



ELC 325B – Spring 2023 Digital Communications

Assignment #2

Submitted to

Dr. Mai

Dr. Hala

Eng. Mohamed Khaled

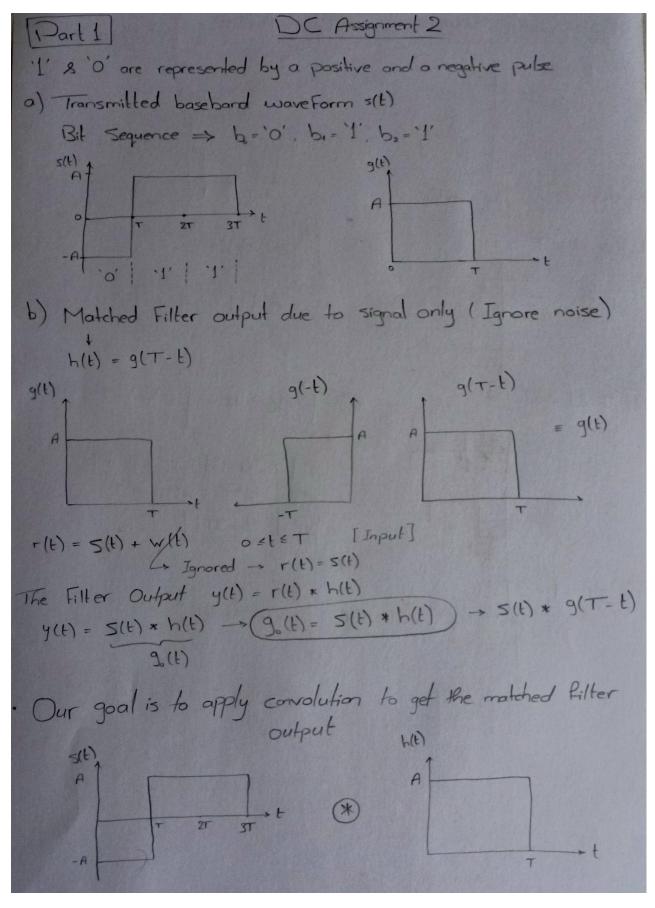
Submitted by

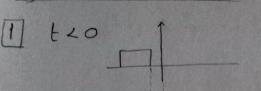
Name	Sec	BN	Code
Abdelrahman Hamdy Ahmed	1	36	9202833
Zeyad Tarek Khairy	1	28	9202588

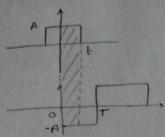
Contents

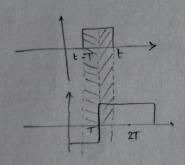
Hand Analysis for Part 1:	3
Hand Analysis for Part 2:	7
Signal:	12
Noise:	12
Noisy Signal:	13
Filter 1 Output:	14
Filter 2 Output:	15
Filter 3 Output:	15
Theoretical and Simulated BER:	16

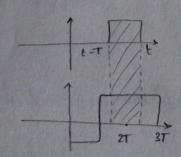
Hand Analysis - Part 1











$$y(t) = r(t) * h(t) = \int_{-\infty}^{\infty} r(t)h(t-t) dt$$

$$y(t) = \int_{0}^{t} (A)(-A) d\tau$$

$$= -A^{2}[\tau]^{t} = \overline{(-A^{2}t)}$$

$$y(t) = \int_{(A)(-A)}^{T} (A)(A) dT + \int_{(A)(A)}^{t} dT$$

$$t - T \qquad T$$

$$= -A^{2} \left[T - (t - T) \right] + A^{2} \left[t - T \right]$$

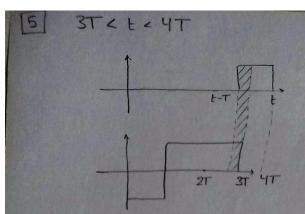
$$= A^{2} t - 2A^{2}T + A^{2}t - A^{2}T$$

$$= A^{2} \left[2t - 3T \right]$$

$$y(t) = \int_{-\infty}^{t} (A)(A) dT$$

$$t-T$$

$$= A^{2} \left[t - (t-T) \right] = A^{2} T$$

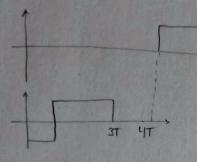


$$y(t) = \int_{(A)(A)}^{3T} (A)(A) dt + \int_{(A)(A)}^{t} (A)(A) dt$$

$$t-T \qquad 3T \rightarrow 0$$

$$y(t) = A^{2} [3T - (t-T)]$$

$$= A^{2} [4T - t]$$

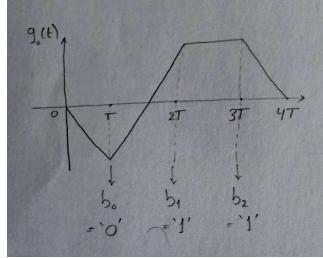


Final Output
$$\begin{cases} 0, & t < 0 \\ -A^2t, & 0 < t < T \end{cases}$$

$$y(t) = \begin{cases} A^2[2t-3T], & T \le t < 2T \\ A^2T, & 2T \le t < 3T \end{cases}$$

$$A^2[4T-t], & 3T \le t < 4T$$

$$0, & t > 4T$$

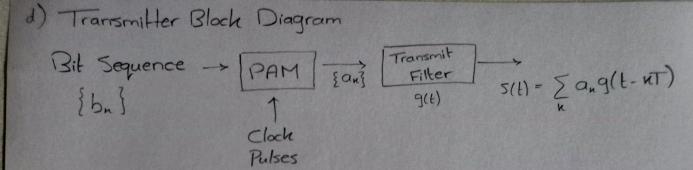


c) Mark the Sampling instants

b. @ t = T -ve Amplifude

b. @ t = 2T +ve Amplifude

b. @ t = 3T +ve Amplifude



{ bul : The input is binary bits, each of duration To

{an}: Sequence of amplitude - modulated short pulses binary PAM -> an = ±1

s(t): Sequence of pulse shaped symbols

PAM: Pulse Amplitude Modulator

e) Receiver Block Diagram

$$y(t) \rightarrow \begin{array}{c} Peceive \\ Filter \end{array} \qquad \begin{array}{c} Decision \\ Device \end{array} \longrightarrow "0" (y(t) < \lambda)$$
 $h(t)$

y(t): Output of the receiver filter. It is sampled at ti = iTb

Synchronously with the transmitter

The Decision device finally decides, based on a threshold 1, whether the sample is "1" or "0"

AWGN: Additive White

Gaussian Noise

Hand Analysis - Part 2

Part 2

Binary Source
$$\rightarrow$$
 Rise \rightarrow channel \rightarrow Peccike Sample Dark Pilter at T to h(E) 5/3.7' Shape \rightarrow h(E) 5/3.7' AWGN

Filter at T to h(E) 5/3.7' AWGN

Total channel [Impulse response \rightarrow S(t)]

Cose o) h(E) is a motohed Rifler with energy h(E) = T (t) g(t) dt

Threshold

Probability of Error if '0' was transmitted

$$P(e|o') = \frac{1}{4\pi N_{o}/T_{o}} \int_{\infty}^{\infty} \frac{(y \cdot A)^{2}}{N_{o}/T_{o}} dy$$

$$= \frac{1}{4\pi} \int_{\infty}^{\infty} e^{-\frac{y^{2}}{2}} dz \iff e^{-\frac{y}{2}} dt$$

$$= \frac{1}{4\pi} \int_{\infty}^{\infty} e^{-\frac{y^{2}}{2}} dt$$

$$= \frac{1}{4\pi} \int_{\infty}^{\infty} e^{-\frac{y^{2}}{2}} dt$$

$$= \frac{1}{4\pi} \int_{\infty}^{\infty} e^{-\frac{y^{2}}{2}} dt$$
Probability of Error if '1' was transmitted
$$P(e|v') = \frac{1}{4\pi} \int_{\infty}^{\infty} e^{-\frac{y^{2}}{2}} dt$$

$$= \frac{1}$$

Case b) h(t) is not existent (ie h(t) =
$$\delta(t)$$
)

 $y(t) = r(t) + h(t) \rightarrow y(t) = r(t) + \delta(t) = r(t)$
 $\xi(t)$
 $y(t) = r(t) + h(t) \rightarrow y(t) = r(t) + \delta(t) = r(t)$
 $\xi(t)$
 $y(t) = r(t) = g(t) + w(t) \Rightarrow y(t) = g(t) + w(t) = \pm A + w(t)$

Mean of $y(t) \rightarrow E[y(t)] = \pm A + E[y(t)] = \pm A$

Variance of $y(t) \rightarrow G^2(y(t)) = G^2(w(t)) = \frac{1}{2}$

Probability of error hollows a normal distribution

 $P(y(t)) \sim N(-A, \frac{N_2}{2})$
 $P(y(t)) \sim N(-A, \frac{N_2}{2})$
 $P(y(t)) \sim N(A, \frac{N_2}{2})$
 $P(y(t))$

Case c) h(t) has the following response A= 13 T=15 r(t) = 9(t) + w(t) The filter output -> y(t) = r(t) * h(t) $y(t) = (g(t) + \omega(t)) * h(t) = g(t) * h(t) + \omega(t) * h(t)$ $g(t) = g(t) * h(t) + \omega(t) * h(t)$ y(t) = g(t) + n(t) $g_{o}(t) = g(t) * h(t) = \int g(\tau) h(t-\tau) d\tau$ $9.(T) = \int g(\tau) h(\tau - \tau) d\tau = \pm \sqrt{3} A \int (\tau - \tau) d\tau$ $9_{o}(T) = \pm \sqrt{3} A \left[T - \frac{T^{2}}{2} \right]^{T} = \pm \sqrt{3} A \left[T^{2} - \frac{T^{2}}{2} \right] = \pm \frac{\sqrt{3}}{2} A T^{2}$ By linearity - The expectation of the random gaussian noise convolved with the Filter h(t) is Zero -> E[n(H] = 0 Variance $\rightarrow \text{Var}[n(t)] = \text{E}[n(t)^2] - \text{E}[n(t)]^2 = \text{E}[n(t)]$ $E[n(t)^2] = \int \int_{N} (y) dy \qquad n(t) = \omega(t) * h(t) \text{ Recall}$ $-5_{N}(y) = 5_{\omega}(y) |H(y)|^{2}$ $5_{\omega}(y) = \frac{N_{o}}{2} (Known)$ $E[n(T)^{2}] = \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} |H(y)|^{2} dy = \frac{\pi}{2} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} |H(y)|^{2} dy$ $= \frac{N_0}{2} \int |h(t)|^2 dt = \frac{N_0}{2} \int 3t^2 dt = \frac{N_0}{2} \left[\frac{3t^3}{3} \right]_0^{-1}$ $= \left[\frac{N_0 - 3}{2} \right] \qquad h(t) = 13t \qquad 5$

Assuming
$$P(0) = P(1) = 0.5$$

$$P(y|0) \sim N\left(\frac{-13}{2}AT^{2}, \frac{NL}{2}T^{3}\right)$$

$$P(y|1) \sim N\left(\frac{13}{2}AT^{2}, \frac{NL}{2}T^{3}\right)$$
Using the Same approach as the previous case
$$P(e|0) = P(e|1) = Q\left(\frac{\frac{13}{2}AT^{2}}{\frac{1}{2}NoT^{3}}\right)$$

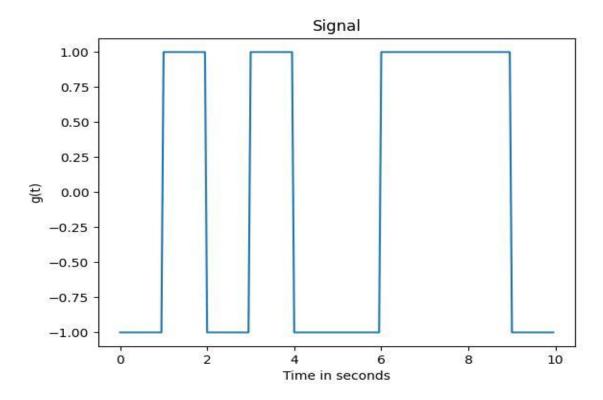
$$= Q\left(\frac{\frac{13}{2}AT^{2}}{\frac{2}{2}NoT^{3}}\right) = Q\left(\frac{\frac{13}{2}AT^{2}}{\frac{1}{2}NoT^{3}}\right)$$

$$P(e) = P(e|0)P(0) + P(e|1)P(1)$$

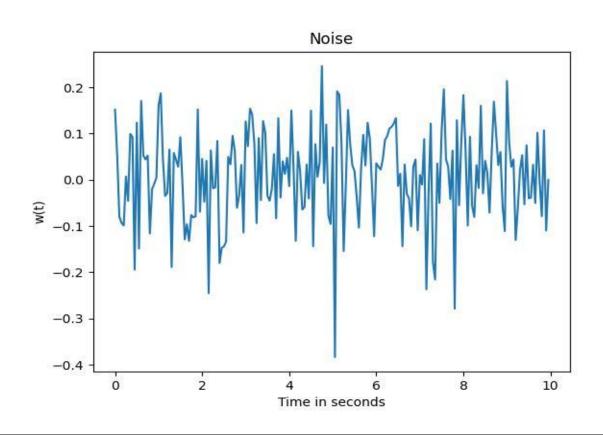
$$= Q\left(\frac{\frac{13}{2}AT^{2}}{\frac{1}{2}NoT^{3}}\right)$$

$$\Rightarrow \frac{1}{2}errc\left(\frac{\frac{13}{2}AT^{2}}{\frac{1}{2}NoT^{3}}\right) = \frac{1}{2}errc\left(\frac{\frac{13}{2}AT^{2}}{\frac{1}{2}NoT^{3}}\right)$$

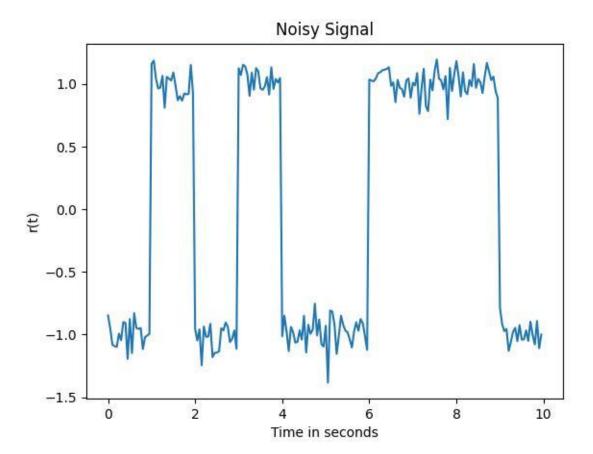
Signal



Noise



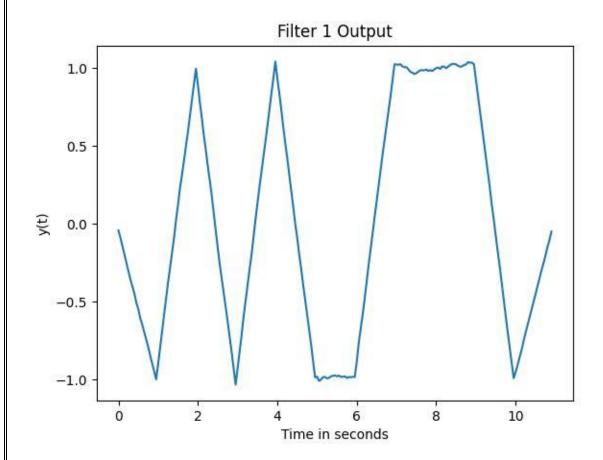
Noisy Signal



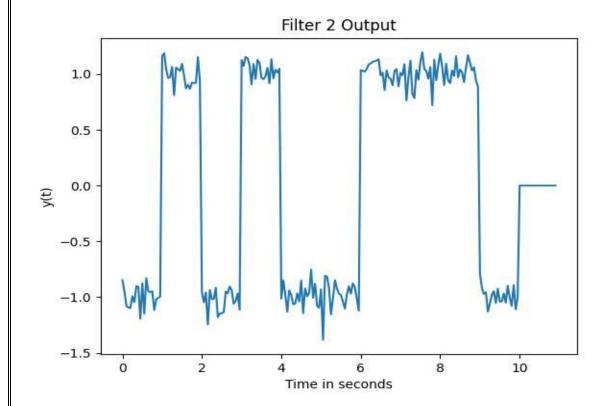
Filter outputs

Number of bits = 10 and one pulse of duration 1 has 20 samples

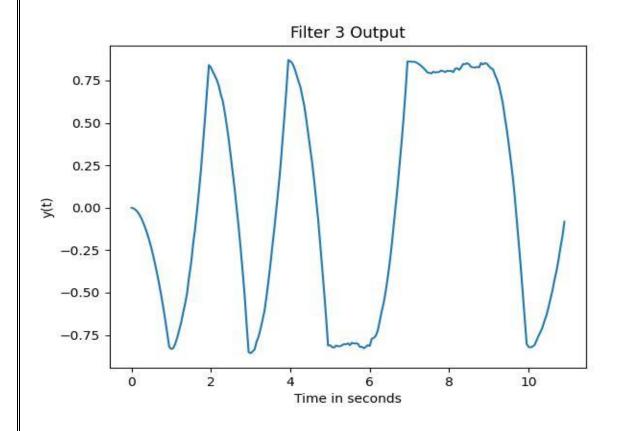
Filter 1 output



Filter 2 output



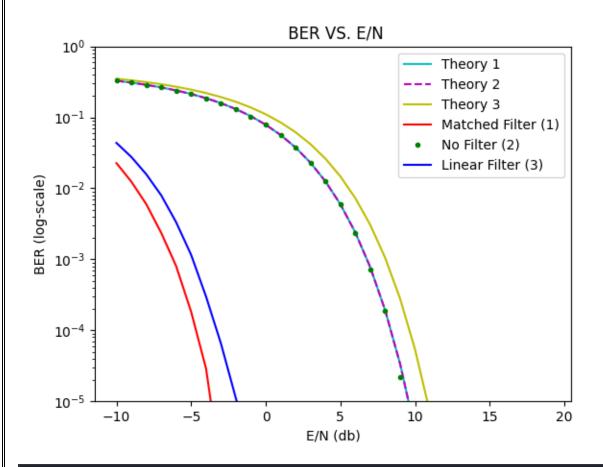
Filter 3 output



Theoretical and simulated Bit Error Rate (BER) Vs

E/No:

Number of bits = 1000000 and one pulse of duration 1 has 20 samples



The Bit Error Rate (BER) decreases as the energy per bit (E) relative to the noise power spectral density (No) increases, which is evident in the plot. This can be explained in various ways:

Using the theoretical expression for BER and noting that the Q function is a decreasing function, it is apparent that Q(a * sqrt(E/No)) for all the cases mentioned in the problem. Therefore, as sqrt is an increasing function, it can be concluded that BER is a decreasing function of E/No.

.....

The case that uses a matched filter has the lowest BER because it employs a filter that is specifically designed to minimize the probability of error by matching the filter to the pulse. By doing so, the matched filter maximizes the peak pulse SNR at the sampling instant, which helps reduce the probability of error.

It is important to note that in the theoretical case, using a filter or not yields the same expression due to our assumptions on variance and PSD.

```
import numpy as np
from math import erfc, sqrt
import matplotlib.pyplot as plt
STEP = 1.0 / 20
PERIOD = int(1 / STEP)
LAMBDA = 0 # THRESHOLD
SIGMA NOISE = 0.1
T = 1
F = 1
def draw(t, signal, xLabel, yLabel, title):
    This function plots a given signal against the
corresponding time axis, with specified labels for the x-
axis and y-axis, and a title. The plot is displayed and
saved as a JPG file using the provided title.
    plt.plot(t, signal)
    plt.xlabel(xLabel)
    plt.ylabel(yLabel)
    plt.title(title)
    plt.savefig(title + '.jpg')
    plt.show()
def sample(bitstream, signal, n):
    This function samples a given signal at a specified
interval and compares the samples with a threshold value. It
```

```
reconstructs a binary bitstream based on the sample
comparison, calculates the Bit Error Rate (BER), and returns
the reconstructed bitstream.
    samples = np.array([signal[PERIOD - 1 + i * PERIOD] for
i in range(n)])
    result = (samples > LAMBDA)
    print("Reconstructed Bitstram:", result)
    print("Total number of bits:", n)
    print("Received Wrong:", np.sum(bitstream != result))
    print("BER:", np.sum(bitstream != result) / n)
    return result
def generateSignal(bitstream):
    This function generates a signal waveform based on a
given binary bitstream using Pulse Amplitude Modulation
(PAM) with a specified pulse shape. The function applies the
pulse shape along the symbol's interval and returns the
resulting signal.
    # Pulse Amplitude Modulation (PAM)
    P = int(T / STEP)
    pulse = np.ones(P) * A
    pulseLength = len(pulse)
    inputLength = len(bitstream)
    # Generate Signal
    signal = np.zeros(inputLength * pulseLength)
    # Apply the pulse shape along the symbol's interval
    for i in range(inputLength):
```

```
signal[(i * pulseLength):((i + 1) * pulseLength)] =
pulse if bitstream[i] == 1 else pulse * -1
    return signal
def getFilters():
    This function retrieves three different filters for the
given communication system.
    Case 1: Matched Filter with unit energy.
    Case 2: Non-existent filter (delta function).
    Case 3: Filter with a specific impulse response.
    The function returns a list containing the three
filters.
    0.00
    # CASE 1
    # h(t) is a Matched Filter with unit energy
    filter1 = np.ones(int(1 / STEP))
    filterLength = len(filter1)
    W = np.zeros(int(1 / STEP) - filterLength)
    filter1 = np.concatenate((filter1, W))
    # CASE 2
    # h(t) is non-existent [h(t) = delta(t)]
    filter2 = np.ones(1)
    filterLength = len(filter2)
    W = np.zeros(int(1 / STEP) - filterLength)
    filter2 = np.concatenate((filter2, W))
    # CASE 3
    # h(t) has the following impulse response
    filter3 = np.sqrt(3) * np.arange(0, 1, STEP)
    filterLength = len(filter3)
    W = np.zeros(int(1 / STEP) - filterLength)
```

```
filter3 = np.concatenate((filter3, W))
    return [filter1, filter2, filter3]
def applyReceiveFilter(signal, filter, num):
    This function applies a receive filter to a given signal
using convolution. The resulting filtered signal is
returned. If the filter is the first or third filter, the
filtered signal is multiplied by the step size.
    # Apply Convolution (y(t) = r(t) * h(t)) where r(t) =
q(t) + w(t)
    result = np.convolve(signal, filter)
    # For the first & third filters, we'll need to multiply
by the step
   # This won't be needed for the non-existent filter
(Delta)
   if (num != 2):
        result = result * STEP
    # Return the receive filter result
    return result
# variance is the noise's variance and f is the filter's
E_N. (1 or 2 or 3)
def BER(var, q, filter, num, bitstream, n):
    This function calculates the Bit Error Rate (BER) for a
given communication system. It generates additive white
Gaussian noise (AWGN) and adds it to the signal. The signal
```

```
is then passed through a receive filter, sampled, and
compared with the original bitstream to compute the BER. The
BER value is returned.
    .....
    # Generate AWGN Noise
    signalLength = len(q)
    w = np.random.normal(0, var, signalLength)
    # Add the randomly generated noise to the signal
    r = q + w
    # Apply the receive filter
    y = applyReceiveFilter(r, filter, num)
    # Sample the output signal
    samplingOutput = sample(bitstream, y, n)
    # Compute the sampling error in the generated bitstream
& return it
    return np.sum(bitstream != samplingOutput) / n
def Q(x):
    This function returns the value of the Q function for a
given input x, which is defined as half the complementary
error function (erfc) of x divided by the square root of 2.
    .....
    return 0.5 * erfc(x / sqrt(2))
def filtersBER(filters):
    This function calculates and plots the Bit Error Rate
(BER) for different filters in a communication system. It
```

```
generates a random bitstream, generates a signal based on
the bitstream, and computes the theoretical and simulated
BERs for each filter under different E/NO values. The BER
values are plotted on a log-scale graph along with the
theoretical BER values.
    # Set the bitstream length
    n = 1000000
    # Input Bitstream
    bitstream = np.random.randint(0, 2, n)
    # Generate Signal
    signal = generateSignal(bitstream)
    # E/NO
    E_N = np.arange(-10, 20, 1)
    N = 1 / (10 ** (E_N / 10))
    # Compute the variance
    variance = np.sqrt(N / 2)
    # BER for each filter
    numberOfFilters = len(filters)
    BERs th = []
    BERs_th.append([Q(1 / var) for var in variance])
    BERs_th.append([Q(1 / var) for var in variance])
    BERs_th.append([0((np.sqrt(3)/2) * (1 / var))  for var in
variancel)
    # Plot Theoretical BER
    plt.semilogy(E_N, BERs_th[0], 'c')
    plt.semilogy(E_N, BERs_th[1], 'm--')
```

```
plt.semilogy(E_N, BERs_th[2], 'y')
    BERs = []
    for i in range(numberOfFilters):
        BERs.append([BER(var, signal, filters[i], i + 1,
bitstream, n)
                    for var in variancel)
    # Plot the Simulated BER
    plt.semilogy(E_N, BERs[0], 'r')
    plt.semilogy(E_N, BERs[1], 'g.')
    plt.semilogy(E_N, BERs[2],
                                'b')
    # Labels/Legend/YLim
    plt.xlabel('E/N (db)')
    plt.ylabel('BER (log-scale)')
    plt.title(' BER VS. E/N')
    plt.legend(['Theory 1', 'Theory 2', 'Theory 3',
               'Matched Filter (1)', 'No Filter (2)',
'Linear Filter (3)'])
    plt.ylim([10 / n, 1])
    plt.savefig('./BitErrorRate.png')
    plt.show()
def run():
    # Define n
    n = 10
    # Define the range t
    t = np.arange(0, n, STEP)
    # Generate a 1D array of random binary values
    bitstream = np.random.randint(0, 2, n)
```

```
# Generate the signal from our bitstream
    signal = generateSignal(bitstream)
    # Plot the Signal
    draw(t, signal, "Time in seconds", "g(t)", "Signal")
    # Generate random Noise (AWGN)
    # Additive White Gaussian Noise
    signalLength = len(signal)
    noise = np.random.normal(0, SIGMA_NOISE, signalLength)
    # Plot the Noise
    draw(t, noise, "Time in seconds", "w(t)", "Noise")
    # Add the random generated noise to the signal
    noisySignal = signal + noise
    # Plot the Noisy Signal
    draw(t, noisySignal, "Time in seconds", "r(t)", "Noisy
Signal")
    # Generate the receive filters for all 3 cases
   filters = getFilters()
    # Receive Filters
    result1 = applyReceiveFilter(noisySignal, filters[0], 1)
    result2 = applyReceiveFilter(noisySignal, filters[1], 2)
    result3 = applyReceiveFilter(noisySignal, filters[2], 3)
    # PLOT: CASE 1
    t = np.arange(0, len(result1) * STEP, STEP)
    draw(t, result1, "Time in seconds", "y(t)", "Filter 1
Output")
    sample(bitstream, result1, n)
```

```
# PLOT: CASE 2
    t = np.arange(0, len(result2) * STEP, STEP)
    draw(t, result2, "Time in seconds", "y(t)", "Filter 2
Output")
    sample(bitstream, result2, n)
    # PLOT: CASE 3
    t = np.arange(0, len(result3) * STEP, STEP)
    draw(t, result3, "Time in seconds", "y(t)", "Filter 3
Output")
    sample(bitstream, result3, n)
    # Compute the BER for each filter h(t)
    filtersBER(filters)
if __name__ == '__main__':
   run()
0.00
Q(5)
The Bit Error Rate (BER) decreases as the energy per bit (E)
relative to the noise power spectral density (No) increases,
which is evident in the plot. This can be explained in
various ways:
Using the theoretical expression for BER and noting that the
Q function is a decreasing function, it is apparent that Q(a
* sqrt(E/No)) for all the cases mentioned in the problem.
Therefore, as sgrt is an increasing function, it can be
concluded that BER is a decreasing function of E/No.
11 11 11
```

11 11 11

Q(6)

The case that uses a matched filter has the lowest BER because it employs a filter that is specifically designed to minimize the probability of error by matching the filter to the pulse. By doing so, the matched filter maximizes the peak pulse SNR at the sampling instant, which helps reduce the probability of error.

It is important to note that in the theoretical case, using a filter or not yields the same expression due to our assumptions on variance and PSD.

11 11 11