ANDA-NI 2024
Advanced Neural Data Analysis and Neuroinformatics School

Training Material for Tutorial
Spectral Analysis of Neural Signals

Dr. Udo Ernst, Maik Schünemann, David Rotermund

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The training material for the tutorial **Spectral Analysis of Neural Signals** consists of two parts. In **Part I**, we provide short exercises for training particular methods for spectral analysis. **Part II** gives you the opportunity to conduct a realistic scientific investigation on an (artificially compiled) 'physiological' data set.

Part I: Methods for spectral analysis

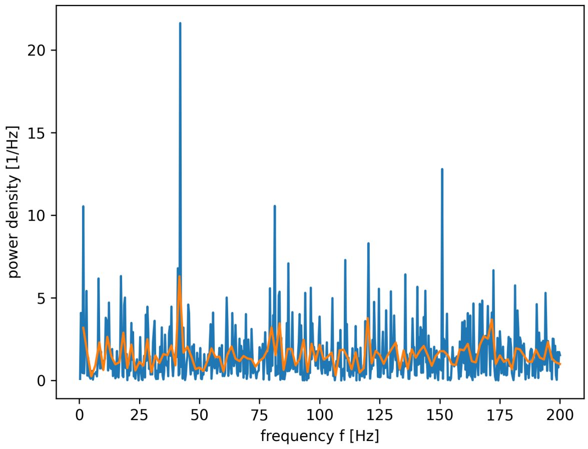
Each of the following exercises can be solved in two ways:

- For a **quick** solution, you can use the module `spectral.py` in which different functions are provided for your convenience. For example, `power` will compute the power spectrum of a signal, hereby taking care whether the signal has an even or odd number of samples, and also provide you with a suitably defined frequency axis for displaying the result. Therefore, you just have to apply these functions properly to the test data generated in our tutorial files.
- For a **detailed** solution, you should ignore the module `spectral.py` and implement the appropriate code on your own. For example, for computing a power spectrum you would have to postprocess the result of a Fourier transform on your own; select one side of the spectrum, take the absolute values and square them etc. etc. etc.

While the **quick** solution allows you to get fast results and then quickly move on to the scientific analysis we propose, the **detailed** solution will provide you with deeper insights into the methods for spectral analysis, and dump you right into typical pitfalls for sharpen your eyes on how to avoid them in more complex projects.

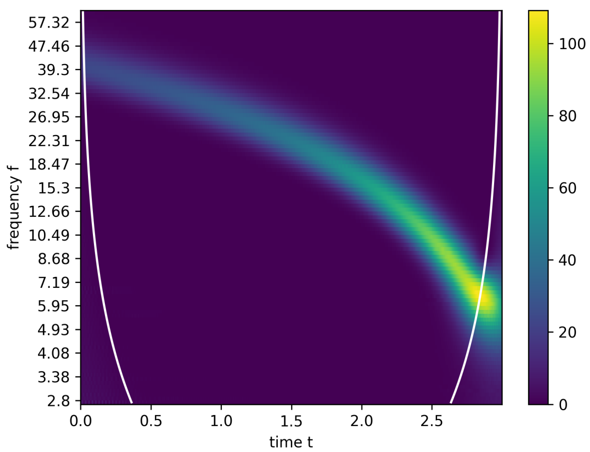
Exercise #1: Fourier transform and power spectra

In test_powerspectrum.ipynb we defined a harmonic function. Your task is to compute their power spectrum, display it, and check whether Parseval's theorem is satisfied. You will also learn how to average over power spectra over part of a time series to reduce noise in your power estimate. For a **detailed** solution we ask you to write a function that takes a signal and computes its power spectrum, and a second function that cuts a signal into different chunks and averages the corresponding power spectra over the chunks.



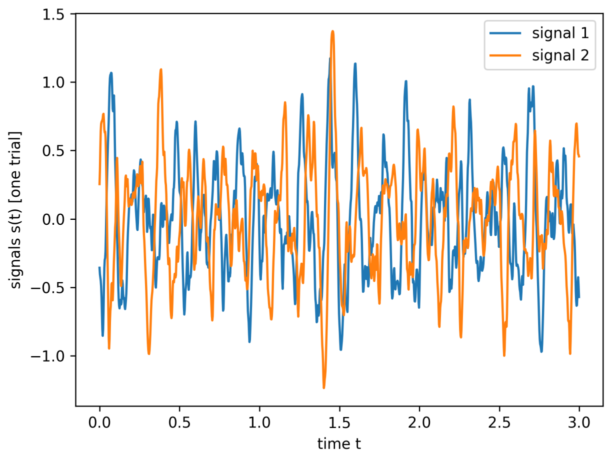
Exercise #2: Time-varying signals and wavelet transform

In test_waveletspectrum.ipynb we provide a signal with time-varying spectral content (a 'chirp'). Your task is to compute a wavelet transform and display spectral power in time-frequency space. For a **detailed** solution, we encourage you to write a function performing a wavelet transform with the Morlet wavelet in a certain frequency range, and which also reveals the cone-of-influence. A second function useful to implement would be a display routine for a wavelet spectrum with a logarithmically scaled frequency axis.



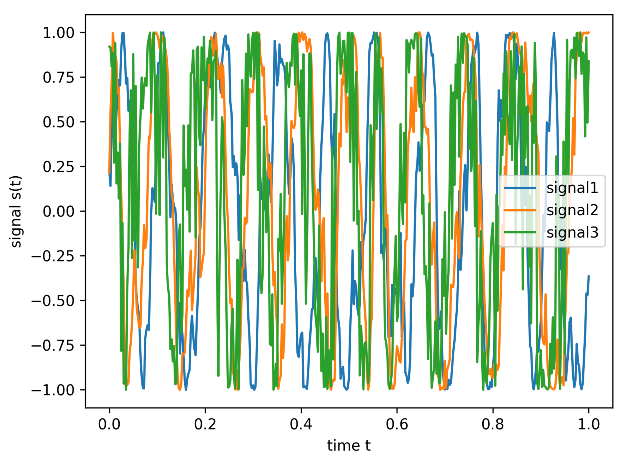
Exercise #3: Spectral coherence

In `test_spectralcoherence.ipynb` we define two signals with a broad spectral content, and an unknown relationship between each other. Your task is to determine how these two signals are interrelated by computing the spectral coherence and displaying it in a similar way as a wavelet spectrum. For a **detailed** solution, we ask you to implement the spectral coherence computation on your own, in a vectorized manner. You'll also need the wavelet transform from the previous task in order to generate the signals that go into spectral coherence computation.



Exercise #4: Bandpassed Hilbert transform and phase locking

In `test_phaselocking.ipynb` we define three signals which are harmonic functions with a jittery phase. We ask you to compute the phase locking between all signal pairs, using the Hilbert transform combined with a bandpass to extract the phase of the signals in a frequency band of interest. For a **detailed** solution, we would like you to implement the phase locking value computation by hand, and also to implement band-pass filtering which does not affect phase by using a forward-backward transform.



Part II: Scientific project
Selective Information Processing in Spider Monkeys

In this project, we will investigate physiological recordings from visual areas V1 and V4 in digital spider monkeys. The experimental setting and scientific background is comparable to the paradigm in [Grothe et al., 2018], but has been simplified to allow data analysis to be performed within a tutorial lasting one or few days.

Each trial started with a baseline period of 500 ms without visual stimulus. Then two visual stimuli were presented for 1000 ms. The task for the animal was to attend one of the two stimuli, and to solve a task associated with that attended stimulus.

During the experiment, local field potential (LFP) recordings were performed with $N = 100$ electrodes in area V1 and a single electrode in area $V4$ whose receptive field (RF) covered both visual stimuli to a similar extent. The two visual stimuli (let's name them A and B) were tagged with independent luminance variations ('flicker') for allowing the scientists to track visual information in the recorded neural signals.

Figure 1: *A digital spider monkey after a successful recording session. While still implanted with a V4 electrode, she already nibbles a well-earned reward! (animal 'Gary' was presented as a gift by the students of the master's course in Neuroscience 2018 in Bremen).*

Previous work in macaque monkeys [Grothe et al., 2018] established that visual signals are selectively routed in dependence on attention: computing the spectral coherence between V4 LFPs and flicker signals A and B revealed a substantially higher signal content of the attended signal as compared to the non-attended signal.

For your convenience, we exported only trials where the animal's attention was devoted to **one** of the two stimuli – **your task will be to find out to which one: A or B?**

Basic Tasks

The data set `ANDA2024_Spectral_DataSets.mat` you received contains three matrices containing the data with a time resolution `dt = 1 ms` from $M = 100$ trial repetitions:

`flicker_signals (MxNxT)` – flicker time series for stimuli A and B
`V1_lfp (MxNxT)` – LFPs for $N = 100$ V1 electrodes
`V4_lfp (MxT)` – LFP for one V4 electrode

This 'physiological' data can be evaluated into different directions, hereby addressing different scientific questions.
We propose you to first work on the tasks in this section. This requires you to use the **Wavelet transform** to generate temporally resolved spectra of the V4 LFP data (and of the flicker time series), and then to compute the **Spectral coherence** for quantifying the signal content contained in the physiological data.
Subsequently, you might try the other investigations suggested to you in the section **Extended Analyses**, for example for detecting gamma oscillations and quantifying inter-areal and intra-areal phase coherence.
Your task for the Basic Analysis will be to quantify stimulus information content in V4 LFPs for the two stimuli A and B, and to determine which of these two stimuli is attended (i.e., the one which provides the larger amount of stimulus content to V4.

a) **Use the wavelet transform to compute the trial-averaged amplitude spectrum over the whole trial duration, and plot it.** Consider the parameters to choose for the analysis – what would be an appropriate frequency range and spacing (linear or logarithmic)? Which part of your result can you trust? – include the cone-of-influence into your plot. Does the presentation of a stimulus generate oscillatory activity, and if yes, in which frequency band? – highlight potential spectral changes after stimulus onset by subtracting the average wavelet spectrum during the baseline period.

b) **Implement a function which takes two Wavelet-transformed signals as input, and computes their spectral coherence.** Let $a_1(t,f), a_2(t,f)$ be the complex wavelet coefficients of the signals. The spectral coherence $c(f,\tau) \in [0,1]$is given by:

$$c(f,\tau) \quad = \quad \frac{\left|\sum_t a_1(t+\tau,f)\overline{a_2(t,f)}\right|^2}{\left(\sum_t |a_1(t,f)|^2\right)\left(\sum_t |a_2(t,f)|^2\right)} \tag{1}$$

Think about how to implement this equation for different time shifts τ, ranging from $-\tau_{\max}$ to $\tau_{\max}$ when using signals of finite length. Note that you will also have to adjust the denominator for each time shift τ to make sure that $c \in [0,1]$.

c) **Compute the spectral coherence between the V4 LFP and the two flicker signals A and B.** Before performing the analysis, think about which part of the full trial you want to use in order to avoid spurious results. Plot the result for the two cases and inspect the data: which one of the signals is better represented in the LFPs (i.e., 'attended')? Average the spectral coherence in a suitable cone of interest and plot signal content versus frequency. Obtaining meaningful results requires averaging over trials. What is a better strategy? Computing the spectral coherence and then averaging over trials, or augmenting the results from the Wavelet transforms of different trials first, and then computing spectral coherence?

Extended Analyses

Here are some ideas for some complementary analyses that can be performed on Gary's data. Please ask your tutors if you want to solve these exercises; they will provide you with more details:

a) **Gamma-oscillatory activity.** It has been suggested that Gary generates Gamma oscillations (50-100Hz) in area V1 when a visual stimulus is presented. Can you check this and determine peak Gamma frequency?

b) **Receptive fields I.** Which of Gary's electrode(s) are maximally driven by the visual stimuli? Find out by computing total spectral power at stimulus onset and gamma power after stimulus onset as two putative proxies for activation, and plot these quantities over the two-dimensional V1 electrode arrangement (`10x10` grid).

c) **Receptive fields II.** Now focus on the sites which are most strongly driven by the stimulus. Use spectral coherence to find our which site is mainly driven by stimulus A, and which site by stimulus B.

d) **Inter-areal phase synchronization.** Some scientists believe that selective information processing goes along with enhanced phase synchronization between the V1 population sending the attended signal and the V4 population receiving V1 input. To check this hypothesis in your data set, filter your signals to the Gamma frequency band which you identified previously (make sure not to induce phase shifts!), use the hilbert transform to get the instantaneous phase of the signals and compute the phase coherence by $< \exp(i\Delta\phi) >$, where $\Delta\phi$ is the difference of instantaneous phases of the two signals.
You may find the functions `filtfilt,butter,hilbert` and from `scipy.signal` helpful for this task.

e) **Intra-areal phase synchronization.** The existence of specific phase relations *between* V1 and V4 implies that also phase relations *within* V1 become organized in a certain manner. Investigate how! To find out, compute the phase coherence between any pair of V1 sites. Think of a suitable visualization. Do you find a spatial pattern of in-phase, anti-phase and no phase synchronization?

References

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