Adaptive Removal of the Transcranial Alternating Current Stimulation Artifact from the Electroencephalogram

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Abstract

Your abstract.

1 Introduction

The combination of transcranial alternating current stimulation (tACS) and electroencephalogram (EEG) has been explored in several recent studies. While the analysis of EEG before or after stimulation posits limited technical challenges, the EEG recording during stimulation is heavily affected by the stimulation artifact.

1.1 Matched Phase and Frequency

Computational simulations suggest that the power of endogenous oscillations would increase most if the frequency of tACS matches the targets eigenfrequency (Kutchko and Fröhlich, 2013; Zaehle et al., 2010). This has been supported by evidence from animal studies (Schmidt et al., 2014), and human studies combining tACS with transcranial magnetic stimulation (TMS) (Guerra et al., 2016), or contrasting pre and post resting state power analysis (Zaehle et al., 2010). It has also been suggested that the phase of neuronal populations would be locked to the phase of the tACS signal (Reato et al., 2013). This has been supported by evidence from studies combining tACS with motor output (Brittain et al., 2013), TMS (Raco et al., 2016; Nakazono et al., 2016) or sensory perception (Gundlach et al., 2016).

This suggests that the effect of tACS can result in neurophysiological effects which are phase-and frequency-matched to the stimulation artifact. Such frequency and phase matching between tACS and EEG recordings can render the removal of the artifact difficult or impossible, as the signal might no longer be separatable from the artifact.

1.2 Non-Stationary Amplitude Modulation

An approach to tackle this issue is to assess the time-course of the EEG signal. Consider the assumption that the artifact is stationary and superpositioned on the physiological signal. Then, modulations in the amplitude of the recorded EEG-signal must be caused by changes in the underlying physiology. This would be the case, even if frequency and phase are matched to the stimulation signal. Approaches assuming such stationarity of the stimulation artifact have been used e.g. by Pogosyan et al. (2009).

Yet, detailed analysis of the stimulation artifact provides evidence that the artifact amplitude is actually not stationary. Instead, the amplitude is modulated by heart-beat and respiration (Noury et al., 2016). Consider furthermore that event-related responses like modulation of skin impedance can also affect the scalp conductance at stimulation electrodes. This would introduce event-related amplitude modulation of the stimulation artifact. In that regard, disentangling true signal from the stimulation artifact stays technically challenging.

1.3 Artifact Distortion

Ideally, the stimulation artifict of tACS resembles a sinusoid. Yet, practical experience suggests that the signal is usually distorted to various degrees (see figure 1).

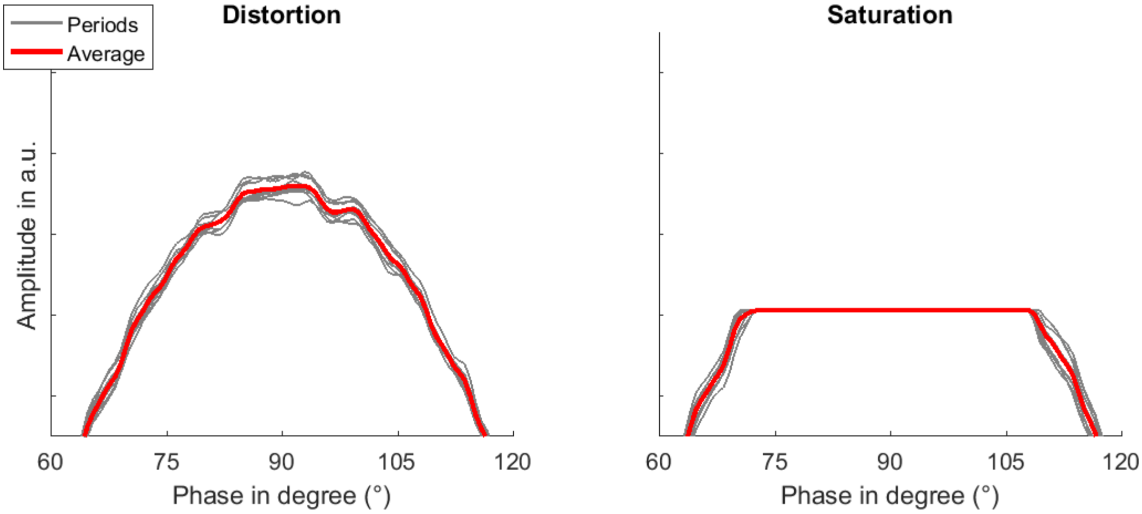

Figure 1: Non-Sinusoidality
It shows the distortion/saturation of the sinus waveform using two exemplary trials of tACS-EEG. The gray traces indicate nine invididual periods, while the red trace indicates their average. In the left figure, note the periodic, but non-sinusoidal waveform. In the right figure, note the saturation.

The temporally and spatially uneven impedance distribution has been suggested as cause of distortion, rendering the resulting waveform periodic, but non-sinusoidal. A major problem is amplifier saturation, i.e. the stimulation artifact exhibiting an amplitude to large for the dynamic range of the amplifier, causing the signal to be cut off and information to be lost. Additionally, non-linearites in the amplifier slew rate can distort the shape even when the signal is close to the saturation threshold.

1.4 Computational Demands

Methods based on adaptive template construction and temporal principal component analysis (tPCA) (Niazy et al., 2005) have been explored for removal of non-stationary and misshaped tACS artifacts (Helfrich et al., 2014). Consider that the process of template construction, the estimation of accurate weights for removal by template subtraction and the suqsequent removal of residual artifacts using tPCA is computationally cumbersome. Additionally, it often requires off-line analysis supported by visual inspection. Such a multi-staged template-approach is therefore of limited utility for on-line artifact removal. Furthermore, critical evaluation has suggested that the residual artifact spans several principal components, and a sufficient artifact removal is therefore not possible with tPCA (Noury et al., 2016).

1.5 Rationale

We were interested in development of a computationally fast approach, feasible for online artifact removal. At the same time, the approach was required to account for the dynamical modulation of the artifact amplitude, and the possibility of non-sinusoidal distortion and saturation. Ideally, the approach should allow to estimate physiological signals at the frequency of stimulation, even if physiological oscillations were phase-locked to the stimulation signal.

2 Approach

The main idea is that at any given time point t, the recorded signal $r(t)$ is a linear superposition of a neurophysiological signal $n(t)$, the stimulation artifact $a(t)$ and a white noise term $e(t)$. The task is to recover $n(t)$ by estimating $a(t)$ and $e(t)$ and subtracting from $r(t)$.

$$r(t) = n(t) + a(t) + e(t) \tag{1}$$
$$n(t) = r(t) - a(t) - e(t) \tag{2}$$

2.1 Periodic Estimation

Assume that the tACS artifact were *non-sinusoidal*, but *stationary and periodic*. At the same time, assume that neurophysiological signals n were absent, but the noise term e remains (3). Then, we could estimate the amplitude of a at any time-point t by using the recorded signal r from any tACS one period length τ_a earlier (4).

$$r(t) = a(t) + e(t) \tag{3}$$
$$\hat{a}(t) = r(t - \tau_a) \tag{4}$$

Consider that the white noise term e is superpositioned on r, and $\langle e \rangle$ converges asymptotically to zero with increased sample size. An optimal approach to achieve an unbiased estimate of the amplitude of a stationary artifact would therefore be to average across as many earlier periods as possible (5). Subsequently, this estimate can be used to remove the artifact from r.

$$\hat{a}(t) = \sum_{n=1}^{N} \frac{r(t - (n\,\tau_a))}{N} \tag{5}$$

Please note that averaging across neighbouring periods M (6) has been suggested before and termed superposition of moving averages (SMA) by Kohli and Casson (2015).

$$\hat{a}(t) = \sum_{n-M/2}^{n+M/2} \frac{r(t - (n\,\tau_a))}{M+1} \tag{6}$$

The approach using only past values (5) returns a causal filter. A causal filter would be able to remove the artifact without the delay of $\frac{M\tau_a}{2}$ necessary for SMA. Additionally, if applied offline on time-flipped signals, a causal filter has the potential to mininize distortion of neurophsyiological signals by mirroring a strong event-related potential.

2.2 Temporal Weighting

In real applications, stimulation duration is limited and computational contraints exist. This is reflected by the fact we have to use a finite number for N. More importantly, the artifact amplitude is non-stationary and dynamically modulated (Noury et al., 2016). In these real applications, equation (5) can return a biased estimate, depending on whether the integral of this modulation over the time-period $N \times \tau_a$ converges to zero. One approach to deal with this issue is using a time-dependent weighting function instead of a constant N (7), with the weighting function designed to reduce a possible bias.

$$\hat{a}(t) = \sum_{n=1}^{N} w_n r(t - (n\,\tau_a)) \tag{7}$$

Note that if the dynamical modulation is known or can be estimated sufficiently, an optimal weighting function can be constructed. Sadly, we rarely know the time course of artifact modulation in advance. Furthermore, the dynamical system governing the modulation can be difficult or impossible to estimate. There are several options to approximate the dynamical system, and justify a generic weighting function.

2.2.1 Linear Weighting

One solution is by linearization, e.g. using a linear decreasing weighting function. This can be implemented by using the triangular number $T_N = \frac{N(N+1)}{2}$ for a given N as a normalizing constant. Hence, equation (8) returns weights for earlier periods based on their linear temporal delay.

$$w_n = \frac{2(N+1-n)}{N(N+1)} \tag{8}$$

2.2.2 Exponential Weighting

Motivated by the fact that exponentials are an essential building block of signal processing, an alternative approach could be an exponential weighting function. The time constant τ_e of an exponential controls its decay across time. To maintain the shape across different N, we consider it reasonable to normalize the time constant τ_e by N (**??**). Hence, equation (9) returns weights for earlier periods based on their exponential temporal delay.

$$w_n = \frac{e^{nx}}{k} \tag{9}$$

with

$$k = \sum_{n=1}^{N} e^{nx} = \frac{1-e^{Nx}}{1-e^{x}} - 1 \tag{10}$$

$$x = \frac{\tau_e}{N} \tag{11}$$

2.2.3 Gaussian Weighting

An alternative approach could be an exponential weighting function.

number $T_N = \frac{N(N+1)}{2}$ for a given N as a normalizing constant and scale the relative weight of an earlier period by its temporal delay n (12).

$$w_n = \frac{2(N+1-n)}{N(N+1)} \tag{12}$$

2.3 Computational Implementation

We implemented the approach by construction a kernel with the respective weights in period length distance. This kernel can subsequently be used to remove the artifact by convolution. Short of changing the weighting function (7), the key parameter to tune the kernel is number of periods N.

Consider an exemplary

For offline analysis, and to keep the kernel causal, we centered it by left-padding with zeros. Depending on the number of periods,

3 Evaluation

4 Conclusion

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