

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 separable 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). It has been argued that unregularized spatial filters might be able to remove this amplitude modulation (Neuling et al., 2017). But if only few channels are recorded, the method can fail, as the estimation of the spatial covariance is insufficient, or impossible in the single-channel-case. 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 artifact of tACS resembles a sinusoid. Yet, practical experience suggests that the signal is usually distorted to various degrees. Figure 1 shows examples of distortion and saturation in two recordings of tACS-EEG. The gray traces indicate nine individual periods, while the red trace indicates their average. In figure 1a, note the periodic, yet non-sinusoidal waveform. In figure 1b, note the saturation.

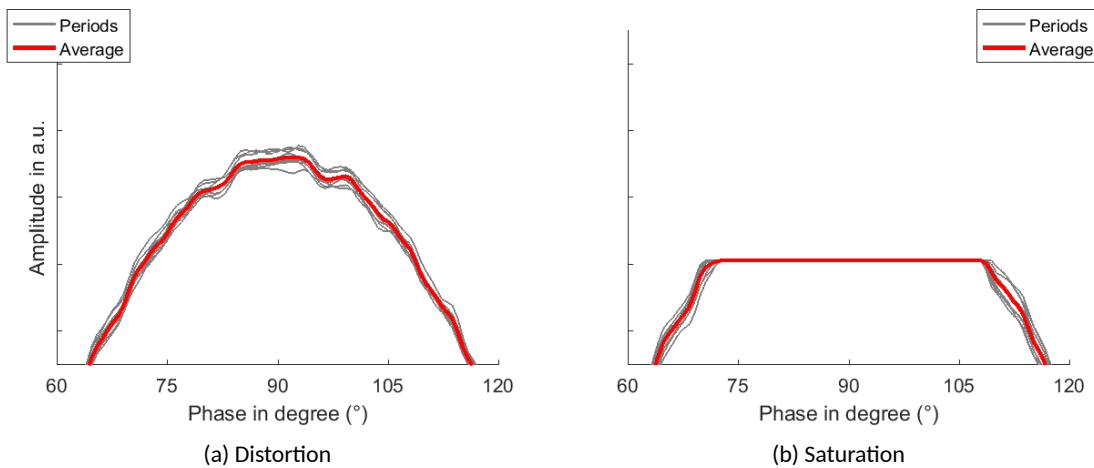


Figure 1: Examples for loss of sinusoidal fidelity

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 too large for the dynamic range of the amplifier, causing the signal to be cut off and information to be lost. Additionally, non-linearities in the amplifier slew rate can distort the shape even when the signal is close to the saturation threshold. Recently, non-linearities in how stimulators control the applied current have been suggested as further source of modulation (Neuling et al., 2017).

1.4 Computational Demands

Methods based on adaptive template construction and temporal principal component analysis (tPCA) (Niaz 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 subsequent 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 $r(t)$.

$$r(t) = n(t) + a(t) + e(t) \quad (1)$$

$$n(t) = r(t) - a(t) - e(t) \quad (2)$$

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. Then, we could estimate the amplitude of a at any time-point t by using the recorded signal r any tACS one period length p earlier (3). Subtraction of a delayed version of the signal is also known as comb filter. Please note that for discretely sampled signals, this approach only works if the frequency of the artifact is an integer divisible of the sampling frequency.

$$\hat{a}(t) = r(t - p) \quad (3)$$

2.1.1 Uniform Comb Filter

Consider that white noise term e is still superpositioned on r . Because white noise $\langle e \rangle$ converges asymptotically to zero with increased sample size, an approach to estimate the artifact amplitude could be to average across as many earlier periods as possible (4). Subsequently, this estimate can be used to remove the artifact from r . In real applications, stimulation duration is limited and computational constraints exist. This is reflected by the fact that we have to use a finite number for N .

$$\hat{a}(t) = \sum_{n=1}^N \frac{r(t - np)}{N} \quad (4)$$

2.1.2 Superposition of Moving Averages

Please note that averaging across neighbouring periods M (5) has been suggested before and termed superposition of moving averages (SMA) by Kohli and Casson (2015).

$$\hat{a}(t) = \sum_{n=M/2}^{n+M/2} \frac{r(t - np)}{M + 1} \quad (5)$$

Consider that the approach using only past values (4) returns a causal filter. Applied online, a causal filter would be able to remove the artifact without the delay of $(Mp)/2$ necessary for SMA. Furthermore, SMA is well-defined only for even M . This motivates the exploration of causal filters for artifact removal.

2.2 Decay Weighting

More importantly, the artifact amplitude has been described to be non-stationary and dynamically modulated (Noury et al., 2016; Neuling et al., 2017). For real applications, equation (4) can therefore return a biased estimate, depending on whether the integral of this modulation over the time-period $N \times p$ converges to zero. One attempt to tackle with this issue can be the use of a time-dependent weighting function instead of a constant N (6), with the weighting function designed to reduce a possible bias.

$$\hat{a}(t) = \sum_{n=1}^N w_n r(t - np) \quad (6)$$

2.2.1 Justification

If the dynamics behind the modulation of the artifacts amplitude are known or can be estimated sufficiently, an optimal weighting function can be constructed. Although it has been suggested that there are event-dependent component of the amplitude modulation (e.g. by heartbeat or respiration Noury et al. (2016) or stimulator impedance check Neuling et al. (2017)), the dynamical system governing the event-independent amplitude modulation are usually unknown.

One approach to model such a unknown dynamical system is with a Lévy-process. The key characteristics of such a process is that it is governed by randomness of the change between time-points. The increments are independent from each other, and are sampled from a continuous probability distribution with is stationary for the whole duration of the process. In that framework, the uncertainty of the estimate changes as a function of lag.

Consider for example a simple comb filter, where we remove the artifact by subtracting the value sampled from any earlier period. Assume now that this values is drawn uniform at random from the last N periods.¹ If the system is fully stationary for the last N periods, performance is virtually identical to the comb filter based on averaging (4). If it is governed by a Levy-Process (at least for the last time-points N), the precision of the estimate degrades as a function of the delay. This rationale justifies non-uniform weights. In the case of the uniform sampling, we have a single shape parameter N , defining how far back we trust a measurement to have the same precision as earlier samples. By controlling the shape parameters of alternative weight functions, we might better match the Levy-Process governing the system. This might allows us to achieve a better artifact estimation and subsequent removal.

The qualifying criteria for these weighting functions are that the sum of all their weights should be equal to one. This keeps the weighting function in agreement with the average (4), returns an unbiased estimate in the case of full stationarity, and keeps the filter stable. In the following sections, we will discuss three weighting functions.

2.2.2 Linear Weighting

One approach is linearization, e.g. using a linear decreasing weighting function. One justification for this approach might be, that dynamical systems are often locally linear. The necessary normalization can easily be implemented by using the triangular number for a given N as normalizing constant k (8). Hence, equation (7) returns weights for earlier periods based on a linear temporal weight decay.

$$w_n = \frac{N - n + 1}{k} \quad (7)$$

with the following normalization

$$k = \sum_{n=1}^N n = \frac{N(N+1)}{2} \quad (8)$$

2.2.3 Exponential Weighting

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

¹Note, that in the case of full stationarity for the last N periods, its expected performance in the long is expected to be similar to averaging

$$w_n = \frac{1}{k} e^{\tau - \tau(n/N)} \quad (9)$$

with the following normalization

$$k = \sum_{n=1}^N e^{\tau - \tau(n/N)} \quad (10)$$

2.2.4 Gaussian Weighting

Assuming the the precision of the estimate decreases over time, a sampling-distribution rationale motivates a Gaussian weighting function. Using a suitable parameterization, and centering on zero, the inverse of the standard deviation $\frac{1}{\sigma^2}$ defines the time constant τ of a Gaussian distribution, which controls its decay. To maintain the shape across different N , we consider it again reasonable to normalize n by N . Hence, equation (11) returns weights for earlier periods based on their exponential temporal weight decay.

$$w_n = \frac{1}{k} f(n/N) \quad (11)$$

with the following generating function and normalization

$$f(x) = \sqrt{\frac{\tau}{2\pi}} e^{-(\tau x^2)/2} \quad (12)$$

$$k = \sum_{n=1}^N f(n/N) \quad (13)$$

2.3 Computational Implementation

We implemented functions for kernel creation in Matlab 2016b on a Windows 10 machine². First, we constructed a kernel based on the respective weighting functions (6) and desired memory, or number of periods N . This kernel was then used to remove the artifact in a recording by convolution. We wanted to evaluate the behavior of the filter in off-line analysis on simulated and real data and decided to use zero-padding for ease of computation.

2.3.1 Exemplary Kernels

Peruse the following exemplary kernels constructed for a sampling rate of 1KHz, a stimulation frequency of 10 Hz and a periodic memory of 10. Please note that we intended to test the approach in offline analysis. To keep the kernel causal, we centered it by left-padding with zeros.

As you can see from figure 2, the (numerically calculated) magnitude responses of the three approaches are highly similar. Their key characteristic is the strong suppression of signals at the target frequency and its integer multiples. Yet, note the slightly higher ringing in the passband for the average combing kernel 2a compared to e.g. the smooth transition for the exponential weighted kernel 2c.

2.3.2 Code Repository

3 Evaluation

4 Conclusion

Negative weights This paper only dicusses real filter weights real, but complex weights might be a solution to tackle artifacts with periods that are not integer divisibles of the sampling frequency.

²<https://github.com/agricolab/ARTACS>

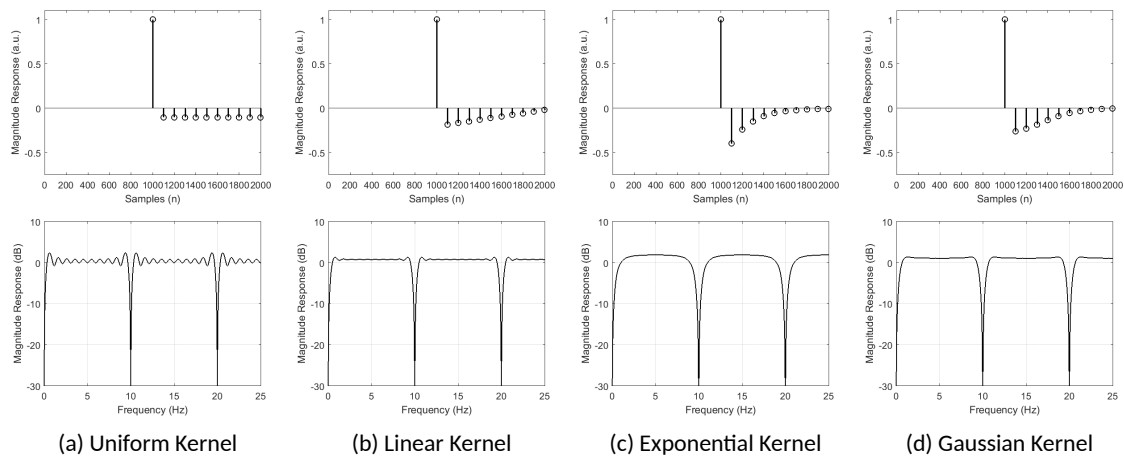


Figure 2: Exemplary Weighted Kernels

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