EEG

August 16, 2022

0.1 EEG Analysis: Epilepsy in pediatric patients

0.1.1 Background

In this notebook we will be analyzing data of pediatric patients with epilepsy. This data is of free acces and can be downloaded from https://openneuro.org/datasets/ds003555/versions/1.0.1/download. The dataset of EEG recordings contains HFO markings for 30 pediatric patients with epilepsy. All the recordings were made with the 10-20 system.

Our objective is to create an algorithm able to detect when an epileptic attack occurs. We know that epileptic seizures occur mostly during the N2 and N3 sleep stages. So the first step would be to be able to divide the recordings in sleep stages

0.1.2 About EEG activity

EEG activity works by placing electrodes in the scalp that are able to measure the electric field generated by brain activity. When a neuron produces an action potential, the flow of current creates an electric dipole. By arranging two electrodes in the direction of this dipole we are able to detect a voltage increase. The more neurons fire in the same orientation of the electrodes, the greater the voltage will be.

In the brain we will measure a vectorial addition of all the action potentials arround the electrodes. The EEG records the postsynaptic potentials generated by cortical neurons. Postsynaptic potentials are the alternation between the excitatory postsynaptic potential (EPSPs) and inhibitory postsynaptic potentials (IPSPs) in apical dendrites of neurons.

In has been observed that in the precence of interaction between the cerebral cortex and the thalami, rhythmic activity is observed.

0.1.3 About epilepsy

According to the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE) an epileptic seizure can be defined as "a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain"(Fisher, 2005). From that definition, epilepsy is "a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures, and by the neurobiologic, cognitive, psychological, and social consequences of this condition" (Fisher, 2005).

Epileptic seizures can be classified according to the onset (focal, generalized or unknown), or according to the cause of the seizure (genetic, metabolic, structural, infectious or autoinmune). The most common method to diagnose epilepsy is MRI and in some cases PET/SPECT.

The relation between epilepsy and sleep is reciprocal. We know that both generalized and focal discharges have an increased probability to occure with the increasing depth of NREM sleep. This relation depends on the specific type of epilepsy. Studies have shown that some types of epilepsy such as jevenile myoclonic epilepsy have an principal occurence upon awakening. Other types such as the Lennox-Gastaut syndrome occur during sleep(mostly N2). It has also been observed that the occurance of epileptic seizures also affects the quality and duration of sleep.

0.1.4 Brain activity during sleep

Altought the division of may vary among different authors, we are able to make a correlation of stages based on the description of each. Here we will work with the following stages: Awake, N1, N2, N3, REM. This convention is preferred because the data we will use is already marked with those stages, so validation will be easier.

Sleep cycles last 90-120 minutes. Approximately 75% of this time consists in NREM sleep and only 25% REM sleep.

Brain activity is usually classified by frequency. There are 5 main types of waves: delta, theta, alpha, beta and gamma, with delta being the one with the lowest frequency and gamma the one with the highest frequency. In the following table we have a summary of how every type of wave is involved in a given sleep stage.

Delta waves: 0.2-4 Hz

Theta waves: 4-8 Hz

Alpha waves: 8-12 Hz

Beta waves: 12-30 Hz

Awake

Dominant rhythm over the occipital regions

```
<td>Main component in anterior leads</td>
```

```
<tr>
```

N1

```
    <td> </td>
    <td> Main activity</td>
```

Disappearance of the alpha rhythm

```
    <td> </td>
```

```
<tr>
```

N2

```
    <td>Bilaterally synchronous theta activity</td>
    <td> </td>
    <td> Sleep spindles or k waves may appear </td>
```

```
<tr>
```

N3

Slow Delta waves

<td> </td>
<td> </td>
<td> K-complexes and sleep spindles may be present</td>

<tr>

REM

<td>Sawtooth waves(2-6 Hz) are seen in frontal and central leads.</td>

Similar to N1 activity

Information obtained from 3, 4, 5.

Notice that the gamma waves were not included. This is because gamma waves are moslty indicators that the suject is conscious and on high alert, so they are not normal in a sleep EEG, however they could be an indicator of muscle activity, so they are important, particularly in the frontal electrodes. Eye movement is characteristic in REM sleep and it can be observed in the electrodes F7 and F8.

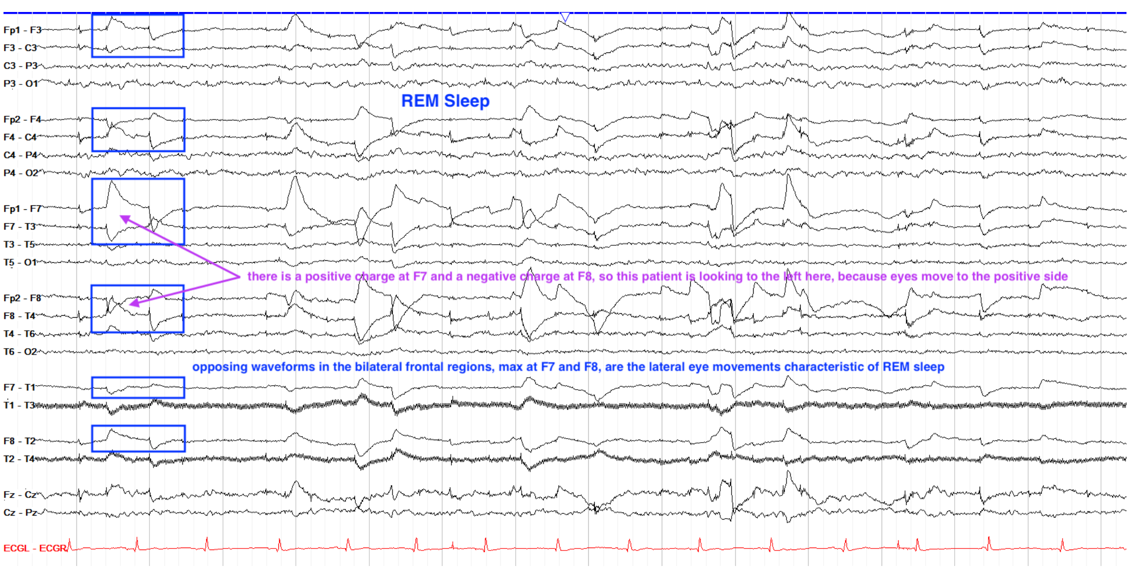


Image obtained from: The Normal Asleep EEG. (2022, July 13). Retrieved from https://www.learningeeg.com/normal-asleep#top

0.1.5 Sleep spindles

Sleep spindles are symetric bursts of activity of 12-14 Hz that last a cuple of secconds. In the analysis of the EEG we would expect to see a biphasic PSD with an increase in the 12-14 Hz components.

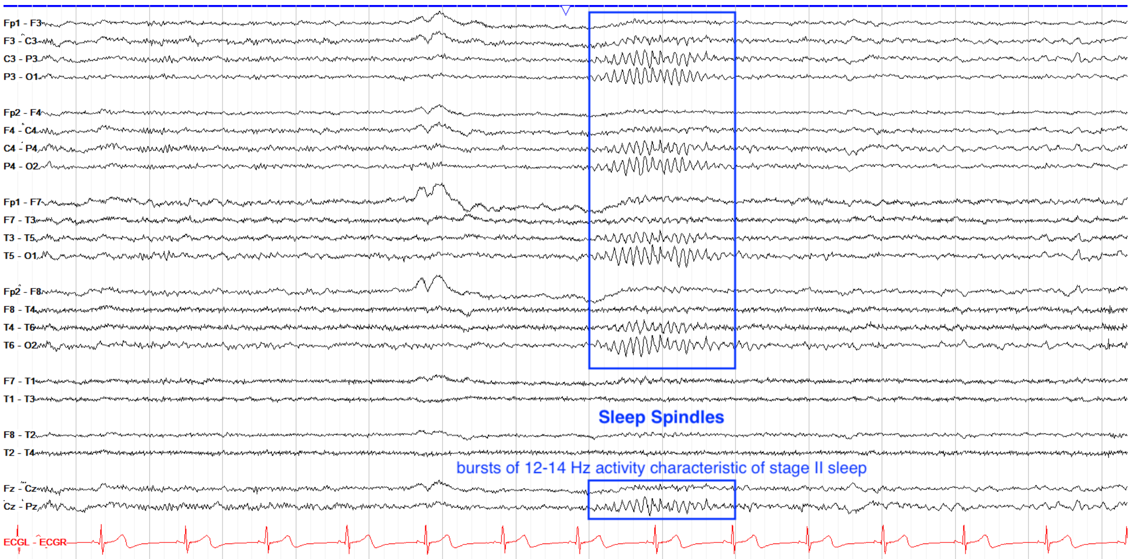


Image obtained from: The Normal Asleep EEG. (2022, July 13). Retrieved from https://www.learningeeg.com/normal-asleep#top

0.1.6 K-waves

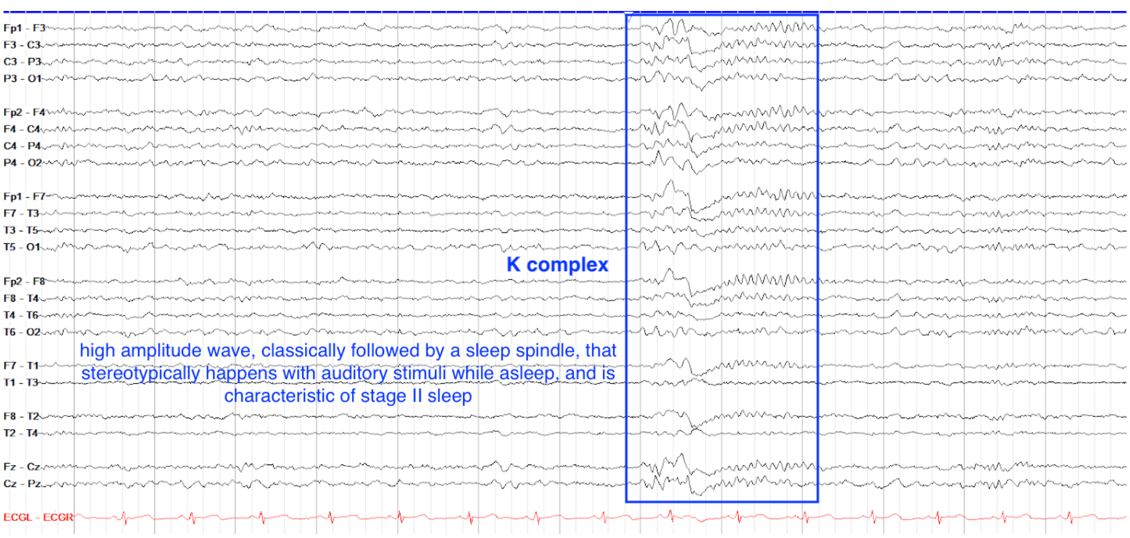


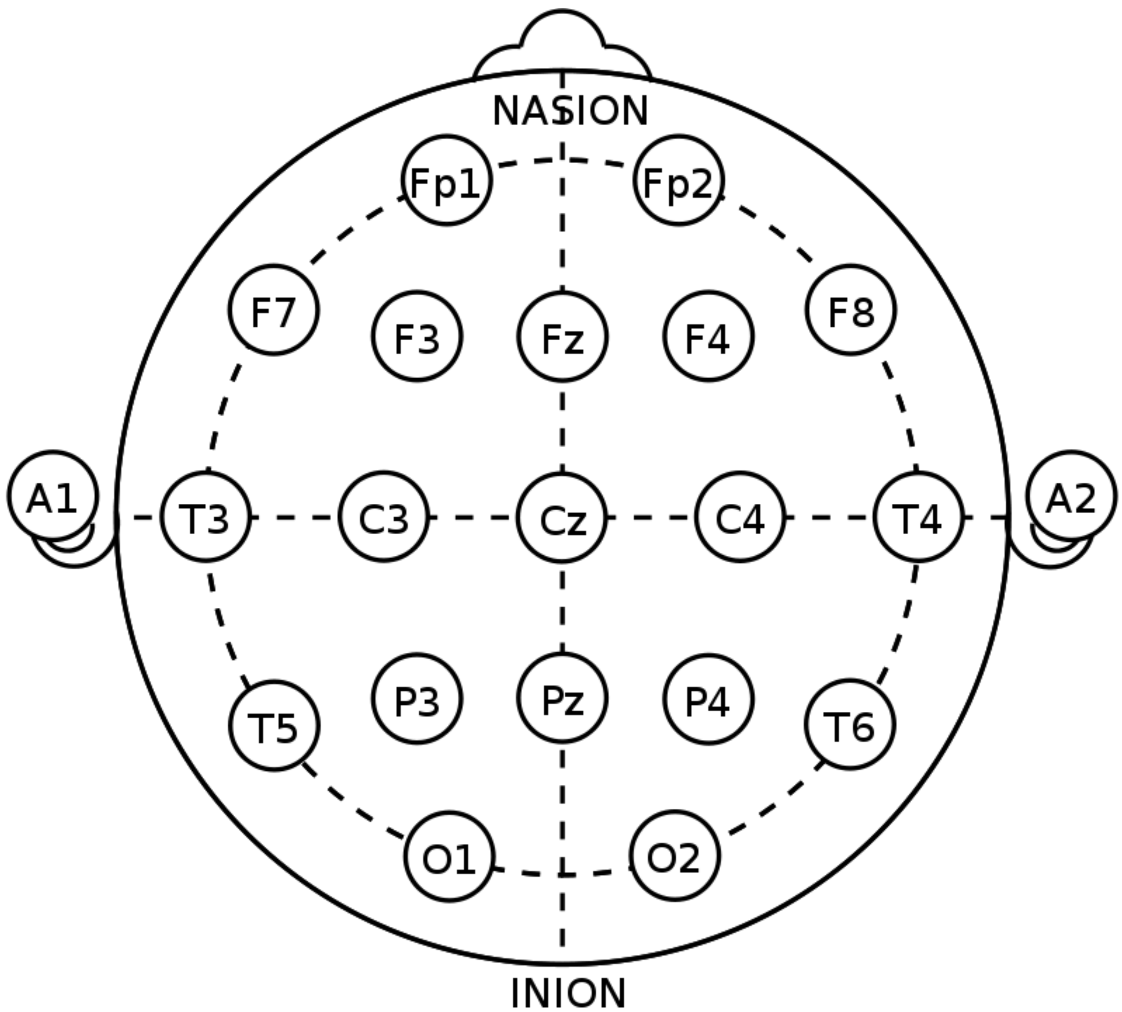
Image obtained from: The Normal Asleep EEG. (2022, July 13). Retrieved from https://www.learningeeg.com/normal-asleep#top

0.1.7 About the 10-20 system

The letters on the electrodes represent the general areas of the brain that are covered by the electrodes. From front to back, the electrodes are labeled as follows: Fp (prefrontal cortex or frontal pole), F (frontal), C (centerline of the brain), T (temporal), P (parietal), and O (Back of the head).). The electrodes between these rows are a combination of several letters placed from front to back. This applies to high density systems.

In addition, the letters M and A may be used to refer to the mastoid process and earlobe, respectively. These locations are typically recorded to serve as (offline) references for signal analysis. The electrode number provides information about the distance from the electrode to the median plane of the brain. At the median, the electrodes are marked with a “z” to represent zero. The number of electrodes increases as you move away from the centerline. Odd numbers represent the electrodes in the left hemisphere, and even numbers represent the electrodes in the right hemisphere.

Accurate results can only be obtained if the head cap is placed correctly and when the electrodes cover the desired location on the scalp. Therefore, it is important to choose the correct size head cap and make sure that Cz is between the nasion and inion and the two congenital eyelid points.



0.2 Similar studies

A study made by the univertsity of Texas intended to extract parameters from EEG recordings that were relevant for sleep stage classification(Estrada, 2004). They found that harmonic parameters as well as spectral density values could help the classification. The best paramereters were the Intakura distance adn a version of the Hjord parameters.

Another paper written by the Ghent University Hospital in Belgum used cluster analysis to predict the sleep stage of EEG recordings (VanHese, 2001). In this studies 3 types of parameters were used: * Parameterers of Hjorth * Harmonic parameters * Relative band energy

They found that these 3 sets of parameters were enough to classify a 10 second segment into a sleep stage.

Finaly, a study made by the University of Southern Queensland in Australia trained complex networks to clasify EEG recordings into sleep stages(Diykh, 2016). In this study, several machine learning structures were used including a decision tree, a support vector machine, a linear discrimination and a k-mean clustering algorithm. Among all of these, the one that proved to be more accurate was the k-means clustering along with a complex netowrk for parameter extraction.

0.3 Suggested aproach

The first objective is to extract valuable parameters from the recordings. Each recording lasts 3 hours and has 23 channels. The fisrt step is to split the data according to sleep phase. It is important to consider that each of the NREM phases are a process with differences that gradually appear. So, in order to avoid borderline effects we will leave out cushions at the beginning and at the end of each phase.

Then, each segment will be splitted into subsegments of 15 s. A set of hermonic properties will then be extracted from each sub-segment

0.3.1 Importing the packagery

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#%matplotlib qt
import scipy as sp
import mne
import seaborn as sns
from scipy.signal import welch, butter,lfilter, filtfilt, freqs
```

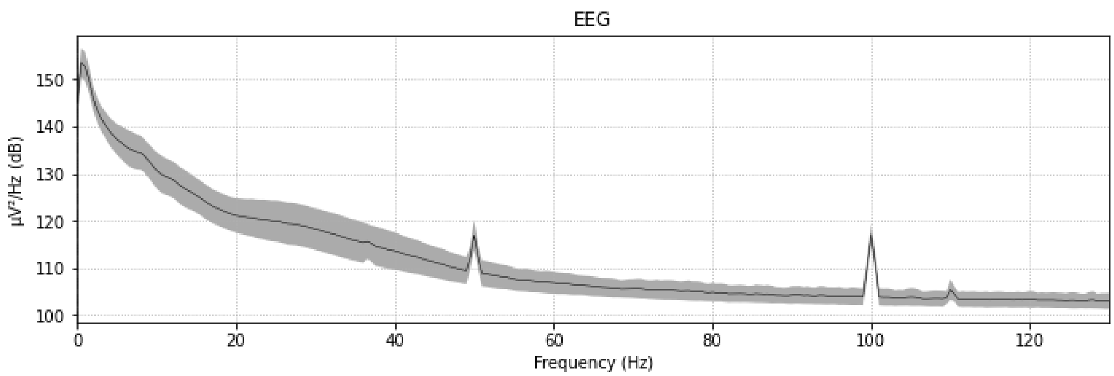
0.3.2 How to import data

[2]:
```
# Subject ID
sub=3
# Segment to be imported
run=1


sub_str="0"+str(sub)
run_str="0"+str(run)
sub=sub_str[-2:]
run=run_str[-2:]
```

[3]:
```
# Import data from path
raw=mne.io.read_raw_edf("sub-"+sub+"/ses-01/eeg/sub-"+sub+"_ses-01_task-hfo_eeg.
 ↪edf", preload=True, verbose=0)
```

[4]:
```
#Plot PSD of the data
fig = raw.plot_psd(fmax=130, average=True)
```

```
Effective window size : 2.000 (s)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  1.2min remaining:    0.0s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  1.2min finished
```



As we can see there are spikes of noise at 50 Hz and 100 Hz. This is caused by the frequency of the power input to the electrode system. This type of noise is more frequently found at 60 Hz in studies made in the US, Mexico and other american countries. In european studies however it is more common to find 50 Hz noise.

Since the filtering process is not part of this proyects objetives it will only be lightly explained, however detailes information on the process may be found in the MNE documentation(https://mne.tools/stable/auto_tutorials/preprocessing/25_background_filtering.html#disc-filtering).

The filtering process consists of convolution filter that is applied on the original data array and the filtered data array. This means that a filtered value is a wheighted average of the previous unfiltered values and the previous filtered values. The wheights are calculated from a transfer funtion in the frequency domain H(z). The mne filtering function automatically calculates the optimal lenght of the convolution window and the coefficients for the desired frequency cutoff.

In this case we are only intrested in the frequencies between 0.2 Hz and 90 Hz. Since we want this values to be the cutoff frequency, the passband edges will be 0.4 Hz and 80 Hz.

[5]:
```
# Band pass filter
raw.filter(0.4, 80)
```

```
Filtering raw data in 1 contiguous segment
Setting up band-pass filter from 0.4 - 80 Hz

FIR filter parameters
---------------------
```

```
Designing a one-pass, zero-phase, non-causal bandpass filter:
- Windowed time-domain design (firwin) method
- Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation
- Lower passband edge: 0.40
- Lower transition bandwidth: 0.40 Hz (-6 dB cutoff frequency: 0.20 Hz)
- Upper passband edge: 80.00 Hz
- Upper transition bandwidth: 20.00 Hz (-6 dB cutoff frequency: 90.00 Hz)
- Filter length: 8449 samples (8.251 sec)


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    4.5s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    6.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:    8.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  23 out of  23 | elapsed:  1.5min finished
```

[5]:
```
<RawEDF | sub-03_ses-01_task-hfo_eeg.edf, 23 x 11059200 (10800.0 s), ~1.90 GB,
data loaded>
```

Now we will remove the 50 Hz noise. We must remember that it is important to apply a band stop filter at the main frequency AND its multiples. In this case we only need to apply 2 notch filters at 50 Hz and 100 Hz.

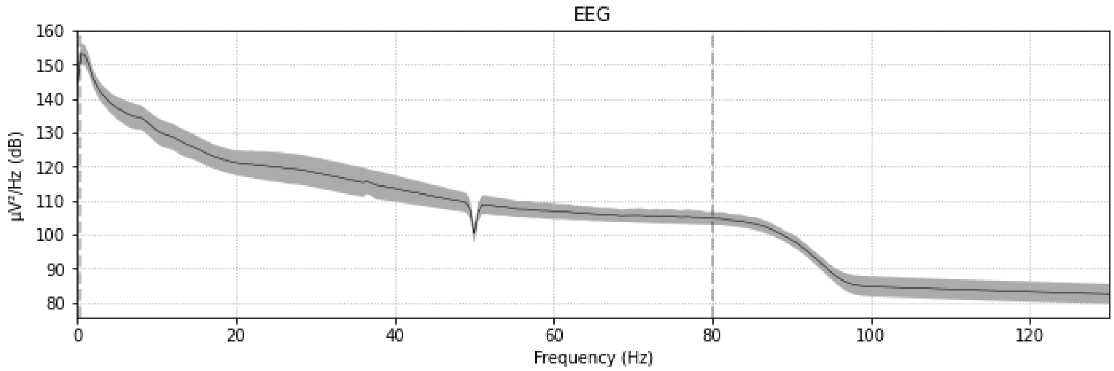
[6]:
```python
# Notch filter to remove 50 Hz noise
raw.notch_filter([50,100])
```

```
Setting up band-stop filter

FIR filter parameters
---------------------
Designing a one-pass, zero-phase, non-causal bandstop filter:
- Windowed time-domain design (firwin) method
- Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation
- Lower transition bandwidth: 0.50 Hz
- Upper transition bandwidth: 0.50 Hz
- Filter length: 6759 samples (6.601 sec)


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    3.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    6.1s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    8.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:   12.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  23 out of  23 | elapsed:  2.4min finished
```

[6]:
```
<RawEDF | sub-03_ses-01_task-hfo_eeg.edf, 23 x 11059200 (10800.0 s), ~1.90 GB,
data loaded>
```

[7]:
```python
# PSD after filtering
fig = raw.plot_psd(fmax=130, average=True)
```

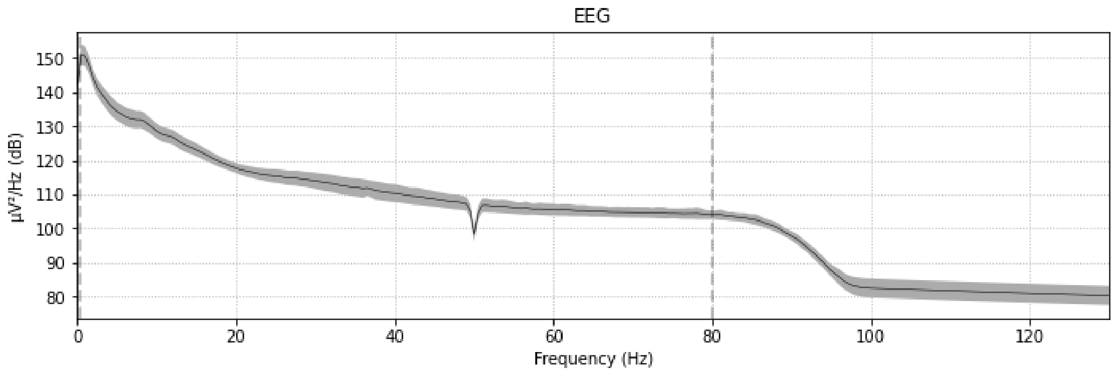
```
Effective window size : 2.000 (s)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  1.6min remaining:    0.0s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  1.6min finished
```



0.3.3 Frontal vs central vs parietal electrodes

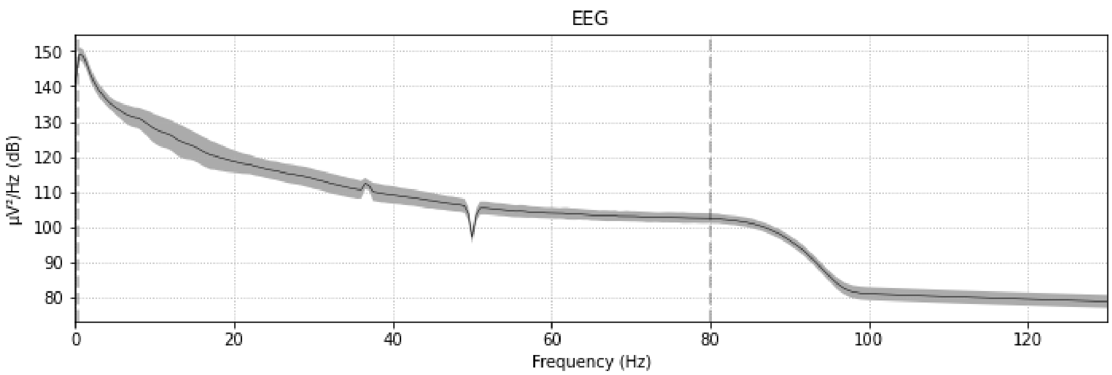
[8]:
```python
#Plot PSD of the data
fig = raw.plot_psd(fmax=130, average=True,␣
 ↪picks=["Fp1","Fp2","F3","F4","F7","F8","Fz"])
```

```
Effective window size : 2.000 (s)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    7.4s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    7.4s finished
```



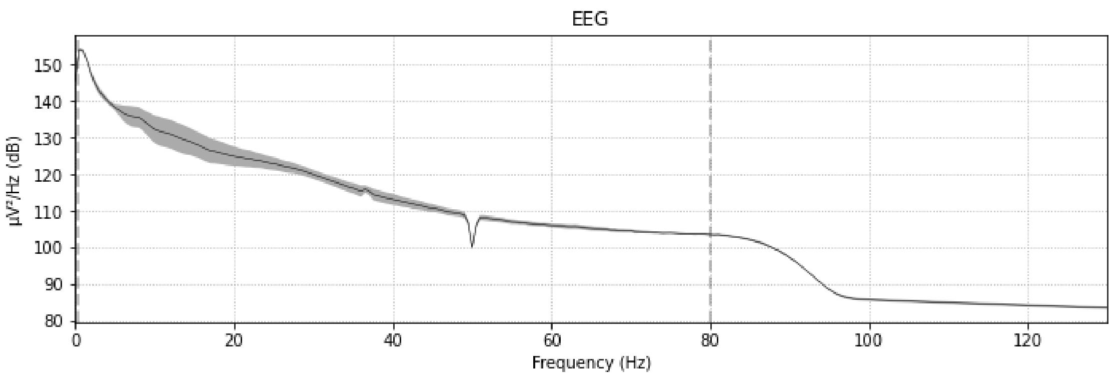
[9]:
```
#Plot PSD of the data
fig = raw.plot_psd(fmax=130, average=True, picks=["C3","Cz","C4"])
```

```
Effective window size : 2.000 (s)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.7s finished
```



[10]:
```
#Plot PSD of the data
fig = raw.plot_psd(fmax=130, average=True, picks=["P3","Pz","P4"])
```

```
Effective window size : 2.000 (s)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.6s finished
```



In the last 3 PSDs it can be observed that the central electrodes don't share a general shape of spectral density with the frontal electrodes nor with the parietal electrodes. This means that even though the central electrodes don't correspond to a cerebral lobe, they should be treated as independent.

0.3.4 Loading the data

By default, MNE does not load data into main memory to conserve resources. inst.filter requires raw data to be loaded.

[11]:
```
# Extract the data
data = raw._data
fs = int(raw.info['sfreq'])
chan = raw.ch_names

# Let's have a look at the data
print('Chan =', chan)
print('Sampling frequency =', fs, 'Hz')
print('Data shape =', data.shape)
```

```
Chan = ['Fp1', 'A2', 'Fp2', 'F7', 'F3', 'Fz', 'F4', 'F8', 'T3', 'C3', 'Cz',
'C4', 'T4', 'T5', 'P3', 'Pz', 'P4', 'T6', 'O1', 'A1', 'O2', 'T1', 'T2']
Sampling frequency = 1024 Hz
Data shape = (23, 11059200)
```

[12]:
```
# Load the events data
events=pd.read_csv("derivatives/sub-"+sub+"/ses-01/eeg/
↪sub-"+sub+"_ses-01_task-hfo_run-"+run+"_events.tsv",sep="\t")
```

[13]:
```
events
```

[13]:
```
     nChannel strChannelName  indStart  indStop  indDuration  Event_RMS  \
0           1        Fp1-Fp2    171777   171861           84   5.933874
1           1        Fp1-Fp2    478079   478147           68   9.489360
2           1        Fp1-Fp2    478264   478351           87   8.365235
3           1        Fp1-Fp2    478431   478525           94   6.740478
4           1        Fp1-Fp2    479181   479239           58   4.905034
..        …              …        …        …           …          …
282        51          T4-F4     95923    95983           60   5.776741
283        51          T4-F4    203353   203446           93   5.798611
284        51          T4-F4    335243   335305           62   6.073245
285        51          T4-F4    481746   481820           74   4.791709
286        51          T4-F4    487179   487234           55   3.764801

     Window_RMS  EventPeak2Peak       SNR     Amplpp  PowerTrough  Ftrough  \
0      3.362942       20.938139  3.113422  37.437634     0.959410     86.0
1      4.763889       32.944284  4.686149  40.786933     1.188129     93.0
2      4.894383       36.389311  3.457903  40.786933     3.832971     83.0
3      5.204053       26.565367  2.110070  40.786933     1.446160    120.0
4      4.743556       16.438231  1.355520  38.556055     1.161556    100.0
..          …             …        …          …            …        …
```

```
282    2.196614        20.073272  6.916056  20.073272     0.902945    118.0
283    2.097479        22.007932  7.642803  22.007932     0.423949    112.0
284    2.190029        23.875211  7.690277  23.875211     1.105948    120.0
285    2.502176        15.804761  3.667289  18.315251     0.789778    158.0
286    2.265691        11.717692  2.761105  21.349461     0.470870    177.0

     PowmaxFR  fmax_FR  EvPassRejection
0    3.728072       85                0
1    1.156296       92                0
2    4.345715       82                0
3    2.703719      119                0
4    1.261460       99                0
..        …        …              …
282  3.187190      117                1
283  0.757264      111                1
284  1.889742      119                1
285  2.674127      157                0
286  2.159051      178                0

[287 rows x 15 columns]
```

Note that the events are given with the channel names of the derivatives and the indexes correspond to the sampling frequency of the derivative resamling at 2 000 Hz.

[14]:
```
# Load the intervals metadata
intervals=pd.read_csv("derivatives/sub-"+sub+"/ses-01/eeg/DataIntervals.
↪tsv",sep="\t")
```

[15]:
```
intervals
```

[15]:
```
    StartInd    EndInd SleepStage  RunNb
0     178270    485470         N3      1
1     485470    792670         N3      2
2     792670   1099870         N3      3
3    1099870   1407070         N3      4
4    1407070   1714270         N3      5
5    1714270   2021470         N3      6
6    2021470   2328670         N3      7
7    2328670   2635870         N3      8
8    2635870   2943070         N3      9
9    2943070   3250270         N3     10
10   3415548   3722748        REM      0
11   3722748   4029948        REM      0
12   4184698   4491898         N2      0
13   4491898   4799098         N2      0
14   4799098   5106298         N2      0
15   5106298   5413498         N2      0
```

```
16   5413498   5720698        N2      0
17   5720698   6027898        N2      0
18   6027898   6335098        N2      0
19   6493262   6800462        N3     11
20   6800462   7107662        N3     12
21   7107662   7414862        N3     13
22   7414862   7722062        N3     14
23   7722062   8029262        N3     15
24   8029262   8336462        N3     16
25   8336462   8643662        N3     17
26   8643662   8950862        N3     18
27   9223497   9530697       REM      0
28   9530697   9837897       REM      0
29   9837897  10145097       REM      0
30  10145097  10452297       REM      0
31  10731384  11038584        N2      0
```

[16]:
```
subjects=pd.read_csv("participants.tsv",sep="\t")
```

[17]:
```
#n: Number of chanels
#N: lenght of the recording
n,N=data.shape
```

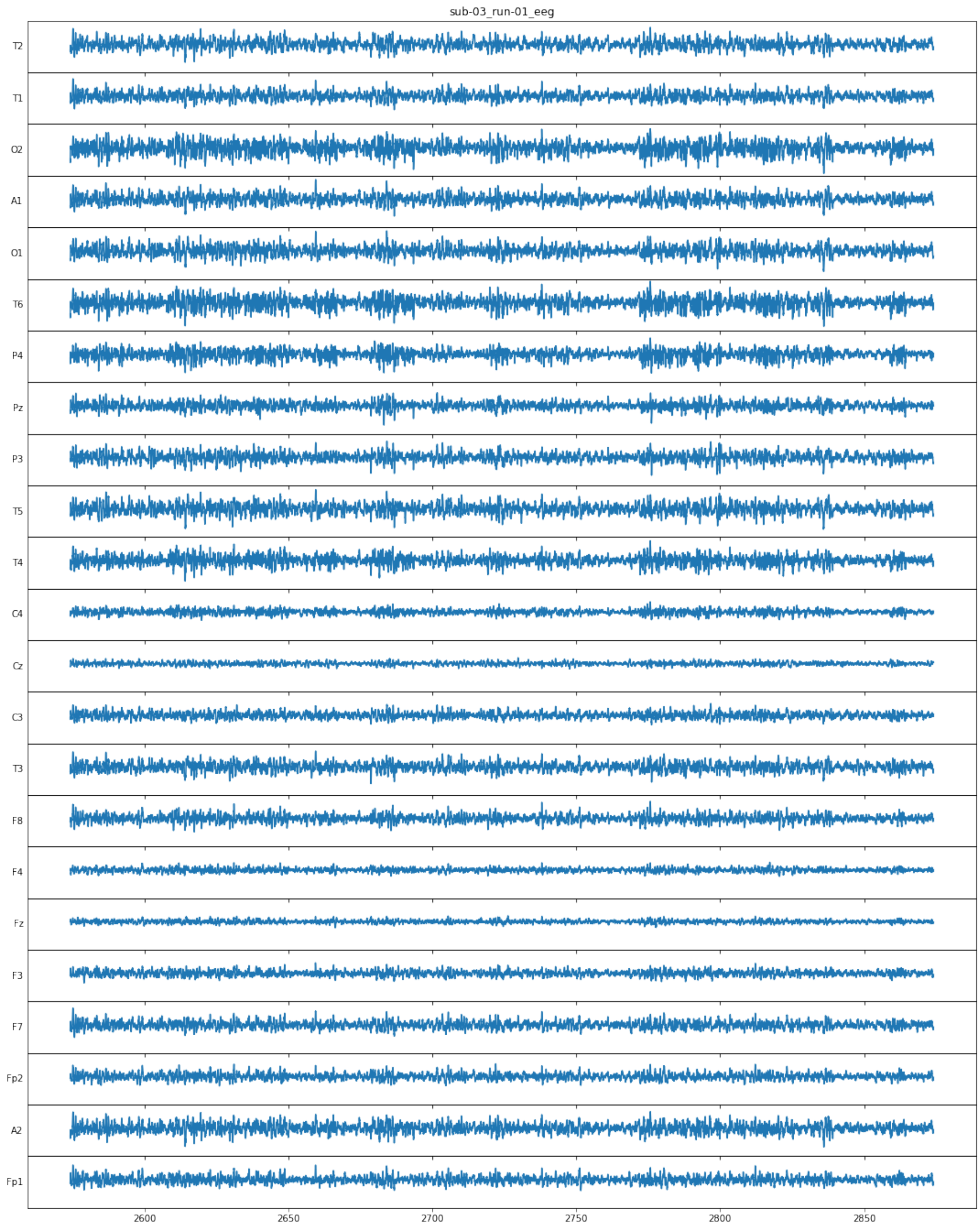
[18]:
```
#tf: Lenght of the recording in time
tf=N/fs
```

[19]:
```
#Time array
time_arr=np.linspace(0,tf,num=N)
```

[20]:
```
#i_s: Start index
#i_e: End index
i_s=intervals[intervals["RunNb"]==int(run)].iloc[0]["StartInd"]
i_e=intervals[intervals["RunNb"]==int(run)].iloc[0]["EndInd"]
```

[60]:
```
# Plot the first segment of data
i_i=i_s
i_f=i_e
fig=plt.figure(figsize=(18,18))
count=0.0
axlist = []
yprops = dict(rotation=0, horizontalalignment='right',␣
 ↪verticalalignment='center')
axprops = dict(yticks=[])
for i in range(0,n):
    ax = fig.add_axes([0.1, count, 0.8, 1/n], **axprops)
    axlist.append(ax)
    axprops['sharex'] = ax
```

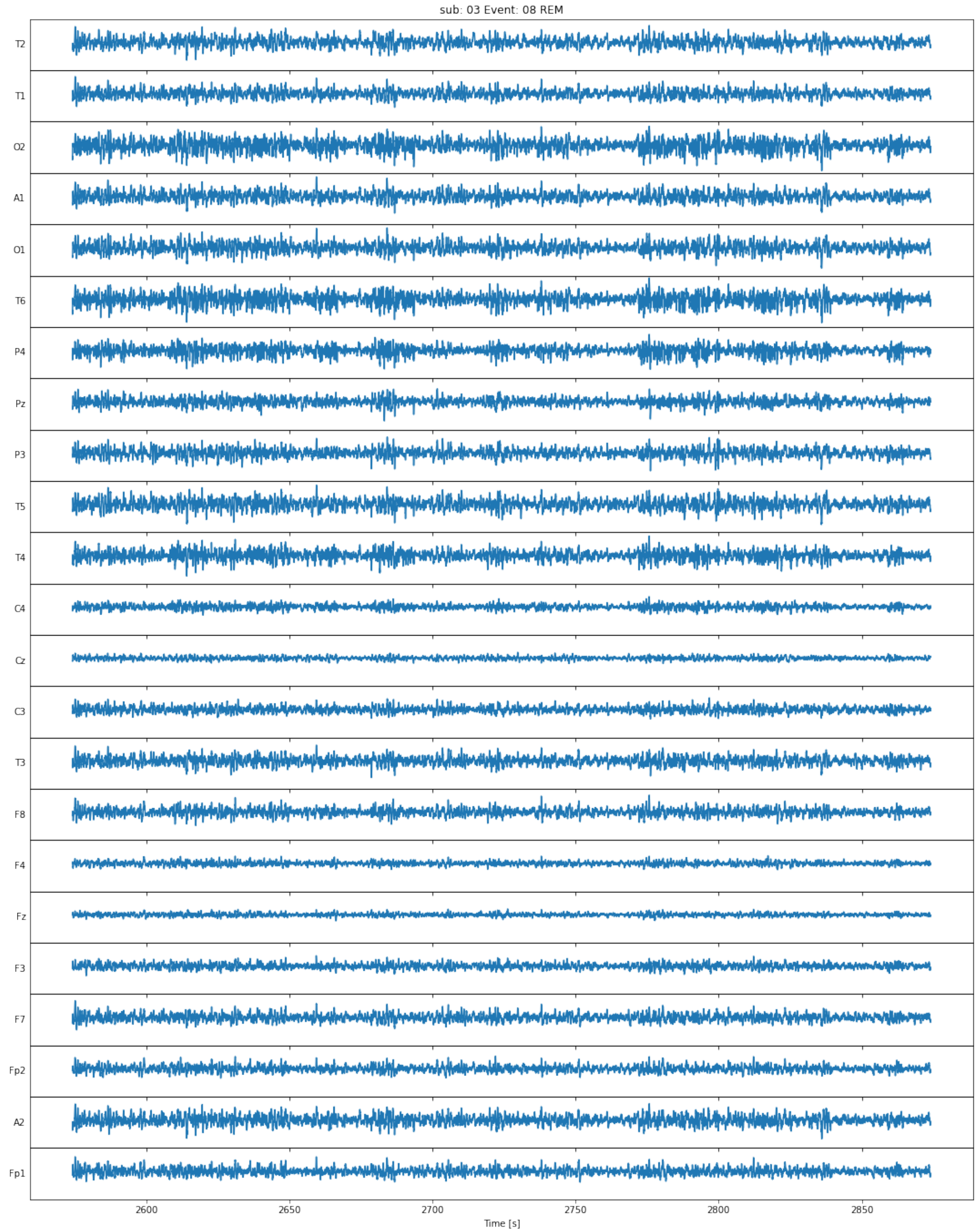
```
    axprops['sharey'] = ax
    ax.plot(time_arr[i_i:i_f],data[i,i_i:i_f])
    ax.set_ylabel(chan[i], **yprops)
    count+=1/n
    if i==0:
        plt.xlabel("Time [s]")
for ax in axlist[1:]:
    plt.setp(ax.get_xticklabels(), visible=False)
plt.title("sub-"+sub+"_run-"+run+"_eeg")
plt.show();
```


sub-03_run-01_eeg
T2
T1
O2
A1
O1
T6
P4
Pz
P3
T5
T4
C4
Cz
C3
T3
F8
F4
Fz
F3
F7
Fp2
A2
Fp1
2600
2650
2700
2750
2800
2850
Time [s]

0.3.5 Events

[22]:
```
i_s=intervals.iloc[8]["StartInd"]
i_e=intervals.iloc[8]["EndInd"]
```

[23]:
```
i_i=i_s
i_f=i_e
fig=plt.figure(figsize=(18,18))
count=0.0
axlist = []
yprops = dict(rotation=0, horizontalalignment='right',␣
↪verticalalignment='center')
axprops = dict(yticks=[])
for i in range(0,n):
    ax = fig.add_axes([0.1, count, 0.8, 1/n], **axprops)
    axlist.append(ax)
    axprops['sharex'] = ax
    axprops['sharey'] = ax
    ax.plot(time_arr[i_i:i_f],data[i,i_i:i_f])
    ax.set_ylabel(chan[i], **yprops)
    count+=1/n
    if i==0:
        plt.xlabel("Time [s]")
for ax in axlist[1:]:
    plt.setp(ax.get_xticklabels(), visible=False)
plt.title("sub: "+sub+" Event: 08 REM")
plt.show();
```



[24]:
```
true_events=events[events["EvPassRejection"]==1]
```

0.3.6 Dividing the run in segments

[25]:
```
#First we calculate the number of 15s windows in the measurment
window_l=15

windows=int(tf/window_l)
```

For the first test we will compute the area under the curve(which corresponds to the relative band energy of the segment for a specific chanel in a specific segment), the mean amplitude for each band, the frequency at which the SPD of a band reaches a maximum and the frequency at which the SPD of a band reaches a minimum. These parameter should be able to characterise the shape of the SPD.

In total we would have 23 chanels, each with 5 frequency bands(delta, theta, alpha, beta and gamma), each with 4 parameters. This means each segment has 460 parameters that describe the funcion.

[26]:
```
waves=np.zeros([n,windows,5,4])
for i in range(0,windows):
    for j in range(0,n):
        #Calculate the fft of the ith segment from the nth chanel of the data
        data_fft=np.absolute(np.fft.rfftn(data[j,i*window_l*fs:
 ↪(i+1)*window_l*fs]))

        #Delta waves: 0.2-4 Hz
        waves[j,i,0,0]=sum(data_fft[:4*window_l])
        waves[j,i,0,1]=np.mean(data_fft[:4*window_l])
        waves[j,i,0,2]=0.2+np.argmax(data_fft[:4*window_l])/window_l
        waves[j,i,0,3]=0.2+np.argmin(data_fft[:4*window_l])/window_l

        # Theta waves: 4-8 Hz
        waves[j,i,1,0]=sum(data_fft[4*window_l:8*window_l])
        waves[j,i,1,1]=np.mean(data_fft[4*window_l:8*window_l])
        waves[j,i,1,2]=4+np.argmax(data_fft[4*window_l:8*window_l])/window_l
        waves[j,i,1,3]=4+np.argmin(data_fft[4*window_l:8*window_l])/window_l

        # Alpha waves: 8-12 Hz
        waves[j,i,2,0]=sum(data_fft[8*window_l:12*window_l])
        waves[j,i,2,1]=np.mean(data_fft[8*window_l:12*window_l])
        waves[j,i,2,2]=8+np.argmax(data_fft[8*window_l:12*window_l])/window_l
        waves[j,i,2,3]=8+np.argmin(data_fft[8*window_l:12*window_l])/window_l

        # Beta waves: 12-30 Hz
        waves[j,i,3,0]=sum(data_fft[12*window_l:30*window_l])
        waves[j,i,3,1]=np.mean(data_fft[12*window_l:30*window_l])
        waves[j,i,3,2]=12+np.argmax(data_fft[12*window_l:30*window_l])/window_l
        waves[j,i,3,3]=12+np.argmin(data_fft[12*window_l:30*window_l])/window_l
```

```
        # Gamma: 30-90 Hz
        waves[j,i,4,0]=sum(data_fft[30*window_l:90*window_l])
        waves[j,i,4,1]=np.mean(data_fft[30*window_l:90*window_l])
        waves[j,i,4,2]=30+np.argmax(data_fft[30*window_l:90*window_l])/window_l
        waves[j,i,4,3]=30+np.argmin(data_fft[30*window_l:90*window_l])/window_l
```

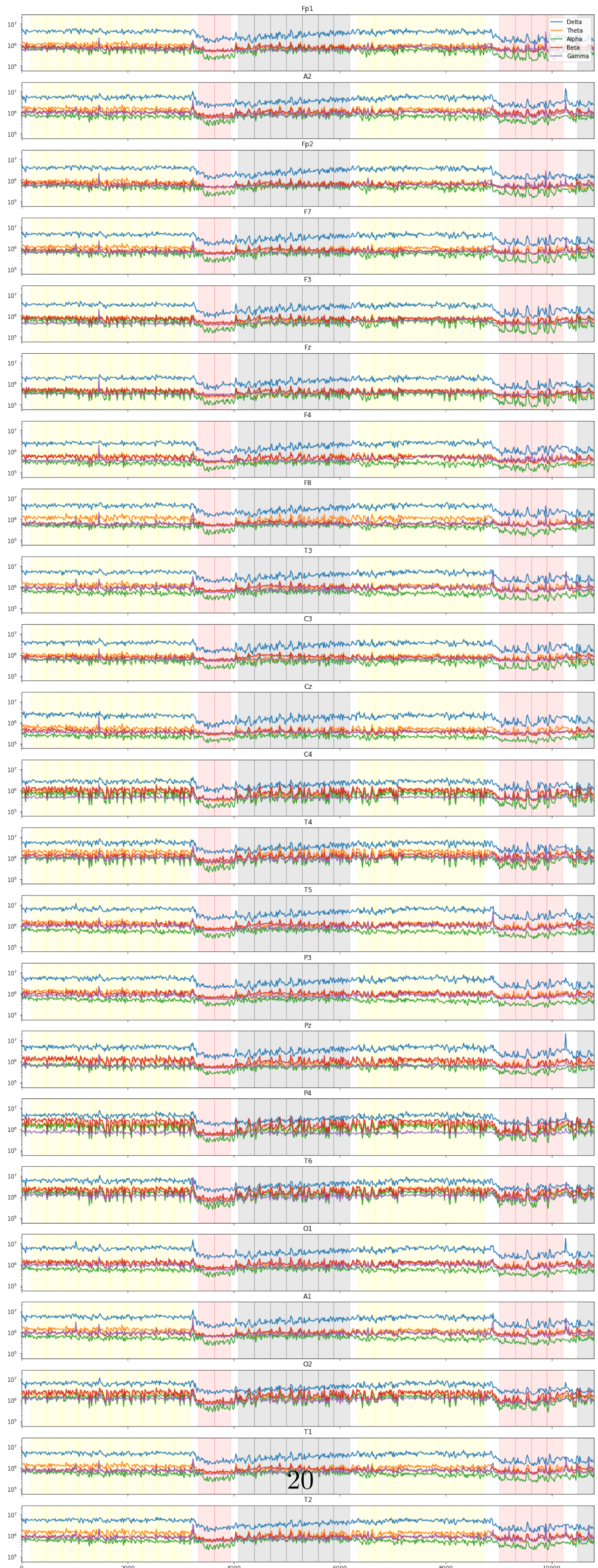
0.3.7 Relative band energy

To have an idea of how valueable a parameter is, we will plot them with markings of the sleep stages. First we will plot the relative band energy (area under the curve).

[27]:
```
bands=["Delta","Theta","Alpha","Beta","Gamma"]
```

[50]:
```
fig, axs = plt.subplots(nrows=n, ncols=1, sharex=True, sharey=True,␣
 ↪figsize=(18,50))
for i in range(0,n):
    for j in range(0,5):
        axs[i].plot(np.linspace(0,tf,windows),waves[i,:,j,0],label=bands[j])
    axs[i].set_title(chan[i])
    #ax.set_ylabel(signal_labels[i], **yprops)
    plt.semilogy()
    #plt.ylim(0,4e6)
    plt.xlim(0,tf)
    if i==n:
        axs[i].set_xlabel('Frequency [Hz]')
    for k in range(0,len(intervals)):
        if intervals.iloc[k]["SleepStage"]!="Awake":
            if intervals.iloc[k]["SleepStage"]=="N2":
                color="green"
            if intervals.iloc[k]["SleepStage"]=="N3":
                color="yellow"
            if intervals.iloc[k]["SleepStage"]=="REM":
                color="red"
            [l.axvspan(time_arr[intervals.
 ↪iloc[k]["StartInd"]],time_arr[intervals.
 ↪iloc[k]["EndInd"]],color=color,alpha=0.005) for l in axs]
fig.suptitle("Area under the curve")
axs[0].legend()
plt.show;
```

Area under the curve



0.4 Welch plots

Now we will make Welch plots for all of the chanels. This information will provide information about the spectral composition of each chanel. Which might give us an idea to later define usefull paramteters. If we can describe the shape of the welch plot with numbers, we might be able to diferentiate each sleep stage.

[30]:
```
subjects.iloc[int(sub)-1]
```

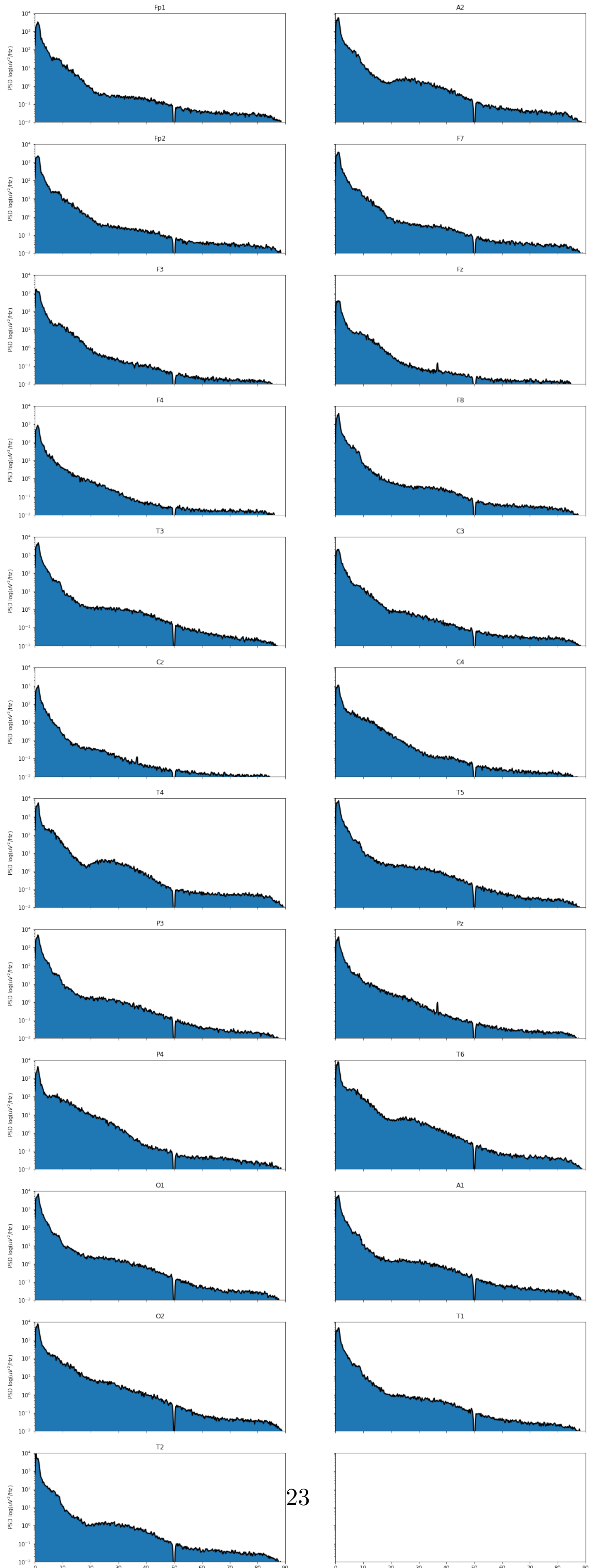
[30]:
```
participant_id                             sub-03
age                                           4.8
sex                                             m
pathology          (radiologic suspicion of) FCD
eeg_montage                        10-20 system
Name: 2, dtype: object
```

[31]:
```
i_s=intervals[intervals["RunNb"]==int(run)].iloc[0]["StartInd"]
i_e=intervals[intervals["RunNb"]==int(run)].iloc[0]["EndInd"]
```

[32]:
```
data_01=data[:,i_s:i_e]
```

[33]:
```
def Welch(data_NREM,sf):
    win = int(5 * sf)  # Window size is set to 5 seconds
    freqs, psd = welch(data_NREM, sf, nperseg=win, average='median')  # Works␣
 ↪with single or multi-channel data

    fig, axs = plt.subplots(nrows=int(np.ceil(len(chan)/2)), ncols=2,␣
 ↪sharex=True, sharey=True, figsize=(18,int(2.3*len(chan))))
    for i in range(0,len(chan)):
        row=int(i/2)
        col=i%2

        # Plot
        axs[row, col].plot(freqs, psd[i], 'k', lw=2)
        axs[row, col].fill_between(freqs, psd[i], cmap='Spectral')
        axs[row, col].set_xlim(0, 90)
        axs[row, col].set_ylim(10e-3,10e3)
        axs[row, col].set_yscale('log')
        axs[row, col].set_title(chan[i])
        if row==int(np.ceil(len(chan)/2))-1:
            axs[row, col].set_xlabel('Frequency [Hz]')
        if col==0:
            axs[row, col].set_ylabel('PSD log($uV^2$/Hz)')
    #fig.suptitle("Welch plots")
```

[34]:
```
Welch(data_01,fs)
```

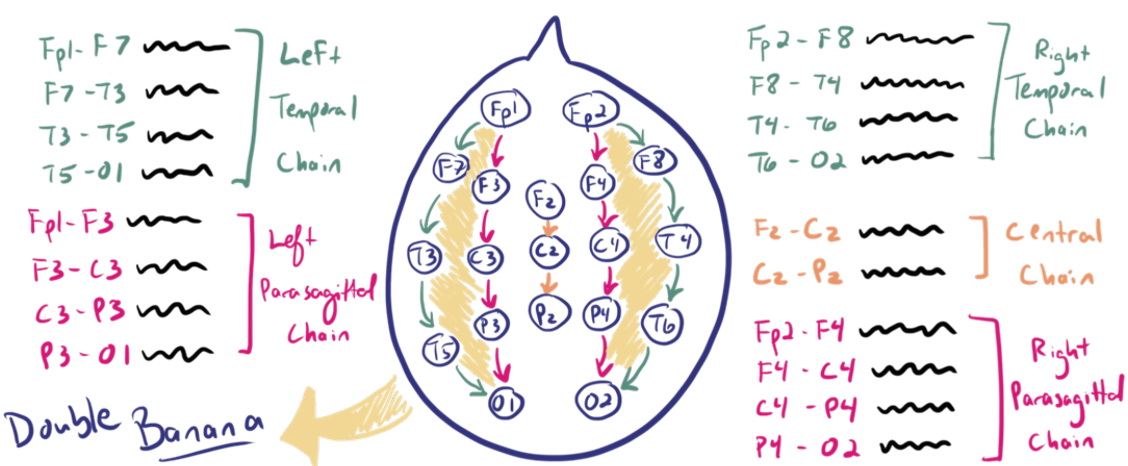

Fp1
A2
Fp2
F7
F3
Fz
F4
F8
T3
C3
Cz
C4
T4
T5
P3
Pz
P4
T6
O1
A1
O2
T1
T2
PSD log(uV²/Hz)
Frequency [Hz]

As you might have noticed, some of the plots are biphasic (T2 for example) or even triphasic(T4 and T6). In this case the average or the median of the plot don't describe the welch plot. There are several ways to fix this. The first is to divide the welch plots in diferent bands of predefined lenght like we did in the first analysis. The area under the curve for each band will be enough to identify the phasicity of the curve if the width of each phase matches the band. Another method could be to divide the area under the curve in relative proportions. This would mean we would place markers when the area under the curve reaches 1/5 of the total area, another when it reaches 2/5 and so on. For each marker we would have a frequency and a relative intensity. All of this options will be explored in the next notebook.

0.5 Derivative channels

In the source of the data we are using there is a folder named "derivatives". This file contains bipolar derivations of the original data. This derivations were obtained by a resampling of the data. The are also files of marked events within the bipolar derivation. Now we will try to obtain the same information as before but with this new channels.

The bipolar derivations used correspond to the "double banana" derivations. In this derivation 5 main antero-posterior chains of electrodes are created forming the shape of a double banana. By ploting this bipolar derivations we are able to watch the flow of current though the brain. Sometimes two adjasent links of a chain of electrodes have a similar spike but inverted. This type of phenomenon is called a phase reversal and is very useful in detection of epilepiform activity and artifact detection.



[35]:
```
der_bi_chan=["Fp1-F7","F7-T3","T3-T5","T5-O1","Fp1-F3","F3-C3","C3-P3","P3-O1","Fz-Cz","Cz-Pz'
                        ,"C4-P4","P4-O2","Fp2-F8","F8-T4","T4-T6","T6-O2",␣
  ↪"F7-T1","T1-T3","F8-T2","T2-T4"]
```

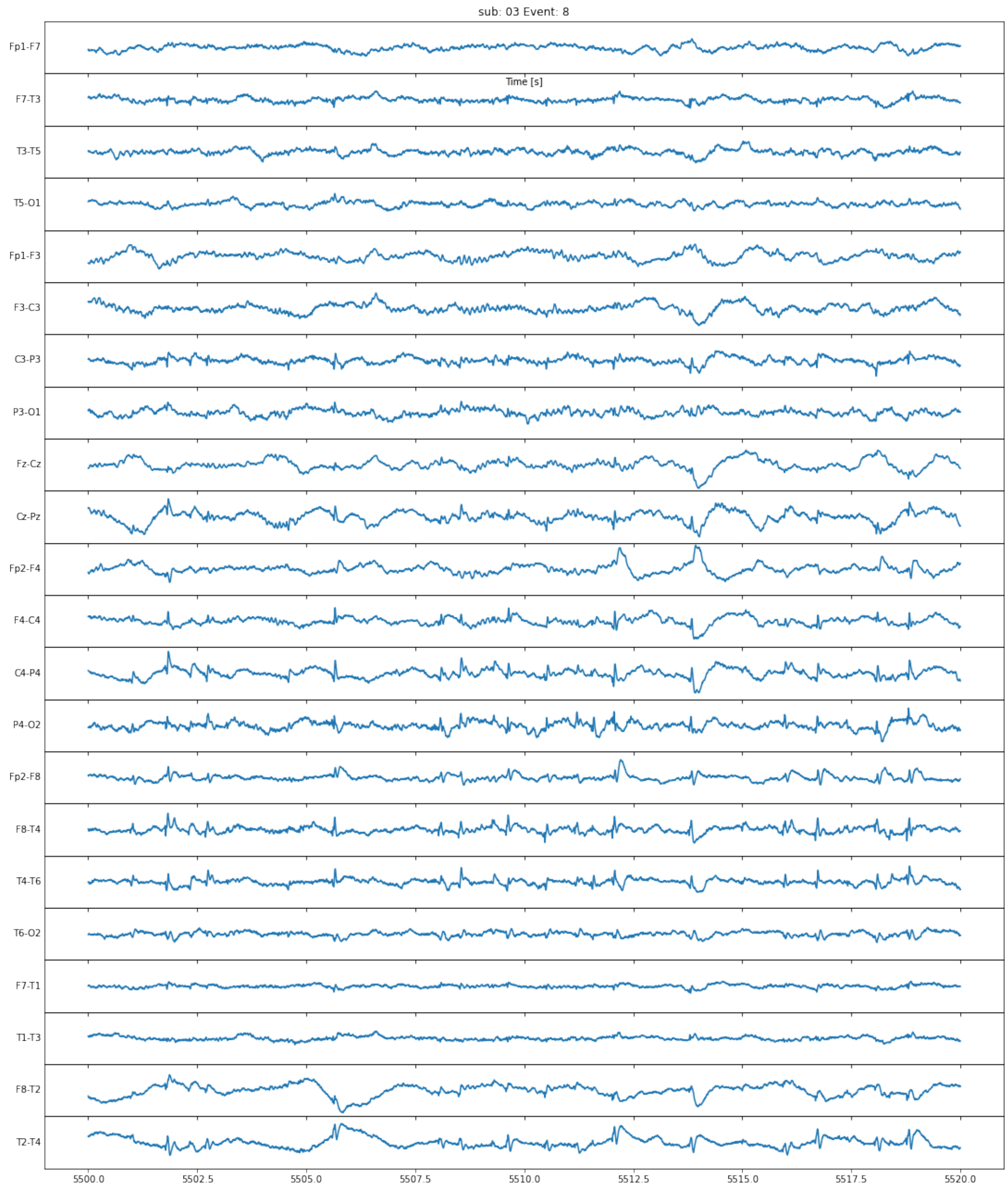
[36]:
```
der_bi_ind=np.zeros([len(der_bi_chan),2],dtype=int)
for i in range(0,len(der_bi_chan)):
    der_bi_ind[i,0]=int(chan.index(der_bi_chan[i].split("-")[0]))
    der_bi_ind[i,1]=int(chan.index(der_bi_chan[i].split("-")[1]))
```

[37]:
```
data_bi=np.zeros([len(der_bi_chan),len(data[0])])
for i in range(0,len(der_bi_chan)):
    data_bi[i]=data[der_bi_ind[i,0]]-data[der_bi_ind[i,1]]
```

0.5.1 Plot of derivative chanels

[38]:
```
event=8
i_s=intervals.iloc[event]["StartInd"]
i_e=intervals.iloc[event]["EndInd"]
```

[64]:
```
i_i=5500*fs
i_f=5520*fs
fig=plt.figure(figsize=(18,18))
count=0.0
axlist = []
yprops = dict(rotation=0, horizontalalignment='right',␣
 ↪verticalalignment='center')
axprops = dict(yticks=[])
for i in range(len(data_bi)-1,-1,-1):
    ax = fig.add_axes([0.1, count, 0.8, 1/n], **axprops)
    axlist.append(ax)
    axprops['sharex'] = ax
    axprops['sharey'] = ax
    ax.plot(time_arr[i_i:i_f],data_bi[i,i_i:i_f])
    ax.set_ylabel(der_bi_chan[i], **yprops)
    count+=1/n
    if i==0:
        plt.xlabel("Time [s]")
for ax in axlist[1:]:
    plt.setp(ax.get_xticklabels(), visible=False)
plt.title("sub: "+sub+" Event: "+str(event))
plt.show();
```



0.5.2 Properties of derivative chanels

For the deriatives we will obtain the relative band energy, the mean intensity of the PSD and the frequency at which the median is found.

[40]:
```
waves_bi=np.zeros([len(data_bi),windows,5,3])
for i in range(0,windows):
```

```
    for j in range(0,len(data_bi)):
        data_fft=np.absolute(np.fft.rfftn(data_bi[j,i*window_l*fs:
↪(i+1)*window_l*fs]))

        #Delta waves: 0.2-4 Hz
        waves_bi[j,i,0,0]=sum(data_fft[:4*window_l])
        waves_bi[j,i,0,1]=np.mean(data_fft[:4*window_l])
        k=0
        temp=0
        while temp<waves_bi[j,i,0,0]/2:
            temp+=data_fft[k]
            k+=1
        waves_bi[j,i,0,2]=k/window_l

        # Theta waves: 4-8 Hz
        waves_bi[j,i,1,0]=sum(data_fft[4*window_l:8*window_l])
        waves_bi[j,i,1,1]=np.mean(data_fft[4*window_l:8*window_l])
        k=0
        temp=0
        while temp<waves_bi[j,i,1,0]/2:
            temp+=data_fft[k]
            k+=1
        waves_bi[j,i,1,2]=k/window_l

        # Alpha waves: 8-12 Hz
        waves_bi[j,i,2,0]=sum(data_fft[8*window_l:12*window_l])
        waves_bi[j,i,2,1]=np.mean(data_fft[8*window_l:12*window_l])
        k=0
        temp=0
        while temp<waves_bi[j,i,2,0]/2:
            temp+=data_fft[k]
            k+=1
        waves_bi[j,i,2,2]=k/window_l

        # Beta waves: 12-30 Hz
        waves_bi[j,i,3,0]=sum(data_fft[12*window_l:30*window_l])
        waves_bi[j,i,3,1]=np.mean(data_fft[12*window_l:30*window_l])
        k=0
        temp=0
        while temp<waves_bi[j,i,3,0]/2:
            temp+=data_fft[k]
            k+=1
        waves_bi[j,i,3,2]=k/window_l

        # Gamma: 30-90 Hz
        waves_bi[j,i,4,0]=sum(data_fft[30*window_l:90*window_l])
        waves_bi[j,i,4,1]=np.mean(data_fft[30*window_l:90*window_l])
```

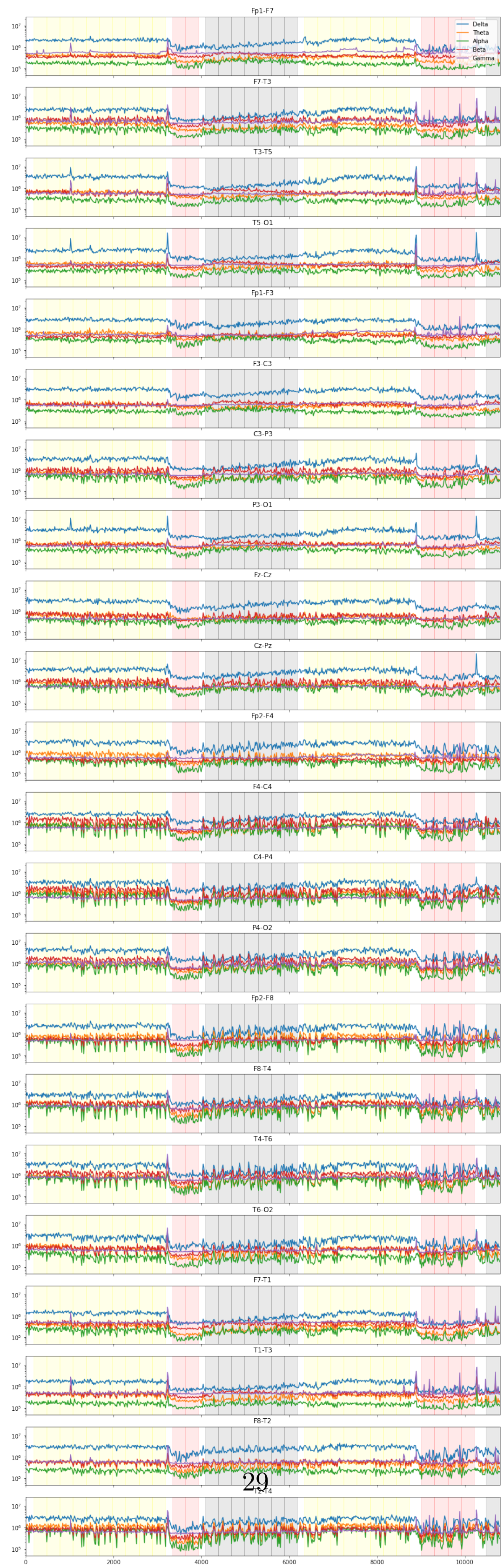
```
        k=0
        temp=0
        while temp<waves_bi[j,i,4,0]/2:
            temp+=data_fft[k]
            k+=1
        waves_bi[j,i,4,2]=k/window_l
```

0.6 Results

[41]:
```
n_bi=len(data_bi)
```

[66]:
```
fig, axs = plt.subplots(nrows=n_bi, ncols=1, sharex=True, sharey=True,␣
 ↪figsize=(15,50))
for i in range(0,n_bi):
    for j in range(0,5):
        axs[i].plot(np.linspace(0,tf,windows),waves_bi[i,:,j,0],label=bands[j])
    axs[i].set_title(der_bi_chan[i])
    #ax.set_ylabel(signal_labels[i], **yprops)
    #plt.ylim(0,4e6)
    plt.xlim(0,tf)
    plt.semilogy()
    if i==n_bi-1:
        axs[i].set_xlabel('Time(s)')
    for k in range(0,len(intervals)):
        if intervals.iloc[k]["SleepStage"]!="Awake":
            if intervals.iloc[k]["SleepStage"]=="N2":
                color="green"
            if intervals.iloc[k]["SleepStage"]=="N3":
                color="yellow"
            if intervals.iloc[k]["SleepStage"]=="REM":
                color="red"
            [l.axvspan(time_arr[intervals.
 ↪iloc[k]["StartInd"]],time_arr[intervals.
 ↪iloc[k]["EndInd"]],color=color,alpha=0.005) for l in axs]
fig.suptitle("Area under the curve")
axs[0].legend()
plt.show;
```

Area under the curve



In the previous plots we can see that there is a drastic difference between the N3 and REM stages, however the difference isn't that big between the other stages. In the N2 stage we can see a high variance in both plots. This might be due to the precence of sleep spindles and k-complexes.

Recap of functions:

[44]:
```
def segments(sub):
    inter_c=pd.DataFrame({"StartInd":[],"EndInd":[],"SleepStage":[]})
    intervals=pd.read_csv("derivatives/sub-"+sub+"/ses-01/eeg/DataIntervals.
↪tsv",sep="\t")
    start=intervals.iloc[0]["StartInd"]
    stage=intervals.iloc[0]["SleepStage"]
    for i in range(1,len(intervals)):
        if stage!=intervals.iloc[i]["SleepStage"]:
            if intervals.iloc[i-1]["EndInd"]-start>5*60*fs:
                   inter_c.loc[len(inter_c)]=[int(start-150*fs+(intervals.
↪iloc[i-1]["EndInd"]-start)/2),int(start+150*fs+(intervals.
↪iloc[i-1]["EndInd"]-start)/2),stage]
            #inter_c.loc[len(inter_c)]=[int(start),int(intervals.
↪iloc[i-1]["EndInd"]),stage]
            start=intervals.iloc[i]["StartInd"]
            stage=intervals.iloc[i]["SleepStage"]
    if stage==intervals.iloc[-1]["SleepStage"]:
        if intervals.iloc[-1]["EndInd"]-start>5*60*fs:
            inter_c.loc[len(inter_c)]=[int(start-150*fs+(intervals.
↪iloc[-1]["EndInd"]-start)/2),int(start+150*fs+(intervals.
↪iloc[-1]["EndInd"]-start)/2),stage]

    return inter_c
```

[45]:
```
def bipolar_der(sub):
    raw=mne.io.read_raw_edf("sub-"+sub+"/ses-01/eeg/
↪sub-"+sub+"_ses-01_task-hfo_eeg.edf", preload=True, verbose=0)
    raw.filter(0.4, 80)
    raw.notch_filter([50,100])

    data = raw._data

    data_bi=np.zeros([len(der_bi_chan),len(data[0])])
    for i in range(0,len(der_bi_chan)):
        data_bi[i]=data[der_bi_ind[i,0]]-data[der_bi_ind[i,1]]
    return data_bi
```

[46]:
```
# data_bi is an array with dimentions of: [bipolar channels, n]
# start is the index in which the segment to be analyzed starts.
```

```
# end is the index in which the segment to be analyzed ends.
def f_waves(data_bi,start,end):
    #We establish windows of 10s
    window_l=10
    windows=(end-start)/(window_l*fs)
    waves_bi=np.zeros([len(data_bi),windows,5,3])
    for i in range(0,windows):
        for j in range(0,len(data_bi)):
            data_fft=np.absolute(np.fft.rfftn(data_bi[j,start+i*window_l*fs:
 ↪start+(i+1)*window_l*fs]))

            #Delta waves: 0.2-4 Hz
            waves_bi[j,i,0,0]=sum(data_fft[:4*window_l])
            waves_bi[j,i,0,1]=np.mean(data_fft[:4*window_l])
            k=0
            temp=0
            while temp<waves_bi[j,i,0,0]/2:
                temp+=data_fft[k]
                k+=1
            waves_bi[j,i,0,2]=k/window_l

            # Theta waves: 4-8 Hz
            waves_bi[j,i,1,0]=sum(data_fft[4*window_l:8*window_l])
            waves_bi[j,i,1,1]=np.mean(data_fft[4*window_l:8*window_l])
            k=0
            temp=0
            while temp<waves_bi[j,i,1,0]/2:
                temp+=data_fft[k]
                k+=1
            waves_bi[j,i,1,2]=k/window_l

            # Alpha waves: 8-12 Hz
            waves_bi[j,i,2,0]=sum(data_fft[8*window_l:12*window_l])
            waves_bi[j,i,2,1]=np.mean(data_fft[8*window_l:12*window_l])
            k=0
            temp=0
            while temp<waves_bi[j,i,2,0]/2:
                temp+=data_fft[k]
                k+=1
            waves_bi[j,i,2,2]=k/window_l

            # Beta waves: 12-30 Hz
            waves_bi[j,i,3,0]=sum(data_fft[12*window_l:30*window_l])
            waves_bi[j,i,3,1]=np.mean(data_fft[12*window_l:30*window_l])
            k=0
            temp=0
            while temp<waves_bi[j,i,3,0]/2:
```

```
                temp+=data_fft[k]
                k+=1
            waves_bi[j,i,3,2]=k/window_l

            # Gamma: 30-90 Hz
            waves_bi[j,i,4,0]=sum(data_fft[30*window_l:90*window_l])
            waves_bi[j,i,4,1]=np.mean(data_fft[30*window_l:90*window_l])
            k=0
            temp=0
            while temp<waves_bi[j,i,4,0]/2:
                temp+=data_fft[k]
                k+=1
            waves_bi[j,i,4,2]=k/window_l

    waves_avg=np.zeros([7,5])
    waves_avg[0]=np.mean(waves_bi[:4,:,:,2],axis=(0,1))
    waves_avg[1]=np.mean(waves_bi[4:8,:,:,2],axis=(0,1))
    waves_avg[2]=np.mean(waves_bi[8:10,:,:,2],axis=(0,1))
    waves_avg[3]=np.mean(waves_bi[10:14,:,:,2],axis=(0,1))
    waves_avg[4]=np.mean(waves_bi[14:18,:,:,2],axis=(0,1))
    waves_avg[5]=np.mean(waves_bi[18:20,:,:,2],axis=(0,1))
    waves_avg[6]=np.mean(waves_bi[20:,:,:,2],axis=(0,1))
    return waves_avg
```

[47]:
```
def data_substarction(data,fs,inter_c):
    for i in range(0,len(inter_c)):
        start=int(inter_c.iloc[i,0]/(15*fs))
        end=int(inter_c.iloc[i,1]/(15*fs))
```

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