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Filtering of Pathological Ventricular Rhythms during MRI Scanning

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Abstract. The detection of pathological ventricular repolarization during Magnetic Resonance Imaging (MRI) examination becomes necessary with the development of MRI guided surgery or electrophysiology and stress-test MRI. The Electrocardiogram (ECG) signal is distorted by the MagnetoHydroDynamic (MHD) effect, arising from blood flow and thus the motion of electrolytes inside a magnetic field. This distortion makes ECG diagnosis impossible; the development of an accurate MHD suppression is thus mandatory.
An extension of the ECG model based nonlinear Bayesian filtering is proposed to deal specifically with the MHD artefact by incorporating a model of the MHD based on Gaussian waves.
The assessment of an MHD suppression technique is difficult due to the high level of noise and the lack of information about the ventricular repolarization. The method has thus been applied on artificial signals, modelling an acquisition of ECG during MRI examination. Two different cases were modelled: one ECG signal with T wave inversion and one exhibiting a prolonged QT interval. The results show promising denoising of the ECG signal enabling detection of pathological ventricular repolarization, but application of this technique on real acquisitions are needed to assess the filtering behaviour on real signals.
Keywords: Bayesian filtering, Electrocardiogram, Magnetic Resonance Imaging

1. Introduction

Magnetic Resonance Imaging (MRI) is an emerging non-invasive radiological technique, whose field of applications is constantly growing. This technique relies on the Nuclear Magnetic Resonance (NMR) phenomenon, and thus requires the patient to lie in a high static magnetic field.
The acquisition of the Electrocardiogram (ECG) during an MRI procedure seems paradoxal but is nevertheless mandatory for two reasons. Firstly, the patient has to be monitored during the whole MRI procedure. Several physiological parameters are recorded for this purpose [Shellock, 2001]. Among them, the ECG signal is one of the most important due to its ability to detect many cardiovascular abnormalities. Secondly, the MRI is a rather slow imaging technique, the acquisition of an image lasting several seconds as it consists of a succession of NMR experiments. While imaging the heart, the motion of this organ has to be considered to avoid smeared images. The use of the ECG signal is the clinical standard in order to synchronise MRI acquisition with heart motion [Scott et al., 2009]. Each NMR experiment is triggered by the detection of the QRS complex.

The MRI environment consists of three major physical characteristics: high static magnetic field, fast varying magnetic fields (gradients) and RadioFrequency (RF) pulses, each of them significantly distorts the ECG signal. The most distorting artefact arises from the presence of the high magnetic field. The blood carries some electrically charged particles, whose motion inside a magnetic field is creating a current source. This effect is called MagnetoHydroDynamic (MHD) effect or Hall effect [Keltner et al., 1990]. The strength of the MRI magnetic field is such that the current source created by the blood flow is about the same magnitude than the heart natural electrical activity. It has been shown that the main contribution of the MHD effect is induced by the blood ejection through the aortic arch, because of the geometry of the arch, the diameter of the artery and the blood velocity [Gupta et al., 2008; Tenforde, 2005]. Given the timing and the amplitude of this phenomenon, the ST to T wave segment of the ECG is hidden behind a high level of noise and the detection of pathological ventricular repolarization is currently impossible during MRI. This is becoming a growing concern with the development of applications such as very high field cardiac imaging [Niendorf et al., 2010], MR guided surgery [Lederman, 2005], cardiac imaging during exercise stress [Jekic et al., 2008], or intra-cardiac electrophysiology guided by real-time MRI [Gutberlet et al., 2012].

In the present study, we propose to extend the use of an ECG model and nonlinear Bayesian filtering for the suppression of the MHD effect. The method was assessed on artificial but realistic models of ECG acquired during MRI. These models illustrate the behaviour of the filter on an ECG with prolonged QT and an ECG with T wave inversion.

2. Material and Methods

2.1. Method

ECG signal has been recently modelled as pseudo periodic signal, each cycle being a sum of Gaussians [McSharry et al., 2003]. It has been shown that the use of seven Gaussians, the two firsts representing the P wave, the three next the QRS complex and the two lasts the T wave, is sufficient for having an accurate representation of the ECG signal [Sayadi et al., 2010]:

$$\begin{cases} \theta_k = (\theta_{k-1} + \omega\delta) \mod 2\pi \\ z_k = -\sum_i \delta \frac{\omega \Delta\theta_{i,k-1}}{b_i^2} G\left(\alpha_i, \Delta\theta_{i,k-1}, b_i\right) + z_{k-1} + \eta \end{cases}, \quad (1)$$

where θ_k is the angular position in the cylindrical coordinates, $\omega= 2\pi/RR$ the angular speed, δ the sampling period. z_k represents the ECG value in mV at time k and α_i, b_i, ξ_i are the amplitude, width and angular position of the i^{th} Gaussian respectively, with $\Delta\theta_{i,k-1} = (\theta_{k-1} - \xi_i)(\mod 2)$ and with $G(a, b, c) = a \exp(-b^2/(2c^2)^{-1})$ a Gaussian wave.

The ECG model can be approximated through the online estimation of its parameters with nonlinear Bayesian filtering [Sayadi et al., 2010]. This method offers both the advantage of using the prior knowledge for accurate denoising and the possibility of following the non-stationarity of the signal.

The MHD effect can also be modelled as a pseudo-periodic signal, the periodicity being exactly the same than that of the ECG signal and each cycle can also be approximated by a sum of Gaussians. The number of Gaussians is depending on the laminarity and turbulence of the blood flow given the subjects and its activity.

Application of nonlinear Bayesian filtering, and especially the Kalman filter, for the separation of the MHD effect is thus conceivable. However, for standard ECG applications, each contribution (e.g. P, QRS and T waves) are temporally separated and thus the Kalman filter has only to consider the evolution of one contribution at a time. For the ECG acquisition during MRI, MHD effect waves overlap ECG main waves, which should not be problematic, since the dynamics of the contributions are modelled in the equations. However, the model of ECG and MHD is not stationary and the estimation of its evolution is made difficult if its dynamics are not temporally separated. To overcome this limitation, a new observation equation is introduced in which a synthetic signal is created by subtracted from the raw ECG observation the prior on the ECG signal (e.g., the sum of Gaussians of the ECG model given the synthetic phase signal). This new observation gives an approximation of the MHD effect.

The introduction of this new observation relies highly on the prior knowledge of the ECG model. As the ECG is non-stationary, the parameters should be allowed to evolve. The integration of the Gaussian parameters in the state vector is proposed. As no prior knowledge on their evolution can be made, their evolution are assumed to follow a random walk. The new observation is modified by adding the MHD contribution and the Gaussians parameters in the state vector (ECG model).

The state space can thus be formulated given the following set of equations:
The evolution equation being:

$$\begin{cases} \theta_k = (\theta_{k-1} + \omega\delta) \mod 2\pi \\ P_k = -\sum_{i=1}^{2} \delta \frac{\omega \Delta\theta_{i,k-1}^E}{b_{i,k-1}^E{}^2} G\left(\alpha_{i,k-1}^E, \Delta\theta_{i,k-1}^E, b_{i,k-1}^E\right) + P_{k-1} + \eta_p \\ Q_k = -\sum_{i=3}^{5} \delta \frac{\omega \Delta\theta_{i,k-1}^E}{b_{i,k-1}^E{}^2} G\left(\alpha_{i,k-1}^E, \Delta\theta_{i,k-1}^E, b_{i,k-1}^E\right) + Q_{k-1} + \eta_{QRS} \\ T_k = -\sum_{i=6}^{7} \delta \frac{\omega \Delta\theta_{i,k-1}^E}{b_{i,k-1}^E{}^2} G\left(\alpha_{i,k-1}^E, \Delta\theta_{i,k-1}^E, b_{i,k-1}^E\right) + T_{k-1} + \eta_T \\ M_k = -\sum_{i} \delta \frac{\omega \Delta\theta_{i,k-1}^M}{b_{i,k-1}^M{}^2} G\left(\alpha_{i,k-1}^M, \Delta\theta_{i,k-1}^M, b_{i,k-1}^M\right) + M_{k-1} + \eta_{MHD} \\ \alpha_{i,k}^E = \alpha_{i,k-1}^E + \varepsilon_{\alpha,i} \\ b_{i,k}^E = b_{i,k-1}^E + \varepsilon_{b,i} \\ \xi_{i,k}^E = \xi_{i,k-1}^E + \varepsilon_{\xi,i} \end{cases}, \quad (2)$$

and the observation being

$$\begin{cases} \varphi_k = \theta_k + v_{1,k} \\ s_k = P_k + Q_k + T_k + M_k + v_{2,k} \\ s_k = M_k + \sum_i G\left(\alpha_{i,k}^E, \Delta\theta_{i,k}^E, b_{i,k}^E\right) + v_{3,k} \end{cases}, \quad (3)$$

where *P, Q, T* and *M* represent the P wave, the QRS complex, the T wave and the MHD effect respectively. $(\alpha_{i,k}^E, \Delta\theta_{i,k}^E, b_i^E \xi i_{,k}^E)$ are the Gaussian parameters for the ECG signal (P, QRS and T waves) and $(\alpha_{i,k}^M, \Delta\theta_{i,k}^M, b_i^M \xi i_{,k}^M)$ those for the MHD effect. The observed signals, s_k is the ECG signal acquired inside the MRI bore and φ_k is an artificial phase signal assigned linearly from 0 to 2π between two consecutive R waves and then rescaled between $-\pi$ and π. Each major component of the ECG signal is represented in the state vector, and the estimated ECG signal (z_k) would then be given by the sum of the three components $z_k = P_k + QRS_k + T_k$. The Gaussian parameters of the MHD contribution are not included in the state vector, even though the signal is non-stationary, but the uncertainty noise η_{MHD} allows to consider it.

An initialization procedure was needed before applying the Bayesian filtering. Ten ECG cycles were recorded outside the MRI, while the subject was prepared for the examination, and the Gaussian parameters of the mean ECG cycle were computed. The subject was then inserted the MRI bore and the first ten ECG cycles were used for computing the Gaussian parameters of the MHD effect, by subtracting the Gaussian waves based ECG model from the mean of these ten ECG cycles. The assumption that over this short period the ECG was almost stationary was thus made. Once all these parameters were initialized, the non-linear Bayesian filtering could be started. For this study, we applied an Extended Kalman Filter (EKF), which has been proven to work well for ECG denoising [Sayadi et al., 2010].

2.2. Data

Assessing the quality of MHD suppression is particularly difficult due to the high level of noise and the overlapping of the ST segment and T wave by the MHD effect. This is made even more difficult in the case of pathological ventricular repolarization since there is no way of knowing the ground truth and the real ECG amplitude. Therefore the development of an accurate model of the ECG acquired during MRI has been an active topic of research in recent years. These models allow an objective assessment of the flaws and strengths of an MHD suppression technique and its ability to detect pathological ventricular repolarization [Gupta et al., 2008].

The MHD effect was modelled by using 4D blood flow measurements from a phase contrast MRI technique. The blood flow was measured in four sections of the aortic arch. 3D models of the aortic arch and the human torso were used to project the current source onto the torso for computing the biopotential on the torso at the different electrode positions [Oster et al., 2012].

The ECG was modelled with the dynamical VCG model, that represents each of the three axis of the VCG by a sum of Gaussians and then applied a Dower transform [Clifford et al., 2010]. In order to model a pathological ventricular repolarization, the parameters of the Gaussian representing the T wave were evolving. The T wave inversion was modelled by inverting the amplitude of the T wave Gaussians with a logistic function over ten cycles. The prolonged QT interval was modelled by moving forward angular position of the T wave Gaussians with a logistic function over 10 cycles with an amplitude of

0.1rad

Finally, to generate realistic recordings, real noise was added from the Noise Stress Test Database [Moody et al., 1984; Goldberger et al., 2000]. Muscle artefact and baseline wander noise recorded form limbs without ECG contamination were superimposed on the artificial ECG at realistic levels. The two leads of the noise data recordings were added onto VCG leads X and Y. Noise for lead Z was derived from the first projection of a Principal Component Analysis of the two other noise leads per Clifford et al. [Clifford et al., 2012]. The level of noise added was such that its energy on each VCG lead was half of the ECG signal energy, which corresponded to a *3dB* SNR without taking into account the MHD effect.

2.3. Quality Assessment

One could easily compute the SNR improvement of the filtering procedure, but we were more interested in the diagnostic quality of the signal and especially the detection of pathological ventricular repolarization, and more precisely QT prolongation and T wave inversion. ECGPUwave algorithm was therefore used for ECG segmentation [Goldberger et al., 2000; Jané et al., 1997]. The QT intervals of each beat were then measured before and after filtering, and compared. Moreover, ECGPUwave also classifies T waves and the detection of T wave inversions could thus also been assessed.

3. Results

The results of the denoising for the two test examples are depicted in Fig 1.

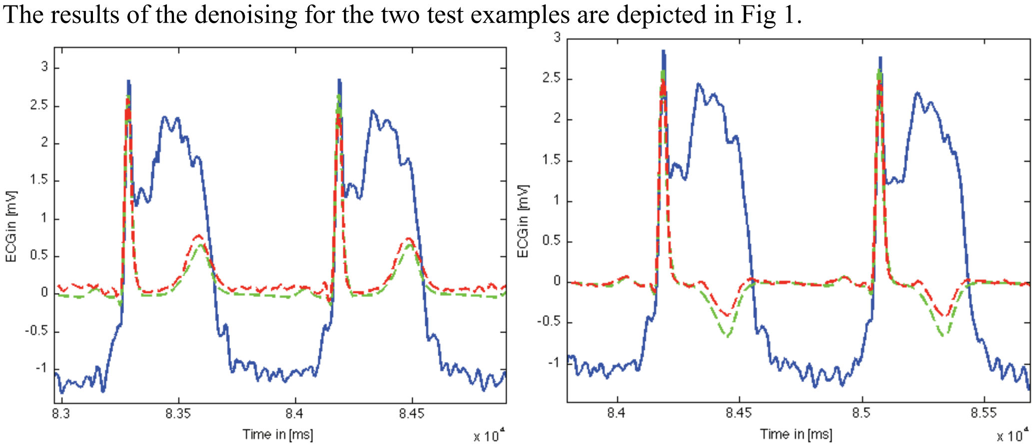

Figure 1. *Denoising of the simulated acquisition of an ECG during MRI, with a prolonged QT (left) and T wave Inversion (right) (blue: raw ECG with MHD noise, green: original –clean—ECG without MHD, red: denoised ECG).*

The annotations for the T wave inversion example are shown in Fig. 2. The T wave inversion is detected on the denoised ECG 14 cycles after the T wave inversion.

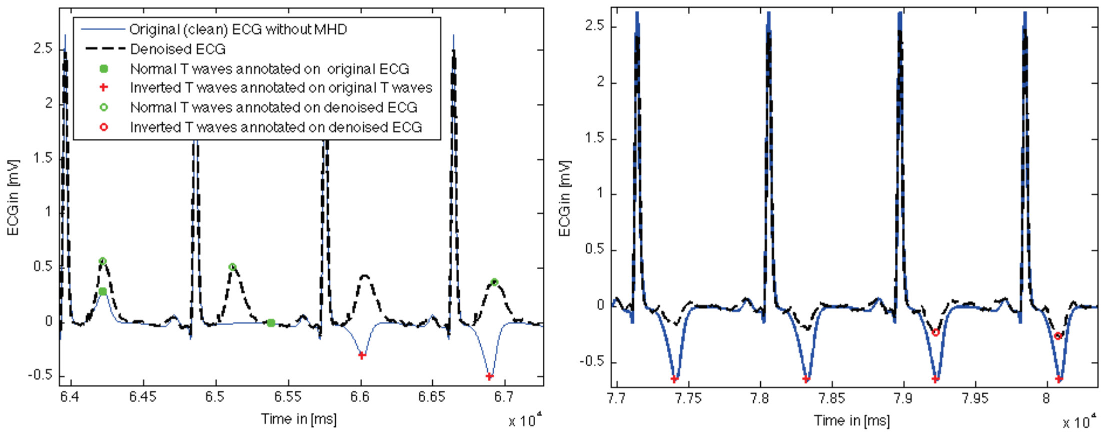

Figure 2. *Annotations of the T waves for the T wave inversion example during the T wave inversion (left) and 12 cycles after inversion (right).*

(blue: original –clean—ECG without MHD, dashed black: denoised ECG, green cross: normal T wave annotation on original ECG, red cross: inverted T wave annotation on original ECG, green circle: normal T wave annotation on denoised ECG, red circle: inverted T wave annotation on denoised ECG).

The estimation of the QT intervals on both clean and denoised ECG are depicted on Fig. 3. The prolongation of the QT interval can be detected almost immediately when it occurs (at the 60th ECG cycle). Nevertheless the QT interval is slightly overestimated on denoised ECG due to the presence of residual noise. The mean absolute difference is *34.3ms±25.9* over the whole segment (only *22.1ms±14.3* before the QT prolongation and *59.5ms±26.2* after). The overestimation is within human error before the elongation, but slightly larger than human error after the prolongation [Christov et al., 2006].

4. Conclusions

A promising technique of MHD suppression and ECG denoising has been presented. It has been shown that pathological ventricular repolarization can be detected even in such a noisy environment. One limitation of this technique is the time convergence of the filter, which could lead to missed transient phenomena. Overestimation of the QT interval, over the threshold for diagnosis quality, was also established in the QT prolongation case. These limitations could be overcome by a finer tuning of the EKF parameters and the use of more accurate segmentation techniques in presence of noise.

The filter behaviour is highly dependent on the parameters initialisation, such as noise observation covariance matrix, and adaptation of such parameters would be useful for non-stationary situations.

Given the conditions of recording in the MRI, the methodology consisting in the modelling of evolving ECG patterns and realistic noise models is a good solution for assessing the possibility of pathological events detection. In this study, the MHD effect was assumed not to evolve significantly, only small variations of the cardiac output were considered.

Nevertheless, pathological ventricular repolarization could also be associated with deformation of the blood flow pattern, especially in case of ischemia, which would modify the MHD effect and this would make it difficult for the Bayesian filter to separate the contributions of the different sources. Moreover, the behaviour of this denoising technique should also be assessed on real acquisitions with potentially varying electrophysiologic signals, such as stress-test or for ischemia induced on porcine subjects.

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References

Christov I, Dotsinsky I, Simova I, Prokopova R, Trendafilova E, Naydenov S, Dataset of manually measured QT intervals in the electrocardiogram. *BioMedical Engineering OnLine*, 5(1): 31, 2006

Clifford GD, Nemati S, and Sameni R. An artificial vector model for generating abnormal electrocardiographic rhythms. *Physiological Measurement,* 31(5):595–609, 2010.

Clifford GD, Behar J, Li Q, and Rezek I. Signal quality indices and data fusion for determining acceptability of electrocardiograms collected in noisy ambulatory environments. *Physiological Measurement, 33(9): 1419—1433, 2012.*

Goldberger A, Amaral L, Glas L, Hausdorff J, Ivanov P, Mark RG, Mietus J, Moody G, Peng C-K, and Stanley E. PhysioBank, PhysioToolkit, and PhysioNet : Components of a New Research Resource for Complex Physiological Signals. *Circulation*, 101:215–220, 2000.

Gupta A, Weeks AR, and Richie SM. Simulation of Elevated T-Waves of an ECG Inside a Static Magnetic Field (MRI). *IEEE Transactions on Biomedical Engineering,* 55(7): 1890–1896, 2008.

Gutberlet M, Grotthoff M, Eitel M, Luecke C, Sommer P, Piorkowski P, and Hindricks G. First clinical experience in man with the IMRICORMR-EP system:Electrophysiology study guided by real-time MRI. Journal of Cardiovascular Magnetic Resonance, 14(Suppl 1):205, 2012.

Jané R, Blasi A, Garcia A, and Laguna P. Evaluation of an automatic threshold based detector of waveform limits in holter ECG with the QT database. *Computers in Cardiology*, 295–298, 1997.

Jekic M, Foster E, Ballinger M, Raman S, and Simonetti O. Cardiac function and myocardial perfusion immediately following maximal treadmill exercise inside the mri room. *Journal of Cardiovascular Magnetic Resonance*, 10(1):3, 2008.

Keltner JR, Roos MS, Brakeman PR, and Budinger TF. Magnetohydrodynamics of blood flow. *Magnetic Resonance in Medicine,* 16:139–149, 1990.

Lederman RJ. Cardiovascular interventional magnetic resonance imaging. *Circulation*, 112(19):3009–3017, 2005.

McSharry P, Clifford GD, Tarassenko L, and Smith LA. A Dynamical Model for Generating Synthetic Electrocardiogram Signals. *IEEE Transactions on Biomedical Engineering*, 50:289–294, 2003.

Moody GB, Muldrow W, and Mark RG. A noise stress test for arrhythmia detectors. *Computers in Cardiology*, 11(3):381–384, 1984.

Niendorf T, Sodickson DK,. Krombach GA, and Schulz-Menger J. Toward cardiovascular MRI at 7 T: clinical needs, technical solutions and research promises. *Eur Radiol*, 20(12):2806–2816, 2010.

Oster J, Llinares R, Tse Z, Schmidt EJ, and Clifford GD. Realistic MHD modeling based on MRI blood flow measurements. In Proceedings of the annual meeting of the Int. Soc. for Magn. Res. in Med., 2012.
Sayadi O, Shamsollahi MB, and Clifford GD. Robust detection of Premature Ventricular Contractions using a wave-based Bayesian framework. *IEEE Transactions on Biomedical Engineering*, 57(2):353–362, 2010.
Scott AD, Keegan J, and Firmin DN. Motion in Cardiovascular MR Imaging. *Radiology*, 250:331–351, 2009.
Shellock FG. Magnetic Resonance Procedures : Health effects and Safety. CRC Press, 2001.
Tenforde TS. Magnetically induced electric fields and currents in the circulatory system. *Progress in Biophysics and Molecular Biology*, 87:279–288, 2005.