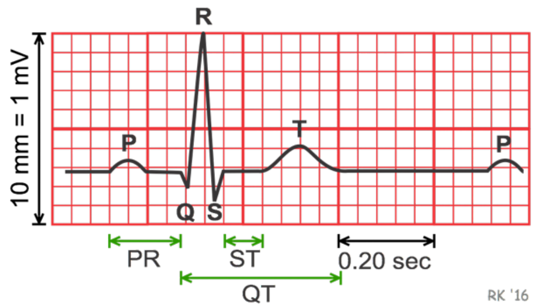
B18 Biomedical Modelling and Monitoring – Wearables Lab Mar 2021

Background & Prep work

The Electrocardiogram

ECG (electrocardiogram) → records the electrical activity generated by the heart as it undergoes depolarisation and repolarisation of the atria and ventricles.

Components of the ECG:
P wave: a small low-voltage deflection caused by the depolarisation of the atria prior to atrial contraction
QRS complex: the largest-amplitude portion of the ECG, caused by current generated when the ventricles depolarise prior to their contraction
T wave: ventricular repolarisation
P-Q interval: the time interval between the beginning of the P wave and the beginning of the QRS complex
Q-T interval: characterises ventricular repolarisation



http://www.cvphysiology.com/Arrhythmias/ A009.htm

V1 = (potential at LA) – (potential at RA)
V2 = (potential at LL) – (potential at RA)
V3 = (potential at LL) – (potential at LA)
Also – 3 augmented unipolar limb leads which are single positive electrodes.
Therefore – 6 bipolar & unipolar leads and can be 6 precordial, unipolar chest leads
From Lab notes:

Figure 2: Electrode placement for (a) the standard *bipolar* 3-lead configuration and Einthoven's triangle construction; (b) *bipolar* limb lead axis and resulting ECG trace; (c) *unipolar* augmented 3-lead axis and resulting ECG trace. Image credit: http://www.cvphysiology.com/Arrhythmias/A013a.htm

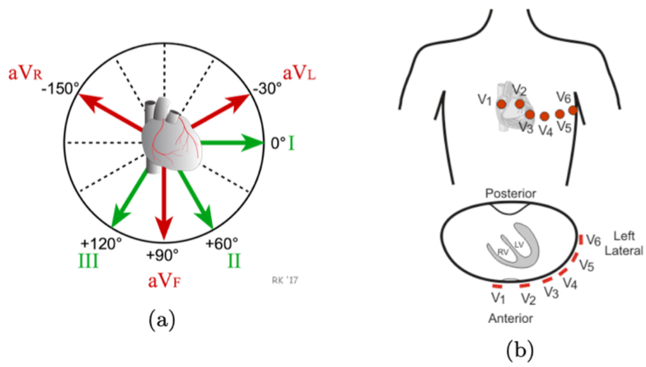


Figure 3: A full 12-lead ECG axis: (a) the combined *bipolar* and *unipolar* 6-axis ECG axis; (b) the ECG chest leads placement. Image credit: http://www.cvphysiology.com/Arrhythmias/A013c.htm

Heart Defects & Diseases:
Atrial fibrillation → irregular and often abnormally fast heart rate

Prep Qs:

1. Explain briefly how the components of the ECG trace (P wave, QRS complex and T waves) are correlated with the electrical activity of the atrial and ventricular muscle;

P wave: a small low-voltage deflection caused by the depolarisation of the atria prior to atrial contraction

QRS complex: the largest-amplitude portion of the ECG, caused by current generated when the ventricles depolarise prior to their contraction

T wave: represents ventricular repolarisation, appearing as a small wave after the QRS complex

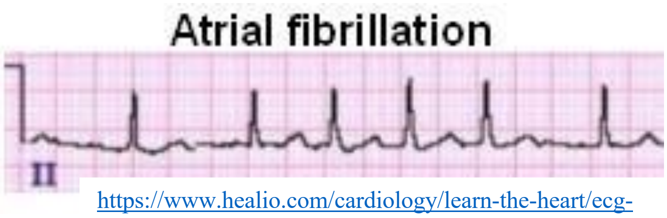
2. Referring to the position of the electrodes, explain why you might expect lead II to give the largest amplitude of the QRS complex;

Lead II, axis goes from the right arm (-) to the left leg (+). It gives the largest amplitude of the QRS complex, as it lies closest to the cardiac axis, crossing the ventricles.

3. Describe some of the typical characteristics of an ECG recording which are noticeable when a patient has atrial fibrillation (AF).

If a patient suffers with atrial fibrillation this can be detected on an ECG, as the ECG will show:

- An irregular rhythm
- Variable ventricular rate
- The QRS complex can be less than 120ms
- Lack of P waves
- Absence of an isoelectric baseline



https://www.healio.com/cardiology/learn-the-heart/ecg-

The Electroencephalogram

EEG → recording of the brain activity; the summation of neural depolarisations in the brain due to stimuli from the five senses as well as from normal brain activity
Surface brain potential ~10mV, in EEG scalp electrodes ~10microV due to attentuation caused by the skull.
Investigates epileptic fits, brain death, language and visual processing.
4 sleep stages, REM(rapid eye movement), 3x non-REM

0.5-30Hz normal EEG range, 5 bands:

- Delta δ (0.5–4 Hz)
- Theta θ (4–8 Hz)
- Alpha α (8–13 Hz)
- Beta β (13–22 Hz)
- Gamma γ (22–30 Hz)

From Lab notes:

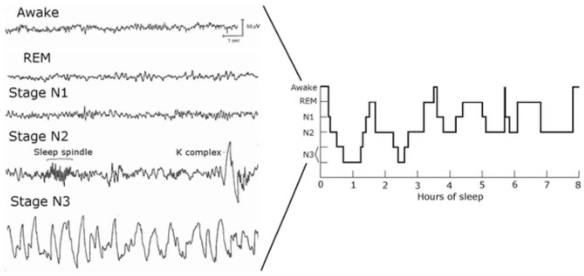
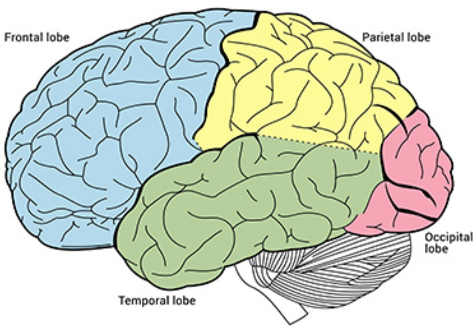


Figure 4: Typical EEG traces of the different stages of adult sleep. On the right is a typical hypnogram, which plots the stage of sleep over time. Note how slow wave sleep (Stage N3) progressively decreases in duration throughout the night, while REM sleep increases in duration. Credit: [1].

__Prep Qs:__

1. Name the major structures (lobes) of the cerebral cortex and their primary function;

- Frontal lobe, largest lobe, located in the front of the cerebral hemisphere → speech & language, prospective memory.
- Parietal lobe, posterior to the frontal lobe and superior to the temporal lobe, classified into two functional regions:
    - Superior parietal lobule → somatosensory (motor planning action)
    - Inferior parietal lobule → visual inputs, auditory inputs, learning, language, spatial recognition, stereognosis (differentiating between objects)
- Temporal lobe, second largest → creating and preserving conscious and long-term memory, visual and sound processing
- Occipital lobe, smallest lobe → visual processing and interpretation



https://qbi.uq.edu.au/brain/brain-anatomy/lobes-brain

2. Name and describe the dominant EEG frequency you might expect to see when a subject is quiet, resting and has their eyes closed?

When a subject is quiet, resting and has their eyes closed the EEG dominant frequency is likely to be in the alpha range, 8-13Hz. Alpha rhythm is attenuated in amplitude and frequency, it is present when the subject is relaxed and is rarely present when eyes are open.

3. Under what conditions might you expect to observe beta (β) waves in an EEG of a subject?

Beta waves are usually present when the subject is actively engaged in mental activities, conscious focus/memory/problem solving.

<u>Physical activity monitoring</u>

<u>Prep Qs:</u>

1. Smartphone and smartwatch devices typically contain a wealth of other sensors besides IMUs. Name one other sensor that these devices could have and a give potential health application this sensor could be used for;

Smart watches, inc Apple Watch, have an ECG app which allows users to easily taken their own ECG readings. Although the app is not as accurate as taking a real ECG, it gives users a good indication of their heartbeat and rhythm, highlighting signs of atrial fibrillation and low or high heart rates.

2. Often you will need to re-orientate a device's inertial sensor with that of gravity, as shown in figure 5. Why might this be an important step to consider in processing IMU data?

IMUs measure a body's angular rate, orientation and specific forces. Smartphone accelerometer's give the device's acceleration in X, Y, Z coordinates. Often the device's inertial sensor will have to be reorientated to give an accurate reading relative to the earth's surface, allowing the local axis to match the global ones the device is set to.

3. Figure 7 presents various boxplot distributions. Briefly describe how to interpret a boxplot and its properties.

Boxplot:

- The minimum value is show at the bottom of the lowest 'whisker'
- The first quartile is the bottom of the box
- The median is shown by a line within the box
- The third quartile is shown by the upper edge of the box
- The largest value is shown by the top of the highest 'whisker'

Section A : The Electrocardiogram

Exercise 1: Exploratory ECG Data Analysis

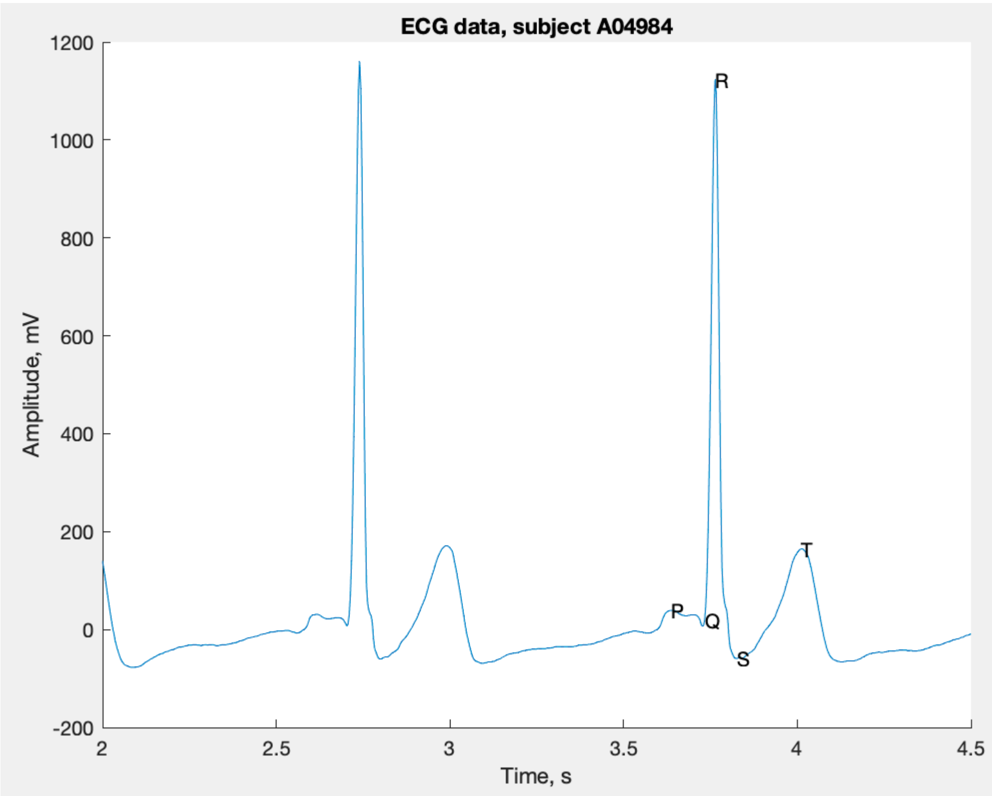
Q1. Load the PhysioNet data into MATLAB and determine the proportion of classes in the dataset from the RecordingInfo table. (hint: use the tabulate.m function)

Table showing the fractional distribution of rhythm classes

Value	Count	Percent
Atrial Fibrillation	499	8.35%
Normal	3678	61.54%
Other Rhythm	1675	28.02%
Noisy Recording	125	2.09%

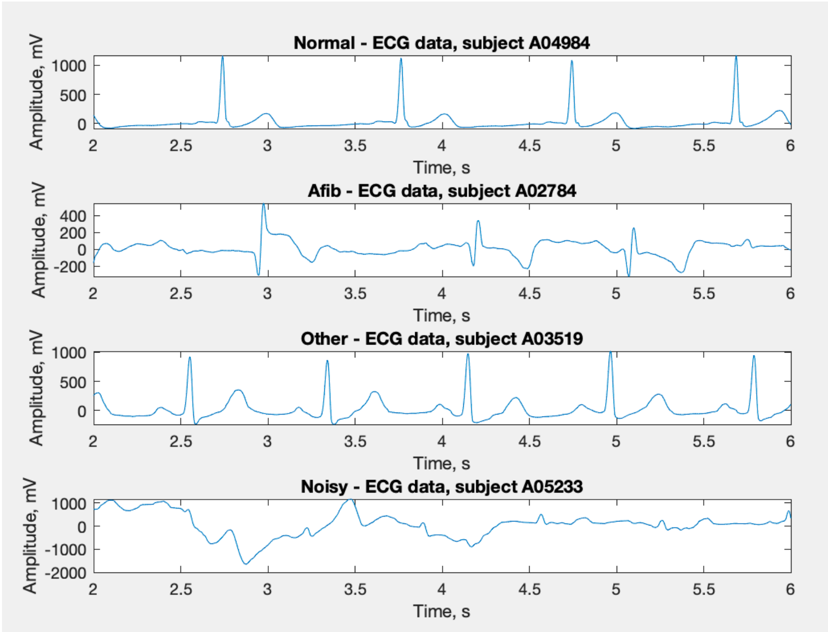
Q2. Plot suitable portion of ECG data from normal subject, which depicts at least 2 heartbeats.

ECG Data for Normal subject - `A04984`



Q3. Visualise a segment of one ECG signal from each of the 4 classes from any chosen set of examples. Label each recording.

ECG signal for Normal, AFib, Other and Noisy data sets.



a)Describe some of the signal characteristics observed that distinguish normal ECG versus AF ECG in your chosen examples. Use extra plots to illustrate your discussion points if required

It can be seen from the above figure that the AF has an irregular rhythm, as seen by the distances between the peaks changing, compared to the normal ECG where the distance is more consistent. The T-P interval fluctuates significantly more for the AF ECG than that of the Normal ECG. Additionally, the AF data has a lack of clear P waves, as seen at ~2.8 seconds on the ECG, the signal is flat then goes straight into the Q wave.

(b) With respect to your chosen noisy ECG example, or any artefacts observed in other examples, briefly discuss some of the reasons why ECG signals can be corrupted or noisy.

Sources of noise:

- Baseline wander → a low-freq component present in ECG signals, mainly due to respiration and body movement. This noise makes it harder to detect the peaks shown in the above figure.
- Channel Noise → when the ECG signal is transmitted through poor channel conditions.
- Electrode contact noise → poor connection between the electrode and the patient's skin can lead to disconnections, meaning the signal doesn't have a clear reading and actually follow the heart's rhythm.
- Electrode-skin impedance → the value of electrode-skin impedance is variable, also depending on how fluid is present between the skin and the electrode

Exercise 2: Pre-Processing ECG

Q1. Detrend the data by subtracting the mean component; then, standardise the detrended data using the z-score approach; Using the same standardised and detrended normal and AF recording examples above:

- To detrend the data, take the signal Normal/AFib and subtract its respective mean.
- To find the z-score normalise the detrended data

Q2. Apply band-pass filtering to each recording using the filter ecg.m file provided

(a) Identify suitable filtering parameters: high-pass and low-pass frequency thresholds, filter order. Justify and discuss your choice of (1) high-pass frequency threshold; (2) low-pass frequency threshold with respect to your understanding of ECG signals;

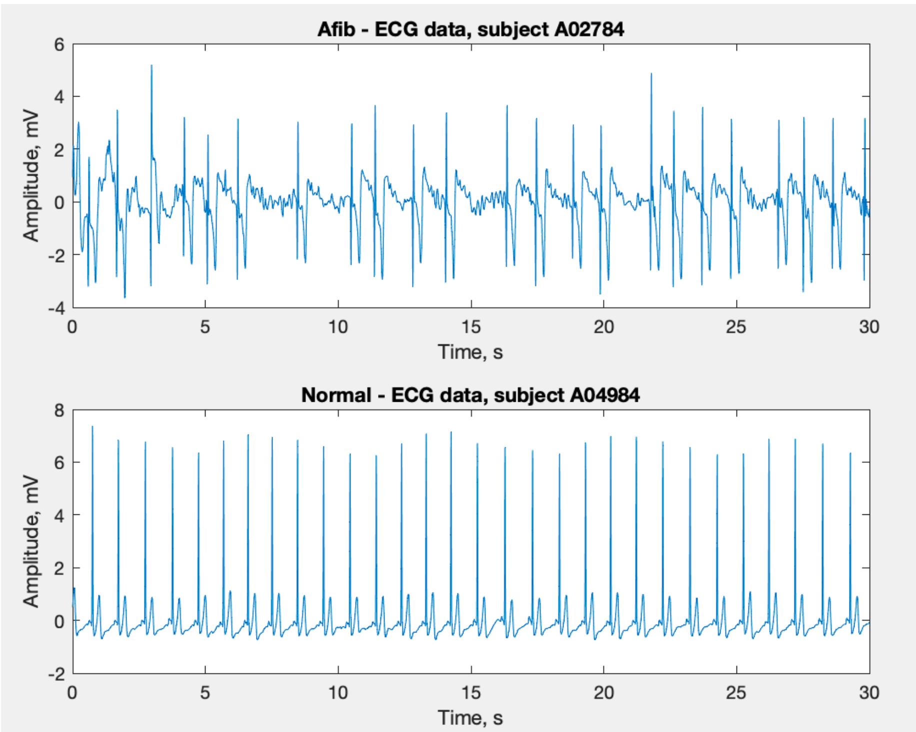
Sampling Freq Hz	Low-pass freq Hz	High-pass freq Hz	Filter Order
300	100	0.5	4

The useful bandwidth of an ECG signal, can range from 0.5-50Hz, general practice for a standard clinical ECG application has a low-pass freq of 100Hz, and a high-pass freq of 0.5Hz.

https://www.analog.com/en/analog-dialogue/articles/ecg-front-end-design-simplified.html#

Q3. Plot the resulting recordings for both your chosen normal and AF examples after detrending, standardisation and filtering has been applied.

ECG data after detrending, standardisation and filtering



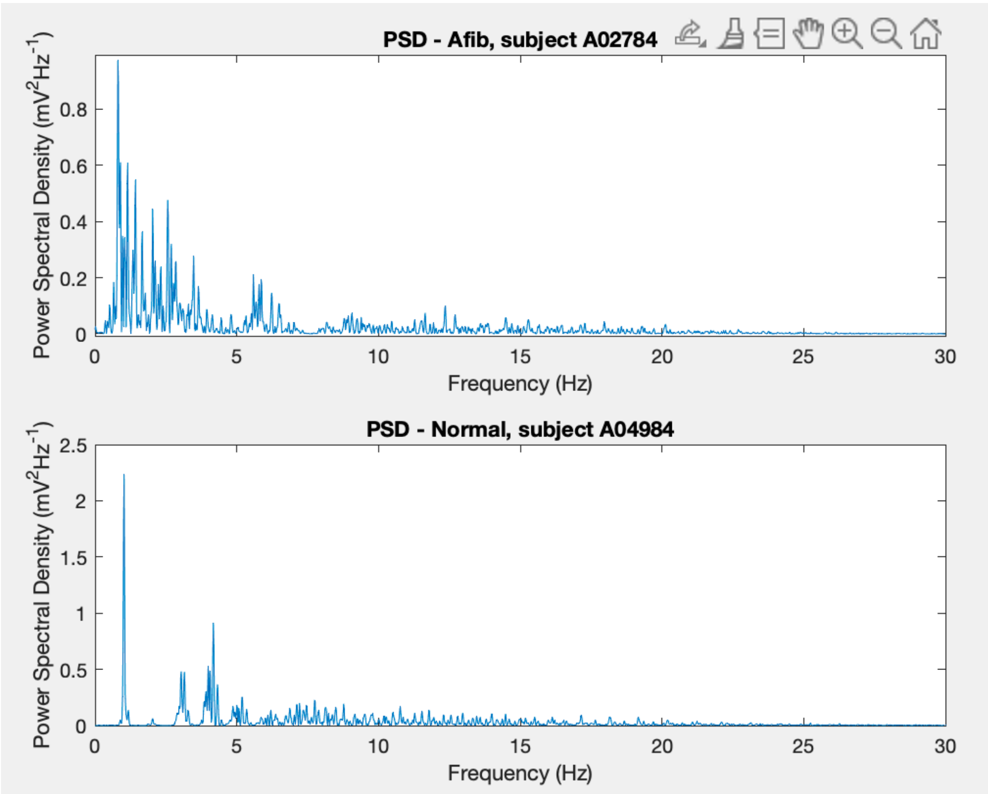
Exercise 3: Frequency Representation of ECG signals

Q1. Plot the modified periodogram PSD estimate for your chosen normal and AF recording examples; identify the dominant frequency and any other prominent peaks in the PSD; comment on their amplitude, frequency and your understanding with respect to ECG.

The dominant frequency for the Normal patient is ~ 0.86Hz, however this patient has another prominent peak at ~3.6Hz. The AFib patient's dominant peak is at a slightly lower frquency at ~0.7Hz, however, this patient has many more prominent peaks, in particular between the dominant peak and 3Hz. This is likely due to the irregularities in the breathing pattern for people with atrial fibrillations. Consequently the PSD values are lower at the dominant peak than in the Normal PSD, as expected there is less clarity between peaks.

When plotting this data the x-axis was changed to be upper limited at 30Hz, as after this value there is negligible PSD values – by shortening this axis we have gain clarity of the peaks near to the origin.

Modified periodogram PSD

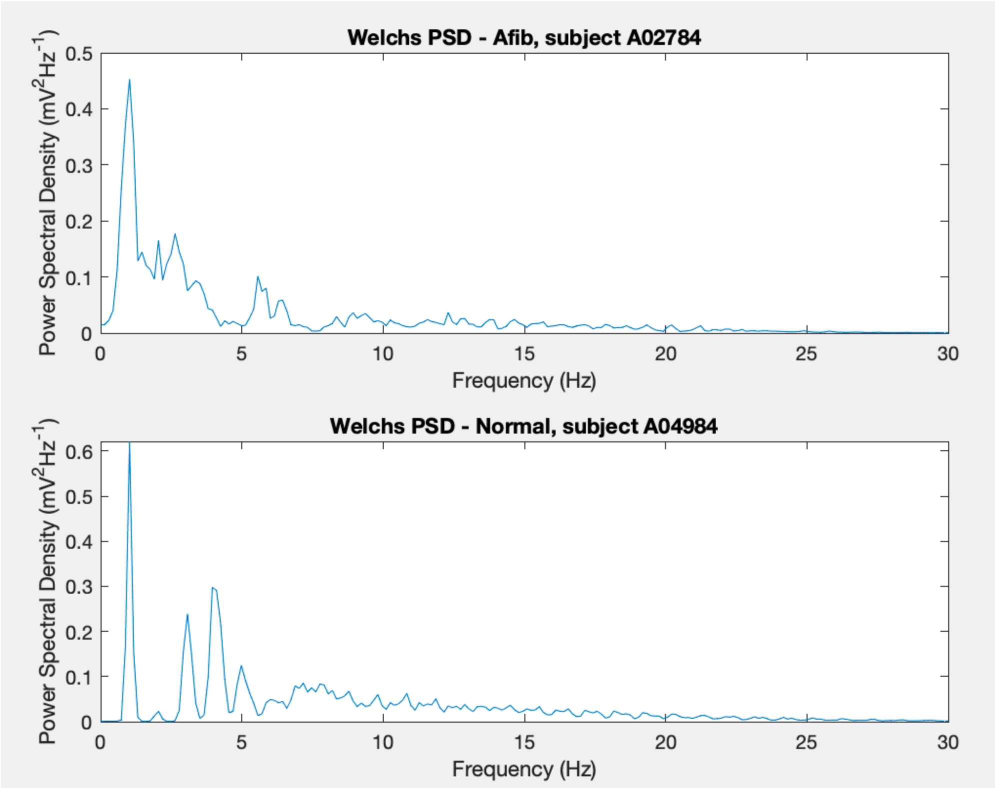


Q2.a)Plot Welch's power spectral density estimate for your chosen normal and AF recording examples;

b) Briefly comment on the differences between both PSD methods. Why might Welch's PSD estimate be preferable for analysing biomedical signals?

Welch's PSD gives a clearer continuous line for the PSD, meaning it is easier to read than the standard PSD method. It is preferable for biomedical signals as the peaks are clearer to identify.

Welch's Power Spectral Density



Exercise 4: Determining Heart Rate and Heart Rate Variability

I: Determining Heart Rate through R-Peak Detection

Using the same standardised, detrended and band-pass filtered data from normal and AF recording examples in exercise A.2.3:

Q1. Perform R-peak detection using the MATLAB findpeaks.m function for your chosen normal and AF recording examples;

a)Choose suitable parameter values for the findpeaks.m function in order to best identify normal and AF R-peaks correctly; b) Justify your parameter value choices;

Freq =300Hz, T= 1/300 = 0.0033

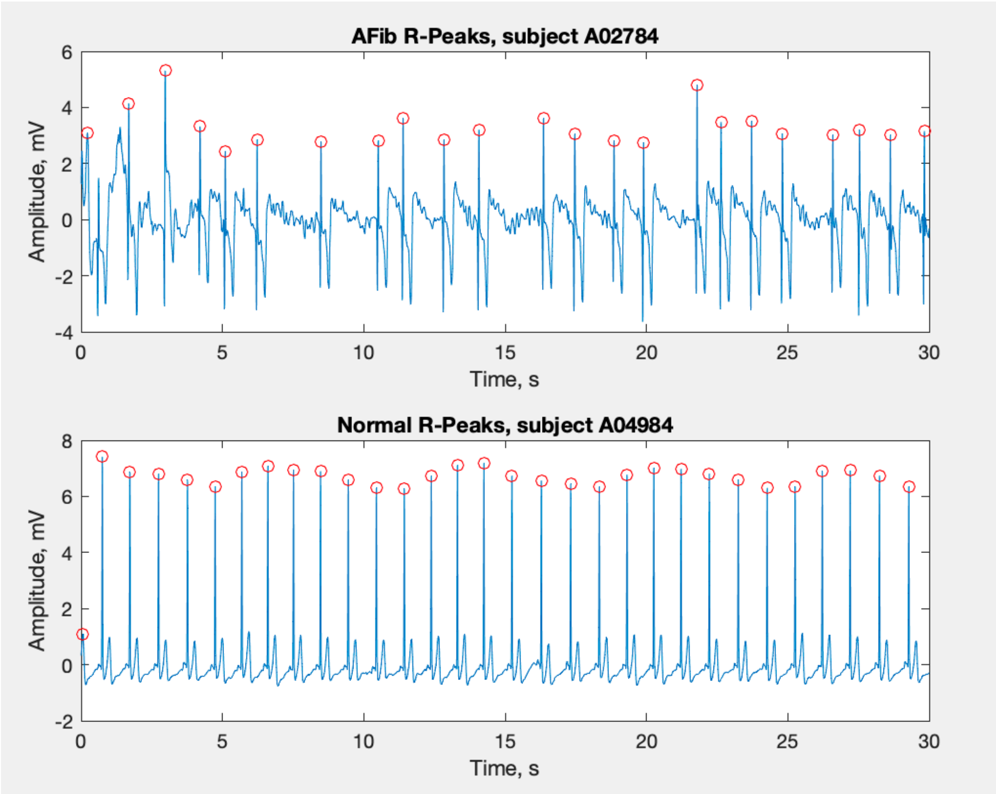
AFib peak occurs Ex2.3 ~0.7secs, therefore MinPeakDistance = 0.7/0.0033 ~200.
MinPeakHeight ~1

Normal peak occurs Ex2.3 ~0.7sec, therefore MinPeakDistance =0.7/0.0033 ~200.
MinPeakHeight ~1

We want the plot to identify and circle the R-peaks of the signal, for the Normal data this MinPeaks successful do this. However, for the AFib an incorrect low peak is highlighted with these values set, when the MinPeakHeight is increased to 2, the error is removed.

(c) Plot the normal and AF recording examples with the with the automatically-detected R-peak locations annotated;

R-Peaks with locations encircled



d) Discuss the limitations of this approach to R-peak detection. Briefly comment on any other methodologies for R-peak detection you have found in the literature, including a citation from a relevant paper

One of the limitations of this method is the fact we are choosing the values of MinPeakHeight and MinPeakDistance by hand, when so the values used are not the ideal values. Hence multiple rounds of modification of these values were conducted in order to have all true R-peaks highlighted without highlighting shorter non R-peaks.

Alternative methods:

- Peak detection that uses an SVD filter and search back system → the ECG signal is detected in two phases. Firstly, a pre-processing phase using a singular value decomposition filter (removes noise), followed by a Butterworth High Pass Filter (to eliminate baseline wander), a moving average (removes remaining noise) and then the signal is squared (to strengthen the signal). Secondly, the decision phase where a threshold is used to set the interval before detecting the R-peak. This processes leads to a relatively low noise signal, allowing the R-peaks to be detected clearly.

  "An R-peak detection method that uses an SVD filter and a search back system", Woo-Hyul Jung, Sang-Good Lee - Department of Multimedia System Engineering, The Catholic University of Korea, Bucheon, Gyeonggi, South Korea

Q2. Determine the mean heart rate from the automatically detected R-peaks for your chosen normal and AF recording examples

To calculate the mean HR, firstly calculate the distance between the R-peaks, followed by the mean of the distance between peaks. Finally, the mean HR can be calculated by dividing 60secs by the mean R-peaks distance:

This calculation produces a mean HR of 62bpm for the Normal rhythm, which is a normal resting heart rate. For the AFib the mean HR is 45bpm which is abnormally low, but as this patient has atrial fibrillation we would expect the them to have an irregular heart rate.

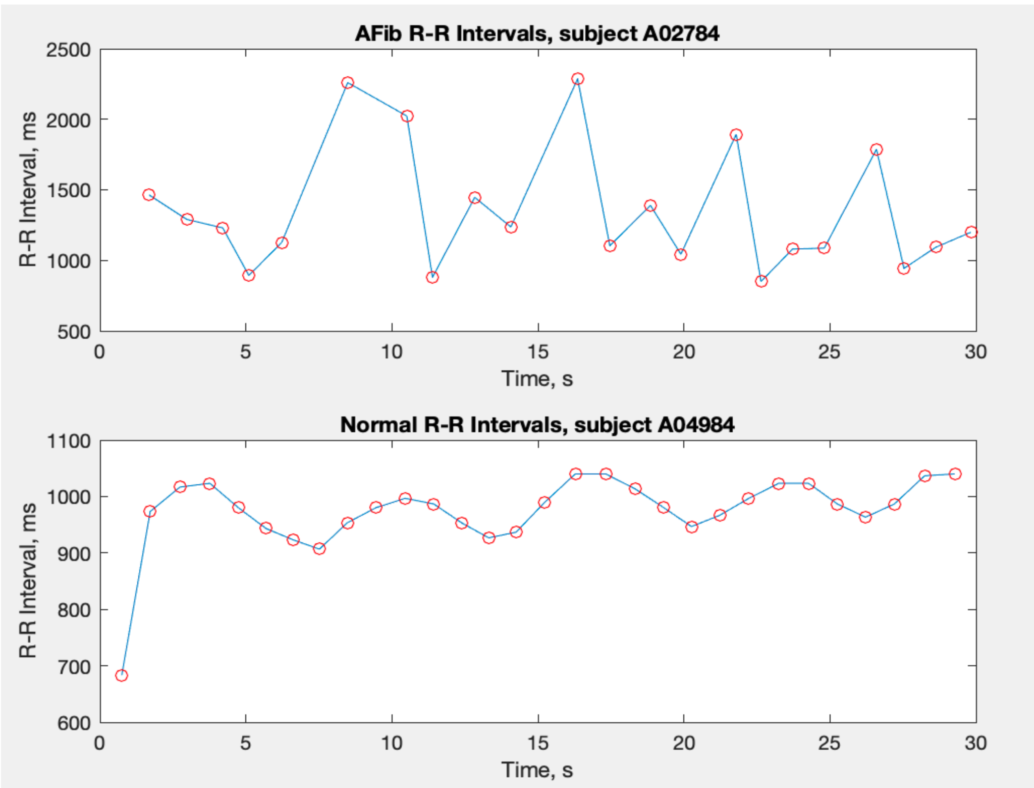
```
%% Q2. Determine mean heart rate
% Mean HR, number of R-Peaks in 60 secs
% 60  / Average distance between peaks
% Mean R-R peak difference
% AFib
Rpk_diffAFib = diff(R_locsAFib)./fs;
Rpk_diffAFib_mean = mean(Rpk_diffAFib);
HRAFib = 60/Rpk_diffAFib_mean

% Normal
Rpk_diffNormal = diff(R_locsNormal)./fs;
Rpk_diffNormal_mean = mean(Rpk_diffNormal);
HRNormal = 60/Rpk_diffNormal_mean
```

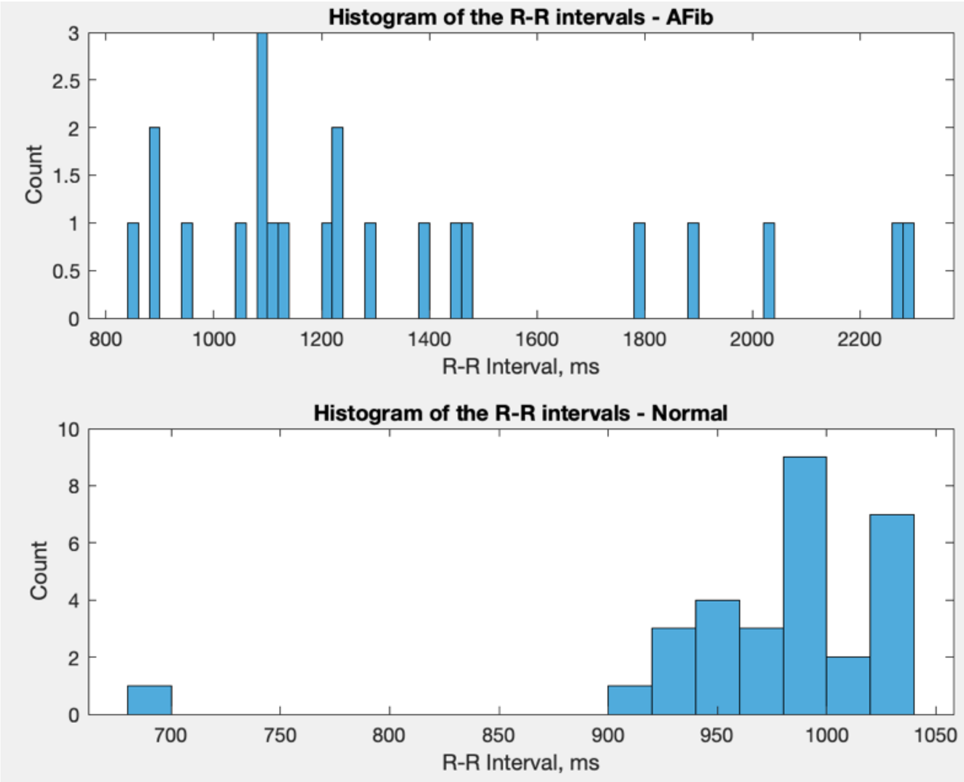
II: Determining Heart Rate Variability Measures

Q3. Plot the R-R interval times over the duration of the recording from the automatically detected R-peaks for your chosen normal and AF recordings

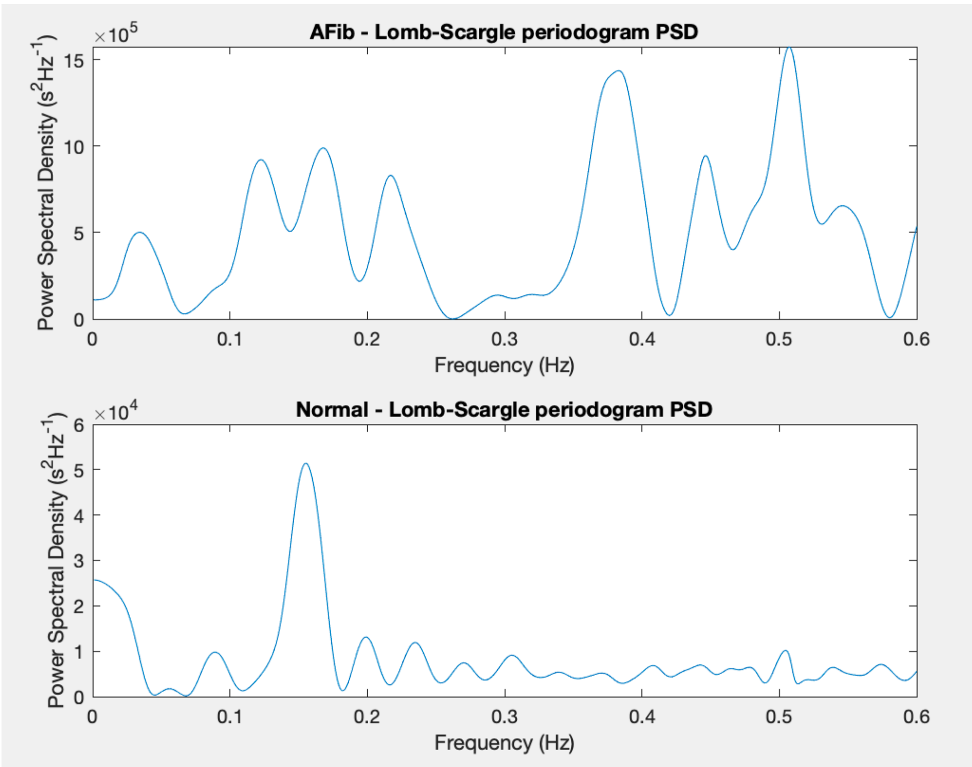
R-R interval timings



Q4. Plot a histogram of the R-R interval times over the duration of the recording from the automatically detected R-peaks for your chosen normal and AF recording examples;



Q5. Plot the Lomb-Scargle periodogram PSD of RR-intervals for your chosen normal and AF recording examples;



Q6. Briefly discuss your findings comparing your chosen normal and AF recording examples in exercise A.4.3 and A.4.4 with respect to heart rate, R-R interval times and heart-rate variability. Compare these findings to what you might expect to observe.

From the R-R intervals plot it is clear that the signal from the AFib is significantly more erratic than the Normal R-R interval. The Normal graph has smooth undulations, usually between ~900 - ~1000ms, compared to AFib's sharp oscillations between ~1000 and ~2300ms, which is a much larger range. Due to the irregularities of AFib heart rates, it is expected that the R-R intervals will fluctuate more than the Normal patient.

Histogram supports the R-R interval plot, the Normal histogram has mainly clumped data between 900-1040Hz, with a single outlier at 700Hz. The AFib graph has bars of the histogram spread out with a lower count between 830-2230Hz suggesting R-R interval fluctuations as supported in the plot in Ex4.3

The Lomb-Scargle uses the time between heart beats as opposed to data from the ECG. As in the above graphs the power spectral density shows that there are fewer clear peaks for the Normal data due to it's consistent HR, compared to the AFib.

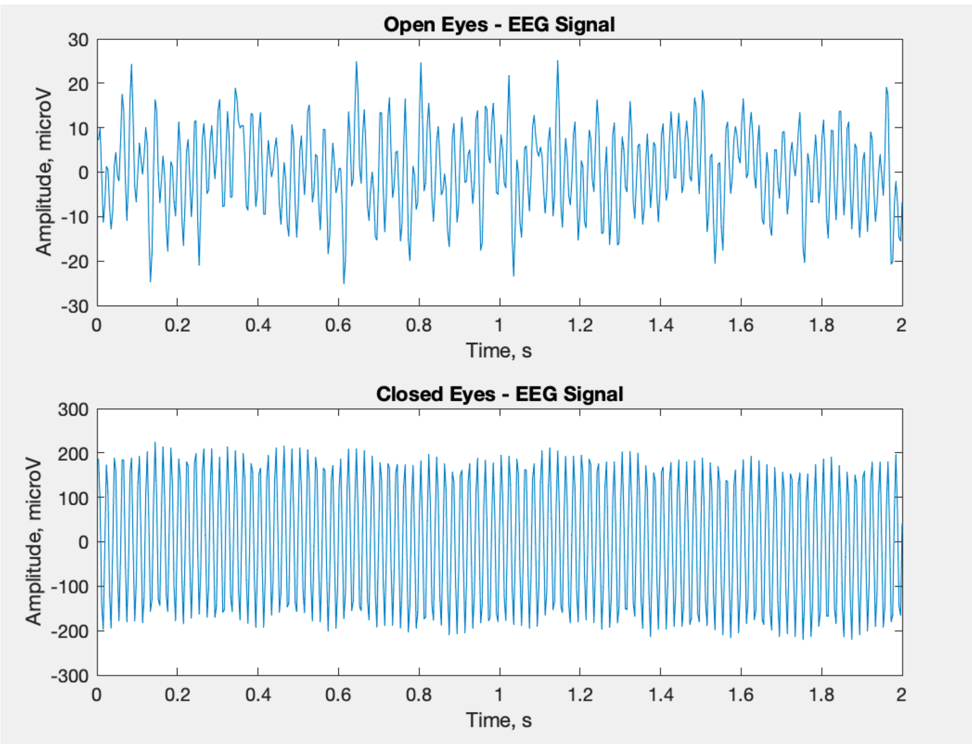
Section B: The Electroencephalogram

Example data from a healthy participant with electrodes placed across the occipital area of the brain, sampled at 256Hz

Exercise 1: Investigating EEG Data

Q1. Load the EEG data: eeg_trial_1.mat; eeg trial 2.mat and plot the entire EEG samples for each for the first 512 samples of each trial;

EEG data from open and closed eyes, @ sampling freq 256Hz for 512 samples

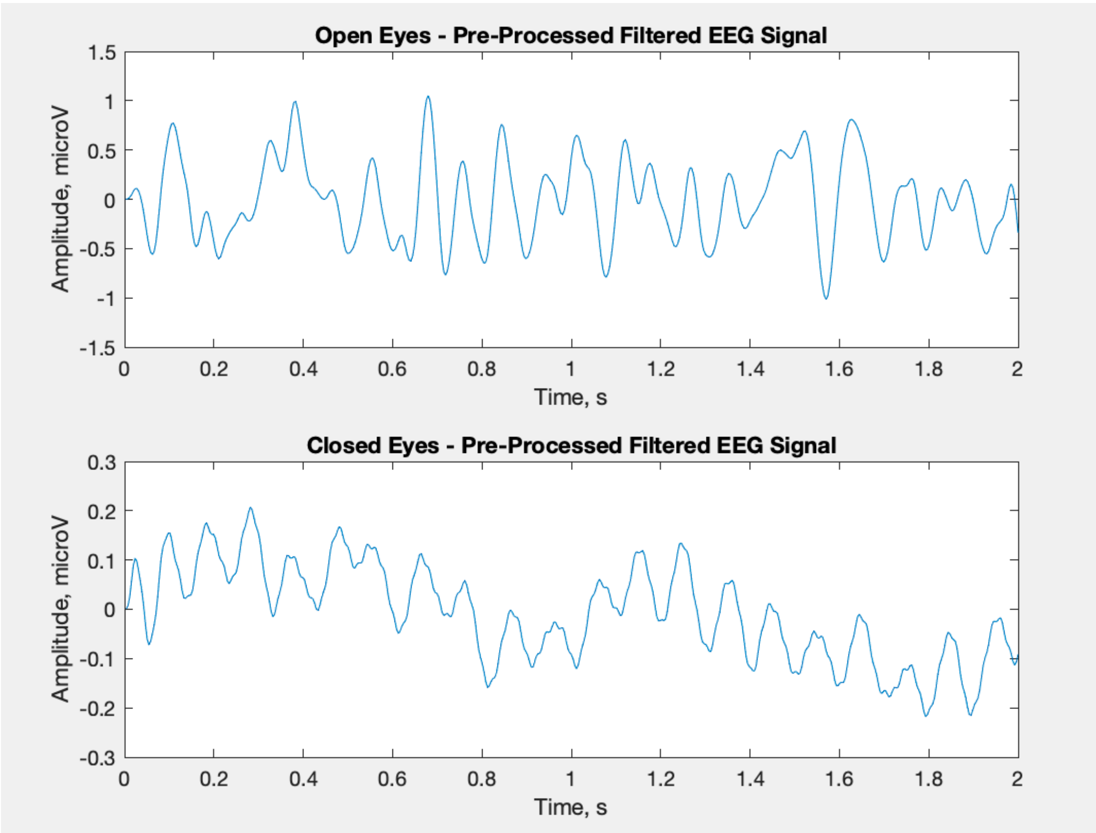


Q2. Pre-process the data by low-pass filtering, detrending, normalising each EEG signal; (a) Determine suitable low-pass filtering parameters by reporting and analysing various parameter combinations (b) Justify your filtering parameters choices with respect to your understanding of analysing EEG signals

The cut-off frequency Wn must be 0.0 < Wn < 1.0; Wn= fc / fs
The normal EEG range is from 0.5-30Hz so say fc =30Hz, given that fs = 256Hz, the Wn criteria is satisfied. The filter order is 4 as in section A.

(c) Plot the EEG samples for the first 512 samples of each trial (#1 & #2) after pre-processing

Pre-processed, filtered EEG signal for the first 512 samples

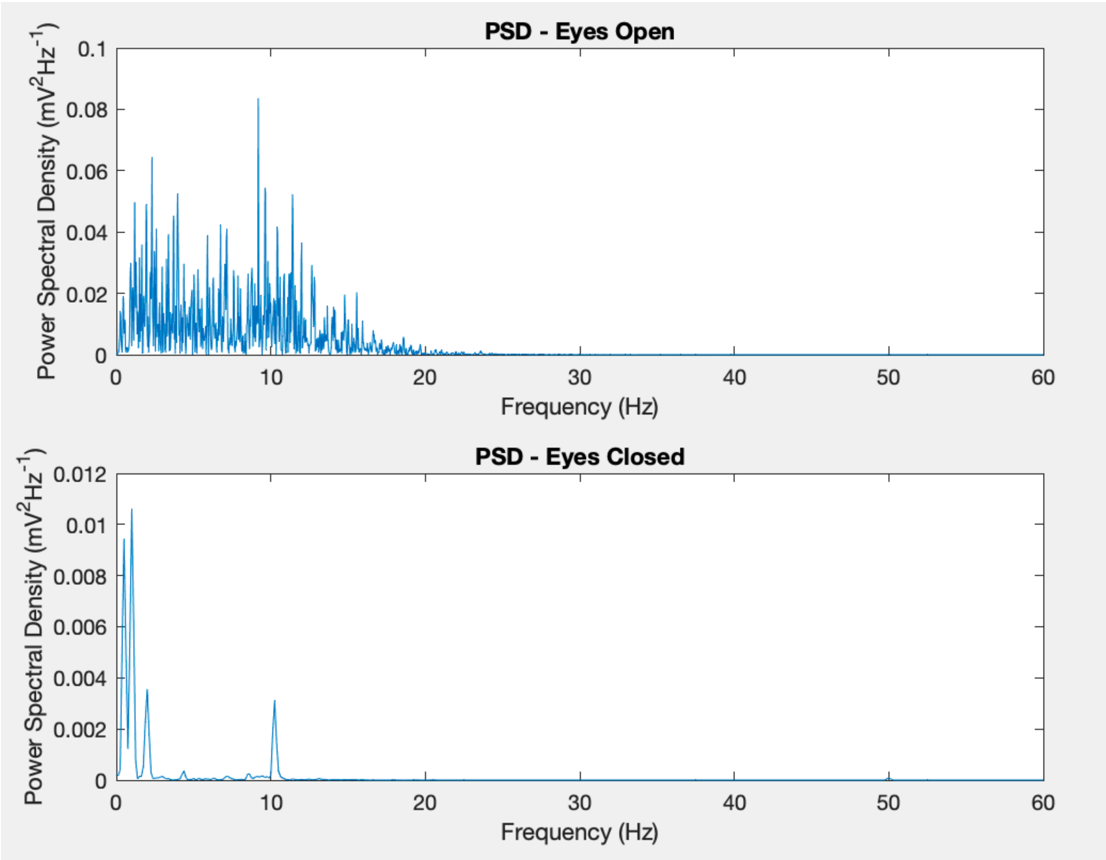


Q4.Plot the modified periodogram PSD estimate of each trial (display only up to 60 Hz); (a) At what frequencies are the four highest components remaining after filtering? Suggest a cause for each; (b) Note, discuss, and compare any significant peaks in each spectrum comparing trial #1 and trial #2;

a)4 highest components remaining after filtering, in descending order:

Eyes open → 9.2Hz, 2.3Hz, 9.7Hz, 4.0Hz. Eyes closed → 1Hz, 0.5Hz, 2Hz, 10.3Hz

Periodogram PSD



b)Compare any significant spectrum peaks in each spectrum comparing eyes open and eyes closed

During eyes open the frequency peaks seen are primarily in the delta and alpha frequencies. The delta phase is often present during deep sleep and the alpha is during relaxation, which would explain why it occurs in eyes open rest.

During eyes closed the frequency peaks seen are primarily in delta, with one peak is in alpha. There are more peaks in delta which is expected as closed eye rest will have a larger relaxed phase, than alpha.

Q4. Describe the main sources of error in EEG experiments. Suggest methods to mitigate or control for these identified sources of error.

Overreading EEGs can cause error in diagnosis, sometimes normal background fluctuations can be misdiagnosed as peaks in the EEG signal → better filtering of the signal can reduce this noise, hence reducing the error. A strict criteria should also be set out make sure spikes in the EEG are correctly identified. Poor signal-to-noise ratio.

https://n.neurology.org/content/neurology/76/12/e57.full.pdf

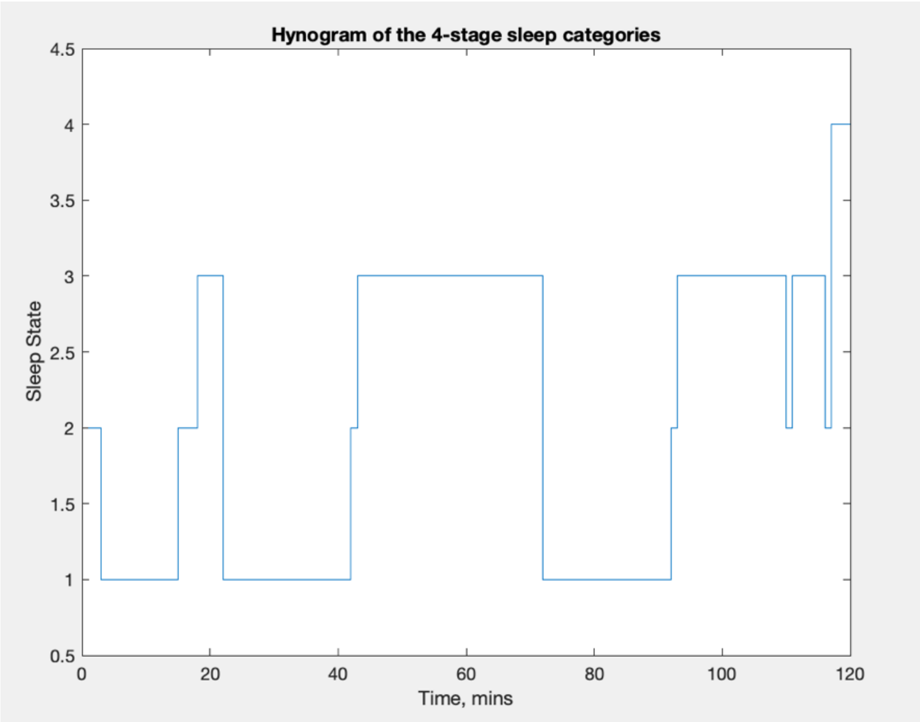
Exercise 2: Quantifying Sleep through EEG

Q1. Load the EEGSleepStateData.mat file.

Q2. Plot a hypnogram of the 4-state sleep categories (sleep category num): quiet sleep (QS), transnational (TA), active sleep (AS) and awake (AW);

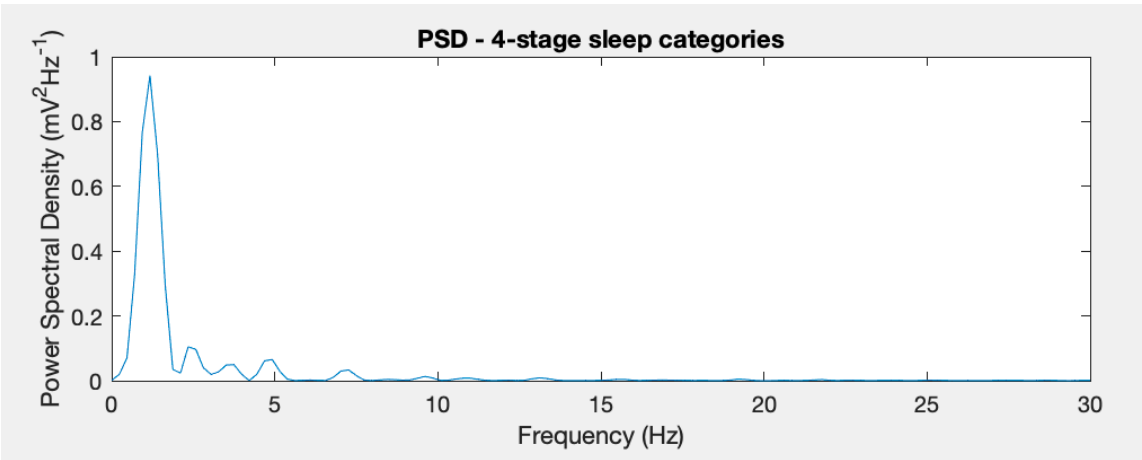
Initial y lim from 0.5-6.5, no value above 4.5. We want to plot for 4-stage sleep categories, however there are 6 stages in the data set so take the hypnogram upper limit to be 4.5. Quiet sleep QS, transnational TA, active sleep AS, awake AW.

Hypnogram of the 4-stage sleep categories



Q3. Plot the modified periodogram PSD estimate of the 4-state sleep categories; (a) Determine the infant sleep-cycle between quiet sleep and active sleep (in cycles/hour) (in this case, the dominant frequency);

Periodogram PSD estimate of the 4-state sleep categories



Frequency at peak = 1.2Hz.

Q4. Give another application example of EEG from the literature besides sleep analysis.

One of the main uses of the EEG is in diagnosis epilepsy, as it can determine changes in brain activity that is useful in diagnosing brain disorders.

Section C: Smartphone Physical Activity Monitoring

Exercise 1: Building a Smartphone Walk Detection and Step Counting Algorithm

Q1. Run the B18 GAIT Exercise 1.m file for any example file of your choice;

a)Pick suitable acc threshold ssd threshold values for walking detection; (b) Pick suitable MinPeakDistance MinPeakHeight values for step detection; (c) Record your parameter values;

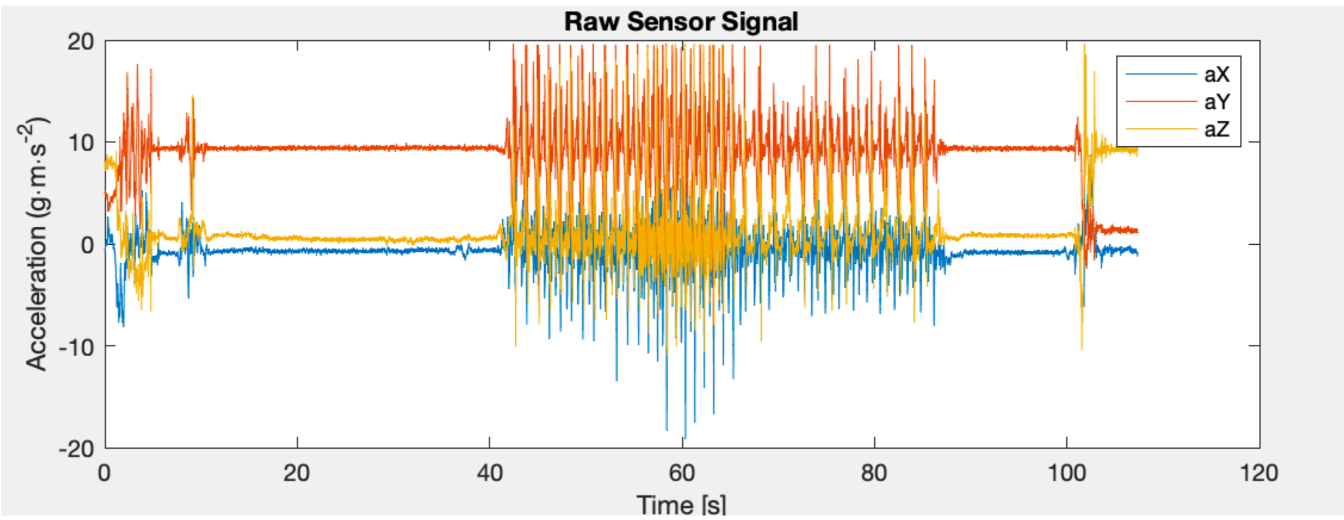
Avg acc threshold	Avg ssd threshold	Time threshold	MinPeakDistance	MinPeakHeight
15%xG	30%xG	5s	0.5s	10%xG

(d) Record the actual number of steps, the number of steps detected and the cadence for those parameter values;

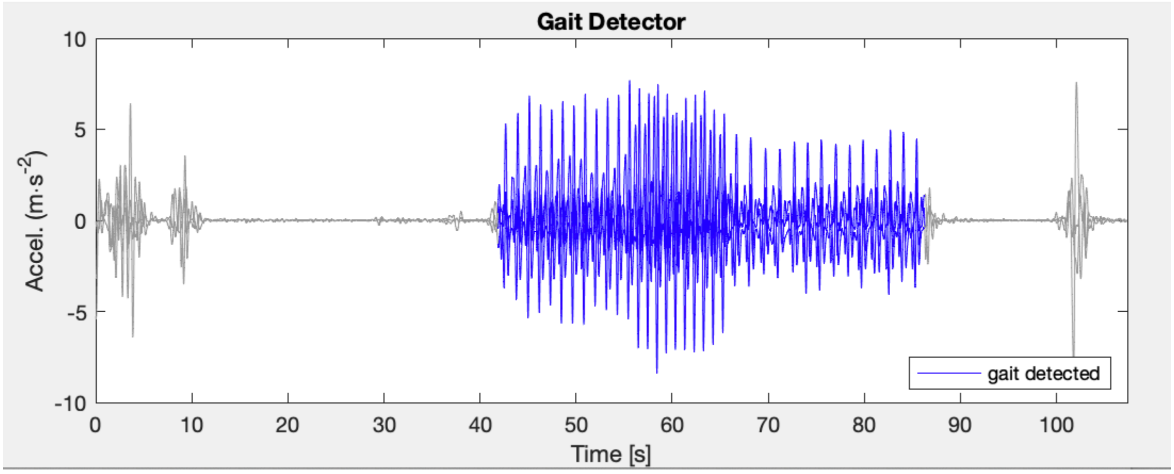
Patient No	Actual no. steps	No. steps detected	Cadence
5	74	40	54.02

Q2. Similar to figure 13, for your chosen file plot:

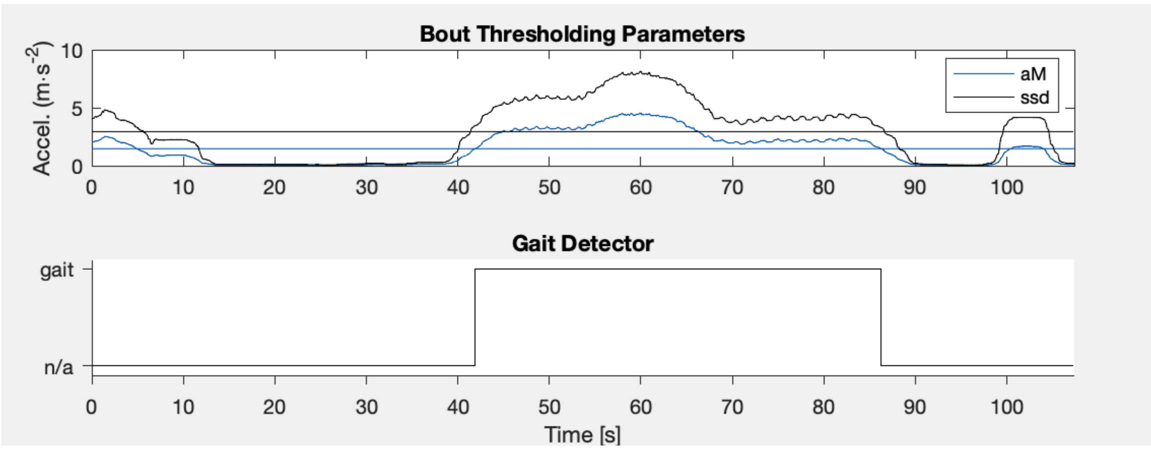
Patient 5 - Raw 3-axis smartphone acceleration signal



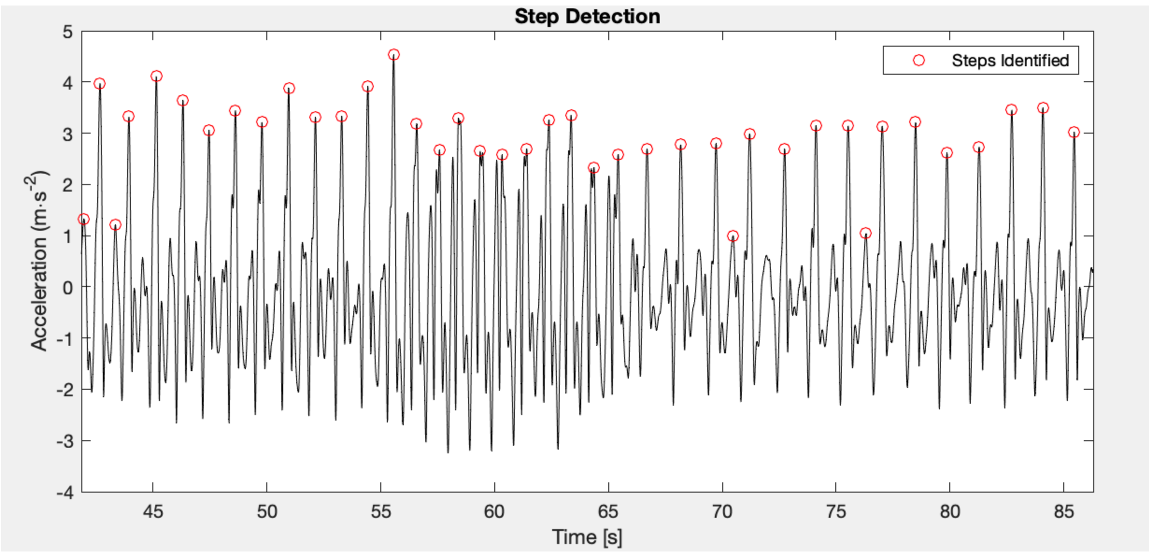
Patient 5 -The walking detection outcome



Patient 5 - The walking detection algorithm parameters chosen



Patient 5 - The step detection annotations



Q3.Repeat steps 1 and 2 for at least one other recording;

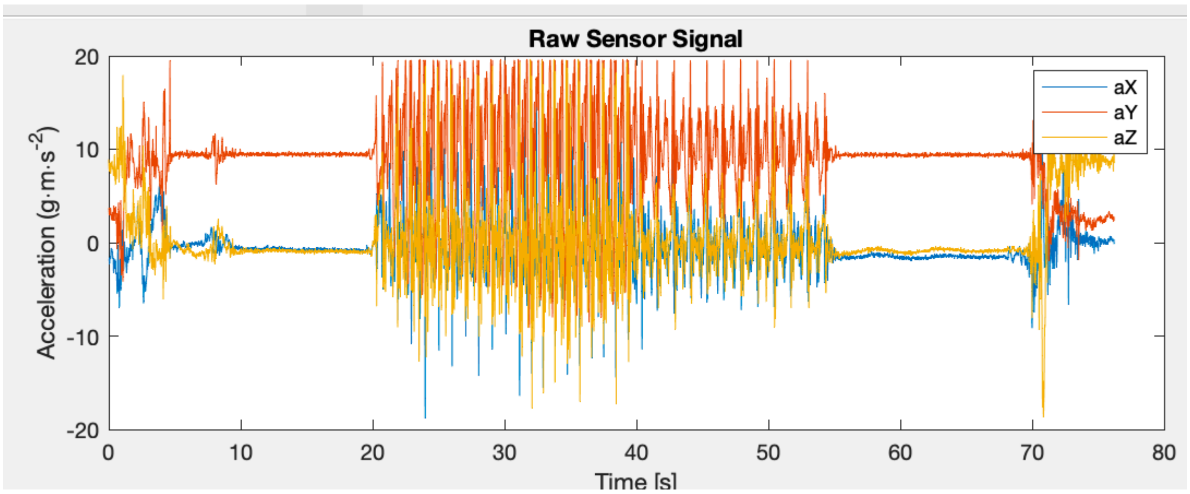
a)Pick suitable acc threshold ssd threshold values for walking detection; (b) Pick suitable MinPeakDistance MinPeakHeight values for step detection; (c) Record your parameter values;

Avg acc threshold	Avg ssd threshold	Time threshold	MinPeakDistance	MinPeakHeight
15%xG	30%xG	5s	0.5s	10%xG

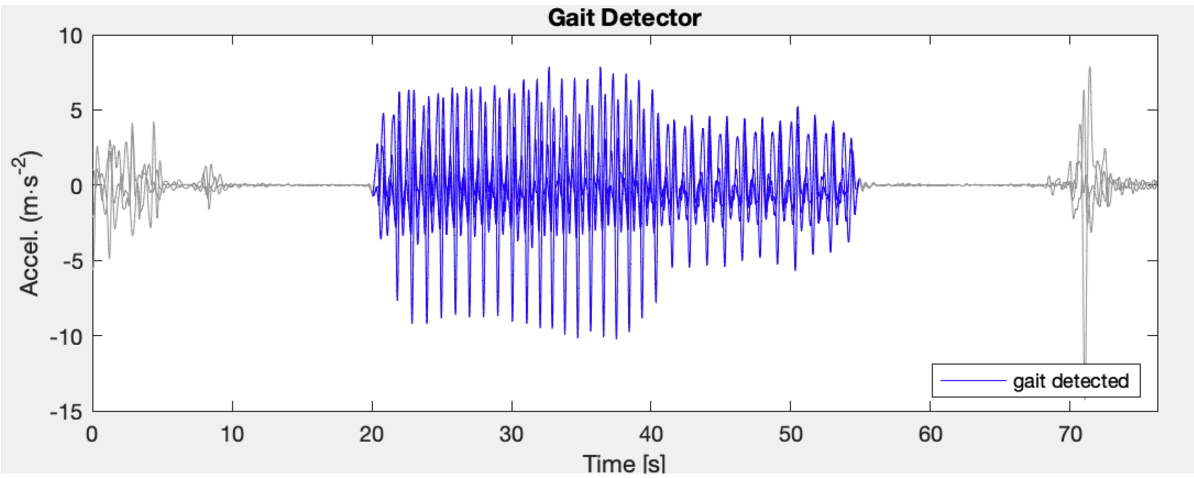
(d) Record the actual number of steps, the number of steps detected and the cadence for those parameter values;

Patient No	Actual no. steps	No. steps detected	Cadence
10	64	40	68.87

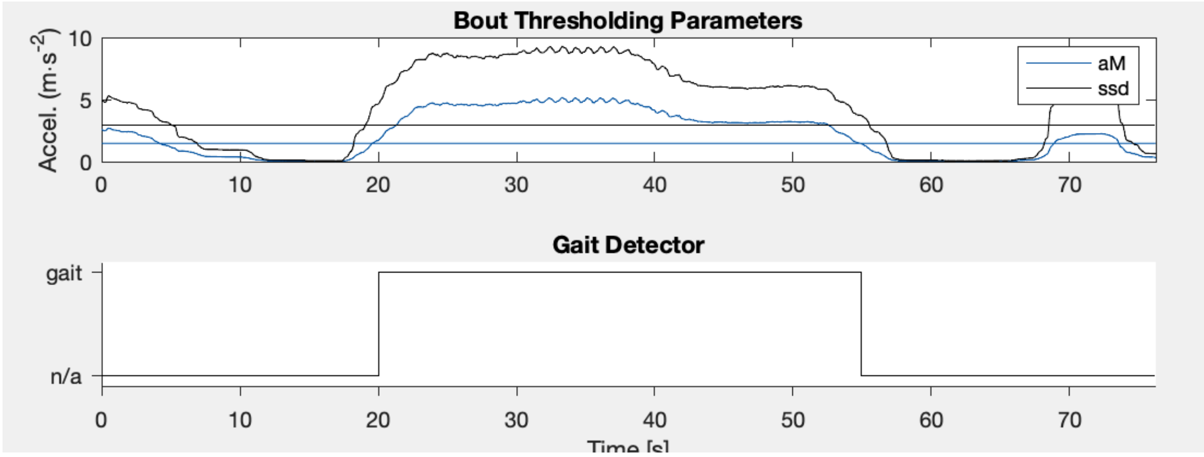
Patient 10 - Raw 3-axis smartphone acceleration signal



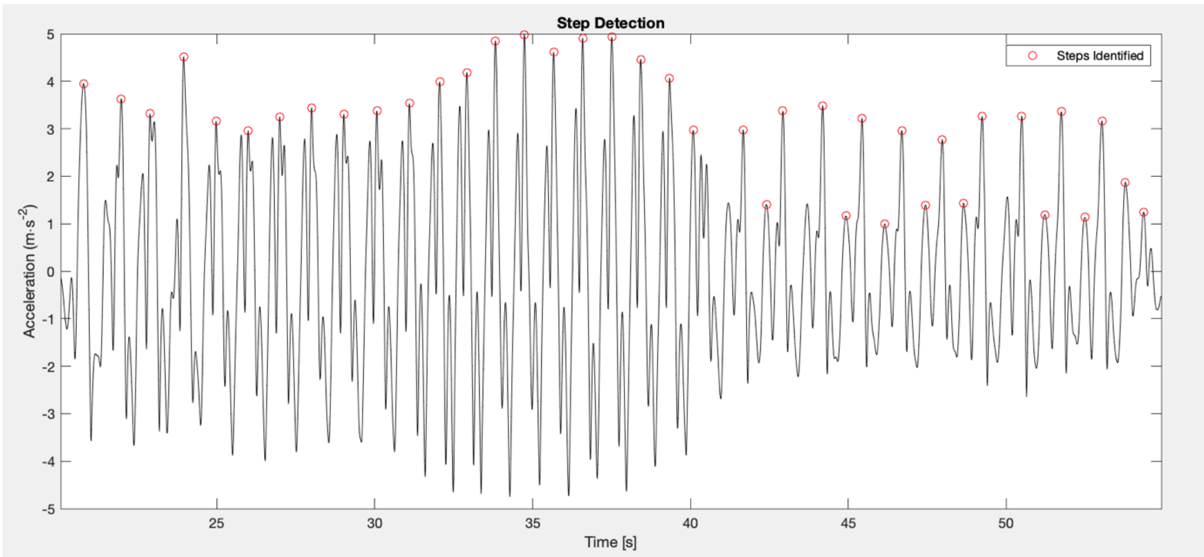
Patient 10 -The walking detection outcome



Patient 10- The walking detection algorithm parameters chosen



Patient 10 - The step detection annotations



Exercise 2: Assessing Step Counting Algorithm Performance

1. Run B18 GAIT Exercise 2.m with your chosen parameter values for acc threshold ssd threshold values for walking detection and MinPeakDistance, MinPeakHeight values for step detection

(a) Plot the boxplot distribution of actual vs. detected number of steps per subject

(b) Plot the scatter plot of the actual vs. detected number of steps per subject

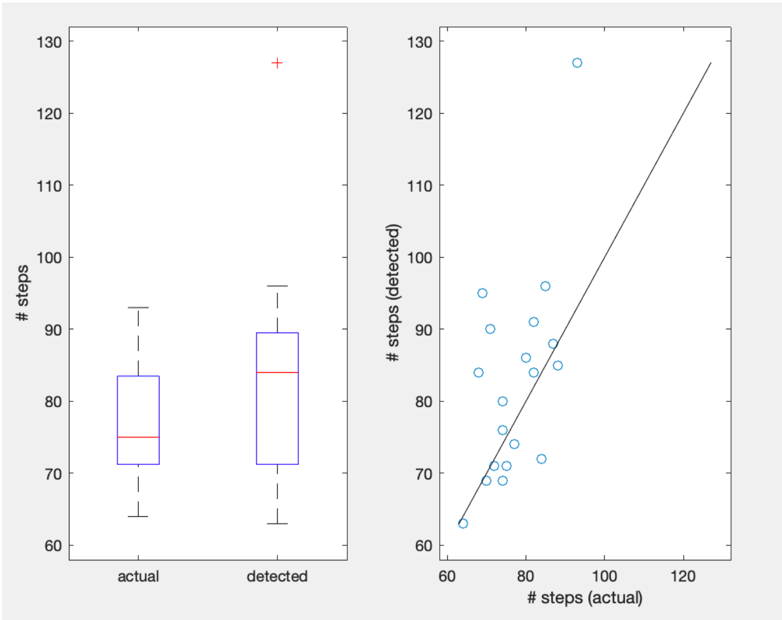
Initially chose values for acc threshold, ssd threshold, MinPeakDistance and MinPeakHeight, however this led to errors in the MATLAB script. Namely because setting a value of 30%xG ssd threshold and 15%xG acc threshold would not record any steps in some of the data. Therefore, I experimented with different values, and settled on 10%xG for both these values showed all the data points.

Additionally, I adjusted the values of MinPeakDistance and MinPeakHeight so that the trend line fit the scatter line best, this also gives a detected number of steps closer to the actual number of steps.

I settled on: MinPeakDistance = 0.2s, MinPeakHeight = 5%xG

Exercise	Actual no. steps	No. steps detected	Cadence
2	70	69	101.66

Boxplot distribution of actual vs. detected number of steps per subject; Scatter plot of the actual vs. detected number of steps per subject



(c) Record the MAE and MSE error metrics between the actual vs. detected number of steps, (d) Briefly discuss the performance of your chosen parameters

MAE = 8.53, MSE = 154.63

Example values from the lab notes: MAE = 5.8, MSE = 80.9

Through the optimisation of the MinPeakDistance and MinPeakHeight, I was able to improve my MAE and MSE values. Eg. decreasing the MinPeakHeight from 0.1 to 0.05 the MAE and MSE dropped from MAE = 10.68, MSE= 223.21

Q2. Briefly discuss some of the difficulties and limitations with the heuristic walking detection and step counting algorithm analysed in section C

One of the issues with the algorithm is that the parameterised thresholds are set before the algorithm is run, so it is like that the values chosen do not lead to the minimum MAE or MSE.

Q3. From the literature, suggest any another method for either walking detection or step counting

"A Novel Walking Detection and Step Counting Algorithm Using Unconstrained Smartphones" – Xiaomin Kang, Baoqi Huang and Guodong Qi.
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5796454/

This novel algorithm can simultaneously detect walking motion and count steps using smartphones. Using the periodicity of the walking motion and sensitivity of gyroscopes, the algorithm extracts the frequency domain from 3D angular velocities of the smartphone through fast Fourier transforms – identifying if the person is walking irrespective of the phone's placement. Additionally, the step count is evaluated in real time but recursively updating the step frequency.