



**THE UNIVERSITY OF HONG KONG**

**DEPARTMENT OF ELECTRICAL & ELECTRONIC ENGINEERING**

**ELEC6081/MEDE4504 Biomedical Signals and Systems**

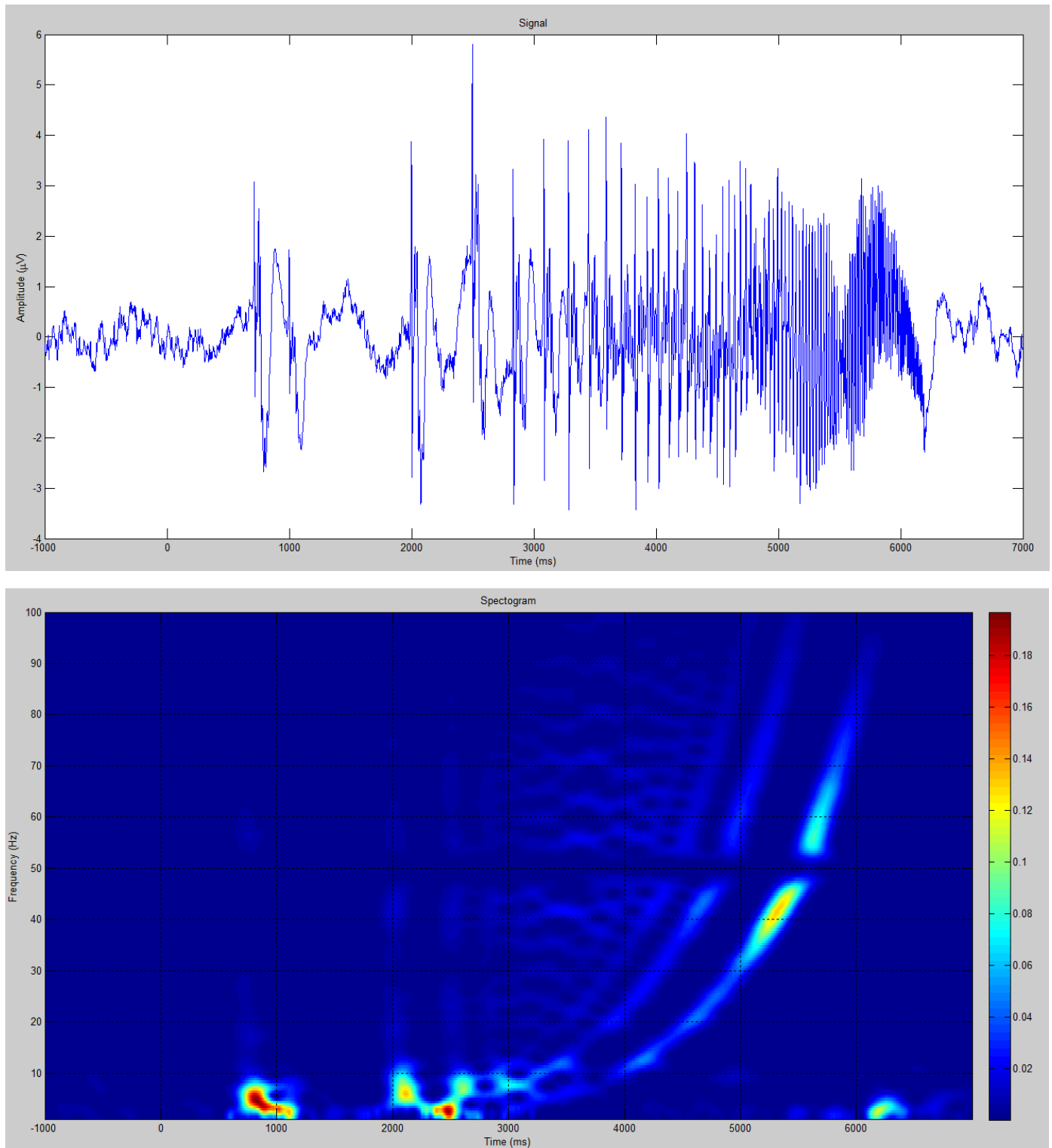
**Assignment Cover Sheet**

<b>Assignment No.:</b>	<b>2</b>
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## 1. Time-frequency Analysis of QSSAEP

### i. QSSAEP Signal and Spectrogram



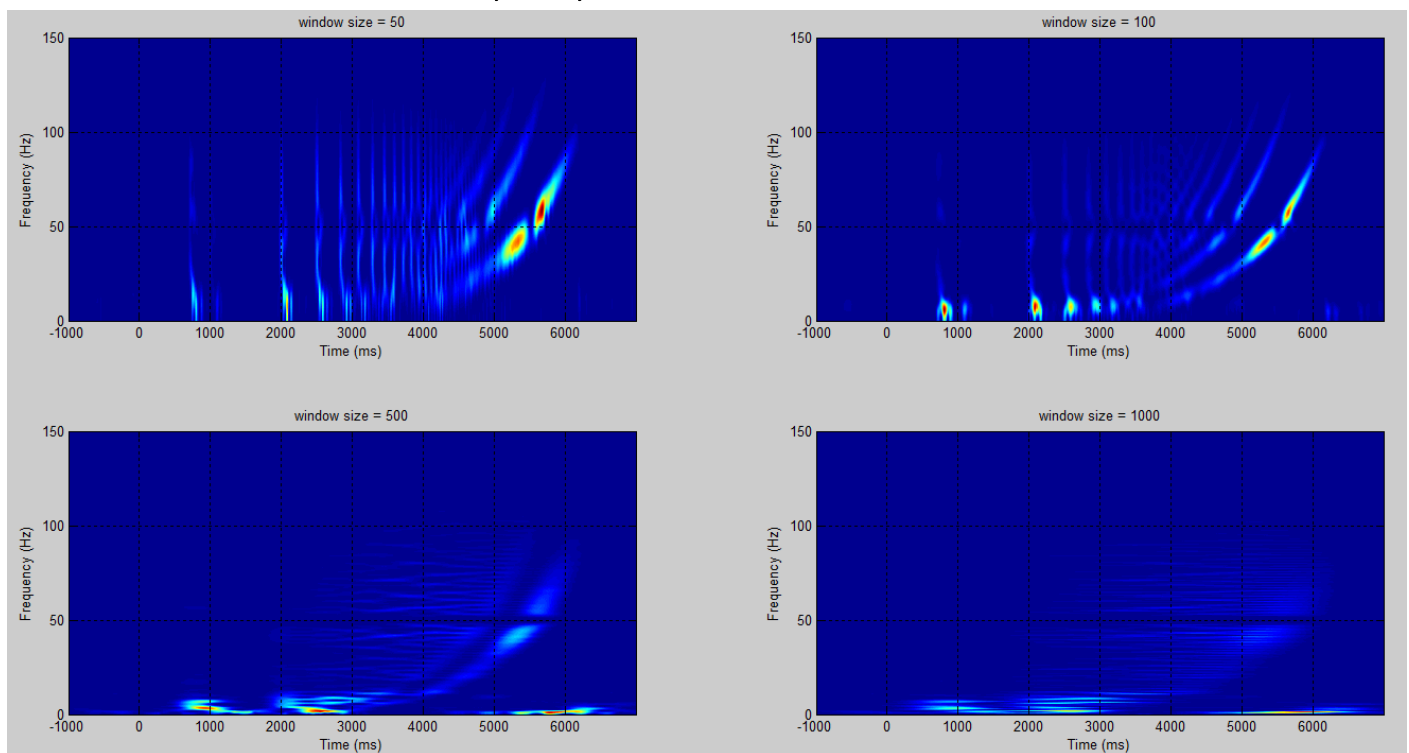
### Describe how the frequency of the major components changes with time.

There is less power at lower frequency components and more power at higher frequency components as time goes on. At 500 ms to 1500 ms there are a lot of power at frequencies between 0 to 10 Hz and again from 2000 ms to 2500 ms there is lot of power at frequencies around 0 to 10 Hz. From 3000 ms onwards there is less power at all frequencies and there is a shift in power towards the higher frequencies. At around 5500 ms there are a lot of power centered at around 40 Hz.

Overall powers centered at:

- 800 ms, 5 Hz, Power Index  $\sim 0.1891$
- 1100 ms, 2.5 Hz, Power Index  $\sim 0.1378$
- 2100 ms, 5.8 Hz, Power Index  $\sim 0.1304$
- 2500 ms, 2 Hz, Power Index  $\sim 0.186$
- 2600 ms, 7.7 Hz, Power Index  $\sim 0.09544$
- 5300 ms, 41 Hz, Power Index  $\sim 0.1274$
- 5650 ms, 67 Hz, Power Index  $\sim 0.0814$
- 6190 ms, 2.93 Hz, Power Index  $\sim 0.1088$

### ii. Window size = 50, 100, 500 and 1000

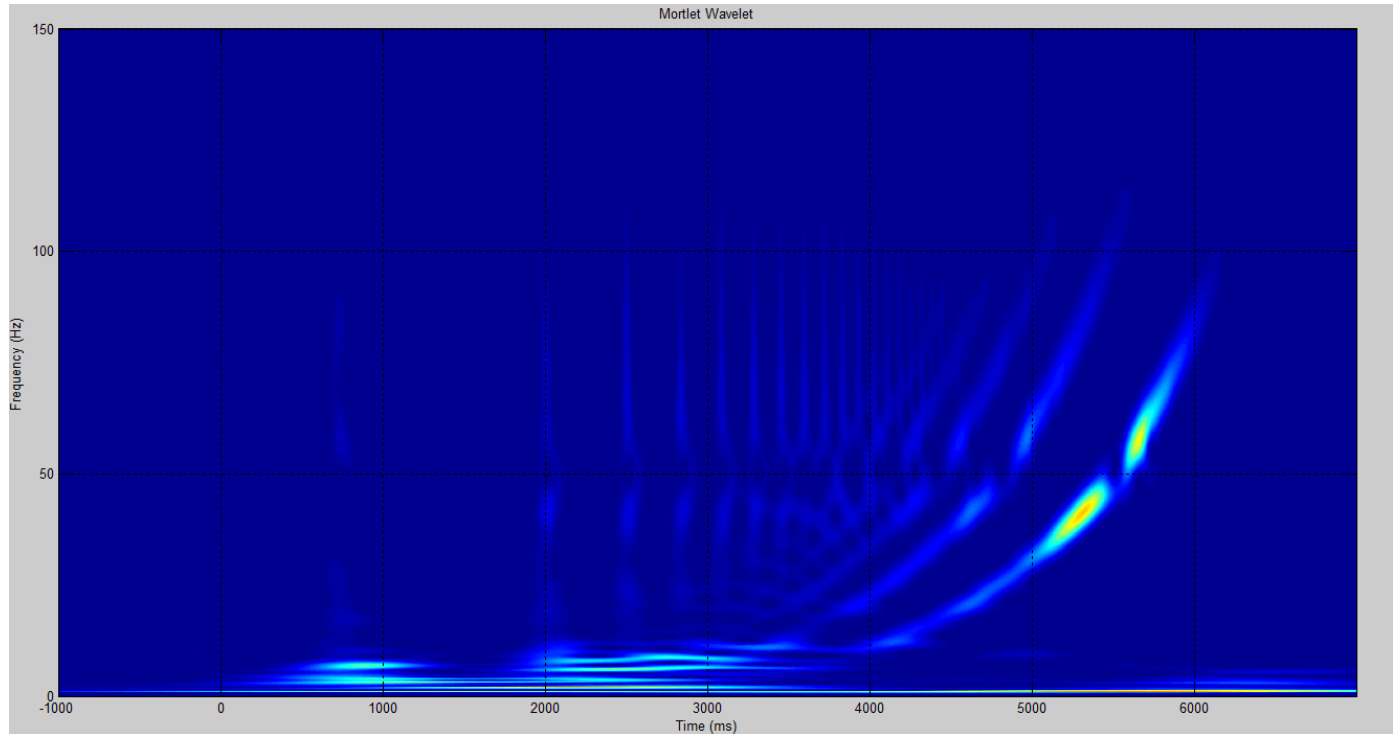


### Describe the difference between these spectrograms.

The spectrograms go from being well defined along the x axis (time) to being well defined along the y axis (frequency), i.e. from vertical lines to horizontal lines, as the window size is increased. Meaning the spectrograms go from having a high time resolution and low frequency resolution to having low time resolution and high frequency resolution with the increase in window size.

**Describe how window size changes the time and frequency resolutions of the spectrogram.**

Increasing the window size (in time domain), increases the frequency resolution and decreases the time resolution.

**iii. Morlet Wavelet****Describe strategy of window selection in CWT.**

The scaling factor ( $\alpha$ ) in CWT is inversely proportional to frequency:  $\alpha = f_0/f$ , where  $f_0$  is the center frequency of the mother wavelet.

A large scale will give a smaller window in the frequency domain, and hence better frequency resolution, but lower time resolution and vice versa. The total uncertainty remains the same. In biomedical signals usually we have short duration high frequency spikes and long duration low frequency components. We are mostly concerned when these spikes occur and the frequency of the long duration frequency components.

So a small scale CWT, which has good time resolution, is good for short duration high frequency spikes. A large scale CWT, which has good frequency resolution is good for long duration low frequency components.

However CWT has limitation in its time-frequency resolution. CWT has poor time resolution for low-frequency components and poor frequency resolution for high-frequency components. So it is not suitable for short-duration low frequency components and long-duration high frequency components.

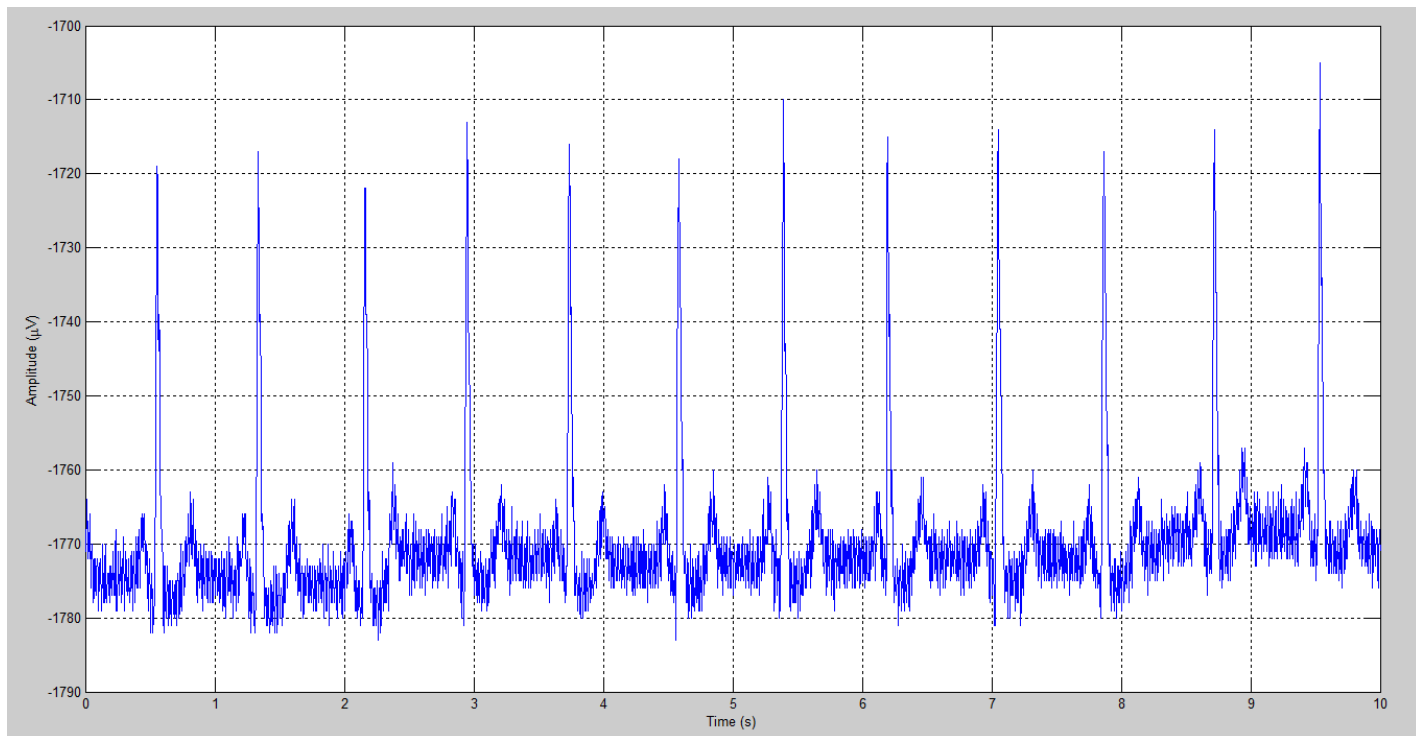
**Explain difference between the CWT and STFT.**

STFT uses a sliding window approach. STFT uses fixed length windows, which leads to fixed time-frequency resolution in the whole time-frequency domain. STFT is a sinusoidal decomposition, which has sine waves that extend to infinity (not localized in time).

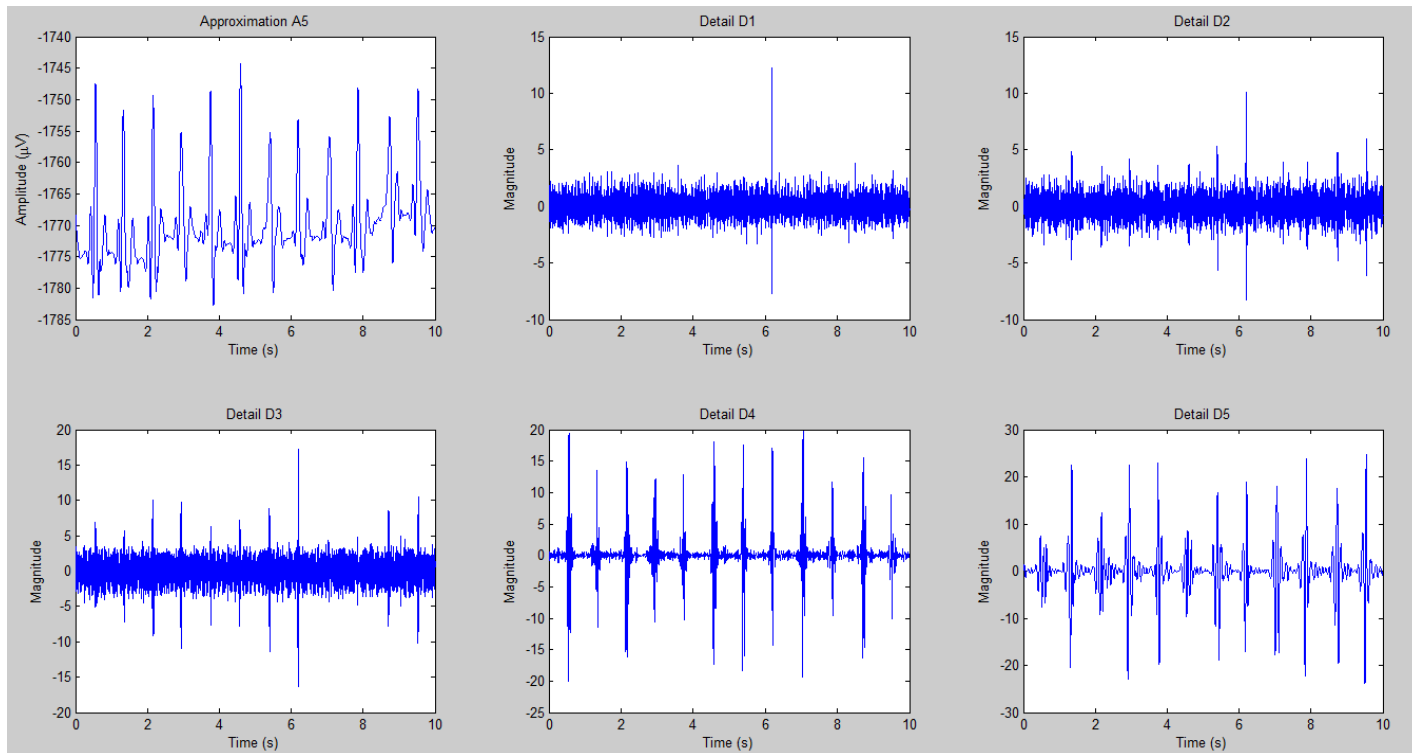
CWT has flexible time-frequency resolution through the use of basis functions that can be localized in frequency (scale) and time (wavelets). CWT is a wavelet decomposition which are localized in time.

## 2. Discrete wavelet analysis of ECG

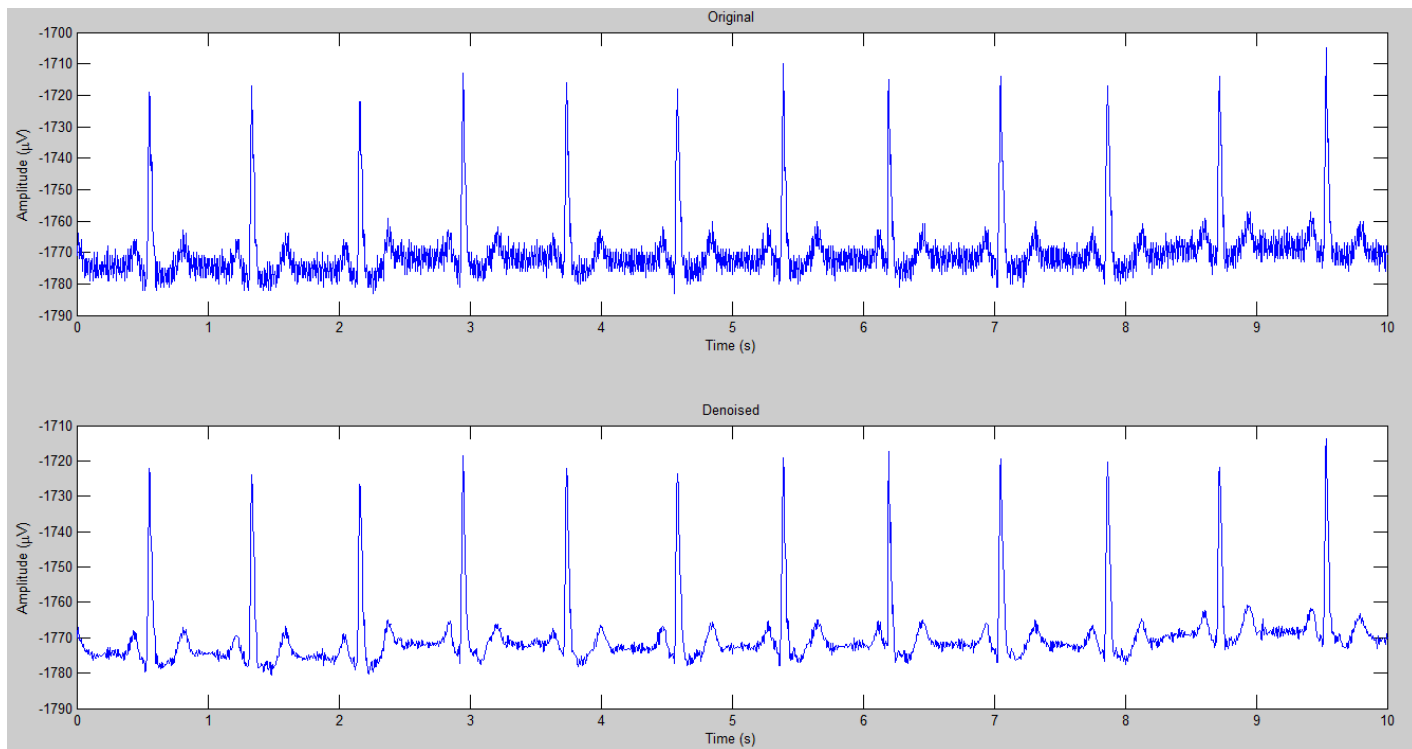
### i. ECG Signal



### ii. Level 5 wavelet decomposition



### iii. Noise removal

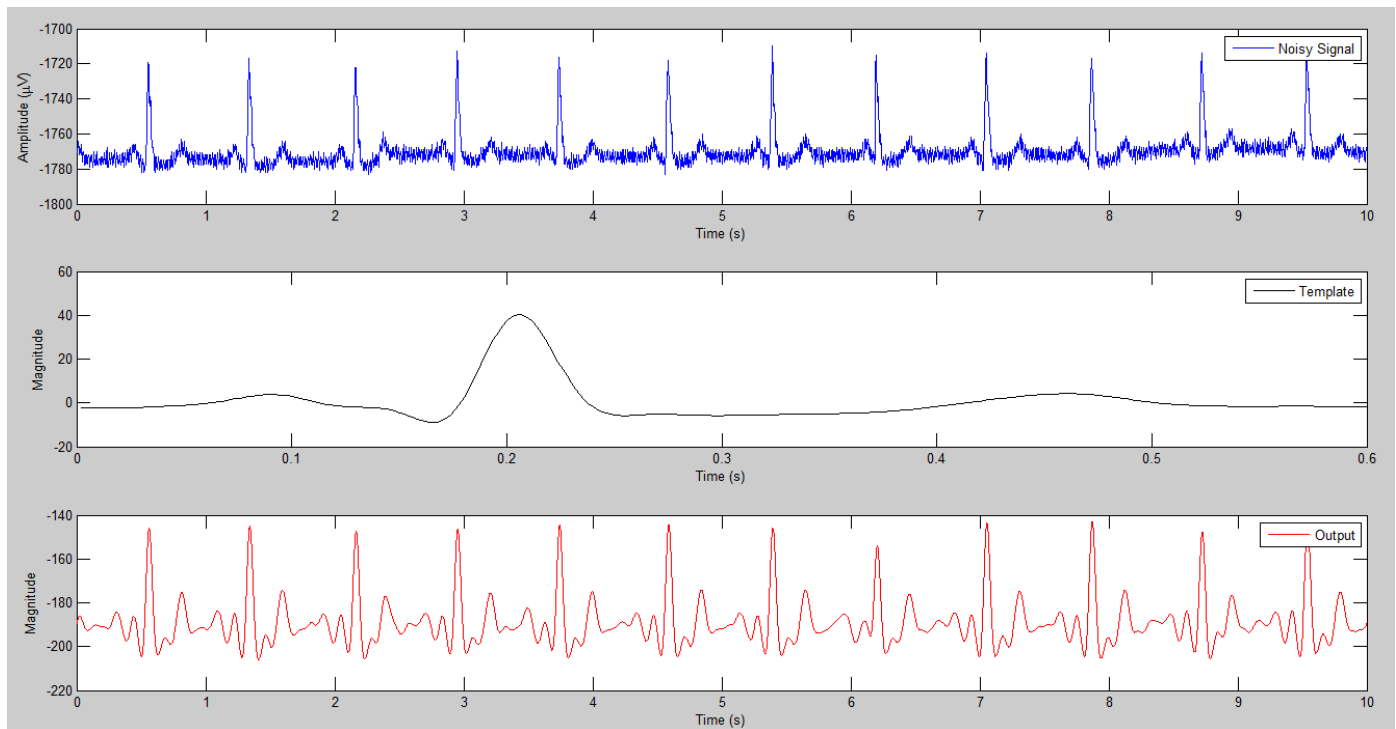


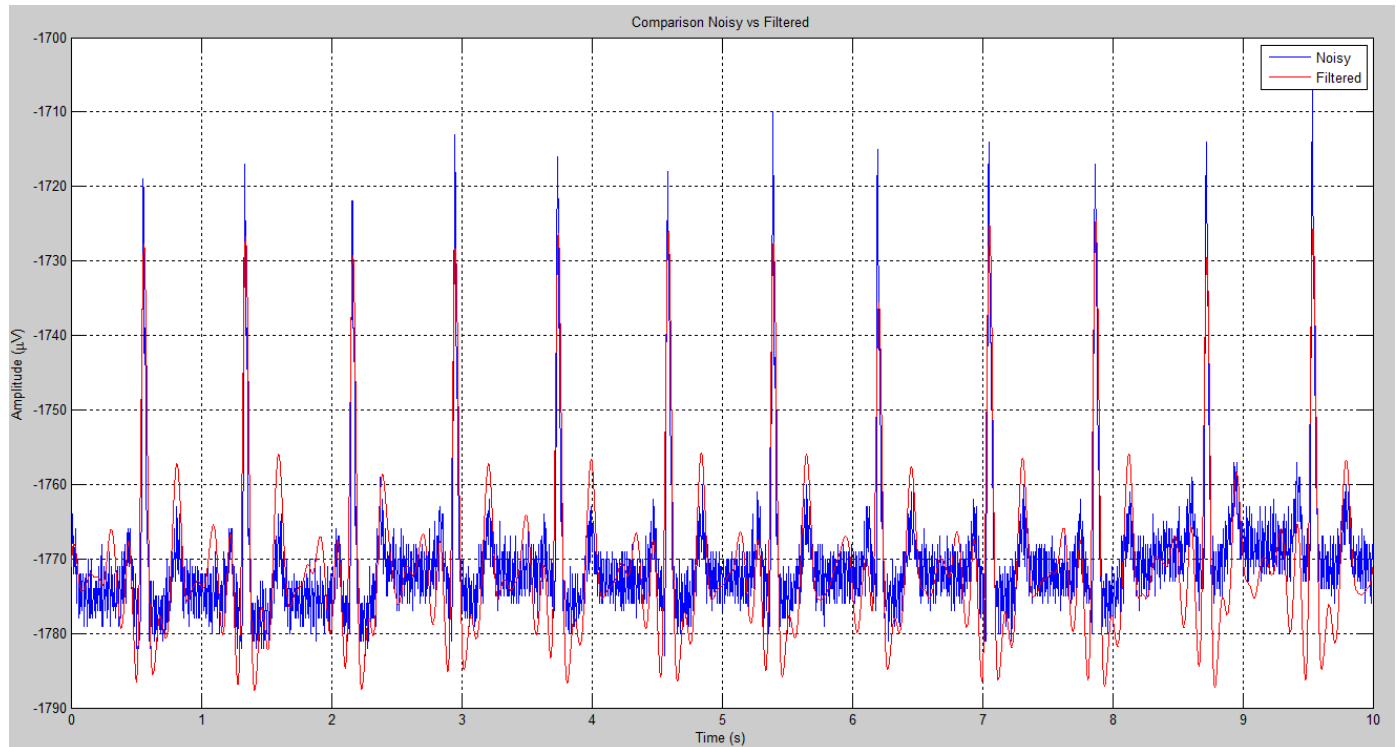
**Describe the difference between wavelet denoising and FIR/IIR denoising.**

FIR/IIR denoising (low-pass, band-pass, etc) actually remove particular frequencies above a threshold or within a certain range and retains the rest of the frequency components of the signal, whereas wavelet denoising removes noise (DWT coefficients below or within a certain threshold) regardless of the signal's frequency, i.e. wavelet denoising removes all noise at any frequency range.

### 3. Optimal Filters

#### i. Matched Filter





**Briefly explain the idea of matched filter.**

Matched filter is an optimal filter for maximizing the signal to noise ratio (SNR) in the presence of additive random noise. A matched filter is obtained by correlating a known signal, called a template, with an unknown signal to detect the presence of the template in the unknown signal.

#### **Additional Information**

The signal,  $x$ , may be described as composed of a template  $s$ , and additive noise  $v$ :

$$x = s + v$$

The output of a filter  $h$  is:

$$y = h^H x = h^H s + h^H v$$

SNR is:

$$SNR = \frac{|h^H s|^2}{E\{|h^H v|^2\}}$$

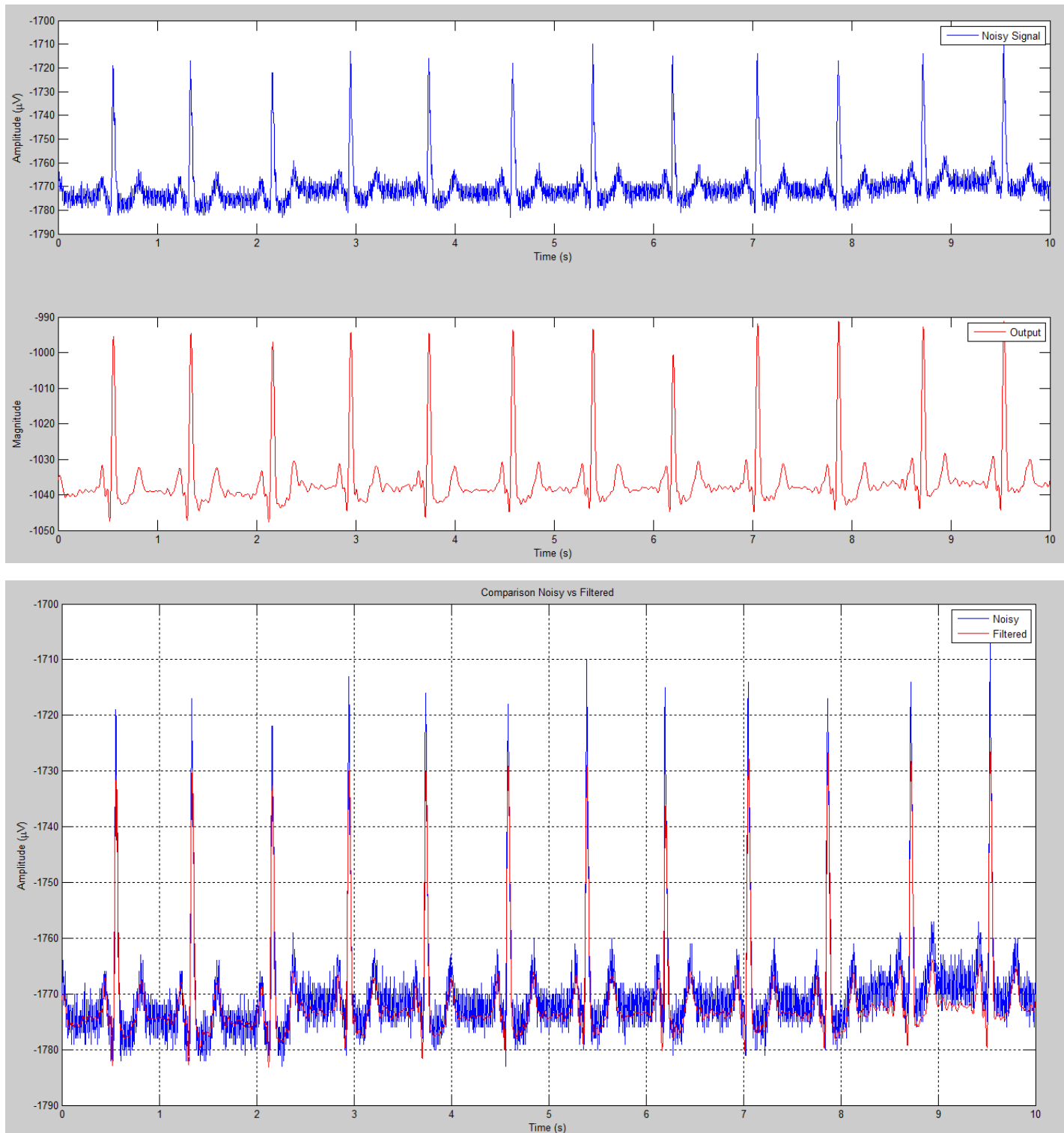
The optimal filter, maximized for SNR is:

$$h = \left( R^{-1} / \sqrt{s^H R_v^{-1} s} \right) s$$

So as a result, a matched filter  $h$  is equivalent to correlating an unknown signal  $x$  with that of a known signal  $s$ .

#### **ii. Wiener Filter**





**Briefly explain the idea of Wiener filter.**

Weiner filter is an optimal filter that produces an estimate of a desired (target) signal by filtering out an observed noisy process and additive noise based on known spectra of the stationary target signal and

noise. The Wiener filter minimizes the mean square error (MSE) between an estimated signal and the desired target signal.

#### Additional information

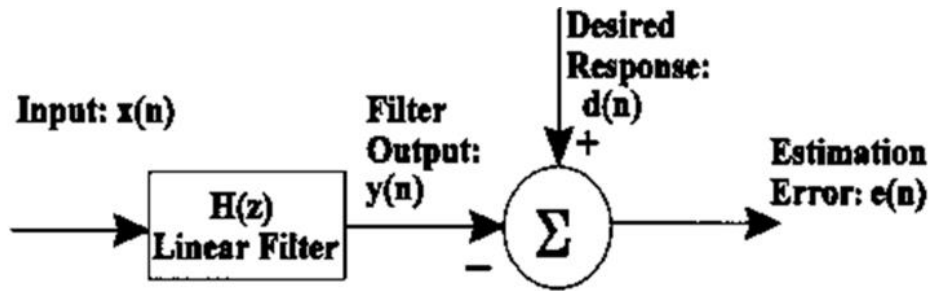


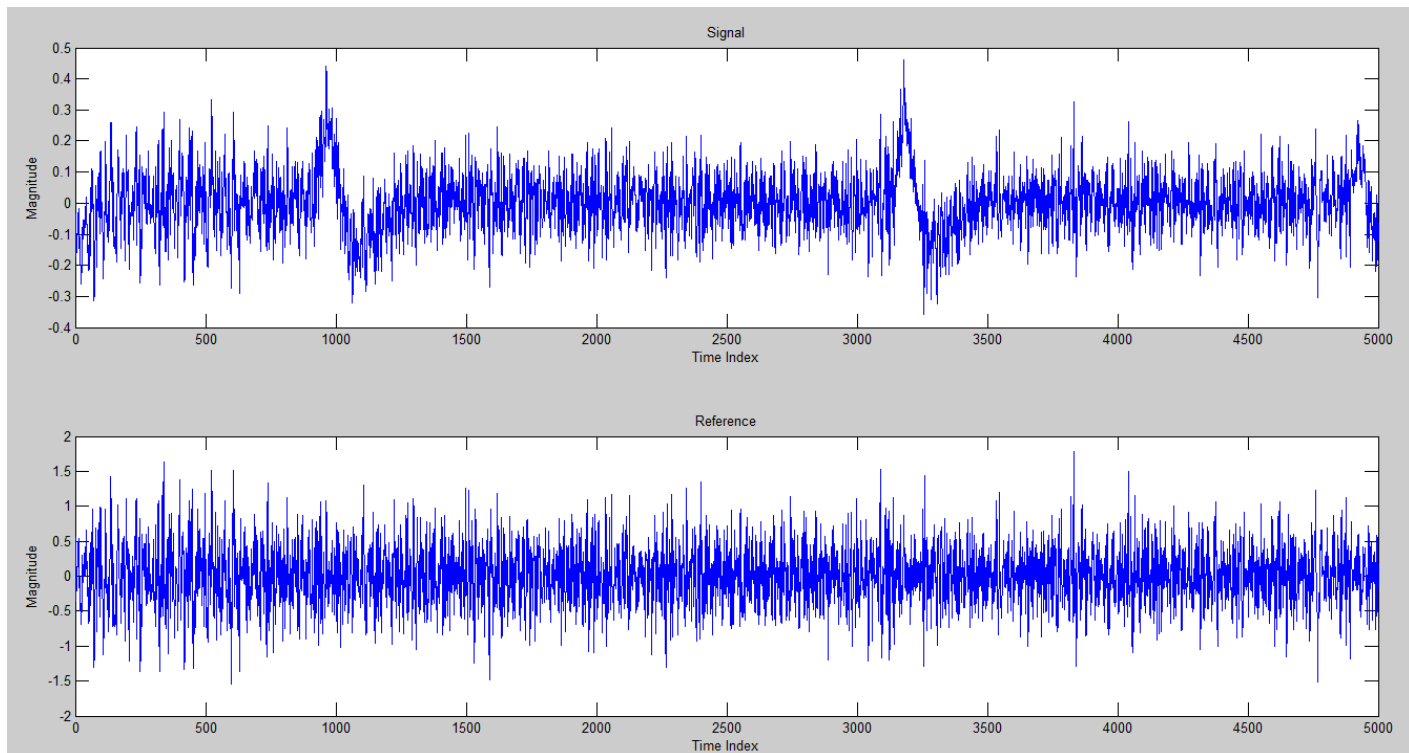
Figure 1: Wiener filter approach (source: Semmlow, Biosignal and Biomedical Image Processin: MATLAB-based Applications 2004)

The input containing both the signal and noise is acted upon by the linear filter  $H(z)$ , which has an impulse response  $h(n)$ . Then the estimation error  $e(n)$  is  $e(n) = d(n) - y(n)$ , where  $d(n)$  is the desired signal and  $y(n)$  is the filter output. MSE is calculated as:

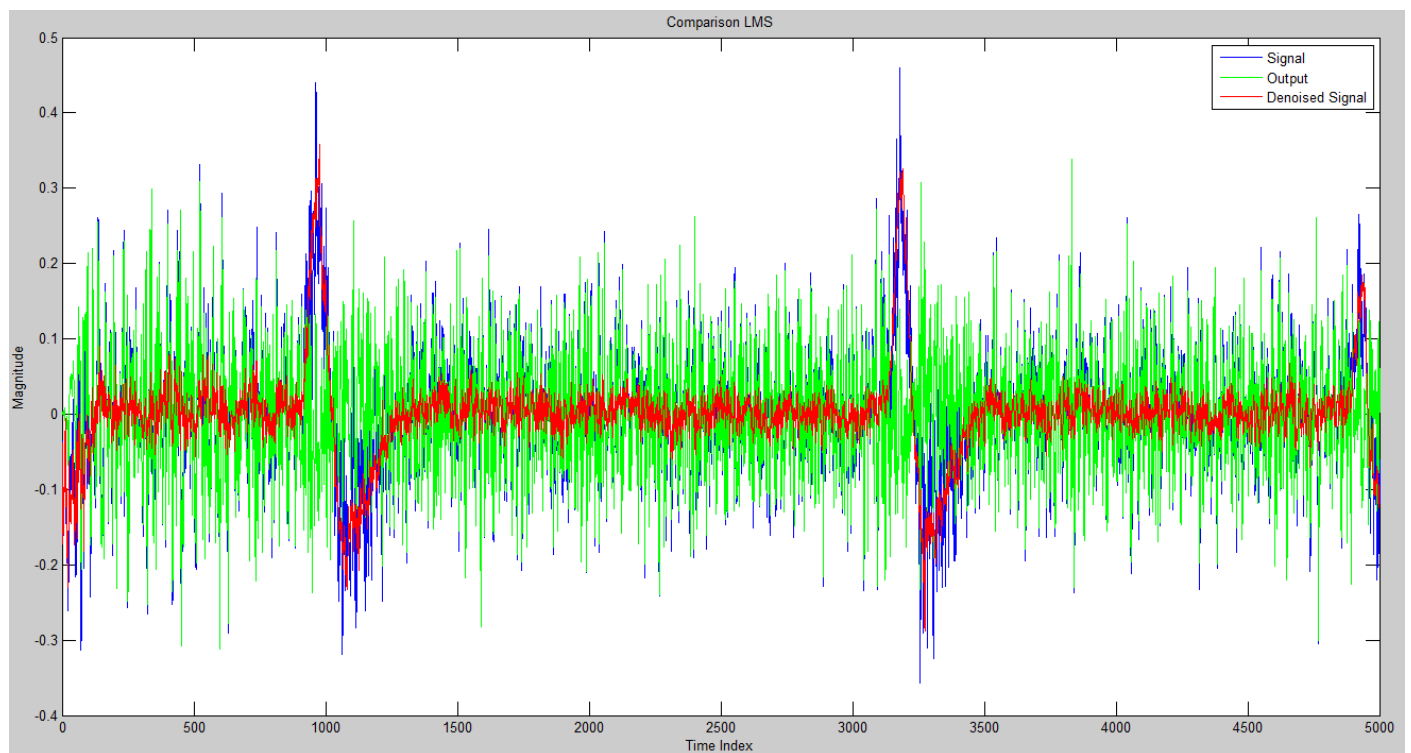
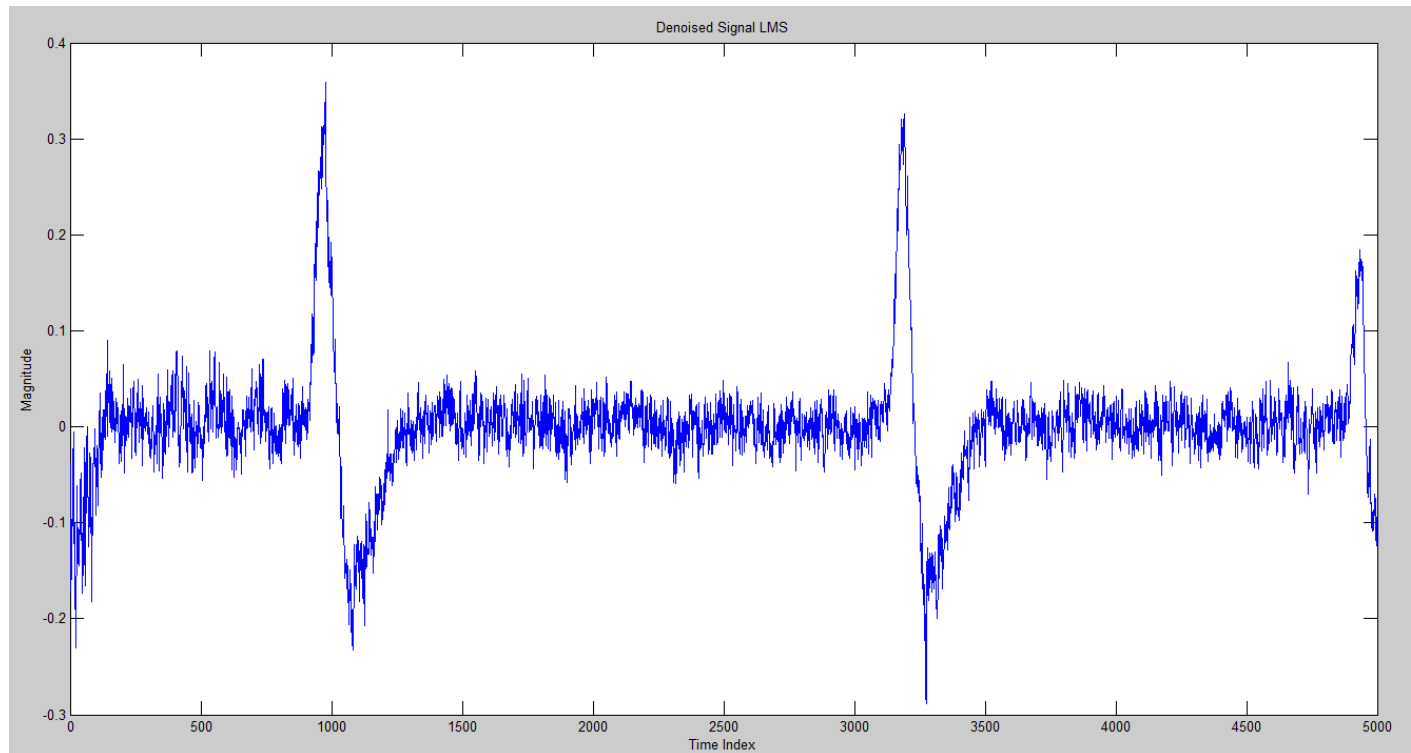
$$MSE = E\{e^2(n)\}$$

## 4. Adaptive Noise Canceller (ANC)

### i. Signal and Reference



### ii. LMS to implement ANC



iii. RLS to implement ANC

