A SPECIFIC QRS DETECTOR FOR ELECTROCARDIOGRAPHY DURING MRI: USING WAVELETS AND LOCAL REGULARITY CHARACTERIZATION

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ABSTRACT

Automatic Electrocardiogram (ECG) analysis, especially QRS detection, is still a challenging task. This is even more the case when ECG is acquired during Magnetic Resonance (MR) examination. The MR environment highly distorts ECG, with Hall Effect, due to the important static magnetic field, and artifacts, caused by fast switching magnetic field gradients. Detection of QRS complexes is then affected. In this paper, a new specific MR QRS detector is presented. This method is based on the modulus maximum lines and on the Lipschitz exponent estimation they offer. The use of this regularity characterization enables to distinguish between QRS complexes and MR artifacts. This detector outperforms existing algorithms with almost 99% sensitivity and positive prediction value.

Index Terms— Electrocardiography, Magnetic Resonance Imaging, Wavelet

1. INTRODUCTION

Electrocardiogram (ECG) is an important diagnostic tool in medicine. Automatic ECG analysis requires accurate wave detections, especially the R-wave (or peak of the main ECG complex (QRS)). Once QRS complexes have been identified, a more detailed examination of the ECG can be performed. This problem is unfortunately tough since QRS complexes have time-varying morphology, are subject to physiological variations and are often corrupted by noise.ECG analysis is also required during Magnetic Resonance (MR) examination, mainly for two reasons: patient monitoring and sequence synchronization. The MR environment, namely high static magnetic field (1.5T- 3T), Radio-Frequency pulses and fast switching magnetic field gradients (33mT/m-50mT/m), unfortunately induces in complicated ECG acquisitions [1]. The blood ejection through the aortic valve generates an artificial wave on ECG [2], called Hall Effect and the magnetic field gradients produce highly disturbing artifacts, which can easily be confused with QRS complexes. In order to deal with these two principal MR artifacts, specific signal processing tools have been designed. Two research avenues have mainly been explored. (a) First a denoising method, using the magnetic field gradient signals, has been developed [1]. Applying existing QRS detection algorithms on these denoised signals can then lead to accurate ECG analysis. This kind of method unfortunately requires a connection to the MR gradient cabinet. (b) A second approach consists in the design of a MR specific QRS detector [3], based on the Vectocardiogram (VCG), a 3D representation of the electrical activity. This method is unable to process low amplitude ECG.

Wavelet transforms have indeed been widely studied these last years and have shown to be well adapted for ECG signal processing [4]. ECG acquired during MR examination (MR-ECG) are however unusual and existing algorithms are not suitable for this problem.

In this paper a new MR specific QRS detector based on Wavelet Transform is proposed, where modulus maximum lines are used to detect singularities in ECG. In order to discriminate MR artifacts from QRS complexes, some regularity characterization is also used, which is an innovation compared to existing wavelet based detectors.

2. THEORY

Mallat *et al.* [5] have demonstrated how it is possible to link singularity detection with the wavelet transform, especially wavelet modulus maximum lines. As R-waves are actually the most important singularity in the ECG signal, the application of Mallat's theory for R wave detection was quasi immediate. Many articles dealing with this problem have then emerged [6–10]. They differ by their application, the wavelet type or by some detection steps, but all rely on the same theory.

Let $f(x) \in L^2(\mathbb{R})$ and $\varphi(x) \in L^2(\mathbb{R})$. The wavelet transform of $f(x)$ is defined as:

$$Wf(s,x) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t)\varphi^*(\frac{t-x}{s})dt, \tag{1}$$

where s is the dilatation parameter and x is the location parameter. The function $\varphi(x)$ is said to be a wavelet if and only if its Fourier Transform $\Phi(\omega)$ satisfies:

$$\int_0^{\infty} \frac{|\Phi(\omega|^2}{|\omega|} d\omega = \int_{-\infty}^{0} \frac{|\Phi(\omega|^2}{|\omega|} d\omega = C_\varphi < \infty. \tag{2}$$

A modulus maximum is then any point (s_0, x_0) such that $|Wf(s_0,x)| < |Wf(s_0,x_0)|$ when x belong to a right (resp. left) neighborhood of x_0, and $|Wf(s_0,x)| \leq |Wf(s_0,x_0)|$ when x belong to the left (resp. right) neighborhood of x_0.

A connected curve in the scale space (s,x) along which all points are modulus maxima is then called a modulus maximum line.

Mallat *et al.* [5] have demonstrated that all singularities of $f(x)$ can be located by following the modulus maximum lines when the scale goes to zero. Moreover the way to characterize the singularities by using the modulus maximum lines has

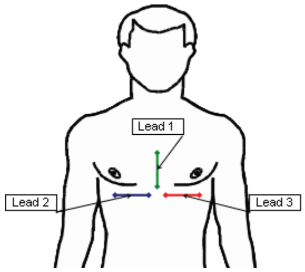

Fig. 1. MR-ECG Lead positioning.

also been illustrated.
In mathematics, the local regularity of a function can be measured with the Lipschitz exponent.
Let n be a positive integer and $n \leq \alpha < n+1$. A function $f(x)$ is said to be Lipschitz α, at x_0, if and only if there exist two constants A and $h_0 > 0$, and a polynomial of order n, $P_n(x)$, such that for $h < h_0$

$$|f(x_0 + h) - P_n(h)| \leq A|h|^{\alpha}. \tag{3}$$

The superior bound of all values α such that $f(x)$ is Lipschitz α at x_0 is called Lipschitz regularity of $f(x)$ at x_0.
Mallat *et al.* have demonstrated that a function $f(x)$ is Lipschitz α at x_0, if and only if there exists a constant B such that

$$\log |Wf(s,x)| \leq log(B) + \alpha \log(s), \tag{4}$$

where $(s,x) \in D_{x_0}$, and $D_{x_0} = \{(s,x)\}$ such that there exists a scale $s_0 > 0$ and a constant C, such that all the modulus maxima verify $|x - x_0| \leq Cs$.
Thus the Lipschitz regularity can be assessed by the maximum slope of straight lines that remain above $\log |Wf(s,x)|$, on a logarithmic scale. The higher is the Lipschitz exponent, the more regular is the function, meaning that artifacts will have much lower Lipschitz exponents than R waves.

3. MATERIALS

There are a large number of conventional ECG databases (MIT-BIH, AHA...) which are unfortunately not relevant for MR-ECG. The lead placement and the gradient related artifacts are specific to MR-ECG acquisitions. So a dedicated database has been built. Appropriate institutional ethics approval and subject consent were obtained. Each subject underwent a MR examination. The MR-ECG leads were positioned as shown in figure 1. MR-ECG was carried out by a custom Maglife (Schiller Médical, Wissembourg, France) and was recorded by the Signal Analyzer and Event Controller (SAEC) [11]. Specific ECG sensors, developed by Schiller for research purposes, with a [0.5-40Hz] bandwidth, were used. The subjects were in a supine position, feet-first on a 1.5T GE SIGNA HDx MR system (General Electric, Milwaukee, WI). As in previous work [11], some MR sequences were used. These sequences were chosen so that observed ECG distortions correspond to all the situations encountered in clinical applications, even worst cases. MRI acquisitions parameter values (slice location (head-hip), field of view (FOV) (24cm-60cm)) varied over a wide range. A total of thirteen healthy subjects was studied, seven were males and six females with an average age of 27.5±7.7, an average weight of $65.5kg \pm 10.5$ and an average body height of $172.7m \pm 9.5$. These subjects represent a database containing 14681 QRS complexes and about 3.5 hours of MR-ECG records.
MR gradient signals were acquired enabling the use of previous methods [1, 11, 12]. In order to correctly describe gradient signals, data acquisitions were made with a 10kHz sampling frequency. Nevertheless, since ECG bandwidth is low enough that such high sampling frequency is not needed, down-sampling at 250Hz was then applied. ECG were annotated, QRS onsets were marked.

4. METHODS

As described in the section 2, the aim of the presented method is to detect the modulus maximum lines corresponding to QRS complexes. In order to discriminate the MR artifacts, a local regularity characterization based on Lipschitz exponent theory is done. For this purpose, the use of continuous wavelet transform allows the modulus maximum lines to be followed more accurately across the scale space and thus the regularity characterization to be more precise. As in [10], the method uses the "Mexican hat" wavelet, which is the second derivative of a gaussian:

$$\varphi(x) = (1 - x^2) \exp\left(\frac{x^2}{2}\right). \tag{5}$$

Let suppose the approximate angle of the QRS complex β_{QRS} to be known.
Let ECG_1 and ECG_3 be the signals acquired on lead 1 and 3 respectively.
Let define $f(x) = r(x)\exp(i\beta(x))$ the complex representation of the Vectocardiogram, $ECG_3 - iECG_1$.
The input signal of the method, $g(x)$, can be defined as the projection of $f(x)$ on the QRS vector, $\exp(i\beta_{QRS})$:

$$g(x) = r(x)(\cos(\beta(x))\cos(\beta_{QRS}) + sin(\beta(x))\sin(\beta_{QRS})). \tag{6}$$

The presented method can be split into two consecutive steps. First, the continuous wavelet of $g(x)$, $Wg(s,x)$ is computed. The modulus maximum lines are then searched across the scales corresponding to the $10.5-21Hz$ frequencies as in [10]. The search starts at the scale s_0 which corresponds to a $15Hz$ frequency and the maxima above a predetermined threshold, $thres_{s_0}$, have solely been kept, the way to determine this threshold will be explained later.
Last, once the modulus maximum lines are found, the slope of $\log |Wf(s,x)|$ on the logarithmic scale is estimated. This estimation is done on two different scale segments, first segment corresponds to a $10.5 - 15Hz$ frequency range and second to a $15 - 21Hz$ range. These two estimations give some information on the regularity of $g(x)$, like a kind of Lipschitz exponent estimation. Let call α_1 and α_2 these two coefficients, which are tested to belong to a predetermined range. If both belong to their respective range, then the singularity is assumed to be a QRS complex.
Let define the way to determine the different coefficients or thresholds used by the method. For each subject, ECG were acquired before entering the MR bore. These acquisitions were then completely free from MR artifacts. In a first step, the QRS complexes has been detected by using the wavelet transform of $r(x)$, the modulus maximum detection threshold

has been set as three times the RMS of $Wr(s_0, x)$. As $r(x)$ is artifact free, all modulus maximum lines are assumed to correspond to QRS complexes. As the QRS complexes are found, the estimation of the approximate QRS angle, β_{QRS}, is possible and by the way $g(x)$ can be generated. The method is then applied for $g(x)$, the modulus maximum detection threshold, $thres_{s_0}$, is then set as two times the RMS of $Wf(s_0, x)$. The coefficients α_1 and α_2 can be estimated, so can their respective mean and standard deviation. These two parameters permit to define the regularity test range as

$$[m_i - 3 \times \max(0.5, std_i) \quad m_i + 3 \times \max(0.5, std_i))] \,, \qquad (7)$$

where $i \in \{1, 2\}$, m_i and std_i are respectively the mean and the standard deviation of the i^{th} coefficient. These two last parameters are adaptively updated as soon as a new QRS complex is found.

All the different steps of the method are illustrated on figure 2. The figure shows these MR artifacts have a negative Lipschitz exponent, whereas QRS have a positive one, and artifacts are discarded by the regularity characterization.

4.1. Validation

The validation was done by assessing QRS detection performance, which is evaluated by the sensitivity and the positive prediction values. These parameters are defined by

$$\text{Sensitivity} = Se = \frac{TP}{TP + FN} \qquad (8)$$

$$\text{Positive Prediction} = +P = \frac{TP}{TP + FP} \quad , \qquad (9)$$

where TP are the true positive, FN the false negative and FP the false positive. These statistics were computed following the ANSI/AAMI EC57 standard recommendations [13].

The presented method will be compared with state of art algorithms: the LMS method [12] followed by the QRS detector implemented in an industrial monitoring device (Argus PB 1000, Schiller AG, Baar, Switzerland) (LMS), the Vectocardiogram method (VCG) [3] and the presented method with the regularity characterization step being ignored (Wavelet).

5. RESULTS

The results are highlighted in table 1.

Method	Leads	Se	$+P$
(a) LMS	1 2 3	99.4	95.5
(b) VCG	1 3	97.1	86.5
Wavelet	1 2 3	99.6	96.0
Presented method	1 2 3	98.8	98.3

Table 1. QRS detection method comparison. Sensibility and Positive prediction value of the different methods.

First point to highlight is the relative low positive prediction value of the VCG, which is due to two subjects with low amplitude ECG. The experiment was reconducted but with these two subjects being discarded, results were better with a 98.6% sensitivity and a 96.1% positive prediction value. VCG can lead to accurate detection with subjects having high amplitude ECG.

The LMS method combined with an industrial QRS detector gives some good results, which prove the robustness of the method. However its main drawback is the need of a connection to the gradient cabinet, which is unfortunately not usually available.

Wavelet almost corresponds to the wavelet based QRS detection method presented in [10]. Its high sensitivity shows it is well adapted for QRS detection, but the positive prediction value illustrates well that MR-ECG acquisitions are very specific and need some custom-made signal processing methods.

Finally the presented method gives the best compromise between sensitivity and positive prediction values. The use of regularity characterization permits to discard both magnetic field gradient artifacts and Hall Effect and thus to accurately monitor patients during MR examination. The little loss of sensitivity compared to wavelet is mainly due to the cases where MR artifacts superimposed QRS complexes, which affects the regularity characterization.

6. DISCUSSION

In conclusion, a new MR specific QRS detector has been presented. The method is based on the wavelet transform, especially the modulus maximum lines and on the Lipschitz exponent theory. The use of this regularity characterization permits to distinguish between QRS complexes, magnetic field gradient artifacts and Hall Effect. This new method enables an accurate patient monitoring during MR examination and outperforms existing algorithms in term of QRS detection, and even in term of needed input information, as only two ECG leads are required and no connection to the MR gradient cabinet is needed.

The use of the regularity coefficients could even be extended to some classification tasks. It is indeed foreseeable to use these coefficients as inputs of some more complex classification algorithms, which would permit to distinguish between QRS complexes and extra-systolic beats.

7. ACKNOWLEDGMENT

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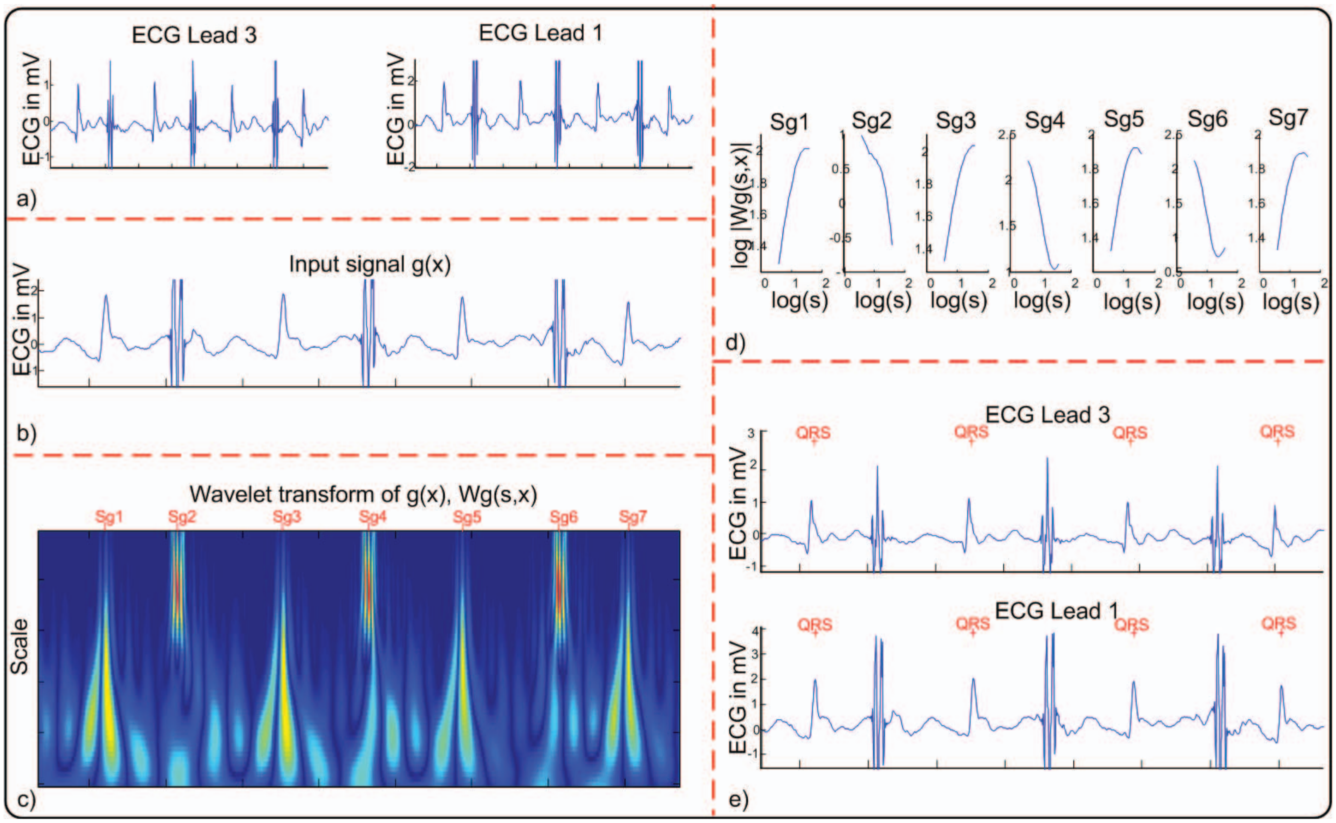

Fig. 2. Description of the presented method. a) Acquisition of two ECG Leads, which correspond to lead 1 and 3 on scheme 1. b) Generation of $g(x)$, which is the projection of the Vectocardiogram on the QRS vector. c) A continuous wavelet transform is applied on $g(x)$. Seven important modulus maximum lines, annotated Sg1 to Sg7 , can be observed on this figure. d) The regularity characterization, the $\log(|Wg(s,x)|)$ curve across $\log(s)$, of these seven modulus maximum lines is drawn. e) The QRS detection is illustrated. QRS detected by the presented method are represented by the cross. The three singularities corresponding to magnetic field gradient artifacts have been correctly identified by the regularity characterization step.

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