Investigating Adaptive Noise Cancellation Of MRI Interference On Electrocardiography Signals Acquired With PRiME System

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Introduction

MRI guided cardiac catheterization procedures offer advantages over traditional X-ray guided interventions, such as increased soft tissue contrast and reduced patient exposure to ionizing radiation. However, strong electromagnetic interference in the MRI environment severely distort hemodynamic measurements such as ECG, which provide diagnostic information necessary for procedural guidance and monitoring patient status. Additionally, features such as the QRS complex are used to gate certain MRI sequences. The PRiME (Physiological Recording in MRI Environment) system uses an adaptive least mean squares (LMS) filtering algorithm to limit MRI-induced noise to make hemodynamic recording suitable for catheterization procedures. This project investigates enhancements to the adaptive noise cancellation algorithms to improve noise reduction while preserving the quality of the ECG signals.

Objectives

- Determine which adaptive algorithm best reduces the ECG noise.
- Investigate improvements in the handling of multiple reference signals within the adaptive algorithm.
- Reduce the amount of human input, such as setting step size or other filter parameters, as much as possible.

Methods

- ECG data was gathered from healthy volunteers and from cardiac catheterization patients undergoing experimental procedures.
- ECG was recorded before MRI scanning, during a 3-plane localizer scan, and during a real time scan.
- The adaptive filtering algorithm uses the three gradient control signals (X, Y, Z) as reference signals (i.e. error signals) for the adaptive filter.
- The recorded data was passed through two adaptive filtering algorithms (LMS, Differentiated LMS) with four methods of handling the three reference signals:
  - Unweighted 3D Gradient (three adaptive filters using one filter per reference signal)
  - Weighted 3D Gradient (three adaptive filters using one filter per weighted reference signal)
  - Unweighted Sum Gradient (one adaptive filter using a summed reference signal)
  - Weighted Sum Gradient (one adaptive filter using a weighted summed reference signal)
- Various quality metrics were examined to quantify the filter performance, including noise size reduction and QRS complex size distortion.

Adaptive Algorithms: Equations and Diagrams

	LMS Filter: minimizes e_n	Differentiated LMS: minimizes $\frac{de_n}{dn}$
FIR Filter:	$e_n = d_n - \overrightarrow{w_n} \cdot \overrightarrow{g_n}$	$e_n = d_n - \overrightarrow{w_n} \cdot \overrightarrow{g_n}$
Adaptive Algorithm:	$\overrightarrow{w_n} = \overrightarrow{w_{n-1}} + \beta(\overrightarrow{g_n})(e_n)$	$\overrightarrow{w_n} = \overrightarrow{w_{n-1}} + \beta(\overrightarrow{g_n} - \overrightarrow{g_{n-1}})(e_n - e_{n-1})$

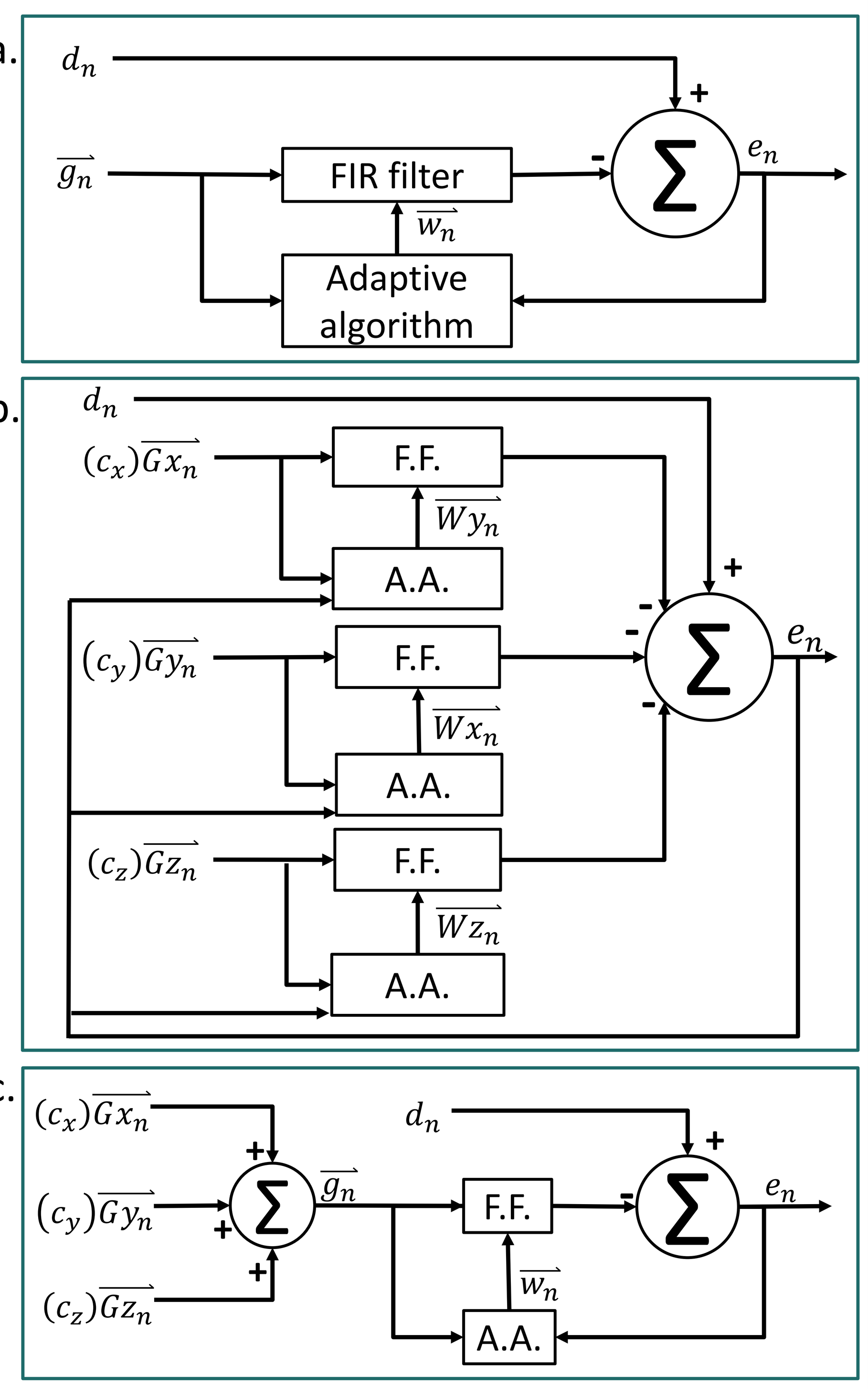

Fig 1. Block diagrams showing adaptive filtering algorithms used. (a) Representation of an ordinary adaptive filter with one noise reference signal, g_n. **(b)** input of 3-dimensional gradient as 3 separate reference signals in 3 separate adaptive filters that sum to one output. Can be weighted or unweighted: for unweighted, $c_x = c_y = c_z = 1$. **(c)** 3 gradient signals are combined into a single noise reference signal g_n using a weighted sum. For unweighted sum, $c_x = c_y = c_z = 1$.

Symbols:
$\boldsymbol{n}$: sample number (time)
$\overrightarrow{\boldsymbol{g_n}}$: array of past L samples of the noise reference signal (MRI gradient), where L is filter length
$\overrightarrow{\boldsymbol{w_n}}$: array of past L weights
$\boldsymbol{e_n}$: error signal (filtered ECG)
$\boldsymbol{d_n}$: unfiltered ECG signal
$\boldsymbol{\beta}$: filter step size
$\overrightarrow{\boldsymbol{Gx}}, \overrightarrow{\boldsymbol{Gy}}, \overrightarrow{\boldsymbol{Gz}}$: 3 dimensional gradients
$\overrightarrow{\boldsymbol{Wx}}, \overrightarrow{\boldsymbol{Wy}}, \overrightarrow{\boldsymbol{Wz}}$: 3 dimensional weights
$\boldsymbol{c_x}, \boldsymbol{c_y}, \boldsymbol{c_z}$: constant weights applied to $\overrightarrow{Gx}, \overrightarrow{Gy}, \overrightarrow{Gz}$
F.F.: FIR (finite impulse response) filter
A.A.: Adaptive Algorithm

Results and Discussion

Performance of the adaptive filtering algorithms was evaluated by measuring fractional reduction in noise level and fractional reduction of QRS complex height. Peak performance occurs when noise reduction is as close to 1 as possible (complete removal) and QRS reduction is as close to 0 as possible (no unwanted distortion). Data from N=16 cases from 3 patients, each 50 seconds in length, were each filtered according the methods described in the Methods section. In addition, performance was compared between using an optimized step size for each individual case versus using a single step size for every case. In typical PRiME use, a default step size is used for all patients as clinical staff are not able to spend time attempting to optimize the beta for a specific patient.

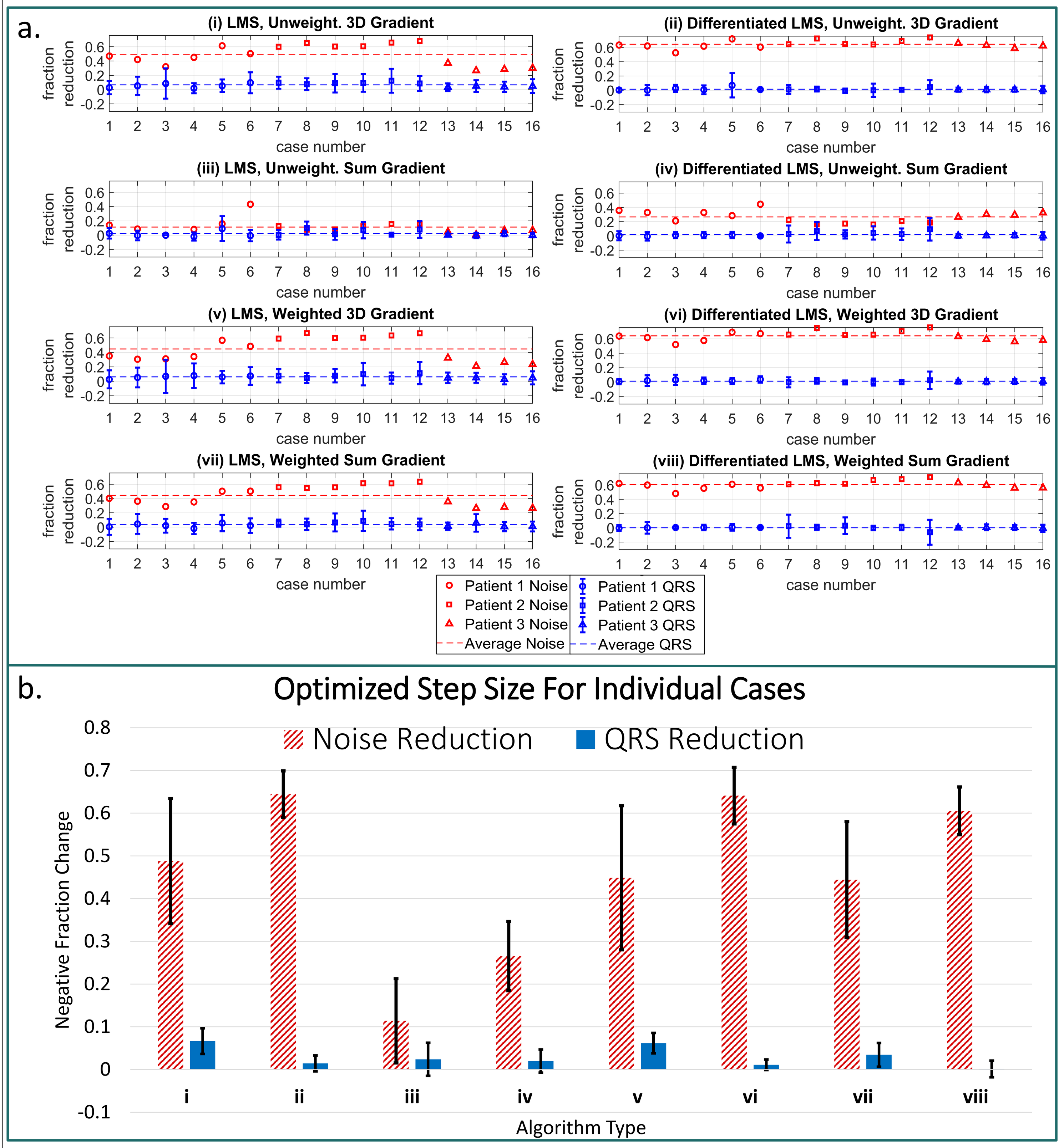

Fig 2. Each individual scan is evaluated at the step size that resulted in minimum noise for that case. Error bars represent one standard deviation in both directions. **(a)** The noise and QRS statistics for each individual scan of each algorithm type. **(b)** The means and variances of all 16 scans of each algorithm type.
Algorithm types: (i) LMS, unweighted 3D gradient; **(ii)** Differentiated LMS, unweighted 3D gradient; **(iii)** LMS, unweighted sum gradient; **(iv)** Differentiated LMS, unweighted sum gradient; **(v)** LMS, weighted 3D gradient; **(vi)** Differentiated LMS, weighted 3D gradient; **(vii)** LMS, weighted sum gradient; **(viii)** Differentiated LMS, weighted sum gradient

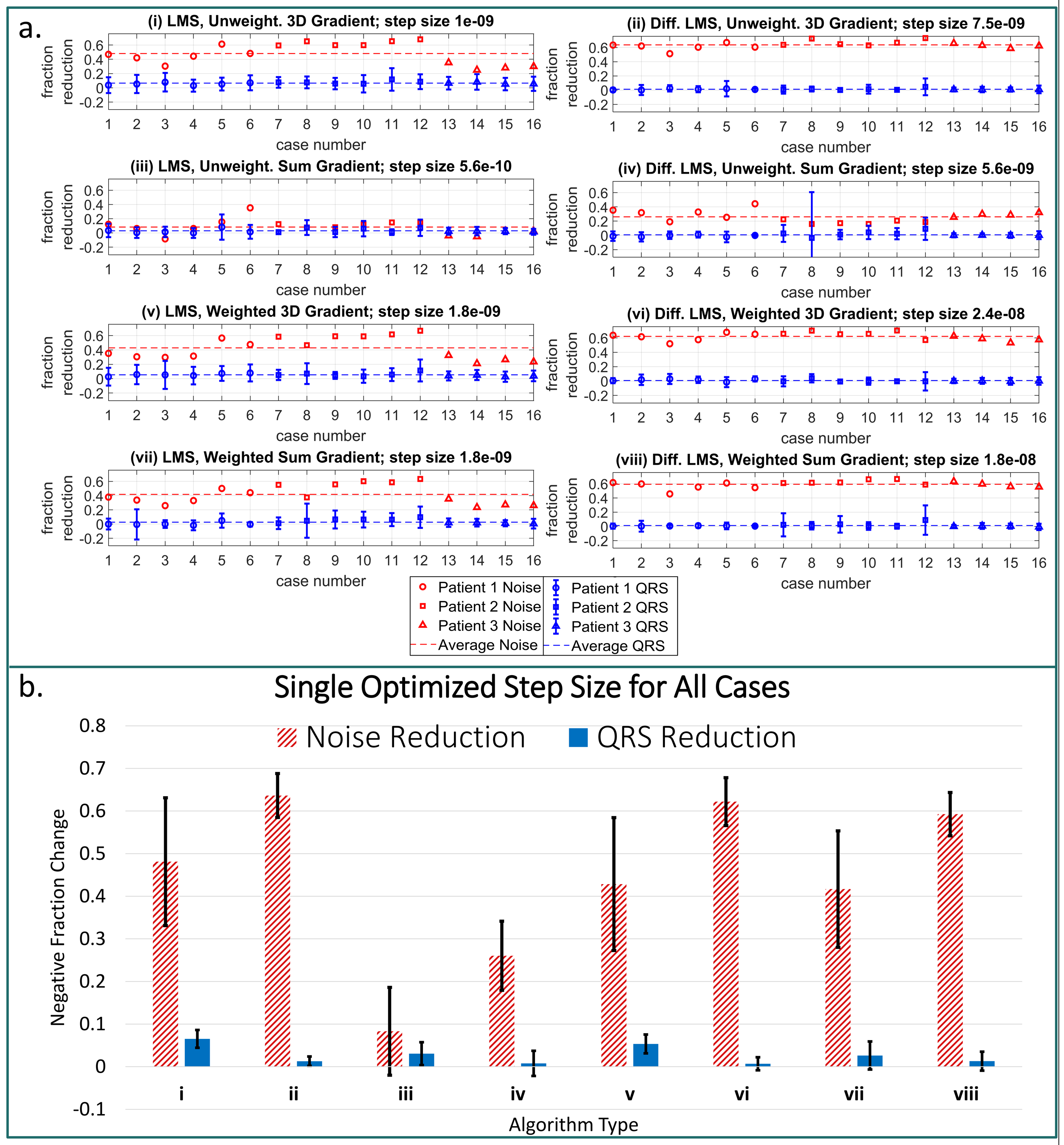

Fig 3. All 16 cases for each algorithm type were evaluated at the same step size. The step size was adjusted such that the algorithm was most effective for the group of 16 scans.. Error bars represent one standard deviation in both directions. **(a)** The noise and QRS statistics for each individual case of each algorithm type. **(b)** The means and variances of all 16 cases of each algorithm type.
Algorithm types: see Fig 2. algorithm types.

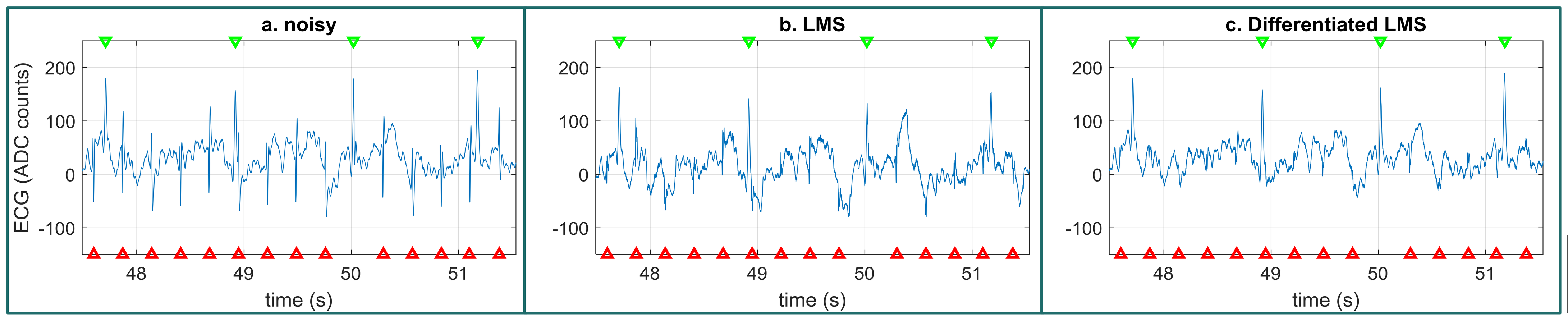

Fig 4. Left Leg ECG Signal distorted by MRI noise, and noise cleaned by adaptive filters. (a) Noisy, unfiltered signal. **(b)** The conventional Least Mean Squares (LMS) algorithm, currently in use by PRiME. **(c)** The differentiated LMS algorithm, a novel adaptive filter devised for this project. In both (b) and (c), three filters were used with one filter per unweighted reference signal.

Conclusions and Future Work

- The differentiated LMS algorithm, a novel adaptive filter devised for the purposes of this project, outperformed the traditional LMS algorithm in removing real-time MRI noise from ECG signals, consistently removing more noise while causing less distortion to the QRS complex on average. Additionally, the differentiated LMS algorithms generally had less variance in noise reduction, suggesting that more consistent results could be achieved for multiple patients by picking an appropriate step size.
  - Using the current method of handling multiple reference signals, compared to the conventional LMS, the differentiated LMS removes 15.7 percentage points more noise and changes the QRS height 5.22 percentage points less.
  - For all 16 case and all reference signal input methods, the differentiated LMS was capable of filtering out more noise than the conventional LMS when the best step size was chosen for each method and individual. With the same step size across all cases, the differentiated LMS removes more noise for all reference signal methods 15 out of 16 times.
- Weighting the gradients using the 3-plane localizer scan has certain advantages. Taking the weighted sum for both LMS algorithms resulted in less QRS distortion but also less noise reduction compared to the unweighted 3D gradient. Weighting but not summing the gradient had a slightly deleterious effect for the LMS and little effect for the differentiated LMS compared to the unweighted 3D gradient. Summing the gradients without weighting them had poor results for both LMS algorithms.
  - Using the conventional LMS with weighted summed gradients, the QRS complex reduction is 3.21 percentage points less than the 3D gradient), but the noise reduction is also 4.34 percentage points less.
  - The differentiated LMS with weighted summed gradients has minimum QRS reduction (0.125%). This reduces 3.9 percentage points less noise than the same with 3D gradients, but 11.8 percentage points more than the conventional LMS.
- Future work should extend this study to a larger sample size with more patients and other MRI sequences. Metrics such as signal-to-noise ratio, QRS power ratio, and cross-correlation ratio, should be considered. Future work should also examine the practicality of determining the gradient weights from the 3-plane localizer signal, specifically how sensitive the performance of the weighted sum and weighted 3D gradient methods are to variations of the gradient weights.

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