

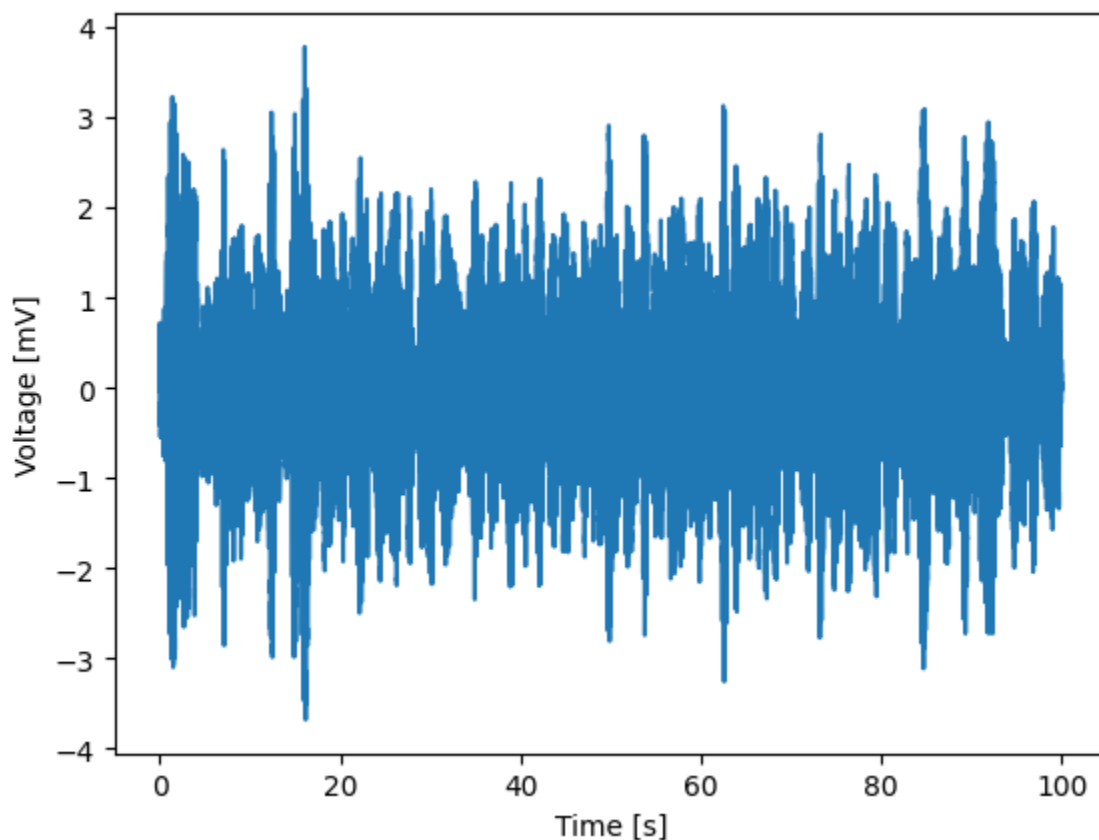
1.) LFP-2.mat

```
In [ ]: from scipy.io import loadmat
import matplotlib.pyplot as plt
import numpy as np
from scipy.signal import spectrogram
from scipy import signal
import random as rand
```

```
In [ ]: # Load the data.
lfp2 = loadmat('LFP-2.mat')           # Load the data,
t = lfp2['t'][0]                       # ... extract t, the time variable,
LFP = lfp2['LFP'][0]                  # ... and LFP, the voltage variable.
dt = t[1] - t[0]                     # Define the sampling interval,
fNQ = 1 / dt / 2                     # ... and Nyquist frequency.
```

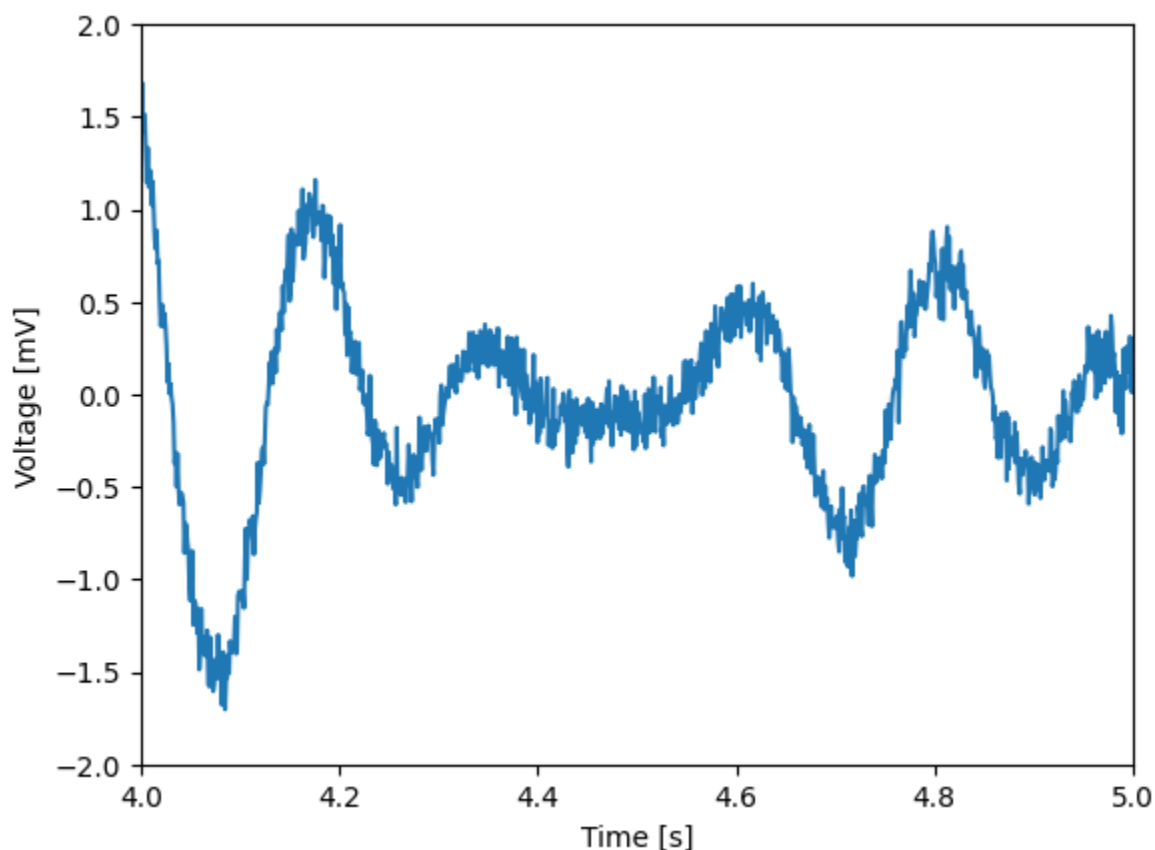
i. Visualize the time series data. What rhythms do you observe? Do you detect evidence for CFC in your visualizations?

```
In [ ]: plt.plot(t,LFP)
plt.xlabel('Time [s]')                # ... with axes labeled.
plt.ylabel('Voltage [mV]');
```



```
In [ ]: #zoom in on 1 second of activity
plt.plot(t,LFP)
plt.xlim([4,5])
plt.ylim([-2, 2])
```

```
plt.xlabel('Time [s]')      # ... with axes labeled.
plt.ylabel('Voltage [mV]');
plt.show()
```



a dominant low-frequency rhythm - not really seeing any evidence of CFC so far

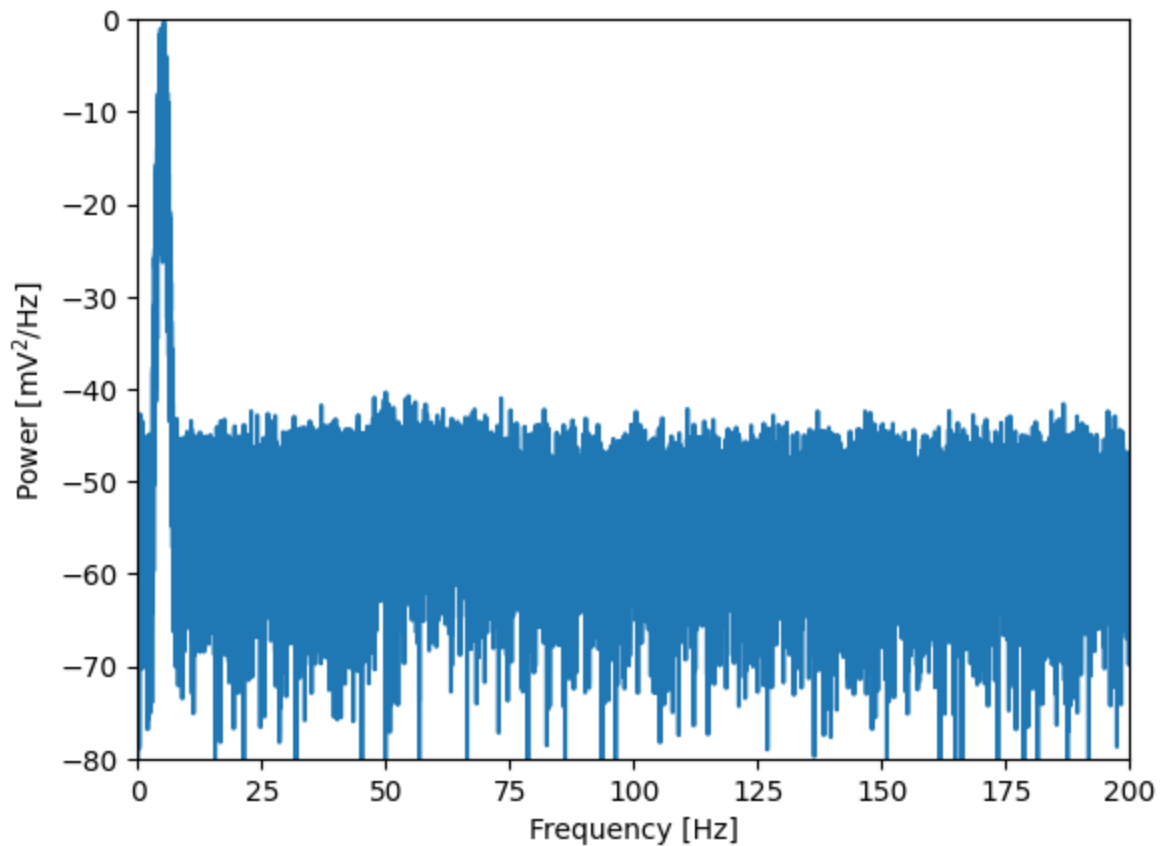
ii.) Plot the spectrum vs the frequency for this data

```
In [ ]: dt = t[1] - t[0]          # Define the sampling interval,
      T = t[-1]                  # ... the duration of the data,
      N = len(LFP)               # ... and the no. of data points

      x = np.hanning(N) * LFP    # Multiply data by a Hanning taper
      xf = np.fft.rfft(x - x.mean()) # Compute Fourier transform
      Sxx = 2*dt**2/T * (xf*np.conj(xf)) # Compute the spectrum
      Sxx = np.real(Sxx)         # Ignore complex components

      df = 1 / T                 # Define frequency resolution,
      fNQ = 1 / dt / 2           # ... and Nyquist frequency.

      faxis = np.arange(0, fNQ + df, df) # Construct freq. axis
      plt.plot(faxis, 10 * np.log10(Sxx)) # Plot spectrum vs freq.
      plt.xlim([0, 200])          # Set freq. range,
      plt.ylim([-80, 0])          # ... and plot. decibel range
      plt.xlabel('Frequency [Hz]') # Label the axes
      plt.ylabel('Power [mV$^2$/Hz]');
```



This highlights a low-frequency peak around 5ish Hz that is also the largest - this corresponds to the dominating slow rhythm we saw last.

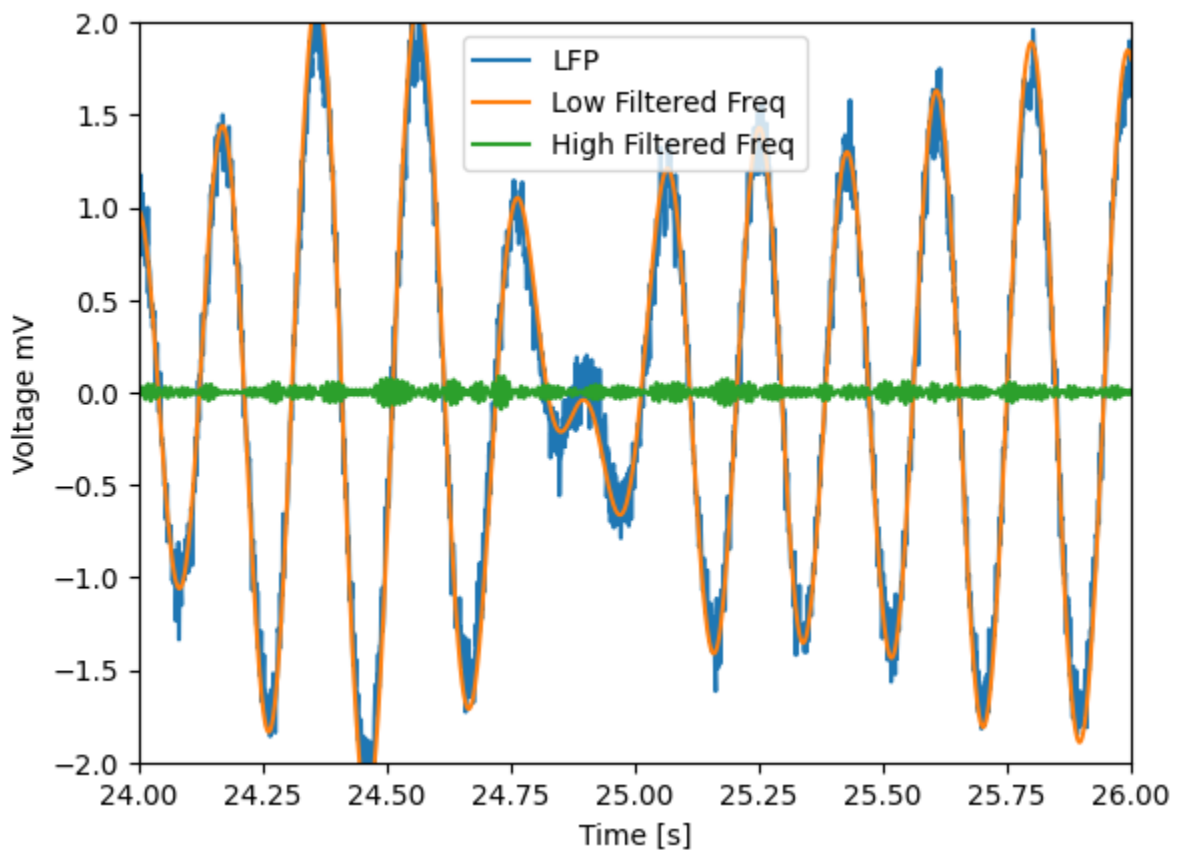
iii.) APPLY the CFC method. What choices will you make, and why? What if any CFC do you find?

```
In [ ]: # Low frequency band. (the dominant)
Wn = [5,7]; # Set the passband for low frequency band
n = 100; # ... and filter order,
# ... build the bandpass filter,
b = signal.firwin(n, Wn, nyq=fNQ, pass_zero=False, window='hamming');
Vlo = signal.filtfilt(b, 1, LFP); # ... and apply it to the data.

# High frequency band.
Wn = [75, 120]; # Set the passband for high frequency band (bu
n = 100; # ... and filter order,
# ... build the bandpass filter,
b = signal.firwin(n, Wn, nyq=fNQ, pass_zero=False, window='hamming');
Vhi = signal.filtfilt(b, 1, LFP); # ... and apply it to the data.
```

```
In [ ]: plt.plot(t, LFP)
plt.plot(t, Vlo) #plot the low peak
plt.plot(t, Vhi) #plot the high freq peak
plt.xlabel('Time [s]')
plt.ylabel('Voltage mV')
plt.xlim([24, 26]); #zoom in a specific time interval to get a more detailed graph,
plt.ylim([-2,2]);
plt.legend(['LFP', 'Low Filtered Freq', 'High Filtered Freq'])
```

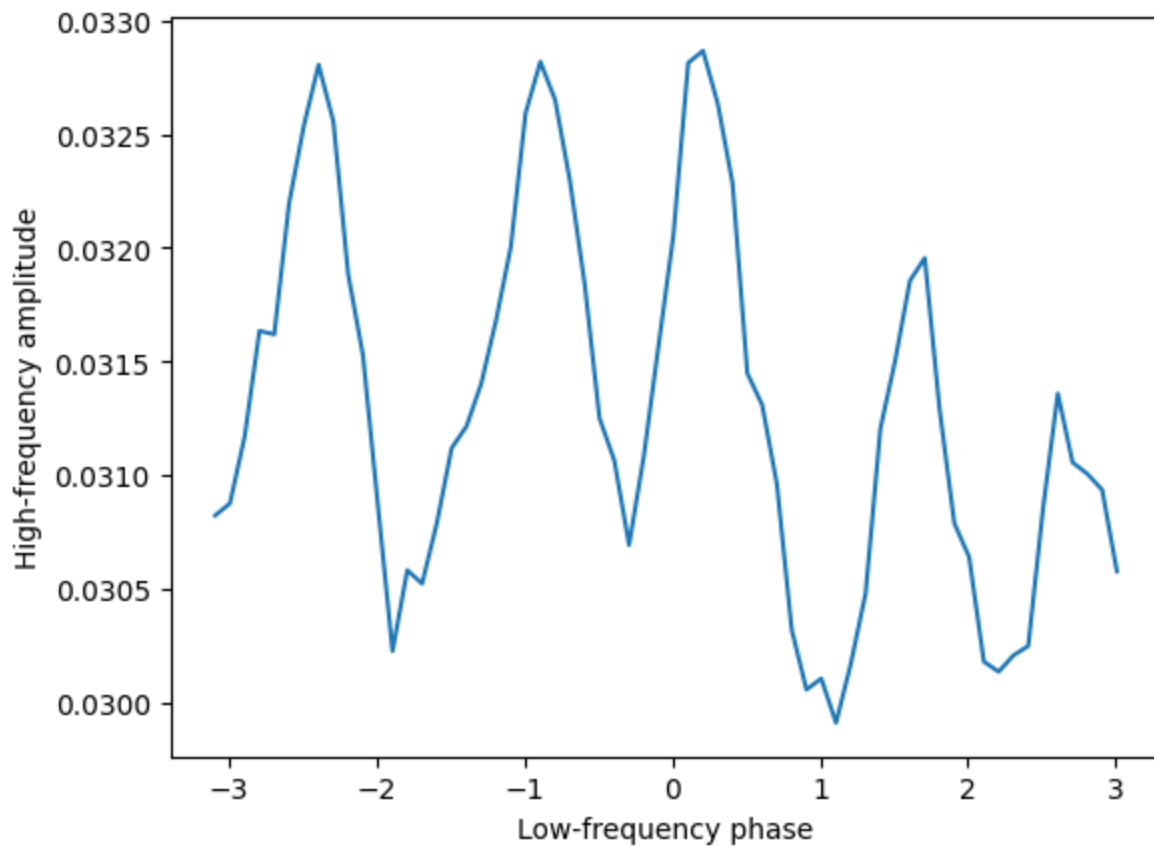
```
plt.show()
```



```
In [ ]: phi = np.angle(signal.hilbert(Vlo)) # Compute phase of Low-freq signal
        amp = abs(signal.hilbert(Vhi))     # Compute amplitude of high-freq signal
```

```
In [ ]: p_bins = np.arange(-np.pi, np.pi, 0.1)
        a_mean = np.zeros(np.size(p_bins)-1)
        p_mean = np.zeros(np.size(p_bins)-1)
        for k in range(np.size(p_bins)-1): #For each phase bin,
            pL = p_bins[k]                  #... Lower phase limit,
            pR = p_bins[k+1]                #... upper phase limit.
            indices=(phi>=pL) & (phi<pR)     #Find phases falling in bin,
            a_mean[k] = np.mean(amp[indices]) #... compute mean amplitude,
            p_mean[k] = np.mean([pL, pR])    #... save center phase.

        plt.plot(p_mean, a_mean)            #Plot the phase versus amplitude,
        plt.ylabel('High-frequency amplitude') #... with axes labeled.
        plt.xlabel('Low-frequency phase');
```



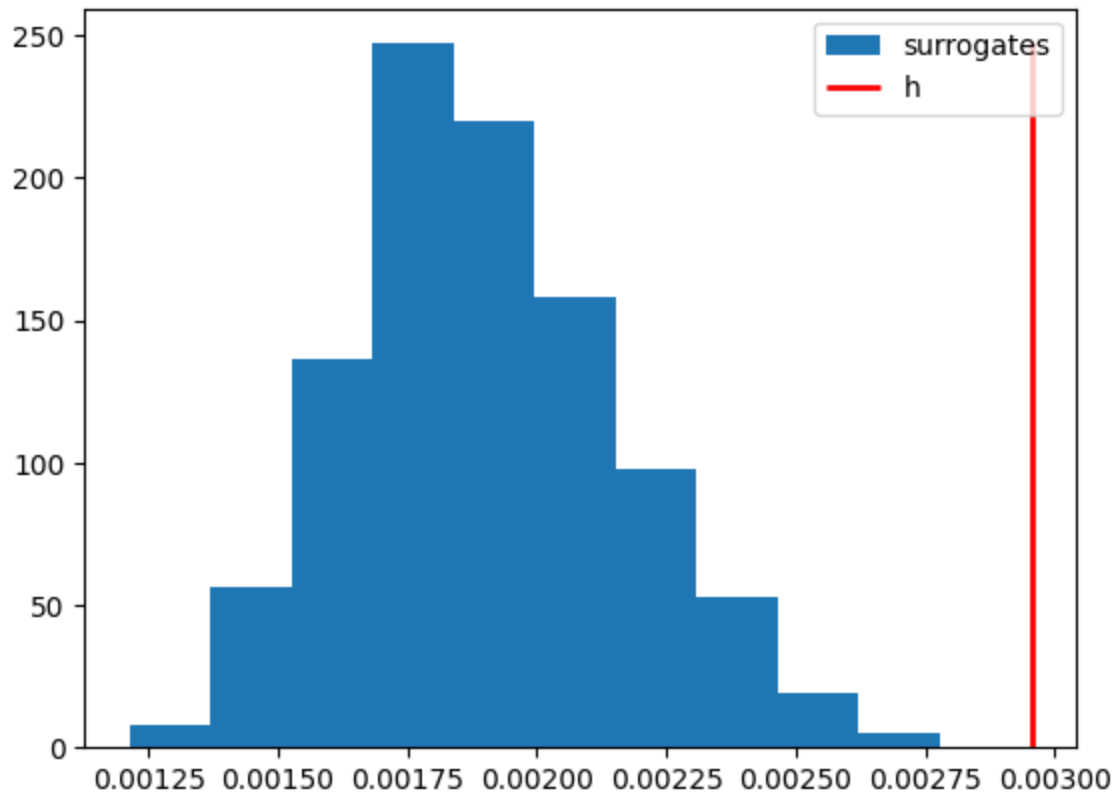
This doesn't seem to suggest a CFC

```
In [ ]: h = max(a_mean)-min(a_mean)
        print(h)
```

0.0029541809184905933

```
In [ ]: n_surrogates = 1000;           #Define no. of surrogates.
        hS = np.zeros(n_surrogates)    #Vector to hold h results.
        for ns in range(n_surrogates): #For each surrogate,
            ampS = amp[np.random.randint(0,N,N)] #Resample amplitude,
            p_bins = np.arange(-np.pi, np.pi, 0.1) #Define the phase bins
            a_mean = np.zeros(np.size(p_bins)-1) #Vector for average amps.
            p_mean = np.zeros(np.size(p_bins)-1) #Vector for phase bins.
            for k in range(np.size(p_bins)-1):
                pL = p_bins[k] #... lower phase limit,
                pR = p_bins[k+1] #... upper phase limit.
                indices=(phi>=pL) & (phi<pR) #Find phases falling in bin,
                a_mean[k] = np.mean(ampS[indices]) #... compute mean amplitude,
                p_mean[k] = np.mean([pL, pR]) #... save center phase.
            hS[ns] = max(a_mean)-min(a_mean) # Store surrogate h.
```

```
In [ ]: counts, _, _ = plt.hist(hS, label='surrogates') # Plot the histogram
        plt.vlines(h, 0, max(counts), colors='red', label='h', lw=2) # Plot the observed h
        plt.legend(); # ... include a legend
```



```
In [ ]: p = sum([s > h for s in hS]) / len(hS) #what is the proportion of surrogate h values
print(p)
```

0.0

We reject the null hypothesis of no CFC between the phase of the 5-7 Hz low-frequency band and the amplitude of the 80-120 Hz high frequency band.