A Simulation-Based Comparison of Methods for Analyzing Aperiodic Neural Activity

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Electrophysiological field data is comprised of both periodic components — neural oscillations — and aperiodic activity, sometimes called scale-free or 1/f activity. Investigations of aperiodic activity have established that it is dynamic and systematically varies within and between individuals, and relates to aging, and task performance. Currently, however, there are a wide variety of conceptual frameworks and methods for interpreting and analyzing aperiodic activity, the relationships between which are unclear. Here, we evaluate extant methods for measuring aperiodic activity in neural data. We briefly summarize available methods, focusing on spectral fitting approaches. We introduce simulation procedures for creating statistically representative neural time series and power spectra. Using simulations with known parameters, we systematically compare available methods, testing those that measure aperiodic activity by fitting 1/f properties in neural power spectra. We find that the most accurate approach is one that explicitly parameterizes neural power spectra. We highlight future plans for extending this framework to explore other available methods, aimed at defining best practices for measuring aperiodic neural activity, and seek to consolidate across currently disparate approaches.

Keywords: electrophysiology; time series analysis; aperiodic activity; 1/f process; scale-free;

Introduction

A key goal of the interaction between cognitive and computational neuroscience is to productively map between the concepts explored in computational and theoretical neuroscience and the measures applied to empirical data. Here we investigate the topic of aperiodic electrophysiological neural activity, which refers to non-periodic signal that commonly decreases in magnitude with increasing frequency, often described as 1/f (or '1/f-like' activity). This aperiodic activity is a major component of electrophysiological field data that has traditionally been under-studied. Here we investigate a number of methods used for quantifying aperiodic activity, employed across differing theoretical frameworks, using simulated data with known ground truth parameters.

Correlates of Aperiodic Neural Activity

Aperiodic neural activity is a dynamic signal, with demonstrated demographic, clinical, cognitive, and physiological correlates. Aperiodic components have been shown to track age (Voytek et al, 2015a), clinical diagnoses (Voytek et al, 2015b), task performance (Podvalny et al, 2015; Waschke et al, 2017), and excitatory-inhibitory balance (Gao et al, 2017). That aperiodic neural activity is dynamic within and between subjects, with a range of correlates, makes it an interesting physiological signal to study. It is also important to note that periodic and aperiodic properties can be easily confounded in many existing analysis approaches, potentially leading to mis-interpretations (Haller et al, 2018), making the methods used for quantifying the aperiodic signal critical.

Theoretical Interpretations

Aperiodic neural activity has been analyzed under multiple conceptual frameworks. Some approaches seek to explore and explain aperiodic activity in terms of physiological models of putative generators of field data (Freeman & Zhai 2009; Gao et al, 2017). Other investigations consider aperiodic activity in terms of the variability, and/or level of 'neural noise' in the system (Voytek et al, 2015a; Waschke, 2017). More functional frameworks also focus on aperiodic activity as a scale-free phenomenon (He, 2014), focusing on fractal properties and self-similarity (Eke et al, 2002;

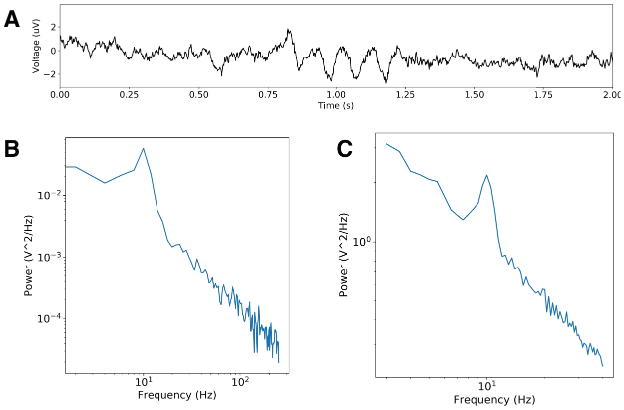

Figure 1: Simulations. A) A simulated time series, with an intermittent 10 Hz oscillation, and a 1/f aperiodic component. B) The power spectrum calculated from A. C) A directly simulated power spectrum, simulated with a 10 Hz peak, and a 1/f aperiodic component.

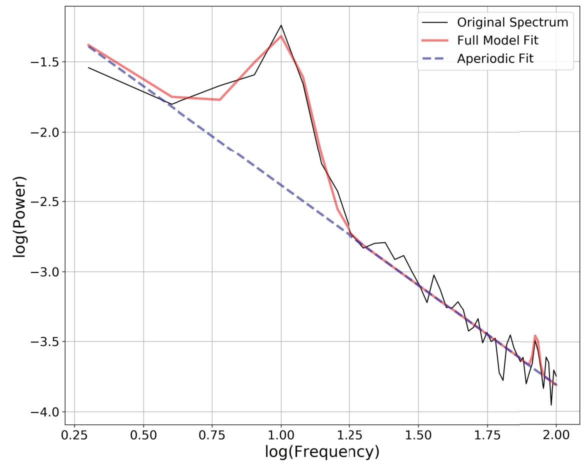

Figure 2: Parameterizing Neural Power Spectra. The parameterized power spectrum from Fig. 1B.

Schaefer et al, 2014) and/or long-term dependencies in time series and/or critical states in dynamical systems (Palva et al, 2013). A full comparison of the conceptual frameworks and interpretations is out of scope of this paper, however future work can use the investigation of the different methods as a way to map between similarities and differences across these conceptual frameworks.

Methods for Measuring Aperiodic Activity

Though there are many methods for measuring aperiodic activity, there are some particular properties of neural time series that need to be considered for any applied methods. The first is that neural time series contain both aperiodic and periodic components —or neural oscillations—that are also variable and diverse. Any method for measuring aperiodic properties of neural data must be robust in dealing with and controlling for periodic components in the data. Another important aspect of neural time series is that aperiodic neural activity is not truly 1/f. Neural signals have regions that are 1/f-like, but they also exhibit 'knees', or frequencies at which the 1/f-like nature of the signal 'bends' (Miller et al, 2009). Methods for measuring aperiodic neural activity must therefore be robust to variations in the 1/f-like properties of the aperiodic activity.

Methods also need to be robust to noise, where noise refers to non-signal components in the sense of artifacts and/or machine noise, and not to statistical noise such as the 1/f itself. Additionally, methods should ideally be computationally efficient so that they can be applied at scale to increasingly large datasets. Finally, methods should ultimately allow for temporally-resolved estimates of the aperiodic signal so that they can be used to analyze task data and other temporal dynamics of aperiodic activity.

Methods

We simulated time series and also separately directly simulated neural power spectra, with neurally-plausible statistics. All data was simulated to have $1/f^{\chi}$ properties. We then evaluate several methods for estimating aperiodic properties, focusing on spectral fitting measures, and evaluate their performance based on their ability to reconstruct the parameter χ, henceforth referred to as the aperiodic exponent.

Simulations

Time series were simulated as combinations of aperiodic and periodic activity. Single 1/f time series were simulated by creating white noise, calculating and then rotating the power spectrum to a specified aperiodic exponent, and applying an inverse Fourier transform (Timmer & Konig, 1995). In another set of simulations, aperiodic activity with a 'knee' was simulated using a physiological model that combines simulated excitatory and inhibitory post-synaptic potentials, giving a 1/f-like signal with a 'knee' (Gao et al, 2017). Simulations including periodic components were created by additively combining aperiodic signals with simulated periodic signals, using different periodic kernels with varying amplitude, frequency and waveform shape characteristics. All time series simulations were generated using the NeuroDSP Python toolbox (Cole et al, 2019).

Power spectra were simulated with an aperiodic component with overlying peaks, reflecting oscillations. Aperiodic components were simulated as exponential functions, and combined with periodic components that were simulated as gaussians. White noise was also added to the power spectra across all frequencies. All power spectra were simulated using the equations and code described in the FOOOF toolbox (Haller et al, 2018).

Aperiodic Estimation Methods

Spectral Line Fitting We employed a series of spectral fitting methods, in which the aperiodic exponent is estimated from fitting a line to the power spectrum (Freeman & Zhai, 2009). We tested several proposed variants of this approach including approaches to fit a linear fit of the power-spectrum, in log-log, as an ordinary least squares (OLS) fit, a robust linear model (RLM) fit, and using the RANSAC robust regression algorithm (RAN). We also tested an exponential fit (EXP) of the power spectrum in semi-log, fit as non-linear least squares curve fitting procedure (*scipy.optimize.curve_fit*). All of the above methods were also fit using oscillation exclusions, excluding a fixed alpha region of 7-14 Hz, as has been suggested and done before (Voytek et al, 2015a).

Parameterizing Neural Power Spectra We also applied a recent algorithm for parameterizing neural power spectra (Haller et al, 2018), which is itself an adapted method for spectral line fitting. Briefly, this approach seeks to jointly model the aperiodic signal using an exponential fit, as well as modeling overlying oscillatory peaks, fit as gaussians. It uses an iterative procedure to fit and remove peaks, allowing for a final fit of the aperiodic signal that is fit on a peak-removed version of the original spectrum.

Results

The distributions of errors for each methods' reconstructions of the aperiodic signal are shown in Figure 3. The global best method was the parameterization approach (FOOOF), with a median error of 0.0344. The best spectral fit measure was RAN, with a median error of 0.0542 without alpha exclusions, and 0.0601 with alpha exclusions.

Error distributions were compared using Wilcoxon rank sum statistical tests. All methods are statistically different from each other ($p < 0.001$), except for the OLS and EXP comparisons (with and without alpha exclusions). Excluding fixed alpha bands significantly improved accuracy for all methods ($p < 0.001$) except for RAN, in which it accuracy decreased ($p < 0.001$).

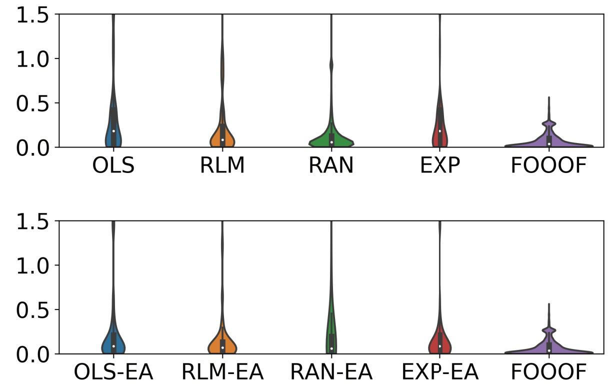

Figure 3: Absolute error of spectral fitting approaches for estimating the aperiodic exponent. Top row: spectral fitting approaches. Bottom row: methods applied excluding alpha region. Note that the parameterization approach, F000F, is reprinted in both rows, for comparison. Each method was evaluated on 3600 spectra across noise levels.

Discussion

Spectral Fitting Methods The current investigation focused on evaluating previously proposed spectral fit measures. On average, median error was fairly low, although the variance was relatively high, indicating that such estimations can sometimes be very inaccurate. The proposal to exclude alpha regions (Voytek et al, 2015a) does improve average errors for most approaches, though does not get rid of the high variance. Though the robust estimation procedure RANSAC is relatively good, surprisingly, it gets worse with alpha exclusions. Overall, however, fitting the aperiodic with a parameterization approach has the lowest average error, and lowest variance, supporting the argument that explicitly and jointly modeling both periodic and aperiodic components is a beneficial approach (Haller et al, 2018).

Method Properties Based on the desired properties for aperiodic methods, the spectrum parameterization procedure is robust to both periodic and aperiodic variations, is robust to noise, and is computationally efficient. However, as it is a measure applied to power spectra, it does not have high temporal resolution, which should be a focus for future work.

Other Aperiodic Methods Methods for measuring aperiodic activity, other than the line-fitting or parameterization approaches described, include resampling time series to estimate the scale-free power spectrum (Wen & Liu, 2016), self-similarity measures such as detrended fluctuation analysis (Schaefer et al, 2014) and information theory measures (Waschke et al, 2017). Ongoing work is currently implementing and testing variants of all these measures against the simulated data, to analyze their accuracy for measuring aperiodic properties, as well as to systematically compare their properties in terms of their robustness to noise, computational efficiency, and temporal-resolution.

Related Work The current approach builds upon and extends recent comparisons of methods that included fewer comparisons, typically focused within one conceptual framework (Eke et al, 2002; Schaefer et al, 2014), and seeks to explore more broadly across methods and include newer approaches.

Future Work As well as exploring additional available methods, future work will seek to use the mapping between employed methods as a grounding for comparing between conceptual frameworks.

Conclusion

Aperiodic electrophysiological neural activity is a prominent and dynamic component of field recordings with many known correlates. Despite this, there is currently no consensus for best practices or comparisons across approaches for quantifying this signal. This is complicated by the many conceptual frameworks that determine the analytical approach used. Here, we use a simulation-driven approach to evaluate the accuracy of, and similarities between, extant methods. We systematically investigate spectral fitting approaches, and show that parameterizing neural power spectra is the most accurate. We note how this simulation testing approach can be extended to cover other methods, which can then allow for a more systematic comparison of the conceptual frameworks involved in aperiodic investigations.

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