BIOMEDICAL SIGNALS

LAB SESSION 8 WITH MATLAB
ADAPTIVE FILTERING WITH LMS ALGORITHM

FIRST PART: FILTERING POWER LINE

Power line is a very important interference when recording bioelectric signals, particularly EMG signals were the power line frequency (50 H or 60 Hz) is in the middle of its bandwidth. Adaptive filtering using LMS algorithm will be applied in signals from different effort levels.

Objectives:

- To analyse the convenience of adaptive filtering in these situations comparing with LTI filters.
- To evaluate the filtering effect of different gains μ,
- To evaluate different weighs initial conditions and converge time.

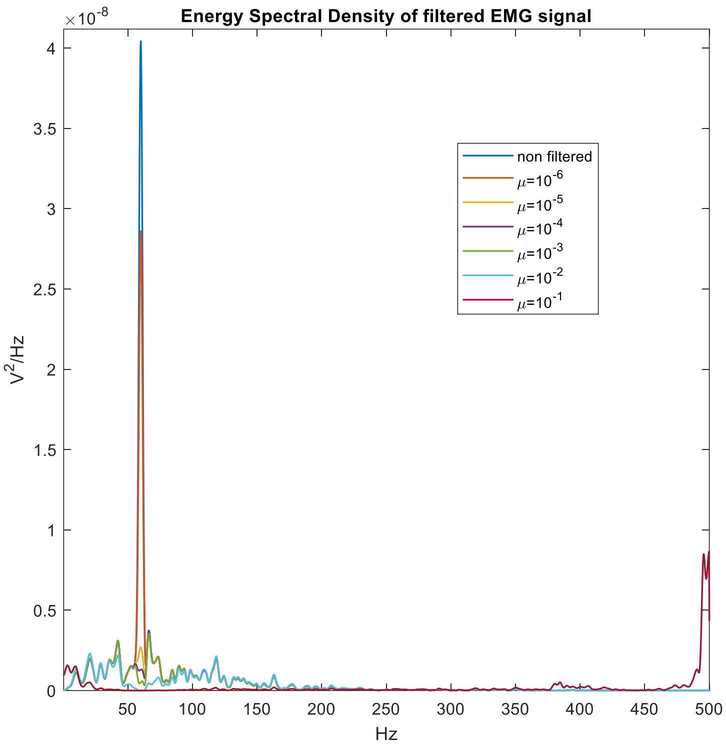
Load the file "pl.mat" and there will be in the workspace two signals or vectors: EMG and inspiratory pressure signals recorded during five respiratory cycles. Sampling frequency is 1 kHz and 40 Hz, respectively. Electrodes were located over the sternomastoid muscle which is an accessory respiratory muscle.

Compute the Energy Spectral Density (ESD) as we did in a previous Lab session to evaluate if the interference of power line is high. I suggest to compute it in the signal segment between 19 and 20 seconds (during the last inspiratory contraction) and to use the Welch periodogram with 4 epochs and 50% of overlapping. Try to observe this interference in time domain when plotting the artifactual EMG signal. It is really difficult to see the powerline in EMG observing the whole signal.

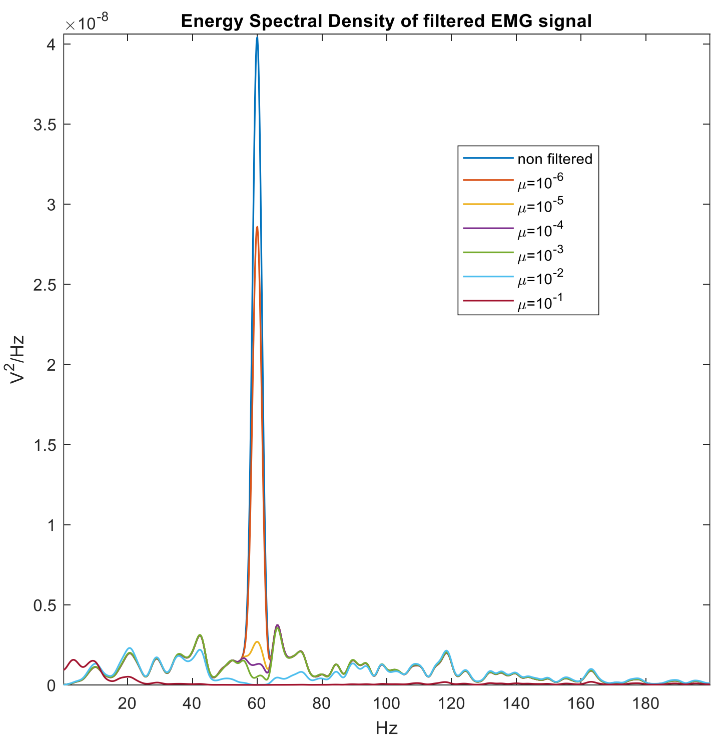
Identify the spectral peak and at which frequency is located. Apply the adaptive filtering using a cosinus signal oscillating at 60 Hz and amplitude 1 as a reference signal. No delay between primary and reference signals are necessary because we plan to remove a pure oscillating interference. To select the weight lengths (filter order) we can think about a full oscillating period: 1/60=16.7 ms which correspond to 16.7 samples when the sampling frequency is 1000 Hz. Thus, 20 weights w(k) seem to be appropriate. Firstly, consider null initial conditions for the filter weights.

Filter the EMG signal using the provided MATLAB routine using different filter gains: $\mu=10^{-6}$, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 0.15 and 0.2. In each case, you can check the filtered EMG signal and especially the ESD to evaluate if the spectral peak has been reduced significantly or not or too much because also EMG components are removed at this frequency. I suggest to overlap the ESD traces in the same figure for comparison.

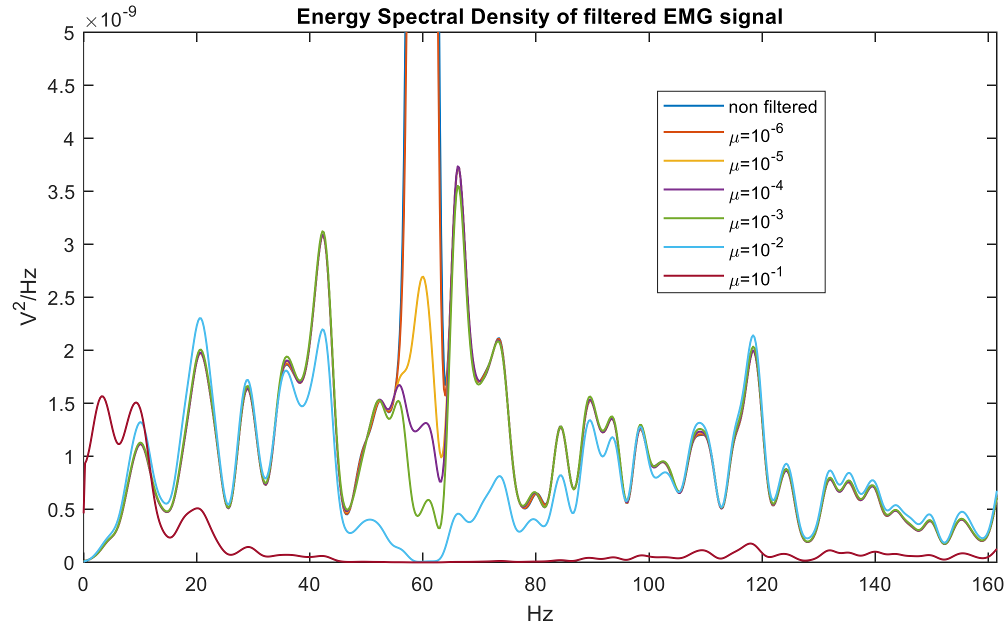
You can see the resulting figure:



Making a zoom:



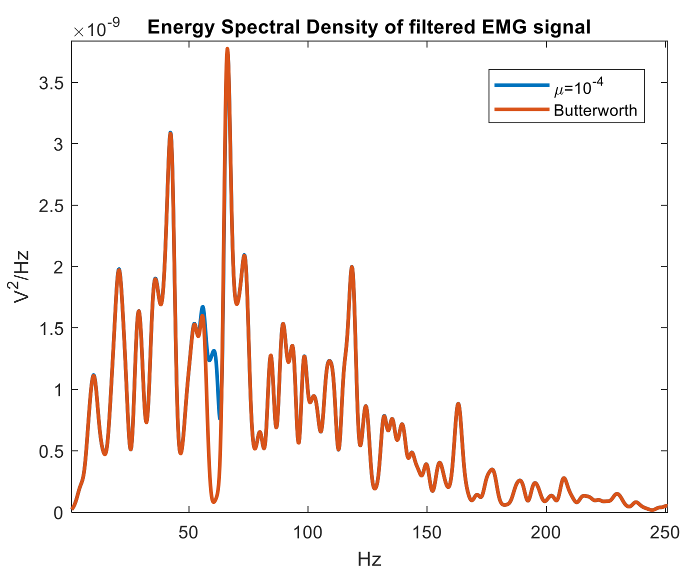
And around 60 Hz:



Conclude which gain is more appropriate in this case and evaluate the convergence plotting the output of the adaptive FIR filter y(n).

Try to improve the convergence when filtering using as initial conditions of the weight vector the last values of w(k) obtained before. Compare the results with null initial conditions of with the appropriate ones plotting the FIR filer output y(n).

Finally, filter the power line interference from the original EMG signal with a notch LTI filter: a 6th order Butterworth filter with a stop band between 58 and 62 Hz (try with a narrower band and you will see that filter is unstable). Compare the ESD obtained in this case with respect to the one obtained using the proper adaptive filtering tried before and extract conclusions:



SECOND PART: FILTERING ECG INTERFERENCE IN EMG SIGNALS

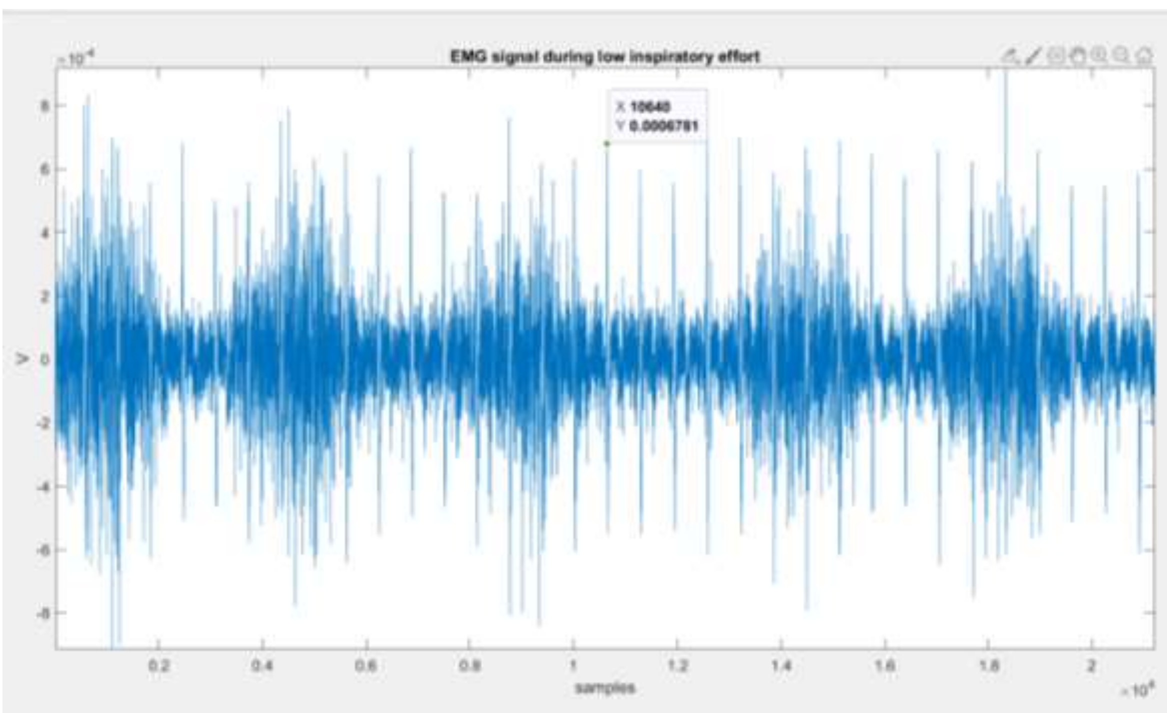
Load the file “adapecg.mat” and there will be in the workspace four signals or vectors: Two EMG and two mouth inspiratory pressure signals recorded with a sampling frequency of 1kHz, and 40 Hz, respectively. Signals are associated with five respiratory cycles during two inspiratory effort levels: low (1) and high (2).

Plot the EMG signals in time domain and you will see clearly the ECG (cardiac) interference, especially with low effort level.

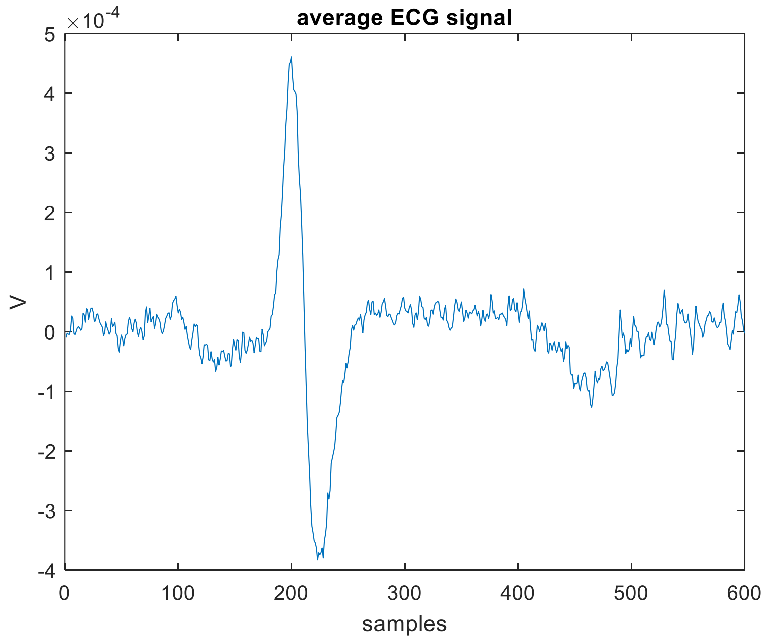
In order to apply adaptive filtering, a reference signal associated with the cardiac activity is necessary. ECG was not recorded separately but it is possible to obtain similar information using the available signals. We’ll use the EMG signal during low inspiratory effort to obtain an “average ECG beat” signal.

In order to facilitate the ECG beat extraction, we’ll filter the EMG signal with a 6th order Butterworth filter. Particularly, with a low pass filter using a cut-off frequency of 70 Hz because most of the energy of cardiac activity is below this frequency.

After filtering, you must select manually the samples where the maximum values from the QRS complexes are. Not select the beats during inspiration because EMG signal amplitude is much higher during contraction and this beat would have a lot of “EMG noise”. It is possible to select 15 beats checking the figure where the EMG signal is plotted and with the cursor try to go to each beat and write down the sample where the maximum is:

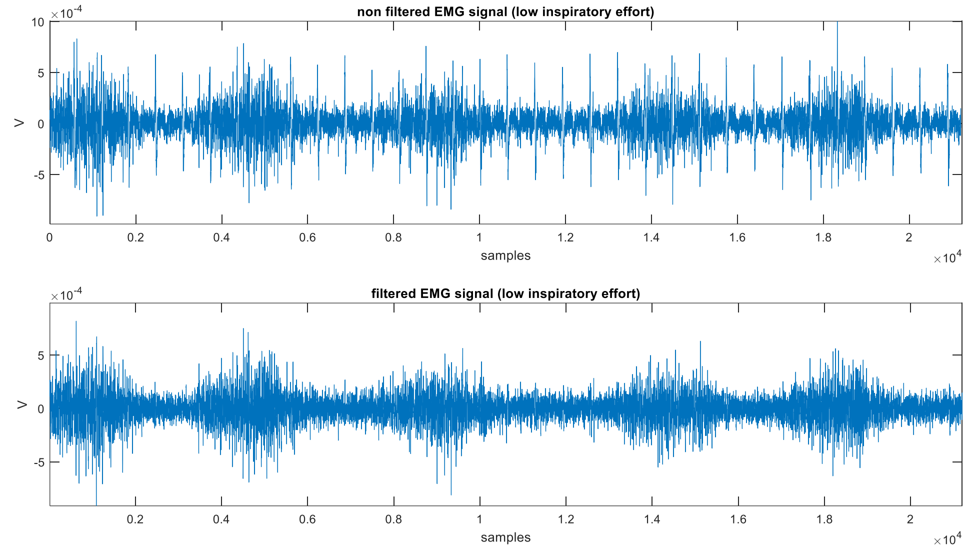


Average the EMG signal using the segments around the marks previously selected and considering 199 and 400 samples before and after, respectively, the samples/marks selected (for example 10640 sample from the figure above). This will permit to have a beat with duration of 600 samples which correspond to 600 ms.
The average ECG beat must be similar to the following one:

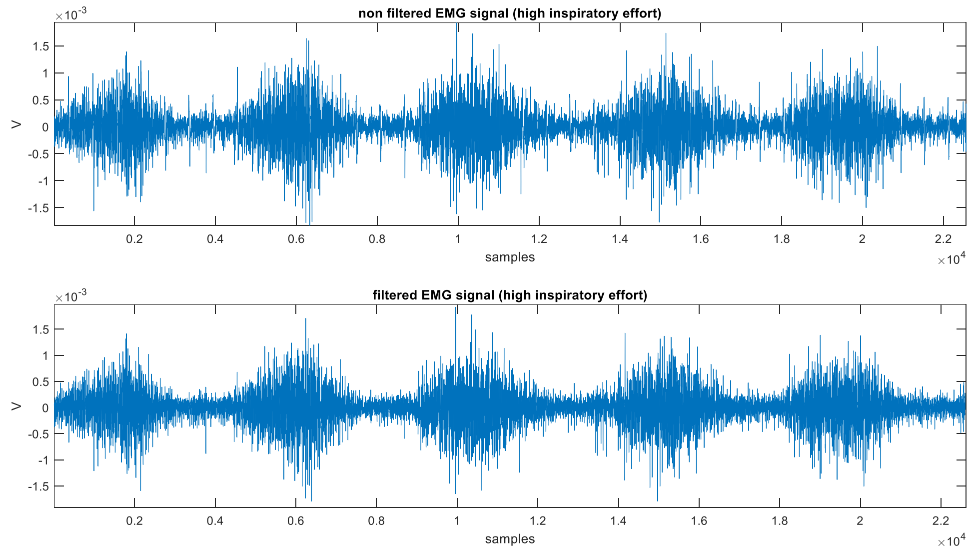


Then, correlate this average ECG with the filtered EMG signal at low inspiratory effort. Maximum values of the cross correlation will appear when a QRS complex appears in the EMG signal. Verify this plotting in the same figure the cross correlation function and the EMG signal. Code an algorithm to detect the samples where the maximum values are located. Notice that these time instants are 200 samples before the maximum of the QRS complexes appear. You must generate a train of unitary impulses in the samples detected with the local maximum of cross correlation. This will be the reference signal for the adapting filter.

Then, apply the adaptive filter without a delay (it is already in the reference signal with respect to the primary one) and with 600 coefficients w(k) in the FIR filter. Start with null initial conditions and gains $\mu=10^{-3}$, 10^{-2}, 10^{-1}. Check the convergence plotting the resulting filtered EMG signal but also plotting the adaptive FIR filter output signal y(n). Think how to solve this issue. Propose to use something that you have already obtained as initial conditions for the adaptive filtering and try again. The filtering effect should be similar to the following figure:



Repeat the process with the EMG signal recorded at high inspiratory effort level using the average ECG obtained before (the ECG will be the same if the subject, session and electrode placement remain). The resulting filtering should be similar to this:



ECG seems to be reduced significantly. This can be observed plotting the adaptive FIR filter output signal y(n). This should be the ECG signal to be removed. Compare it when using different gains.