Technical University of Denmark

Automatic QRS complex detection algorithm designed for a novel wearable, wireless electrocardiogram recording device

Saadi, Dorthe Bodholt; Egstrup, Kenneth; Branebjerg, Jens; Andersen, Gunnar; Sørensen, Helge Bjarup Dissing

Published in:
IEEE Engineering in medicine and biology society conference proceedings

Link to article, DOI:
10.1109/EMBC.2012.6346573

Publication date:
2012

Document Version
Publisher's PDF, also known as Version of record

34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Automatic QRS Complex Detection Algorithm Designed for a Novel Wearable, Wireless Electrocardiogram Recording Device*

Dorthe B. Nielsen[ab], Kenneth Egstrup[c], Jens Branebjerg[b], Gunnar B. Andersen[b] and Helge B.D. Sorensen[a]

Abstract— **We have designed and optimized an automatic QRS complex detection algorithm for electrocardiogram (ECG) signals recorded with the DELTA ePatch platform. The algorithm is able to automatically switch between single-channel and multi-channel analysis mode. This preliminary study includes data from 11 patients measured with the DELTA ePatch platform and the algorithm achieves an average QRS sensitivity and positive predictivity of 99.57% and 99.57%, respectively. The algorithm was also evaluated on all 48 records from the MIT-BIH Arrhythmia Database (MITDB) with an average sensitivity and positive predictivity of 99.63% and 99.63%, respectively.**

I. INTRODUCTION

The advantages of a small, wireless electrocardiogram (ECG) recording device for ambulatory ECG monitoring are numerous. Therefore, DELTA has developed the ePatch. This is a small wireless prototype ECG recorder that measures two ECG channels on the sternum. These channels do not correspond to any standard HOLTER leads. The projections of the electrical activity of the heart, and hereby the recorded ECG signals, are thus slightly different from standard HOLTER leads. This requires special attention in the design of new algorithms that are specialized for analysis of these signals. The basis for being able to perform ECG analysis is a robust, reliable and automatic QRS detection algorithm. Therefore this study is aimed at the design of a novel QRS detection algorithm that is optimized for the special ePatch ECG signals.

Many QRS detection algorithms described in the literature are designed for one channel analysis only [9], [8]. However, several different approaches have also been proposed for two or three channel QRS detection [1], [2], [3]. The motivation for including more channels arise from the assumption that the signal quality of one channel might occasionally or permanently decrease during a long term ambulatory recording. Noise is often only contaminating one of the channels. Therefore, the inclusion of clean ECG from addition channels is expected to improve detection performance. In [3], information from three different ECG channels is constantly applied for QRS detection. This approach may have some limitations: High amounts of noise in one channel might deteriote otherwise good performance obtained from analysis of the other channel [1]. Furthermore, the application of more channels, introduces more computational complexity. This is especially important when designing algorithms for a small wearable device. Another important aspect of automatic QRS detection is the ability to correctly detect QRS complexes with abnormal morphologies. The appearance of abnormal beats may be different in two different ECG channels. Therefore, the inclusion of an addition channel might increase the QRS detection performance of anormal beats. This study is thus focosed on the design of an automatic, intelligent algorithm that is able to apply information from both available ECG channels. To overcome some of the mentioned limitations, the proposed QRS detection algorithm can be applied in two different modes: Single-channel and multi-channel mode. The multi-channel mode applies information from both available channels. The single-channel mode is derived from the multi-channel mode, but with the exclusion of information from one channel. The algorithm can automatically switch between the two modes when predefined artefacts are present in one channel. If these artefacts are present in both channels, a complete shutdown occurs. The idea of generally applying both channels and then exclude a potentially noisy channel was also investigated by the authors of [1]. A slightly different approach was introduced by the authors of [2]. In this study, the QRS detection is generally based on channel I of the MIT-BIH Arrhythmia Database (MITDB), and then a combination of the two channels is applyed if the current RR interval exceeds a predefined interval.

II. METHODOLOGY

A. Data

The applied ePatch database contains data recorded from 11 different patients. The patients were hospitalized at Svendborg Hospital for diagnostic monitoring during the recordings and they were simultaneously monitored with conventionel telemetry equipment. The 2 ECG channels were recorded with a sampling frequency of 500 Hz and a resolution of 13 bits. The electrode placement is illustrated in Fig. 1. Records with 30 minutes of data were extracted from each measurement. For all patients, the 30 minutes were extracted one hour after the beginning of the recording. The patients were allowed to move around in the monitoring unit during the recordings. This ensures a fair amount of realistic in-hospital artefacts in each record. A reference annotation

*This research and this paper has been co-financed by the Danish Agency for Science, Technology and Innovation as part of a Performance Contract with DELTA 2010-2012.

Corresponding author: Dorthe B. Nielsen, dbni@elektro.dtu.dk

Contact information: HBDS: hbs@elektro.dtu.dk, JB: jab@delta.dk, GBA: gba@delta.dk, KE: Kenneth.Egstrup@ouh.regionsyddanmark.dk

[a]DTU Electrical Eng., Ørsteds Plads, Bldg. 349, DK-2800 Kgs. Lyngby

[b]DELTA, Venlighedsvej 4, DK-2970 Hørsholm

[c]OUH Svendborg Sygehus, Valdemarsgade 53, DK-5700 Svendborg

file was created for each record, cf. Fig 1. During the first three steps, all beats were annotated as ”normal”. During the final manual scoring by the cardiologist (KE), the beats were divided into different beat types, cf. Fig 1.

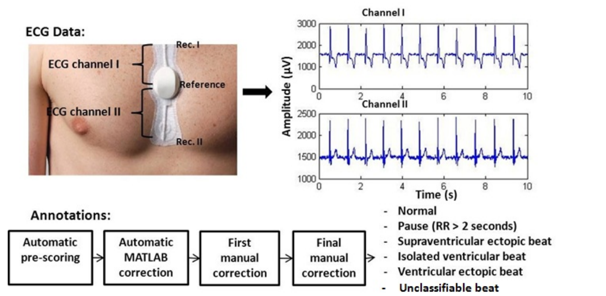

Fig. 1. Illustration of the DELTA ECG ePatch platform and the electrode placements. The annotation file was created in several steps: Automatic pre-scoring using the ”sqrs” program available from [4], automatic placement correction with a maximum algorithm in MATLAB, manual correction by one of the authours (using ”WAVE” - available from [4]), and finally manual correction by the cardiologist (KE) (using ”WAVE”). Noise annotations were also included as well as indication of atrial fibrillation (AF).

To further evaluate the algorithm and allow comparison with other studies, all 48 records from the MITDB were applied [5]. Each record contains 2 ECG channels digitalized with a sampling frequency of 360 Hz. In compliance with [6], each record was re-sampled to 500 Hz using the ”xform” program available from [4]. The automatic QRS complex detection algorithm was implemented in MATLAB R2010b. The WFDB Toolbox for MATLAB [4] was applied to convert the data files between WFDB readable files and mat-files.

B. Automatic QRS Complex Detection Algorithm

An overview of the algorithm is provided in Fig. 2. The channel exclusion block marks the point of separation of the single-channel and multi-channel modes. The channel exlusion, high maximum removal, adaptive threshold calcuation, and decision fusion blocks were executed in 1 second non-overlapping analysis windows.

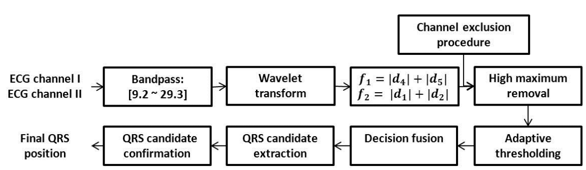

Fig. 2. Schematic overview of the QRS complex detection algorithm.

1) Channel Exclusion Criteria: Saturation of the raw ECG signals produces false detections and disturbs the adaptive algorithm parameters. The channel was therefore excluded if the raw ADC counts of 15 consecutive samples in the current analysis window obtained the maximum or minimum possible value. Furthermore, it was expected that the feature signals might be disturbed immediately after a saturation. The channel was therefore also shutdown in the first ”clean” analysis window after saturation. The threshold of 15 samples was found by visual and experimental analysis of challenging ECG examples.

2) Bandpass Filtering: The raw ECG signals were band-passed filtered to reduce baseline wandering, power line interference and high frequency muscle artifacts. A simple FIR bandpass filter with integer coefficients and passband between 9.2 and 29.3 Hz was designed in line with [7]. After correction for the filter delay, the bandpass filtered signal will ideally have a zero-crossing at the R peak position in the raw ECG signal.

3) Wavelet Transform: The non-downsampling *a trous algorithm* has been widely applied for wavelet transformation (WT) of ECG signals [8], [3]. Some advantages of the WT are a good balance between detection performance and efficient hardware implementation [8], and the possibililty of dividing the ECG signal into different relevant frequency subbands [3]. The WT consists of a cascade of lowpass (LP) and highpass (HP) filters. The WT output of level m was implemented as [8]:

$$a_m(n) = \sum_l h_{LP,m}(l) \cdot a_{m-1}(n-l) \tag{1}$$

$$d_m(n) = \sum_l h_{HP,m}(l) \cdot a_{m-1}(n-l) \tag{2}$$

where a_m is the LP output and d_m is the HP output. The impulse responses were implemented as described in [8]. In each filtering step throughout the algorithm, the input signal was padded with the last value of the signal, and the filter delay was corrected to ensure correct location of the QRS complexes relative to the original signal.

The frequency content of the QRS complex is mainly in the interval 5-15 Hz [9]. With a sampling frequency of f_s = 500 Hz, this correpsonds approximately to d_4 and d_5 of the WT. Therefore the first feature was calculated from eq. 3. The absolute value was used to ensure equal detection of QRS complexes with positive and negative polarity. However, in some cases this feature signal obtained high values at the P and T wave locations. Therefore an additional feature signal representing the higher frequency components was computed using eq. 4. Both features were calculated for both channels.

$$f_1 = |d_4| + |d_5| \tag{3}$$

$$f_2 = |d_1| + |d_2| \tag{4}$$

It is thus expected that f_1 obtains high values during QRS complexes as well as during high P and T waves, whereas f_2 should obtain high values during QRS complexes and high frequency noise. Periods where both feature signals obtain high values are thus expected to correspond to the location of QRS complexes.

4) Detection of QRS Candidates: To detect QRS candidates, an adaptive threshold was calculated for each of the feature signals in eq. 3 and 4 in each analysis window:

$$T_k = \lambda \cdot T_{k-1} + (1-\lambda) \cdot (\mu_k + c \cdot \sigma_k), \tag{5}$$

where $0 < \lambda < 1$ is a forgetting factor, c is a scaling parameter, T_k is the final threshold in the current window,

T_{k-1} is the threshold value in the previous window, σ_k and μ_k are the mean and standard deviation of the feature signal in the current window. This threshold calculation ensures a smooth adaptation to changes in the feature signal. Based on simulations on the ePatch database $\lambda = 0.4$ and $c = 0.8$ was chosen. In cases with abnormal beat morphologies, the threshold might be increased to a level that hinder detection of subsequent QRS complexes. To avoid this, a high maximum removal was applied before the threshold calculation. This block contains information about the maximum value in the 8 previous analysis windows. Application of the 8 most recent beats (approximately corresponding to the 8 previously 1 second analysis windows) has also been applied for tracking the "normal" behaviour of an ECG signal in other studies [9]. Any samples in the current analysis window excedding the median value of this maximum register were set to the median value before the threshold calculation. The adaptive threshold and the maximum register were not updated for channel j when it was excluded from the analysis. Based on the adaptive thresholds, binary feature signals were created from:

$$f_{bin} = \{1 \text{ if } f > T_k,\ 0 \text{ otherwise}\} \quad (6)$$

These binary signals were then combined in a decision fusion scheme to detect QRS candidates: If both channels were selected for analysis, at least three of the four binary features should be asserted to indicate a QRS candidate. If one channel was excluded from the analysis, both binary features from the other channel should be asserted. The new binary feature signal was denoted f_{final} and it contained the QRS candidates. To the best knowledge of authors, this combintation of wavelet based features is novel. As is the later described confirmation block.

5) QRS Localization and Confirmation Block : The temporary duration of the QRS candidate was defined from the rising edge of f_{final} and 100 ms forward. The bandpass filtered signal was investigated for zero crossings in this time interval. The QRS candidate was confirmed if at least one active channel possessed at least one zero crossing during this period. This zero-crossing corresponds to a peak in the original signal. The first zero-crossing in this interval might correspond to the position of the Q peak. It was therefore decided to apply the location of the second zero-crossing if more than one zero-crossing occurred in the bandpass filtered signal during this time interval. The position of the selected zero-crossing was extracted for each active channel. In multi-channel mode, the final QRS position was estimated as the minimum sample number suggested by the two active channels. This location was saved as the new position of the QRS candidate. To further decrease the number of false detections, an additional confirmation block with three possible outputs was implemented: *Case 1:* Accept both the previously detected QRS complex and the current QRS candidate, *Case 2:* Delete the previously detected QRS complex, and accpet the current QRS candidate, and *Case 3:* Accept the previously detected QRS complex, but reject the current QRS candidate. This block was initiated if the current RR interval was less than half the median of the 8 previous RR intervals. The assumption in this block was that the feature values of two closely located QRS complexes should not vary significantly. This was measured with the maximum amplitude value in both feature signals (f_1 and f_2) in all active channels. For each of the included feature signals, the maximum value was calcluated in a 100 ms interval around the position of the previously detected QRS complex (F_{old}) and the current QRS candidate (F_{new}). The decision rule depends on the algorithm mode, cf. Table I. This block was developed based on experiments and visual inspection of different challenging ECG examples. After confirmation of a QRS candidate, a refractory period of 200 ms was implemented in line with [9].

TABLE I
DECISION RULE IN THE FINAL QRS CONFIRMATION BLOCK.

Case	Multi-channel	Single-channel
1	At least 3 of 4 maximun values should satisfy the requirement: $\frac{F_{old}}{2} < F_{new} < 2 \cdot F_{old}$	Both maximun values should satisfy the requirement: $\frac{F_{old}}{2} < F_{new} < 2 \cdot F_{old}$
2	At least 3 of 4 maximun values should satisfy the requirement: $F_{new} \geq 2 \cdot F_{old}$	Both maximun values should satisfy the requirement: $F_{new} \geq 2 \cdot F_{old}$
3	Otherwise	Otherwise

III. RESULTS

In compliance with [6], the beat detection accuracy was evaluated using the QRS sensitivity, Se, and positive predictivity, $+P$. The mean QRS detection performance on the ePatch database is stated with both the gross and the average statistics [6], see Table II. The statistics was calculated with the default settings of the "bxb" and "sumstats" programs available in the WFDB Software Package [4] (match window = 150 ms, 5 minutes initiation time). The performance was evaluated using only channel I, only channel II (single-channel modes) and both channels (multi-channel mode). The QRS detection sensitivity in multi-channel mode was 100% with respect to both supraventricular ectopic beats (SVEBs) and ventricular ectopic beats (VEBs).

The detection performance on the 48 records of the MITDB using the ePatch optimized algorithm is provided in Table III. In compliance with [6], episodes of ventricular flutter or fibrillation were excluded from the performance evaluation. Table III also contains detection accuracy for three other studies using multi-channel QRS detection. However, the authors of [3] evaluated their multi-channel approach using only channel I of the MITDB.

IV. DISCUSSION

The multi-channel detection performance on the 11 records from the ePatch database is acceptable, but not excellent. The poorer performance originates from 2 records with considarable amounts of artefacts: Record 11 contains approximately 2.5 minutes with very poor data quality, and

TABLE II

DETECTION PERFORMACE ON THE EPATCH DATABASE. THE AVERAGE AND GROSS STATISTICS ARE INDICATED BY μ_1 AND μ_2, RESPECTIVELY.

Pt. #	# of beats	Channel I Se(%)	Channel I +P(%)	Channel II Se(%)	Channel II +P(%)	Both channels Se(%)	Both channels +P(%)
1	1450	99.52	98.97	99.52	99.31	99.93	99.52
2	1617	100	100	100	100	100	100
3	1594	99.69	99.94	99.94	100	99.87	100
4	1727	99.94	100	99.07	92.69	100	100
5	1465	99.66	99.59	98.98	99.72	99.86	99.80
6	3049	99.97	100	99.93	100	100	100
7	1762	99.72	100	99.89	100	100	100
8	1984	99.80	100	99.55	99.95	99.95	100
9	2562	99.49	94.69	99.88	96.46	99.88	96.75
10	1651	99.94	99.94	100	100	99.94	99.94
11	3219	92.58	92.00	97.20	99.36	95.84	99.26
μ_1	22080	99.12	98.65	99.45	98.86	99.57	99.57
μ_2	22080	98.73	98.09	99.34	98.81	99.35	99.46

TABLE III

COMPARISION OF QRS DETECTION PERFORMACE ON THE MITDB FOR DIFFERENT STUDIES. NA = NOT AVAILABLE. TW = THIS WORK.

Algorithm	Number of beats	Overall QRS Se(%)	Overall QRS +P(%)	SVEB Se(%)	VEB Se(%)
TW, channel I & II	91285	99.63	99.63	98.80	98.71
TW, channel I	91285	99.63	99.43	98.25	98.52
TW, channel II,	91285	99.03	95.22	98.43	97.95
Ghaffari et al. [3],	109428	99.94	99.91	NA	NA
Boqiang et al. [2],	109496	99.91	99.93	NA	NA
Chiarugi et al. [1],	109494	99.76	99.81	NA	NA

record 9 contains a number of episodes with high frequency noise. The average Se and $+P$ on the remaining 9 patients in the multi-channel mode were 99.95% and 99.92%, respectively, which is an excellent performance. Furthermore, the sensitivity for detection of abnormal beats is considered to be very high.

Even though the algorithm was designed and optimized for the ePatch data, the performance on the MITDB is only slightly lower than [1]. The lower performance might be caused by the optimization to the ePatch database or the very simple channel exclusion criteria. The performance is lower than obtained in [2]. However, this study used a different approach, where channel I was used for analysis unless no R peak was detected in a predefined interval. Since the general appearance of QRS complexes is better in channel I of the MITDB [4], it might be uncertain whether this approach will provide a reliable result in a real-life situation with no prior knowledge about the optimal channel. The performance difference between the two individual channels on the MITDB is clearly observed from Table III. As with the ePatch database, the sensitivity to detection of abnormal beat morphologies is considered fairly high. However, it is difficult to compare these results with other studies since these sensitivities are rarely stated in spite of their importance for subsequent arrhythmia analysis. This study shows that the sensitivity regarding detection of these beats increases with the inclusion of an additional channel. Furthermore, it is observed for the ePatch database that both single-channel modes obtains a considerably lower performance than the multi-channel mode. This furthermore indicates the importance of applying both channels in the analysis. During a real-life recording, it would probably be impossible to know the optimal channel on before hand and the optimal channel might even change during the recording. The overall detection performance is furthermore not decreased by the inclusion of the addition channel on the MITDB, and this method is thus considered ”safer” than a single-channel appraoch using an abitrary channel. It should, of course, be mentioned that the channel I performance on the MITDB is slightly lower than other studies using only channel I [8]. However, their approaches are developed for single-channel use, and it would be interesting to know the performance on channel II of the database to clarify how the performance would be if this channel was arbitrary selected for the single-channel analysis.

The overall conclusion of this preliminary study is that the proposed algorithm achieves good performance. The algorithm might be further improved by implementation of more sophisticated channel exclusion criterias. This might be able to lower the false detections. However, the potential decrease in false detections should not be achieved at the expense of the high detection sensitivity to abnormal beats. The benefits from more sophisticated channel exclusion criterias should therefore be carefully investigated and the algorithm should generally be evaluated on a larger ePatch dataset.

REFERENCES

[1] F. Chiarugi, V. Sakkalis, D. Emmanouilidou, T. Krontiris, M. Varanini, and I. Tollis, Adaptive threshold QRS detector with best channel selection based on a noise rating system, Comput. Cardiol., pp. 157160, 2007.

[2] H. Boqiang and W. Yuanyuan, Detecting QRS complexes of two-channel ECG signals by using combined wavelet entropy, 3rd International Conference on Bioinformatics and Biomedical Engineering, vols. 1-11, pp. 24392442, 2009.

[3] A. Ghaffari, M. R. Homaeinezhad, and M. M. Daevaeiha, High resolution ambulatory holter ECG events detection-delineation via modified multi-lead wavelet-based features analysis: Detection and quantification of heart rate turbulence, Expert Syst. Appl., vol. 38, no. 5, pp. 52995310, 2011.

[4] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, and H. E. Stanley, PhysioBank, PhysioToolkit and PhysioNet: Components of a new research resource for complex physiologic signals, Circulation, vol. 101, no. 23, pp. e215220, June 2000.

[5] G. B. Moody and R. G Mark, The impact of the MIT-BIH arrhythmia database, IEEE Eng. Med. Bio. Mag, vol. 20, no. 3, pp. 4550, May-June 2001.

[6] Association for the Advancement of Medical Instrumentation (AAMI), ANSI/AAMI EC57:1998/(R)2003: Testing and reporting performance results of cardiac rhythm and ST-segment measurement algorithms, 1999.

[7] M. Cvikl, F. Jager, and A. Zemva, Hardware implementation of a modified delay-coordinate mapping-based QRS complex detection algorithm, EURASIP Journal on Advances in Signal Processing, vol. 2007, pp. 57286, 2007.

[8] X. Liu, Y. Zheng, M. W. Phyu, B. Zhao, M. Je, and X. Yuan, Multiple functional ECG signal is processing for wearable applications of long-term cardiac monitoring, IEEE Trans. Biomed. Eng., vol. 58, no. 2, pp. 380389, Feb. 2011.

[9] J. Pan and W. J. Tompkins, A real-time QRS detection algorithm, IEEE Trans. Biomed. Eng., vol. 32, no. 3, pp. 230236, Mar. 1985.