

# HW6 Q1 Energy of Modulated Signal

Thursday, December 04, 2014 11:11 PM

$$p(t) = g(t) \cos(2\pi f_c t + \phi) = \frac{g(t)}{2} \left( e^{j(2\pi f_c t + \phi)} + e^{-j(2\pi f_c t + \phi)} \right)$$

$\uparrow$   
 $\cos A = \frac{e^{jA} + e^{-jA}}{2}$

$$= \frac{g(t)}{2} e^{j\phi} e^{j2\pi f_c t} + \frac{g(t)}{2} e^{-j\phi} e^{-j2\pi f_c t}$$

$\downarrow \mathcal{F}$   
 $\downarrow$

$$P(f) = \frac{e^{j\phi}}{2} G(f-f_c) + \frac{e^{-j\phi}}{2} G(f+f_c)$$

$$E_p = \langle p(t), p(t) \rangle = \langle P(f), P(f) \rangle = \int_{-\infty}^{\infty} P(f) P^*(f) df$$

$$= \int_{-\infty}^{\infty} \left( \underbrace{\frac{e^{j\phi}}{2} G(f-f_c)}_A + \underbrace{\frac{e^{-j\phi}}{2} G(f+f_c)}_B \right) \left( \underbrace{\frac{e^{-j\phi}}{2} G^*(f-f_c)}_C + \underbrace{\frac{e^{j\phi}}{2} G^*(f+f_c)}_D \right) df$$

$$= \int_{-\infty}^{\infty} (A+B)(C+D) df = \int_{-\infty}^{\infty} AC df + \int_{-\infty}^{\infty} AD df + \int_{-\infty}^{\infty} BC df + \int_{-\infty}^{\infty} BD df$$

Now, note that

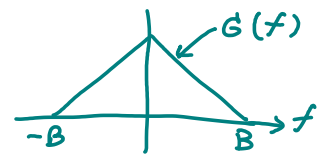
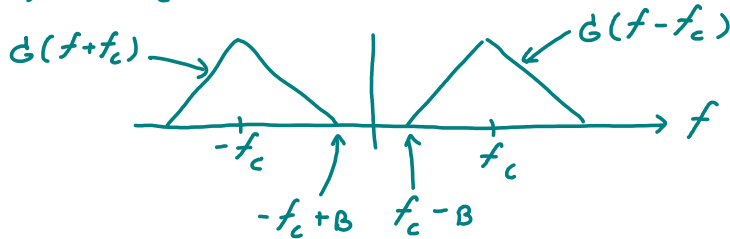
$$AC = \frac{1}{4} |G(f-f_c)|^2$$

$$BD = \frac{1}{4} |G(f+f_c)|^2$$

suppose we assume that  $G(f)$  is band-limited to  $\pm B$ , i.e.,

$$G(f) = 0 \text{ when } |f| > B.$$

Then, if  $f_c > B$ ,



the non-zero parts of  $G(f-f_c)$  and  $G(f+f_c)$  do not overlap.

Therefore,  $\left. \begin{matrix} BC \equiv 0 \\ AD \equiv 0 \end{matrix} \right\}$  across all  $f$ .

$$\text{so, } E_p = \int_{-\infty}^{\infty} \frac{1}{4} |G(f-f_c)|^2 df + 0 + 0 + \int_{-\infty}^{\infty} \frac{1}{4} |G(f+f_c)|^2 df$$

$$\begin{aligned}
 \text{so, } E_p &= \int_{-\infty}^{\infty} \frac{1}{4} |G(f-f_c)|^2 df + 0 + 0 + \int_{-\infty}^{\infty} \frac{1}{4} |G(f+f_c)|^2 df \\
 &= \int_{-\infty}^{\infty} \frac{1}{4} |G(u)|^2 du + \int_{-\infty}^{\infty} \frac{1}{4} |G(u)|^2 du \quad \begin{array}{l} \text{(change of} \\ \text{variables)} \end{array} \\
 &= \frac{1}{4} E_g + \frac{1}{4} E_g = \frac{E_g}{2}.
 \end{aligned}$$

This formula is valid when  $G(f) = 0$  for  $|f| \geq f_c$ .

# HW6 Q2: Average Symbol Energy

Thursday, December 4, 2014 11:30 PM

Recall that  $E_{\vec{s}} = \sum_{j=1}^M p_j E_j$  where  $E_j = \text{energy of } \vec{s}_j(t) = \langle \vec{s}_j(t), \vec{s}_j(t) \rangle$   
 $= \text{energy of } \vec{s}^{(j)} = \langle \vec{s}^{(j)}, \vec{s}^{(j)} \rangle$

There are three possible  $\vec{s}$   
 $\hookrightarrow \vec{s}^{(1)}, \vec{s}^{(2)}, \vec{s}^{(3)}$

Here,  $M = 3$  and  $K = 1$ .

$\vec{s}$  is one-dimensional  
(a scalar)

$$= \sum_{i=1}^K |\underline{s}_i^{(j)}|^2$$

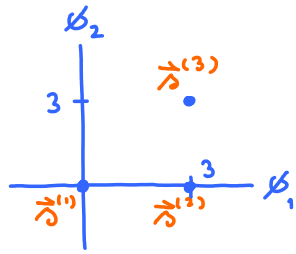
↑  
the  $i^{\text{th}}$  element  
in vector  $\vec{s}^{(j)}$

$$\text{so, } E_j = |\vec{s}^{(j)}|^2 \quad \text{and} \quad E_s = \sum_{j=1}^3 p_j |\vec{s}^{(j)}|^2$$
$$= 0.41 \times (-1)^2 + 0.08 \times (1)^2 + 0.51 \times 4^2 = 8.65$$

# HW6 Q3: Minimum Energy for Constellation

Thursday, September 05, 2013 3:31 PM

(a)



$$\vec{d}^{(1)} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\vec{d}^{(2)} = \begin{pmatrix} 3 \\ 0 \end{pmatrix}$$

$$\vec{d}^{(3)} = \begin{pmatrix} 0 \\ 3 \end{pmatrix}$$

$$E_s = \frac{1}{3} (0^2 + 3^2 + 3^2 + 3^2) = 9$$

\* dimensions. Here,  $K = 2$ .

$$(b) E_s = \sum_{j=1}^M p_j E_j = \sum_{j=1}^M p_j \sum_{i=1}^K |\vec{d}_i^{(j)}|^2 = \sum_{i=1}^K \sum_{j=1}^M p_j |\vec{d}_i^{(j)}|^2$$

energy of  $\vec{d}^{(j)}$   
probability of  $\vec{d}^{(j)}$   
the  $i$ <sup>th</sup> element in the vector  $\vec{d}^{(j)}$

$$= \frac{1}{3} \left( (0-a_1)^2 + (2-a_1)^2 + (2-a_1)^2 \right) + \frac{1}{3} \left( (0-a_2)^2 + (0-a_2)^2 + (2-a_2)^2 \right)$$

In general, we have to minimize terms of the form  $\sum_{j=1}^M p_j (x_j - a)^2$ .

Method 1:

$$\sum_{j=1}^M p_j (x_j - a)^2 = \mathbb{E}[(X - a)^2] = \mathbb{E}[(X - \underbrace{\mathbb{E}X}_0 + \mathbb{E}X - a)^2]$$

$$= \text{Var} X + 2 \mathbb{E}[(X - \mathbb{E}X)] (\mathbb{E}X - a) + (\mathbb{E}X - a)^2$$

$$= \text{Var} X + \underbrace{(\mathbb{E}X - a)^2}$$

This is the only term that depends on  $a$ .  
Minimum value of 0 is achieved when  $a = \mathbb{E}X$ .

Method 2:

$$\sum_{j=1}^M p_j (x_j - a)^2 = \sum_{j=1}^M p_j (x_j^2 - 2ax_j + a^2) = a^2 - 2a \mathbb{E}X + \mathbb{E}[x^2]$$

As a function of " $a$ ", this is a parabola with minimum at  $a = \mathbb{E}X$ .

$$a = \mathbb{E}X.$$

set  $\frac{d}{da}(\ ) = 0$ . Then solve for  $a$ .

Method 3:

$$\frac{d}{da} \sum_{j=1}^M p_j (x_j - a)^2 = \sum_{j=1}^M p_j 2(x_j - a) = 2(\mathbb{E}X - a)$$

The derivative above is 0 when  $a = \mathbb{E}X$ .

So, the minimum value occurs when  $a = \mathbb{E}X = \sum_i p_i x_i$

Minimum  $E_s$  occurs when

$$a_1 = \frac{1}{3}(0+3+3) = 2$$

The first elements  
in the vectors.

$$a_2 = \frac{1}{3}(0+0+3) = 1.$$

The second elements  
in the vectors.

HW6 Q4: 1-D MAP Detector and Uniform Noise

Monday, July 15, 2013 1:33 PM

Recall that the uniform pdf on  $[a, b]$  is given by

$$f_N(n) = \begin{cases} \frac{1}{b-a}, & a < n < b, \\ 0, & \text{otherwise.} \end{cases}$$

Here,  $a=4$  and  $b=-4$ . So,  $f_N(n) = \begin{cases} 1/8, & -4 < n < 4, \\ 0, & \text{otherwise.} \end{cases}$

(a) Again, the MAP detector is given by

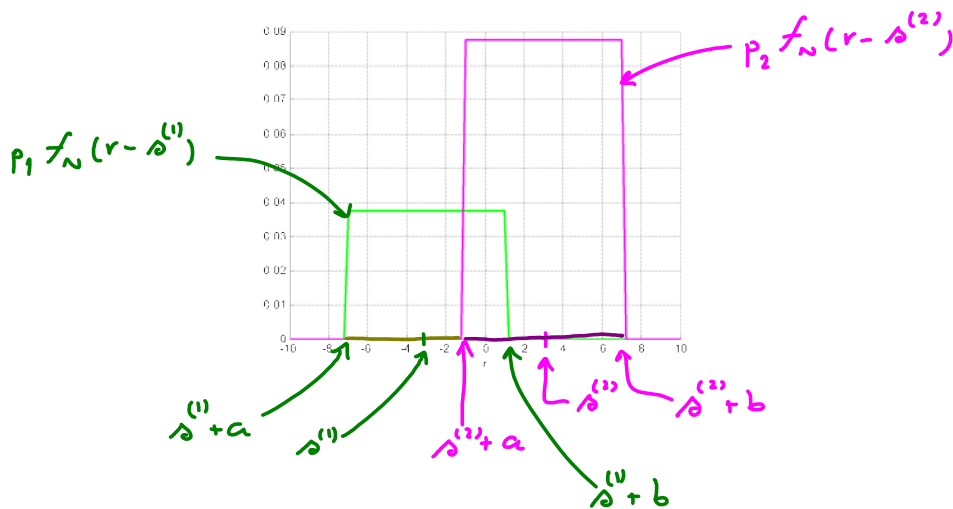
$$\hat{s}_{MAP}(r) = \arg \max_s p_s f_N(r-s).$$

This is true regardless of the pdf of the noise

Here, there are two possible values for  $s$ .

So we compare  $p_1 f_N(r-s^{(1)})$  and  $p_2 f_N(r-s^{(2)})$

$\uparrow$                        $\uparrow$                        $\uparrow$                        $\uparrow$   
 $0.3$                        $-3$                        $0.7$                        $3$



Observe that

① When  $s^{(1)}+a < r < s^{(2)}+a$ ,  $p_1 f_N(r-s^{(1)}) > p_2 f_N(r-s^{(2)})$ .

Therefore,  $\hat{s}_{MAP}(r) = s^{(1)}$  in this region.

② When  $s^{(1)}+a < r < s^{(2)}+b$ ,  $p_1 f_N(r-s^{(1)}) < p_2 f_N(r-s^{(2)})$ .

Therefore,  $\hat{\Delta}_{MAP}(r) = \Delta^{(2)}$  in this region.

③ When  $r < \Delta^{(1)} + a$  or  $r > \Delta^{(2)} + b$ , the pdf in both cases are 0. So, these are the impossible regions. The received signal  $R$  won't fall in these regions. Therefore, it does not matter how the detector behaves in this region.

$$\text{Conclusion: } \hat{\Delta}_{MAP}(r) = \begin{cases} \Delta^{(1)}, & \Delta^{(1)} + a < r < \Delta^{(2)} + a, \\ \Delta^{(2)}, & \Delta^{(2)} + a < r < \Delta^{(2)} + b, \\ \text{anything,} & \text{otherwise} \end{cases}$$

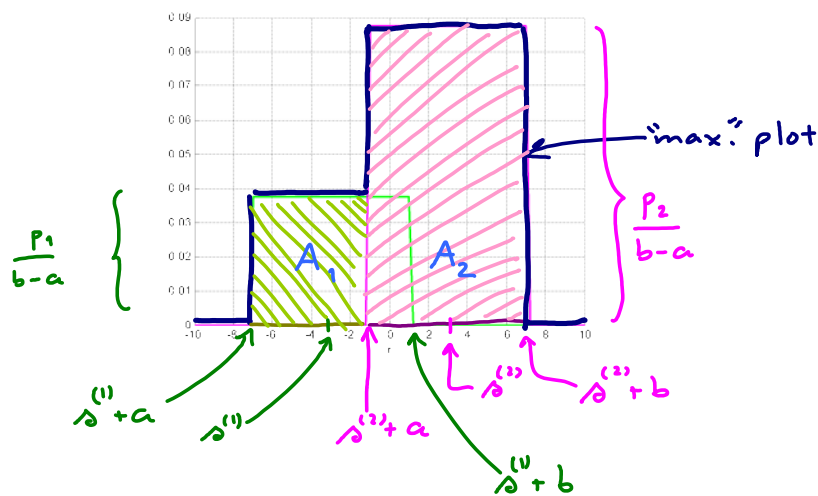
Note that at  $r = \Delta^{(1)} + a, \Delta^{(2)} + a, \Delta^{(2)} + b$  (the boundaries), the comparison of  $p_1 f_N(r - \Delta^{(1)})$  and  $p_2 f_N(r - \Delta^{(2)})$  depends on how the pdf of noise is defined at its boundaries. However, the probability that the received signal  $R$  will be exactly any one of these three points is zero. Therefore, we can define  $\hat{\Delta}_{MAP}(r)$  to be anything here.

To further simplify the expression, we choose the "anything" parts above in a way that they can be combined into adjacent intervals. This gives

$$\hat{\Delta}_{MAP}(r) = \begin{cases} \Delta^{(1)}, & r < \Delta^{(2)} + a \\ \Delta^{(2)}, & r \geq \Delta^{(2)} + a \end{cases} = \begin{cases} -3, & r < -1 \\ 3, & r \geq -1 \end{cases}$$

$\tau^* = \Delta^{(2)} + a$   
 $= 3 + (-4)$   
 $= -1$

(b) Recall that for MAP detector,  $P(C) = \text{area under the "max." plot}$ .



$$\text{Area } A_2 = \frac{p_1}{b-a} \times ((\Delta^{(2)} + a) - (\Delta^{(1)} + a)) = \frac{p_1}{b-a} (\Delta^{(2)} - \Delta^{(1)})$$

NOTO

$$\text{Area } A_1 = \frac{p_1}{b-a} \times ((s^{(2)}+a) - (s^{(1)}+a)) = \frac{p_1}{b-a} (s^{(2)} - s^{(1)})$$

$$\text{Area } A_2 = \frac{p_2}{b-a} \times ((s^{(2)}+b) - (s^{(1)}+a)) = p_2$$

$$\text{So, } P(C) = \frac{p_1}{b-a} (s^{(2)} - s^{(1)}) + p_2.$$

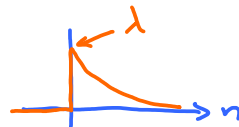
$$\begin{aligned} \text{Therefore, } P(E) &= 1 - P(C) = p_1 - \frac{p_1}{b-a} (s^{(2)} - s^{(1)}) = p_1 \left( 1 - \frac{s^{(2)} - s^{(1)}}{b-a} \right) \\ &= 0.3 \left( 1 + \frac{3 - (-3)}{4 - (-4)} \right) = 0.3 \left( 1 - \frac{3}{4} \right) = 0.3 \times \frac{1}{4} = 0.075 \end{aligned}$$

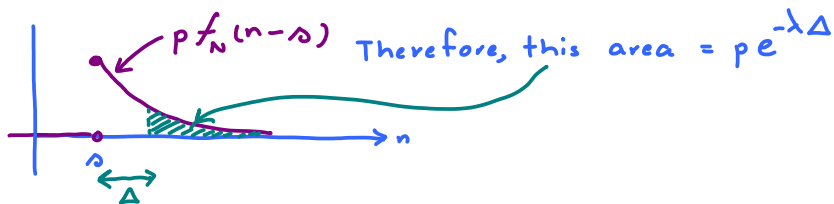


# HW6 Q5: 1-D MAP Detector and Exponential Noise

Monday, July 15, 2013 10:58 AM

Some facts about exponential noise:

- ①  $f_N(n) = \begin{cases} \lambda e^{-\lambda n}, & n \geq 0, \\ 0, & \text{otherwise.} \end{cases}$  
- ②  $E[N] = \frac{1}{\lambda}$  and  $\text{Var} N = \frac{1}{\lambda^2}$
- ③ MATLAB use  $E[N]$  as the parameter instead of  $\lambda$
- ④  $P[N > n] = \int_n^{\infty} f_N(n) dn = \begin{cases} e^{-\lambda n}, & n \geq 0 \\ 1, & n < 0 \end{cases}$

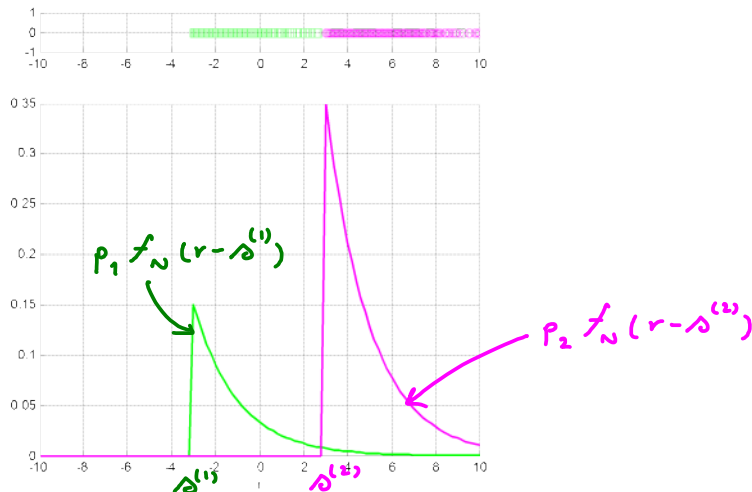


In this question,  $\lambda = \frac{1}{2}$  and  $E[N] = \frac{1}{\lambda} = 2$ .

(a) MAP Detector: Recall that  $\hat{\Delta}_{MAP}(r) = \arg \max_{\Delta} P_{\Delta} f_N(r - \Delta)$   
 This is true regardless of the pdf of the noise

Here, there are two possible values for  $\Delta$ .

So we compare  $P_1 f_N(r - \Delta^{(1)})$  and  $P_2 f_N(r - \Delta^{(2)})$   
 $\uparrow \quad \quad \quad \uparrow \quad \quad \quad \uparrow \quad \quad \quad \uparrow$   
 0.3  $\quad \quad \quad$  -3  $\quad \quad \quad$  0.7  $\quad \quad \quad$  3



From the graph, it is clear that

①  $R < \delta^{(1)}$  is impossible. So, the detector can do anything in this region without affecting its performance.

② When  $\delta^{(1)} < r < \delta^{(2)}$ ,  $p_1 f_N(r - \delta^{(1)}) > p_2 f_N(r - \delta^{(2)})$ .  
So, in this region,  $\hat{\delta}_{MAP}(r) = \delta^{(1)}$ .

③ When  $r > \delta^{(2)}$ ,  $p_1 f_N(r - \delta^{(1)}) < p_2 f_N(r - \delta^{(2)})$ .  
So, in this region,  $\hat{\delta}_{MAP}(r) = \delta^{(2)}$ .

Conclusion:

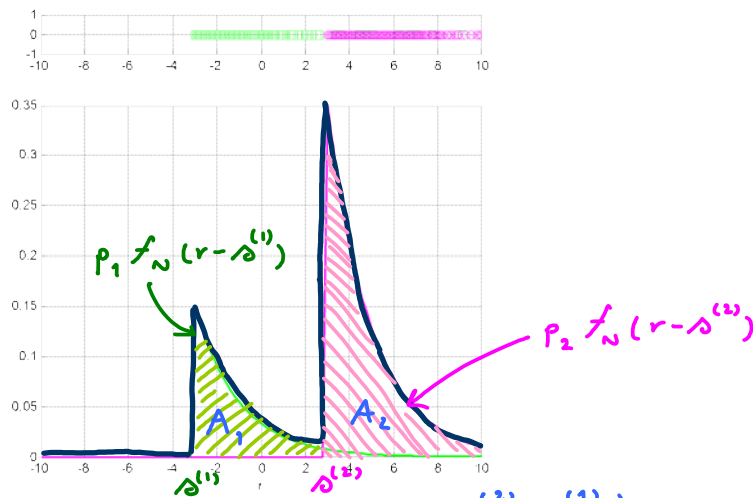
$$\hat{\delta}_{MAP}(r) = \begin{cases} \delta^{(1)}, & \delta^{(1)} < r < \delta^{(2)}, \\ \delta^{(2)}, & r > \delta^{(2)}, \\ \text{anything, otherwise} & \end{cases} = \begin{cases} \delta^{(1)}, & r < \delta^{(2)} \\ \delta^{(2)}, & r \geq \delta^{(2)} \end{cases}$$

↑  
Simplification

$$= \begin{cases} -3, & r < 3 \\ 3, & r \geq 3 \end{cases}$$

$\delta^{(2)} = 3$

(b) Recall that for MAP detector,  $P(C) = \text{area under the "max." plot.}$



$$\text{Area } A_1 = p_1 - p_1 e^{-\lambda(\delta^{(2)} - \delta^{(1)})}$$

$$\text{Area } A_2 = p_2$$

$$\text{So, } P(C) = 1 - p_1 e^{-\lambda(\delta^{(2)} - \delta^{(1)})} \text{ and}$$

$$P(E) = 1 - P(C) = p_1 e^{-\lambda(\delta^{(2)} - \delta^{(1)})} = 0.3 e^{-\frac{1}{2}(3 - (-3))}$$

$$= 0.3 e^{-3} \approx 0.0149$$