Adaptive step size LMS for ECG artefact reduction during MRI

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Abstract

During cardiac MRI, fast switching gradients cause artifacts on the electrocardiogram (ECG), disturbing both triggering and patient monitoring. To cancel this noise, the Least Mean Squares (LMS) algorithm is a simple and efficient method. LMS uses one main parameter, its step size, which influences the quality of artifact reduction. We propose a method using the MR gradient variance to choose this parameter accurately using information about the sequence played by the MR scanner. The proposed method achieved systematically better results than the standard LMS with a 1.5T ECG database.

1. Introduction

In order to achieve high spatial and temporal resolution during cardiac MRI, acquisitions need to be spanned over multiple heart beats. To avoid blurring due to heart movement, the detection of cardiac cycles is of paramount importance to trigger the MR acquisition, and can as well be used to monitor the patient[1]. However, during cardiac MRI, both the switching of magnetic field gradients and the magneto-hydrodynamic effect (MHD) constitute additional signals that alter the ECG. The altered ECG is less suitable, both for triggering and monitoring. To denoise the ECG, the Least Mean Square (LMS) algorithm [4, 5] is a proficient method because it is a simple and efficient adaptive filter[2]–[4] . Inside the MR bore, the measured ECG signal can be seen as the sum of three main components: the actual ECG, the magnetohydrodynamic (MHD) effect, and MR gradient induced artifacts [2]. This last component can be modeled as the output of a filter which input is the MR gradients. The LMS algorithm approximates the impulse response of this filter to remove the MR gradient artifacts from the ECG, as presented in Fig1. The filter models the system composed of the inside of the MR bore, the patient and the devices (antenna, ECG sensor …). It responds to the gradient signal with an electric response, seen as an artifact on the ECG. The impulse response is the main characteristic of this system and changes during the imaging.

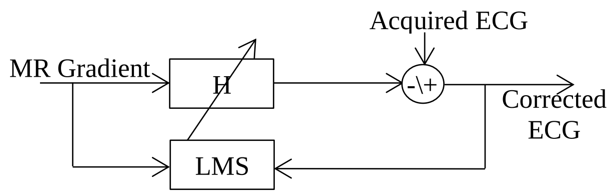

Figure 1: LMS correction system for one gradient lead. This system is parallelized three times, once for each gradient lead.

The LMS uses a parameter μ that influences directly the speed of adaptation of the algorithm to new events . A too big value for μ will cause the LMS to diverge, whereas a too small value will impair the LMS capacity to denoise. The parameter μ has a large range of possible values (from 10^{-5} to 10^{-1})

According to Widrow[5], the theoretical optimal μ is :

$$\mu_{th} = \frac{1}{M} \frac{2}{\lambda_{max} + \lambda_{min}} \tag{1}$$

Where λ_{max} and λ_{min} are the highest and lowest eigenvalues of the autocorrelation matrix of the gradients written as R. M is the length of the impulse response the algorithm is looking for, expressed in number of samples. As the calculation of the eigenvalues of R is often too complex, the following approximation has been used:

$$\mu_{th} \simeq \frac{1}{M} \frac{2}{tr(R)} \tag{2}$$

Indeed, the duration of the adaptation phase has to be short when compared to the duration of the acquisition sequence.

In our case, we assume that knowing the gradient of magnetic field variance enables to calculate an optimal adaptive personalized value for μ.

2. Material & Methods

2.1. Population

To validate our method, we used ECG records during MRI sequence and outside MRI with a standard ECG recorder. 13 healthy volunteers and 3 patients during a MRI acquisition of approximately 45 min corresponding to 18469 QRS complexes. All subjects/patients complied with the Declaration of Helsinki concerning medical research on human subjects and was approved by a local ethical committee. Among the three patients, one had a right bundle branch block, the two others had frequent ventricular extrasystoles (more than five per minute during the clinical ECG).

ECG signals were acquired during various clinical MR sequences [6]. All signals were anonymously recorded on a home-made database system Archimed along with the DICOM images and the clinical 12-lead ECG previously acquired (with Schiller CS200 device) for diagnosis.

Acquisitions were composed of ECG signals recorded by 3 optical ECG sensors (type3 ECG sensor, Schiller Medical, Wissembourg, France) modified for a larger frequency bandwidth (1Hz-60Hz) placed on the torso. MRI magnetic field gradient signals were recorded directly from the MR imager (GE Healthcare 1.5T imager). ECG signals were centralized by an MRI monitoring device (Maglife C, Schiller Medical, Wissembourg, France). These signals were digitalized and recorded by a home-made data-processing computer already reported. All signals were sampled at 1kHz.

2.2. 3D Wiener filtering

To assess the LMS artifact reduction efficiency, LMS was compared to the best possible offline filter estimator within linear time invariant theory[2] : a 3D Wiener filter.

The wiener filter used as reference to evaluate the efficiency of the LMS was built on the following cost function :

$$\varphi(h) = \|A.h - s\|_2^2 + \lambda\|Dh\|_2^2$$

Where:

$G = (G_X, G_Y, G_Z) = (G_1, G_2, G_3)$: gradient signal, shape (3xN)

s : ECG signal (only one lead), shape (1xN).

h : impulse response of the three gradient leads, shape (3xN)

$$A = \begin{bmatrix} G_{1,0} & \cdots & G_{3,0} \\ \vdots & \ddots & \vdots \\ G_{1,N-M} & \cdots & G_{3,N-M} \end{bmatrix}$$

$$G_{i,j} = G_i(j+1, j+2, \dots, j+M)$$

$D = diag(h_0)$,

h_0 : reference impulse response

λ : regularization strength parameter. Set to 1.

The cost function was divided into two parts : $\varphi(h) = \varphi_1(h) + \lambda\varphi_2(h)$

The first part, $\varphi_1(h) = \|A.h - s\|_2^2$ will lead h toward a solution that fits the data.

The second part $\varphi_2(h) = \|Dh\|_2^2$ will lead h toward a solution that looks like the reference impulse response.

Minimizing $\varphi(h)$ leads to :

$$h = (A^tA + \lambda D^tD)^{-1}A^ts$$

2.3. Step size optimization

The theoretical optimal μ was calculated using (1) for each of three gradient lead, and the minimum was kept for each acquisition.

$$\mu_{th} = \frac{2}{M}\min\big(\mu_{th}(X), \mu_{th}(Y), \mu_{th}(Z)\big) = \frac{2}{M}\min\left(\frac{1}{tr(R_X)}, \frac{1}{tr(R_Y)}, \frac{1}{tr(R_Z)}\right) \quad (3)$$

In order to quantify the efficiency of the LMS algorithm during an acquisition, we computed the energy of the difference between LMS-corrected ECG and 3D Wiener-corrected ECG during gradient emission, divided by the time of gradient emission. This represents the power of the remaining noise P(μ). The better the artifact reduction, the smaller the noise power.

$$P(\mu) = \|(ECG_{LMS}(\mu) - ECG_{wiener3D})\| \quad (4)$$

The minimizer of this power, called "experimental optimal step size" called (μ_{exp}) was found for each sequence, and kept as reference for optimal LMS artifact reduction. The power of remaining noise using our predicted optimal parameterization ($P(\mu_{th})$) was computed and compared to experimental optimal parameterization power ($P(\mu_{exp})$) as follows :

$$\varepsilon(\mu_{th}) = 100.\frac{|P(\mu_{th}) - P(\mu_{exp})|}{P(0)} \quad (5)$$

Finally we perform an artifact reduction with an LMS filter with a standard μ value, chosen as half the minimum of all optimal μ to ensure convergence in all cases.

$$\mu_{stand} = \frac{1}{2}\min(\mu_{exp}) \quad (6)$$

$$\varepsilon(\mu_{stand}) = 100.\frac{|P(\mu_{stand}) - P(\mu_{exp})|}{P(0)} \quad (7)$$

We compared ε_{stand} and ε_{exp} to show the impact of choosing a different value for μ on the quantity of noise power removed from the ECG.

4. Results

The variances of magnetic field gradient during each sequence are grouped in Tab1. The optimal values of μ_{th} calculated with (2) are presented in Tab2. Values of μ_{th} are different for each sequence, with quite narrow ranges.

	X-lead	Y-lead	Z-lead
FIESTA	3,47	$2{,}89e^{-1}$	3,30
FSE	$9{,}90e^{-2}$	$4{,}21e^{-2}$	$2{,}49e^{-1}$
Diffusion	$9{,}66e^{-1}$	$8{,}58e^{-1}$	1,14
EPI	$4{,}70e^{-2}$	$1{,}14e^{-1}$	$3{,}92e^{-1}$
SPGR	$1{,}55e^{-1}$	$7{,}08e^{-1}$	$2{,}50e^{-1}$
SSFSE	$3{,}54e^{-1}$	$4{,}22e^{-2}$	$1{,}60e^{-1}$

Table 1. Mean gradient variances for each sequence.

	min	mean	max
FIESTA	$1{,}40e^{-3}$	$1{,}69e^{-3}$	$2{,}51e^{-3}$
FSE	$1{,}57e^{-2}$	$2{,}48e^{-2}$	$3{,}89e^{-2}$
Diffusion	$3{,}31e^{-3}$	$4{,}71e^{-3}$	$5{,}55e^{-3}$
EPI	$9{,}73e^{-3}$	$1{,}62e^{-2}$	$2{,}47e^{-2}$
SPGR	$3{,}61e^{-3}$	$1{,}39e^{-2}$	$3{,}50e^{-2}$
SSFSE	$9{,}30e^{-3}$	$1{,}69e^{-2}$	$3{,}08e^{-2}$

Table 2. Resultant optimal theoretical μ for each sequence.

For each sequence, we represented the power (4) of remaining noise after LMS in a graph such as in Fig2. The power curve is converging toward a constant for very small values of μ (10^{-3} to 10^{-5}). This constant is different for each patient and is the full energy of gradient-induced noise on ECG for this acquisition.

While μ is getting bigger, the artifact power is decreasing, until it reaches a point where it is minimum. Afterwards, the artifact power increases rapidly, taking values higher than E(0). This means that the LMS induces more noise than the gradients themselves, i.e. that the LMS has diverged and is not correcting the artifacts anymore.

In Tab3, are presented for each patient and sequence $\mu_{exp}=\min\{P(\mu)\}$, corresponding $P(\mu_{exp})$, the optimal theoretical values μ_{th} and corresponding $P(\mu_{th})$.

In Tab4 we presented the percentages of noise not removed by LMS with μ_{th} : $\varepsilon_{th/exp}$, and the percentages of noise not removed by LMS with μ_{stand} : $\varepsilon_{stand/exp}$. $\varepsilon_{th/exp}$ was never superior to 100% (with a maximum of 75,5% for the worst case during a diffusion sequence), so the artifact reduction was always effective.

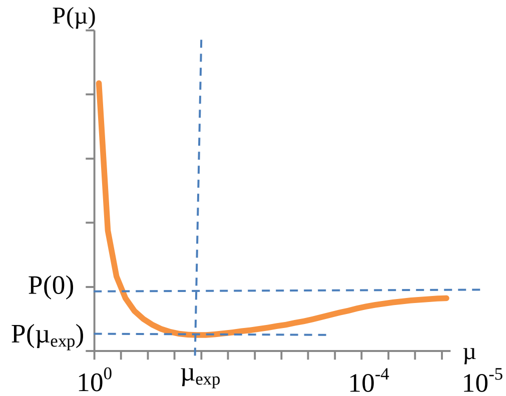

Figure 2. Power of remaining noise P(μ) after LMS for a FIESTA sequence for one volunteer. P(0) is the asymptote value, $P(\mu_{exp})$ is the minimum and μ_{exp} is the experimental optimal μ.

The diffusion sequence put aside, we achieve an LMS correction with less than 10% remaining noise which is systematically better than standard LMS. However, the diffusion sequence gives the worst results by far ($\varepsilon(\mu_{th})$=21,60% against $\varepsilon(\mu_{stand})$=41,26%).

Fig3 shows an ECG sample with gradient artefacts, corrected by LMS with optimal step size, and by LMS with standard step size. With optimal parameterization, the algorithm adapts its correction very quickly to any change in the system, whereas with standard parameterization; it is very low and takes time to come back to efficient artifact reduction.

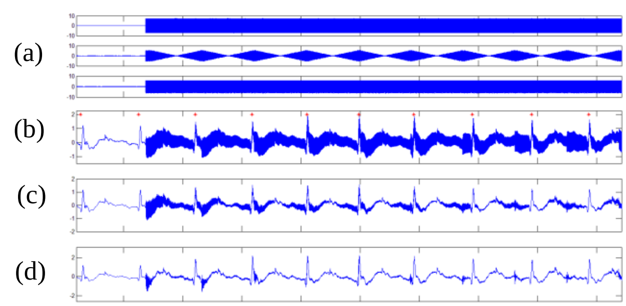

Figure 3 : MR gradients (a), Raw ECG (b), "standard" LMS correction of ECG (c), optimal LMS correction of ECG (d)

	μ_{exp}	$P(\mu_{exp})$	μ_{th}	$P(\mu_{th})$
FIESTA	$1{,}17e^{-2}$	**$3{,}75e^{-4}$**	$1{,}69e^{-3}$	**$5{,}49e^{-4}$**
FSE	$3{,}85e^{-2}$	**$3{,}87e^{-4}$**	$2{,}48e^{-2}$	**$4{,}07e^{-4}$**
Diffusion	$2{,}20e^{-2}$	**$3{,}12e^{-3}$**	$4{,}71e^{-3}$	**$4{,}87e^{-3}$**
EPI	$4{,}97e^{-2}$	**$6{,}13e^{-4}$**	$1{,}62e^{-2}$	**$7{,}79e^{-4}$**
SPGR	$2{,}66e^{-2}$	**$3{,}90e^{-4}$**	$1{,}39e^{-2}$	**$4{,}59e^{-4}$**
SSFSE	$9{,}39e^{-3}$	**$5{,}46e^{-4}$**	$1{,}69e^{-2}$	**$6{,}78e^{-4}$**

Table 3: Mean values of optimal μ_{exp} and μ_{th}, with corresponding powers of remaining artefacts P(μ) for the database.

	$\varepsilon_{standard/exp}$ (%)	$\varepsilon_{th/exp}$ (%)
FIESTA	37,02	9,47
FSE	118,51	1,54
Diffusion	48,92	21,6
EPI	56,67	8,19
SPGR	8,22	2,21
SSFSE	41,26	3,58

Table 4. Mean values of optimal μ_{exp} and μ_{th}, with corresponding energies of remaining artefacts E(μ) for the database.

5. Discussion & conclusion

We proved that LMS theoretical optimal parameterization that depends on the gradient shape i.e. on the MR sequence parameters approaches in terms of remaining noise energy the LMS experimental optimal parameterization. This implies that knowing the sequence to be played and its main parameters (TE, TR, flip angle, …) we are able to seriously improve LMS behavior by adapting its coefficient μ.

Most medical examinations use the same sequence several times in a row, editing few parameters, thus not changing significantly the gradient shape. To that extent, we think that calculating the variance of the gradient online and adapting the μ value could be a much more reliable option than using a default value for μ, chosen low enough to avoid divergence issues.

Moreover, we expect LMS quality to improve by using as input the gradients measured inside the MR bore [7], instead of the gradient command of the MR control unit. That would suppress some non-linearities caused by the Eddy currents inside the magnet.

However, our optimal parametrization gives arguably correct results on the diffusion sequence. This can be explained by the poor quality of LMS correction for this type of sequences, involving very high amplitude MR gradients in several directions. Actually the LMS diverges immediately at $\mu=2{,}51e^{-2}$ for this sequence, without reaching a stable minimum. However we assumed with (2) that LMS was in stable state to reach optimal performances. In consequences, the step size calculated with (2) is not appropriate to reach optimal performances for this sequence. Yet, the proposed formula still gives a better artifact reduction than a standard LMS.

Even with optimal parameterization, LMS filtering cannot achieve good noise reduction on such sequences due to the fact that artifacts induced by the three gradient leads are not distinguished by the algorithm, and thus the learnt impulse response for each gradient contains information from other leads, causing errors. This can be avoided by treating the gradient information as a unique 3D information, instead of 3 separate leads, as it is done in the wiener3D algorithm used as reference, but is not done by the LMS.

Finally, our approach improved the efficiency of the LMS and proves that the parameter μ can be adapted. This opens the doors for an enlarged family of algorithms, the variable step size LMS algorithms, which use various techniques to control the value of μ during the acquisitions.

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