A Temporally Discrete Method for Biosignal Enhancement: Application to Achieve Improved Artifact Correction of NIRS Data

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Background: There are many instances where neuroimaging—based on recordings of either bioelectric or hemodynamic signals—would have scientific or clinical value, but conditions for collection of time-varying biosignals are suboptimal. This includes, but is not limited to, data collection in open environments where a host of ambient signals may be present, or may be introduced by changes in sensor contact fidelity by physiological effects of sudden muscle movements or changes in body orientation, among other factors. Situations where these conditions are typical include: measurements taken by first responders during emergency care situations, measurements obtained during an epileptic seizure, gait studies, acute manipulations during intraoperative procedures, and acute corruption of data by a stimulus during multimodal measurements (e.g., MRI pulsing sequence effects on recorded EEG measures [1]).

In many cases, biosignals have characteristic spectral content. For this reason, relatively simple frequency filtering methods can be applied to denoise, separate, enhance and classify features of these signals. In contrast, artifacts often have a transient nature with an unspecified waveform, and are not optimally characterized by their (frequency) spectral content, but are best understood in the time domain. Consequently, biosignals corrupted by transient artifacts are not amenable to restoration using either frequency-domain filtering or purely time domain methods.

An ideal methodology would separate undesired signals from desired or background without affecting the latter. For the class of corrupted signals considered here, the methodology described below accomplishes this by employing a combination of a linear time-invariant (LTI) filter and a sparse derivative denoising (SDD) algorithm, hereafter referred by the acronym LTISDD. The linkage of these methods serves to exploit the respective information content of artifacts (transient type waveforms) and biosignals (having well defined spectral properties).

Prior Methods to Achieve Signal Separation: Prior efforts to achieve separation of corrupted signals have led to development of a broad array of methods well known to those in the field of signal processing. Broadly speaking, these fall into two principal domains: simple and advanced methods. Among the former are the techniques of frequency and median filtering, and related generalizations and thresholding techniques. The latter comprises a large class that includes Kalman filtering, principal component analysis (PCA), Blind Source Separation Methods (e.g., PCA/ICA [Independent Component Analysis]), adaptive filtering, machine learning algorithms, wavelet and other time-frequency methods, and non-negative matrix factorization (NMF) methods. One notable characteristic of several of these methods is their reliance on the availability of more than one time-varying signal. Another is their reliance on the availability of sufficient training data of artifact separation. Still another characteristic is their reliance on the predictability of the occurrence and/or form of the artifact. Yet another characteristic is the assumption that the artifact and biosignal can be well separated in either the time-frequency domain or other domains, either learned or pre-specified.

In the limiting cases wherein acquired signals are a linear mixture, the method of PCA and its related method of ICA can be successfully applied to decompose the mixture into its individual components. Inherent to this approach, however, is the expectation that multiple signals have been recorded. Not infrequently, only a single signal is available, in which case signal decomposition using these methods is not possible, or if multiple signals are available, the expectation that the computed "sources" correspond to biological processes that are uncorrelated and/or independent may only be weakly or poorly met. Certainly, a basic consideration of dynamic biological processes is that most are spatially and temporally correlated to some extent.

In yet another limiting case, the background (desired) signal is affected by some other well-defined, time-varying signal. Here, a number of methods can be adopted to achieve signal separation. In cases where the undesired signal has a frequency structure different from the desired signal, simple frequency filtering methods (e.g., low-pass, high-pass, band-pass) are appropriate. In cases where both classes of signals are frequency-rich but have different temporal structures, adoption of machine learning methods can prove useful. To be effective, it is important that the structure of the training data have features substantially similar to that of the target set.

Returning to the consideration of measures in open environments, not uncommon is the presence of artifacts that have the effect of introducing discrete changes in mean signal values, or simply a discrete disturbance in the signal amplitude. With sufficient experience, empirical correction methods are often used to deal with signal distortions of this type. For instance, a discrete change in the mean signal amplitude can be corrected by simply subtracting the difference in mean values taken before and after the disturbance, to yield a corrected time series. Alternatively, a discrete disturbance can be simply ignored, allowing for examination of undisturbed time periods. While these empirical strategies can be effective, they are often unsatisfactory should they occur during a time period of interest (e.g., detection of hemodynamic measures during an epileptic seizure).

Signal Characteristics Explored With LTISSD Algorithm: Whereas each of the above-mentioned methods has utility for operating on different signal compositions, each has notable limitations in terms of types of signals to which it can be successfully applied. The described LTISDD algorithm possesses a number of unique properties:

1) Operates on single channel data
2) Artifacts can overlap the desired signal component in both frequency and time
3) Employs a Minimally Assumptive Strategy
4) Does not require specific prior knowledge of temporal characteristic of desired and undesired signals
5) Reference signal not required
6) Artifact composition need not have a defined parametric form
7) Artifact composition need not have a repetitive structure
8) Artifact and biosignal need not be separated time-frequency or other domain
9) Artifact composition need not be predictable from prior knowledge

Algorithm Features

1) Computationally efficient due to use of linear algebraic operations on sparse matrices
2) Only a few parameters needed to achieve signal separation
3) Combines traditional signal filtering (useful and simple) with sparse optimization methods (well suited for signals containing transients).

Mathematical Formulation of the Problem

$$\arg\min_{\mathbf{x}} \left\{ \|\mathbf{H}(\mathbf{y}-\mathbf{x})\|_2^2 + \lambda_0 \|\mathbf{x}\|_1 + \lambda_1 \|\mathbf{D}\mathbf{x}\|_1 \right\}$$

$\mathbf{y}$ = measurement-data time series (background + transient + noise)
$\mathbf{x}$ = filtered data time series (transient component)
$\mathbf{H}$ = high-pass filter matrix
$= \mathbf{A}^{-1}\mathbf{B}$ (standard linear time-invariant filter formulation: $\mathbf{A}\mathbf{y} = \mathbf{B}\mathbf{x}$)
$\mathbf{D}$ = discrete first-derivative matrix
λ_0 = regularization parameter for the transient component
λ_1 = regularization parameter for the derivative of the transient component

Equivalently:

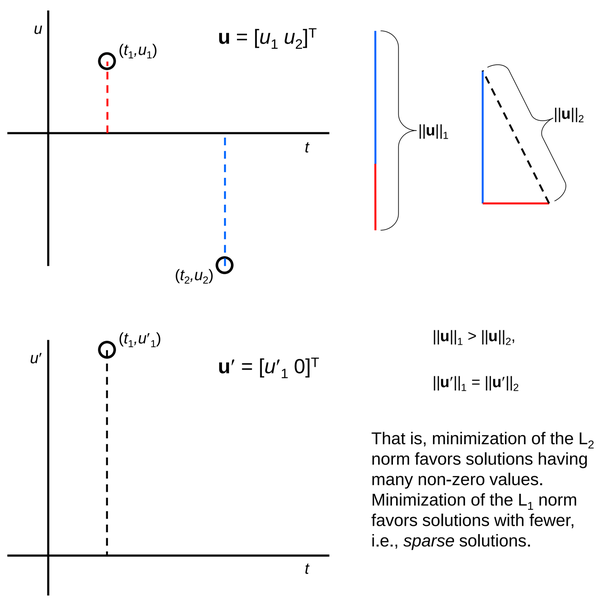
$$\arg\min_{\mathbf{x},\mathbf{v}} \left\{ \|\mathbf{H}(\mathbf{y}-\mathbf{x})\|_2^2 + \lambda_0 \|\mathbf{v}\|_1 + \lambda_1 \|\mathbf{D}\mathbf{v}\|_1 \right\},$$

such that $\mathbf{v} = \mathbf{x}$.

(That is, our problem is a special case of a more general one, which we already know how to solve [2].)

Algorithm

1. $\mathbf{v} = 0$
2. $\mathbf{d} = 0$
3. $\mathbf{b} = \mathbf{B}^{\mathsf{T}} \left(\mathbf{A}\mathbf{A}^{\mathsf{T}}\right)^{-1} \mathbf{B}\mathbf{y} \big/ \mu$
   μ = convergence-rate control parameter
4. Repeat...
5. $\mathbf{g} = \mathbf{b} + \mathbf{v} - \mathbf{d}$
6. $\mathbf{x} = \mathbf{g} - \mathbf{B}^{\mathsf{T}} \left(\mathbf{A}\mathbf{A}^{\mathsf{T}} + \mathbf{B}\mathbf{B}^{\mathsf{T}}\right)^{-1} \mathbf{B}\mathbf{g}$
7. $v = soft\left(tvd\left(\mathbf{x}+\mathbf{d}, \lambda_1/\mu\right), 0.5\,\lambda_0/\mu\right)$
   $soft(z,K) = \begin{cases} z - K\left(z/|z|\right), & |z| > K \\ 0, & |z| \le K \end{cases}$
   $tvd(z,\alpha)$: total-variation denoising, using algorithm of [3].
8. $\mathbf{d} = \mathbf{d} - \mathbf{v} + \mathbf{x}$
9. ...until convergence
10. $\mathbf{f} = (\mathbf{y}-\mathbf{x}) - \mathbf{A}^{-1}\mathbf{B}(\mathbf{y}-\mathbf{x})$ (background component)



$\|\mathbf{u}\|_1 > \|\mathbf{u}\|_2$,

$\|\mathbf{u}'\|_1 = \|\mathbf{u}'\|_2$

That is, minimization of the L_2 norm favors solutions having many non-zero values. Minimization of the L_1 norm favors solutions with fewer, i.e., *sparse* solutions.

Sketch identifying appropriateness of hybrid-norm functional for separation of mixtures of continuous and transient components.

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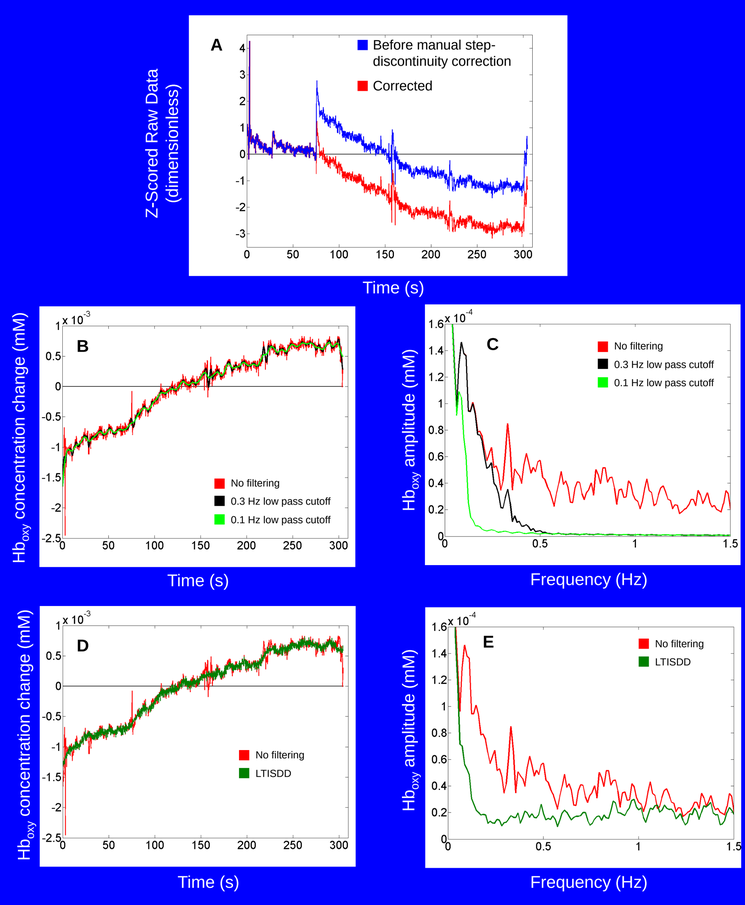
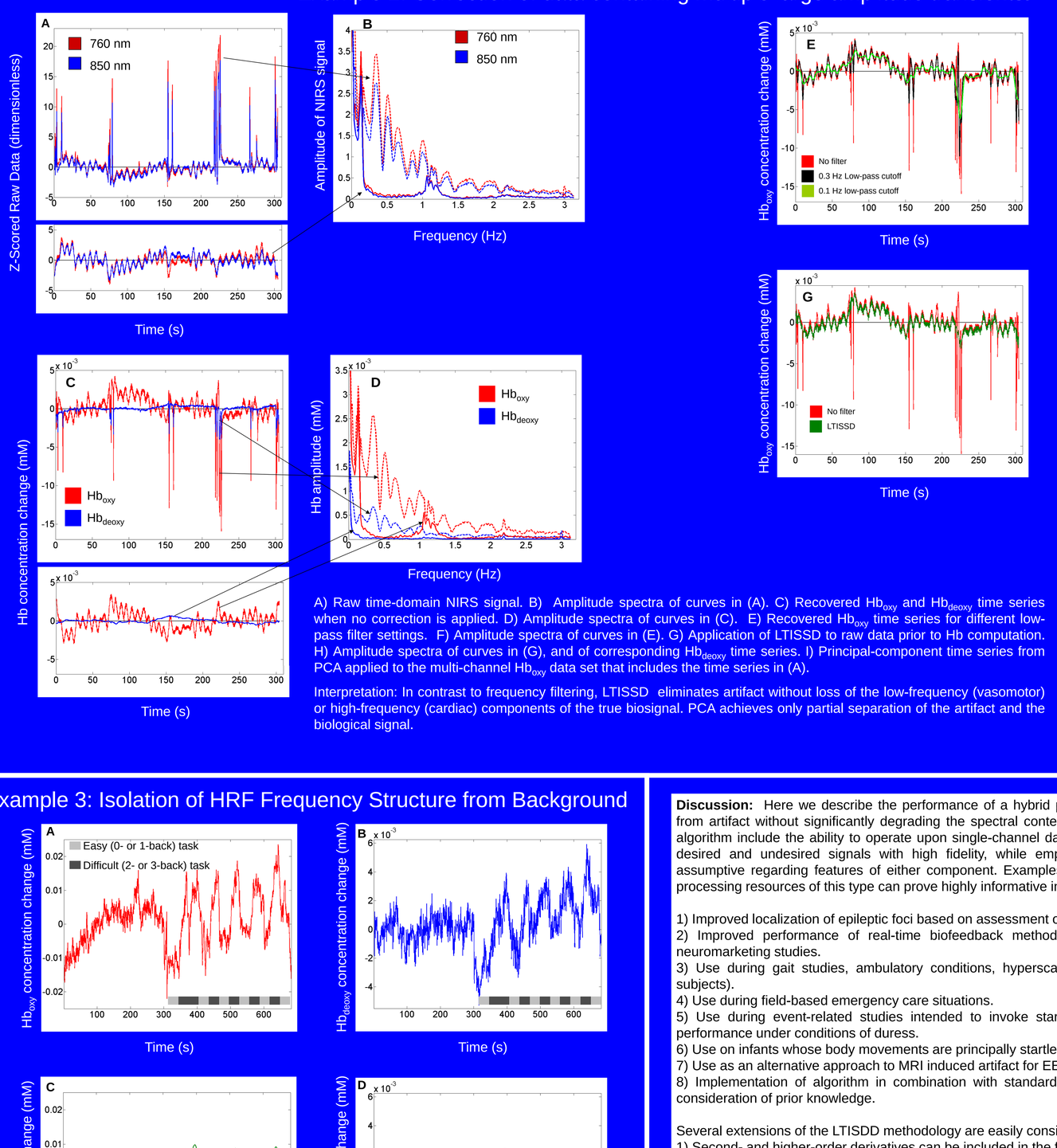
Example 1: Correction of data with abrupt mean shift plus transients.



A) Raw time-domain NIRS signal. B) Recovered Hb_{oxy} time series for different low-pass filter settings. C) Amplitude spectra of curves in (B). D) Application of LTISSD to raw data prior to Hb computation. E) Amplitude spectra of curves in (D).

Interpretation: Frequency filtering that removes artifact artificially suppresses vasomotor amplitude. LTISSD eliminates artifact without loss of vasomotor signal.

Example 2: Correction of data containing multiple large amplitude transients.



A) Raw time-domain NIRS signal. B) Amplitude spectra of curves in (A). C) Recovered Hb_{oxy} and Hb_{deoxy} time series when no correction is applied. D) Amplitude spectra of curves in (C). E) Recovered Hb_{oxy} time series for different low-pass filter settings. F) Amplitude spectra of curves in (E). G) Application of LTISSD to raw data prior to Hb computation. H) Amplitude spectra of curves in (G), and of corresponding Hb_{deoxy} time series. I) Principal-component time series from PCA applied to the multi-channel Hb_{oxy} data set that includes the time series in (A).

Interpretation: In contrast to frequency filtering, LTISSD eliminates artifact without loss of the low-frequency (vasomotor) or high-frequency (cardiac) components of the true biosignal. PCA achieves only partial separation of the artifact and the biological signal.

Example 3: Isolation of HRF Frequency Structure from Background

A) Hb_{oxy} time series recovered from untreated time-domain NIRS signal. B) Hb_{deoxy} time series recovered from untreated time-domain NIRS signal. C) Hb_{oxy} time series recovered after application of LTISSD (red) or band-pass filtering (green). E) Hb_{deoxy} time series recovered after application of LTISSD (blue) or band-pass filtering (magenta).

Interpretation: In contrast to frequency filtering, LTISSD preserves the shape information (i.e., high-frequency content) of the hemodynamic response to an N-back task. This permits consideration of higher-order analyses such as estimation of the hemodynamic response function (HRF) from the Hb time series.

Discussion: Here we describe the performance of a hybrid processing scheme intended to isolate biosignals from artifact without significantly degrading the spectral content of the original signal. Notable features of the algorithm include the ability to operate upon single-channel data, high computational efficiency, and isolation of desired and undesired signals with high fidelity, while employing a processing strategy that is minimally assumptive regarding features of either component. Examples of instances and applications where access to processing resources of this type can prove highly informative include:

1) Improved localization of epileptic foci based on assessment of bioelectric or hemodynamic signals.
2) Improved performance of real-time biofeedback methods, brain computer interface (BCI) applications, neuromarketing studies.
3) Use during gait studies, ambulatory conditions, hyperscanning (simultaneous measures on two or more subjects).
4) Use during field-based emergency care situations.
5) Use during event-related studies intended to invoke startle, or during conditioning to achieve improved performance under conditions of duress.
6) Use on infants whose body movements are principally startle type.
7) Use as an alternative approach to MRI induced artifact for EEG studies.
8) Implementation of algorithm in combination with standard methods to address above examples including consideration of prior knowledge.

Several extensions of the LTISDD methodology are easily considered:

1) Second- and higher-order derivatives can be included in the functional that is minimized
2) The L_1 norm can be replaced by other measures of sparsity that promote sparsity more strongly.
3) Penalty functions can be used that reflect other sparsity properties, such as group sparsity.
4) The optimization algorithm described in this work can be replaced by other iterative algorithms, especially as appropriate to the modifications such as those just mentioned
5) Implementation of algorithm as a component of data analysis pipelines.
6) Implementation of algorithm to improve elements of computational steering.

References

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