ABSTRACT

Electrocardiogram (ECG) is required during Magnetic Resonance Imaging (MRI) for two reasons, patient monitoring and MRI sequence synchronization for cardiovascular imaging. The MRI environment severely distorts ECG signals. The Magnetic Field Gradients (MFG) especially induce artifacts, which make ECG analysis during MRI acquisition challenging. Specific signal processing is thus required. An MFG artifact modeling has been proposed for their suppression. However the resulting techniques do not take the ECG signals into account during the model parameter estimation. Recently, ECG denoising based on an artificial ECG model and nonlinear Bayesian filtering has been presented. In this paper, a new MFG artifact suppression method based on nonlinear Bayesian filtering and the unification of the ECG and MFG models is proposed. This new approach enables accurate patient monitoring and outperforms state-of-the-art methods in terms of both QRS detection quality and signal to noise ratio.

Index Terms— Electrocardiography, Magnetic Resonance Imaging, Kalman Filtering

1. INTRODUCTION

Electrocardiogram (ECG) is an important cardiovascular diagnosis tool. ECG is furthermore required during Magnetic Resonance Imaging (MRI) for two purposes:

• Monitoring. Physiological signals have to be acquired in many circumstances [1]. Among all physiological signals, ECG is of premium importance since it gives information on cardiac activity.

• Triggering. MRI acquisition consists in a sequential procedure, which is a succession of Nuclear Magnetic Resonance (NMR) experiments. In case of cardiac imaging, these NMR experiments have to be synchronized with heart activity. ECG is therefore the signal of reference [2], each experiment being launched after a fixed delay following a QRS complex detection.

ECG analysis usually first consists in the QRS complex detection. The R wave location brings information on cardiac rhythm, deducted from the time between two consecutive R waves, also called RR interval. ECG analysis is complicated by the hostile MRI environment and its three characteristic physical components: high static magnetic field, presence of Radio-Frequency (RF) pulses and Magnetic Field Gradients (MFG). The static magnetic field (1.5T-3T in clinical scanners) creates an undesirable signal, called MagnetoHydroDynamic (MHD) effect, due to the displacement of electrical particles present in blood after ejection from the right ventricle. RF pulses impose a shortening of the ECG wires, to prevent from burn hazards. As a consequence, ECG signals acquired during MRI (MR-ECG) suffer from a great patient-to-patient variability. The main distortions are caused by the MFG, due to the induction of electrical fields inside the body. These electrical fields are also acquired and MFG artifacts are superimposed to ECG signals, making accurate ECG analysis almost impossible during MRI acquisition.

Despite hardware developments, MR-ECG signals are still distorted by the MRI environment and require therefore specific signal processing. Two avenues of research have been explored. First approaches consist in the development of MR specific QRS detectors. A first method has taken advantage of the Vectocardiogram (VCG) representation of the heart electrical activity [3]. The authors assume that, in the VCG space, the MRI environment distortions, especially the MFG artifacts, are oriented in another direction than the heart electrical axis. A major drawback of this method is the inability to process low ECG amplitude signals. Another method using wavelet transforms has been presented [4]. The detector is based on singularity detection and on their characterization provided by the wavelet modulus maximum lines. A classification step enables to discard MFG artifact detections. Nevertheless the methods of this class do not provide any clean signal suitable for patient monitoring. Other approaches consist in MFG artifact suppression methods [5, 6, 7] applied before a standard QRS detector is used. These techniques are based on a MFG artifact modeling [5] and on the knowledge of the MFG command signals, thanks to a connection to the MRI electronic system. The methods of this class suffer from one main drawback: ECG signal is not taken into account during the model parameter estimation, since the SQ segment (ECG apart from the QRS complex) is assumed to be noise.

Recently, new ECG denoising methods, based on an artificial ECG model, have been presented [8, 9]. The authors propose to combine nonlinear Bayesian filtering and an ECG model for accurate denoising, but also segmentation and compression. In this paper, a novel MR-ECG denoising method will be presented. This new technique based nonlinear Bayesian filtering uses a new "state-space" formulation resulting from the unification of the ECG and MFG modelings.

2. THEORY

2.1. ECG Model

Mc Sharry et al. [10] have modeled the ECG as a pseudo periodic signal, of which each cycle is composed of a sum of five Gaussians
functions (Fig. 1A). This model has been used to create artificial ECG signals for evaluation of denoising techniques.

ECG can be approximated by an artificial pseudo periodic signal represented by its phase $\theta_k$ and its amplitude in mV $z_k$ whose evolutions can be written as:

$$\begin{align*}
\theta_k &= (\theta_{k-1} + \omega \delta) \mod 2\pi \\
z_k &= -\sum_{i} \delta \frac{\alpha_{i,\omega}}{b_i} \Delta \theta_{i,k-1} \exp \left( -\frac{\Delta \theta_{i,k-1}^2}{2b_i^2} \right) + z_{k-1} + \eta
\end{align*}$$

(1)

where $\omega = 2\pi / RR$, $RR$ being the RR interval length, $\delta$ is the sample period, $\alpha_i, b_i$ and $\xi_i$ are respectively the amplitude, the angular position and the width of the $i^{th}$ Gaussian function and $\Delta \theta_{i,k-1} = (\theta_{k-1} - \xi_i) \mod 2\pi$, $\eta$ is a noise resulting from the modeling error made by substituting the real ECG signal by the model. It is known as the inductive bias and is a white centered noise.

2.2. MFG modeling

MR-ECG is mainly distorted by MFG artifacts, making accurate analysis almost impossible during MRI acquisition. These MFG have been demonstrated to be the recordings of the electrical fields induced inside the body by the magnetic field. Fellbinger et al. [5] have introduced a MFG artifact modeling, aiming at simplifying the denoising procedure, as it is easier to estimate model parameters than to blindly separate sources. The authors have assumed the MR-ECG to be a convolutive mixture of ECG and the three MFG command signals filtered by a finite impulse response:

$$s_k = s_{\text{ECG,k}} + \sum_{i \in \{X,Y,Z\}} \left( \sum_{l=0}^{N-1} h^i_l g_{i,k-l} \right) + \mu_k,$$

(2)

where $g_{i,k}$ is the signal that commands the MFG in the direction $i \in \{X,Y,Z\}$, $h^i_l$ is the impulse response corresponding to $g_{i,k}$ and $\mu_k$ represents all other contributions of noise. The impulse response, $h^i_l$, models the whole physical process occurring between the installation of the current in the MFG coils and the acquisition of MR-ECG signals.

Considering the ECG as white noise, methods based on this model [5, 6, 7] do not take the ECG contribution $s_{\text{ECG,k}}$ into account during the model parameter ($h^i_l$) estimation and can thus lead to a biased estimation and create some undesirable MR-ECG distortions.

2.3. Bayesian filtering for parameter estimation

The models of sections 2.1 and 2.2 are parametric. The best set of parameters that fits the model has to be estimated [8, 9] from data. This estimation should ideally be performed on-line with a continuous parameter tracking to take the non stationnarity of the ECG into account. Bayesian filtering techniques are well-suited for this task. Bayesian filtering is a general paradigm aiming at estimating the posterior distribution $p(\mathbf{z}|\mathbf{x})$ of hidden random variables (here the parameter vector) given a sequence of noisy observations $\mathbf{y}_i = \{y_1, y_2, \ldots, y_N\}$. To do so, the parameters are supposed to be random variables evolving according to an evolution equation while they are observed through a measurement equation. These equations constitute the state-space formulation of the estimation problem and are required prior knowledge:

$$\begin{align*}
\mathbf{x}_k &= f(\mathbf{x}_{k-1}, \mathbf{w}_{k-1}, k-1) \\
\mathbf{y}_k &= g(\mathbf{x}_k, \mathbf{u}_k, k)
\end{align*}$$

(evolution equation)

(measurement equation)

(3)

where $\mathbf{x}_k$ is the parameter vector (also called state vector in the Bayesian filtering literature) and $\mathbf{y}_k$ the observation vector. $w$ and $v$ are white centered noises. Bayesian filtering was used by Sayadi et al. [9] for denoising purposes using the model of section 2.1. It is here proposed to modify this model to take MFG into account using the model of section 2.2.

3. MATERIAL AND METHOD

3.1. Material

There is a large number of conventional ECG databases (MIT-BIH, AHA...) which are unfortunately not relevant for MR-ECG. The lead placement and the MFG 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 MRI examination. The MR-ECG leads were positioned as shown in figure 1C. MR-ECG was carried out by a custom Maglife (Schiller Médical, Wissembourg, France) and was recorded by the Signal Analyzer and Event Controller (SAEC) [7]. 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 [7], MRI sequences were chosen so that observed ECG distortions correspond to all the situations encountered in clinical applications, even worst cases. MRI acquisition parameter values (slice location (head-hip), field of view (FOV) (24cm-60cm)) varied over a wide range. A total of thirteen healthy subjects were studied, seven were males and six females with an average age of 27.5 ± 7.7, an average weight of 65.5kg ± 10.5 and an average body height of 172.7cm ± 9.5. These subjects represent a database of 14681 QRS complexes and about 3.5 hours of MR-ECG records. Recordings were manually classified in two sets, in accordance to their noise level. Set 1 contains low-noise MR-ECG acquisitions, corresponding to 12444 QRS complexes, and set 2 contains the most disturbed MR-ECG with 2239 QRS complexes.

MRG signals were acquired enabling the use of previous methods [5, 6, 7]. Sampling frequency was set at 250Hz. ECG were annotated by a cardiologist. QRS onsets were marked and MFG artifacts regions were specified for validation purpose.

3.2. Method

The presented method merges the ECG and the MFG models. In [9] the authors have used the ECG model and assumed the Gaussian parameters ($\alpha_i, \xi_i, b_i$) to follow random walks (which is a common solution when nothing is known about the evolution): $\mathbf{z}_k = \begin{bmatrix} \theta_k, z_k, \alpha_{i,k}, b_{i,k}, \xi_{i,k} \end{bmatrix}^T$, with $i = (1 \ldots 5)$. Here MFG impulse responses, $h^i_l$, have been considered as following random walks as well and they have been added to the parameter vector:

$$\mathbf{z}_k = \begin{bmatrix} \theta_k, z_k, \alpha_{i,k}, b_{i,k}, \xi_{i,k}, h^1_{1,k}, \ldots, h^N_{1,k} \end{bmatrix}^T,$$

(4)

whose evolution is governed by the following evolution equations:

$$\begin{align*}
\theta_k &= \theta_{k-1} + \omega \delta \mod 2\pi \\
z_k &= z_{k-1} - \sum_{i} \delta \frac{\alpha_{i,\omega}}{b_i} \Delta \theta_{i,k-1} \exp \left( -\frac{\Delta \theta_{i,k-1}^2}{2b_i^2} \right) + \eta_{k-1}
\end{align*}$$

(5)
where $\varepsilon_{i,k-1}$ and $\varepsilon_{i,k-1}^b$ are the noises of the random walks of respectively $\alpha_{i,k}$, $b_{i,k}$, $\xi_{i,k}$, $h_{j,k}$, and $\sigma_{i,k-1}^2$, $\sigma_{i,k-1}^b$, with $i \in \{1 \ldots 5\}$ and $j \in \{X, Y, Z\}$.

Two signals are then observed as in [9], the MR-ECG signal, $s_k$ and an artificial phase signal, $\varphi_k$ resulting from a linear phase assignment between two consecutive R waves, whose locations are detected by the wavelet-based method presented in [4] (Fig. 1B), $y_k = [s_k, \varphi_k]$.

As some prior information is needed for Bayesian filtering, the model parameters have to be correctly initialized. The first 30 heart cycles are used for initialization. The ECG model parameters are estimated with a nonlinear quadratic optimization technique, as presented in [8] and $b_0^1$ is set to zero.

The MR-ECG denoising simply consists in the implementation of the Extended Kalman Filter (EKF). EKF has been chosen for the sake of simplicity and robustness. Its implementation is conceivable since the model can be linearized and the smoothness of Gaussian functions makes the linearization approximation possible.

At each new QRS detection, the signal $\varphi_k$ can be computed and so can be the EKF. The creation of this phase induces a delay of at least one heart cycle, meaning that this method can only be applied for patient monitoring.

### 3.3. Validation

MR-ECG signal processing quality can be assessed by two criteria: QRS detection performance and a pseudo signal to noise ratio measure.

The QRS detection algorithm applied on the denoised ECG is the one used in an industrial monitoring device (Argus PB 1000, Schiller AG, Baar, Switzerland). The performances of the different methods are evaluated by the sensitivity (Se) and the positive predictivity (+P). These statistics are computed following the ANSI/AAMI EC57 standard recommendations [11].

The algorithm efficiency is also estimated with a pseudo signal to noise ratio (SNR) enhancement. Signal energy is restricted to QRS and noise to gradient artifacts. SQ segment were not supposed to be null, but due to Hall Effect the most relevant information in MR-ECG is contained in the QRS. The pseudo SNR will then be defined as the ratio of QRS energy on artifact energy and called pseudo SNR enhancement (PSNRE). Thanks to annotations, the energy of each part could easily be computed and pseudo SNR is then evaluated.

The evolution of QRS and artifact energy, respectively signal energy evolution (SEE) and noise energy evolution (NEE), were also computed as follows:

$$
S E E = 10 \left( \log \left( \sum_{i \in Q R S} | x_{d e n}(i) |^2 \right) - \log \left( \sum_{i \in Q R S} | x_{r a w}(i) |^2 \right) \right)
$$

and

$$
N E E = 10 \left( \log \left( \sum_{i \in A r t} | x_{d e n}(i) |^2 \right) - \log \left( \sum_{i \in A r t} | x_{r a w}(i) |^2 \right) \right),
$$

where $Q R S$ represents the QRS regions, $A r t$ the MFG artifacts, $x_{r a w}(i)$ the raw ECG at time $i$ and $x_{d e n}(i)$ the denoised ECG at time i. PSNRE is then easily evaluated by $P S N R E = S E E - N E E$. These three criteria were evaluated on lead 3. The ideal method yields the highest PSNRE, combined with the lowest NEE and a zero SEE, meaning that QRS is not altered.

The presented method results are compared with state-of-the-art ones. Among them, an industrial QRS detector (Argus PB-1000, Schiller, Baar, Switzerland) applied on Raw signals (Raw), specific MR QRS detectors, (VCG), which was implemented as explained in [3], and the wavelet-based detector presented in [4] (Wavelet). Other denoising methods, combined with an industrial detector (Argus PB-1000, Schiller, Baar, Switzerland), have also been tested: the adaptive filter based [6] (LMS) and ECG model combined with Bayesian filtering as presented in [9] (Bayesian).

### 4. RESULTS

QRS detection results are assembled in table 1. Raw results are relatively poor, highlighting the need of specific signal processing. VCG ones are disappointing, due to the presence of subjects having low ECG amplitude signals, which are not processed accurately. LMS yields an improvement for both sensitivity (+1%) and positive predictivity (+5%) toward Raw, but it can be seen that positive predictivity (89.6%) can be improved on Set 2. Bayesian method presented in [9] does not accurately denoise signals from Set 2 (noisy signals), yielding a lower positive predictivity than LMS (9.7%). This result demonstrates the need of taking the MFG artifacts into account in the model. Wavelet results are quite good, especially on Set 2 with a 94.1% positive predictivity, but the presented method outperforms all existing ones, with a very accurate QRS detection, especially the positive predictivity on set 2 (97.0%), which demonstrates its ability to process very noisy MR-ECG acquisitions. The denoising quality results are assembled in Table 2. As for QRS detection, Bayesian results demonstrate the specificity of MR-ECG. By not considering the MFG artifacts, the Bayesian filtering alters signal quality ($S E E = -26 dB$) and leads to a poor denoising quality, with the lowest PSNRE. The presented method outperforms the LMS, in terms of NEE ($-0.62dB$) and PSNRE ($+0.50dB$). SEE results are quite similar for both methods ($S E E \approx -0.06, -0.08$), which illustrates MR-ECG is not altered by denoising.
5. DISCUSSION

The quality of the presented method has been demonstrated in section 4. This new technique has been shown to be the most effective MR patient monitoring method, being able to process MR-ECG even during very disturbing MRI acquisitions.

Synthesis of the phase signal induces, however, a delay which is incompatible with triggering purpose. Several avenues of research are conceivable to overcome this limitation. During the Bayesian filtering procedure, the impulse response parameters are estimated. These estimates could be used for a semi-online filtering of the MR-ECG, where the delayed impulse response estimations are used to filter in real-time the MFG command signals for MFG artifact suppression. An online phase assignment procedure is also conceivable, by using a RR interval prediction [12].

The unification of ECG and MFG models for Bayesian filtering overcomes state-of-the-art MR-ECG signal processing limitations and opens the way of accurate interpretation during a complete MRI examination.

6. REFERENCES