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m03_ex1_ecg_50_hz_complete

October 3, 2024

The objective of this exercise is to study the influence of the parameterization of the Welch spectral estimator in order to highlight a 50 Hz perturbation in an ECG signal.

[2]:
```
import numpy as np
import pylab as py
py.ion()
py.close('all')
import scipy.signal as sp
```

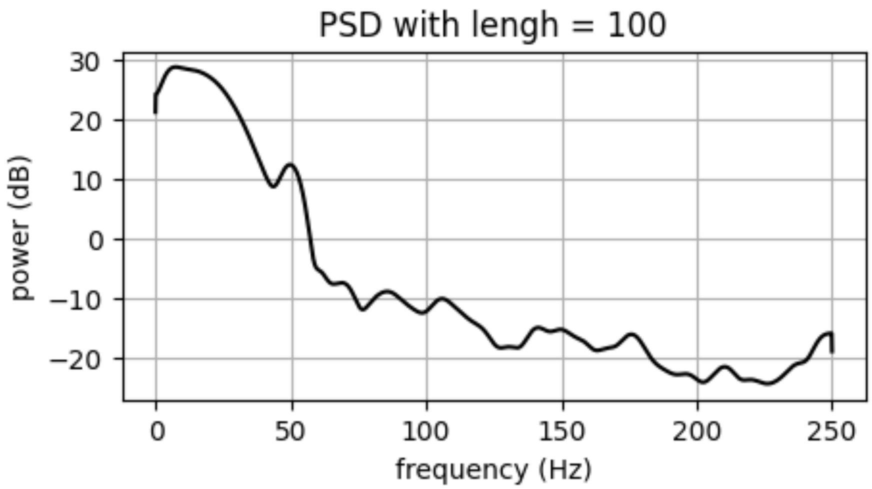
[3]:
```
x = np.genfromtxt('ecg.dat')
fs = 500
```

Objective: Compare spectral estimation for different window lengths using welch estimation. Plot the log spectrum of the signal using windows of 100, 500, 2000. Q: Comment the results. Q: Which windows length is the most suitable for the observation of 50 Hz? Q: Why?

[4]:
```
f,X_100 = sp.welch(x, nperseg=100, nfft=4096, fs=fs)
f,X_500 = sp.welch(x, nperseg=500, nfft=4096, fs=fs)
f,X_2000 = sp.welch(x, nperseg=2000, nfft=4096, fs=fs)
```

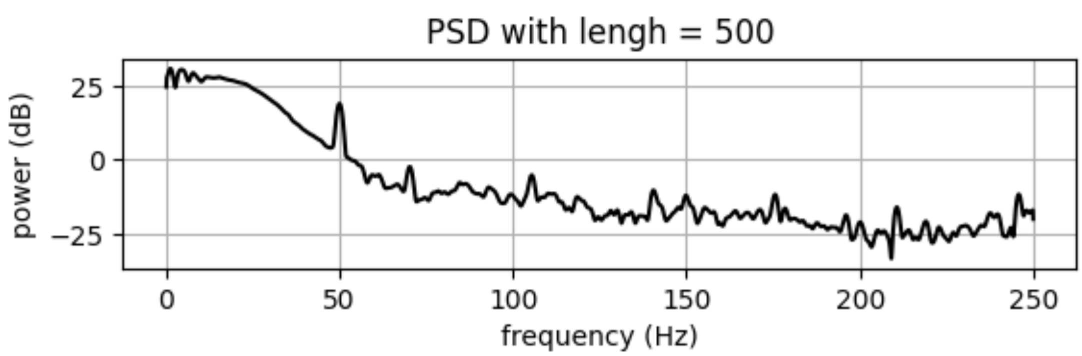
[5]:
```
py.figure(1, figsize=[5,8])
py.clf()
py.subplot(3,1,1)
py.plot(f, 10*np.log10(X_100), 'k')
py.grid()
py.xlabel('frequency (Hz)')
py.ylabel('power (dB)')
py.title('PSD with lengh = 100')
```

[5]:
```
Text(0.5, 1.0, 'PSD with lengh = 100')
```



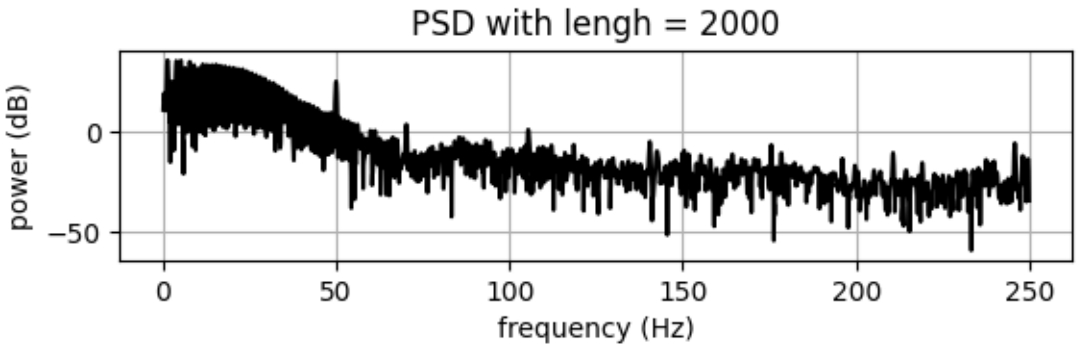
[6]:
```
py.subplot(3,1,2)
py.plot(f, 10*np.log10(X_500), 'k')
py.grid()
py.xlabel('frequency (Hz)')
py.ylabel('power (dB)')
py.title('PSD with lengh = 500')
```

[6]: Text(0.5, 1.0, 'PSD with lengh = 500')



[7]:
```
py.subplot(3,1,3)
py.plot(f, 10*np.log10(X_2000), 'k')
py.grid()
py.xlabel('frequency (Hz)')
py.ylabel('power (dB)')
py.title('PSD with lengh = 2000')
```

[7]: Text(0.5, 1.0, 'PSD with lengh = 2000')



0.0.1 Answer

From the three figures above, it is clear that using a window length of 2000 introduced a lot of noise. The frequency located at 50Hz, which is the interesting frequency is not clearly highlighted.

Concerning the two remaining sizes, we can say that regarding the first one, the curve lacks of details and therefore the peak at 50Hz is too much attenuated compared to the rest of the signal. This can be explained by the fact that taking a length of 100 will cut some important part of the signal.

Finally, a length of 500 is a good compromise, discarding the noise, while keeping the relevant part of the signal. The peak at 50Hz is distinct from the other frequencies.

m03_ex2_ans_control_complete_vincent

October 3, 2024

The objective of this exercice is to analyse the control of the autonomic nervous system at rest and after alcool consumption using breathing, mean blood pressure and interbeat signals.

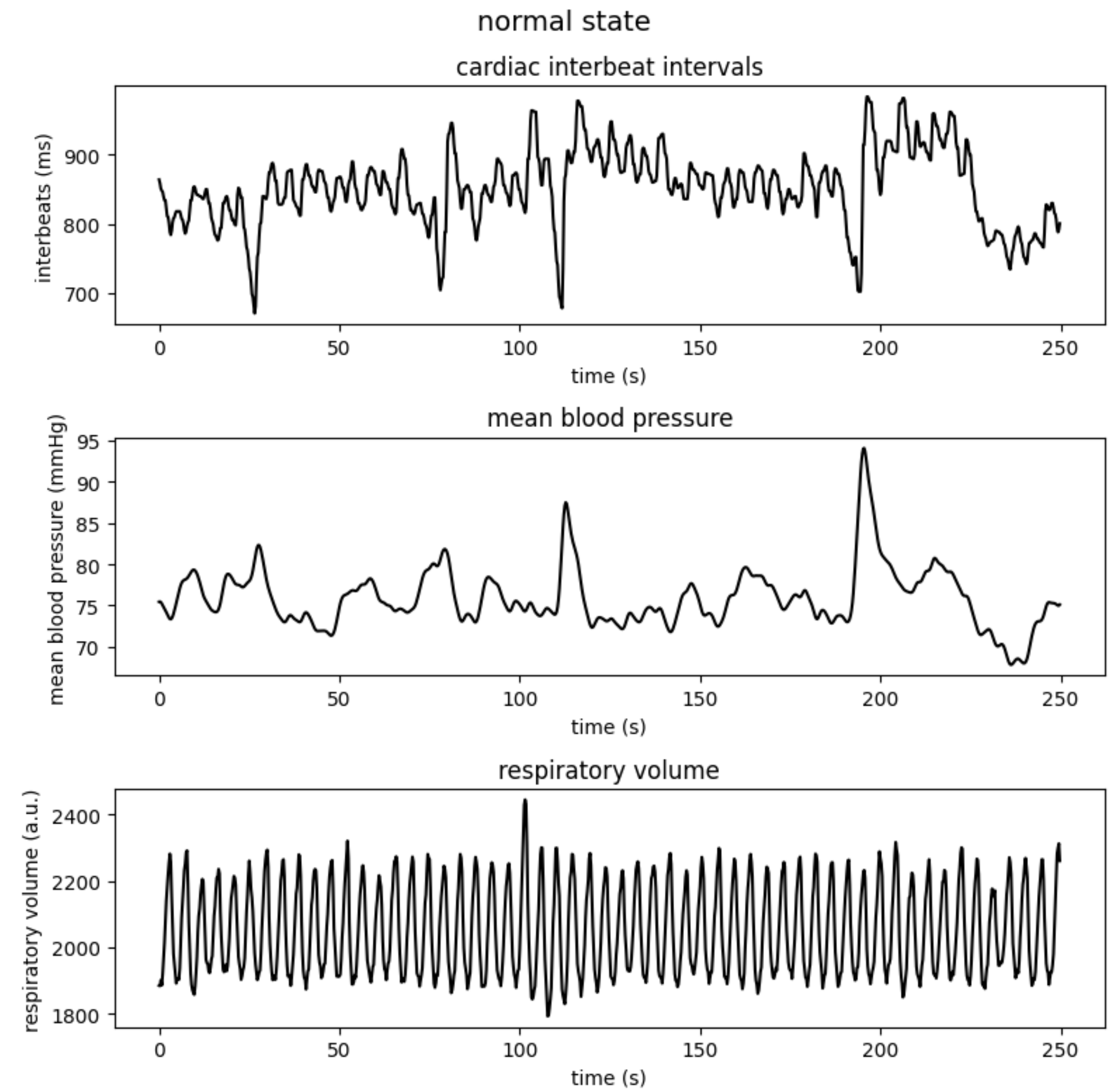
[1]:
```
import numpy as np
import pylab as py
py.ion()
py.close('all')
import scipy.signal as sp
import m03_ex2_ext as my_plot
```

Load signals of a subject at rest.

[2]:
```
x = np.genfromtxt('heart_1.dat', delimiter='  ').T
x = {'rr':x[0], 'bp':x[1], 'resp':x[2]}
# Load signals of a subject after alcool consumption.
y = np.genfromtxt('heart_2.dat', delimiter='  ').T
y = {'rr':y[0], 'bp':y[1], 'resp':y[2]}
# Signals are sampled at 4 Hz.
fs = 4
# Generate the time for the recordings.
t = np.arange(len(x['rr']))/fs
```

Cardiac interbeats, mean blood pressure and respiration volume of a subject at rest. Q: Comment the different signals and their realtionships. Q: Which signals are related and how?

[3]:
```
my_plot.plot_time(x, t, 'normal state')
```



0.0.1 Answer

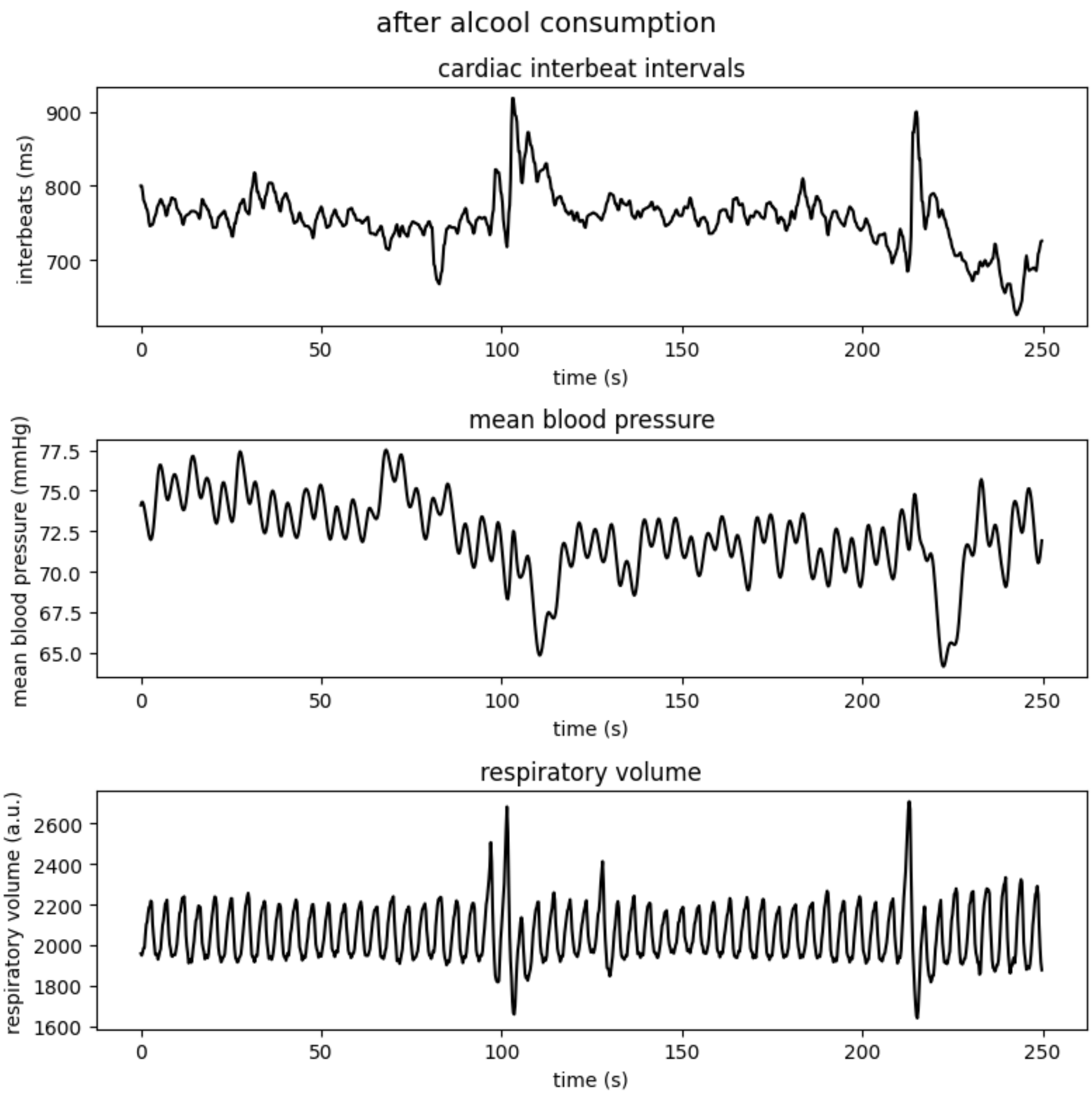
The three signals have different characteristics. First, the *respiratory volume* is close to a sinusoidal and is therefore the most deterministic signal between the three. Secondly, the *mean blood pressure* is almost a pure stochastic signal. Finally, the *cardiac interbeat intervals* is between the two other signals in term of determinism.

Concerning the relationships between signals, several conclusions can be drawn. From the graph above, *cardiac interbeat intervals* and *mean blood pressure* can be related, as we can see a corresponding peak in the two signals. Respectively, a minimum peak in *cardiac interbeat intervals* corresponds to a maximum peak in *mean blood pressure*.

The relationship between these two signals and the *respiratory signal* is not clearly identifiable in this graph. However, respiratory patterns influence heart rate variability, as inhalation typically leads to an increase in heart rate, while exhalation results in a decrease, even if this effect is not obvious here.

Cardiac interbeats, mean blood pressure and respiration volume of a subject after alcool consumption. Q: Comment the different signals and their realtionships. Q: Which signals are related and how? Q: What are the differences with rest recording of previous figure?

[4]:
```
my_plot.plot_time(y, t, 'after alcool consumption')
```



0.0.2 Answer

1. **Cardiac interbeat intervals**: Compared to the plot before alcool consumption, we can see that there is less variation in the *cardiac interbeat intervals*, which confirms the theory. Peaks appearing approximately every 100sec can still be observed. Furthermore, it seems that the

signal has less variations now, which confirms that when the parasympathetic system takes over, there are less variations in the HRV.

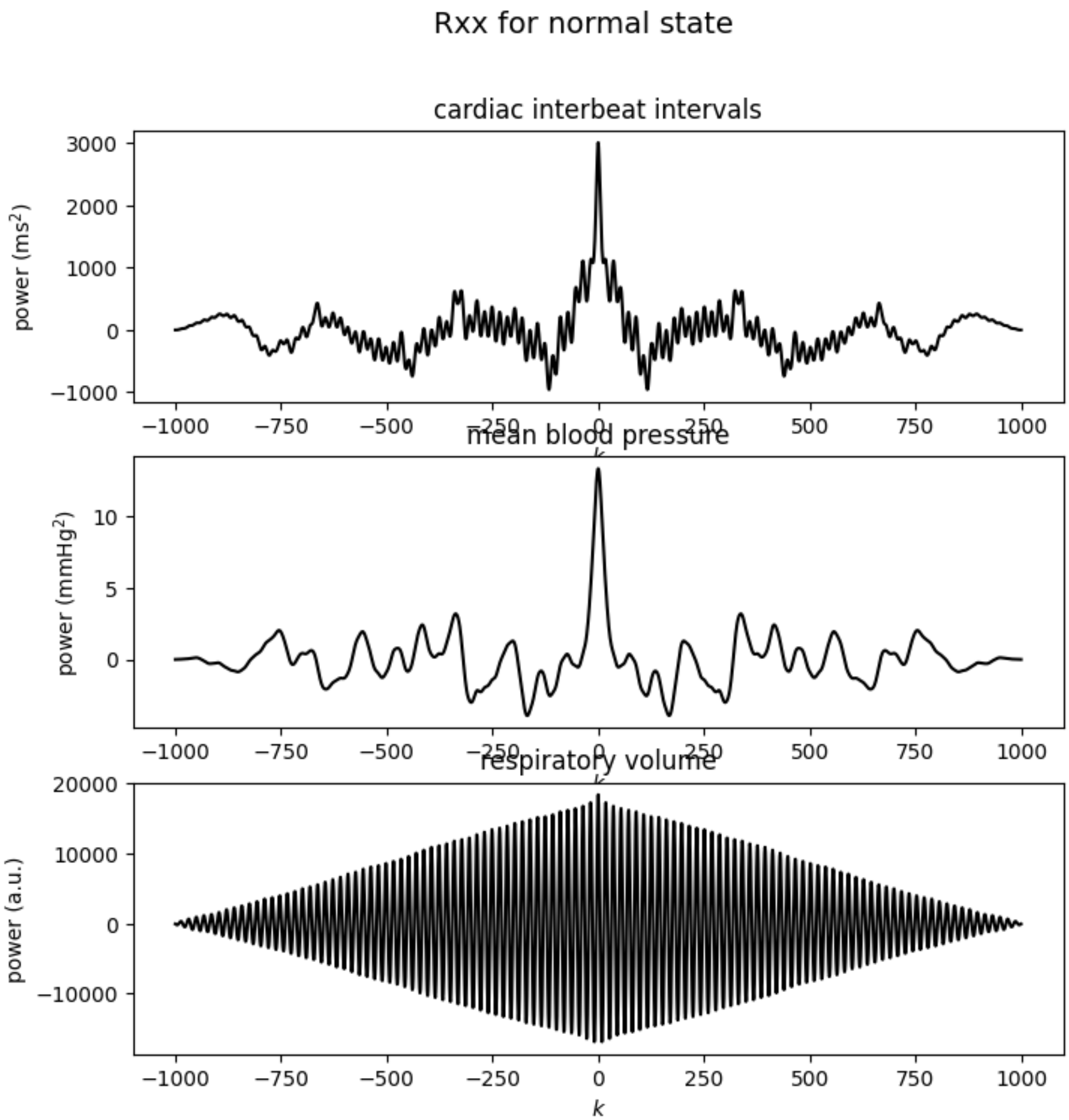
2. **Mean blood pressure**: This signal shows a similar behavior as the *cardiac interbeat intervall*. Peaks can still be observed as the same location as the first signal.
3. **Respiratory volume**: This signal still expresses periodicity. But this time, same peaks can be oberseved, which induced a correlation between this signal and the two others. This correlation was not obvious in the first case.

Compute the intercorrelation of the signals of the subject at rest. Q: Comment the oscillation present in the different signals. Q: Which signals are related and how.

[5]:
```
def my_corr(x):
    rxx = np.correlate(x-np.mean(x), x-np.mean(x), mode='full')/len(x)
    return rxx
```

[6]:
```
x['rxx_rr'] = my_corr(x['rr'])
x['rxx_bp'] = my_corr(x['bp'])
x['rxx_resp'] = my_corr(x['resp'])
```

[7]:
```
my_plot.plot_rxx(x, 'Rxx for normal state')
```



0.0.3 Answer

1. **Cardiac interbeat intervals**: The signal exhibits a strong peak located at zero, which corresponds to the power of the signal. The general pattern is close to a white gaussian noise signal, which confirms the previous answer. As we can see, the autocorrelation signal is not periodical, which confirm the fact that the original signal is not periodical. Furthermore, small oscillations can be seen in the autocorrelation. This appears at the same frequency as the respiratory. These oscillations are due to the adapatation of the cardiac interbeat by the ANS.

2. **Mean blood pressure**: This signal has a similiar shape as the first one, suggesting a correlation between these two signals. The strong peak at zero is still present. The non-periodicity

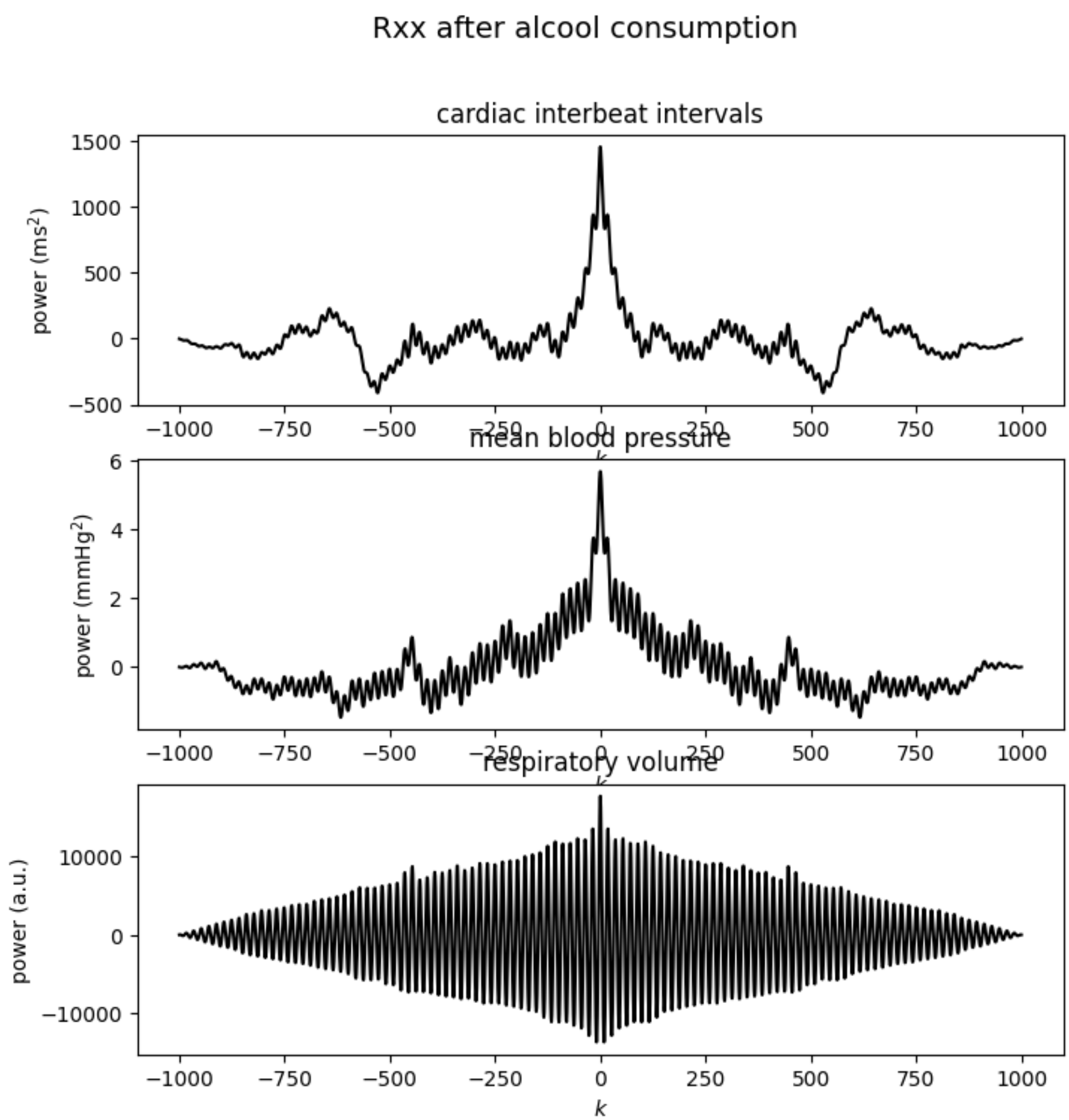
of the power indicates that the original signal is neither periodic. No small oscillations are observed, meaning that the mechanism of adaptation works as expected.

3. **Respiratory volume**: Conversely, the third signal has a complete different shape. We can see that the power decreases symetrically when the delay increases. Assuming that a biased estimator has been used, this lozenge shape can highlight the periodicity of the signal. This decrease is explained by the factor $\frac{1}{n}$, which dominates when the lag increases. Moreover, the strong difference with the two other signals shows their dissimilarity.

Compute the intercorrelation of the signals of the subject after alcool consumption. Q: Comment the oscillation present in the different signals. Q: Which signals are related and how. Q: What difference do you observe with the previous figure?

[8]:
```
y['rxx_rr'] = my_corr(y['rr'])
y['rxx_bp'] = my_corr(y['bp'])
y['rxx_resp'] = my_corr(y['resp'])
```

[9]:
```
my_plot.plot_rxx(y, 'Rxx after alcool consumption')
```



0.0.4 Answer

The three signals have barely the same shape as before, but with minor differences. Secondary peaks can be observed at approx. $k = \pm 500$ for all the three signals. These peaks are due to a slight change in the respiratory volume that is not completely compensated by the ANS and therefore appear in the cardiac interbeat intervals and in the mean blood pressure graphs.

1. **Cardiac interbeat intervals**: the small oscillations have a much lower amplitude after alcohol consumption than before.

2. **Mean blood pressure**: Oscillations in the signal can be observed. These oscillations were not present before alcool consumption, meaning that taking alcohol, indeed affects the mechanism described in the previous answer.

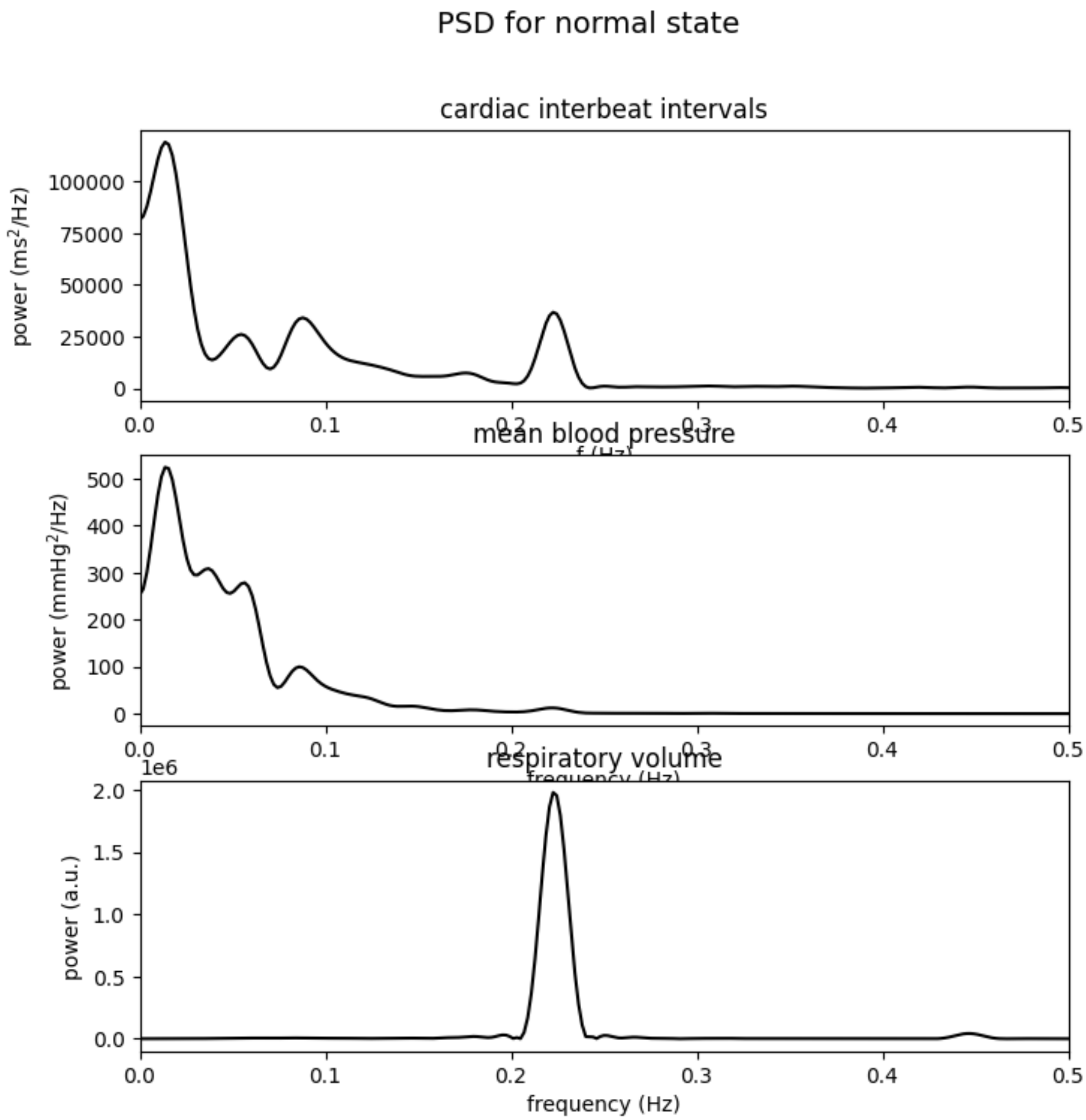
3. **Respiratory volume**: The shape of the lozenge is reduced and peaks in the autocorrelation can be seen at the same location as the two other signals.

Compute the PSD of the signal for the subject at rest. Q: How the different peaks are related to the control of the autonomic nervous system? Q: Do the positions and amplitude of the peaks confirm you previous findings;

[10]:
```
def my_psd(x, half_win=250):
    interval = np.arange(-half_win,half_win+1)+len(x)//2
    x_sub = x[interval]
    psd = np.abs(np.fft.fft(sp.windows.hann(len(interval))*x_sub, 2048))
    return psd
```

[11]:
```
x['RR'] = my_psd(x['rxx_rr'])
x['BP'] = my_psd(x['rxx_bp'])
x['RESP'] = my_psd(x['rxx_resp'])
```

[12]:
```
my_plot.plot_X(x, fs, 'PSD for normal state')
```



1 Answer

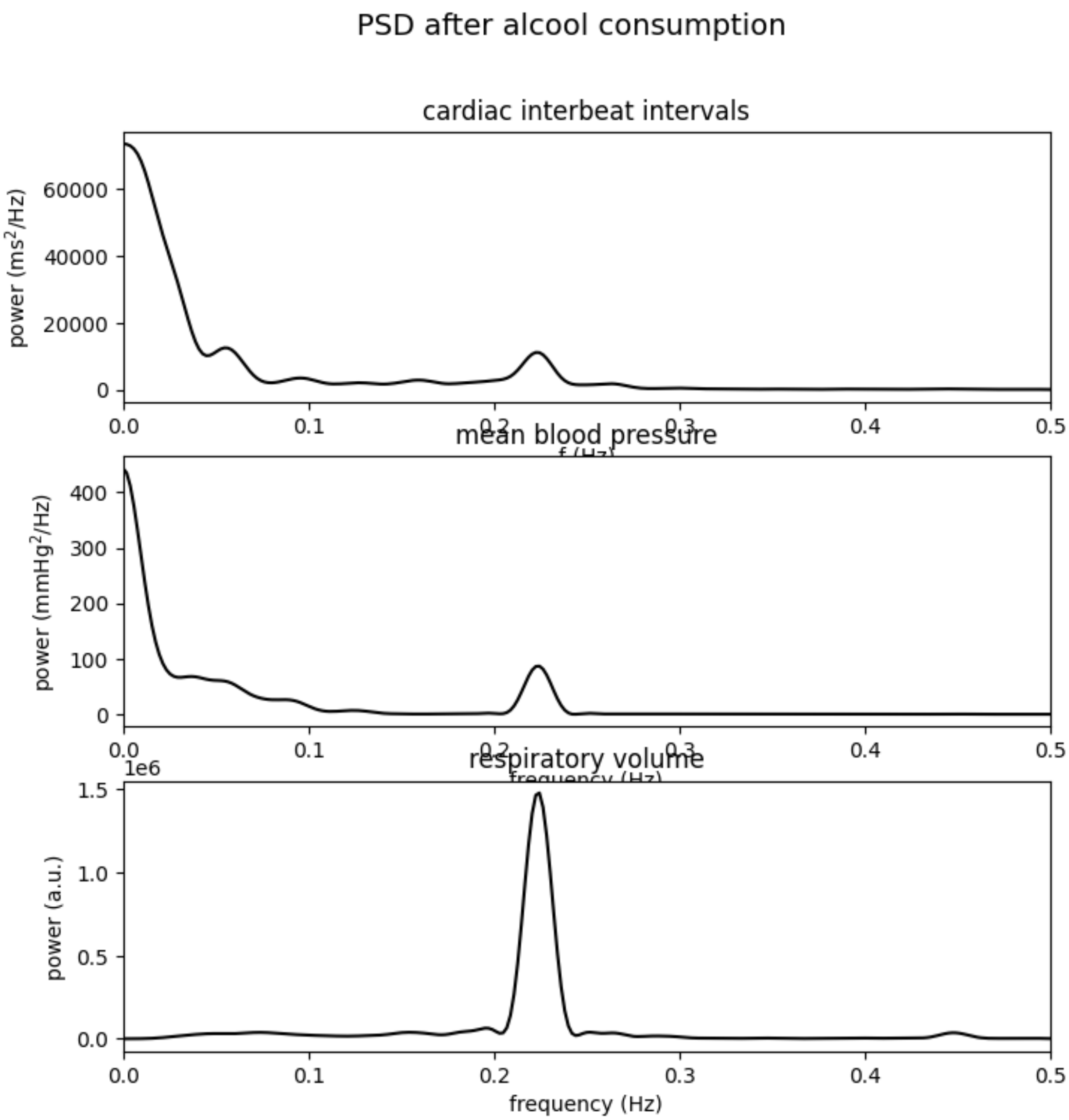
- Peaks in the 0.15–0.5 Hz range reflect the parasympathetic control of heart rate through respiratory influences, especially visible in cardiac interbeat intervals and slightly in mean blood pressure. Peaks in the 0.05–0.15 Hz range show the balance of sympathetic and parasympathetic control, relating to both heart rate variability and blood pressure regulation. Very low-frequency peaks highlight the slower physiological processes managed primarily by the sympathetic nervous system, which may contribute to fluctuations in both mean blood pressure and cardiac interbeat intervals.
- The frequency peak slightly above 0.2 Hz is clear for the cardiac interbeat intervals and respiratory volume signals, as observed before.

- The strong peak in respiration confirms the periodicity and regularity of respiration.
- We see the relationship highlighted in previous points between the cardiac interbeat and mean blood pressure, with slightly similar peaks in the 0–0.2 Hz range.

Compute the PSD of the signal for the subject after alcool consumption. Q: How the different peaks are related to the control of the autonomic nervous system? Q: Do the positions and amplitude of the peaks confirm you previous findings;

[13]:
```
y['RR'] = my_psd(y['rxx_rr'])
y['BP'] = my_psd(y['rxx_bp'])
y['RESP'] = my_psd(y['rxx_resp'])
```

[14]:
```
my_plot.plot_X(y, fs, 'PSD after alcool consumption')
```

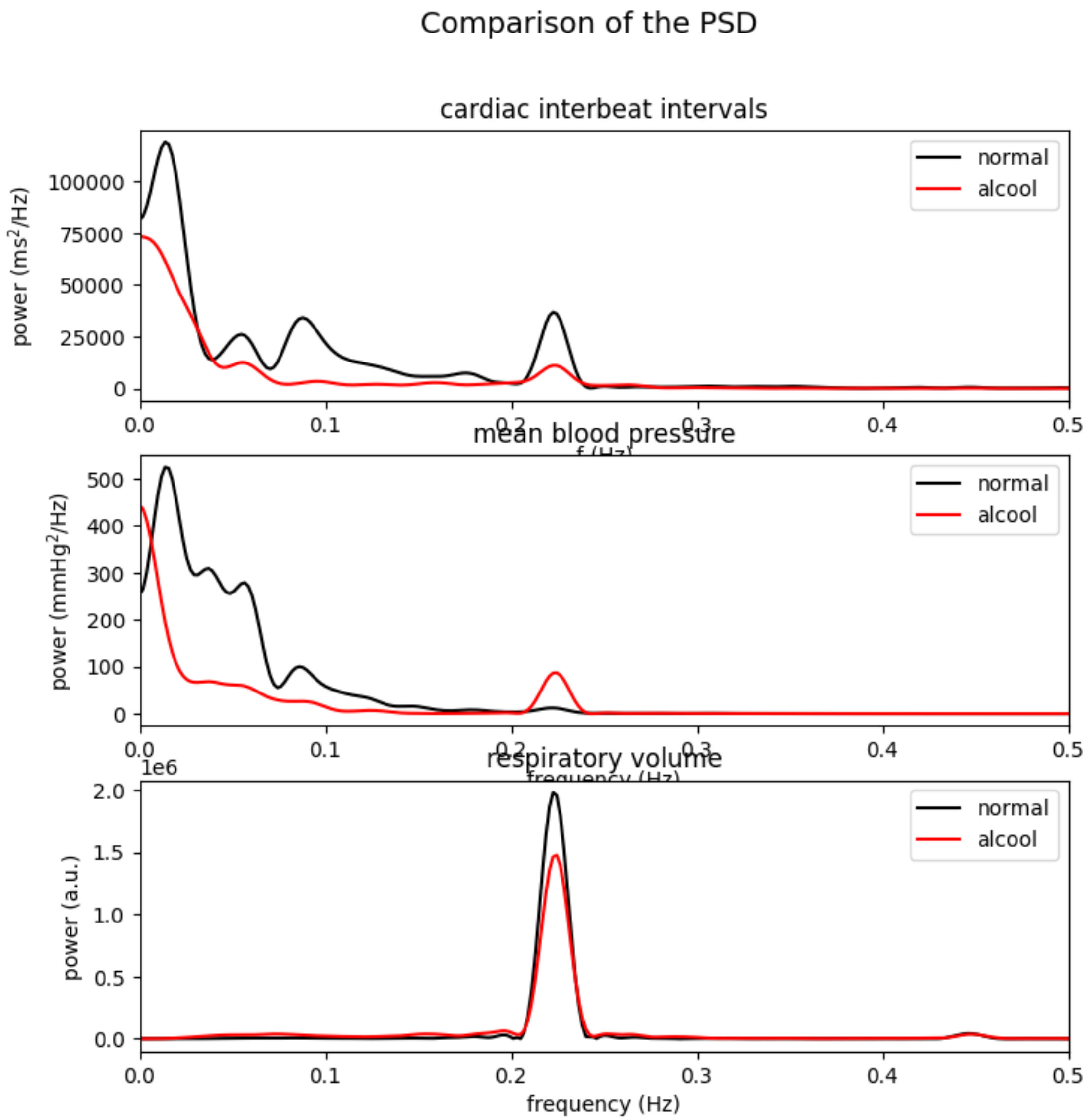


2 Answer

- With alcohol consumption, the peaks in the 0.15–0.4 Hz range still reflect parasympathetic control of heart rate through respiratory influences, but the effects are less pronounced compared to the resting state for the cardiac interbeat intervals, while being more pronounced in mean blood pressure.
- The peaks in the 0.05–0.15 Hz range continue to indicate the balance of sympathetic and parasympathetic control, but there is a reduction in their relative amplitudes, suggesting altered heart rate variability and blood pressure regulation due to alcohol.
- Very low-frequency peaks still highlight slower physiological processes managed primarily by the sympathetic nervous system; however, the influence of alcohol introduces fewer variations in frequency and a smoother range of frequencies.
- The frequency peak slightly above 0.2 Hz is still evident for the cardiac interbeat intervals and respiratory volume signals, though the overall amplitude is reduced compared to the resting state. On the other hand, the peak in mean blood pressure has considerably increased.
- The strong peak in respiration remains, confirming the periodicity and regularity of respiration, but it may also show irregularities compared to the baseline measurements.
- The relationship between the cardiac interbeat intervals and mean blood pressure persists, but the peaks in the 0–0.2 Hz range show altered amplitudes, indicating a slightly changed interaction between these signals under the influence of alcohol.
- All three signals indeed now have a dominant frequency close to 0.2 Hz, as observed before.

Plot the PSDs of the signals for the two conditions. Q: Discuss the differences.

[15]:
```
my_plot.plot_XY(x, y, fs, 'Comparison of the PSD')
```



2.0.1 Answer

NOUVELLE REPONSE

We can notice in the PSD of the cardiac interbeat intervals and the mean blood pressure that there is less power in the lower frequencies when consuming alcohol. This is due to the fact that alcohol consumption increases the ANS time response and makes it more sloppy, hence the two previously mentioned parameters are not as much regulated as before. Furthermore, the frequency range 0.15 - 0.5 Hz, which represents the regulation effect of the respiratory, is also affected by the alcohol, as it can be seen in the *cardiac interbeat* plot where the power is reduced in this range.

Alcohol consumption generally reduces the power in both the low-frequency components and the respiratory-driven frequency components, indicating a diminished regulatory capacity across the cardiovascular system.

m03_ex3_atrial_fibrilation

October 3, 2024

The objective of this exercise is to study the signal of ECG during atrial fibrilation (AF). The signal analysed contains different type of AF with stable repolarisation loops and random AF.

[1]:
```
import numpy as np
import pylab as py
py.ion()
py.close('all')
import scipy.signal as sp
```

The first signal is an ECG with atrial fibrilation. Q: What are the differences of this ECG with a normal ECG?

0.0.1 Answer

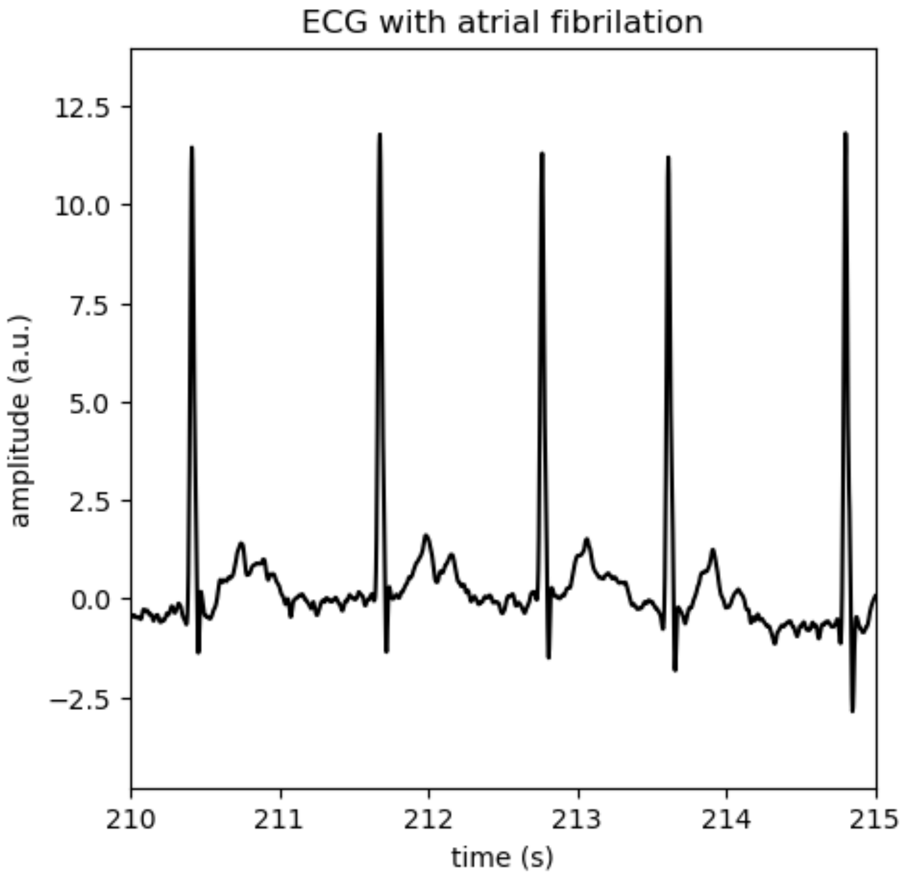
The main differences we can notice are the following :

- The QRS complexes are not evenly spaced. We can notice this by looking at the R peaks ;
- The P waves that should occur are pretty much non-existant and are replaced by some noise coming from the fibrillatory waves ;
- The S waves are also really noisy.

[2]:
```
ecg = np.genfromtxt('ecg_af.dat')
ecg_fs = 300
t_ecg = np.arange(len(ecg))/ecg_fs
```

[3]:
```
py.figure(1,figsize=[5,5])
py.plot(t_ecg, ecg, 'k')
py.xlabel('time (s)')
py.ylabel('amplitude (a.u.)')
py.title('ECG with atrial fibrilation')
py.xlim(210, 215)
```

[3]:
```
(210.0, 215.0)
```



We compute the autocorelation of the ECG signal. In order to discard the modulation of the baseline we first apply a high-pass filter with a cut-off frequency of 0.5 Hz. Q: Do you see a specific pattern that permits to characterize the atrial fibrilation?

0.0.2 Answer

The autocorrelation of a signal gives the relationship between this signal and a shifted version of itself, meaning if our ECG were normal we would have peaks at each period of the heartbeat, each being obviously smaller than $R_{xx}(0)$ but we would still notice peaks. Here, apart from the peak at $R_{xx}(0)$ the autocorrelation averages around 0, which shows the irregular pattern of atrial fibrilation.

[4]:
```
b, a = sp.butter(2, 0.5/ecg_fs*2, btype='high')
```

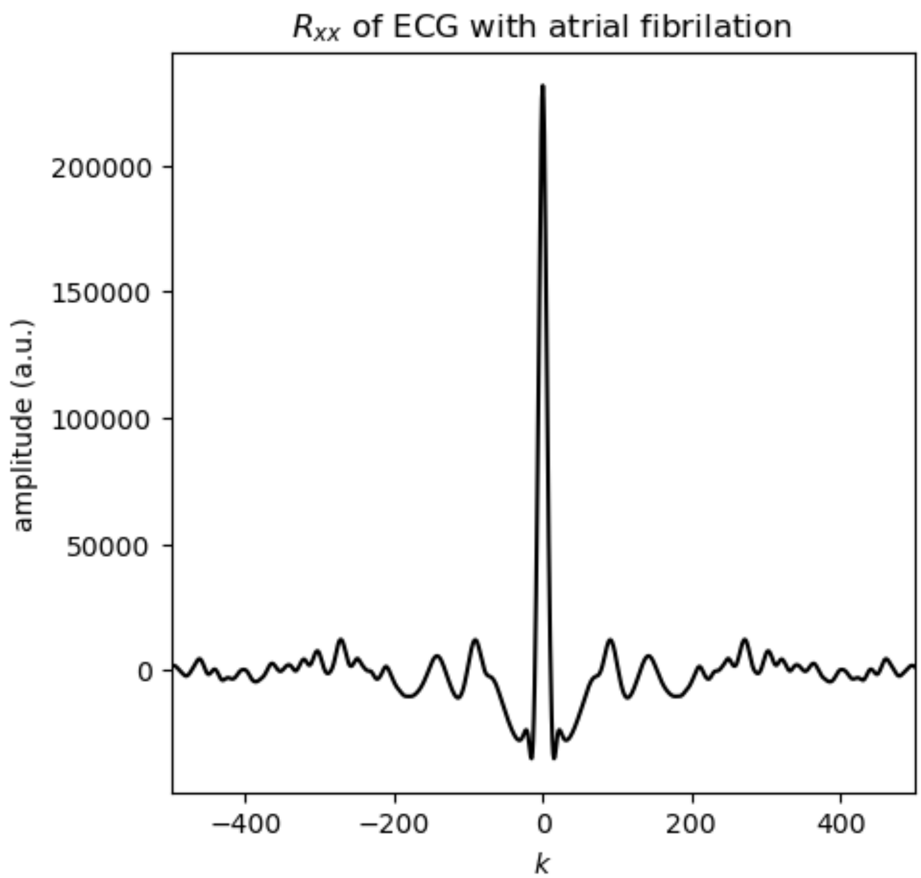
[5]:
```
ecg_hp = sp.filtfilt(b, a, ecg)
```

[6]:
```
rxx_ecg = np.correlate(ecg_hp, ecg_hp, mode='full')
k = np.arange(len(rxx_ecg))-len(rxx_ecg)//2
```

[7]:

```
py.figure(2,figsize=[5,5])
py.plot(k, rxx_ecg, 'k')
py.xlabel('$k$')
py.ylabel('amplitude (a.u.)')
py.title('$R_{xx}$ of ECG with atrial fibrilation')
py.xlim(-500, 500)
```

[7]: (-500.0, 500.0)



Compute the PSD of the ECG signal. Q: What do you see?

0.0.3 Answer

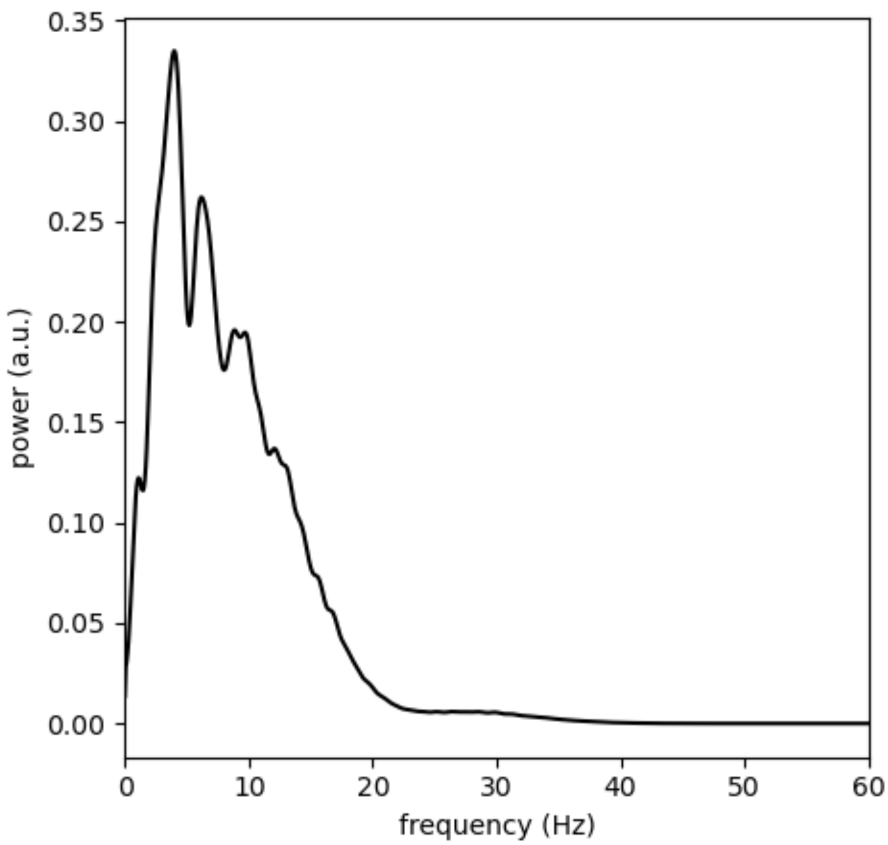
We notice that there is no distinct frequency to highlight when there is an atrial fibrilation, the power of our signal is much more spread out in the higher frequencies which is probably caused by the atrial fibrilations. This is to be expected, since we have an irregular signal.

[8]:

```
f, ECG = sp.welch(ecg_hp, nperseg=500, nfft=4096, noverlap=250, fs=ecg_fs)
```

[9]:
```
py.figure(3, figsize=[5,5])
py.clf()
py.plot(f, ECG, 'k')
py.xlabel('frequency (Hz)')
py.ylabel('power (a.u.)')
py.xlim(0,60)
```

[9]: (0.0, 60.0)



In order to higlight the signal related to the repolarisation of the atria and ECG signal with atrial fibrilation has been process, keeping only the P wave (repolarisation of the atria) and the QRST waves have been removed. During the measurement 4 time segments exhibit different behaviors. Q: What are the difference between the different segments ?

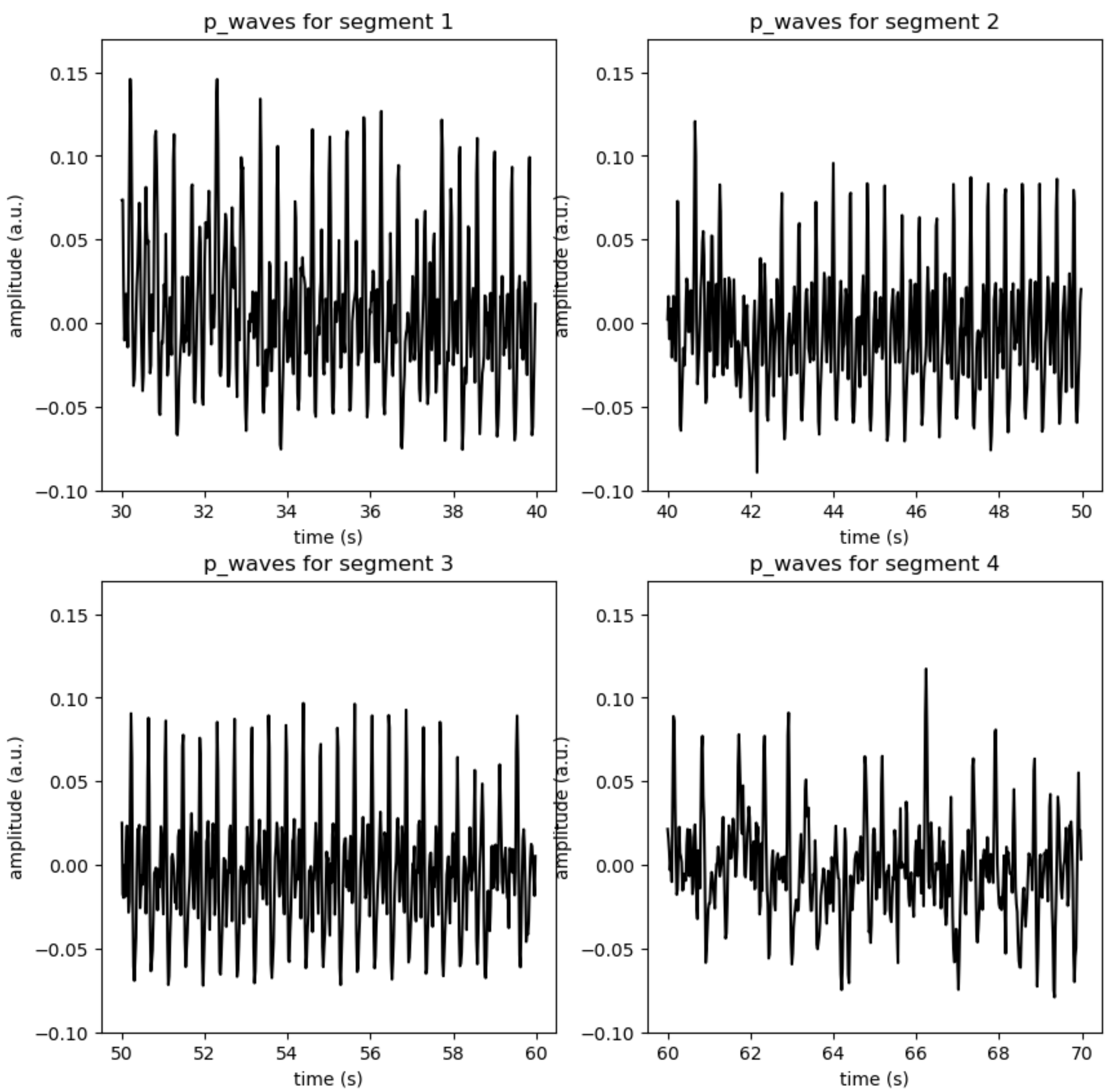
0.0.4 Answer

Segment 1 is the one with the highest variability in amplitude compared to the other segments. Segment 3 has a fairly regular amplitude, but shows some irregularity in-between its peaks. Segment 4 is probably the most chaotic of all segments, with its varying peak amplitudes and its irregular pulse.

[10]:
```python
p_wave = np.genfromtxt('AF_sync.dat')
p_wave_fs = 50
t_p_wave = np.arange(len(p_wave))/p_wave_fs
```

[11]:
```python
segments = [1500, 2000, 2500, 3000, 3500]
```

[21]:
```python
py.figure(4,figsize=[10,10])
for n in range(len(segments)-1):
    py.subplot(2, 2, int(n+1))
    idx = np.arange(segments[n], segments[n+1])
    py.plot(t_p_wave[idx], p_wave[idx], 'k')
    py.xlabel('time (s)')
    py.ylabel('amplitude (a.u.)')
    py.ylim([-0.1,0.17]) # Added line to notice the differences easier
    py.title('p_waves for segment '+str(n+1))
```



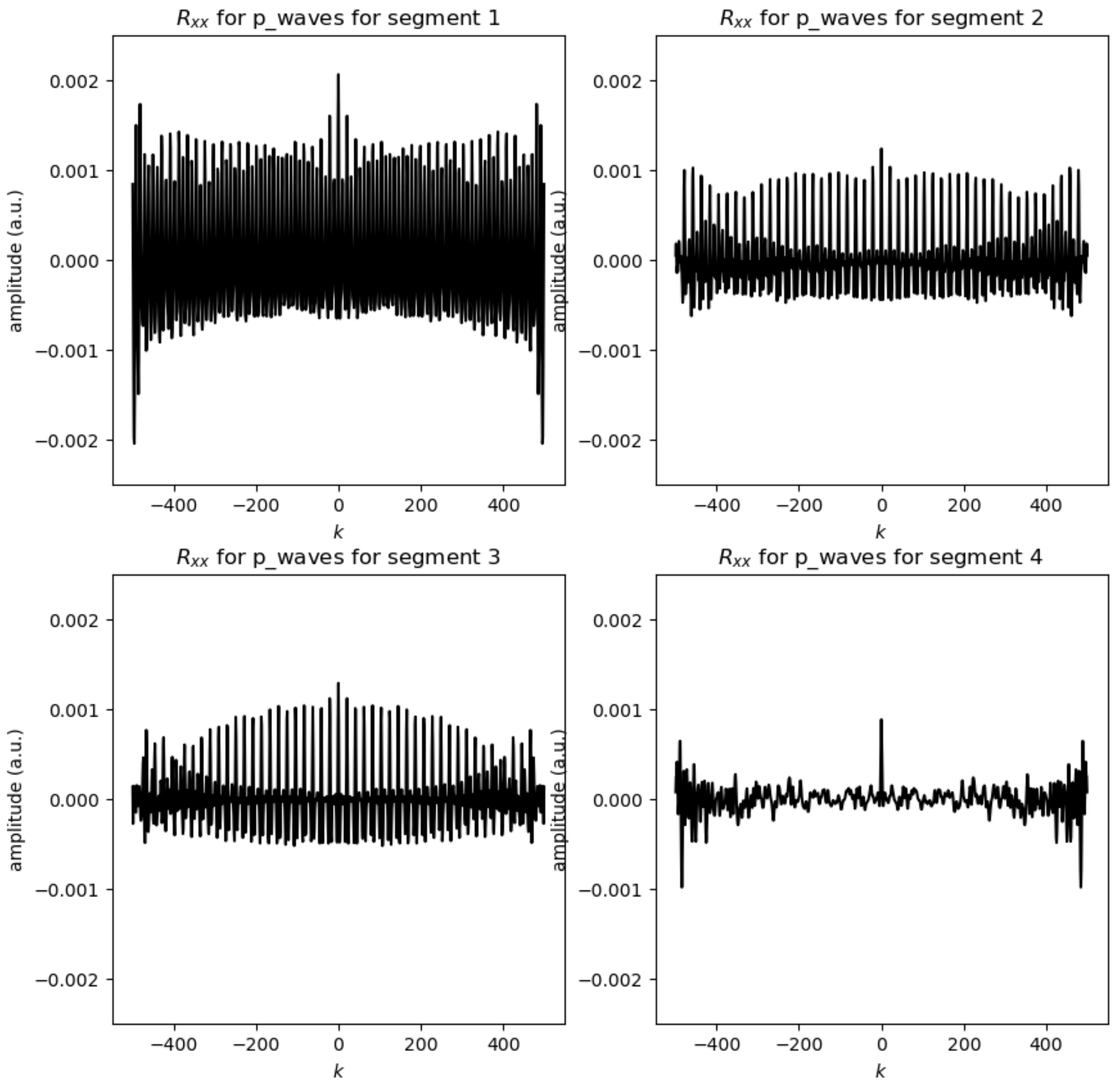
We compute the autocorelation of the p_wave signal. In order to dircard the modulation of the baseline we first apply a high-pass filter with a cut-off frequency of 0.5 Hz. Q: Do you see a specific pattern that permits to characterize the atrial fibrilation? Q: Discuss the organisation of the signals. Which one is the more organised, which one is closer to a noise?

0.0.5 Answer

The P wave should be a regular lobe before the PR segment., meaning there should not be so many peaks in our segments since most of the time our signal should not be identical. These peaks are due to the fibrillatory waves in the heart.

The segment that looks the most like noise is the fourth one, since it does not show peaks apart from where $k = 0$, which corresponds to the autocorrelation of noise.

[22]:
```
py.figure(5,figsize=[10,10])
for n in range(len(segments)-1):
    py.subplot(2, 2, int(n+1))
    idx = np.arange(segments[n], segments[n+1])
    rxx_p_wave = np.correlate(p_wave[idx], p_wave[idx], mode='full')
    rxx_p_wave /= np.correlate(np.ones(len(idx)), np.ones(len(idx)),␣
 ↪mode='full')
    k = np.arange(len(rxx_p_wave))-len(rxx_p_wave)//2
    py.plot(k, rxx_p_wave, 'k')
    py.xlabel('$k$')
    py.ylabel('amplitude (a.u.)')
    py.ylim([-0.0025,0.0025]) # Added line to notice the differences easier
    py.title('$R_{xx}$ for p_waves for segment '+str(n+1))
```



Compute the PSD of the p_wave signal. Q: What do you see? Q: Which one is the more organised? Q: Which ones looks like a noise? Q: Which ones exhibit a sustained repolarisation loop?

0.1 Answer

This shows that segment 4 looks like a noise signal with very low power at each frequency compared to the other signals. As we stated before, segment 3 looks very regular, it has very distinct high-power frequencies, hence this is the most organised segment.

The one exhibiting a sustained repolarisation loop is the segment 4, as we can see low amplitudes in the low frequencies. There are also a lot of irregularities in this PSD.

[24]:
```
py.figure(7, figsize=[10,10])
for n in range(len(segments)-1):
    idx = np.arange(segments[n], segments[n+1])
```

```
    f, P_WAVE = sp.welch(p_wave[idx], nperseg=250, nfft=4096, noverlap=100,␣
↪fs=p_wave_fs)
    py.subplot(2, 2, int(n+1))
    py.plot(f, P_WAVE, 'k')
    py.xlabel('frequency (Hz)')
    py.ylabel('power (a.u.)')
    py.xlim(0,25)
    py.title('PSD for p_waves for segment '+str(n+1))
```