Transient Artifact Reduction Algorithm (TARA) using Sparse Optimization and Filtering

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In this work, we address the problem of attenuating artifacts arising in biomedical time series, such as those acquired using near infrared spectroscopic (NIRS) imaging devices. Our approach is to formulate an optimization problem, which in turn is based on a signal model that is intended to capture the primary characteristics of the artifacts. We presume only that the artifacts are transient in nature. Specifically, we model the measured time series, $y(t)$, as

$$y(t) = f(t) + x_1(t) + x_2(t) + w(t)$$

where $f(t)$ is a low-pass signal, $x_i(t)$ are two distinct types of artifact signals, and $w(t)$ is a white Gaussian noise process. The 'Type 1' artifact signal, $x_1(t)$, is intended to model 'spikes' and sharp, brief waves, while the 'Type 2' artifact signal, $x_2(t)$, is intended to model additive step discontinuities. Both types of artifacts are observed in NIRS time series.

For the purpose of flexibility and generality, we avoid defining the artifact signals in terms of precise rules or templates. Instead, we define them in terms of sparsity.

1. The 'Type 1' artifact signal x1(t) is defined as being sparse and having a sparse derivative. That is, it usually adheres to a baseline value of zero, as does its derivative. We use sparsity to encode the transient (brief) nature of the artifacts. Modeling the derivative of x1(t) as sparse helps to distinguish it from noise.
2. The 'Type 2' artifact signal is defined as having a sparse derivative. That is, its derivative is mostly zero; hence, x2(t) is an approximately piecewise constant signal. This type of artifact signal is composed of step discontinuities (or approximate step discontinuities), and it does not adhere to a baseline value of zero.

The suppression of Type 1 and Type 2 artifacts individually was addressed in our previous work.[1] However, we had assumed that the measured time series is affected by the presence of either Type 1 or Type 2 artifacts, but not both. Complex artifacts often comprise both types. To handle both types simultaneously, in this work we develop a new algorithm, denoted 'Transient Artifact Reduction Algorithm' (TARA). TARA performs joint optimization to explicitly estimate both types of artifacts. After the artifacts are estimated, they are subtracted from the raw data to obtain a corrected time series.

The TARA approach is non-parametric in the sense that the transients are not modeled through the use of any specified parametric shape. The method is flexible and general enough to encompass a variety of low-frequency background and artifact behaviors, through the tuning of the three parameters and the selection of the low-pass filter.

TARA was devised to have high computational efficiency and low memory requirements by constraining all matrices to be banded, which allows us to leverage fast solvers for banded systems. Moreover, the new algorithm does not require the user to specify auxiliary parameters, such as step sizes, etc. In order to attain computational efficiency and avoid algorithm parameters beyond those appearing in the cost function, the algorithm requires several techniques beyond those used in the previous work.

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[1] I.W. Selesnick, H.L. Graber, D.S. Pfeil, and R.L. Barbour, "Simultaneous low-pass filtering and total variation denoising," *IEEE Transactions on Signal Processing* **62**, 1109-1124 (2014).