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A theoretical limit and simulation of time-domain event detection in the EEG*

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Abstract— **Scalp recordings of cortical activations, Electroencephalography (EEG), are commonly used clinically to detect diseases or injuries to the underlying cortical physiology. Unfortunately, the EEG signal is also artifact prone and these artifacts can exhibit a similar temporal and spectral profile as that caused by the potential disease. We have created a model of simulated (synthetic) EEG and artifacts to explore their interplay and the theoretical limits of detection when artifacts may not be separable from clinical events of interest. A theoretical limit of separation without an EEG signal is derived and then simulated upper bounds for time-domain event detection are created using simulated EEG data.**

I. INTRODUCTION

The EEG began widespread clinical use in the 1950-1960's [1, 2] and automated analysis began in the 1960s [3, 4]. By the 1970's digital analysis of the EEG showed enough promise that researchers began investigating automated detection of events [5, 6, 7]. While many of these event detectors had efficacy that was useful, they were not widely accepted for a variety of reasons. One of the primary reasons was that the detectors had difficulty in distinguishing artifact from clinical event.

Many early interpretations of the EEG focused on graphical representations of the recorded data. These methods are still widely used to assist trained experts in interpreting very complicated signals [3, 8, 9, 10]. More recent automated analyses of EEG signals has focused specifically on removing artifacts from the signal or ignoring periods of artifact before applying other algorithms. These approaches have shown better success in clinical efficacy [11, 12]. When an event detector has difficulty distinguishing a common artifact from a rare event, the false alarm rate becomes much higher than the correct detection rate. This phenomenon has become prevalent in clinical EEG and, as a result, the users of the automated systems commonly ignore alerts for event detection [13]. By exploring the limits based on these potentially inseparable artifacts, we seek to explain this phenomenon and discuss ways that it can be alleviated and improved.

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Given the level of development in artifact rejection algorithms, the correct detection of applicable events is generally limited by the amplitude of artifacts in the signal. Here, we provide support that this limitation can be described within a theoretical framework. Correct detection poses unique challenges when artifacts are present due to the similar temporal and spectral profile of this content within the EEG signal. These artifacts cannot easily be removed from the signal and thus a theoretical limit will be reached for correct detections compared to false positives. This limit is dependent on the power of the baseline EEG relative to power of the artifacts and events. This study derives such an upper limit using a simulated model of EEG and artifacts (synthetic data). First a theoretical limit for separation of events and artifacts is derived without EEG, with both events and artifacts modeled as Gaussian random variables in time-domain. Next a model of simulated EEG data as a random walk process is created, and it is determined that artifacts have negligible effect on event-detection relative to the EEG signal at below about −6 dB SNR. At higher artifact levels, the model reveals an upper bound on how well time-domain event detectors can be expected to perform, at different signal-to-noise ratios of events, artifacts and EEG signal.

II. METHODS

A. Theoretical limitation of time-domain event detection

The signal of interest was created assuming that the samples of the event and the artifact were given by independent Gaussian random variables, i.e., Gaussian white noise. The standard deviation of each random variable thus determined the RMS power of each signal. For an actual signal classifier in time domain, event detection could be performed by applying a threshold to the rectified signal. However, for the purposes of the theoretical bound (1) the ongoing EEG was assumed to be zero, (2) true positives were scored as any event samples that occurred above a given threshold level and (3) false positives were scored as any artifact samples that occurred above the same threshold. Thus, true positives and false positives were both given by the Gaussian cumulative distribution function for the event and artifact random variables, respectively.

B. Simulation of event detection within ongoing EEG

The EEG was assumed to be a random walk process [14, 15, 16]. For each event and artifact level, 20 repeats of 65 seconds (2^{16} samples) at 1 kHz sampling rate were used. The duration and number of repeats were chosen so that the standard error of the mean for receiver operator characteristic

(ROC) curves was below 1% rate. The sampling rate was chosen arbitrarily, however the only requirement for our purposes was that the rate exceeded the Nyquist frequency rate for the frequency range of interest. The random walk process for the ongoing EEG was created as a cumulative sum of a uniformly distributed variable (Matlab `rand`), where the limits of the distribution determined the power of the EEG. The EEG was then filtered (Butterworth, 10th order, Matlab SOS filter) to the frequency range of interest for the EEG (0.1 - 100 Hz). The ongoing EEG was then summed with the artifact for half of the time period and with the event for half of the time period, that is for 32 seconds each (2^{15} samples) such that the added artifact and event were not overlapping. The standard deviation of the "event" for the simulation thus represented the combined contribution of both the event and the artifact during the event duration. This method was chosen instead of merely adding the artifact for the entire duration because 0 dB for both event and artifact conveniently represents an event that is effectively undetectable above chance from the artifact. This was consistent with 0 dB defined in the derivation of the theoretical limitation. Event detection was performed strictly in time domain by applying thresholds on the rectified signal in order to create the ROC curves. Any samples that exceeded a particular threshold were considered events. False positives were scored when an event was detected outside of the time period containing the event random variable.

III. RESULTS

A. Theoretical limitation of time-domain event detection

As a first approximation as to the utility of a time domain event detection procedure, both the event and artifact were treated as Gaussian random variables and receiver operator characteristic (ROC) analysis was applied. In this case the ongoing EEG is assumed to be zero and both event and artifact are samples of two different Gaussian random variables with zero mean and different variances. The variance of the artifact is assumed to be less than or equal to that of the event. The standard deviations of event and artifact random variables thus are equal to the RMS level of the event and artifact signals respectively. An event is detected when the rectified signal exceeds a threshold. The threshold is then used to parameterize the ROC curve as

$$ROC = \left[\Phi\left(\frac{t}{\sigma_{artifact}}\right), \Phi\left(\frac{t}{\sigma_{event}}\right)\right], \quad \text{for } t \geq 0, \quad (1)$$

where t is the time-domain threshold, $\sigma_{artifact}$ and σ_{event} are the RMS power of the artifact and event signals (also standard deviations of the Gaussian random variable distributions) and Φ is the standard normal cumulative density function. Sample ROC curves at different signal to noise ratios for the event relative to the artifact are shown in Fig. 1A. The parameterized ROC curve is then integrated with respect to the false positives (the dependent variable) to obtain the area under the ROC curve (AUROC).

$$AUROC = 4\int_0^\infty \Phi\left(\frac{t}{\sigma_{event}}\right)\phi\left(\frac{t}{\sigma_{artifact}}\right)dt, \quad (2)$$

where ϕ is the standard normal probability density function. The solution to the integral demonstrates that the area under the ROC curve is simply a function of the ratio of the standard deviations of the random variables, given by

$$AUROC = \frac{2}{\pi}\,\mathrm{ArcTan}\left(\frac{\sigma_{event}}{\sigma_{artifact}}\right). \quad (3)$$

Because the ratio given in eq. 3 represents the signal levels, the solution to the area under the ROC curve can be given as a function of the ratio of event to artifact levels in dB (Fig. 1B). This solution offers an upper bound to how well any time domain EEG event detection can perform under the assumption that the event itself and the artifact both have Gaussian statistics. Next it is demonstrated that the addition of a more realistic EEG signal affects the potential performance of a time domain threshold technique for detecting events embedded in the artifact noise.

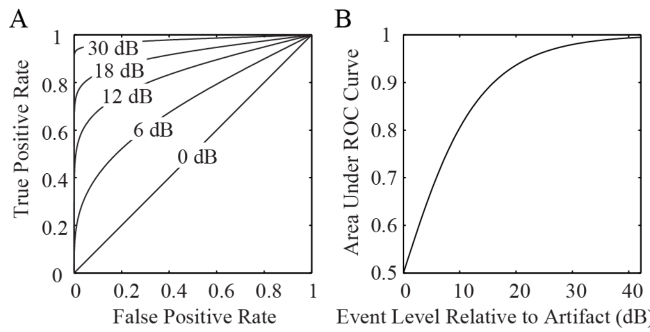

Fig. 1. Theoretical limit on time-domain event detection in EEG. (A) ROC curves at different levels of event relative to artifact. At 0 dB, detection is at chance. (B) Area under ROC curve as a function of event level relative to artifact.

B. Simulation of event detection within ongoing EEG

As a first order approximation of the ongoing EEG, the EEG is simulated as a random walk process. The power spectral density of a random walk signal is proportional to $1/f^2$ [17]. The random walk is filtered to the appropriate range for the EEG signal. This results in a signal (Fig. 2A) with power spectral density matching a power law, roughly bounded by 1/f and $1/f^2$ (dark lines in Fig. 2B).

The ongoing EEG is added to event and artifact at different levels relative to the EEG (Fig. 3). Event detection is then performed in time domain using a threshold to the rectified signal. The level during the event duration is chosen (see Methods) such that ROC analysis parameterized by this threshold again performs at chance (area under ROC is 0.5) when the event and artifact both have the same signal power of 0 dB relative to the ongoing EEG. At a fixed artifact level of 0 dB relative to the EEG, the performance of the event-detector improves with increasing event level (Fig. 4A). Comparing Fig. 1A and Fig. 4A highlights that this does

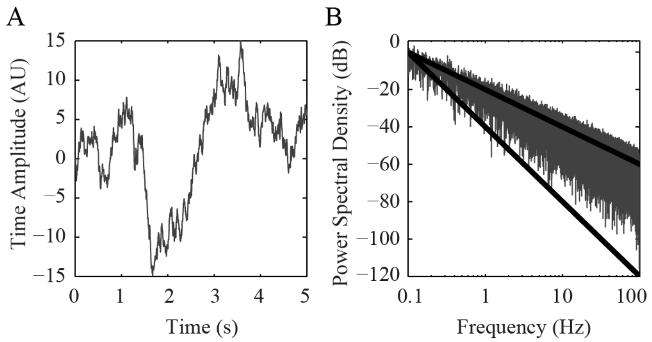

Fig. 2. Sample simulated EEG modeled as random walk. (A) Sample time-amplitude waveform of stimulated random walk EEG filtered between 0.1-100 Hz with arbitrary units (AU) for amplitude. (B) Power spectral density of simulated EEG from (A) with general trend between 1/f (top line) and 1/f2 (bottom line).

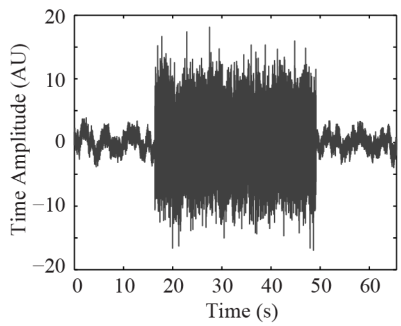

Fig. 3. Sample simulated EEG with artifact (−6 dB) and containing simulated event (12 dB) in the middle half of the duration with arbitrary units (AU) for amplitude.

not occur at the same rate as in the theoretical performance given by eq. 3. This is due to the effect of the ongoing EEG itself triggering false positives in addition to those triggered by the artifact alone. A direct comparison of the theoretical limitation of detecting events in artifact only (dashed line labeled "No EEG" in Fig. 4B) and detecting events in combined ongoing EEG and artifact (line labeled "0 dB" in Fig. 4B) directly demonstrates the reduced performance of time-domain event detection under these more realistic conditions. Comparison with the 0 dB artifact condition is shown so that the x-axes from the two plots are equivalent, i.e., the levels of the ongoing EEG and the artifact are matched relative to the level of the event. Decreasing the artifact level improves the performance of the detector (lines labeled "−6 dB" and "−12 dB" in Fig. 4B). For artifact levels below approximately −6 dB relative to the EEG, the artifact did not have much effect on the signal detection. This could represent situations where the artifact is simply due to line noise or low-level biological noise (for example, EMG or EKG). This would not apply to more realistic situations where the artifacts are likely to include higher levels of biological noise. Thus, given parameters that more typical for clinical usage of EEG event detection, our simulation provides an estimate as to the best a time-domain event detector can be expected to perform.

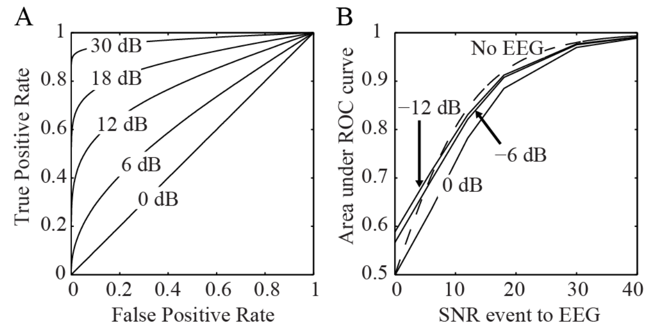

Fig. 4. Limit on time-domain event detection in EEG based on simulated EEG data. (A) ROC curves at different levels to event relative to EEG with constant 0 dB artifact relative to event level. At 0 dB, detection is at chance. (B) Area under ROC curve as a function of event level relative to EEG. Multiple curves are shown at different artifact levels relative to EEG. For comparison, curve from theoretical limit (Fig 1A) overlaid to demonstrate that for the same artifact level (0 dB) the time-domain event detection cannot exceed this theoretical limit when the EEG is present.

IV. DISCUSSION

This model was created to explore the interplay between events and artifacts with similar statistics. Of particular interest is how this may affect the performance of commercial-style event detectors that primarily rely on time-domain analysis. These results show that if artifacts are modeled as additive and containing the same time-domain statistics, then the outputs of these detectors show poor performance. In particular, at above about −6 dB SNR between events and artifacts, the performance upper bound of time-domain detectors is limited. This finding is limited to real-world application under the assumptions of the model that (1) EEG is given by a random walk process; (2) events and artifacts are given by Gaussian random variables in time-domain; (3) the EEG, events, and artifacts are additive and (4) event detection is performed by thresholding the signal in time-domain. Although these may be simplifying assumptions for a strong statement regarding EEG event-detection in time-domain, this is anticipated to serve as a basis for future work. By exploring the ways that artifacts are statistically different from the EEG and events, both in time-domain and in frequency-domain, methods with better performance could potentially be designed.

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