Università di Padova - Dipartimento di Ingegneria dell'Informazione
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Final Project
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Professor: Alberto Zucchetta

Students:
Ahmadian Arash - studentID: 2049580
Favero Manuele - studentID: 2096408
Takafouyan Mohammad - studentID: 2041469
Zanin Daria - studentID: 2089062

ProjectRESP: Respiratory Rate Estimation

Abstract

In recent years, cardiovascular diseases are on the rise, and they entail enormous health burdens on global economies. Cardiac vibrations yield a wide and rich spectrum of essential information regarding the functioning of the heart, and thus it is necessary to take advantage of this data to better monitor cardiac health by way of prevention in early stages. Seismocardiography [1] [2] is a very promising technique to measure the Heart Rate (HR) and Respiratory Rate (RR) with a detector positioned above the sternum. It is generally based on accelerometer and gyroscope readings or a combination of them. Specifically, Ballistocardiography [3] is an another technique to estimate heart and respiratory rate with a combination of both an accelerometer and a gyroscope. It is an indirect evaluation of HR and RR since the contact between the device and the body of the subject is not required (e.g., the

accelerometer platform can be mounted under the slats of the bed).
MuSe (Multi-Sensor miniaturized, low-power, wireless IMU) is an Inertial Measurement Unit [4] provided by [5]. In the context of this project, it allows to record the inertial data necessary for the estimation of SCG and BCG.
The goal of this assignment is to estimate the respiratory rate of an healthy subject, given the linear acceleration and angular velocity measurements recorded by using the aforementioned MuSe platform.

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1 Data Set Exploration

The data is provided in *.txt* files. During this study, two healthy subjects were involved with their informed consent. The first dataset was recorded on one subject, while all the other datasets were recorded on the second subject.
This is the first mandatory file:

- *center_sternum.txt*: MuSe placed on the center of the sternum. The subject was lying supine on his left and right side, respectively.

The other datasets are:

- *1_Stave_supine_static.txt*: Sensor placed on a bed stave, under the mattress at the level of the chest. The subject was lying supine on his left and right side.
- *2_Mattress_supine.txt*: Sensor placed on the mattress, near one corner but not under the pillow. The subject laid in the same position as above.
- *3_Subject_sitting_chair.txt*: Sensor placed on the desk: the subject, sitting on a chair, leaned forearms and hands on the desk.
- *4_Chest_sweater.txt*: Sensor placed on the subject chest directly on a sweater.
- *5_Under_chair.txt*: Subject sitting on a chair, sensor placed under the seat of the chair.

All *.txt* files have 16 columns, containing:

- *Log Freq* stands for the acquisition in Hz (i.e., sampling interval is constant).

- *AccX, AccY, AccZ* are the measured magnitude of linear acceleration along each axis.
- *GyroX, GyroY, GyroZ* are the measured magnitude of angular velocity along each axis.
- *MagnX, MagnY, MagnZ* are the measured magnitude of magnetic field along each axis.
- *qw, qi, qj, qk* are the quaternion components, representing the spatial orientation of the Muse system.

Each data set includes, in addition to the data, one file containing the adopted configuration of the MuSe(*config_1.txt* for the first measurement, and in *config_5.txt* for the other measurement).
The data set chosen for the second analysis is *3_Subject_sitting_chair.txt*. The results highlight a predictable general more noise than in the mandatory set. However thanks to the following implemented noise-cleaning techniques is still possible to extract the respiratory information on some signal components.
After a first data exploration, it appears that the sampling frequency is not constant during the observation interval. In particular, the observation interval can be divided in frames of duration equals to 1 second. During each frame the sampling speed takes different values. This can be noticed after plotting the timestamps corresponding to each samples as in Figure 1.

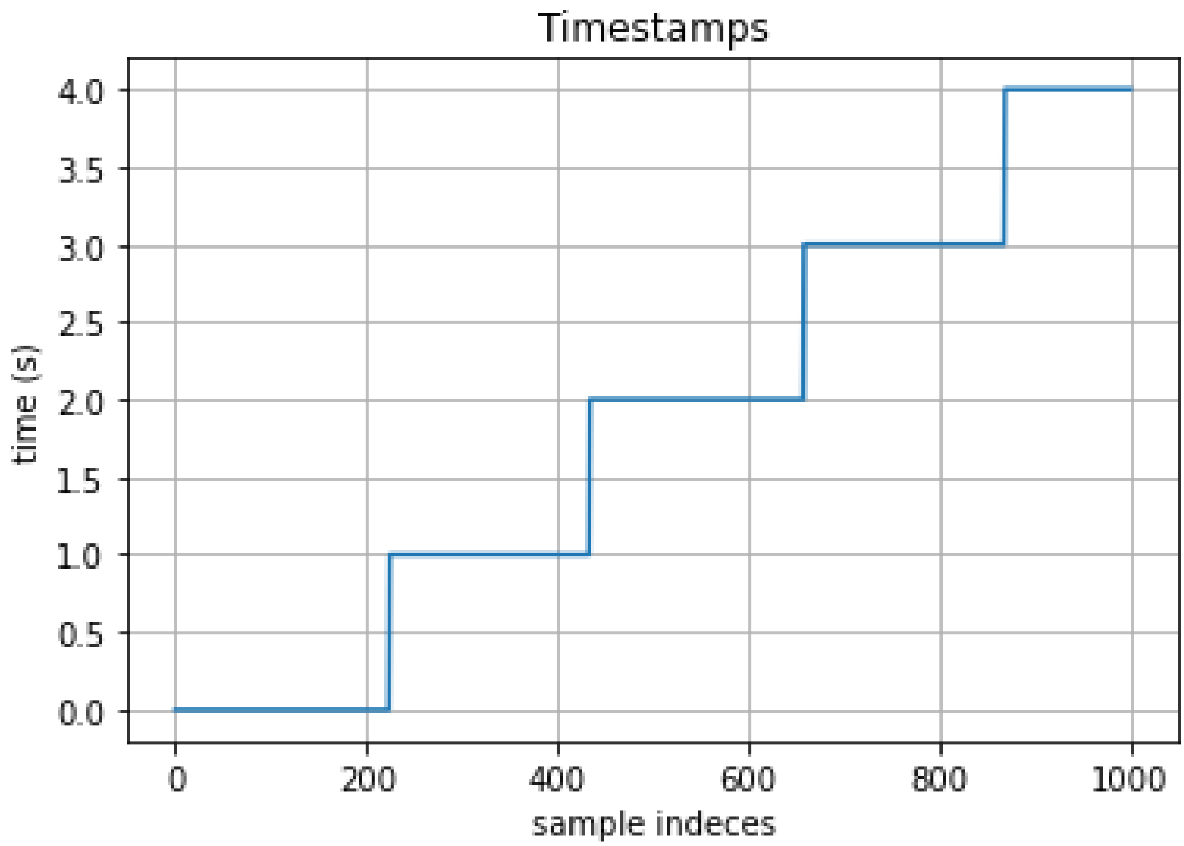
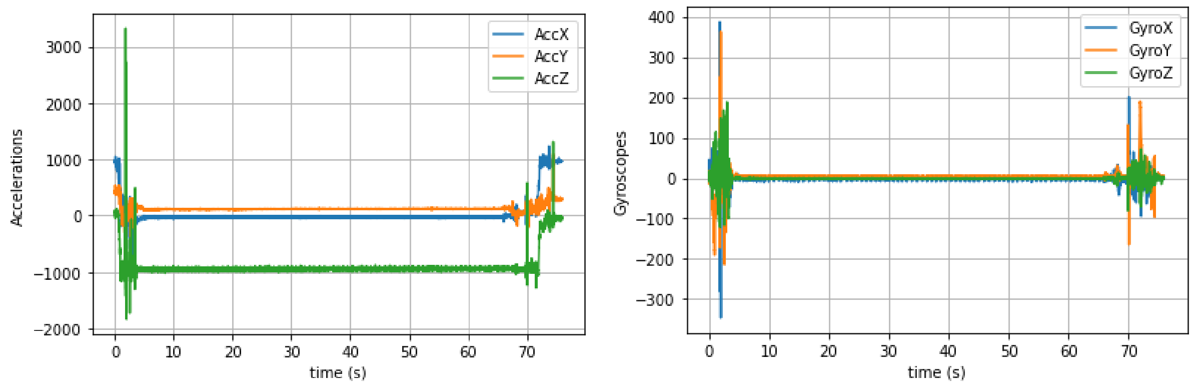
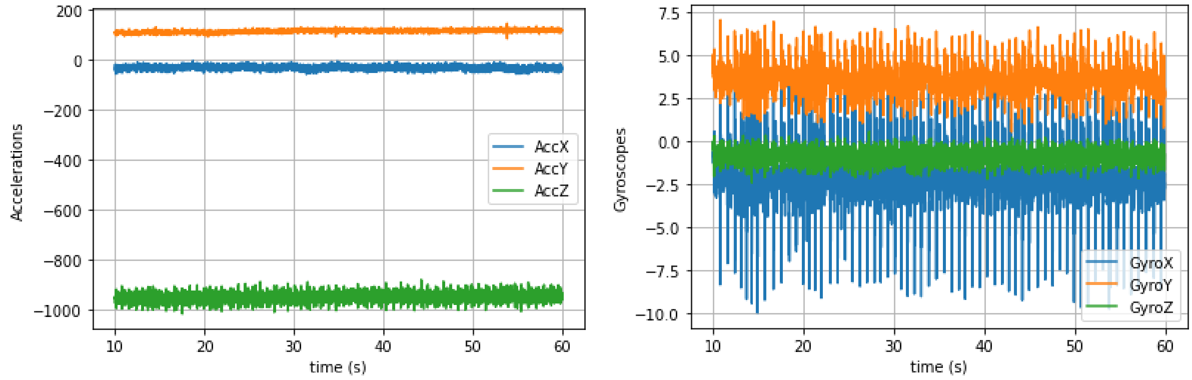


Figure 1: Initial 1000 time stamps of *center_sternum.txt*

Excluding the first and the last seconds from the observation interval, for the *center_sternum.txt* the values are in {210, 224}, for all the other dataset the values are in {98, 112}. Moreover, each dataset has a noisy initial and final part of the recording. Hence, this noisy part is removed in order to analyze only the significant part of the data (see Figure 2).



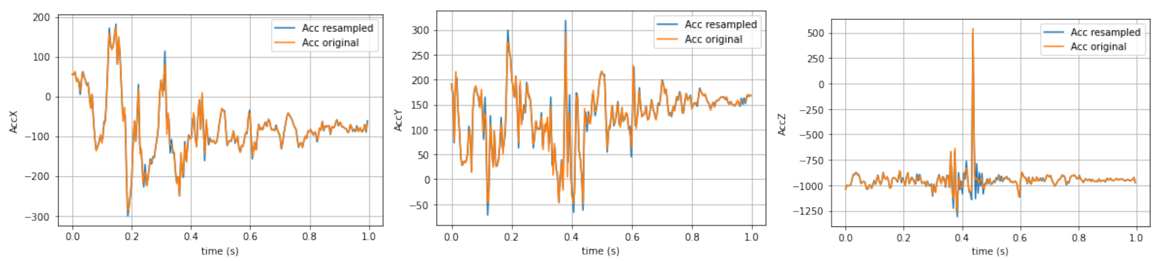
(a) Accelerations: full recording (b) Gyroscopes: full recording



(c) Accelerations: initial and final part removed (d) Gyroscopes: initial and final part removed

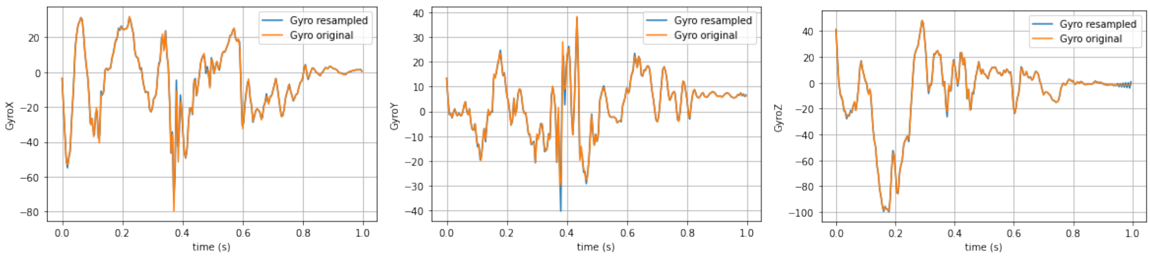
Figure 2: *center_sternum.txt* Accelerations and Gyroscopes signals

In order to cope with the different sampling rates used when recording the data, signal resampling has been applied to have a constant sampling frequency equals to the highest used. In Figures 3 and 4 the effect of resampling is shown.



(a) AccX (b) AccY (c) AccZ

Figure 3: Resampling of acceleration signals

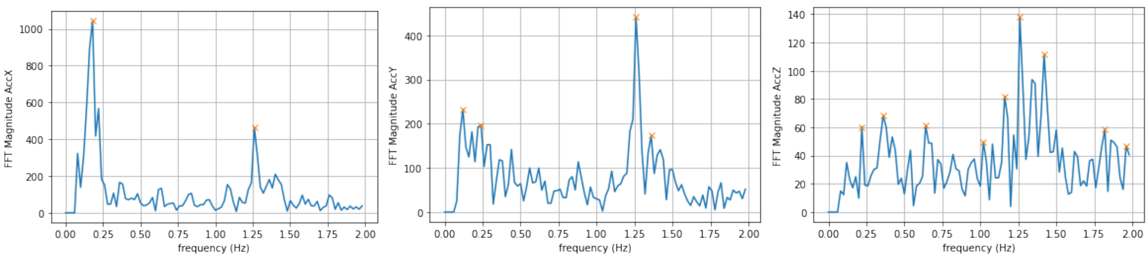


(a) GyroX (b) GyroY (c) GyroZ

Figure 4: Resampling of gyroscope signals

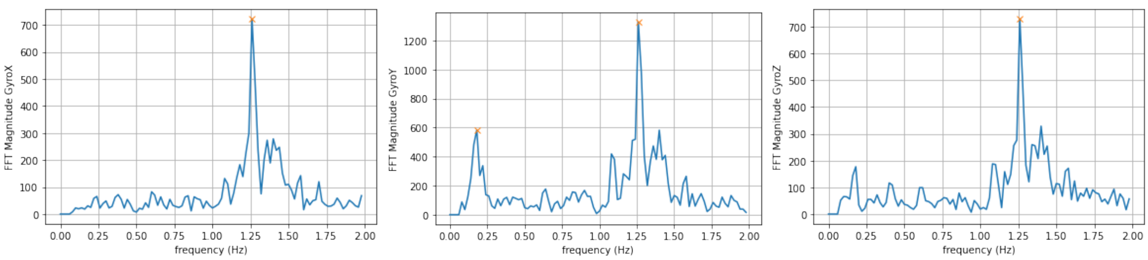
2 Frequency analysis

In order to detect the relevant RR and HR frequencies, the resampled signals are analyzed via Fast Fourier Transform (FFT). In particular, the standard HR ranges in [40-100] bpm (beats per minute), while the adults at rest RR typically ranges in [10-20] bpm (breaths per minute). So a frequency span from [0-2] Hz is enough to capture the highest frequencies in place. In Figure 5 and 6 the FFTs for the relevant *center_sternum.txt* signals are shown.



(a) AccX FFT (b) AccY FFT (c) AccZ FFT

Figure 5: FFT of acceleration *center_sternum.txt* signals



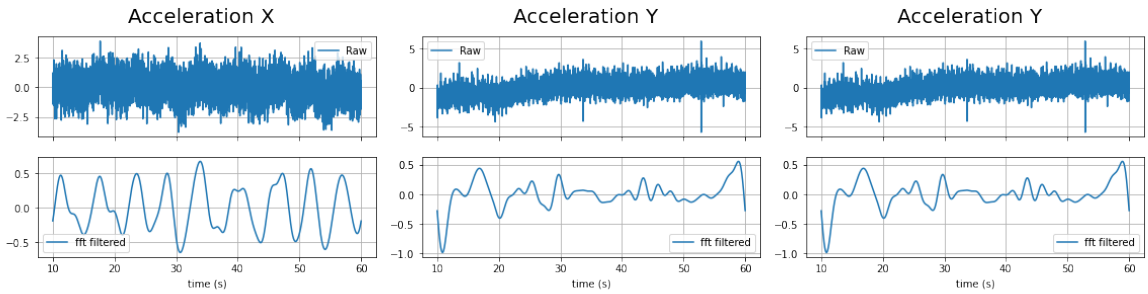
(a) GyroX FFT (b) GyroY FFT (c) GyroZ FFT

Figure 6: FFT of gyroscope *center_sternum.txt* signals

The low frequency peak in AccX signals corresponds to RR signal, while the higher frequency peaks in Accelerations and Gyroscopes components are due to HR beats.

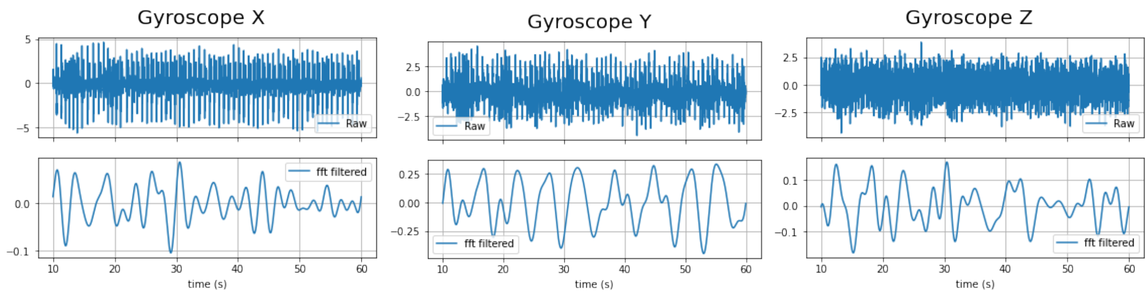
3 Frequency Domain Filtering

In order to recover the relevant RR, the resampled signals can be filtered in frequency domain after zeroing the undesidered frequency components. The resulting signals for the *center_sternum.txt* are shown in Figures 7 and 8.



(a) AccX raw and filtered (b) AccY raw and filtered (c) AccZ raw and filtered

Figure 7: FFT domain filtering of acceleration *center_sternum.txt* signals



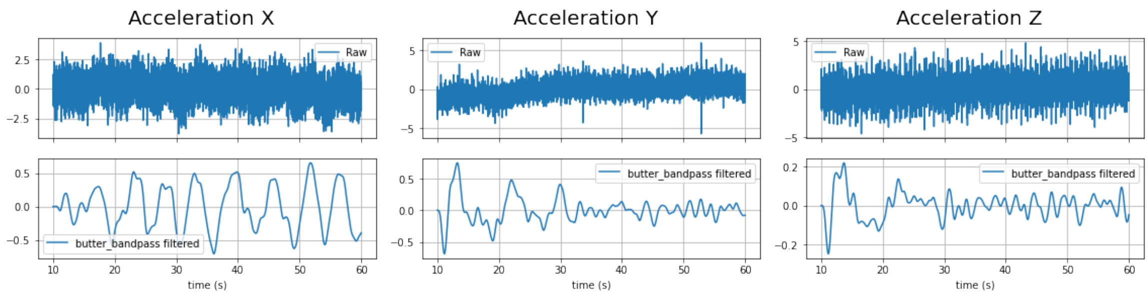
(a) GyroX raw and filtered (b) GyroY raw and filtered (c) GyroZ raw and filtered

Figure 8: FFT domain filtering of gyroscope *center_sternum.txt* signals

It is relevant to notice the different scales of the vertical axis in the raw and filtered signals. These differences mean that the RR signals have intensities well below than the HR and noise present in the measurements.

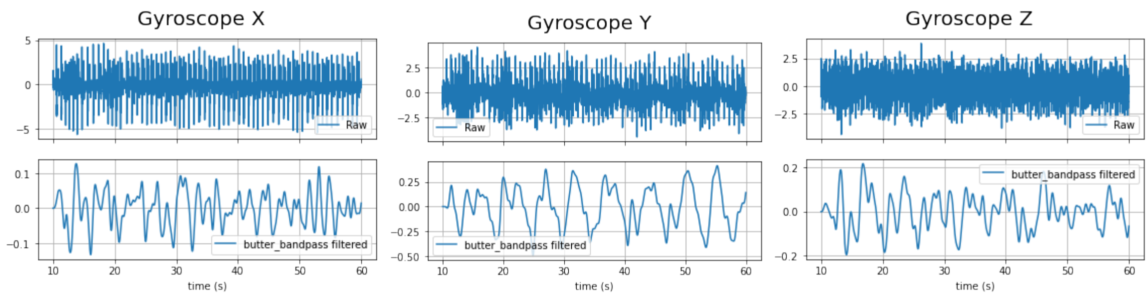
4 Time Domain Filtering

As in the previous section, the resampled signals are here filtered in time domain using a Butterworth band pass filter. The resulting signals for the *center_sternum.txt* are shown in Figures 9 and 10.



(a) AccX raw and filtered (b) AccY raw and filtered (c) AccZ raw and filtered

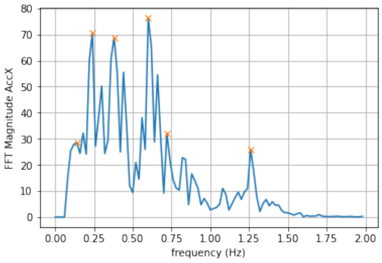
Figure 9: Time domain filtering of acceleration *center_sternum.txt* signals



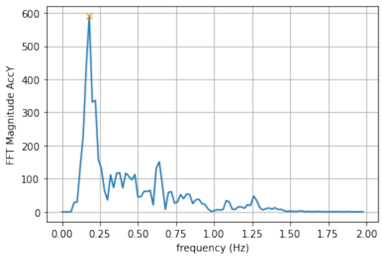
(a) GyroX raw and filtered (b) GyroY raw and filtered (c) GyroZ raw and filtered

Figure 10: Time domain filtering of gyroscope *center_sternum.txt* signals

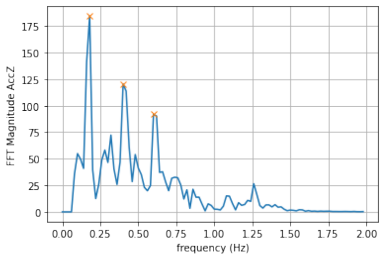
Figures 11 and 12 report the FFT of the *center_sternum.txt* acceleration and gyroscope signals after the application of the band pass Butterworth filter.



(a) AccX FFT

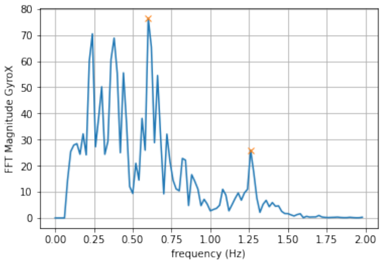


(b) AccY FFT

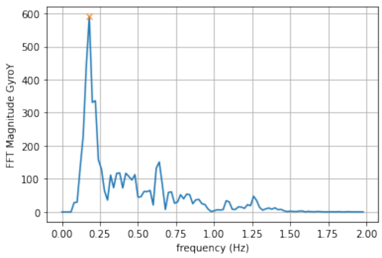


(c) AccZ FFT

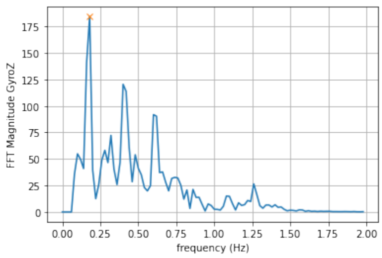
Figure 11: FFT of butterworth filtered acceleration *center_sternum.txt* signals



(a) GyroX FFT



(b) GyroY FFT

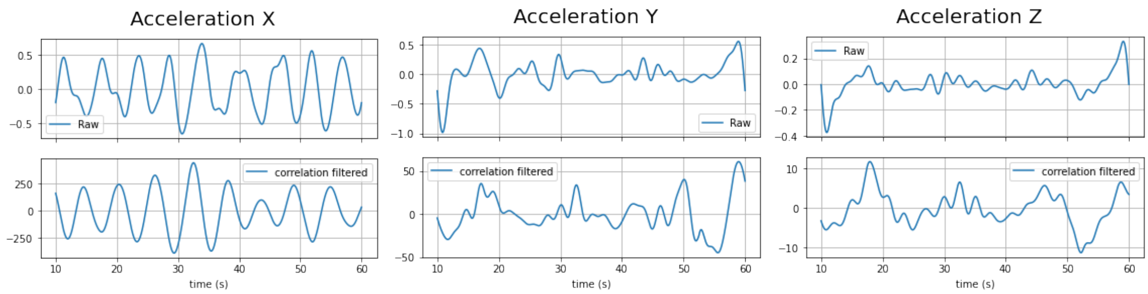


(c) GyroZ FFT

Figure 12: FFT of butterworth filtered gyroscope *center_sternum.txt* signals

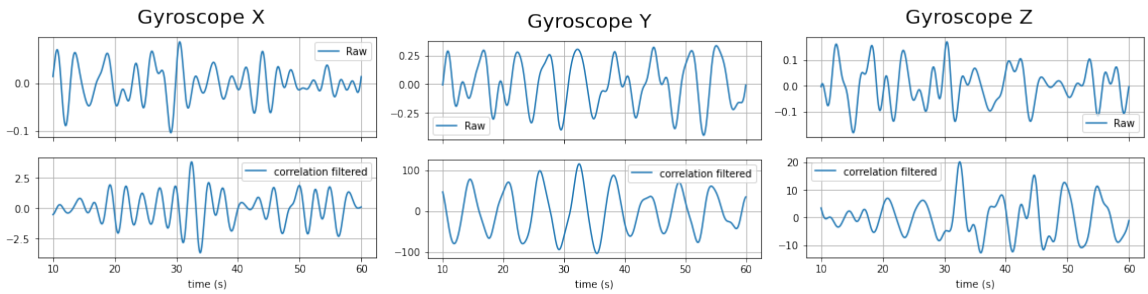
5 Correlation Analysis

In this section a Correlation Analysis has been perfomed on the previously filtered signals. From the properties of autocorrelation it follows that the autocorrelation of noise signal decays rapidly, while the autocorrelation of a periodic signal is still a periodic signal of the same frequency. These properties can be used to separate periodic signals from the noises. Figures 13 and 14 report the results of Correlation Analysis of the relevant fft-filtered *center_sternum.txt* signals.



(a) AccX raw and filtered (b) AccY raw and filtered (c) AccZ v

Figure 13: Correlation of FFT filtered acceleration *center_sternum.txt* signals



(a) GyroX raw and filtered (b) Gyroy raw and filtered (c) GyroZ raw and filtered

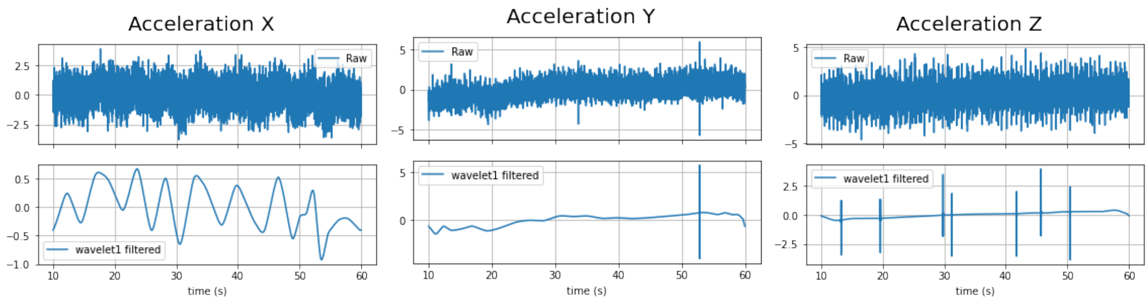
Figure 14: Correlation of FFT filtered gyroscope *center_sternum.txt* signals

6 Wavelet denoising

As mentioned in [6], Wavelet Analysis is a feasible choice for de-noising and has indeed been adopted in many biomedical application.
Therefore, in this paragraph a wavelet decomposition has been conducted to extract the information related to respiration from normalized but not filtered relevant signals. In particular, two methods has been explored by using respectively:

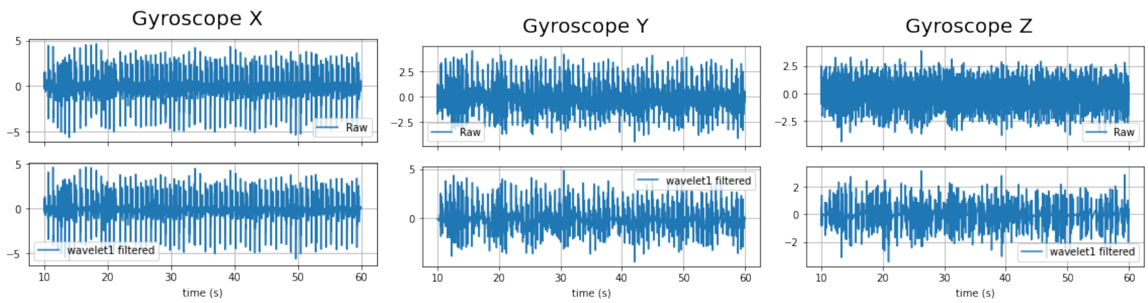
- *PyWavelets (pywt)* Python library
- *denoise_wavelet* function from the *scikit-image restoration* Python packet

Among all the available wavelet transforms in the former library the *Biorthogonal 5.5 (bior5.5)* is selected.
In Figure 15 and 16 the relevant *center_sternum.txt* signals before and after wavelet filtering with *pywt* are shown.



(a) AccX raw and filtered (b) AccY raw and filtered (c) AccZ raw and filtered

Figure 15: Wavelet filtering of acceleration *center_sternum.txt* signals



(a) GyroX raw and filtered (b) GyroY raw and filtered (c) GyroZ raw and filtered

Figure 16: Wavelet filtering of gyroscope *center_sternum.txt* signals

The second method makes use of the *denoise_wavelet* function provided by *scikit-image*. In particular *Symlets 8 (sym8)* wavelet has been used. For the purpose of extracting the respiratory information, two filters are applied consecutively: the *denoise_wavelet* function is executed on normalized but not filtered signals and then, on the obtained signals the FFT filtering is applicated.

Figures 17 and 18 report the results of this second method for de-noising and filtering.

Figure 17: Wavelet filtering of acceleration *center_sternum.txt* signals

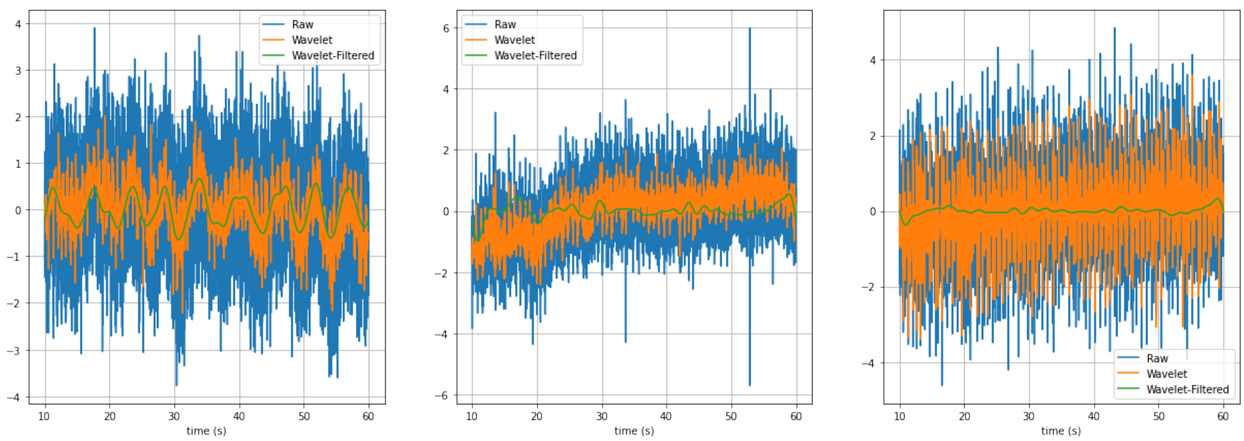
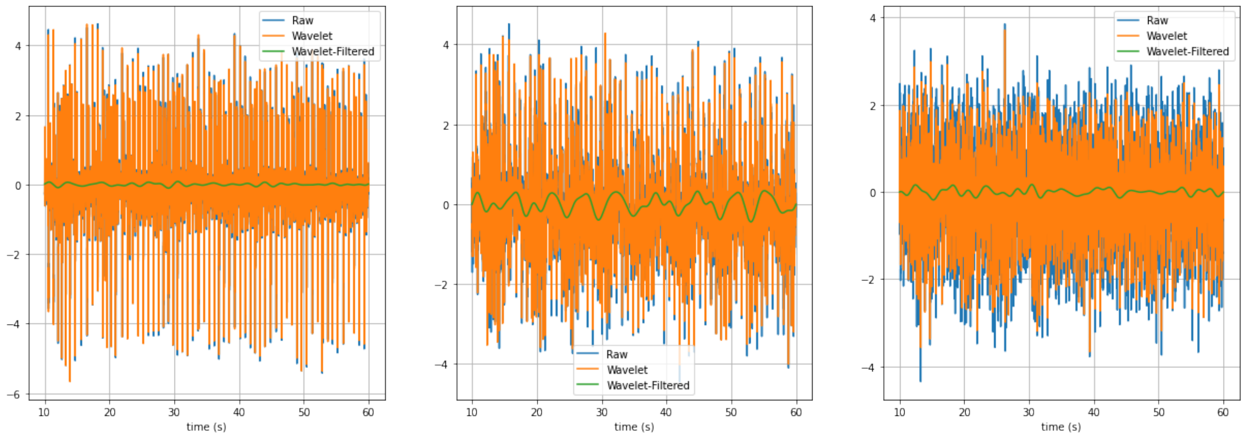


Figure 18: Wavelet filtering of gyroscope *center_sternum.txt* signals

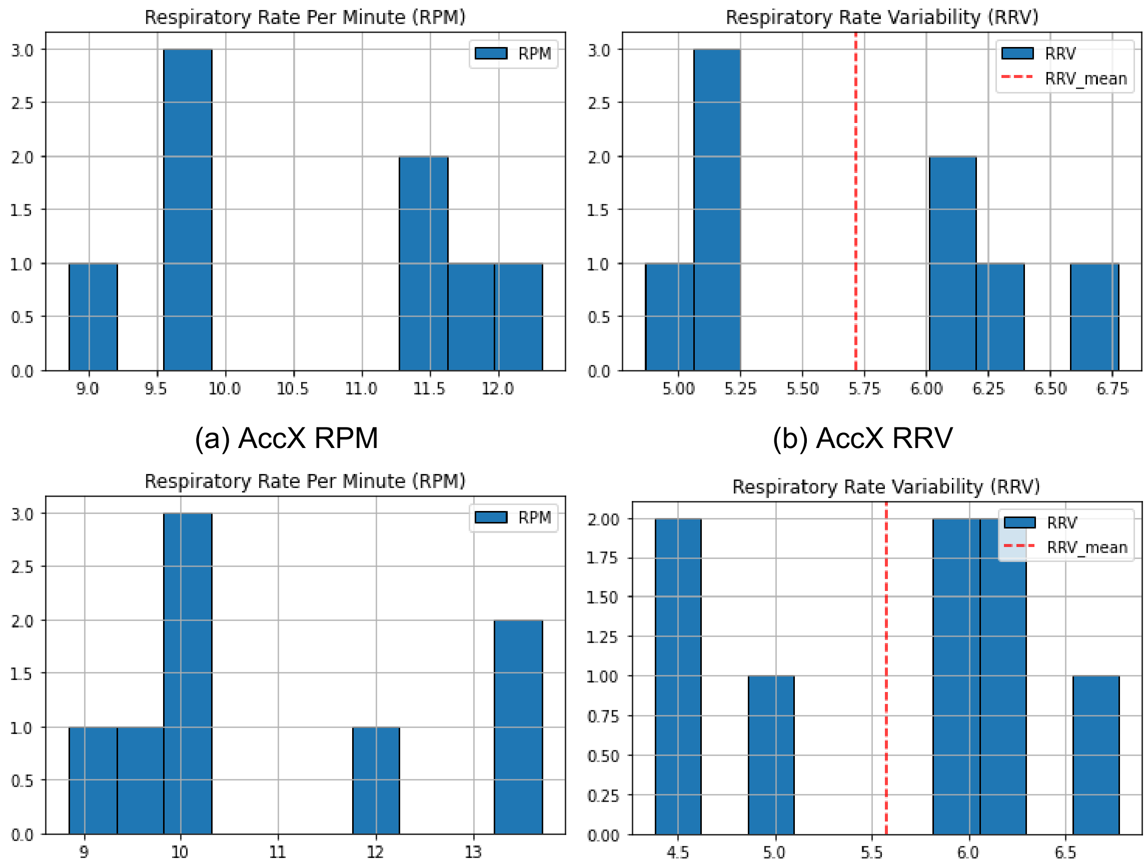


7 Metrics

In this last part RPM and RRV analysis is performed on the signals cleaned with the wavelet method.
Two different functions have been implemented:

- *rpm_plot*
- *rsp_calc*

The first one, upon receiving the cleaned signal, tracks the peaks and calculates the respiratory periods, the mean of respiratory rate variability and the respiratory rate per minute.
The second function makes usage of *neurokit2* which is a package providing easy access to advanced biosignal processing routines [7].
RPM and RRV have been computed only on the acceleration and gyroscope components having a more-cleaned respiratory information.
For the *center_sternum.txt* data set the X and Y components of, respectevely, acceleration and gyroscope are selected (Figure 19).



(a) AccX RPM

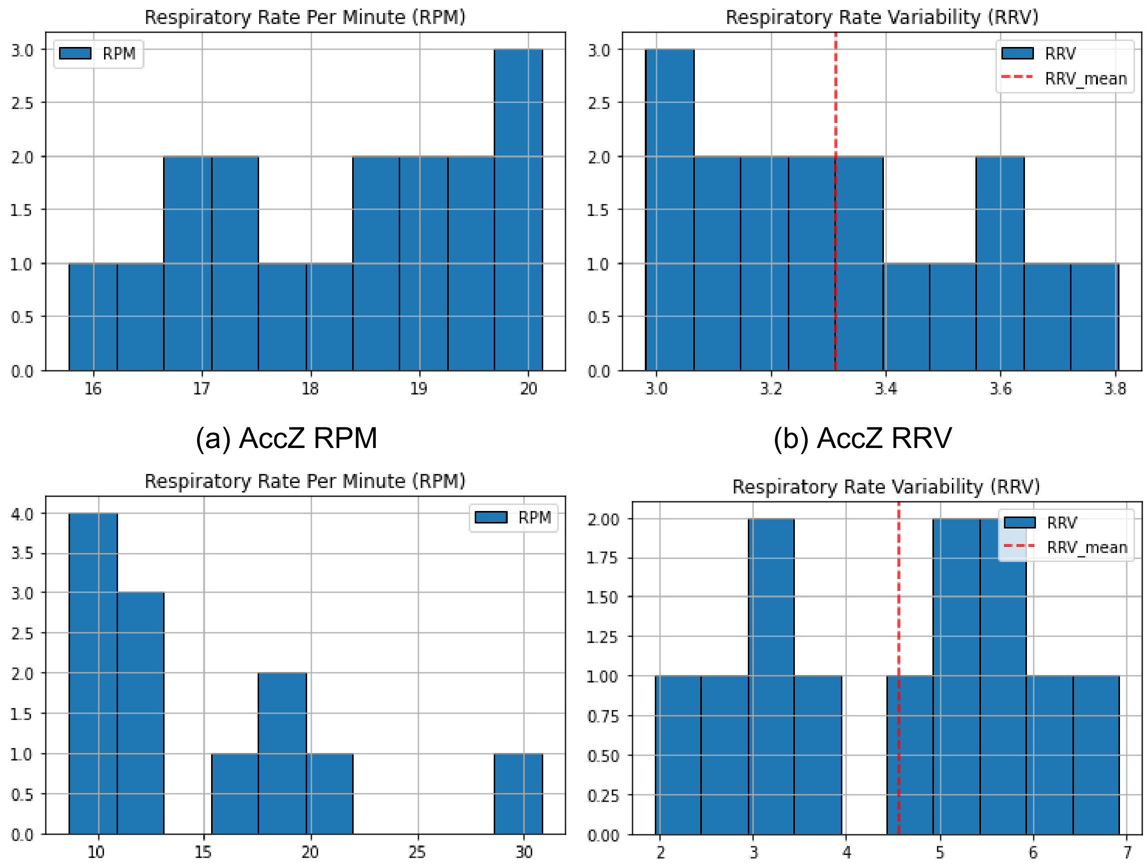
(b) AccX RRV

(c) GyroY RPM

(d) GyroY RRV

Figure 19: RPM and RRV of *center_sternum.txt* selected components

For the *3_Subject_sitting_chair.txt* data set the chosen component is Z for both acceleration and gyroscope (Figure 20).



(a) AccZ RPM

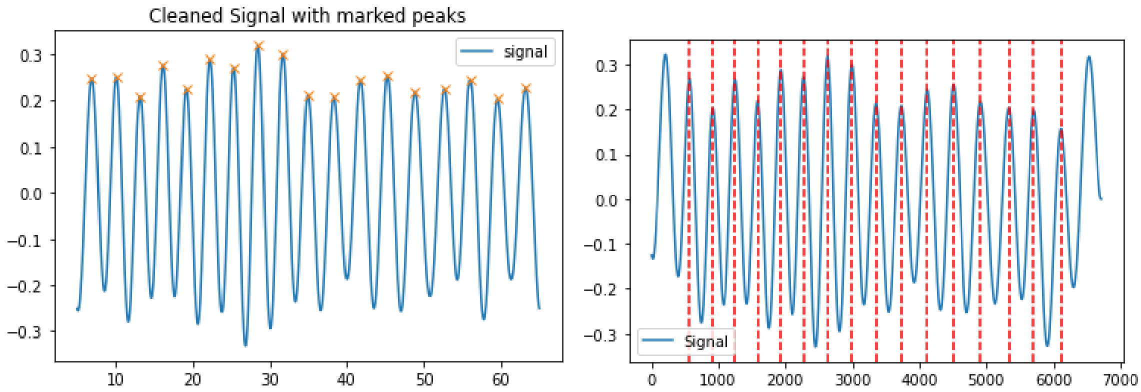
(b) AccZ RRV

(c) GyroZ RPM

(d) GyroZ RRV

Figure 20: RPM and RRV of *3_Subject_sitting_chair.txt* selected components

The *rsp_calc* method experiences some issues in finding the first and last peak of both acceleration and gyroscope signals, however the computed avarage RRV corresponds to the result obtained with the previous function(Figure 21).



(a) rpm_plot peaks finding

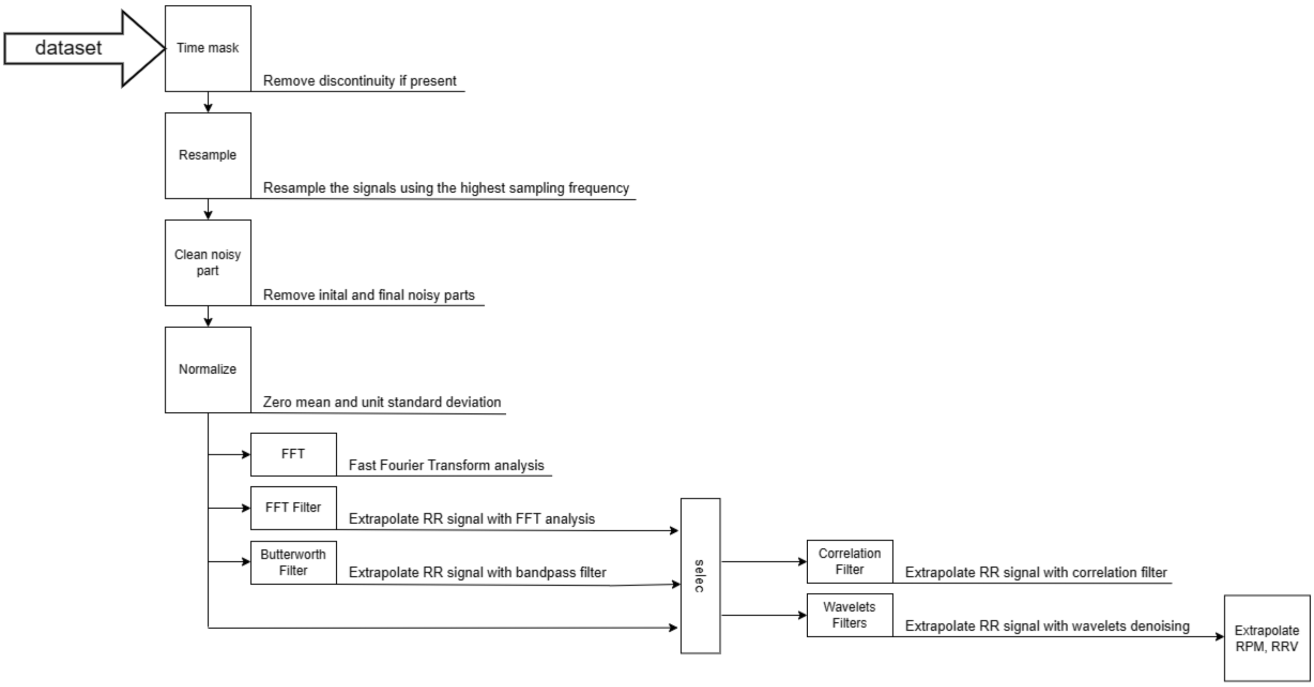
(b) rsp_calc peaks finding (neurokit2)

Figure 21: Differences in peak finding with rpm_plot and rsp_calc (neurokit2).

8 Conclusions

In Figure 22 is reported a graph summarizing the work development.

Figure 22: Project work flow



In order to achieve a reliable final value for the Respiratory Rate Frequency, after applying each filter, the FFT has been computed on the obtained filtered and normalized signals.
Proceeding in this way has resulted in a collection of RR estimations and from all the collected values, the one detected most of the times is selected. In specific:

- for *center_sternum.txt* data set the found RR value is approximately 10.8
- for *3_Subject_sitting_chair.txt* data set the found RR value is approximately 15.0

It is remarkable to notice that the final estimated RR values are the ones detected in the less noisy components of acceleration and gyroscope signals (accX and gyroZ for *center_sternum.txt*, accZ and gyroZ for *3_Subject_sitting_chair.txt*).
An estimation of the Signal to Noise Ratios (SNRs) for accelerations and gyroscopes signals of both datasets is shown in Figure 23.

Figure 23: SNR of respiratory signal estimation

	AccelerationX	AccelerationY	AccelerationZ	GyroscopeX	GyroscopeY	GyroscopeZ
SNR center_sternum	-9.13167498	-12.91095325	-21.07096274	-31.63320087	-14.2263748	-24.4198912
SNR sitting_chair	-24.52891585	-23.19764222	-14.96852379	-18.54831792	-23.73333849	-20.30990202

It is interesting to notice that, as mentioned at the beginning of the report, the *3_Subject_sitting_chair.txt* data set has a lower SNR meaning that the provided recording sample has more noise.
Most relevant contributions given by this project solution are:

- Signal resampling in order to have a constant sampling frequency
- Development of filters for extrapolating the respiratory signal
- Selection of the more relevant components regarding the respiratory signal
- Metrics analysis with RPM and RRV results

Contribution of each student:

- Ahmadian Arash mainly contributed to ”Time and Frequency Analysis”.
- Favero Manuele mainly contributed to ”Metrics Analysis”, to the selection of the second dataset and application of the developed code to it and to the report.
- Takafouyan Mohammad mainly contributed to ”Metrics Analysis”.
- Zanin Daria mainly contributed to ”Data preparation”, ”Filter Analysis” and to the report.

Bibliography

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[2] Deepak Rai, Hiren Kumar Thakkar, Shyam Rajput, Jose Santamaria, Chintan Bhatt, and Francisco Roca. A comprehensive review on seismocardiogram: Current advancements on acquisition, annotation, and applications. *Mathematics*, 9:2243, 09 2021.

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[6] Yue-Der Lin and Ya-Fen Jhou. Estimation of heart rate and respiratory rate from the seismocardiogram under resting state. *Biomedical Signal Processing and Control*, 57:101779, 03 2020.

[7] `https://neuropsychology.github.io/NeuroKit/`.