MAGNETIC FIELD GRADIENT ARTIFACT REDUCTION ON ECG FOR IMPROVED TRIGGERING

J. Oster^{1,2}, O. Pietquin^{1,3}, M. Kraemer⁴, and J. Felblinger^{1,2}
¹U947, Inserm, Vandoeuvre-les-Nancy, France, ²IADI, Nancy-Université, Nancy, France, ³IMS Research Group, Supelec Metz Campus, Metz, France, ⁴Schiller Médical, Wissembourg, France

INTRODUCTION: Due to heart motion, cardiac MRI is made difficult and image acquisitions have to be synchronized with heart activity to suppress cardiac motion artifacts. Electrocardiogram (ECG) is therefore the state-of-the-art signal [1], each MRI acquisition being launched after a fixed delay following a QRS complex detection. The complex MRI environment highly distorts ECG signals, due to the presence of a high static magnetic field and mainly to fast switching Magnetic Field Gradients (MFG). Many hardware developments have been suggested to reduce these undesirable effects, but MFG artifacts remain an open problem and require specific signal processing methods. Two avenues of research have been explored: (a) first solution has been based on the development of MR specific ORS detectors. A well-known solution has taken advantage of the vectocardiogram (VCG) representation of heart activity [2]. (b) Second class of methods consists in MFG artifact suppression. MFG artifacts are the responses of the MFG through a linear time invariant (LTI) system, modeled as three Finite Impulse Response (FIR) filters, one for each direction of the MFG [3]. The MFG artifact suppression relies on the estimation of these three FIR filters and can be achieved with adaptive filtering [4]. One major drawback of this method is that the ECG is considered as noise in the modeling, adaptive filtering tends to cancel all contributions as soon as MFG are played. ECG signal can thus be altered when MFG artifacts overlap QRS complexes. In order to overcome this limitation, a new MFG artifact suppression method, which takes the ECG signal into account during the FIR filter estimation, is presented.

METHOD: ECG Model: An accurate ECG denoising has recently been proposed [5], by using an ECG model. ECG is considered as a pseudo-periodic signal, where each ECG cycle can be modeled as a sum of five Gaussian functions. ECG denoising consists in an online estimation of the model parameters, which can be performed with Bayesian filtering. This filtering technique requires the observation of two signals, the ECG signal and the cardiac phase, which is created after the QRS detection.

A linear phase between $-\pi$ and π is then assigned between two consecutives R waves. The Bayesian filtering can thus only be performed with at least one cardiac cycle delay.

ECG+MFG model: ECG acquired during MRI is mainly distorted by MFG artifacts, these artifacts have been modeled as outputs of three FIR filters. Artifact reduction is currently performed by estimating these filters while considering ECG signal as noise. The herein presented method suggests a new model by merging the MFG artifact and ECG models. This new modeling can be written in a state-space formulation, as in [5], where the FIR filters are integrated in the state vector and the observation equation takes the MFG artifacts into account. A recursive estimation of all model parameters can be performed thanks to nonlinear Bayesian filtering, namely Extended Kalman Filter (EKF) (Fig. 1).

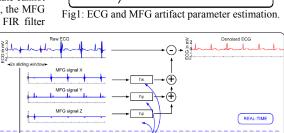
As the observation of the cardiac phase is required for the parameter estimation, the ECG signal estimate cannot be directly used for triggering purpose. In order to deal with the severe time constraints of triggering, the MFG artifact suppression can be applied on a semi-online way, by filtering the ECG signal with the FIR filter

parameters estimated during the previous cardiac cycle. Let assume that at time n the last EKF update has been performed at time k, (meaning the estimation has an n-k+1 delay). The ECG can be processed by suppressing the MFG artifact estimation computed by filtering MFG signals with FIR filters estimated at time k as:

$$\hat{z}_n = s_n - \sum_{j \in \{X,Y,Z\}} \left(\underline{h}_k^j\right)^T \cdot \underline{g}_{j,n}.$$

where z_n is the denoised ECG, h_k^i the FIR filter estimated at time k and $g_{j,n}$, the j^{th} MFG signal at time n (Fig. 2).

Material: A MRI specific ECG database has been built. 13 subjects underwent an MR examination on a 1.5T GE Signa HDx MR system (GE, Milwaukee, WI). Appropriate institutional ethics approval and subject consent were obtained. ECG was carried out by a custom Maglife Monitoring system (Schiller Médical, Wissembourg, France) and recorded on an homemade electronic system [6] Three ECG leads were positioned on the subject thorax and specific ECG sensors, with a [0.5-40Hz] bandwidth were used. A set of MR sequences were played to



ECG s

Fig.2: Flowchart of BAGARRE-T

Nonlinear Bayesian filtering: Estimation of the parameters of both ECG and MFG artifact models

observe all possible ECG distortions encountered in clinical examination. ECG recordings were annotated by a cardiologist. The whole database corresponds to 3h35 of ECG recordings and contains 14683 QRS complexes. It was divided in two sets of recordings depending on their noise levels. First set contains low noise ECG recordings and Set 2 contains ECG recordings that are highly distorted by the MRI environment, which represents 2239 QRS complexes.

Validation: Triggering quality can be quantified by assessing the QRS detection performance. The ANSI/AAMI EC57 standard recommendations were followed and the sensitivity (Se) and the positive predictivity (+P) were computed. The QRS detection performance was evaluated for three methods: First an industrial QRS detector (Argus PB-1000, Schiller, Baar, Switzerland) was applied on raw ECG signals (Raw). Second, an MFG artifact suppression method, based on adaptive filtering, was applied and followed by the same industrial QRS detector (LMS) [4]. Last, the same QRS detector was applied on ECG denoised by the herein presented method, called BAyesian Gradient ARtifact Reduction for Triggering (BAGARRE-T).

Method	database		Set 1		Set 2	
	Se	+P	Se	+P	Se	+P
Raw	98.4	92.6	99.6	98.0	91.8	69.5
LMS	99.5	97.6	99.7	99.2	98.3	89.6
BAGARRE-T	99.6	98.3	99.8	99.6	98.9	93.2

Table 1: QRS detection results.

RESULTS: QRS detection results are assembled on table 1. Raw results highlight the fact that ECG acquired during MRI is highly distorted and require specific signal processing. LMS yields an improvement for both sensitivity (+1.1%) and positive predictivity (+5.0%) toward Raw, proving that MFG artifact modeling is efficient. BAGARRE-T offers the best QRS detection results for both statistics. This shows the importance of taking the ECG signal into account in the MFG artifact suppression, which induces a 3.6% positive predictivity

improvement toward the LMS on set 2. An example of QRS complex and MFG artifact overlapping is shown on Fig. 3, where it can be seen that BAGARRE-T does not alter the ECG signal contrary to LMS.

DISCUSSION: The quality of the presented method has been presented. The merging of ECG and MFG artifact models for nonlinear Bayesian filtering overcomes state-of-the art ECG denoising method limitations and enables accurate triggering. It also opens the way of many prospects for the future, as an online Premature Ventricular Contraction detection or online Hall Effect suppression.

REFERENCES: [1] Scott et al; RSNA, 250, 331-351, 2009; [2] Fischer et al., MRM, 42, 361-370, 1999; [3] Felblinger et al., MRM, 41,715-721, 1999; [4] Abächerli et al., Magma, 18, 41-50, 2005; [5] Sayadi et al., IEEE TBME, 55, 2240-2248, 2008; [6] Odille et al., IEEE TBME, 54, 2172-2185, 2007.

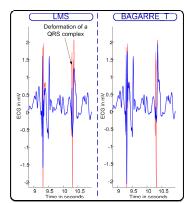


Fig.3: MFG artifact suppression comparison