

# Module 3 Lab Report

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Please find the answer of each question written as a markdown cell after the question.

## Part 1: Ecg 50Hz

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.

```
In [7]: import numpy as np
import pylab as py
import scipy.signal as sp

py.ion()
py.close('all')
```

```
In [8]: 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.

### Answer:

- The log spectrum plots show how the choice of window length affects the frequency resolution and noise averaging in the Welch estimator.
- With a short window (100), the PSD is the smoothest since the Welch estimator averages over many segments. However, the 50 Hz peak is broad and not distinct due to poor frequency resolution.
- With a medium window (500), the frequency resolution is improved and the 50Hz interference is much clearer. Additionally, the spectrum is still relatively smooth (though not as much as with 100 windows) due to a reasonable number of averages.
- With a long window (2000), the frequency resolution is the highest, therefore the 50 Hz peak is sharp. However, since there are fewer segments to average, the spectrum looks quite noisy and jagged overall.

Q: Which window length is the most suitable for the observation of 50 Hz?

**Answer:** The 500-sample window is the best choice for detecting the 50Hz interference.

Q: Why?

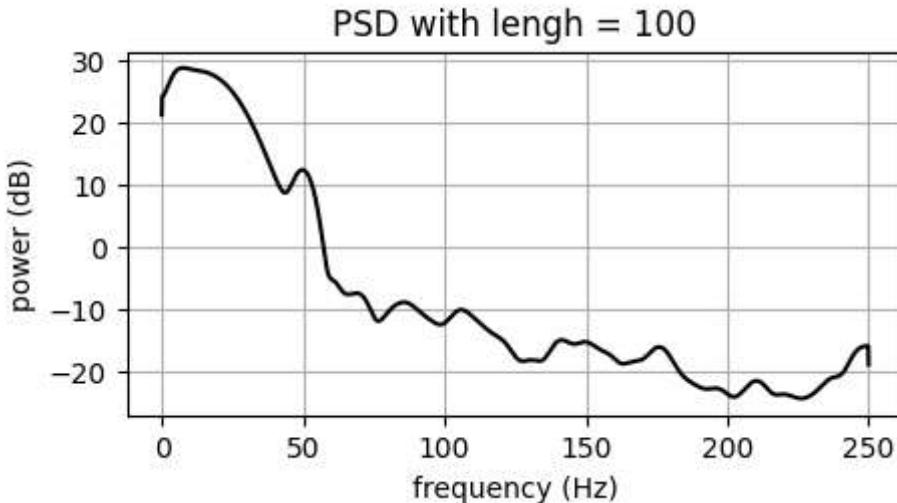
**Answer:** The 500-sample window provides a good balance by providing enough

resolution to isolate the narrow 50Hz peak while still averaging enough segments to keep the PSD stable. The 2000-sample window does have slightly better resolution, but it has a high variance, making the spectrum harder to interpret. Therefore, if the goal is simply to observe the interference with high precision, then the 2000-sample window would be better, but for overall understandability, the 500-sample window provides good readability while still highlighting the 50HZ interference.

```
In [9]: 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)
```

```
In [10]: 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 length = 100')
```

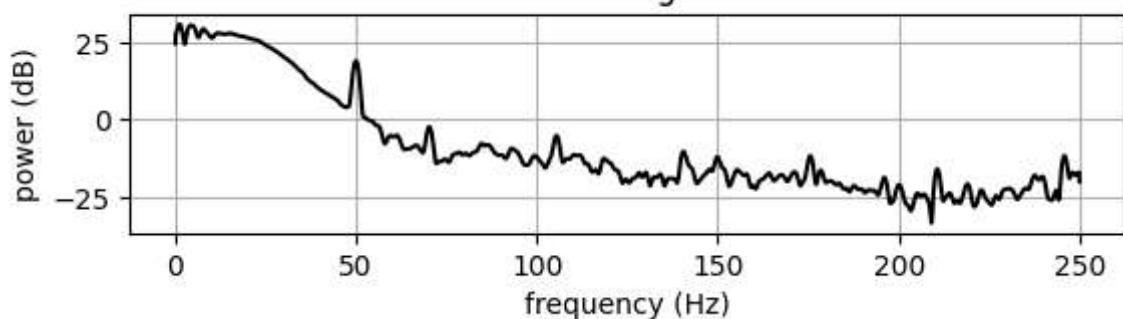
Out[10]: Text(0.5, 1.0, 'PSD with length = 100')



```
In [11]: 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 length = 500')
```

Out[11]: Text(0.5, 1.0, 'PSD with length = 500')

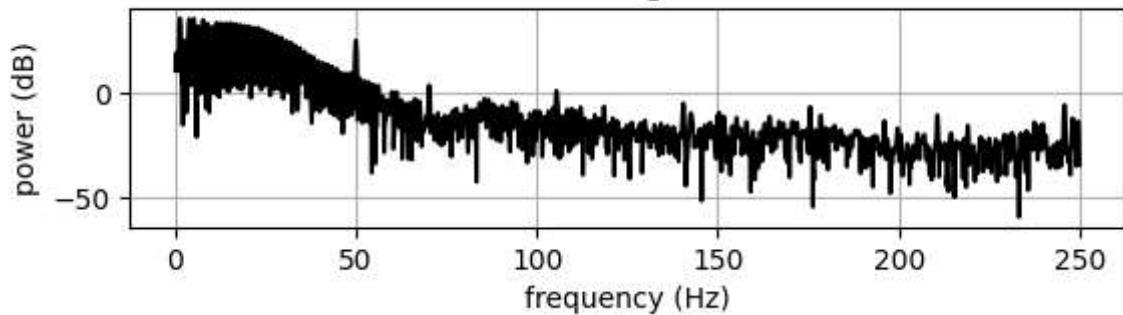
PSD with length = 500



```
In [12]: 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 length = 2000')
```

Out[12]: Text(0.5, 1.0, 'PSD with length = 2000')

PSD with length = 2000



## Part 3: atrial fibrillation

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

```
In [15]: import numpy as np
import pylab as py
import scipy.signal as sp

py.ion()
py.close('all')
```

The first signal is an ECG with atrial fibrillation.

Q: What are the differences of this ECG with a normal ECG?

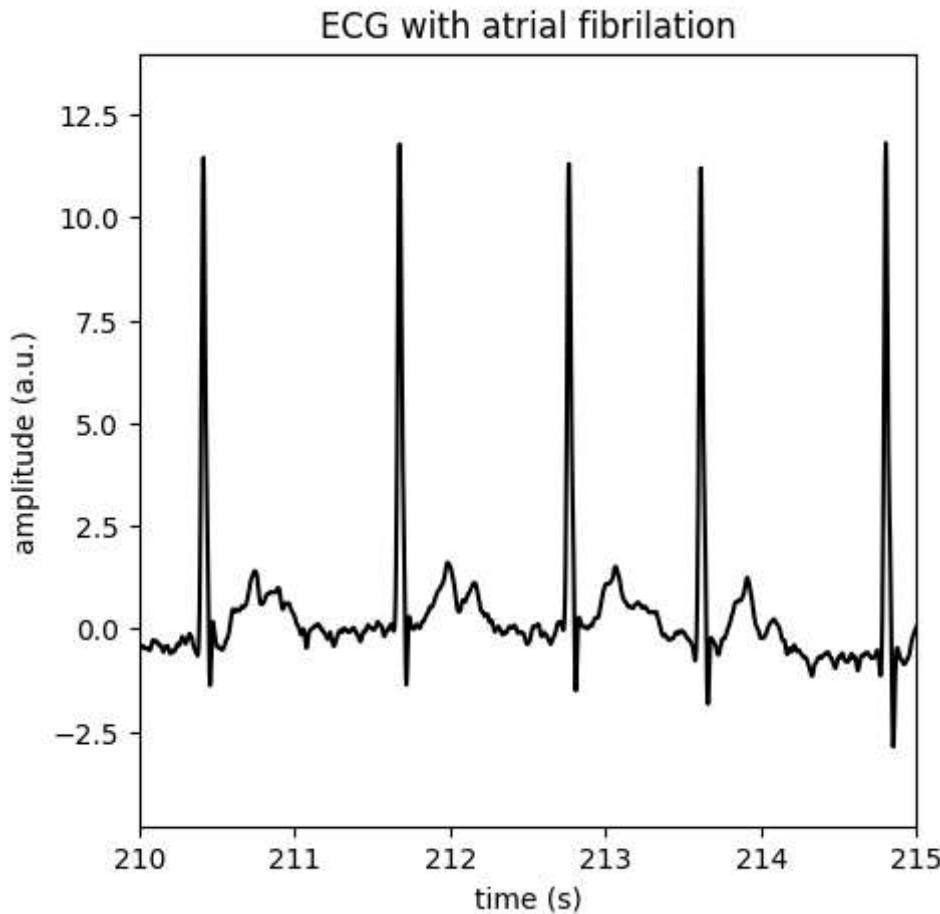
**Answer:**

- The ECG with atrial fibrillation lacks the regular, distinct P waves seen in normal ECGs, reflecting disorganized atrial activity.
- The R-R intervals (time between heartbeats) are highly irregular, whereas they are regular in normal sinus rhythm.
- The baseline may appear more chaotic or noisy due to the absence of coordinated atrial depolarization.

```
In [16]: ecg = np.genfromtxt('ecg_af.dat')
ecg_fs = 300
t_ecg = np.arange(len(ecg))/ecg_fs
```

```
In [17]: 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 fibrillation')
py.xlim(210, 215)
```

```
Out[17]: (210.0, 215.0)
```



We compute the autocorrelation 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 fibrillation?

**Answer:**

- The autocorrelation of the ECG signal with atrial fibrillation typically shows reduced periodicity and less pronounced peaks compared to normal sinus rhythm. This reflects the irregular timing of heartbeats and the absence of organized atrial activity. The lack of regular repeating patterns in the autocorrelation is a sign of atrial fibrillation.

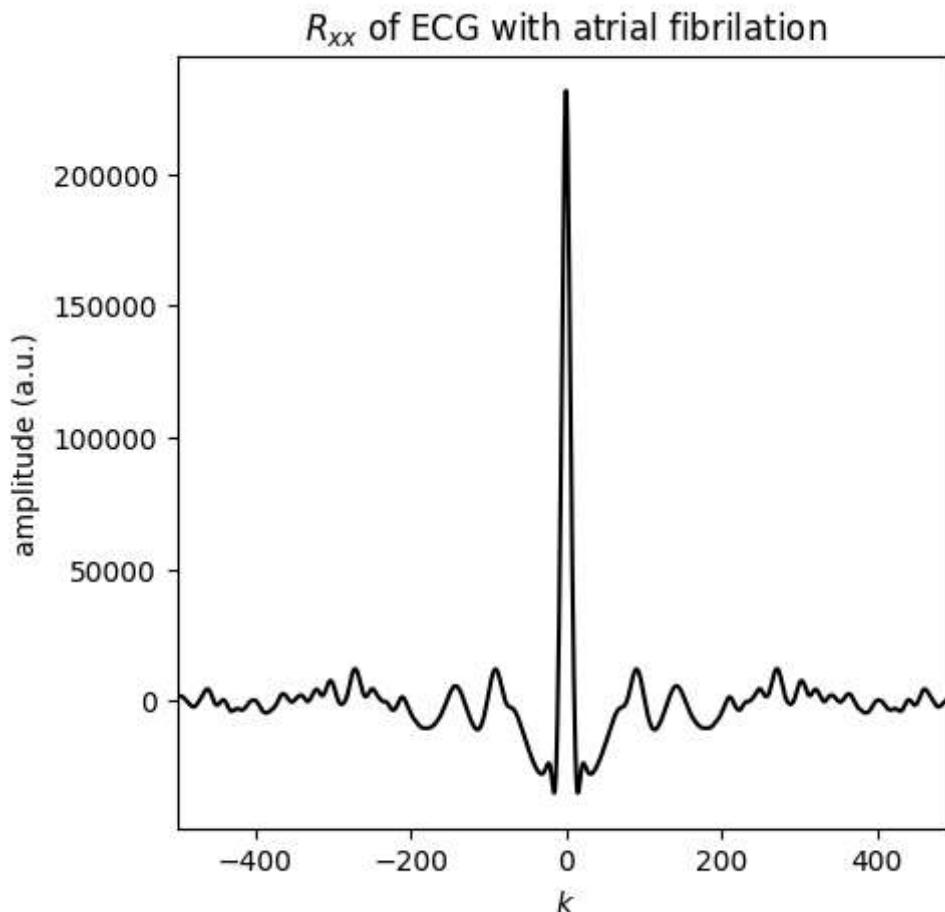
```
In [18]: b, a = sp.butter(2, 0.5/ecg_fs*2, btype='high')
```

```
In [19]: ecg_hp = sp.filtfilt(b, a, ecg)
```

```
In [20]: rxx_ecg = np.correlate(ecg_hp, ecg_hp, mode='full')
k = np.arange(len(rxx_ecg))-len(rxx_ecg)//2
```

```
In [21]: 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 fibrillation')
py.xlim(-500, 500)
```

```
Out[21]: (-500.0, 500.0)
```



Compute the PSD of the ECG signal.

Q: What do you see?

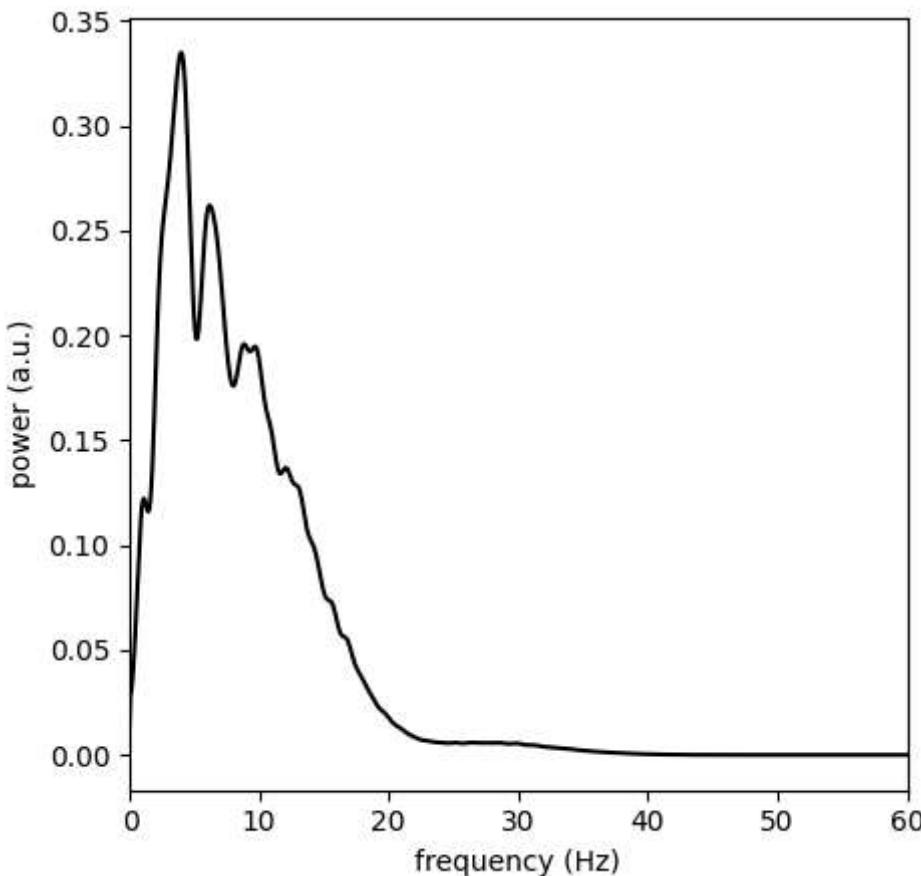
**Answer:**

- The PSD of the ECG signal with atrial fibrillation shows a broad frequency distribution, with less distinct peaks compared to normal rhythm. This indicates a more chaotic and less organized electrical activity in the atria. The absence of sharp peaks at regular intervals is characteristic of atrial fibrillation.

```
In [22]: f, ECG = sp.welch(ecg_hp, nperseg=500, nfft=4096, noverlap=250, fs=ecg_fs)
```

```
In [23]: 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)
```

```
Out[23]: (0.0, 60.0)
```



In order to highlight the signal related to the repolarisation of the atria, the ECG signal with atrial fibrillation has been processed, 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 differences between the different segments?

**Answer:**

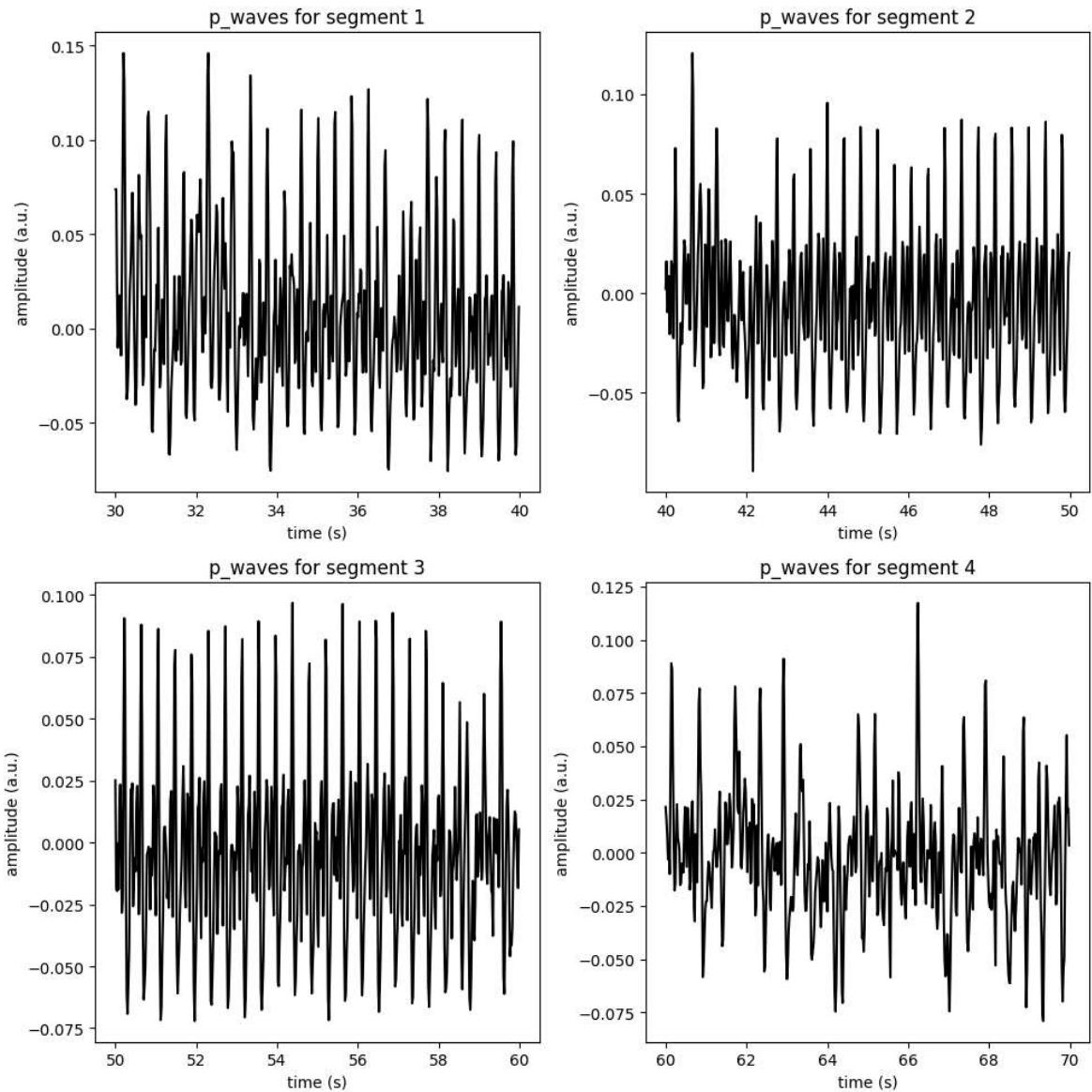
- The different segments may show varying degrees of organization in the P wave signal. Some segments may exhibit more regular oscillations, while others appear more chaotic or noisy. This is due to the fact that atrial fibrillation can have periods of relative organization and periods of highly irregular activity. The presence or absence of sustained oscillatory patterns in the P wave can help characterize the underlying atrial activity.

```
In [24]: p_wave = np.genfromtxt('AF_sync.dat')
p_wave_fs = 50
t_p_wave = np.arange(len(p_wave))/p_wave_fs
```

```
In [25]: segments = [1500, 2000, 2500, 3000, 3500]
```

```
In [26]: 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.title('p_waves for segment '+str(n+1))
py.tight_layout()
```



We compute the autocorrelation of the p\_wave 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 fibrillation?

**Answer:**

- The autocorrelation of the p\_wave signal in atrial fibrillation generally lacks strong, regular peaks, reflecting the disorganized and chaotic nature of atrial activity. Some segments may show weak or irregular periodicity, but overall, the absence of consistent repeating patterns in the autocorrelation is characteristic of atrial fibrillation.

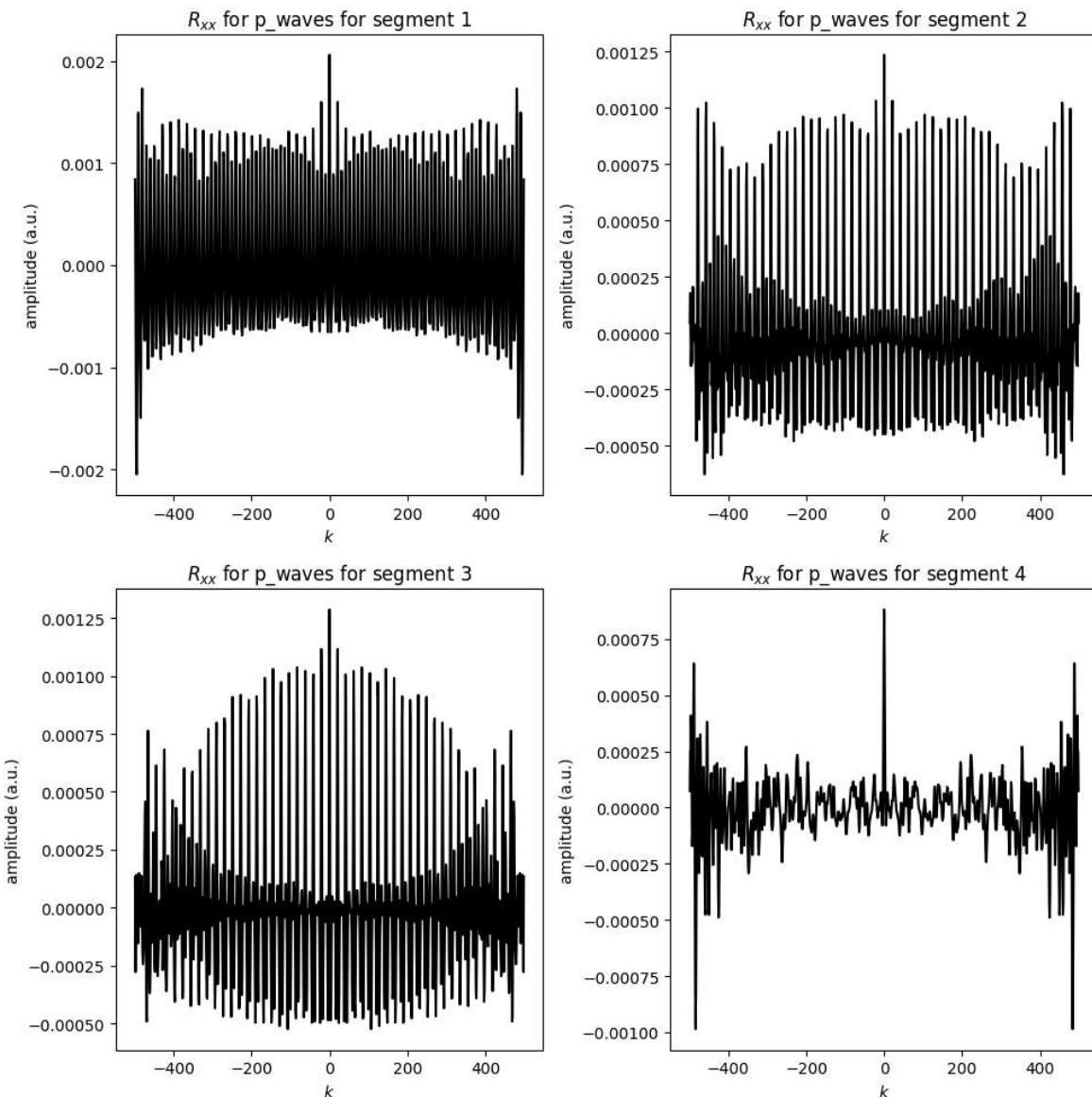
Q: Discuss the organisation of the signals. Which one is the more organised, which one is closer to a noise?

**Answer:**

- Segments with clear, repeating peaks in the autocorrelation are more organized and may represent periods of partial atrial coordination. Segments with flat or noisy

autocorrelation are less organized and resemble random noise, typical of chaotic atrial fibrillation. By this reasoning the signal for segment 4 is closer to a noise, and the signal for segment 1 is more organised.

```
In [27]: 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.title('$R_{xx}$ for p_waves for segment '+str(n+1))
    py.tight_layout()
```



Compute the PSD of the p\_wave signal.

Q: What do you see?

**Answer:**

- The PSD of the P wave signal for the fourth segment shows broad frequency content with less pronounced peaks, indicating disorganized atrial activity. The PSD of the P waves for the other segments (particularly segments 2 and 3) show more defined peaks, suggesting transient organization.

Q: Which one is the more organised?

**Answer:**

- Segments with clear, narrow peaks in the PSD are more organized, reflecting periods of coordinated atrial repolarization. In this case we can rank the segments from more organised to less organised in the following order : segment 3, segment 2, segment 1, segment 4.

Q: Which ones look like a noise?

**Answer:**

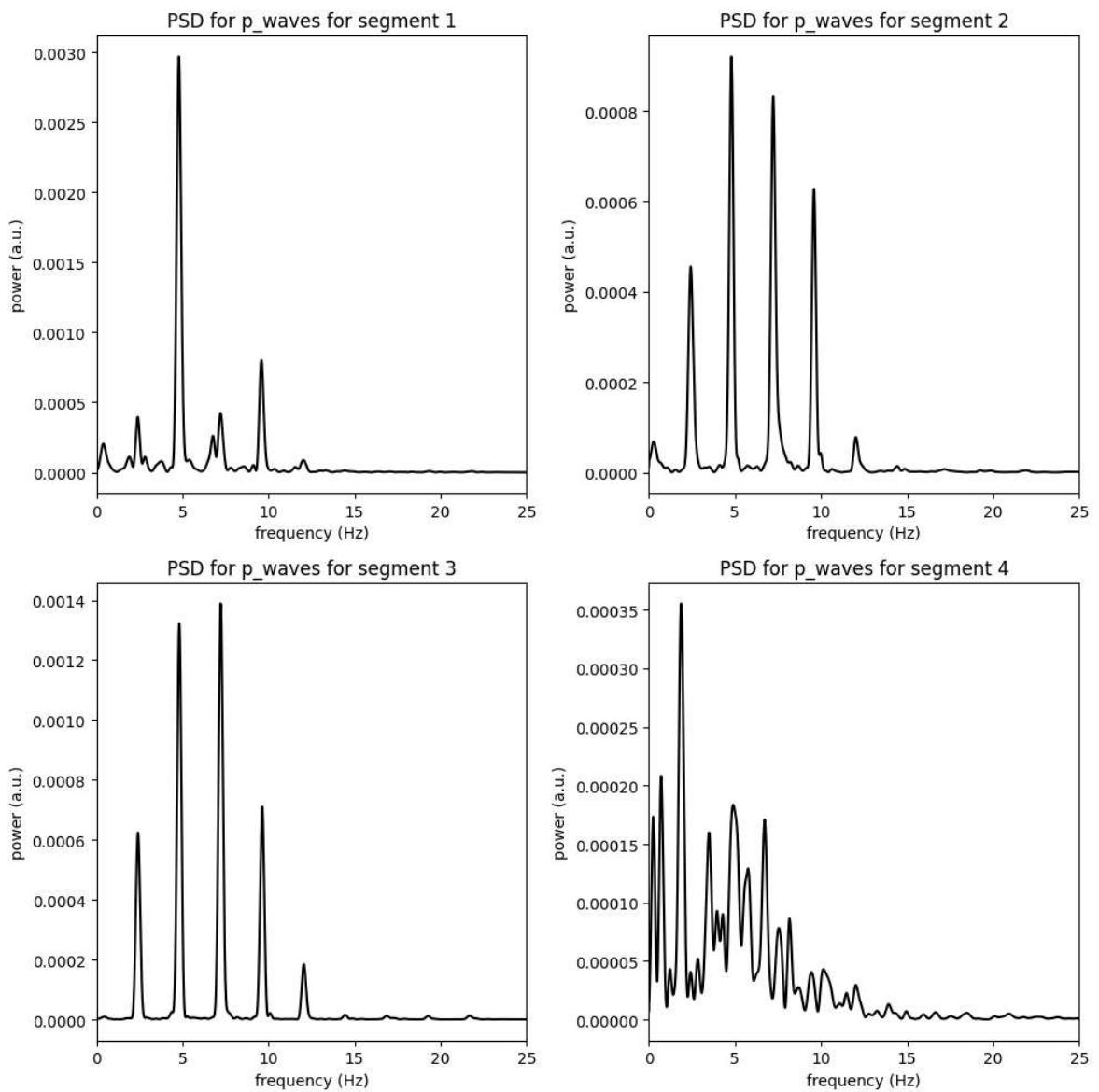
- Segments with flat, broad PSD and no distinct peaks resemble noise, typical of chaotic atrial fibrillation. Segment 4 is closer to this description.

Q: Which ones exhibit a sustained repolarisation loop?

**Answer:**

- Because of atrial fibrillation, a sustained repolarization loop would be irregular. Thus this would be characterized by a broadband spectrum, because the oscillations are not consistent enough to reinforce sharp spectral lines. Segment 4 is the only one whose PSD for the p\_wave exhibits this behaviour.

```
In [28]: 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)
    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))
    py.tight_layout()
```



## Part 2: Ans control

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.

```
In [16]: import numpy as np
import pylab as py
import scipy.signal as sp
import m03_ex2_ext as my_plot

py.ion()
py.close('all')
```

Load signals of a subject at rest.

```
In [17]: x = np.genfromtxt('heart_1.dat', delimiter=' ')
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=' ')
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.

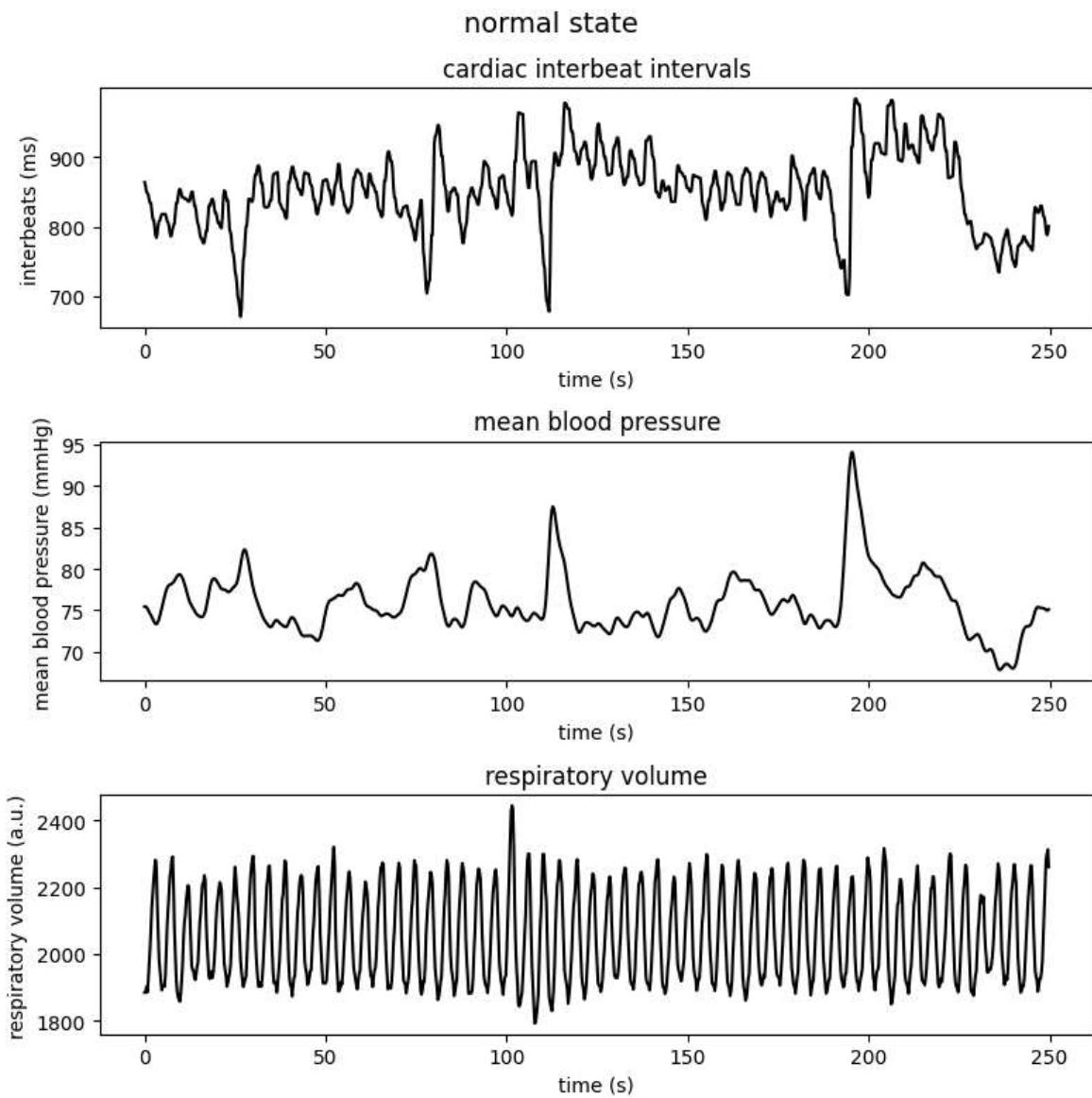
Q: Comment the different signals and their relationships.

**Answer:** The cardiac interbeats, mean blood pressure, and respiration signals show distinct physiological patterns at rest. Respiration signal shows breathing cycles and is oscillatory and smooth. The cardiac interbeats signal shows heart rate variability and oscillates in sync with respiration. The mean blood pressure signal also shows slower oscillations and its peaks align with the minima points in the cardiac interbeats signal.

Q: Which signals are related and how?

**Answer:** Respiration drives fluctuations in both mean blood pressure and cardiac interbeats. This is evident in the cardiac interbeats signal through "respiratory sinus arrhythmia" meaning heart rate increases during inspiration and decreases during expiration. Respiration and mean blood pressure signals are also related via "baroreflex mechanisms" meaning changes in blood pressure trigger compensatory changes in heart rate. A rise in blood pressure triggers a reflex slowing down the heart rate creating longer intervals, and when blood pressure falls the reflex speeds up the heart rate resulting in shorter intervals.

```
In [18]: my_plot.plot_time(x, t, 'normal state')
```



Cardiac interbeats, mean blood pressure and respiration volume of a subject after alcohol consumption.

Q: Comment the different signals and their relationships.

**Answer:** After alcohol consumption, the signals show altered patterns compared to rest. Cardiac interbeat intervals show less variability, while mean blood pressure seems to have more fluctuations. Respiratory volume is still oscillatory but weaker with a few prominent peaks.

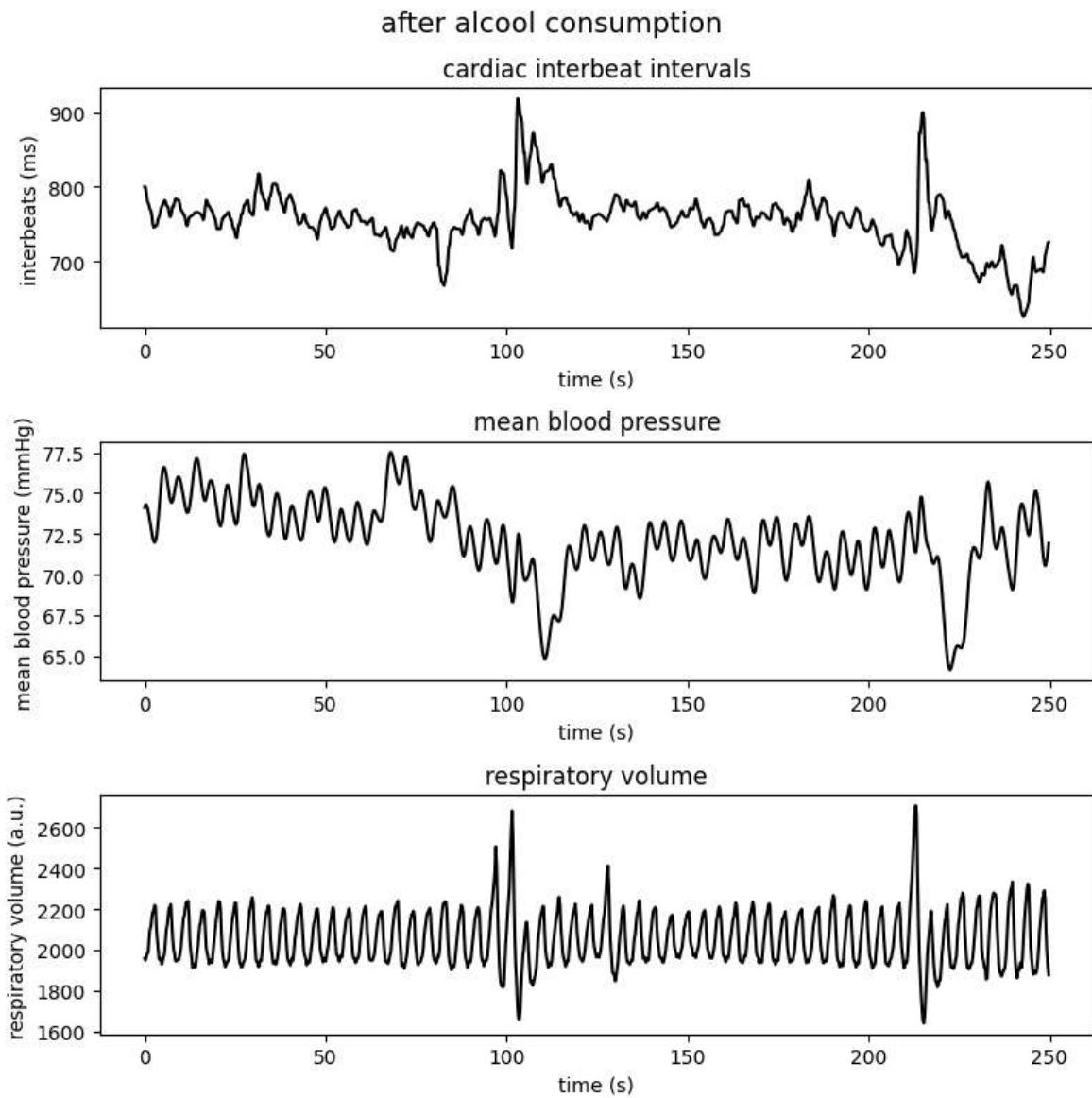
Q: Which signals are related and how?

**Answer:** The relationships between respective signals persist, but seem to be slightly weakened due to the effects of alcohol on autonomic control.

Q: What are the differences with rest recording of previous figure?

**Answer:** Compared to rest, alcohol consumption has reduced heart rate variability and increased mean blood pressure fluctuations and the sinus arrhythmia is less clear. The coupling between signals is less pronounced, indicating impaired autonomic regulation.

```
In [19]: my_plot.plot_time(y, t, 'after alcohol consumption')
```



Compute the intercorrelation of the signals of the subject at rest.

Q: Comment the oscillation present in the different signals.

**Answer:** The autocorrelations show periodic oscillations, corresponding to the breathing cycle frequency. Respiration signal autocorrelation clearly has the cleanest rhythm. Cardiac interbeats autocorrelation show rhythmic oscillations matching the respiration period confirming respiratory sinus arrhythmia. The mean blood pressure signal autocorrelation oscillates more slowly but shows coupling with respiration.

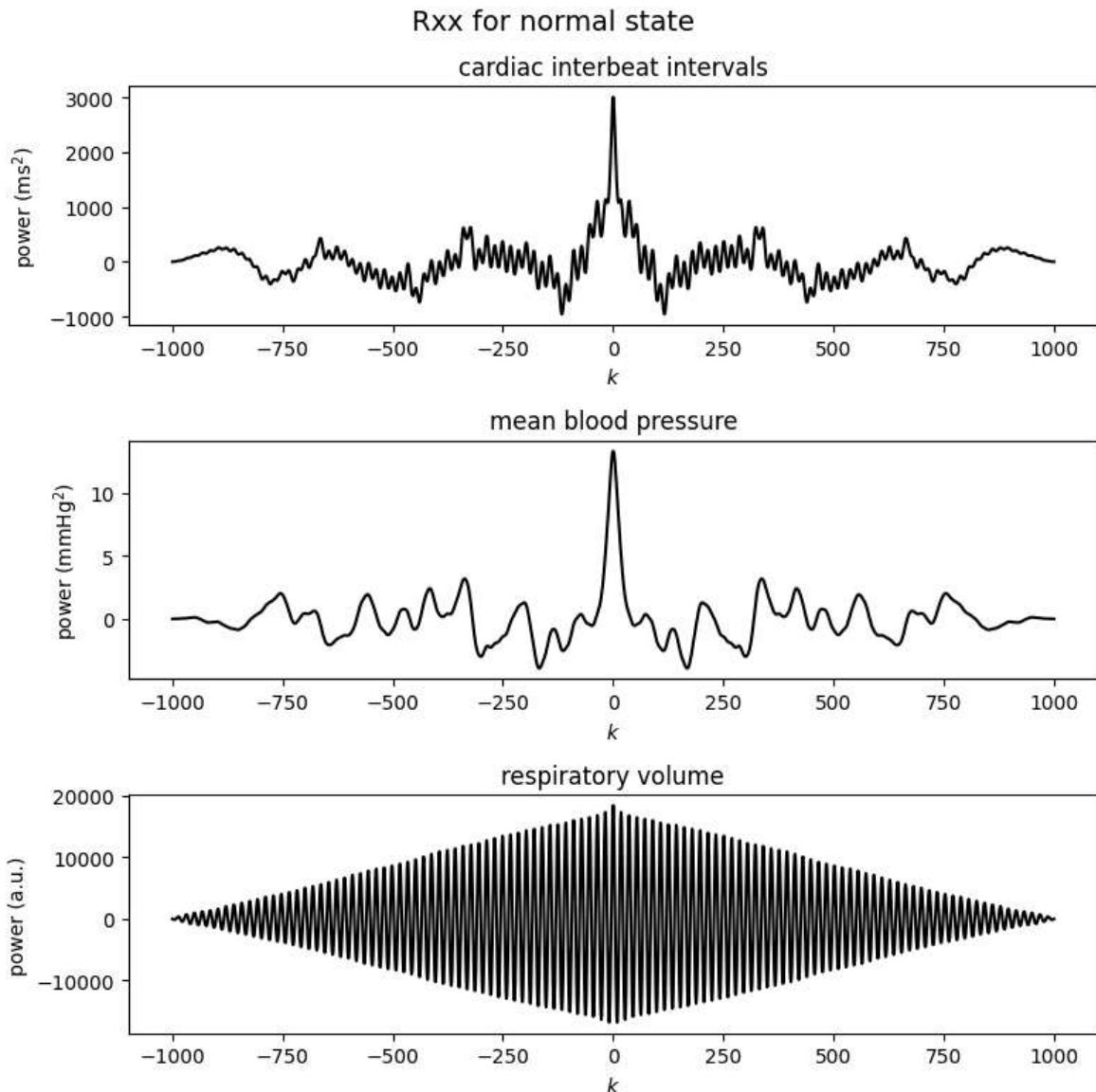
Q: Which signals are related and how.

**Answer:** Peaks in the cross-correlation between cardiac interbeats and respiration signals indicate respiratory sinus arrhythmia. Correlation between mean blood pressure and cardiac interbeats signals reflects baroreflex activity. Strong periodicity and coupling at rest indicate healthy autonomic control.

```
In [20]: def my_corr(x):
    rxx = np.correlate(x-np.mean(x), x-np.mean(x), mode='full')/len(x)
    return rxx
```

```
In [21]: x['rxx_rr'] = my_corr(x['rr'])
x['rxx_bp'] = my_corr(x['bp'])
x['rxx_resp'] = my_corr(x['resp'])
```

```
In [22]: my_plot.plot_rxx(x, 'Rxx for normal state')
```



Compute the intercorrelation of the signals of the subject after alcohol consumption.

Q: Comment the oscillation present in the different signals.

**Answer:** After alcohol consumption, the respiration signal autocorrelation is still periodic but the peaks appear less smooth. For the other two signals the oscillations in the autocorrelation functions are less regular. The cardiac interbeats signal autocorrelation is flatter showing reduced variability, while the mean blood pressure signal autocorrelation appears less regular and noisier.

Q: Which signals are related and how.

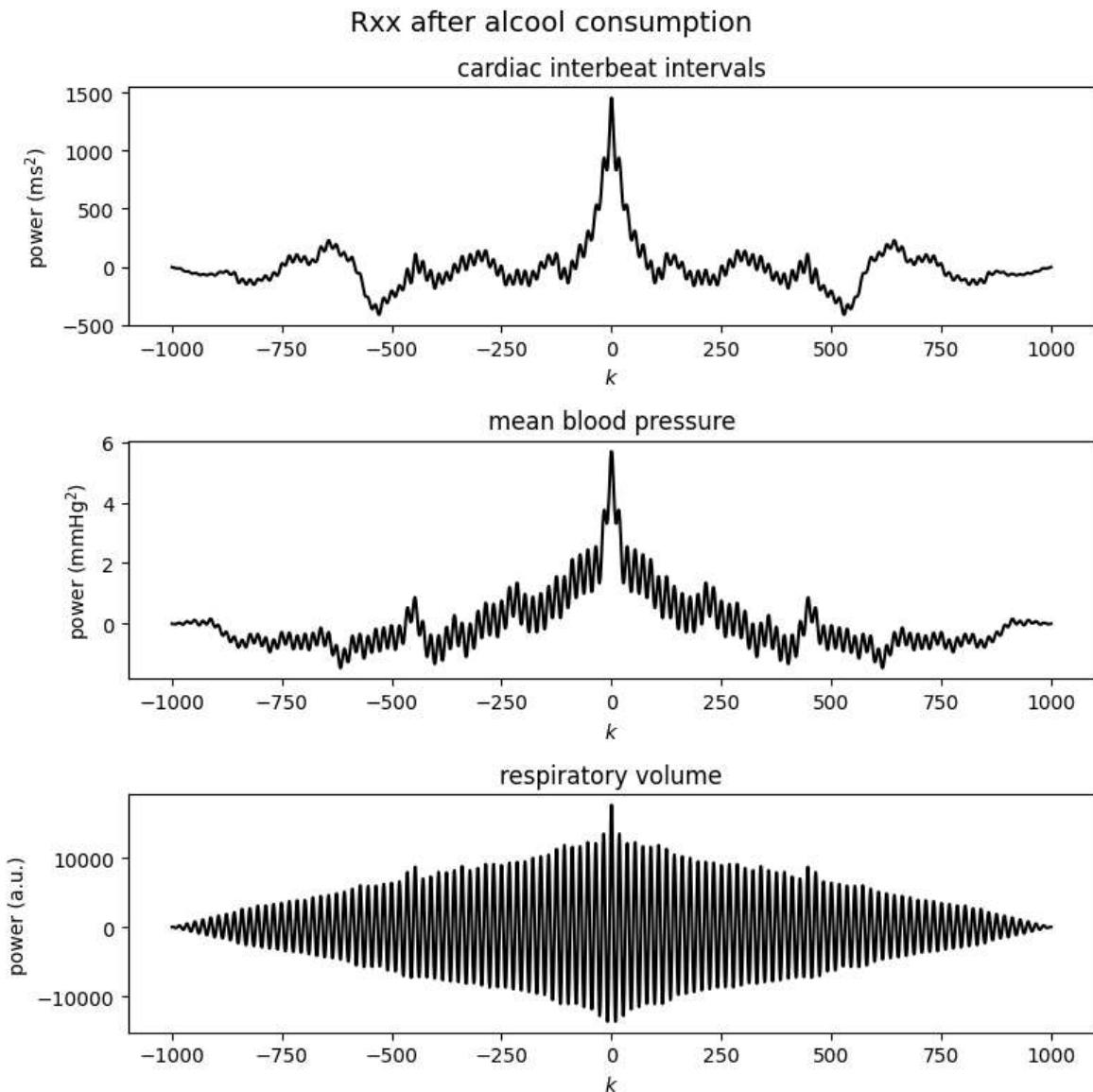
**Answer:** The relationships between the signals are weaker, with less pronounced cross-correlation peaks. This suggests impaired coupling between heart rate, blood pressure, and respiration.

Q: What difference do you observe with the previous figure?

**Answer:** After alcohol consumption, the signals show reduced regularity and weaker interrelationships, reflecting dampened autonomic system control.

```
In [23]: y['rxx_rr'] = my_corr(y['rr'])
y['rxx_bp'] = my_corr(y['bp'])
y['rxx_resp'] = my_corr(y['resp'])
```

```
In [24]: my_plot.plot_rxx(y, 'Rxx after alcohol consumption')
```



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?

**Answer:** PSDs show clear peaks: The low frequency peaks (< 0.1 Hz) reflect sympathetic and parasympathetic activity such as baroreflex and blood pressure oscillations. The high frequency peaks (0.2 - 0.25 Hz) match breathing rate and are associated with parasympathetic activity and respiratory modulation. The PSDs of both cardiac interbeats and respiration signals show a strong high frequency peak confirming that respiration drives heart rate variability, while in the case of mean blood pressure and cardiac interbeats signals strong low frequency peaks also appear reflecting baroreflex activity.

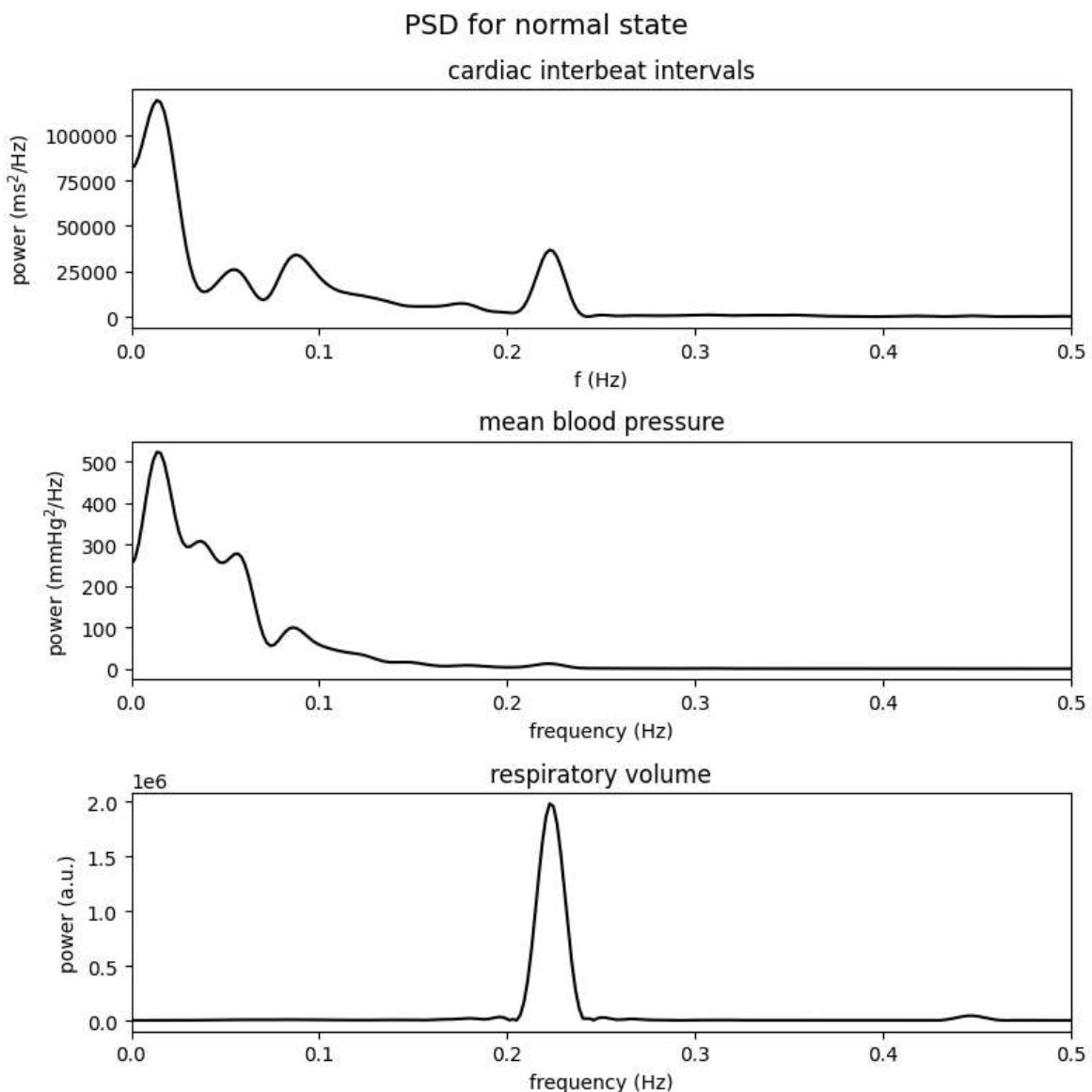
Q: Do the positions and amplitude of the peaks confirm your previous findings?

**Answer:** Yes, the presence of distinct peaks at expected frequencies confirms healthy autonomic regulation and the relationships observed in the time and correlation analyses.

```
In [25]: 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
```

```
In [26]: x['RR'] = my_psd(x['rxx_rr'])
x['BP'] = my_psd(x['rxx_bp'])
x['RESP'] = my_psd(x['rxx_resp'])
```

```
In [27]: my_plot.plot_X(x, fs, 'PSD for normal state')
```



Compute the PSD of the signal for the subject after alcohol consumption.

Q: How the different peaks are related to the control of the autonomic nervous system?

**Answer:** In the PSDs after alcohol consumption we can see that the low frequency peaks

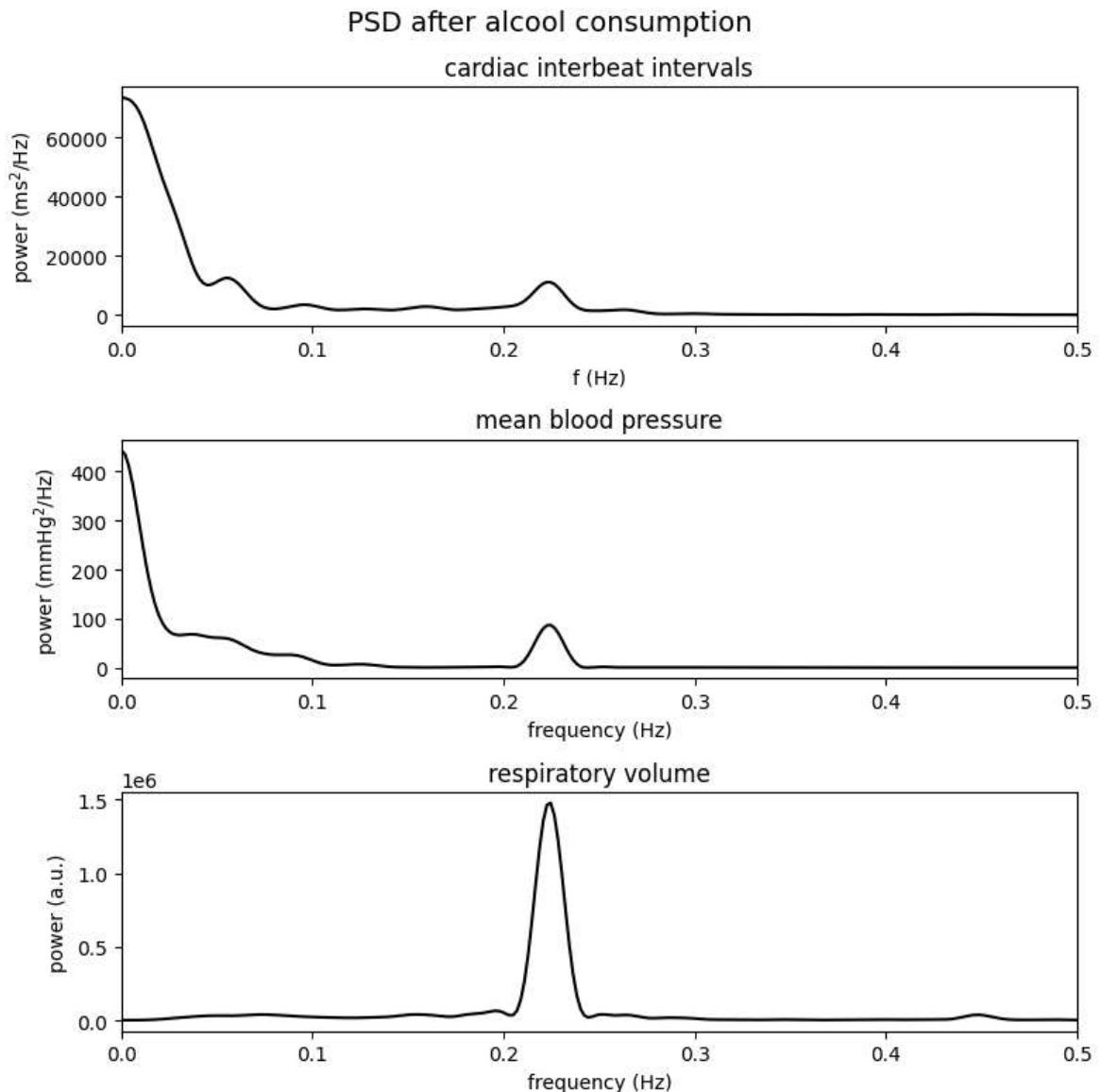
in cardiac interbeats and mean blood pressure signals as well as the high frequency peaks (related to respiratory modulation) in the cardiac interbeats and respiratory signals have significantly diminished showing weaker respiratory sinus arrhythmia and reduced autonomic modulation. The high frequency peak at around 0.2 Hz (matching the respiratory frequency) present in mean blood pressure signal PSD indicates stronger respiration-linked oscillations in blood pressure which is consistent with reduced baroreflex buffering.

Q: Do the positions and amplitude of the peaks confirm your previous findings?

**Answer:** Yes, the changes in peak amplitudes confirm impaired autonomic regulation and reduced coupling between physiological signals, as seen in previous analyses.

```
In [28]: y['RR'] = my_psd(y['rxx_rr'])
y['BP'] = my_psd(y['rxx_bp'])
y['RESP'] = my_psd(y['rxx_resp'])
```

```
In [29]: my_plot.plot_X(y, fs, 'PSD after alcohol consumption')
```



Plot the PSDs of the signals for the two conditions.

Q: Discuss the differences.

**Answer:** Comparing the PSDs for rest and after alcohol consumption, the rest condition shows more pronounced and regular peaks, indicating healthy autonomic control. After alcohol consumption, the PSDs are generally flatter and peaks are less distinct, reflecting reduced variability and impaired autonomic function. These differences highlight the impact of alcohol on the autonomic nervous system, reducing its ability to regulate heart rate, blood pressure, baroreflex, and respiration effectively.

```
In [30]: my_plot.plot_XY(x, y, fs, 'Comparison of the PSD')
```

