A real-time QRS detector based on higher-order statistics for ECG gated cardiac MRI

Marcus Schmidt[1], Johannes W Krug[1], Andreas Gierstorfer[2], Georg Rose[1]

[1]Department of Medical Engineering, Otto-von-Guericke-University of Magdeburg, Germany
[2]MIPM - Mammendorfer Institut für Physik und Medizin GmbH, Mammendorf, Germany

Abstract

Nowadays, Cardiovascular Magnetic Resonance (CMR) is gaining popularity in medical imaging and diagnosis. The acquisition of CMR images needs to be synchronized with the current cardiac phase to compensate the motion of the beating heart. The Electrocardiogram (ECG) signal can be used for such applications by detecting the QRS complex. However, the magnetic fields of the MR scanner contaminate the ECG signal which hampers QRS detection during CMR imaging.

This paper presents a new real-time QRS detection algorithm for CMR gating applications based on the higher order statistics of the ECG signal. The algorithm uses the 4th order central moment to detect the R-peak. The algorithm was tested using two different databases. One database consisted of 12-lead ECGs which were acquired from 9 subjects inside a 3 T Magnetic Resonance Imaging (MRI) scanner with a total of 9241 QRS complexes. The 12-lead ECG arrhythmia database from the St. Petersburg Institute of Cardiological Technics (InCarT) served as the second database. 168341 QRS complexes were used from this database. For the ECG database acquired inside the MRI scanner, the proposed algorithm achieved a sensitivity (Se) of 99.99% and positive predictive value (+P) of 99.60%. Using the InCarT database, Se=99.43% and +P=99.91% were achieved. Hence, this algorithm enables a reliable R-peak detection in real-time for triggering purposes in CMR imaging.

1. Introduction

Cardiovascular Magnet Resonance (CMR) imaging is one of the most increasing noninvasive methods for detecting cardiovascular diseases [1]. For clinical applications, magnetic field strengths of up to 3 T are used to obtain high quality CMR images to ensure an accurate diagnose [2, 3].

However, respiratory and cardiac motion can cause artifacts in CMR images. Cardiac motion can be compensated by synchronizing the cardiac phase with the CMR data acquisition. This synchronization is called gating or triggering. A widely used method for synchronization is to trigger on the Electrocardiogram (ECG) signal. Here the QRS complex represents a contrast to the other components as the T-wave or the P-wave and provides a good trigger signal.

Detecting the QRS complex and especially the R-peak inside a Magnet Resonance Imaging (MRI) scanner is a difficult task because of the fast switching magnetic field gradients and the static magnetic field. Several methods were proposed to filter the gradient artifacts, e.g. by using adaptive or Kalman filters [4, 5]. After filtering the gradients from the ECG, the magnetohydrodynamic (MHD) effect can hamper the detection of the R-peaks. The MHD effect has its origin in the displacement of electrical particles in the blood which flows perpendicular to the static magnetic field [6]. The MHD voltages are picked up by the ECG electrodes and superimpose the ECG signal. In previous works MR specific QRS detectors were developed using a wavelet transform [5], the vectorcardiogram [7] or independent component analysis (ICA) [8].

An MR specific QRS detector based on higher order statistics (HOS) and an adaptive threshold is developed in this work. A HOS (skewness and kurtosis) based QRS detector was developed by Panoulas et. al. [9] but only evaluated for ECG data outside MRI. The presented algorithm is evaluated using a 12-lead ECG database recorded in a 3 T MRI scanner and a 12-lead ECG arrhythmia database recorded by the St. Petersburg Institute of Cardiological Technics (InCarT) [10].

2. Theory

Stationary signals have time invariant statistical properties. Besides the mean value or the variance, the 4th order central moment is one of them. It can be defined as:

$$m_4 = E[(X - E(X))^4] \qquad (1)$$

where E(X) is the expectation value from a signal X. When X is a discrete signal $x(i), i \in \mathbb{N}$ equation 1 can be written as

$$m_4 = \frac{1}{n}\sum_{i=1}^{n}(x(i) - \overline{x})^4. \qquad (2)$$

where $\overline{x}$ is the mean value of the process.

For a transient in a stationary signal, the 4th order central moment exhibits high values which allows to distinguish this transient from the other components. This is also the case for non-stationary signals such as the ECG. The ECG's QRS complex represents such a transient component which shows a high 4th central moment when compared to other ECG components as the P-wave or the T-wave. The properties of the 4th central moment are used to enhance the QRS complex and to attenuate the contaminations from the MHD effect.

3. Material

Two different databases were used for the evaluation of the algorithm. The first database (ECG_{MRI}) consisted of ECG signals acquired inside a 3 T MR scanner (Skyra, Siemens, Germany). Therefore, a standard 12-lead Holter ECG (CardioMem CM3000-12, GETEMED, Germany) with a sampling frequency (f_s) of 1024 Hz, a bandwidth of 0.05-100 Hz, a resolution of 12 bits and an input voltage range of $\pm$6 mV was used. The 12-lead ECGs include the limb leads (I, II, III), the augmented limb leads (aVR, aVL, aVF) and the six precordial leads (V1-V6) [11]. ECG signals were acquired from 9 healthy subjects (2 female, 7 male) aged between 23 and 31 years (27.6$\pm$2.8). The ECG datasets were acquired in two different positions: head-first and feet-first. Radio-frequency pulses and fast switching magnetic field gradients were switched off during the measurements. The acquired datasets had an overall length of 2.25 hours corresponding to 9241 QRS complexes.

The second database (ECG_{InCarT}) was composed from the 12-lead ECG InCarT database [10]. The InCarT database contained 75 half-hour arrhythmic ECG records sampled with a frequency of 257 Hz and with over 175000 annotated beats. The age of the patients (15 female, 17 male) ranged from 18 and 80 years with a mean age of 58 years. Only 72 records were used for the evaluation because of low signal quality in certain leads in datasets 54, 57 and 58. Dataset 54 was excluded because of the low SNR and datasets 57 and 58 were excluded because of zero line. Hence, 168341 QRS complexes were available for the evaluation.

4. Methods

The presented QRS detection algorithm utilized the 4th central moment. The principle of the algorithm is shown in Fig. 1.

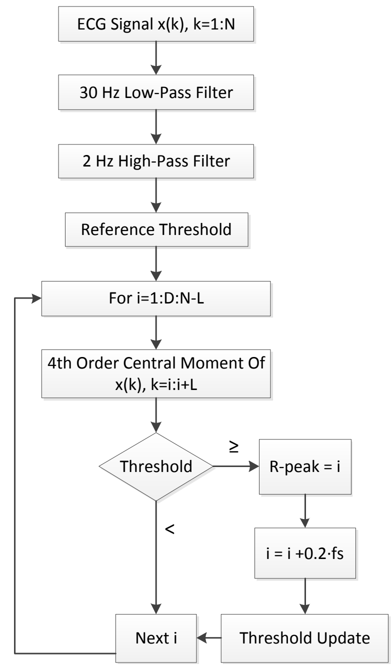

Figure 1. Block diagram of the presented algorithm.

Due to their close proximity to the myocardium, the R-peaks exhibit high amplitudes in the precordial leads [11]. Lead V4 shows the highest R-peak amplitudes because it is located closely to the apex of the heart. Hence, lead V4 was used for QRS detection.

The ECG signal was filtered with a 30 Hz low pass filter to reduce muscle noise and high frequency components like motion artifacts. A 2 Hz high pass filter was used to remove respiratory signal components. Both filters were implemented as 5th order Butterworth filters. The 4th central moment was calculated according to equation 2 in a sliding window of length $L=0.02\cdot f_s$ and a step width D=L/4. The mean value $\overline{x}$ from equation 2 was determined for each sliding window.

A reference vector was required to calculate a threshold for the QRS detection. The reference vector contained the last 10 maxima of the 4th central moments of the ECG signal. The threshold was defined from the median of the reference vector multiplied with a constant factor. The median was used to suppress the influence of outliers. The constant factor was estimated from a training dataset which consisted of ECG_{MRI} signals from three subjects acquired in head-first and feet-first positions (2347 beats, 33.5 min) and from ECG_{InCarT} signals from 10 subjects (26091 beats, 300 min). This was necessary because arrhythmic and normal QRS complexes have different 4th order central moments. The resultant constant threshold factor was then used for R-peak detection in both ECG databases.

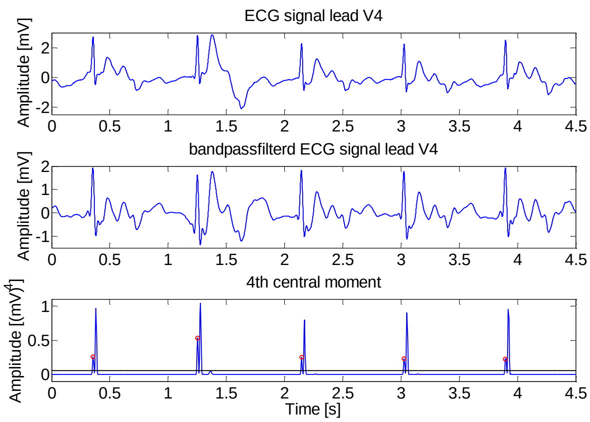

Figure 2. ECG before and after filtering and the detected beats. ECG recorded in head-first position from a 30 years old subject. The black horizontal line marks the threshold.

An R-peak was detected if the calculated moment exceeded the threshold. It is physiologically not possible that a second R-peak occurs 200 ms after another R-peak [12]. This fact was considered by the algorithm. During runtime, the reference vector was updated with the maximum of the fourth central moment of the latest peak using a First In, First Out (FIFO) technique.

For the $\mathrm{ECG_{MRI}}$ database with f_s=1024 Hz a sliding window of length L=20 ms and a step width D=7 ms were used. The datasets from the $\mathrm{ECG_{InCarT}}$ database were sampled with 257 Hz [10]. For these datasets, a sliding window of length L=5 ms and a step width D=1 ms were used for the calculation of the 4th central moment. The algorithm was implemented using Matlab 2013b. Fig. 2 depicts the ECG before and after filtering and the corresponding 4th order moments.

The algorithm was evaluated by the sensitivity (Se) and the positive predictive value (+P). These statistical parameters were defined by the ANSI/AAMI EC57 standard [13] and were estimated by

$$Se = \frac{TP}{TP + FN} \tag{3}$$

and

$$+P = \frac{TP}{TP + FP}. \tag{4}$$

where TP are the true positives, FN are the false negatives and FP are the false positives. The detecting error rate (DER) was estimated by

$$DER = \frac{FP + FN}{TP + FN}. \tag{5}$$

The presented algorithm was compared to two other methods based on ICA (M1) [8] and on a Pan/Tompkins-based algorithm (M2) [14]. Method M1 required all 12 ECG leads. For the evaluation of method M2, lead V4 was used. Both methods were configured such that only one peak could occur within 200 ms. Methods M1 and M2 also used an adaptive threshold for R-peak detection.

5. Results

Best results for the training database were achieved for a threshold of 5% of the reference vector's median. This threshold allowed the detection of normal and arrhythmic QRS complexes. The peaks caused by the MHD effect were at least 25 times lower than the peaks caused by the QRS complex. Hence, the MHD peaks were not detected by the algorithm.

Table 1 summarizes the QRS detection results for the $\mathrm{ECG_{MRI}}$ database. The method based on the 4th central moment had a sensitivity of 99.99% and a positive predictive value of 99.60% with a DER of 0.41%. The delay between the annotated and the detected beats was 7.77 ms with a jitter of 2.89 ms.

Table 2 shows the results for the $\mathrm{ECG_{InCarT}}$ database. With the presented method 167811 of the 168341 QRS complexes were detected which corresponds to sensitivity of 99.43%. 179 false beats were detected corresponding to a +P value of 99.91% and a DER of 0.66%. The average time delay was 12.16 ms and the jitter was 7.17 ms.

The moment based method achieved the highest Se in $\mathrm{ECG_{MRI}}$, the highest +P in the $\mathrm{ECG_{InCarT}}$ and the lowest jitter in both databases.

6. Discussion

The presented algorithm was successfully applied to several ECG datasets acquired inside an MRI scanner and to a larger arrhythmic ECG database. The same configuration was used for both databases, i.e. the threshold factor required for the detection of the QRS complex remained constant. This was also the case for the QRS detection methods M1 and M2.

A jitter of less than 15 ms is required to avoid blurring of the CMR images [15]. With the proposed method, a jitter of 2.71 ms was obtained for ($\mathrm{ECG_{MRI}}$) which is an ideal prerequisite for CMR imaging.

A 12-lead ECG signal is required for the proposed method. The hardware which was used to record the 12-lead ECGs is not MR safe and cannot be used during MR imaging. Currently, there is no MR safe 12-lead ECG available on the market. However, it was shown previously that it is possible to make a standard 12-lead ECG device MR-compatible [16]. The delay times shown in Tables 1 and 2 do not include the delay which is caused by the low and high pass filters.

Table 1. R-peak detection performance of the ECG_{MRI} database.

Method	Beats	TP	FP	FN	+P [%]	Se [%]	DER [%]	Delay [ms]	Jitter [ms]
Moment based method	9241	9240	37	1	99.60	99.99	0.41	7.77	2.89
M1	9241	9234	31	7	99.66	99.92	0.41	10.32	5.90
M2	9241	9226	103	13	98.89	99.86	1.26	4.19	7.88

Table 2. R-Peak-Detection performance of the ECG_{InCarT} database.

Method	Beats	TP	FP	FN	+P [%]	Se [%]	DER [%]	Delay [ms]	Jitter [ms]
Moment based method	168341	167381	157	960	99.91	99.43	0.66	12.16	7.17
M1	168341	167725	292	616	99.83	99.63	0.54	14.40	12.60
M2	168341	166378	158	1744	99.91	98.96	1.13	9.33	9.26

7. Conclusion

A new real-time QRS detector based on the 4th order central moment was presented. The algorithm was evaluated using 12-lead ECGs recorded inside an MRI scanner and a 12-lead ECG arrhythmia database. The algorithm provides a reliable and accurate QRS detection for both ECG databases in real-time. Hence, it is suited for triggering CMR imaging sequences. A future study will include ECG signals from arrhythmic patients acquired during MRI.

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Address for correspondence:

Marcus Schmidt
Department of Medical Engineering
Universitaetsplatz 2 // 39106 Magdeburg // Germany
marcus.schmidt@ovgu.de