**Bayesian Neural Power Spectrum Estimation for Robust Neural Feature Extraction**

**Summary**

There is a significant push for using parametric description of Neural Power Spectrum. In particular, parametrizing neural power spectra into periodic and aperiodic components [1], has been introduced recently and it gained significant attention in the field. This algorithm suggested a parametric model to estimate Power Spectrum density of neural brain activities. This algorithm defines two periodic and aperiodic components, in which both of them carry information of physiological activities of the brain signals. However, this parametric algorithm provides an interesting framework to assess frequency domain time-series data; it suffers from numerous of shortages. This parametric neural power spectrum model is not able to provide a robust frequency estimation, fails to control variability of parameters, and cannot include the notion of continuity of neural signals through time. In this research, we are introducing a Bayesian neural power spectrum model which addresses multiple issues of the previous model including time continuity over time, much more flexibility in controlling specific frequency bands, and also rather than providing a point estimate for each free parameter, the proposed model will provide a posterior estimation of each parameter of the model. We also develop a toolbox which can be used for a wide range of different kinds of time series data, including EEG, iEEG, and LFP, without having the expertise of the field. This model would be a significant endeavor in the computational neuroscience field to provide a parametric model of the Power Spectrum Density, which is very important notion in Neuroscience data analysis.

**Additional Details**

Neural power spectrum has been conflated of two main components: aperiodic and periodic parts. The aperiodic component which has a like distribution, plays a major role in physiological interpretation of the brain activity. The periodic component, which reflects the narrow-band frequency oscillations with a center frequency, carries information of a wide range of neural activities including cognitive tasks, behavioral tasks, and disease dysfunctions [1]. These two main components of neural power spectrum can be modelled in a parametric model as [1]:

|  |  |
| --- | --- |
|  | (1.a) |
|  | (1.b) |
|  | (1.c) |

Where indicates time window, models the aperiodic component in which is the broad-band offset, is the knee, is a vector of frequency values [1]. The periodic activities are modeled by , in which indicates number of periodic activities, is amplitude, is center frequency, and is the variance of the the periodic activity. comprises power spectrum of aperiodic and periodic activities [1] and it provides the parametric power spectrum. We assume is providing an estimation of the observed , which is Multitaper power spectrum of time series data, with the residual error . follows a multivariate normal distribution with dimension , which is the length of .

|  |  |
| --- | --- |
|  | (2.a) |
|  | (2.b) |
|  | (2.c) |

where is a zero vector with length . Our preliminary observation indicates that there is an adjacency correlation between near frequencies content in power spectrum. reflects this adjacent effect in its structure by defining the free parameter .

If the observation model parameters – – and the hyper parameters - are known, the likelihood of observation at time window is defined by

|  |  |
| --- | --- |
|  | (3) |

where defines the likelihood of array of frequencies at a time window . To do parameter estimation based on given likelihood function we use PYMC3 toolbox [2] in python. PYMC3 uses gradient based Markov Chain Mount Carlo (MCMC) algorithm to estimate posteriors of the parameters. To solve this Bayesian problem, we need to define prior distributions for model’s parameters. Beta distribution with different configurations has been used as prior for all free parameters. After running MCMC algorithm and find the posterior estimation of at time interval , we need to move one time window forward and we use estimated posterior of as prior of free parameters in time window .

|  |  |
| --- | --- |
|  | (4) |

HERE TALK ABOUT KEN METHOD AND USE POSTERIOR OF TIME K AS PRIOR OF TIME K+1

Reference of Ken paper [3]

* Defiing of Ken relation transition
* Real Data result
* Talks about Bayesian advantages

**References**

[1] T. Donoghue *et al.*, “Parameterizing neural power spectra into periodic and aperiodic components,” *Nature Neuroscience 2020 23:12*, vol. 23, no. 12, pp. 1655–1665, Nov. 2020, doi: 10.1038/s41593-020-00744-x.

[2] J. Salvatier, T. v. Wiecki, and C. Fonnesbeck, “Probabilistic programming in Python using PyMC3,” *PeerJ Computer Science*, vol. 2016, no. 4, p. e55, Apr. 2016, doi: 10.7717/PEERJ-CS.55/FIG-7.

[3] K. Arai, D. F. Liu, L. M. Frank, and U. T. Eden, “Marked point process filter for clusterless and adaptive encoding-decoding of multiunit activity,” *bioRxiv*, p. 438440, Oct. 2018, doi: 10.1101/438440.