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Short-time windowed covariance: A metric for identifying non-stationary, event-related covariant cortical sites

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HIGHLIGHTS

- Short-time windowed covariance (STWC): a metric quantifying temporal relationships of cortical activity.
- STWC shows event-related increases in cortical signal covariance.
- Applied STWC to human electrocorticographic (ECoG) signals recorded from the cortical surface.
- Demonstrated temporal directionality in high frequency ECoG during finger flexion.
- A software implementation of STWC that uses consumer graphics processing units (GPUs).

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ABSTRACT

Background: Electrocorticography (ECoG) signals can provide high spatio-temporal resolution and high signal to noise ratio recordings of local neural activity from the surface of the brain. Previous studies have shown that broad-band, spatially focal, high-frequency increases in ECoG signals are highly correlated with movement and other cognitive tasks and can be volitionally modulated. However, significant additional information may be present in inter-electrode interactions, but adding additional higher order inter-electrode interactions can be impractical from a computational aspect, if not impossible.
New method: In this paper we present a new method of calculating high frequency interactions between electrodes called Short-Time Windowed Covariance (STWC) that builds on mathematical techniques currently used in neural signal analysis, along with an implementation that accelerates the algorithm by orders of magnitude by leveraging commodity, off-the-shelf graphics processing unit (GPU) hardware.
Results: Using the hardware-accelerated implementation of STWC, we identify many types of event-related inter-electrode interactions from human ECoG recordings on global and local scales that have not been identified by previous methods. Unique temporal patterns are observed for digit flexion in both low- (10 mm spacing) and high-resolution (3 mm spacing) electrode arrays.
Comparison with existing methods: Covariance is a commonly used metric for identifying correlated signals, but the standard covariance calculations do not allow for temporally varying covariance. In contrast STWC allows and identifies event-driven changes in covariance without identifying spurious noise correlations.
Conclusions: STWC can be used to identify event-related neural interactions whose high computational load is well suited to GPU capabilities.

1. Introduction

Electrocorticographical (ECoG) recordings have provided the computational neuroscience community with unprecedented spatial and temporal resolution of brain activity. Because of the high signal-to-noise ratio and single-trial fidelity, ECoG is increasingly explored in a variety of tasks, including motor function. ECoG has been shown to be a viable control signal for use in brain–machine interfaces (Pfurtscheller et al., 2000; Wolpaw et al., 2003; Miller et al., 2008; Blakely et al., 2009; Brunner et al., 2011; Leuthardt et al., 2011) and is also used during cortical mapping (Crone et al., 1998, 2006; Sinai et al., 2005; Hermes et al., 2012; Wray et al., 2012). Though the neuroanatomy underlying the signals recorded by ECoG are up for discussion (see Crone et al., 1998; Sarnthein

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et al., 2003; Miller et al., 2007), there are measurable characteristic changes that are highly correlated with local neural activity nonetheless.

Characteristic spectral changes have been identified that are robust across patients, experimental methods, and brain areas. Decreases in low-frequency ("beta", "mu" and "alpha" ranges) are seen over large areas of cortex during motor movement, while broad-band high frequency increases occur in spatially focal areas that have been previously associated with their respective movement (Sinai et al., 2005; Crone et al., 2006; Miller et al., 2007, 2009, 2010; Blakely et al., 2008).

Because the brain is highly connected and these broad-band increases are not limited to one area of the brain (Darvas et al., 2004; Anderson et al., 2013; Wander et al., 2013), it is only natural to assume that areas of the brain interact and communicate information.

One of the most prominent issues with exploring multi-electrode interaction is the issue of dimensionality explosion. Calculating a metric for any permutation of two channels is a large space to explore, and adding additional parameters to explore can increase the number of calculations by an order of magnitude or more. For example, checking 5 frequency bands across pairs in a total of 64 electrodes requires 20,480 separate calculations. If the time required for each calculation is even as short as a single second, performing such a calculation would take upwards of 6 h in total.

This effect is compounded when looking for non-stationary, event-related correlations. The human brain operates in a highly redundant, parallel fashion; action potentials and synaptic neurotransmitter release occurs in nearly all regions of the brain. That does not exclude forms of cortical synchronization such as thalamocortical rhythms, commonly implicated in motor control (Sinai et al., 2005; Miller et al., 2009, 2010), but it is entirely possible that areas of the brain can initiate transfer of information from one area to a spatially remote area via a transiently-activated network, only to cease communication over this pathway once the information transfer is complete. To identify these event-related interactions, it is necessary to do finer-scale calculations by dividing the data up into smaller sections. Many algorithms make the assumption that brain areas are continuously correlated due to computational constraints, which would likely not illuminate short timescale event-related correlations.

We present a new method of exploring high dimensional cortical data under the assumption that event-related high frequency increases in one area of cortex are closely correlated with a remote area for only short periods of time. Short-time windowed covariance (STWC) is a measurement of lagged covariance of two signals over a short time period. Calculating the covariance of two recorded signals implies that the two recorded signals are continuously correlated during that time period. STWC, as its name implies, calculates the covariance over a short window lagged by $\pm\,\delta$ samples. This window is recalculated along every time point recorded for every pair of channels, across a number of different lags (δ). Exploring such a high dimensional space has a high computational load associated with it; to solve that problem, we provide an implementation of the algorithm on a consumer-grade graphics processing unit (GPU) commonly found in desktop computers today. Repurposing GPU hardware (originally designed to do streaming manipulation of geometric primitives) allows us to take advantage of the massively parallel architecture available within the chipset, greatly speeding up the algorithm. By leveraging hardware acceleration, exploring high dimensional spaces with STWC is no longer impractical nor impossible.

2. Method

2.1. Short-time windowed covariance (STWC)

STWC calculates covariance measures (with the option to normalize to correlation) over two signals at every time point. A covariance calculation is performed with a small sample window of the source channel centered on sample t with multiple windows of the remote channel:

$$Q(x, y, t, \tau, \delta) = \sum_{i=t-\frac{\tau}{2}}^{t+\frac{\tau}{2}} \frac{(x_i - \bar{x})(y_{\delta+i} - \bar{y_\delta})}{\tau + 1} \tag{1}$$

where x and y are the source and destination channels, τ is the window size, and δ is the number of samples the window by which y is shifted. This calculation is performed over the permutation of possible channels x and y, with each pair iterating through all possible samples of t, for each lagged value δ from the desired lag window of $[-\Delta,\Delta]$ (see Fig. 1). It is easy to see that while the complexity of an individual calculation is low, the number of possible combinations of parameters can be extraordinarily large.

The selected windows in the second channel are the same length of the source channel's window but shifted from $-\delta$ to δ, giving $2 \times \delta + 1$ covariance measures for each sample point t.

While at first glance it would appear that cross-covariance and STWC would give similar answers given that the method deals with lagged windows of data, they answer fundamentally different questions. Cross-covariance takes time-locked signals at the same time point and shifts them forward and backward in time, asking the question "what is the covariance between signals x and y, taken from the same sample, if we shift them in time?". In contrast, STWC provides a measurement of how covariant two signals are over time when one is lagged by δ samples, asking "what is the covariance between two windows from x and y when a window of data is taken at time point t and one is taken at sample $t+\delta$, over the range $\delta = [-\Delta,\Delta]$?" By keeping the two signals being compared at a fixed lag and computing over each sample, STWC computes correlated activity in one channel relative to another on a given timescale and allows the strength of this covariance to change over time.

One of the largest advantages to this measurement is that covariance is a well-understood and widely known mathematical technique that has been widely used in previous neuroscience studies (Crone et al., 1998; Mechelli et al., 2005; Wang et al., 2010). STWC builds on covariance by calculating values on short segments of data allowing the covariance to change over time. This is the key factor when looking for remote interactions of correlated neural activity: brain-regions that are not normally covariant but become correlated only around an event that requires coordination between two or more areas of cortex.

2.2. CUDA

STWC is calculated in such a way that each calculation of parameters is independent for all values of t, τ and δ. Therefore each covariance calculation can be computed simultaneously and in parallel, a form of parallelism known as *embarrassingly parallel*. In contrast to modern computer processors that have two or four cores – units capable of simultaneous computation – modern graphics processor units (GPUs) have hundreds of cores, giving them the capability to perform embarrassingly parallel tasks orders of magnitude faster. Though their core count often comes with trade-offs like limited memory and the inability to change programs mid-execution, they are particularly well suited to perform vector calculations on large amounts of input data; exactly the type of computation required by STWC.