# Biomedical Signals
# Lab 7 - Adaptive Filtering

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# ADAPTIVE FILTERING WITH LMS ALGORITHM

## 1 Introduction

The accurate recording and analysis of bioelectric signals, such as the Electromyogram (EMG), are **fundamental to physiological monitoring and clinical diagnostics**. However, these signals are frequently contaminated by significant non-biological interference, making accurate analysis challenging. Effective filtering techniques are therefore **essential to isolate the signal** of interest from unwanted noise.

One of the most pervasive sources of interference in EMG recordings is the **power line artifact**, typically oscillating at 50 Hz or 60 Hz. Since the power line frequency falls within the operational bandwidth of the EMG signal, its removal is critical, yet challenging, as traditional **linear time-invariant (LTI) filters** can inadvertently remove desired biological signal components alongside the noise.

This document explores the application of **Adaptive Filtering** using the **Least Mean Squares (LMS) algorithm** as a dynamic solution to interference cancellation. Unlike fixed-coefficient LTI filters (such as the Butterworth Notch filter), the LMS algorithm adjusts its filter weights iteratively to track and minimize the interference component in the primary signal.

The work is structured in two main parts:

1. **Filtering Power Line Interference**: We apply the LMS algorithm to remove 60 Hz power line noise from EMG signals. The performance is evaluated using the **Energy Spectral Density (ESD)** and compared against a fixed-coefficient LTI filter to assess the trade-offs in noise reduction and signal preservation.

2. **Filtering ECG Interference in EMG Signals** : We address the more complex issue of removing cardiac activity (ECG) artifacts from EMG signals. Since a separate ECG reference signal is not available, we synthesize the required reference by extracting an **"average ECG beat"** and using cross-correlation to generate an impulse train.

Ultimately, this study aims to analyze the **convenience** and performance of adaptive filtering in handling both simple (sinusoidal, 60 Hz) and complex (morphological, ECG) interference components in biomedical signals.

# 2 filtering ECG Interference from EMG Signals

In this section, we address the challenge of removing ECG interference from EMG signals recorded during different inspiratory efforts. The presence of ECG artifacts can significantly distort the EMG signal, making it difficult to analyze muscle activity accurately. We will employ adaptive filtering techniques to mitigate this interference, using a template derived from the low-effort EMG signal as a reference.

## 2.1 Signal Visualization

The dataset `adapecg.mat` was loaded, containing electromyography (EMG) signals recorded from the sternomastoid muscle during five respiratory cycles at two different inspiratory effort levels: low and high.

The raw signals are visualized in Figure 1. Both signals exhibit significant cardiac interference, characterized by sharp, periodic QRS complexes. In the "High Effort" scenario, the amplitude of the EMG activity increases drastically during inspiratory bursts, partially masking the ECG artifacts.

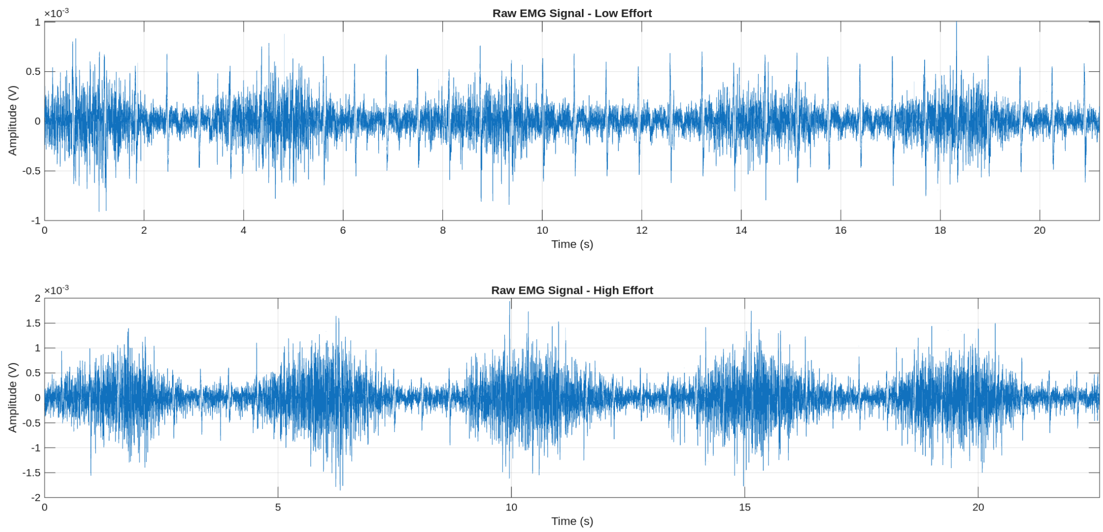


Figure 1: Raw EMG signals recorded during Low Effort (top) and High Effort (bottom). The periodic spikes correspond to the ECG interference.

## 2.2 Manual Beat Selection

To derive a clean template of the ECG interference, it is crucial to select beats that are not contaminated by the high-amplitude EMG activity occurring during inspiration. Following the laboratory guidelines, the Low Effort EMG signal was filtered (Butterworth, 6th order, 70 Hz cutoff) to facilitate visualization.

We manually identified 15 QRS complexes during the "quiet" expiratory phases. The sample indices of these peaks were recorded to serve as synchronization points for template extraction.

```
% Manually selected indices during expiratory phases
manual_peak_locs = [1823, 2459, 3083, 3727, 5600, ...
                    6227, 6865, 7498, 10643, 11284, ...
                    11933, 12571, 13211, 15740, 17035];
```

Listing 1: Manual selection of QRS peak indices

## 2.3 Generation of Average ECG Beat Template

Using the manually selected indices, we extracted segments of the raw EMG signal to construct an average beat. A window of 600 samples was defined around each peak: 199 samples before the peak and 400 samples after. This window length (600 ms) is sufficient to capture the P-wave, QRS complex, and T-wave.

```
function avg_beat = extract_average_beat(signal, peak_locs, window_pre,
   window_post)

    num_peaks = length(peak_locs);
    beat_segments = [];

    for i = 1:num_peaks
        start_idx = peak_locs(i) - window_pre;
        end_idx = peak_locs(i) + window_post;

        if start_idx > 0 && end_idx <= length(signal)
            segment = signal(start_idx:end_idx);
            beat_segments = [beat_segments; segment(:)];
        end
    end

    avg_beat = mean(beat_segments, 1);
end
```

Listing 2: Extraction of the average ECG beat

The resulting template, shown in Figure 2, displays a distinct cardiac morphology with minimal high-frequency noise, validating the manual selection strategy.

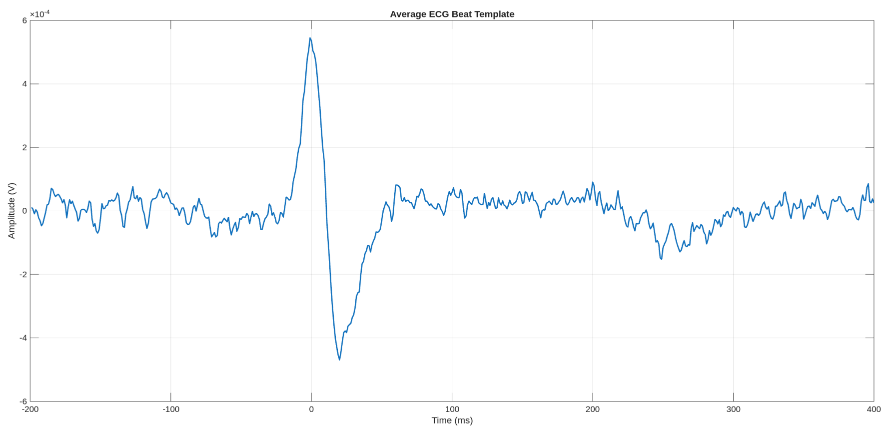


Figure 2: Average ECG beat template derived from the 15 manually selected indices. The P, QRS, and T waves are clearly visible.

## 2.4 Adaptive Filtering of Low-Effort EMG

### 2.4.1 Reference Signal Generation and Alignment

To apply the LMS adaptive filter, a reference signal $x(n)$ correlated with the interference is required. We generated a train of unit impulses by cross-correlating the `avg_beat` template with the filtered EMG signal to detect all heartbeats.

A critical design consideration was the **alignment** of these impulses. Since the adaptive filter is causal, the impulse must trigger the filter at the *start* of the beat window, not at the peak. Therefore, impulses were placed approximately 200 samples before the QRS peak. Figure 3 confirms this alignment, showing the impulses (red triangles) start before the QRS complexes.

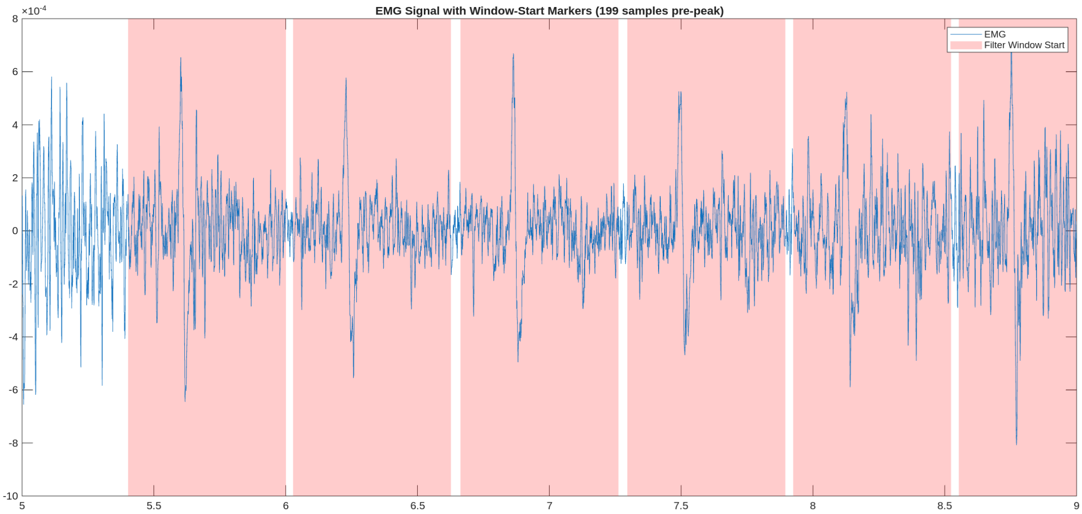


Figure 3: The reference impulses (red) start at the onset of the cardiac cycle, enabling causal reconstruction of the artifact.

### 2.4.2 LMS Filtering Results

The LMS algorithm was applied with a filter order of $N = 600$. We evaluated three step sizes: $\mu \in \{0.001, 0.01, 0.1\}$.

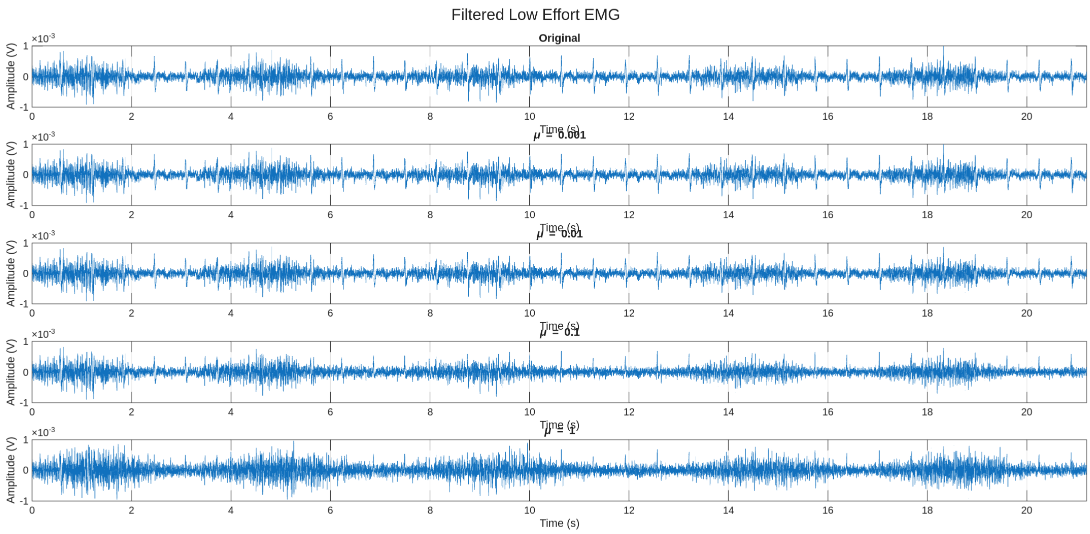


Figure 4: Filtered Low-Effort EMG signals. $\mu = 0.1$ (bottom) removes the spikes and keeps the signal with good resolution.

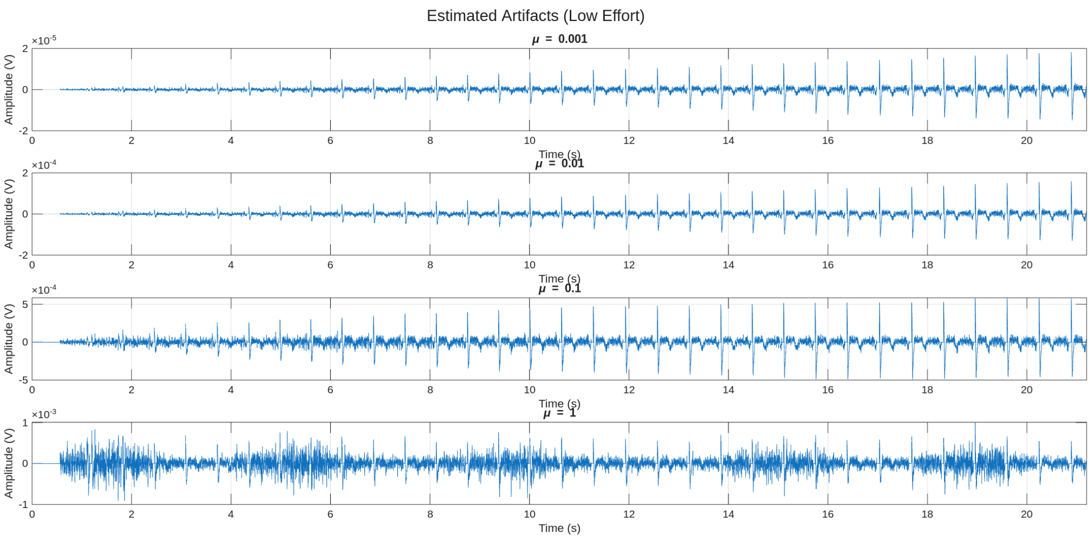


Figure 5: Estimated artifacts $y(n)$. It can be observed that the best results are achieved with the parameter $\mu = 0.1$ (below).

The results indicate that $\mu = 0.1$ provides the better results. Smaller step size ($\mu = 0.001$) results in slower convergence, failing to estimate the full amplitude of the first few beats.

## 2.5 Adaptive Filtering of High-Effort EMG

The adaptive filter, tuned on the low-effort signal ($\mu = 0.1$, Order 600, Smart Initialization), was applied to the High-Effort EMG signal. Reference impulses were generated using the same `avg_beat` template.

Despite the significantly higher amplitude of the respiratory muscle activity, the filter successfully isolated and removed the ECG interference (Figure 6), with better results with the $\mu = 0.1$

parameter. The underlying EMG bursts are preserved, and the periodic cardiac spikes are attenuated significantly.

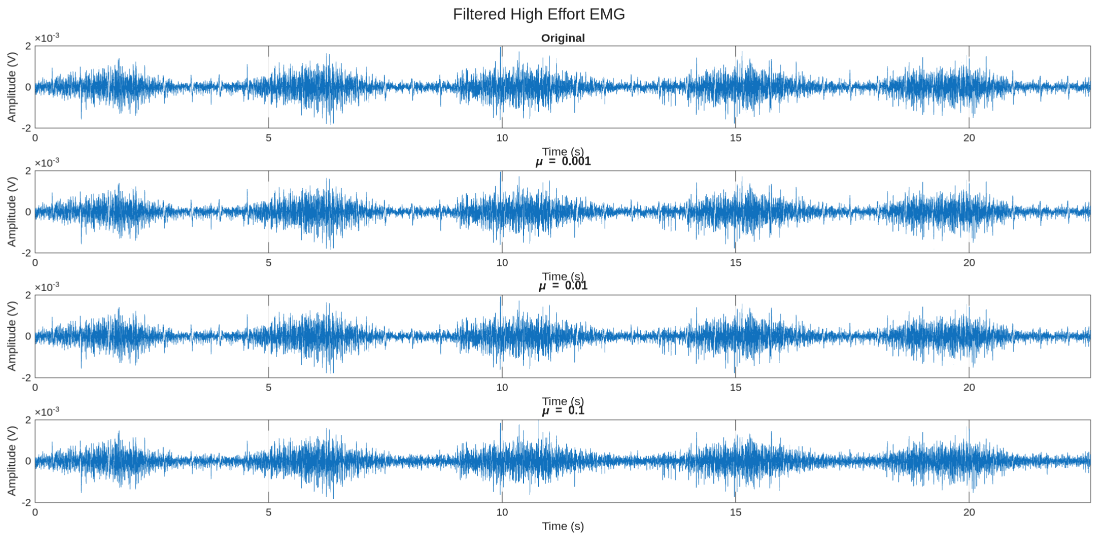


Figure 6: Filtered High-Effort EMG. The adaptive filter remains robust even in the presence of high-energy muscle contraction.

## 2.6 Convergence Improvement

### 2.6.1 The Initialization Problem

Standard adaptive filters (LMS) are typically initialized with a weight vector of zeros ($w[0] = 0$). This assumes no prior knowledge of the interference signal. Theoretically, the filter requires a "learning period" (convergence time) to adjust its weights, during which the interference is not removed.

### 2.6.2 Smart Initialization with Template

To eliminate this potential delay, we proposed a "Smart Initialization" strategy. Using the computed `avg_beat` template (which represents the optimal impulse response), we initialized the filter weights:

$$w_{initial} = \text{avg\_beat}$$

By seeding the LMS algorithm with this prior knowledge, the filter starts in a state closer to the optimal solution.

### 2.6.3 Results Analysis

Figure 7 compares the filtered output of both methods during the first second of recording, using a step size of $\mu = 0.1$.

- **Observation:** Contrary to the theoretical expectation of a distinct "learning curve," both the Null and Smart initializations produce very similar results. The first QRS complex is attenuated in both cases, with no significant visual difference in the residual artifact.

- **Explanation of Fast Convergence:** The chosen step size ($\mu = 0.1$) is sufficiently large to allow the LMS algorithm to adapt extremely rapidly. In the Null case, the filter weights adjust from zero to the required magnitude within the duration of the first QRS complex itself (approx. 50-100 ms). This ultra-fast adaptation renders the initialization phase negligible for visual inspection.

- **Template Mismatch:** Furthermore, the Smart Initialization relies on an *average* beat template. Since the specific amplitude and shape of the very first heartbeat in the raw signal naturally deviate from this average, the "Smart" filter still produces a residual error (due to imperfect subtraction). This residual is comparable in magnitude to the initial error of the rapidly adapting Null filter, leading to the observed similarity.

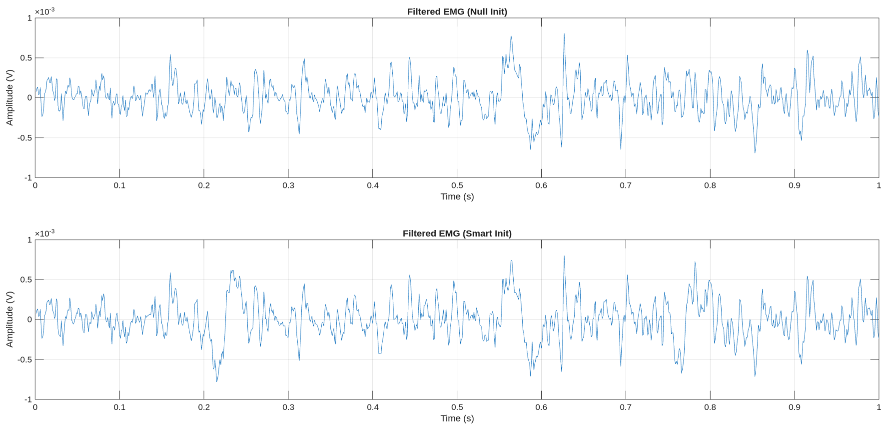


Figure 7: Comparison of filter convergence during the first second. **Top:** Null Initialization. **Bottom:** Smart Initialization. Due to the high adaptation speed ($\mu = 0.1$) and natural amplitude variance of the first beat, the visual performance is nearly identical in both cases, with no clear advantage observed for the template-based initialization in this specific scenario.