Department of Electronic & Telecommunication Engineering

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MATLAB Assignment: Signal Estimation

BM4112 - Medical Electronics and Instrumentation

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Contents

1 Wiener Filter for ECG Denoising

1.1 Loading Ideal ECG and Noisy ECG Files Into MATLAB

Below is the MATLAB code used to load and visualize the provided ECG data.

```
%% 1. Wiener Filter for ECG Denoising

clear; clc; close all;

%% (i) Load and visualize ECG data
% Load the provided noisy and ideal ECG signals
load("ECG_rec (2).mat");
load("idealECG (1).mat");

% Assign local variable names
ecg_noisy = nECG(:);        % Noisy ECG
ecg_clean = idealECG(:);    % Ideal ECG
```

Listing 1: MATLAB: Load and prepare ECG signals.

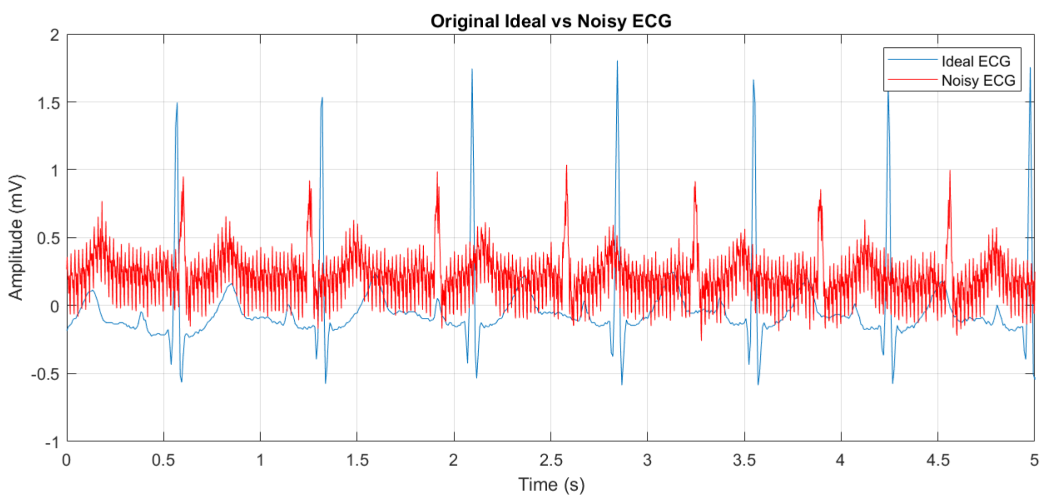

Figure 1.1: Comparison between original noisy and ideal ECG signals. The ideal ECG serves as the reference for Wiener filter design.

Since the sampling ratios of the signals are different, `idealECG` signal was upsampled from 128 Hz to 500 Hz. The following code segment is used for that.

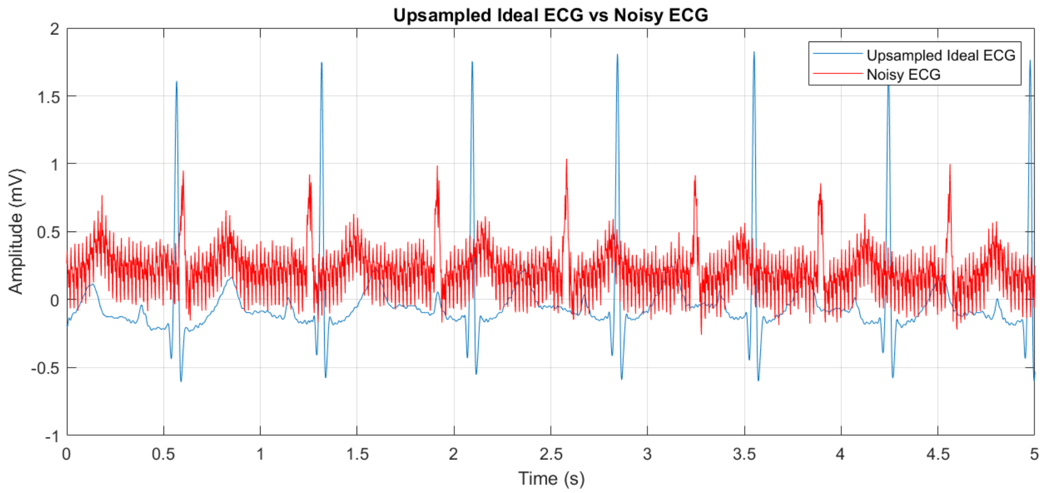

Figure 1.2: Upsampled ideal ECG aligned with the noisy signal for filter application.

Then a noise-free ECG segment and a noisy ECG segment were extracted from the signals `idealECG` and `nECG`, respectively.

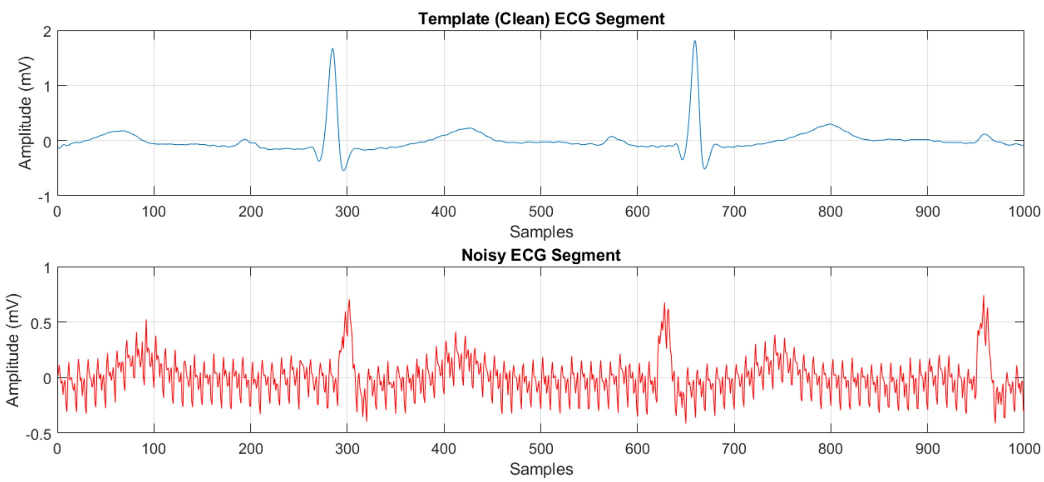

Figure 1.3: Clean and noisy ECG segments extracted for Wiener coefficient estimation.

1.2 Wiener Filter Design and Application

```
%% (ii) Wiener filter design and application
filter_len = 30;

% Compute cross- and auto-correlation functions
Rxy = xcorr(noisy_seg, clean_seg, filter_len, 'biased');
Rxx = xcorr(noisy_seg, filter_len, 'biased');
Rxx_mat = toeplitz(Rxx(filter_len+1:end));

% Solve Wiener-Hopf equations for optimal weights
w_opt = Rxx_mat \ Rxy(filter_len+1:end);

% Apply Wiener filter to the full noisy ECG
ecg_noisy_dc = ecg_noisy - mean(ecg_noisy);
```

```
ecg_filtered = filter(w_opt, 1, ecg_noisy_dc);
```

Listing 2: MATLAB: Wiener filter design and application.

1.3 Plotting the time domain and time-frequency domain plots

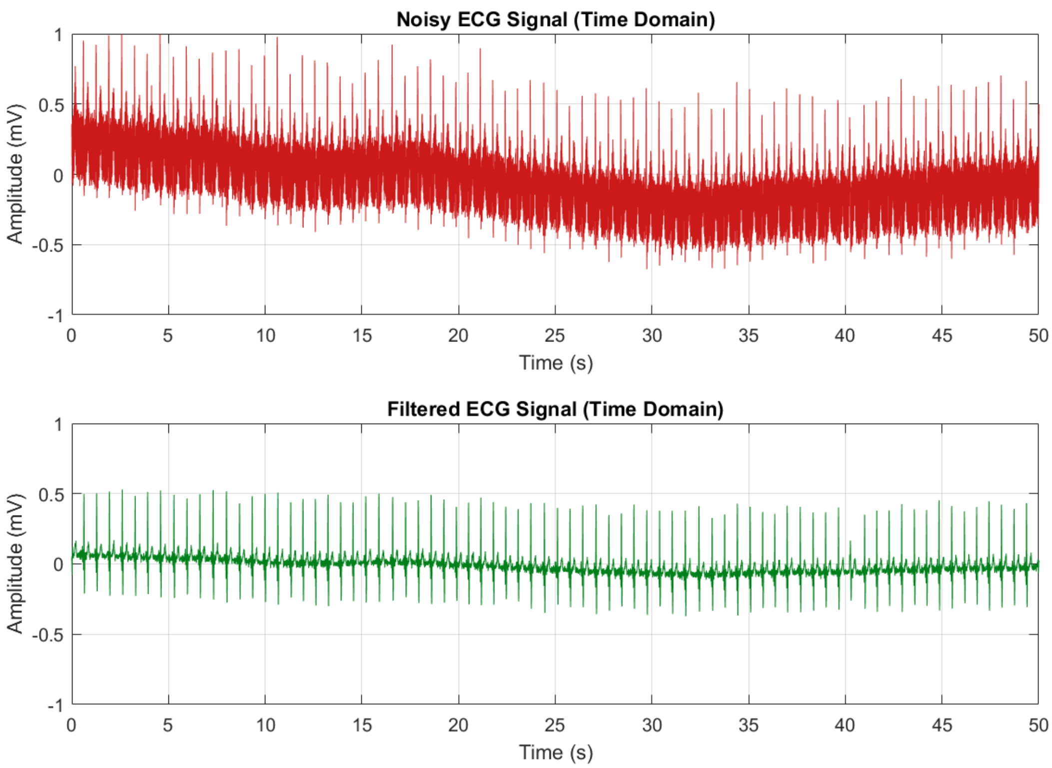

Figure 1.4: Noisy ECG vs Wiener filtered ECG

The filter suppresses high-frequency noise and smooths the baseline.

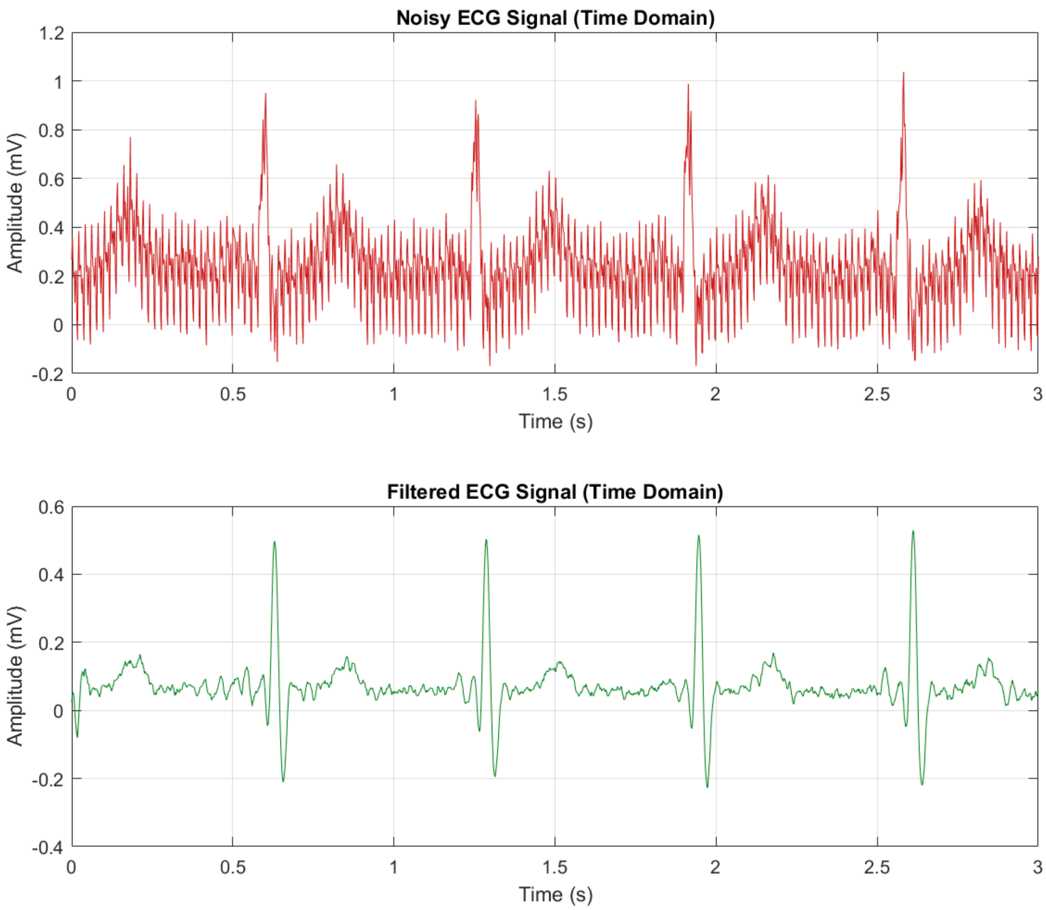

Figure 1.5: Noisy ECG vs Wiener filtered ECG: From 0 to 3 seconds

Time-domain comparison shows clearer QRS complexes after Wiener filtering. Below code was used to plot the time-frequency domain plots.

```
%% (iii) Visualization     time-frequency (spectrogram)
figure('Position', [100, 100, 1000, 800]);
% ... compute trimmed signals ...
spectrogram(ecg_noisy_plot, 256, 200, 256, fs_noisy, 'yaxis');
spectrogram(ecg_filtered_plot, 256, 200, 256, fs_noisy, 'yaxis');
```

Listing 3: MATLAB: Spectrogram comparison (noisy vs filtered).

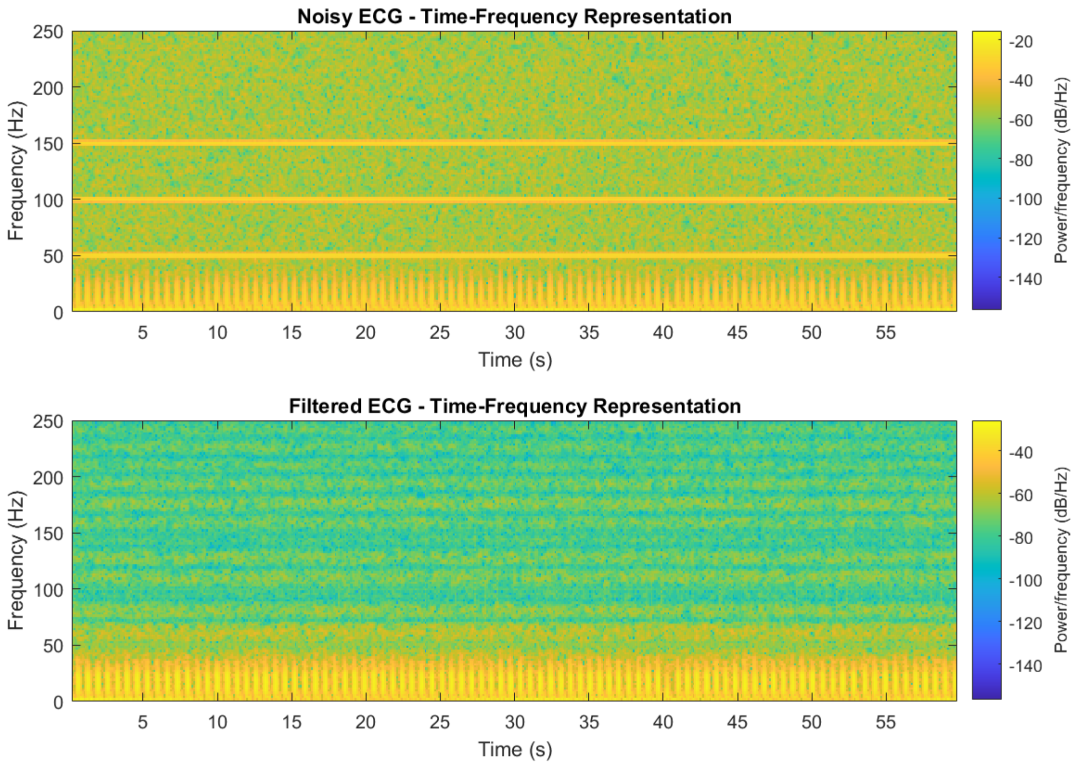

Figure 1.6: Spectrograms of noisy (top) and Wiener-filtered (bottom) ECG signals for the first 60 seconds. High-frequency noise components are effectively reduced.

In the spectrograms, a clear difference in the magnitudes of the frequency components can be observed. In the spectrogram of the noisy signal, three distinct horizontal lines appear consistently over time, corresponding to frequencies of approximately 50 Hz, 100 Hz, and 150 Hz, representing the powerline interference and its harmonics. In the spectrogram of the filtered signal, the power magnitudes of these lines are significantly reduced, while the lower-frequency components remain nearly unchanged. This indicates that the useful information content of the ECG signal has been preserved and not mistakenly removed as noise.

2 Kalman Filter for ECG Denoising

2.1 Kalman Design and Implementation

```
%% 2. Kalman Filter for ECG Denoising
load('wiener_weights.mat','w_opt');

% (i) Kalman filter design
x_est = mean(w_opt);      % Initial state (Wiener mean)
P_est = 1;                % Initial estimate covariance
Q = 0.1;                  % Process noise covariance
R = 4;                    % Measurement noise covariance

filtered_ECG = zeros(minLen,1);
input_ECG = ecg_noisy - mean(ecg_noisy);  % DC offset correction

%% Apply Kalman filter
for k = 1:minLen
    % Prediction
    x_pred = x_est;
    P_pred = P_est + Q;

    % Update
    K = P_pred / (P_pred + R);
    x_est = x_pred + K * (input_ECG(k) - x_pred);
    P_est = (1 - K) * P_pred;

    % Store filtered output
    filtered_ECG(k) = x_est;
end
```

Listing 4: MATLAB: Kalman filter implementation initialized by Wiener weights.

2.2 Plotting the time domain and time-frequency domain plots

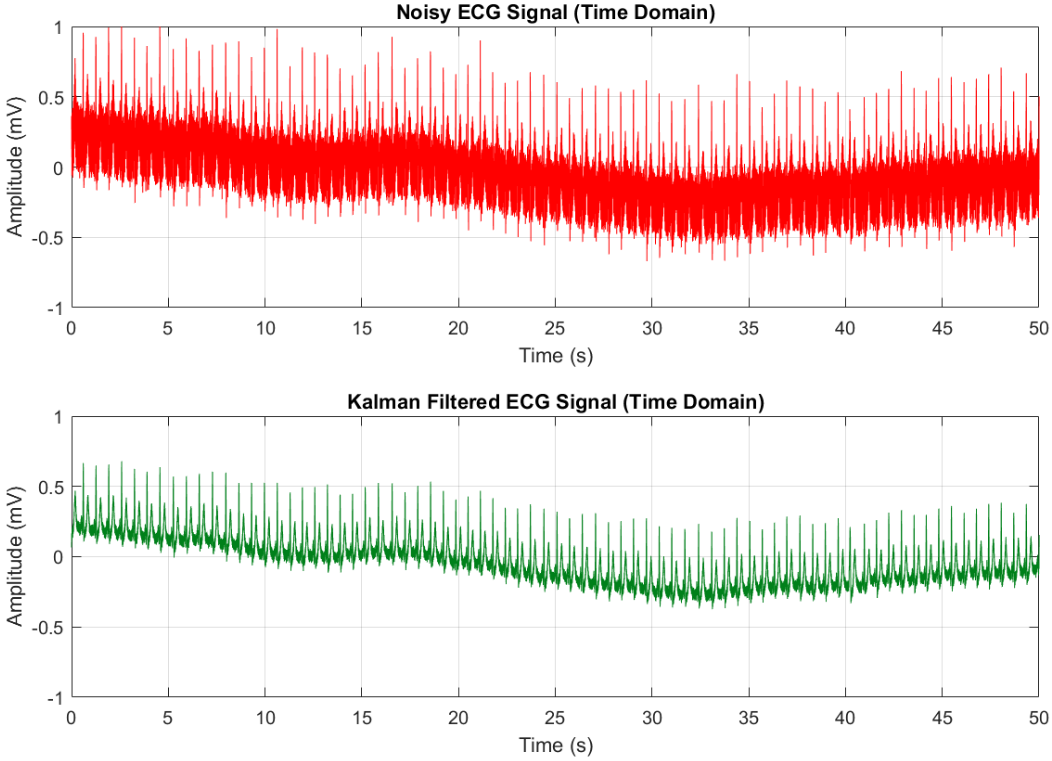

Figure 2.1: Noisy ECG vs Kalman filtered ECG

Baseline wander is not removed with kalman filter.

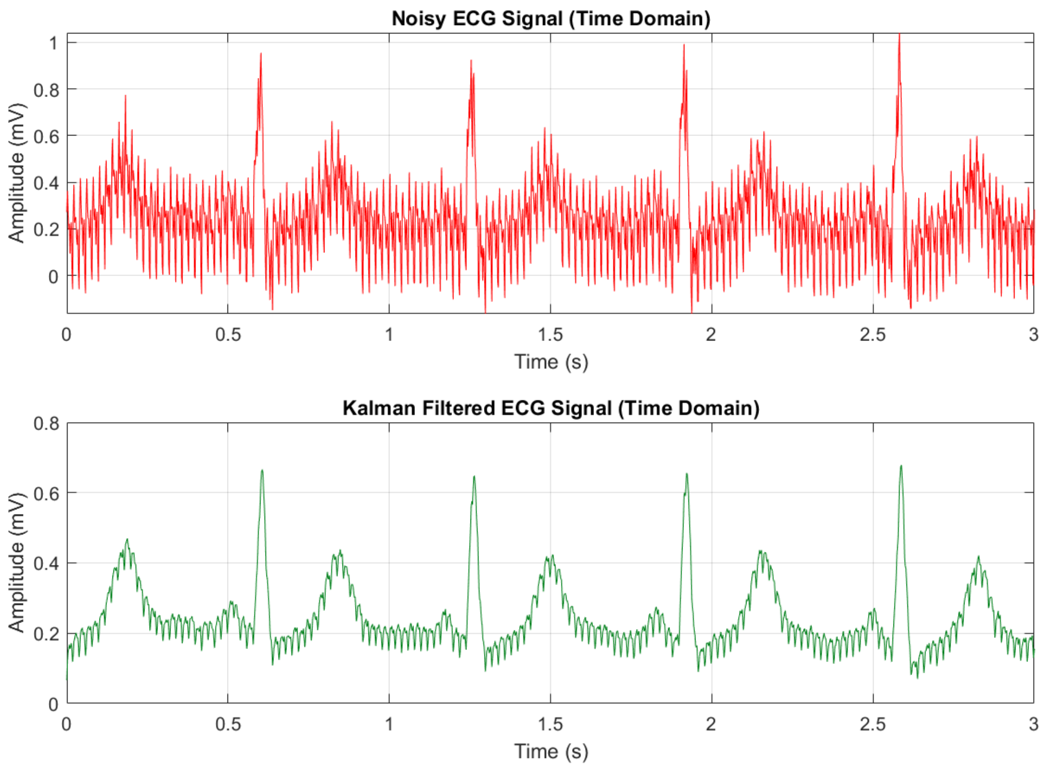

Figure 2.2: Noisy ECG vs Kalman filtered ECG: From 0 to 3 seconds

High frequency noise is removed adaptively but the 50Hz poweline noise is not removed

```
%% (ii) T i m e frequency comparison
figure('Position',[100,100,1000,800]);
spectrogram(input_ECG, 256, 200, 256, fs, 'yaxis');
spectrogram(filtered_ECG, 256, 200, 256, fs, 'yaxis');
```

Listing 5: MATLAB: Spectrogram comparison for Kalman output.

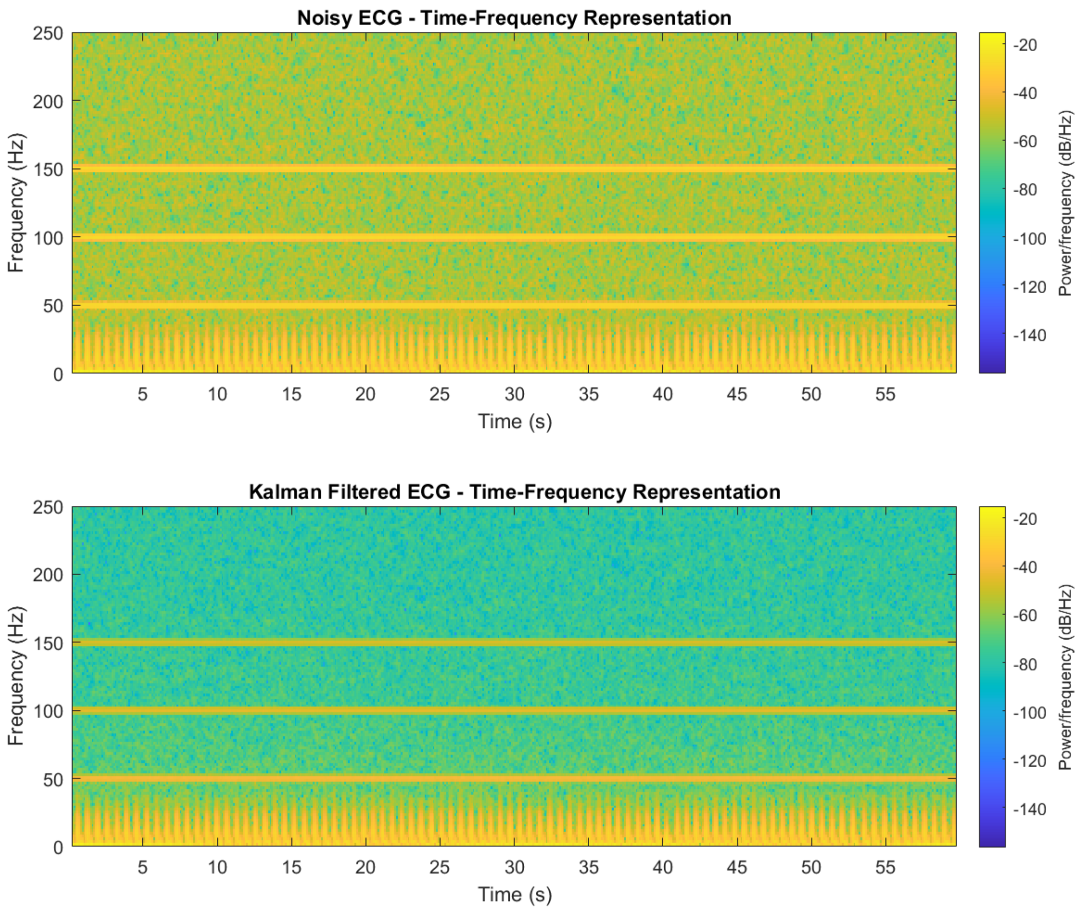

Figure 2.3: Spectrograms of noisy and Kalman-filtered ECG signals.

The Kalman filter dynamically suppresses time-varying high-frequency noise.

2.3 Which method/filter enhances the ECG signal better?

The Wiener filter enhances the ECG signal better by effectively reducing noise while preserving the morphological features of the waveform.

2.4 Comparison Between Wiener Filter and Kalman Filter

Wiener Filter

- Highly effective at reducing fixed-frequency noise, particularly the powerline interference at 50 Hz and its harmonics (100 Hz and 150 Hz). This is evident from the reduced magnitudes of these frequency components in the spectrogram.
- Successfully removes baseline wandering, resulting in a smoother ECG signal with a stable baseline.
- Preserves the essential lower-frequency components of the ECG, ensuring that the main waveform features remain intact.

Kalman Filter

- Capable of reducing noise across a broader range of frequencies but less effective in suppressing fixed-frequency components such as powerline noise. These frequencies are still visible in the spectrogram of the filtered signal.
- Maintains the overall structure of the ECG waveform but does not effectively remove baseline wandering.
- Preserves the important lower-frequency components, keeping the key ECG features recognizable.

In summary, the Wiener filter performs better in this scenario because it can specifically target and attenuate constant, predictable noise such as powerline interference while also correcting baseline drift. This makes it particularly suitable for clinical ECG analysis, where accurate interpretation of heart activity is essential and persistent noise can lead to diagnostic errors. Although the Kalman filter offers adaptive noise reduction, its performance depends heavily on parameter tuning. With optimal parameter selection, it could potentially match or even surpass the Wiener filter's performance.