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

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## Abstract

*We address suppression of artifacts in NIRS time-series imaging. We report a fast algorithm, combining sparse optimization and filtering, that jointly estimates two explicitly modeled artifact types: transient disruptions and step discontinuities.*

## Introduction

This work addresses the attenuation of artifacts arising in biomedical time series, such as those acquired using near infrared spectroscopic (NIRS) imaging devices [1]. We model the measured time series, $y(t)$, as

$$y(t) = f(t) + x_1(t) + x_2(t) + w(t) \quad t \in \mathbb{R}, \tag{1}$$

- $f(t)$ is a low-pass signal, i.e., $\text{HPF}\{f\} \approx 0$.
- $x_1(t)$ is a 'Type 1' artifact signal, intended to model spikes. We model a Type 1 artifact signal as being sparse and having a sparse derivative. It adheres to a baseline value of zero.
- $x_2(t)$ is a 'Type 2' artifact signal, intended to model additive step discontinuities. We model a Type 2 artifact signal as having a sparse derivative. It is composed of (approximate) step discontinuities.
- $w(t)$ is white Gaussian noise.

•We devise the 'Transient Artifact Reduction Algorithm' (TARA) to estimate both artifacts types simultaneously, so they can be subtracted from the raw data. TARA has high computational efficiency and low memory requirements.

## Problem Formulation

We address the problem in the discrete-time setting. We propose the optimization problem

$$\{\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2\} = \arg\min_{\mathbf{x}_1,\mathbf{x}_2} \Big\{ \frac{1}{2} \|\mathbf{H}(\mathbf{y} - \mathbf{x}_1 - \mathbf{x}_2)\|_2^2 + \lambda_0 \sum_n \phi_0([\mathbf{x}_1]_n) + \lambda_1 \sum_n \phi_1([\mathbf{D}\mathbf{x}_1]_n) + \lambda_2 \sum_n \phi_2([\mathbf{D}\mathbf{x}_2]_n) \Big\}, \quad \lambda_i > 0. \tag{2}$$

$\mathbf{H}$ denotes the high-pass filter suppressing the low-pass signal $\mathbf{f}$. $\mathbf{D}$ is discrete-time first-order difference operator, given by $[\mathbf{D}\mathbf{x}]_n = [\mathbf{x}]_{n+1} - [\mathbf{x}]_n$. The low-pass signal is estimated as

$$\hat{\mathbf{f}} = \mathbf{L}(\mathbf{y} - \hat{\mathbf{x}}_1 - \hat{\mathbf{x}}_2) \tag{3}$$

where $\mathbf{L}$ denotes the low-pass filter $\mathbf{L} = \mathbf{I} - \mathbf{H}$.
The functions $\phi_i$ are chosen to promote sparsity, e.g.,

$$\phi(u) = \frac{2}{a\sqrt{3}} \left( \tan^{-1}\left( \frac{1 + 2a|u|}{\sqrt{3}} \right) - \frac{\pi}{6} \right), \ a > 0.$$

The high-pass filter, $\mathbf{H}$, is implemented as

$$\mathbf{H} = \mathbf{B}\mathbf{A}^{-1}, \tag{4}$$

where $\mathbf{A}$ and $\mathbf{B}$ are banded matrices.

## Example 1

A special case of TARA is for Type 1 artifacts only ($\mathbf{x}_2$ is absent from (2)). We use a simulated signal (Fig. 1(a)) consisting of additive step-transients. With $(\lambda_0, \lambda_1) = (\lambda_0^*, 0)$, $\hat{\mathbf{x}}$ deviates infrequently from the baseline value of zero (Fig. 2(a)). With $(\lambda_0, \lambda_1) = (0, \lambda_1^*)$, it is approximately piecewise constant but does not adhere to a baseline of zero (Fig. 2(b)). With

$$(\lambda_0, \lambda_1) = (\theta\lambda_0^*, (1-\theta)\lambda_1^*), \quad 0 \leqslant \theta \leqslant 1, \tag{5}$$

with $\theta$ tuned to $0.3$, it is reasonably sparse and has a sparse derivative (Fig. 2(c)). The interpolation given by (5) provides a trade-off.

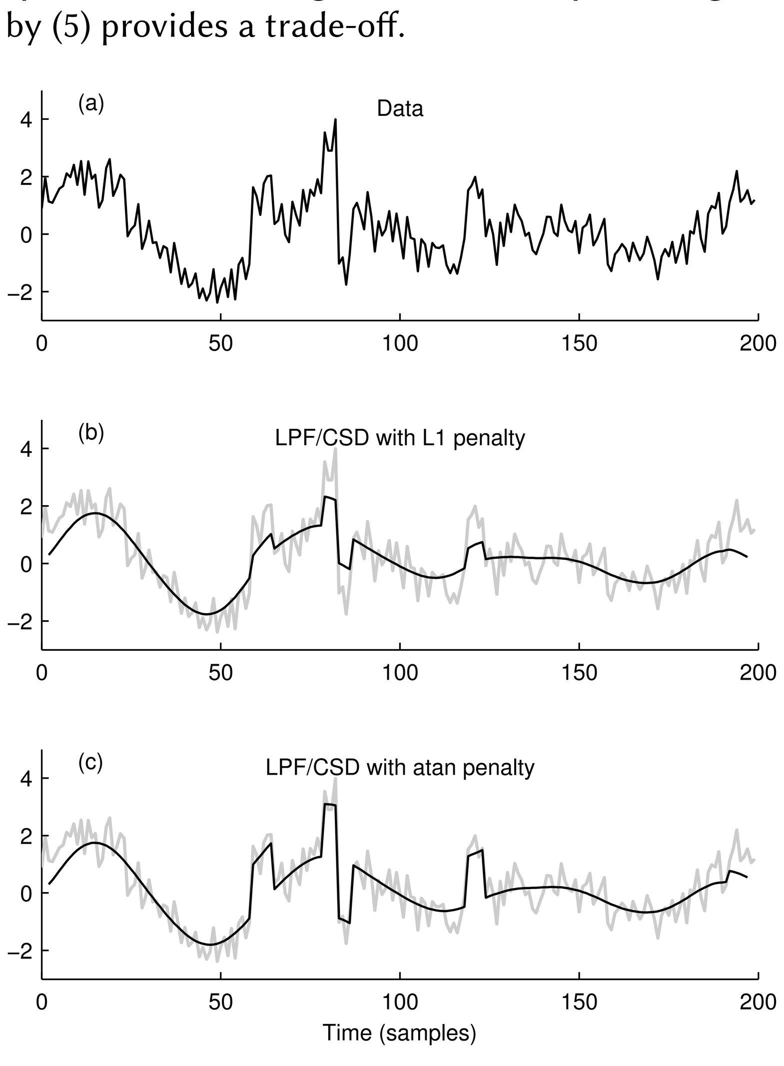



**Figure 1:** *(a) Simulated data. Processing with the $\ell_1$-norm penalty (b) and the arctangent penalty (c).*

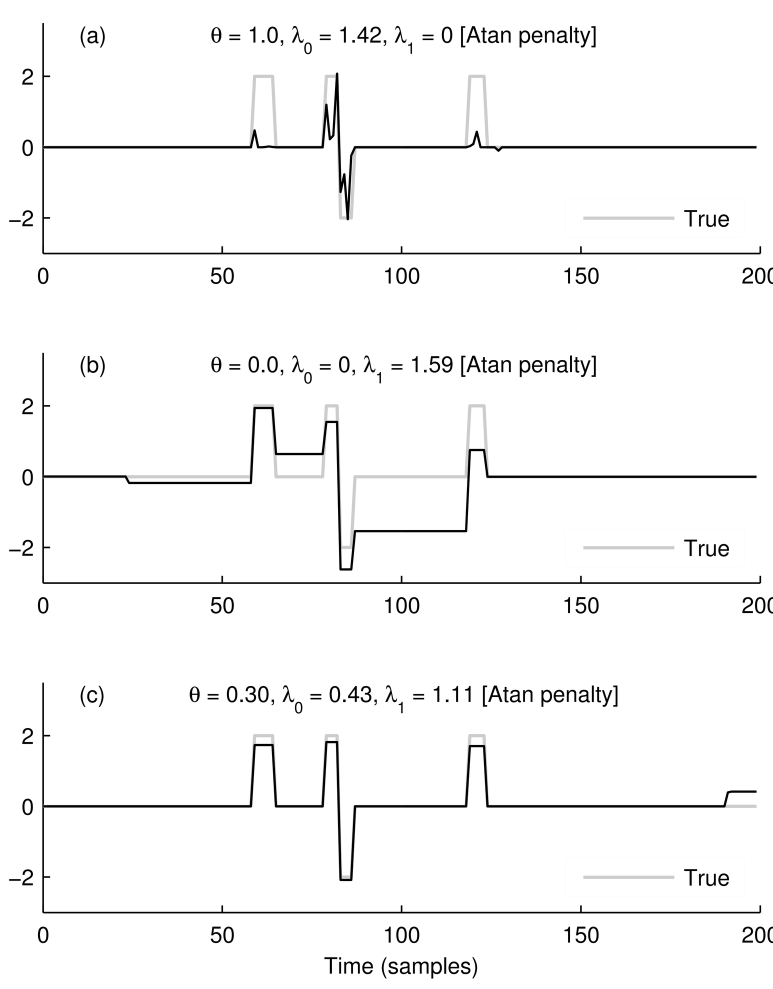



**Figure 2:** *Estimated transient signals, $\hat{\mathbf{x}}$, obtained with various $(\lambda_0, \lambda_1)$. (a) $\theta = 1$. (b) $\theta = 0$. (c) $\theta = 0.3$.*

•The result $x_1(t)$ shown in Fig. 2(c) is used to generate the signal $f(t) + x_1(t)$ shown in Fig. 1(c). It can be seen that the arctangent penalty $\phi$ better preserves the full height of transients compared to the L1 norm penalty shown in Fig. 1(b).

## Example 2

This example shows TARA, for Type 1 artifacts, as applied to a near infrared spectroscopic (NIRS) time series. The data exhibits artifacts due to eye blinks. Signals corresponding to $(\lambda_0^*, 0)$ and $(0, \lambda_1^*)$ are shown in Figs. 3(b, c). With $(\lambda_0, \lambda_1)$ set using (5) with $\theta = 0.05$, we obtain an apparently accurate estimate of the transient artifacts (Fig. 3(d)). The corrected time series is obtained by subtracting the estimated artifact signal $\hat{\mathbf{x}}$ from the original data (Fig. 3(e)). The algorithm run time was about 80 milliseconds.

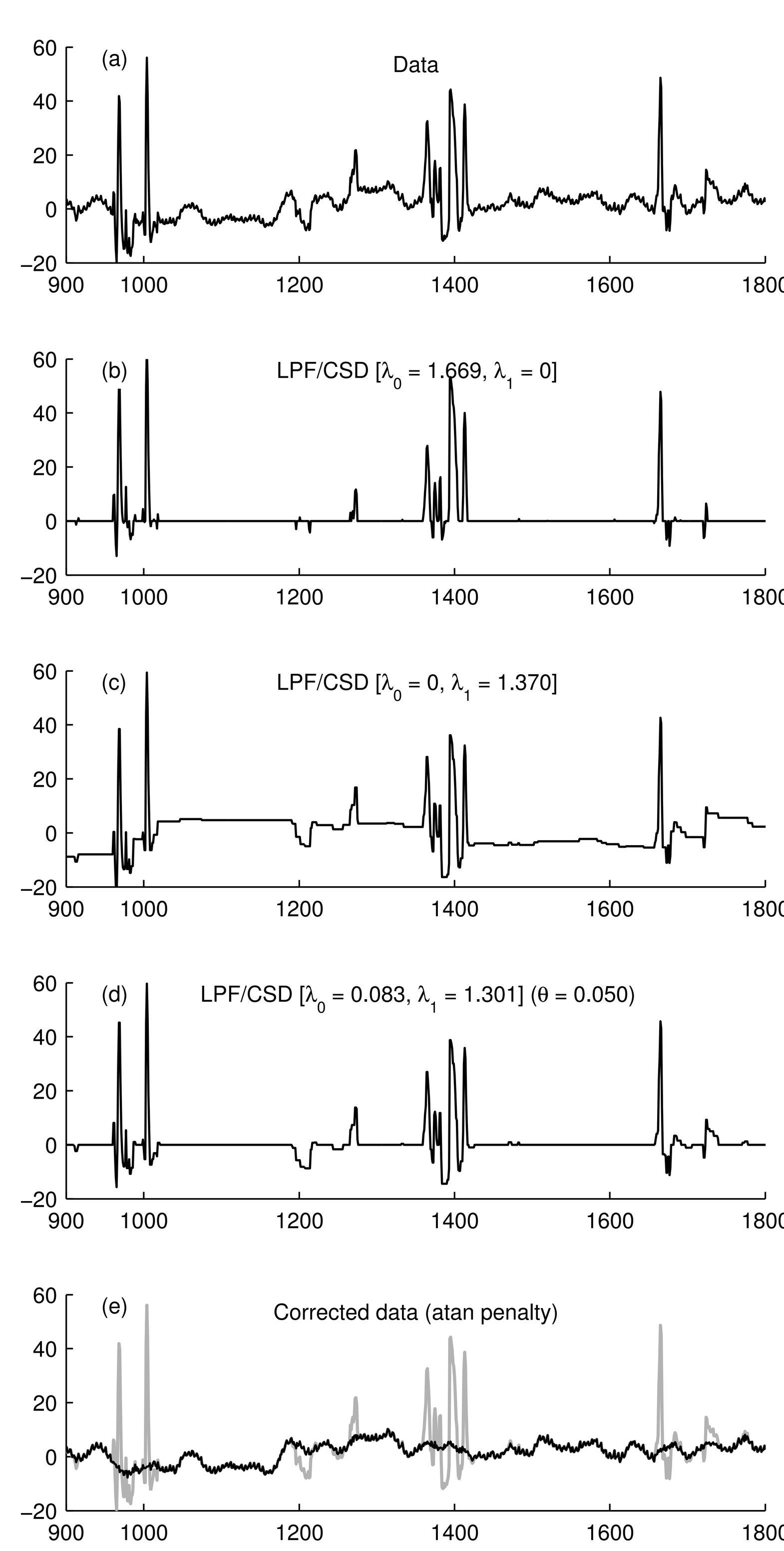



**Figure 3:** *Reduction of transient artifacts in NIRS time-series data. (a) Raw data. (b, c, d) Artifact estimation with $(\lambda_0^*, 0)$, $(0, \lambda_1^*)$, and (5). (e) Corrected data.*

## Example 3

•TARA is applied to a NIRS time series acquired using a pair of optodes on the back of a subject's head. The data exhibits a motion-induced abrupt shift of the baseline, at time index 470. Other motion artifacts also are visible.

•The Type 1 and Type 2 artifact signals as estimated by TARA, are sparse and approximately piecewise constant, as intended. Note that the corrected time series has both low-frequency and high-frequency spectral content.

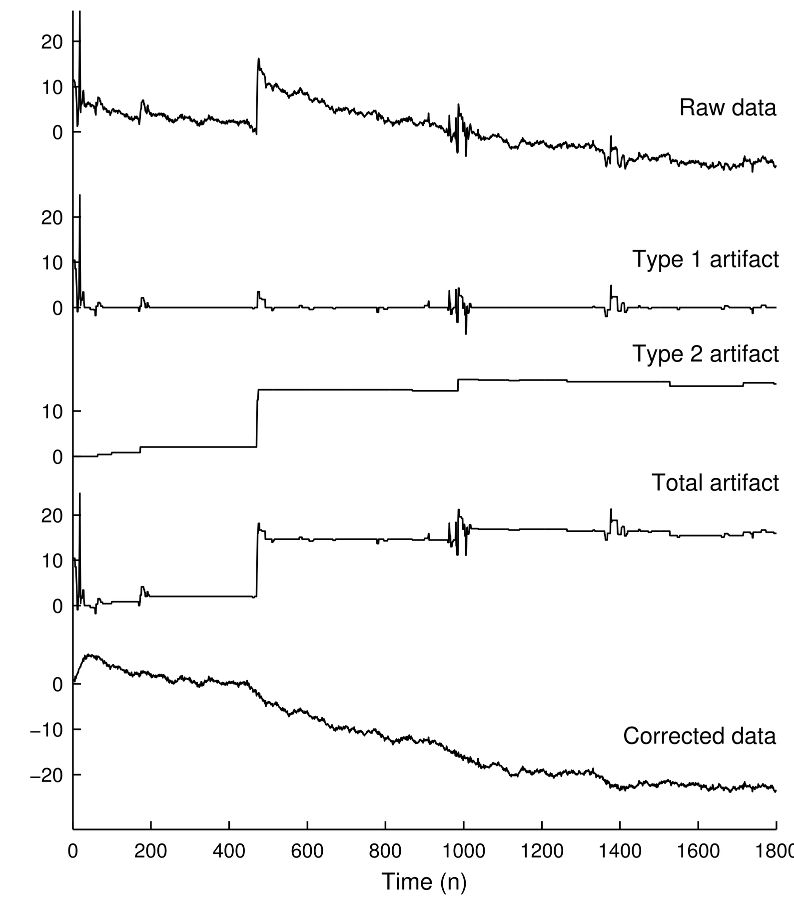



**Figure 4:** *Artifact reduction with TARA as applied to a NIRS time series.*

**Wavelet artifact estimation.** Wavelet methods compare favorably to other methods for the correction of motion artifacts in single-channel NIRS time series [2, 3, 4]. In comparison with TARA, the wavelet method does not correct additive step discontinuities as well. The wavelet-estimated artifact signal smooths the additive step discontinuity.

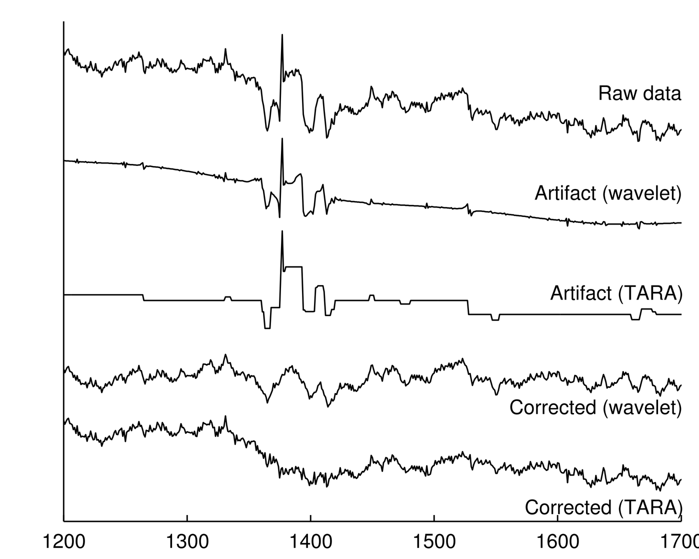
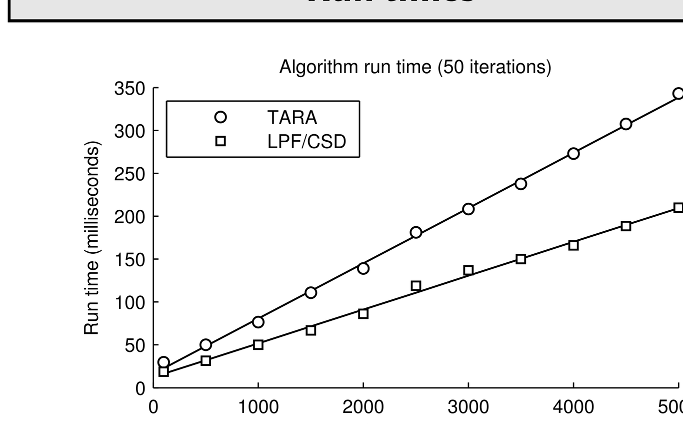



**Figure 5:** *Artifact estimation and correction using wavelets and TARA.*

The artifact in the interval 1370-1420 is estimated by TARA with distinct pre- and post-artifact baseline values; whereas the wavelet-estimated artifact signal exhibits a small change. In addition, TARA finds an abrupt change at time index 1530; while the wavelet method exhibits only a small bi-phasic (zero-mean) pulse at that instant. TARA is better able to estimate abrupt step-changes than the wavelet method because it is explicitly based on a two-component model.

## Run times




TARA is fast. Run times measured using a 2013 MacBook Pro (2.5 GHz Intel Core i5) running Matlab R2011a.

## Preservation of hemodynamic response

•Physiological time-series data (e.g., NIRS, EEG) are often acquired in multichannel form. We apply TARA to multichannel data (Fig. 6, black) using the same (shape) parameters for all channels. To avoid cumulative baseline drift, each corrected time series has been filtered with a zero-phase second-order recursive dc-notch filter.

•TARA effectively reduces transient artifacts in most channels, without introducing substantial distortion.

•In the course of suppressing artifacts, biological information of interest should not be distorted or attenuated. For NIRS, any hemodynamic response (HR) waveforms present should be preserved. To test TARA in this regard, we add a simulated HR to each channel of the considered multichannel data. Signals with the simulated HR is shown in gray in Fig. 6. The gray-colored artifact signals, obtained from the HR-added data, are nearly indistinguishable from the original artifact signals.

$\Longrightarrow$ TARA accurately preserves the HR in the corrected data.

•To compare TARA with wavelets, we apply wavelets to the same data, with and without the added HR.

The wavelet-estimated artifact signals (Fig. 7) exhibit a noticeable portion of the HR in about half the channels. Consequently, the HR is more attenuated and distorted in the wavelet-corrected data than in the TARA-corrected data.

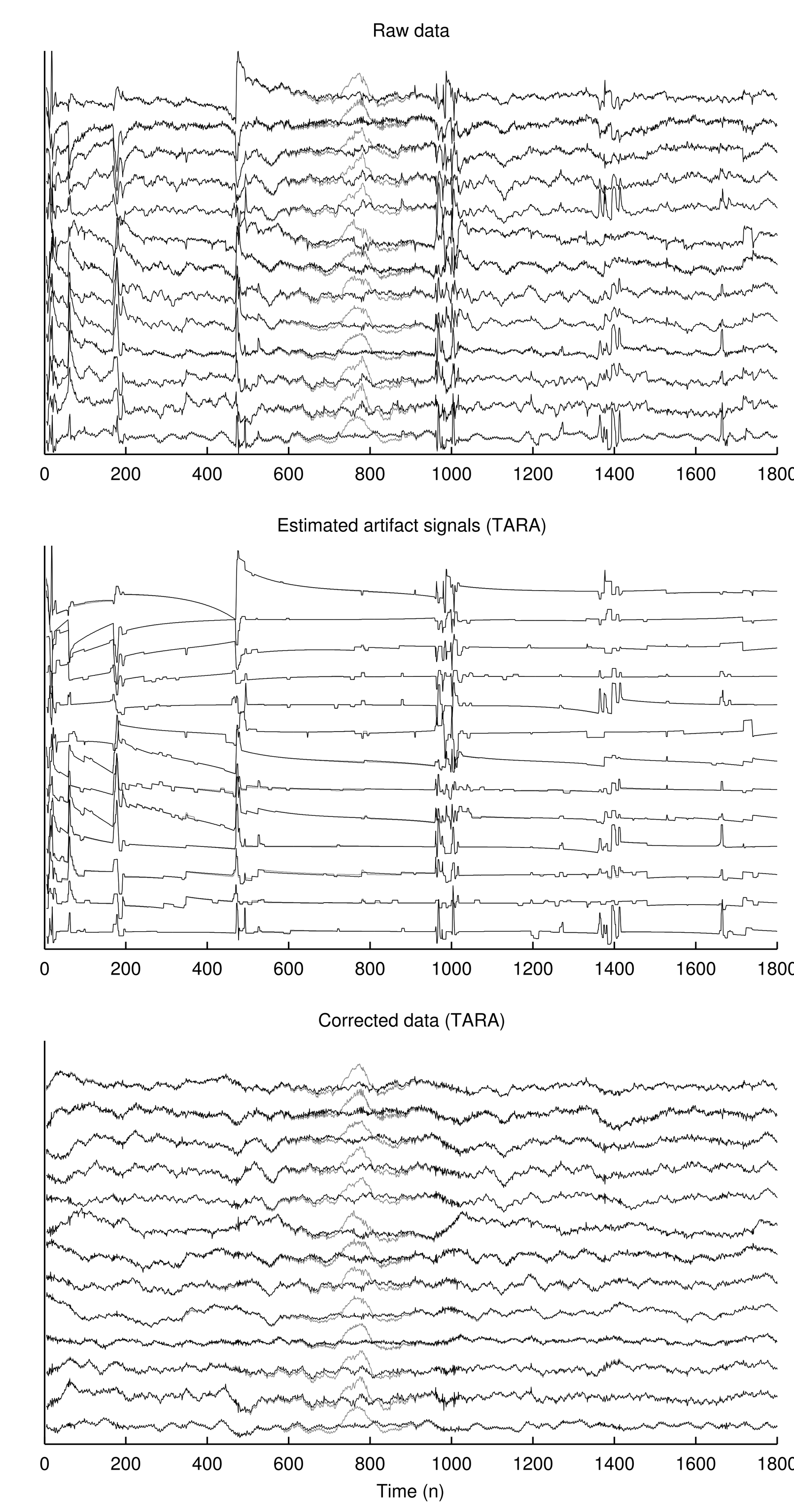



**Figure 6:** *TARA applied to multichannel data.*

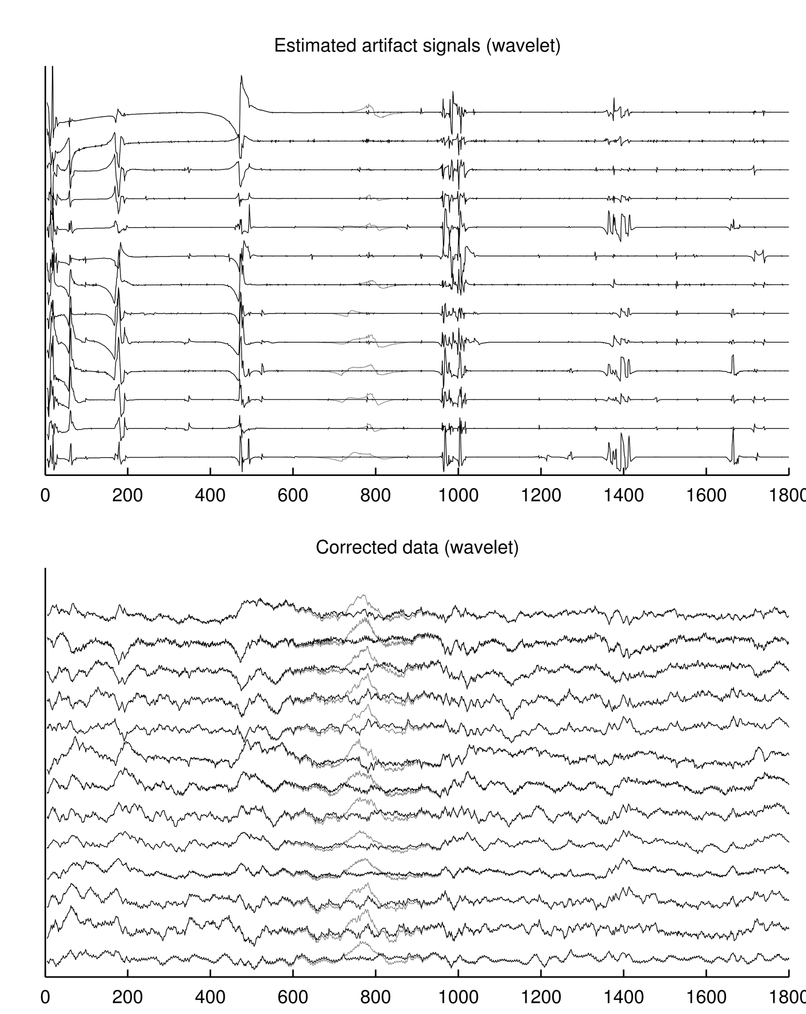



**Figure 7:** *Wavelet transient artifact reduction of multichannel data.*

•In quantitative terms, we measure the root-mean-square deviation over the HR interval (700-880) between the HR and non-HR artifact signals. The value is 0.18 for TARA and 0.53 for wavelets. By this measure, the wavelet method is affected by the HR 2.9 times more than TARA, and so TARA better preserves the HR.

## References

[1] R. Al abdi, H. L. Graber, Y. Xu, and R. L. Barbour. Optomechanical imaging system for breast cancer detection. *J. Opt. Soc. Am. A*, 28(12):2473–2493, December 2011.

[2] S. Brigadoi et al. Motion artifacts in functional near-infrared spectroscopy: A comparison of motion correction techniques applied to real cognitive data. *NeuroImage*, 85:181–191, 2014.

[3] M. K. Islam, A. Rastegarnia, A. T. Nguyen, and Z. Yang. Artifact characterization and removal for *in vivo* neural recording. *J. Neuroscience Methods*, 226:110–123, 2014.

[4] B. Molavi and G. A. Dumont. Wavelet-based motion artifact removal for functional near-infrared spectroscopy. *Physio. Meas.*, 33(2):259, 2012.

[5] I. W. Selesnick, H. L. Graber, D. S. Pfeil, and R. L. Barbour. Simultaneous low-pass filtering and total variation denoising. *IEEE Trans. Signal Process.*, 62(5):1109–1124, March 2014.

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