#Summary of Papers – LFP Timescales related

*Parameterizing neural power spectra into periodic and aperiodic components – Donoghue et al 2020*

Changes in narrow band frequency power can be misinterpreted as changes in oscillatory power even when no osicallation is present. (fig 1c,d). In The fluctuations that arise from changes in broadband frequecy power or the aperiodic exponent can give rise to identical changes in total narrowband power. In neural data, this aperiodic activity has a 1/f distribution, with exponentially decreasing power across increasing frequencies. This aperiodic component can be characterised by a , refers to the aperiodic exponent. In the log-log space, , wil be equivalent to the negative slope of the power spectrum. In the log-log space, the aperiodic offset, has been found to be correlated with neuronal population spiking. (read papers 13,14). In contrast, the exponent has been related to the integration of the undelying synaptic currents, which have a stereotyped doube-exponential shape in the time domain. Currents with faster time constants, such as excitatory (E) AMPA, have relatively constant power at lower frequencies before quickly decaying. On the other hand, inhibitory (GABA) current power decays are generally slower as a function of frequency. Thus, the decay exponent will have lower values when the E (excitatory currents) >> I (inhibitory currents) and larger values when the reverse is true. Amongst other physiological parameters, aperiod component partially relfects the excitation/inhibition balance (ref 19)

Main result – They gave an alogrithm to estimate the oscillatory and the aperiodic components of neural activity (fooof method). (Fig2) .

The main steps are as follow:

The PSD is first fit with an estimated aperiofic component.

This estimated aperiodic component is then subtracted from the PSD signal which leaves us with the noise and the oscillatory components in the signal.

Next you estimate the noise threshold and find the peaks above this threshold. For each peak, a Gaussian fit is estimated around it and subtracted. This step is iterated untill the maximum number of peaks is found in the signal.

Having identified the number of putative oscillations, based on the number of peaks above the noise threshold, multi-Gaussian fitting is then performed on the aperiodic-adjusted signal from to account for the joint power contributed by all of the putative oscillations together.

This multi Gaussian model is then subtracted from the original PSD. On this subtracted signal, a new fit for the aperiodic component is estimated—one that is less corrupted by the large oscillations present in the original PSD.

This re-fit aperiodic component is combined with the multi-Gaussian model to give the final fit on the original PSD.

Methods : Algorithm parameterization: The algorithm operates on PSDs in semilog space, which is lineary spaced frequeices and log-spaced power values .

The PSD is formulated as a combination of L (aperiodic component) and the summation of gaussian fits to total number of peaks found in the power spectrum.

Focussing on the aperiodic component, L, is modelled using a Lorentzian function written as (Eq1) , where b is the offset , is th exponent and the k is the ‘knee’ parameter. When k is 0, the Eq1 follows example of a line fit in the log-log space where the slope is (-).

The final outputs of the algorithm are the parametrs defining the best fit for the aperiodic components and the N Gaussians.

Understanding the estimation of knee frequency: In the alogorithm, the inintial seed values for offset and exponent are set to the power of the first frequency in the PSD and an estimated slope, calculated between first and last points of the spectrum. Then basically the steps mentioned above to find the final fit is done by the algorithm. Goodness of fit is estimated by comparing each fit with the original power spectrum in terms of the MAE (median absolute error) of the fit as well as the R2 of the fit. The fitting algorithm has some settings that can be provided by the user, one of which defines the aperiodic mode, with options of ‘fixed’ or ‘knee’, which dictates whether to fit the aperiodic component with a knee.

From the online model documentation - (<https://fooof-tools.github.io/fooof/auto_tutorials/plot_05-AperiodicFitting.html#sphx-glr-auto-tutorials-plot-05-aperiodicfitting-py>)

k which is returned from the model is dependent on the frequency at which the aperiodic fit transforms from horizonal to negative slope. To interpret this parameter as frequency, we need to take the xth root of k. Knee frequency =

*Neuronal timescales are functionally dynamic and shaped by cortical microarchitecture - Gao et al, 2020*

The researchers put forward the idea that neural timescales can also be estimated in the frequency domain from the PSD, in addition to the traditonal method of autocorrelation functions. PSDs of neural time series often follow a Lorentzinian function of the form [power = b 1/(,)].(Eq2)

Note here, if I do the log of Eq2, it becoems the form of Eq1. Knee frequency or k reflects the frequency at which the power of the aperiodic component spectra decays or bends to follow a power law. In other word, the power remains approximately constant till the knee frequency, after which it bends to follow a power law (1/f decrease).

From the knee frequency of the aperiodic component, neural timescale (decay constant) can then be computed exactly as .

Timescale can be computed from the parameter k as ., where is approximated to be the ‘knee frequency’, at which a bend or knee in the power spectrum occurs.

(Fig 2) - Timescales inferred from EcoG (using their PSD and fooof method )are consistently approx 10 times faster than single-unit spiking timescales in macaques, corroborating the fact that field potential signals mainly reflect fast trans-membrane and synaptic currents (Buzsáki et al 2012), whose timescales are related to, but distinct from, single unit timescales in previous studies. The spiking tau values were taken from the published single-unit timescales by *Murray et al 2014.*

[*https://github.com/rdgao/field-echos/blob/master/notebooks/4\_analysis\_human\_wm.ipynb*](https://github.com/rdgao/field-echos/blob/master/notebooks/4_analysis_human_wm.ipynb)

In the codes it seems like the psd was computed over the entire sampling frequency range(in their case its 0-2000Hz) but the fooof fits were done in the range between (2 and 80). For the fooof algorithm, man\_n\_peaks = 2. Also the knee frequency is computed by np.sqrt(knee value). That is irrespective of the exp value obatained from the fit, the knee frequency is compute by the square root of knee.

<https://github.com/rdgao/field-echos/blob/master/notebooks/2_viz_NeuroTycho-SU.ipynb>

In the last part of the notebook here where they mention there is a correlation between knee and exponent of the aperiodic component. Even after take the signal just after the knee frequency, basically the part which follows 1/f power law , the exponent remains negatively correlated with the timescale.

They explain this by saying that exponential decay constant (knee) may arise from synaptic time constant, while the power law relation may be from population spiking autocorrelation.

But the knee depends on what then !!!

T*he timescale and magnitude of 1/f aperiodic activity decrease with cortical 1 depth in humans, macaques, and mice – Halgren et al 2021- bioarchive*

In this paper, the authors also suggest the estimation of characteristic timescale from the LFP signal. But in this case, the timescale is represented by the slope of the 1/f decay, or the aperiodic component of the LFP signal. So this is not the same as the previous paper by Gao where they suggest estimation of timescale from the knee value. Lower slopes (that is flat slopes of 0) indicates no history dependence whereas large magnitude slopes indicates strong history dependence.

Specifically, they explore the 1/f dynamics across cortical depth. They found that the slope and offset of 1/f dyanmics decrease from superficially to deepeer layers. (long to short timescale characteristic dynamics)

Model subjects : laminar microelectrode recordings from 16 patients. PSDs were computed from bipolar referenced LFPs. 1 macaque and mice

Physiological inference of 1/f slopes :

The decrease in slope and offset in 1/f dynamics with cortical depth indicates less history dependence, in other words, fast timescales (short tau). The 1/f dynamics is said to arise from mean firing rates (Miller et al 2009a) whch is reflected in the post synamptic conductances(PSG). A greater inhibition balance over excitation (i.e. more GABA than AMPA PSGs) is associated with steeper 1/f slopes. Thus a slower PSGs would give rise to slower aperiodic dynamics and therefore steeper slopes. Also, presence of a higher postsynaptic receptor density can also give rise to slower aperiodic dynamics and thus steeper slopes.

Since LFP reflects the activity of active postsynaptic channels, channels with slower timescales (long tau) will lead to steeper slopes.

They also compared the absolute 1/f slope and offset values across different recordings (basically done for individual subject). This was done to avoid differences in hardware and ambient noise across different recordings.

Why have they not used the knee frequency to understand timescales?

They have used the aperiodic exponent and the offset to indirectly understand the timescales in the cortical layers. This is because they did not find any spectral knee present in their data.

*Interpreting the electrophysiological power spectrum: Richard Gao, 2016*

Power law in log form : : f is frequency

Observations from before – Manning et al (2009) observed that the increased firing rate of a neural population to a given stimulus correlted with increase/change in offset (logA) but the slope remained stable. This was also supported by Miller and colleagues who observed acitivation related shifts but stable slopes in power spectra in response to stimuli, after having a bend ~70Hz.

The existing studies found that, sometimes there can be in a change only in slope (rotation) only in the high frequency range irrespective of the overall spectra. In addition to this, Podvalny et al 2015, found that the rotation of the spectrum can also occur in lower frequencies which could be correlated to increase in gamma power. Thus the change in spectral slope can be attributed to multiple factors that just a simple change in value. To account for this, Gao proposed an updated model of the power specteum, with the addition of a constant signal that will give a flat power spectrum. This flat power spectrum was proposed to correspond to the decorrelated firing in a larger neuronal population.

The signal represented by B resembles white noise and experiences a constant gain in all frequencies in response to an increased firing rate (Fig. 1A).

* So there are 3 main ideas from Fig1A and Fig 1B. Let’s say the value of is constant (Fig 1B). Deoending on the flat signal B, the slope changes as shown by the linear fits. The slope is the maximum with maximum firing rate of neuron . (simulated Poisson convolution) .
* When the linear fit is applied, it can be observed that the rotation occurs because of the increase in power in the higher frequencies.
* The frequency at which the rotation occurs is negatively correlated with the relative change in power at higher frequencies. That is, more the relative power at higher freqencies (more firing rate of neurons), the rotation occurs at a lesser frequency.

Here they have modelled between 10-100 Hz.

Under the proposed model, the LFP has two explicitly separate contributors: the first is synaptic events, which canonically have been the leading explanation for the origin of the LFP and depend largely on the activity of the presynaptic population. These events give rise to the general 1/f background. The flat-spectrum signal, I propose, arises from the aggregate spiking activity of the local population, which has been previously cited as a probable contributor to the LFP.

Questions

How do I know if my knee frequency is right. ? – currently uisng (2,80)- for now the fits looks okay .

Should I try to avoid the oscillations near 30 Hz to find the fits ? – maybe between 40-60 Hz ??

Why is it related to timscales ?

* : Connecting this EI balance with the idea of knee. As we can see as the inhibitory conducance decreases, the signal becomes flatter. This can be reflected in knee freq, which is basically the freq after which the signal follows 1/f power law. This knee is affected by the increase in gamma power at higher frequencies. So less knee frequency mean longer timescales which is directly related to slower aperiodic dynamics caused by increased inhibitory conductances.

*Inferring synaptic excitation/inhibition balance from field potentials – Gao et al 2017*

Here the authors have addressed an important gap in methodology to measure E:I ratio with broad population coverage and fine temporal resolution.

Fig 1D. – E:I ratio drives 1/f changes in simulation.

In Fig 1A-D, an LFP signal is simulated from Poisson spike trains from an independent excitatory and an inhibitory population. 1/f power decay can be observed after 20Hz frequency in this LFP signal. It is important to note here that the freq at which this decay starts in the LFP signal depends on the excitatory and inhibitory components driving this signal. For example in Fig 1D, the inhibitory signal starts decaying at a frequency lower than the excitatory signal (more flat). This E-I components in turn depend on the rise and decay time contansts of the AMPA – and GABA conductance profiles.

To note here, also the idea given in Halgren et al 2021, inhibitory population of neurons create slower dynamics, which can be reflected in the steeper slopes.

It was found that as the E:I ratio was increased, the PSD slope increased betweenn 30-50 Hz range. (that is the spetrum became flatter). In this E:I ratio was increased, which means the inhibitory influence became lesser (GABA conductances in the denominator).

The LFP model here suggests that E:I ratio is monotonically related to LFP-PSD slope in a range between 30 and 70 Hz, when uncorrupted by oscillatory peaks, and that increasing E:I ratio increases (flattens) PSD slope.

My thoughts : Connecting this EI balance with the idea of knee. As we can see as the inhibitory conducance decreases, the signal becomes flatter. This can be reflected in knee freq, which is basically the freq after which the signal follows 1/f power law. This knee is affected by the increase in gamma power at higher frequencies. So less knee frequency mean longer timescales which is directly related to slower aperiodic dynamics caused by increased inhibitory conductances.

Fig 2C and 2D: Second it was found that the PSD slope across depth was significantly correlated with the AMPA-GABA synapse ratio in rat CA1 neurons. Increased in AMPA synapses with depth and the slope values changed from higher negative to lower negative values

**Hence, we propose that slope changes in a particular frequency region (30–70 Hz) correspond to changes in E:I balance, while making no claims about other frequency regions, and our multivariate model in the CA1 analysis reveals that both inhibition alone and E:I ratio predict spectral slope better than excitation alone**

**Note to Myself: As mentioned here in this paper, as E:I balance increases with depth (inhibitory conductance decreases), the slopes becomes less negative. This is why you can see a positive correlation between slope value and the E:I ratio. But on the other hand what it means, that the slopes actually become flatter with depth, that is., the slope decreases, as found in Halgren et al 2021. In this paper thye found in humans, that the slope and offset decrease with cortical depth.**

*Intrinsic Neural Timescales in the Temporal Lobe Support an Auditory Processing Hierarchy – Cusinato et al 2023*

Estimation of intrinsic neural timescales

But they are using the baseline period from the eeg data

For estimating intrinsic neural timescales, they computed the ACF on the signal from each electrode and defined timescales as the time lag at wihc the ACF reaches the value 1/e .

But apart from this they did some control analysis to esnsure that the estimation of timescales was not trivially driven by neural oscillations.

First, we fitted a curve of the form f(t) = a\*exp(–t/t) 1 (1 – a)\*cos(2pft) to the ACF with (a, t,f) as parameters to be optimized (Zeraati et al., 2022); a represents the amplitude parameter, f the putative oscillatory frequency, and t the estimated timescale.

In a second control analysis, we computed timescales as the inverse of the knee frequency in power spectra, estimated as fk =k1/exp with k being the knee parameter and exp the spectral exponent, as implemented in the specparam toolbox (Donoghue et al., 2020)in“knee” mode. The spectral exponent was computed separately from two frequiency ranges, 2-35 and 80-150 Hz.

Mainly the spectral exponent in the 20-35Hz and 80-100Hz showed significant main effect of region.

All the three methods showed similar gradient of timescales across the 4 regions. After this, they tried to see a gradient of timescales within each anatomical structure in the AP anteromedial and posterolateral axis. This gradient was only found in the temporal and enorhinal cotices, but not in amygdala and hippocampus.