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Signal Preprocessing techniques

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1. Presentation and Solutions to the multiple ECG Noises

I will here present the main causes of ecg noises and the several solutions that have been implemented in order to suppress that noise. I do not think that I will implement all these methods, out of lack of time. However, this will definitely be some fine-tuning I will be doing should we have some more time.

1.1 Baseline wandering

1.1.1 Presentation

Removal of baseline wander is required in order to minimize changes in beat morphology that do not have cardiac origin, which is especially important when subtle changes in the "low-frequency" ST segment are analyzed for the diagnosis of ischemia. The frequency content of baseline wander is usually in the range **below 0.5 Hz**. However, increased movements of the body during the latter stages of a stress test further increases the frequency content of baseline wander.

The design of a linear, time-invariant, **highpass filter** for removal of baseline wander involves several considerations, of which the most crucial are the choice of filter cut-off frequency and phase response characteristic. The cutoff frequency should obviously be chosen so that the clinical information in the ECG signal remains undistorted while as much as possible of the baseline wander is removed. There are two possible approaches [5]:

- Find the lowest frequency component of the ECG spectrum. In general, the slowest heart rate is considered to define this particular frequency component. In order to compute this cut-off frequency, I will refer to [4]
- Couple the cut-off frequency to the prevailing heart rate: Linear filtering with time-variable cut-off frequency. **Hard to implement** (equivalent to fitting a spline polynomial to our signal)
  .

The phase response is also an important consideration. This will dictate our choice of filter design. We do not want any phase distorsion. This is why we will use Forward-Backward IIR filtering.

1.1.2 Experiments

It is usually suggested to use a Highpass recursive filter, FIR or IIR with a frequency cut-off of 0.5Hz. However, we need to pay a special attention to the behavior of the ST segment ([4]). We will instead perform several experiments and find ourselves the cut-off frequency giving the best results in terms of F_β on validation set. We will use order 3 filters in order to perform these experiments. The lowest cut-off frequency we will be using will be 0.01Hz ([8]), the highest will be 2.2 Hz (see [12]). We will also use the heartbeat frequence of the ecg, which is **à trouver**. At a later stage, we will perform a dichotomy approach to find the best frequency to use.

Cut-off frequency	F_β validation set	F_β test set	F_β^{STD}	F_β^{STE}
0.01 Hz				
0.05 Hz				
0.1 Hz				
Heartbeat frequency= Hz				
0.5 Hz	0.76 +/- 0.03	0.76	0.73	0.44
1 Hz				
2.2 Hz	0.71 +/- 0.03	0.69	0.43	0.36

Last, once we would have found the best cut-off frequency for the removal of baseline wandering, we will implement a wavelet technique, decomposing the signal according to several frequencies. We will only retain the frequencies above the cut-off frequency. It is argued that this method is better than using a Highpass filter (the phase is not disturbed).

1.2 Powerline interference

1.2.1 Definitions

- An adaptive filter presents the propriety of estimating the present noise according to previous estimations. Therefore, the transfer function of the filter is not defined in a static way, it is always defined in order toapproximate in a better way the noise.
- A non adaptive filter is a static filter. You define a priori the design, order of your filter and the signal will be filtered no matter what specificity is encountered during the filtering process.
- Finite Impulse Response filter (FIR) is a discrete time filter, which characterizes its response only with a finite number of input signal's values
- Infinite Impulse Response filter (IIR) is a continuous time filter, which characterizes its response only with a infinite number of input signal's values

1.2.2 Presentation

Electromagnetic fields caused by a powerline represent a common noise source in the ECG that is characterized by **50 or 60 Hz** sinusoidal interference, possibly accompanied by a number of harmonics. It is said that 50Hz interference is for **European ECGs** whereas 60Hz interference is for **American ECGs**. Since our data comes from 11 different hospitals, see [2], we will need to try the powerline interference interference for each frequency separately, and then altogether (should not pose problems since we will be using adaptive filters) .Such narrowband noise renders the analysis of the ECG more difficult. A major concern when filtering out powerline interference is the degree to which the QRS complexes influence the output of the filter. The QRS complex acts, in fact, as an unwanted, large-amplitude impulse input to the filter. As linear, time-invariant notch filters are generally more sensitive to the presence of such impulses, powerline filters with a non linear structure may be preferable. This is argued in [3] where adaptive and non adaptive 60Hz notch filters' performances are compared. The experiments revealed that using Ahlstrom and Tompkins' filter allowed to reduced the signal entropy more than when using a non adaptive filter [7].

1.2.3 Implementation

We will use two different types of adaptive filters, both using the same paradigm Pan-Tompkins introduced: FIR and IIR filters, with Recurrent Least Mean Squares techniques in order to compute the coefficients of the filter [9], [13].
We will be using the python pyroomacoustics library filter which implements several blocks of RLS filters. We will compare the performances of these filters with the one already implemented in matlab, see Matlab Filters.

1.2.4 Experiments using an adaptive filter

We will perform a two-step experiments in order to design a suited filter to remove the 50Hz or 60Hz power-line interference in our signal.

1.2.4.1 Filter selection

In order to perform a preliminary selection of filters, we will want to compute the MSE error of the filter. We will select subsamples of size 500 in order to compute this error. Furthermore, we will impose to compute the error in a reasonable time. Since the hidden test set comprises roughly 3000 samples, with 12 leads each which is roughly 30 000 leads to preprocess, and since our time limit is 24 hours, we will impose to compute the error

0.5 sec after the filter initialization.

Filter Model	MSE, 50 Hz Notch	MSE, 60 Hz Notch
Matlab: Block LMS		
Matlab: FilteredXLMS		
Matlab: LMS Filter		
Matlab: Normalized LMS Filter		
Matlab: RLS Filter		
Matlab: Affine Projection Filter		
Matlab: Frequency Domain Adaptative Filter		
Matlab: Lattice Based Adaptative Filter		
Python: Block RLS		
Python: Exponentially weighted RLS		

1.2.4.2 Filter validation

Amongst the 3 filters retained, we will extract the relevant features for this pathology and see how well the preprocessing deals fith the metrics of our challenge.

Filter Model	F_β validation set	F_β test set
Matlab:		
Matlab:		
Matlab:		

1.2.5 Using a non adaptive filter

I wanted to cross-validate the results of the research [11] on our data. This is why I performed power line interference removal with a stationnary filter, ie a bandpass filter, or a **notch filter** according to the litterature. The implementation I will use is a bandpass IIR or FIR filter already implemented in Python. I will try with a Notch frequence of 50Hz, 60Hz and both depending on the spectral decomposition of the signal (respectively, my low cut-off frequency will be 2Hz less and my high cut-off frequency will be 2Hz higher and the filter order with be a second-order filter). A risk of such filters is that we suppress some valuable information, mainly some steep slopes in the QRS complex. Therefore, we may lose some valuable information in the detection of PVC and PAC. I will also try to quantify how much valuable information we lose in the R-peaks.

Filter Model	F_β validation set	F_β test set	F_β^{PVC}	F_β^{PAC}
Python: IIR Notch Filter at 50Hz				
Python: IIR Notch Filter at 60Hz				
Python: IIR Notch Filter at 50Hz or 60Hz				
Python: FIR Notch Filter at 50Hz				
Python: FIR Notch Filter at 60Hz				
Python: FIR Notch Filter at 50Hz or 60Hz				

1.3 Muscle Artifacts = Electromyography Noise

Electrocardiogram recordings are very often contaminated by EMG disturbances due to involuntary muscle contractions (tremor). In order to suppress those high frequency components, it is advocated that using a Savitzky-Golay filter helps to remove this high-frequency noise, and also removing the high-frequency noise. This filter combines the strength of Moving Averages with splines fitting [1]. The parameters of this filter are: polynomial degree and number of points in the window considered. It is suggested to use a degree 3 polynomial approximation. We will fine-tune the window's number of points. Once again, the pathologies "at risk" when smoothing the signal are PAC and PVC.

Filter Model	F_β validation set	F_β test set	F_β^{PVC}	F_β^{PAC}
Savgol Filter, window size = 5 points				
Savgol Filter, window size = 10 points				
Savgol Filter, window size = 15 points				
Savgol Filter, window size = 20 points				

1.4 Patient-Electrod Motion Artifacts

Motion artifacts are baseline changes which are caused by electrode motion. Usually vibrations, movement, or respiration of the subject contribute to motion artifacts. The peak amplitude and duration of the artifact depend on various unknown quantities such as the electrode properties, electrolyte properties, skin impedance, and the movement of the patient. In ECG signal, the baseline drift occurs at an unusually low frequency (approximately 0.014Hz), and most likely results from very slow changes in the skin-electrode impedance. This noise can also be observed on the Fourier power spectrum, the large peak nearest to DC [10]. We will see if we effectively remove these Artifacts by analyzing the Spectrum of our signal after preprocessing.

1.5 Contact Noise

Position of the heart with respect to the electrodes (variation) and changes in the propagation medium between the heart and the electrodesinitiateElectrode contact noise.This causes sudden changes in the amplitude of the ECG signal, and low frequency baseline shifts. In addition, poor conductivity between the electrodes and the skin both reduces the signal amplitude of the ECG signal and thereby increases the probability of disturbances (by reducing SNR). The mechanism responsible for baseline disturbances is electrode-skin impedance variation. The larger the electrode-skin impedance, smaller are the relative impedance change which is required to cause a major shift in the baseline of the ECG signal. If the skin impedance is significantly high, it might be impossible to detect the signal features reliably in the presence of body movement. Sudden changes in the skin-electrode impedance induce sharp baseline transients which decay exponentially to the baseline value. This transition may occur only once or rapidly several times in succession. Amplitude of the initial transition and the time constant of the decay are the major characteristics of such noise. The solution commonly designed to remove such Artifacts is a lowpass filter with a cutoff frequency of around 100Hz. Therefore, we will try to implement several lowpass filters with different cutoff frequencies. The pathologies at risk when using a lowpass filter are the ones leveraging R-peaks amplitudes: PAC and PVC.

High Cutoff Frequency	F_β validation set	F_β test set	F_β^{PVC}	F_β^{PAC}
80 Hz				
90 Hz				
100 Hz				
110 Hz				

1.6 Final filter

1.6.1 Spectral Decomposition

1.6.2 Scores

1.7 Signal Quality

I will implement an indicator of beat quality. using several QRS complexes detection, we will see the detection stability across several methods. After having done all this preprocessing, there may be some bad quality signals, for reasons we do not understand, or causes that we can robustly prevent. This is why we need a *a posteriori* indicator telling us if we should include or not this signal in the training of our classifier: this will be the signal quality. We will need to fine-tune the threshold in order to retain signals to be trained.

Threshold	Number of leads suppressed	F_β validation set
0.9		
0.85		
0.8		
0.75		
0.7		

2. Further work

2.1 Adaptive Filter in order to suppress baseline wandering

2.2 Substraction method for powerline interference and EMG Noise

See [6]

2.3 Data Compression

2.4 Wavelet denoising

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