Digital Biomarkers HS24 Exercises

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3 General

- Bring figures for each exercise (screenshot each output of the exercise)
- Code is not expected to be presented
- Comment on code if he shows you some, but don't bring your own code
- Why does the output look like, is it reasonable?
- Understand the distance measurements
- ||y1-y2||→ what is it? Distance
- ||Y2-lambda * y1 || → what is lambda, what is vector, what is scaling

Per Exercise 1 Slide, answering questions about how did you solve, what do you see..

4 Imaging

5 Signal Processing

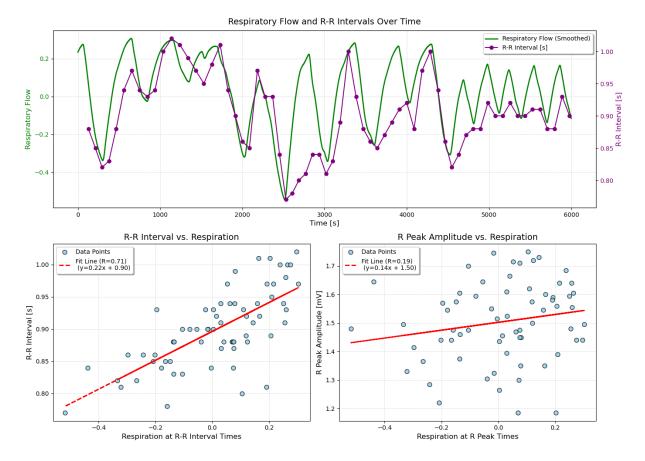
5.1 Exercise 1 – RR-Intervals & Respiration

How did I solve it?

The R-R interval is the time interval between two consecutive R-Waves (peaks) in an ECG signal. (It reflects the time between two successive heartbeats)

Questions:

- Is there a correlation between the rr interval and the respiratory flow?
- Is there a correlation between the r_peak and respiration?
- How did you extract the r-peaks?
 - Setting the threshold of the find_peak function to height = 0.8, so that only the highest values found to be a peak.
 - Algorithm looks at each datapoint and checks if it is a <u>local maximum</u>. <u>Local maximum</u>, is a point where its value is greater than its immediate neighbours.
 Only peaks greater than 0.8 height are considered to be valid peaks.
 - y[i] > y[i−1] and y[i]>y[i+1]
- Assume that you have to identify the position and height of the t-waves from an ecg, what are possible difficulties and how do you handle them?
 - T-Waves may overlap with the QRS-complex (if the heart rate is very fast or unhealthy), apply filtering
 - T-Waves can vary in shape (flat, biphasic, or inverted) depending on health conditions = finding the peaks is harder. Solution: template matching, clustering techniques.
 - Noise (muscle movement, baseline wander). Solution: Low-pass filter, highpass filter to address high frequency noise



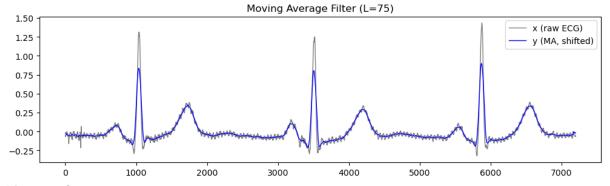
- <u>Top Plot</u>: green-curve shows respiration flow, purple markers indicate the time between two consecutive heartbeats (R-R Interval).
 - Time between heartbeats vary a lot 0.8 1 second, with mean of 0.9, relating to heartbeat of 67 heart beats per minute (bpm)
- <u>Bottom Left</u>: Scatter plot shows R-R interval (time between heartbeats) against the respiration at R-Peaks times.
 - Positive trend is visible, higher R-R intervals correlate to higher respiration values
 - Slope: 0.22403276883896822
 Intercept: 0.8963000648782656
 R-Value: 0.7080134252087623
 P-Value: 2.965662696088793e-11
 - o STD Error: 0.027932328978557863
- <u>Bottom Right</u>: Scatter plot shows relationship between R-Peaks amplitudes (voltage measured at the R-Peak, electrical activity during heartbeat) and respiration at respiration R-Peak times.
 - Weak positive trend, means minimal dependency between respiration at peak time and the measured electrical activity at R-Peak amplitudes.
 - Slope: 0.1375911872433881
 - o Intercept: 1.5022731152409803
 - R-Value: 0.18533343877202338
 - P-Value: 0.13626940895025494
 - o STD Error: 0.09119206718113497

5.2 Exercise 2 – Moving Average

How did I solve it?

Applying an Ifilter with

- L = 75 (last 75 datapoints),
- 1 = FIR-Filters,
- X = signal input
- Delay = (L 1) // 2 (delay introduced is half the filter-length)



Observations:

- Grey curve is the raw ECG-Signal, having sharp peaks representing the QRS-Complex
- Blue Curve is the moving average filter (with L=75)
- Noise and small fluctuations in the signal are suppressed.
- R-Peaks, P-Waves, T-Waves are preserved in the signals but slightly blunted

MA is commonly used for Noise Reduction, Feature Detection (R-Peaks, T-Wave) amplitudes becomes easier.

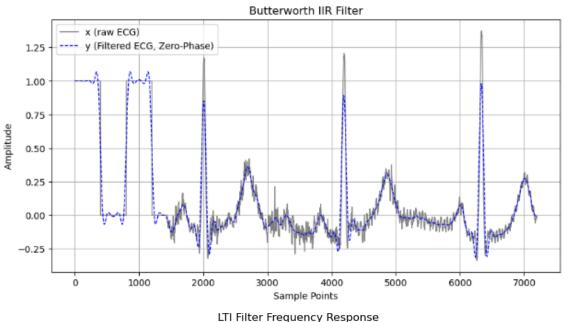
5.3 Exercise 3 - Filters

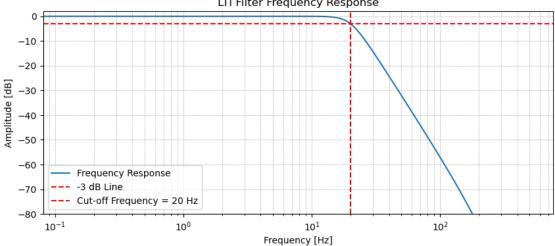
5.3.1 Butterworth Filter

How did I solve it?

Applying an <u>IIR-filter</u> with order = 4, fc = 20Hz & zero-phase filtering, fillfit to apply the filter forward and backwards. By doing this the distortions introduced in the forward filterting are canceled out in the backwards pass.

Cut-Off: Butterworth filters are designed to introduce minimal distortion in frequencies below the cut-off rate: 20Hz



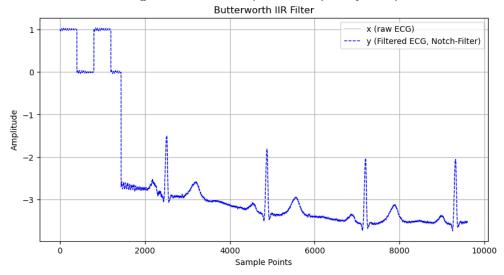


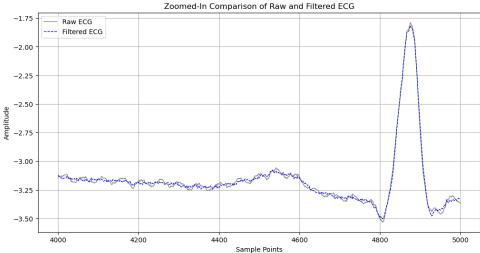
- Raw signal is noisy (visible by the high-frequency noise)
- Effect of the Butterworth filter:
 - Achieved, Reduce high-frequency noise (it becomes visible in the lowamplitude regions (P & T-Waves)
 - Achieved, The QRS Complexes are preserved yet somehow a bit reduced by
 0.30 (filfit) & 0.26 (lfit), the sharp peaks as well as the P & T-Waves)
 - Achieved, Filter does not shift thanks to zero-phase filtering (shifting)
 - Unable to filter the strong noise in the beginning (~1200 samples)
 - Padding the first few artifacts could mitigate the starting behavior

5.3.2 Notch Filters

How did I solve?

F0 = 50 (frequency to remove), Q = 30 (quality Factor, defines filter bandwidth relative to f0) Notch filters are designed to remove specific frequency components.



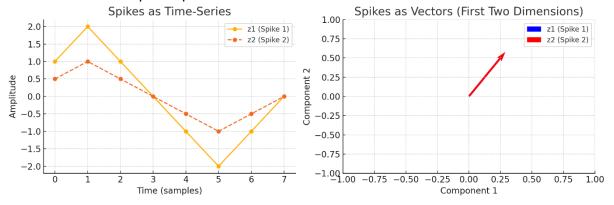


- Noise removal, in low-amplitude regions
- QRS-Complex fully preserved, thanks to the high quality factor.(ECG usually (1-40Hz) are not affected by notch-filter
- Amplitude Reduction: -0.04

5.4 Exercise 4 – Neural Spike detection

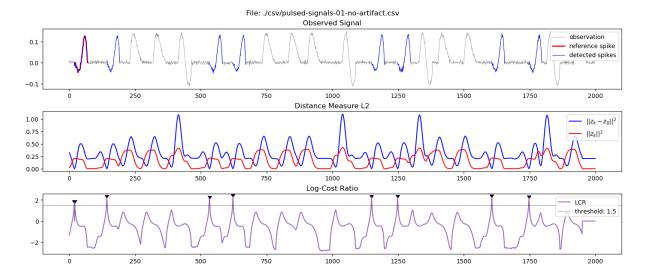
5.4.1 Detection

- We observe neural spikes as shown below, In your opinion, which shapes are similar? Explain! How do you define similarity?
 - If the waveforms are similar (shape, amplitude, duration)
- Which kind of distance measures do you know?
 - Euclidean Distance, Scale-Invariant, Cosine, Euclidean distance between centered (mean)
- What is the Euclidean distance between two 1D shapes of fixed length L?
 - Square root of sum of the squared differences z1, z2
 - \circ Z1=[1,2,3], z2=[4,0,3]; [1-4, 2-0, 3-3]; [(-3)^2, 2^2, 0]; 9 + 4 + 0; sqrt(13) = 3.61
- What is the effect/consequence on the example below when applying these distance measures?
 - Spike that look similar to the reference spike have smaller Euclidean distances, and are flagged as similar.
- Wha is the key difference between using cosine distance versus cosine similarity? What do you need to know about a feature or 1D biomarker in order to correctly choose between the two methods?
 - Cosine Similarity: Measures similarity (angles of two vectors, magnitude irrelevant), -1 to +1, high value = similar, directional similarity
 - np.inner(z, z_ref) / (np.linalg.norm(z) * np.linalg.norm(z_ref))
 - Cosine Distance: Measures dissimilarity (based on the angle btwn. Them), 0 to 2, Low value = similar, directional dissimilarity
- Draw the shapes / spikes as vectors



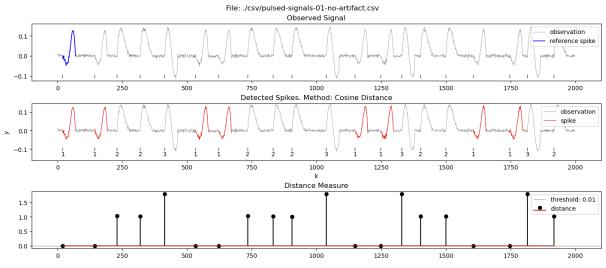
What do I see:

- Squared Distance: ||zk-z0||^2 squared distance to the z0 (reference spike), the lower the distance, the higher the similarity.
- Energy: ||zk||^2 amplitude squared (of the spike), spikes with similar energy often share similar amplitudes = similar shape
- LCR: normalizes distance by the energy -0.5 * log(distance / energy), high LCR = high similarity in Distance-Energy Ratio.
- LCR_TRESHOLD = 1.5



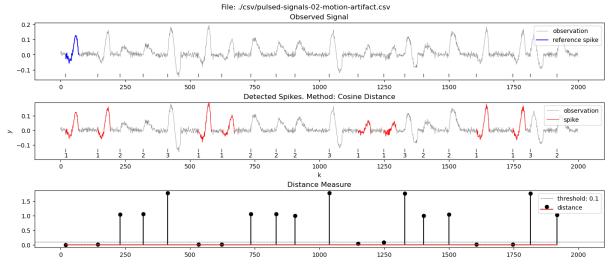
5.4.2 Sorting

5.4.2.1 No-Artifact



- All distance measures worked well, Euclidean (0.06), Scale Invariant (0.15), Cosine (0.01), mean centered (0.1)
- Cosine Distance is very effective in identifying spike similar to Label1, this is due to the signals have very similar shapes leading to angles close to 0° (1 – cosine similarity], amplitude only vary only slightly.

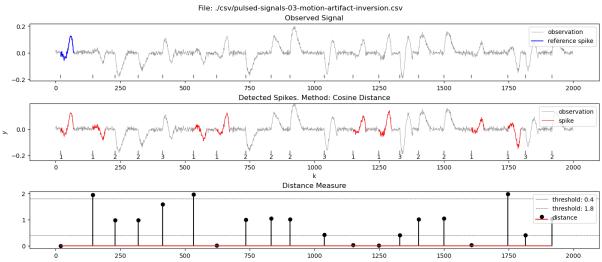
5.4.2.2 Motion Artifact



Observations:

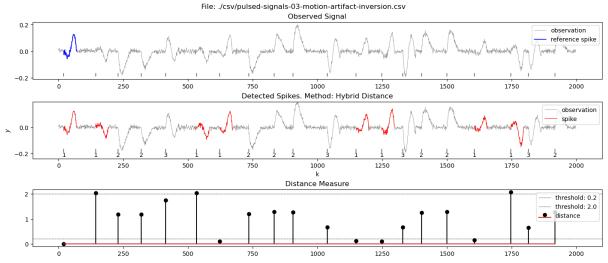
- Again, dissimilar spikes produce higher cosine distances, higher than the threshold of 0.1
- The shape remains almost the same (despite noise introduced), amplitude variations are removed due to distance normalization.

5.4.2.3 Motion Artifact - Inversion



Observations:

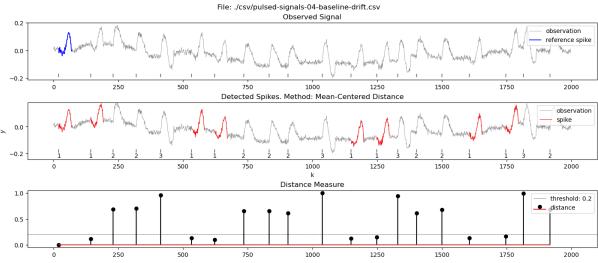
- Problem solved by introducing a upper & lower threshold. Inverted similarity, vectors inverted.



Observations:

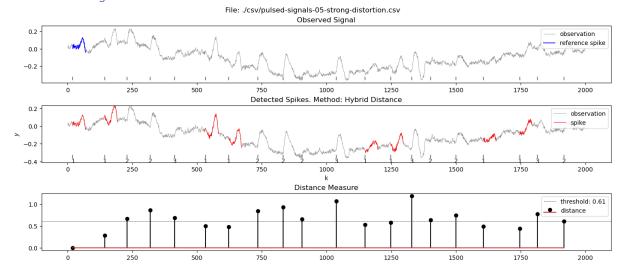
- {'euclidean': 0.0, 'scale_invariant': 0.4, 'cosine': 0.6, 'mean_centered': 0.1}
- Trying to maximize the invertion, by adding scaling of the amplitudes.
 - Scale invariant: helps to detect amplitude variation
 - Cosine: Helps to match similar shape as the angle of vector is measured (also if inverted, TOP_THRESHOLD)

5.4.2.4 Baseline Drift



- Cosine Distance had one false-positive, mean-centered performed better
- The baseline-drift changes overall direction of the vectors, by adding a constant offset to the signal.
- By substracting the mean (centering around 0), eliminates the drift.

5.4.2.5 Strong distortion



- Grid-Search approach to find the best weights (Accuracy 100%):
 - o {'euclidean': 0.0, 'scale_invariant': 0.1, 'cosine': 0.1, 'mean_centered': 0.8}
 - Mean-Centered Distance addresses the (baseline drift)
 - o Captures angular alignment (noise)
 - Scale-Invariant: accounting spikes with different magnitudes (amplitudes)