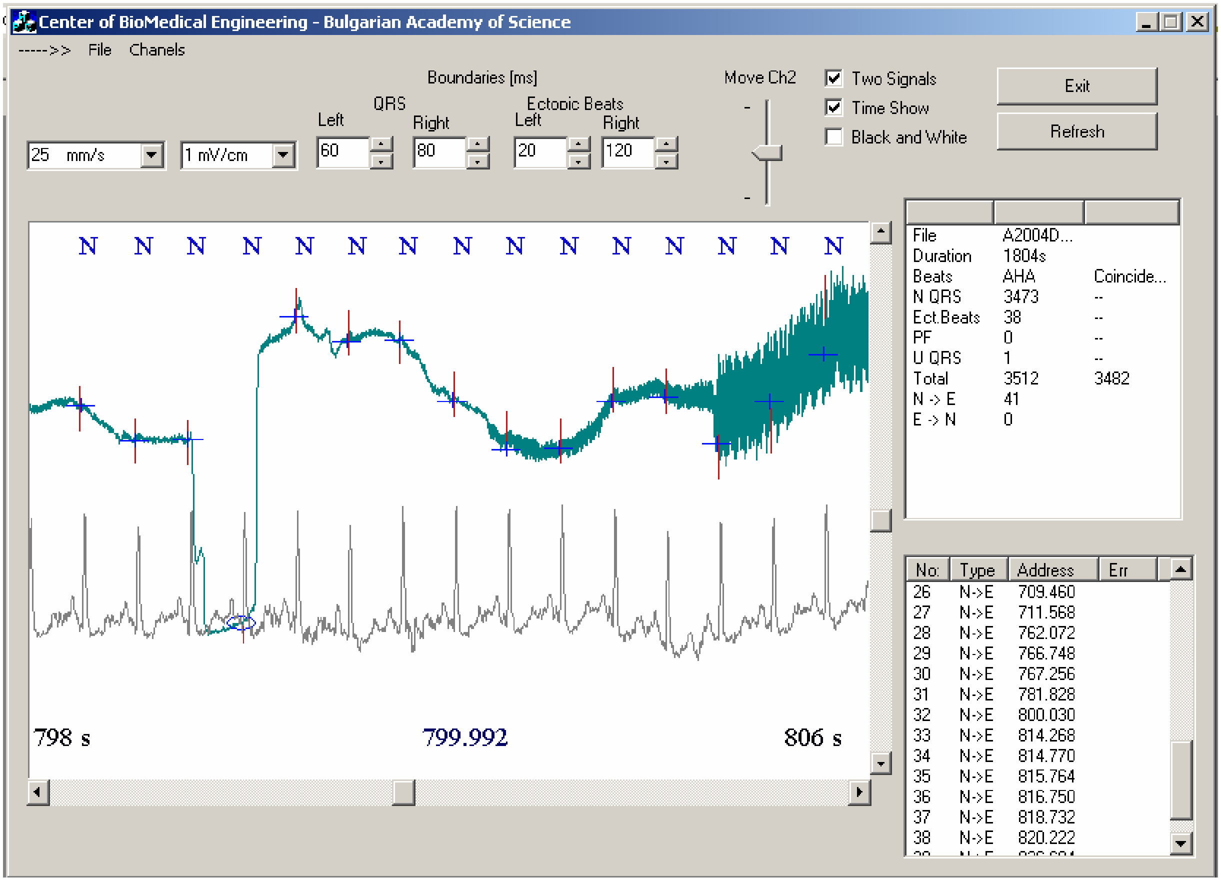

Fig. 7 Illustration of the good functioning of the algorithm in cases when one of the channels gets to noisy or it is missing due to displacement of patient cables. The AHA beat annotations are shown with red |. While the allocations of the algorithm are marked with blue +.

References

1. Afonso V. X., W. J. Tompkins, T. Q. Nguyen, Shen Luo (1999). ECG Beat Detection using Filter Banks, IEEE Transaction on Biomedical Engineering, 46, 192-201.
2. Bakardjian H. (1992). Ventricular Beat Classifier using Fractal Number Clustering, Medical & Biological Engineering & Computing, 30, 495-502.
3. Christov I. I. (2004). Real Time Electrocardiogram QRS Detection using Combined Adaptive Threshold, Biomedical Engineering Online, 3, http://www.biomedical-engineering-online.com/content/3/1/28.
4. Christov I. (2004). Automatic Classification of Ventricular and Supraventricular Ectopic Beats in the Electrocardiogram, Electrotechniques & Electronics E+E, 11-12, 21-27, (in Bulgarian), http://www.clbme.bas.bg/pwp/Ivaylo_Christov/Publications/Ectopic_class_2004_ee.pdf
5. Dotsinsky I., T. Stoyanov (2004). Ventricular Beat Detection in Single Channel Electrocardiograms, Biomedical Engineering Online, 3, http://www.biomedical-engineering-online.com/content/3/1/3.
6. Englese W.-H, C. Zeelenberg (1979). A Single Scan Algorithm for QRS Detection and Feature Extraction, Computers in Cardiology, 6, 37-42.

7. Li C., C. Zheng, C. Tai (1995). Detection of ECG Characteristic Points using Wavelet Transforms, IEEE Transaction on Biomedical Engineering, 42, 21-28.
8. Moreas J.-B., M. O. Seixas, F. N. Vilani, E. V. Costa (2002). A QRS Complex Detection Algorithm using Electrocardiogram Leads. Computers in Cardiology, 29, 205-208.
9. Pan J., W. Tompkins (1985). A Real-time QRS Detection Algorithm, IEEE Transaction on Biomedical Engineering, 32, 230-236.
10. Poli R., S. Cagnoni, G. Valli (1995). Generic Design of Optimum Linear and Nonlinear QRS Detection, IEEE Transaction on Biomedical Engineering, 42, 1137-1141.
11. Stoyanov T. (2004). Computer Processing and Analysis of Electrocardiograms, PhD thesis, Bulgarian Academy of Science, 1-121, (in Bulgarian).