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Modeling MR Induced Artifacts Contaminating Electrophysiological Signals Recorded During MRI

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Abstract— **The purpose of this paper is to present a novel parametric model for Magnetic Resonance (MR) induced artifacts contaminating electrophysiological signals (ECG, EEG, EMG, etc.) recorded simultaneously during MRI. The aim to construct an analytical representation of these artifacts is of great importance as it helps to understand and make appropriate hypotheses about the artifacts' generation process. The model presented in this paper assumes a periodic and stationary nature of these artifacts. Statistical KPSS tests were applied to confirm that observed artifacts are weak-sense stationary. The model based on a sum of sinusoids of different amplitudes, frequencies and phase delays $\{A, f, \Phi\}$ was most suited to represent these artifacts. The sinusoidal model parameters $\{A, f, \Phi\}$ were estimated by BFGS optimization. The lowest mean square error (MSE) is used to determine the model with the optimum parameters. Pearson's correlation coefficients were used as indices to evaluate the accuracy of the calculated model.**

I. Introduction

The constant development of Magnetic Resonance Imaging (MRI) techniques allows the production of higher resolution and higher contrast non-invasive images. By manipulating MR parameters, it is possible to optimize the pulse sequence to identify certain pathologies. When undergoing MR examination, the patient lies down inside the MRI tunnel and is exposed to a high magnetic field of 1.5T, which is usually used in hospitals. Under this field strength, protons of the patient's body will align in a relaxed state in the same and opposite direction of the magnetic field. To acquire a MR image, the protons in the desired image area are excited with a pulse sequence of events: radiofrequency (RF) pulses, gradient switches and signal processing. Resonance occurs when RF pulses excite the body's protons at Larmor's frequency, which is equal to the same spinning frequency of these protons. When the RF excitation stops, the protons return to their relaxed state, releasing a signal, called an "echo" in the form of RF energy. The receiving antenna captures the echo signal, which is sampled during readout and is used to reconstruct an image of the examined area. Gradients switches allow for signal coding in the acquisition *k*-space matrix. Signal processing based on Fourier transform techniques is used to generate the image from *k*-space data. One pulse sequence is responsible for filling in one line of data in the *k*-space. For a basic MRI sequence, such as the Gradient-Echo, whose pulse sequence diagram is shown in Fig.1, the RF pulse sequence process is repeated periodically to fill up the entire *k*-space. Advances in biomedical technologies made it possible for physicians to record electrophysiological signals during a MRI exam. This is especially essential for patient monitoring, or for synchronizing the MR images with a specific physiological event such as cardiac triggering [1]. The combination of these technologies also has many clinical applications such as the diagnosis of functional neurological disorders, functional exploration of the heart, etc. Recording electrophysiological signals inside the high magnetic field has its drawbacks. These signals are subject to various types of artifacts, mainly artifacts due to motion (movements of the patient, beating of the heart, respiration, etc.), and static (B_0) and dynamic (RF and Gradients) magnetic fields [2]. One standard solution used to suppress MR induced artifacts is the average artifact subtraction (AAS) [3]; however, this method assumes that the artifact shape remains constant. Bresch *et al.* state that the artifacts contaminating audio signals acquired through the microphone and used to communicate with the patient from the control room during the MRI examination are periodic and stationary [4]. These same artifacts are responsible for contaminating electrophysiological signals, e.g., EEG, ECG or EMG recorded during the MRI examination. This is true in the sense that in a pulse sequence gradients switch on and off periodically in order to encode spatial information into images. The aim in this paper is to find simple parametric models specific to MR pulse sequences. These models will help on one hand to bypass the unknown transfer function estimating the gradient artifacts [5] and on the other hand, to obtain a robust and efficient optimal filter algorithm for extracting clean electrophysiological signal components from recorded noisy signals.

II. Materials and Methods

A. Experimental Setup and Data Acquisition

Experiments were conducted on a 1.5T MRI system (GE Signa HDxt 1.5T, GE Healthcare) equipped with a 33 mT/m gradient system. A box-shaped human-tissue mimicking phantom (20x15x10 cm^3) made from 5% gelatin from bovine skin type B (Sigma-Aldrich, Inc. St. Louis,MO, USA) was placed inside the MRI tunnel. During the scanning period, the experimental MR induced signals were acquired using three carbon electrodes (3M™ RedDot™ Radiolucent Electrode), then low-pass filtered (0.5–350 Hz) and sampled

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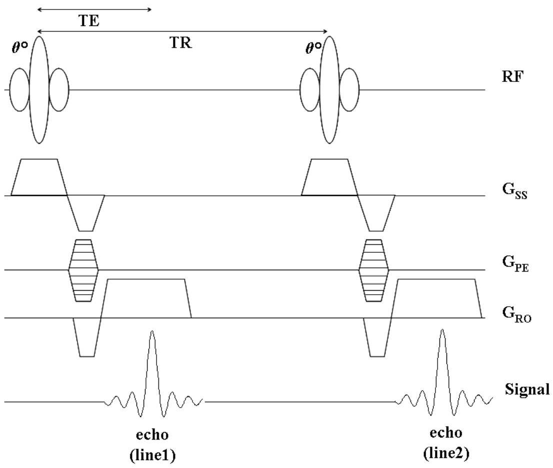

Fig. 1. Gradient-Echo pulse sequence. TE: echo time. TR: repetition time. RF: radiofrequency excitation impulse with a flip angle θ, G_{SS}: slice selection gradient, G_{PE}: phase encoding gradient, G_{RO}: readout gradient, the echo is the recoded MR signal, which is sampled into the k-space matrix

TABLE I

MRI SEQUENCE PARAMETERS

Fast Spin Echo	
TR/TE	500/12
Number of slices	13
NEX	1
FOV	15x15
Matrix	128x128

at 10 kHz. Data acquisition storage and processing were carried out outside the Faraday cage using a digital signal acquisition and processing system (NI USB 6229-BNC Daq Device, National Instruments France, and a PC with Matlab 2008b, Mathworks, Natick, MA). The signals were amplified in situ and converted into optical signals, which were transmitted to the outside of the Faraday cage by means of optical fibers. This acquisition system was also designed to reduce RF interferences. Ten seconds of signal were recorded using the Fast Spin Echo (FSE) imaging sequence. The scan parameters of these sequences are reported in Table I.

B. Signal Segmentation

A simple signal segmentation algorithm was developed to extract epochs of the recorded signal. Each epoch was determined by applying a threshold to the time signal squared. Fifty epochs corresponding to the dominant readout gradient artifacts were extracted.

C. Stationarity Identification

By definition, a process is said to be strictly stationary if and only if its statistical moments are time independent. In reality, an acquired time series will never have moments of all order, a reason to consider weaker stationarity definition. A random process is considered weakly stationary if its first and second moments do not vary in time. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is widely used in econometrics for testing a null hypothesis in which a time series is weakly stationary against the alternative of a unit root [7]. This test is also used by Korürek and Özkaya to test for the stationarity of EEG [8]. In order to verify the Bresch et al. statement that the MR induced artifacts are stationary [4], the KPSS test was run on the recorded signal. The KPSS test proposes that a time signal can be estimated by a sum of a deterministic trend, a random walk, and stationary error according to (1)

$$y(t) = \beta t + \mu_t + \epsilon_t \tag{1}$$

where βt is the deterministic trend and ϵ_t is the stationary noise. The random walk μ_t can be represented as

$$\mu_t = \mu_{t-1} + \boldsymbol{u_t} \tag{2}$$

where $\boldsymbol{u_t} \sim idd(0, \sigma_u^2)$. Under the null hypothesis, the signal is trend-stationary; i.e., $\sigma_u^2 = 0$. In a special case where $\beta = 0$, the KPSS test can be used to check that the signal is weak-sense stationary.

D. Sum-of-Sinusoids Representation

In this section, a sinusoidal representation of MR induced artifacts is introduced. The sum-of-sinusoids representation of signals is widely used in speech signal analysis to model voiced speech, which is represented as a periodic signal. The sum-of-sinusoids model can be written as

$$x(n) = \sum_{n=0}^{N-1} A_n sin(2\pi f_n t + \phi_n) \tag{3}$$

where N is the number of sinusoids, and A_n, f_n, and ϕ_n are the amplitude, frequency and phase shift of the nth sinusoid, respectively. We assume that N is fixed *a priori* [6]. The final model of the observed MR artifacts is

$$\boldsymbol{y}(A_n, f_n, \phi_n) = \sum_{n=0}^{N-1} \sum_{k=0}^{K-1} A_n sin(2\pi f_n t_k + \phi_n) + \boldsymbol{\eta} \tag{4}$$

where $\boldsymbol{y} = [y_0, ..., y_{K-1}]^T$ are the observed signal samples at the time instants $[t_0, ..., t_{K-1}]^T$ and $\boldsymbol{\eta}$ is the additive global noise due to the static magnetic field and other electronic devices. $\boldsymbol{\eta}$ is approximated by minimizing the cost function with the respect to the parameter vector $\boldsymbol{\theta}$ according to (5)

$$\parallel \boldsymbol{\eta} \parallel^2 = \min_{\boldsymbol{\theta} \in \mathbb{R}^{3N}} J(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta} \in \mathbb{R}^{3N}} \frac{1}{2} \parallel \boldsymbol{y}(\boldsymbol{\theta}) - \boldsymbol{S} \parallel \tag{5}$$

with $\boldsymbol{\theta} = [A_n, f_n, \phi_n]^T$, $\boldsymbol{S}$ is the recorded signal and $\parallel \bullet \parallel$ is the Euclidean norm.

E. BFGS Optimization Method

The cost function presented in (5) is non-linear with respect to the parameter vector $\boldsymbol{\theta}$. Solving this minimization problem is very complicated and many algorithms have been proposed to approximate $\boldsymbol{\theta}$. This problem was chosen to be solved by applying the gradient descent Broyden-Fletcher-Goldfarb-Shano (BFGS) optimization method as a best effective method to obtain optimum parameters that minimizes the mean square error $\| \boldsymbol{\eta} \|^2$ [6]. The rule to update the model parameters is given by

$$\boldsymbol{\theta}^{k+1} = \boldsymbol{\theta}^{k} - \mu_{k+1} \boldsymbol{M}_{k+1} \nabla J(\boldsymbol{\theta}) \tag{6}$$

where $\boldsymbol{\mu}$ is a scalar called the descent step and $\boldsymbol{M}_{k+1}$ is an interative approximation of the inverse of the Hessian matrix of the cost function J calculated according to [9].

The BFGS algorithm steps are:

(i) At iteration 0: Initialization $\boldsymbol{\theta}_0$ of the parameter vector $\boldsymbol{\theta}$ and $\boldsymbol{M}_0$ (for example: $\boldsymbol{M}_0 = \boldsymbol{I}$) of $\boldsymbol{M}$, and μ_0 at a small value ($\mu_0 = 0.001$)

(ii) At iteration k:

- Update the parameter vector $\boldsymbol{\theta}_{k+1}$ according to (6).
- Verify the descent condition; i.e., $J(\boldsymbol{\theta}^{k+1}) < J(\boldsymbol{\theta}^{k+1})$.
- If the descent condition is not verified, then multiply the step by a factor less than 1.
- Repeat the above steps until the cost function is less then a predefined threshold or until the maximum number of iterations is reached.

III. Results

In Fig. 2–3 the quasi-periodicity of the acquired signal can easily be verified qualitatively by observing the temporal signal and its line spectrum. The period T is defined as the inverse of the slice acquisition frequency defined by

$$T = \frac{Nslice}{TR} \tag{7}$$

where $Nslice$ is number of slices defined in imaging sequence. In this case, $T = 38.5ms$.

The KPSS test was run on the periods corresponding to the readout gradient noise. The KPSS test result showed clearly that the signal is stationary ($\hat{\eta}_\tau = 0.047$, 5% critical value = 0.146 [7, Table 1]). The critical values of the test can be found in [7]. The results of the segmentation are shown in Fig. 4. The BFGS model was calculated on the average epoch (Fig. 5). The model, which is obtained by summing 16 sinusoids, is then validated by calculating the average cross-correlation coefficient between the model and the 50 epochs (average cross-correlation coefficient = 0.973).

IV. Discussion and Conclusion

This paper has shown a novel model for MR imaging artifacts that can contaminate electrophysiological signals. The simple segmentation method showed to be robust without losing much of the signal information (mean squared error < 5%). The advantage of BFGS is that it allows the

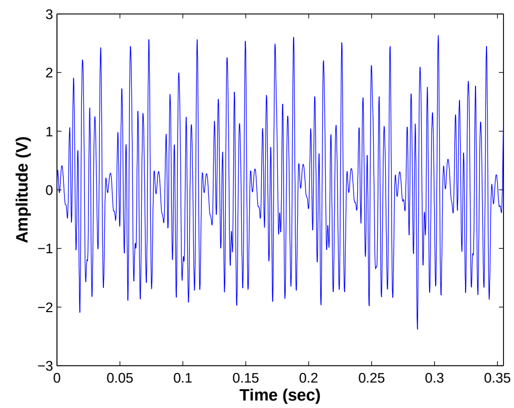

Fig. 2. Recording of MR induced artifacts for a FSE sequence

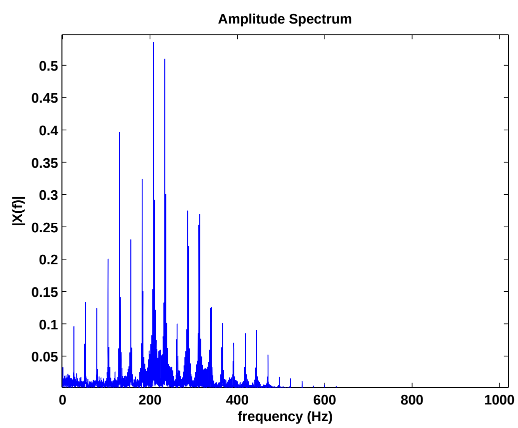

Fig. 3. Amplitude spectrum of the recorded MR induced artifacts for a FSE sequence

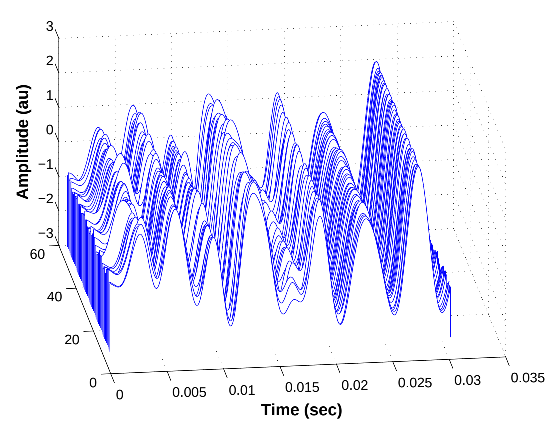

Fig. 4. Periods of readout gradient noise extracted from signal in Fig. 2

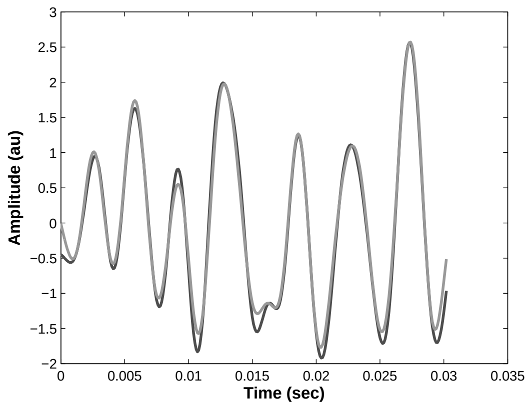

Fig. 5. In dark gray: the recorded average MR induced Artifact. In light gray: the BFGS model obtained as a sum of 16 sinusoids

bypass of the calculation of inverse Hessian matrix,which can be very costly. However, the main drawbacks is that the inappropriate initialization of the parameter vector and under- or over-estimation of the descend step will cause the algorithm to diverge from the optimal solution.

It should be noted that this model is specific to the imaging sequence specified in this paper; however, this method can be applied to generate models to artifacts recorded by other MRI sequences. Further experiments need to be conducted in order to first, integrate MRI sequence parameters in this model and second, to validate the model on the other hand. Recent studies show that current artifact removing methods are less efficient for signal frequencies above 50 Hz [10]. The next step is to validate this model on other MRI sequences, such as the Gradient Echo sequence, in order to design optimal filters adapted to reduce MRI artifacts contaminating large bandwidth signals such as EMG signals, which vary between 0 and 500 Hz.

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