University of Moratuwa

Department of Electronic and Telecommunication Engineering

BM4112

Medical Electronics and Instrumentation

MATLAB Assignment: Signal Estimation

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Task 01 – Wiener Filter for ECG Denoising

ii) MATLAB script named as *"Wiener_Filter.m"* contains the Wiener filter implementation.

iii)

When calculating the wiener filter weights for ECG denoising it requires an ideal ECG signal and a noisy ECG signal. Typically for this task we will use a single ECG beat. Hence, I used the first 500 samples which contains a single ECG beat. The noisy ECG signal that we use along with this ideal ECG signal should be a noise added version to this ideal ECG signal

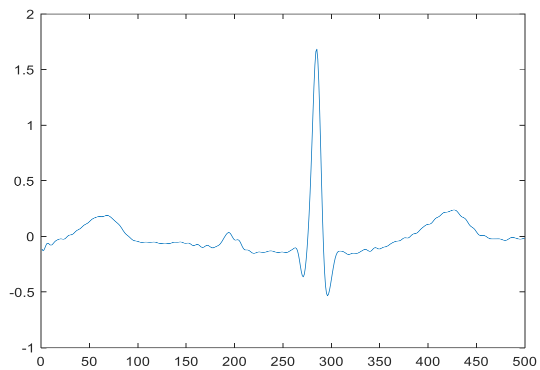

Fig.1. Ideal ECG signal for Wiener filter weight calculation

Then the Wiener filter weights are calculated using the Wiener Hopf equation and using obtained weights filtered signal is obtained by using MATLAB filter() function.

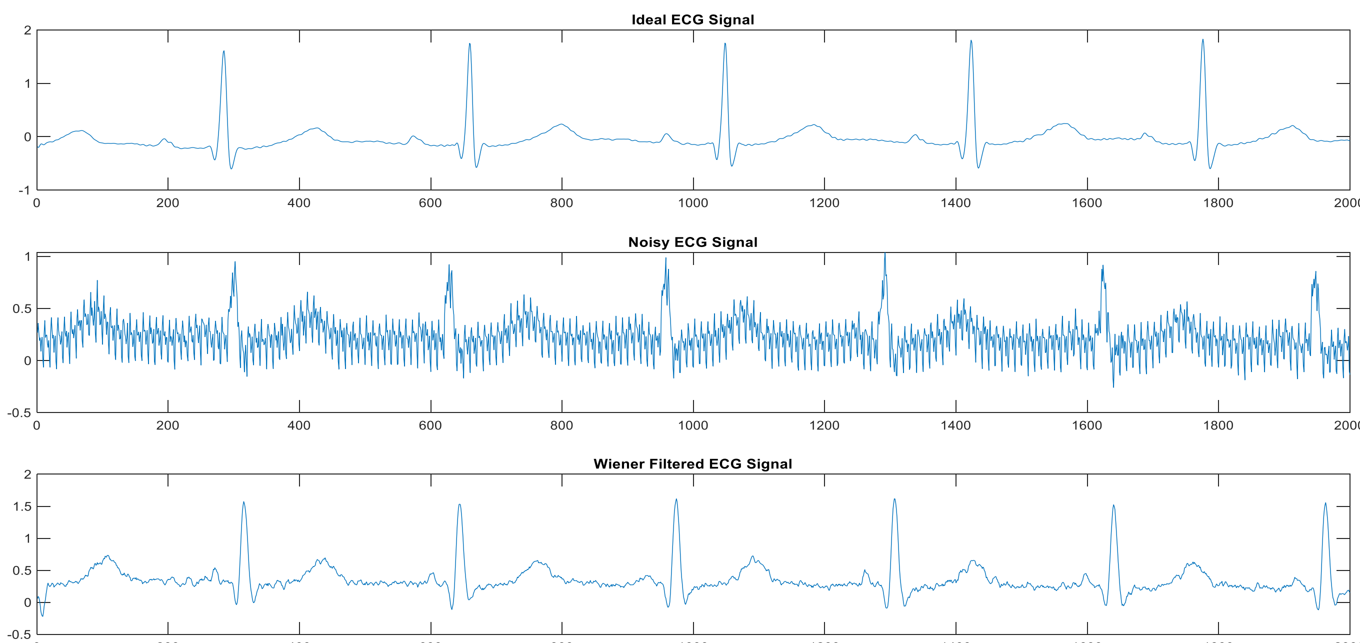

Fig.2. (a) Ideal ECG signal, (b) Noisy ECG signal, and (c) Filtered ECG signal using the Wiener filter

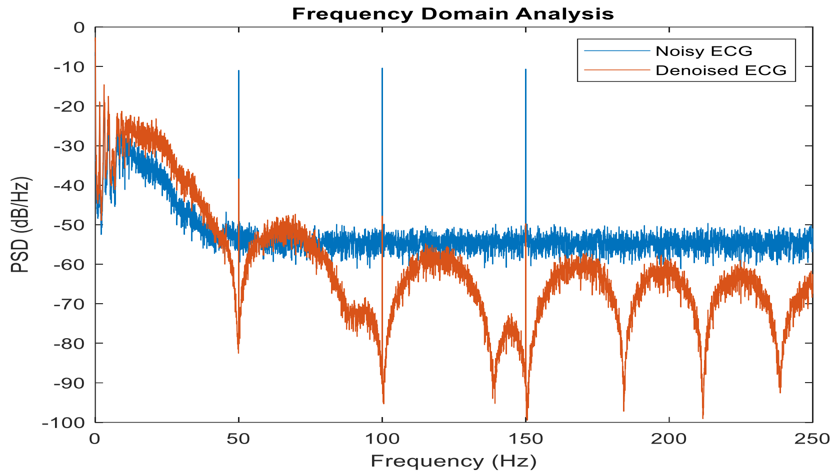

Fig.2. Frequency domain analysis (PSDs) of noisy and filtered ECGs.

Observing the results, we can clearly see that the Wiener filter has removed almost all the noise effectively. This is because the noise is stationary and does not vary over time. A significant portion of the noise is due to power line interference, which is also stationary. Since the Wiener filter is well-suited for removing stationary noise, it has successfully removed the noise.

Task 02 – : Kalman Filter for ECG Denoising

i) MATLAB script named as *"Kalman_Filter.m"* contains the Kalman Filter implementation. Scalar state – scalar observation Kalman filter is used for the implementation.

Model parameters,

a = 1

$\sigma_u = 0.32 \; - State\ Transition\ Noise$

$\sigma_n = 2 - Measurement\ Noise$

Transition noise and Measurement noise are obtained using the trial-and-error method, in practice the measurement error can be obtained looking at the sensor data as well.

ii) The results are shown below.

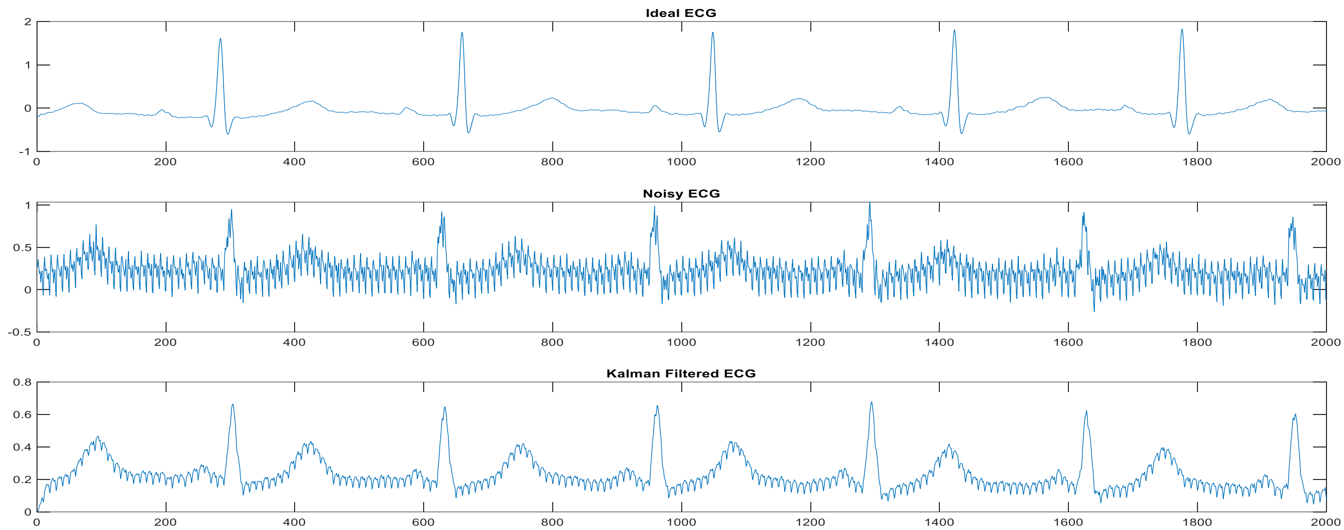

Fig.3. (a) Ideal ECG signal, (b) Noisy ECG signal, and (c) Filtered ECG signal using the Kalman filter

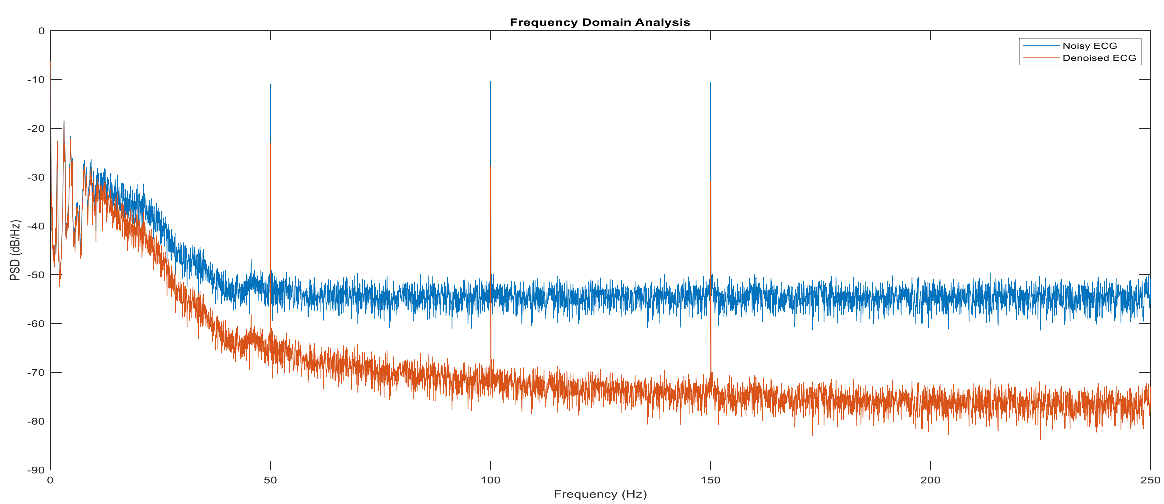

Fig.4. Frequency domain analysis (PSDs) of noisy and filtered ECGs.

Kalman filter has significantly reduced the high frequency noise, Whereas some ripples in time domain signal and spikes in frequency domain signal are visible since it hasn't reduced the powerline noise well.

iii) According to both time-domain and frequency-domain analyses, we can observe that both Kalman filter and Wiener filter have significantly reduced the noise. However, compared to the Wiener filter, the Kalman filter has not effectively filtered out the power line noise and its harmonics at 50 Hz, 100 Hz, and 150 Hz. Consequently, ripples are visible in the time domain, and spikes appear at 50 Hz, 100 Hz, and 150 Hz. On the other hand, other high-frequency noise (such as white noise) has been removed more effectively than by the Wiener filter. Therefore, for the given noisy signal wiener filter has performed better than the Kalman filter.

iv) As explained in section (iii), the Kalman filter has filtered high-frequency Gaussian white noise more effectively than the Wiener filter but fails to filter powerline noise as good as wiener filter, whereas the Wiener filter has reduced both high-frequency gaussian and the power line noise effectively. This is because, in Kalman filtering, we assume that the measurement noise is Gaussian, making it less effective in reducing power line noise. However, the Wiener filter has effectively reduced the power line noise because it does not assume Gaussian noise. The Wiener filter works well when both the noise and the signal are stationary. Here, since both the signal and the noise are nearly stationary, the Wiener filter performs better than the Kalman filter. However, if either the noise or the signal is non-stationary, the Wiener filter may not perform well, while the Kalman filter would likely perform better.

Another reason for the difference in performance could be that we do not know the exact state transition noise and measurement noise. We chose them through trial and error, so if we had accurate values (at least for the measurement noise), it might lead to better results.