2012 Fall: The Final Exam

1. (Chapter 11)

(a) (6%) There are two kinds of convolutions in literature:

$$\begin{cases} \text{linear convolution} & x_k \star I_k = \sum_{n=0}^{P-1} x_n \cdot I_{k-n} \\ N\text{-point circular convolution} & x_k \otimes I_k = \sum_{n=0}^{P-1} x_{n \, \text{mod} \, N} \cdot I_{(k-n) \, \text{mod} \, N} = \sum_{n=0}^{P-1} x_n \cdot I_{(k-n) \, \text{mod} \, N} \end{cases}$$

where $\{x_n\}$ is a discrete causal filter satisfying that $x_n \neq 0$ only at $0 \leq n \leq P-1$, and "mod" stands for modulo operation. Denote

$$y_k = x_k \star I_k$$
 and $\tilde{y}_k = x_k \otimes I_k$

for $k=0,1,\ldots,N-1$. Is $y_k=\tilde{y}_k$ for every $k=0,1,\ldots,N-1$? Construct a counterexample if the answer is negative.

Hint: You may wish to compare the two convolutions at small N and P such as N=2 and P=2.

(b) (6%) Follow (a) and suppose N=5 and P=3. For a block of data sequence of size N (i.e., I_0, I_1, \ldots, I_4), the cycle prefix (CP) technique will prefix the sequence with $I_{-P}, I_{-P+1}, \ldots, I_{-1}$ satisfying that

$$I_{-P} = I_{N-P}, \quad I_{-P+1} = I_{N-P+1}, \dots, I_{-1} = I_{N-1}.$$
 (1)

Show that for unknown (or varying) $\{x_n\}_{n=1}^{P-1}$, the condition $y_k = \tilde{y}_k$ for every $k = 0, 1, \dots, N-1$ holds if, and only if, CP condition (1) holds.

Hint: For unknowns $x_0, x_1, \ldots, x_{P-1}$, the linear equations below are solvable for non-zeros unknowns if, and only if, $a_1 = a_2 = \cdots = a_{P-1} = 0$.

$$\begin{cases} x_1 \cdot a_1 + x_2 \cdot a_2 + x_3 \cdot a_3 + \dots + x_{P-1} \cdot a_{P-1} = 0 \\ x_2 \cdot a_1 + x_3 \cdot a_2 + \dots + x_{P-1} \cdot a_{P-2} = 0 \\ \vdots \\ x_{P-2} \cdot a_1 + x_{P-1} \cdot a_2 = 0 \\ x_{P-1} \cdot a_1 = 0 \end{cases}$$

Note: The statement in (b) holds actually for any N and P with N > P. Thus, CP is the one and only technique that can guarantee $y_k = \tilde{y}_k$ for every k = 0, 1, ..., N - 1. However, to lower your load, I only demand the proof for a specific case of N = 5 and P = 3.

(c) (6%) Under N > P and based on the discrete Fourier transform (DFT) pair given below,

$$\begin{cases}
DFT & X_k = \sum_{m=0}^{N-1} x_m e^{-i2\pi \frac{mk}{N}} \quad k = 0, 1, \dots, N-1 \\
iDFT & x_m = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{i2\pi \frac{mk}{N}} \quad m = 0, 1, \dots, N-1
\end{cases}$$
(2)

prove that $\tilde{y}_k = x_k \otimes I_k$ for k = 0, 1, ..., N - 1 implies $\tilde{Y}_k = X_k \cdot \mathfrak{I}_k$ for k = 0, 1, ..., N - 1, where $Y_k = \text{DFT}\{y_k\}$, $X_k = \text{DFT}\{x_k\}$ and $\mathfrak{I}_k = \text{DFT}\{I_k\}$.

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Hint: Perform

$$\begin{split} \tilde{Y}_k &= \sum_{m=0}^{N-1} \tilde{y}_m e^{-\imath 2\pi \frac{mk}{N}} \\ &= \sum_{m=0}^{N-1} \left(\sum_{n=0}^{P-1} x_n \cdot I_{(m-n) \bmod N} \right) e^{-\imath 2\pi \frac{mk}{N}} \\ &= \sum_{n=0}^{P-1} x_n \sum_{m=0}^{N-1} I_{(m-n) \bmod N} e^{-\imath 2\pi \frac{mk}{N}} \end{split}$$

and remove the modulo index by performing

$$\sum_{m=0}^{N-1} I_{(m-n) \bmod N} e^{-\imath 2\pi \frac{mk}{N}} = \sum_{m=0}^{n-1} I_{(m-n) \bmod N} e^{-\imath 2\pi \frac{mk}{N}} + \sum_{m=n}^{N-1} I_{(m-n) \bmod N} e^{-\imath 2\pi \frac{mk}{N}}.$$

(d) (6%) Follow (c). Is $y_k = x_k \star I_k$ implying $Y_k = X_k \cdot \mathfrak{I}_k$? Construct a counterexample if the answer is negative.

Hint: Think of why we need to introduce CP! Also consider the case that $y_k \neq \tilde{y}_k$ in (a).

Solutions.

(a) Let N=2 and P=2. Then, we have

$$\begin{cases} \text{linear convolution} & y_k = x_0 \cdot I_k + x_1 \cdot I_{k-1} \\ \text{circular convolution} & \tilde{y}_k = x_0 \cdot I_{k \, \text{mod} \, 2} + x_1 \cdot I_{(k-1) \, \text{mod} \, 2} \end{cases}$$

Hence,

$$\begin{cases} y_0 = x_0 \cdot I_0 + x_1 \cdot I_{-1} & \text{and} & y_1 = x_0 \cdot I_1 + x_1 \cdot I_0 \\ \tilde{y}_0 = x_0 \cdot I_0 + x_1 \cdot I_1 & \text{and} & \tilde{y}_1 = x_0 \cdot I_1 + x_1 \cdot I_0 \end{cases}$$

which implies that if $I_0 \neq I_{-1}$, then $y_0 \neq \tilde{y}_0$.

(b) $\begin{cases} \text{linear convolution} & y_k = x_0 \cdot I_k + x_1 \cdot I_{k-1} + x_2 \cdot I_{k-2} \\ \text{circular convolution} & \tilde{y}_k = x_0 \cdot I_{k \, \text{mod} \, 5} + x_1 \cdot I_{(k-1) \, \text{mod} \, 5} + x_2 \cdot I_{(k-2) \, \text{mod} \, 5} \end{cases}$

Hence, for $2 \le k \le 4$, $y_k = \tilde{y}_k$ is always valid. So we only need to consider the cases for $0 \le k \le 1$, which gives

$$\begin{cases} y_0 = x_0 \cdot I_0 + x_1 \cdot I_{-1} + x_2 \cdot I_{-2} = x_0 \cdot I_0 + x_1 \cdot I_4 + x_2 \cdot I_3 = \tilde{y}_0 \\ y_1 = x_0 \cdot I_1 + x_1 \cdot I_0 + x_2 \cdot I_{-1} = x_0 \cdot I_1 + x_1 \cdot I_0 + x_2 \cdot I_4 = \tilde{y}_1 \end{cases}$$

We then obtain

$$\begin{cases} x_1 \cdot (I_{-1} - I_4) + x_2 \cdot (I_{-2} - I_3) = 0 \\ x_2 \cdot (I_{-1} - I_4) = 0 \end{cases}$$

By treating $\{x_n\}$ as unknowns, these equations are solvable for non-zero $\{x_n\}$ if, and only if.

$$I_{-2} = I_3$$
 and $I_{-1} = I_4$.

(c)

$$\begin{split} \tilde{Y}_{k} &= \sum_{m=0}^{N-1} \tilde{y}_{m} e^{-i2\pi \frac{mk}{N}} \\ &= \sum_{m=0}^{N-1} \left(\sum_{n=0}^{P-1} x_{n} \cdot I_{(m-n) \bmod N} \right) e^{-i2\pi \frac{mk}{N}} \\ &= \sum_{n=0}^{P-1} x_{n} \sum_{m=0}^{N-1} I_{(m-n) \bmod N} e^{-i2\pi \frac{mk}{N}} \\ &= \sum_{n=0}^{P-1} x_{n} \left(\sum_{m=0}^{n-1} I_{m-n+N} e^{-i2\pi \frac{mk}{N}} + \sum_{m=n}^{N-1} I_{m-n} e^{-i2\pi \frac{mk}{N}} \right) \\ &= \sum_{n=0}^{P-1} x_{n} \left(\sum_{\ell'=N-n}^{N-1} I_{\ell'} e^{-i2\pi \frac{(\ell'+n-N)k}{N}} + \sum_{\ell=0}^{N-1-n} I_{\ell} e^{-i2\pi \frac{(\ell+n)k}{N}} \right) \\ &= \left(\sum_{n=0}^{P-1} x_{n} e^{-i2\pi \frac{nk}{N}} \right) \left(\sum_{\ell=0}^{N-1} I_{\ell} e^{-i2\pi \frac{\ell k}{N}} \right) \\ &= \left(\sum_{n=0}^{N-1} x_{n} e^{-i2\pi \frac{nk}{N}} \right) \left(\sum_{\ell=0}^{N-1} I_{\ell} e^{-i2\pi \frac{\ell k}{N}} \right) \\ &= X_{k} \cdot I_{k} \end{split}$$

(d) Since DFT and iDFT are duality operations, subproblem (c) indicates that $\tilde{y}_k = x_k \otimes I_k$ for k = 0, 1, ..., N-1 if, and only if, $\tilde{Y}_k = X_k \cdot \mathfrak{I}_k$ for k = 0, 1, ..., N-1. Together with subproblem (a), one can infer that $\tilde{y}_k = y_k$ for k = 0, 1, ..., N-1 may not be true; so the answer to this question should be negative.

As for the counterexample, take N=2 and P=2. Also take $x_0=x_1=I_0=I_1=1$ but $I_{-1}=-1$. Then

$$\begin{cases} y_0 = x_0 \cdot I_0 + x_1 \cdot I_{-1} = 0 \\ y_1 = x_0 \cdot I_1 + x_1 \cdot I_0 = 2 \end{cases}$$

$$\begin{cases} I_0 = 1 \\ I_1 = 1 \end{cases}$$

$$Y_0 = \sum_{m=0}^{1} y_m = 2$$

$$Y_1 = \sum_{m=0}^{1} y_m e^{-i2\pi \frac{m}{2}} = 2e^{-i\pi} = -2 \end{cases}$$

$$\begin{cases} I_0 = 1 \\ I_1 = 1 \end{cases}$$

$$\Im_0 = \sum_{m=0}^{1} I_m = 2$$

$$\Im_1 = \sum_{m=0}^{1} I_m e^{-i2\pi \frac{m}{2}} = 1 + e^{-i\pi} = 0$$

and

$$\begin{cases} x_0 = 1 \\ x_1 = 1 \\ X_0 = \sum_{m=0}^{1} x_m = 2 \\ X_1 = \sum_{m=0}^{1} x_m e^{-i2\pi \frac{m}{2}} = 1 + e^{-i\pi} = 0 \end{cases}$$

So

$$2 = Y_0 \neq X_0 \cdot \mathfrak{I}_0 = 4$$
 and $-2 = Y_1 \neq X_1 \cdot \mathfrak{I}_1 = 0$.

(Note that if we change I_{-1} to 1. Then, Y_0 and Y_1 become 4 and 0, respectively; so the statement in (c) can be applied!)

2. (Chapter 11)

(a) (6%) An OFDM (baseband) signal can be formulated as

$$s_{\ell}(t) = \sum_{n=-\infty}^{\infty} \left(\sum_{k=0}^{Q-1} X_{k,n} e^{i2\pi \frac{k}{T}t} \right) g(t - nT)$$

where $\{X_{k,n}\}$ are random in nature. If $\{X_{k,n}\}$ are zero-mean i.i.d. both in k and n, then its autocorrelation can be computed as:

$$R_{s_{\ell}}(t+\tau,t) = \mathbb{E}\left[\left(\sum_{n=-\infty}^{\infty} \sum_{k=0}^{Q-1} X_{k,n} g(t+\tau-nT) e^{i2\pi \frac{k}{T}(t+\tau)}\right) \left(\sum_{m=-\infty}^{\infty} \sum_{j=0}^{Q-1} X_{j,m}^* g^*(t-mT) e^{-i2\pi \frac{j}{T}t}\right)\right]$$

$$= \sigma^2 \sum_{k=0}^{Q-1} e^{i2\pi \frac{k}{T}\tau} \sum_{n=-\infty}^{\infty} g(t+\tau-nT) g^*(t-nT)$$

where σ^2 is the variance of $X_{k,n}$. Now if $\{X_{k,n}\}$ remains i.i.d. both in k and n but are with a (complex-valued) mean μ (i.e., $\mathbb{E}[X_{k,n}] = \mu$) and variance σ^2 , what will its autocorrelation become?

(b) (6%) Follow (a). Find the time-average autocorrelation function of $s_{\ell}(t)$ at $\mu = 0$, and prove that the time-average power spectrum density is

$$\bar{S}_{s_{\ell}}(f) = \frac{\sigma^2}{T} \sum_{k=0}^{Q-1} \left| G\left(f - \frac{k}{T}\right) \right|^2.$$

(c) (6%) Follow (a). If

$$x_{\ell,n} = \frac{1}{N} \sum_{k=0}^{Q-1} X_{k,n} e^{i2\pi \frac{\ell k}{N}} \quad \ell = 0, 1, \dots, N-1$$

and N > Q, prove that

$$s_{\ell}(t) = \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - \ell/N))} e^{i\pi (t(N-1)/T + \ell/N)} g(t - nT)$$

Hint: Re-express $\{X_{k,n}\}$ in terms of $\{x_{\ell,n}\}$ using iDFT formula in (2).

(d) (6%) Continue from (d). What will be the value of $s_{\ell}(mT/N)$, where $0 \le m \le N-1$, if $g(t) = \begin{cases} 1, & 0 \le t < T \\ 0, & \text{otherwise} \end{cases}$?

Hint: $\lim_{t \uparrow \frac{m}{N}T} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - \ell/N))} e^{i\pi (t(N-1)/T + \ell/N)} = 0$ for $\ell \neq m$.

Solutions.

(a)

$$\begin{split} R_{s_{\ell}}(t+\tau,t) &= \mathbb{E}\left[\left(\sum_{n=-\infty}^{\infty}\sum_{k=0}^{Q-1}X_{k,n}g(t+\tau-nT)e^{i2\pi\frac{k}{T}(t+\tau)}\right) \\ &-\left(\sum_{m=-\infty}^{\infty}\sum_{j=0}^{Q-1}X_{j,m}^{*}g^{*}(t-mT)e^{-i2\pi\frac{j}{T}t}\right)\right] \\ &= \sum_{n=-\infty}^{\infty}\sum_{k=0}^{Q-1}\sum_{m=-\infty}^{\infty}\sum_{j=0}^{Q-1}\mathbb{E}\left[X_{k,n}X_{j,m}^{*}\right]g(t+\tau-nT)e^{i2\pi\frac{k}{T}(t+\tau)}g^{*}(t-mT)e^{-i2\pi\frac{j}{T}t} \\ &= |\mu|^{2}\sum_{k=0}^{Q-1}e^{i2\pi\frac{k}{T}\tau}\sum_{j=0}^{Q-1}e^{i2\pi\frac{(k-j)}{T}t}\sum_{n=-\infty}^{\infty}\sum_{m=-\infty}^{\infty}g(t+\tau-nT)g^{*}(t-mT) \\ &+\sigma^{2}\sum_{k=0}^{Q-1}e^{i2\pi\frac{k}{T}\tau}\sum_{m=-\infty}^{\infty}g(t+\tau-nT)g^{*}(t-mT) \end{split}$$

(b)

$$\begin{split} \bar{R}_{s_{\ell}}(\tau) &= \frac{1}{T} \int_{0}^{T} R_{s_{\ell}}(t+\tau,t) dt \\ &= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} e^{i2\pi \frac{k}{T}\tau} \sum_{n=-\infty}^{\infty} \int_{0}^{T} g(t+\tau-nT) g^{*}(t-nT) dt \\ &= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} e^{i2\pi \frac{k}{T}\tau} \sum_{n=-\infty}^{\infty} \int_{-nT}^{-(n-1)T} g(u+\tau) g^{*}(u) du \\ &= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} e^{i2\pi \frac{k}{T}\tau} \int_{-\infty}^{\infty} g(t+\tau) g^{*}(t) dt \end{split}$$

$$\bar{S}_{s_{\ell}}(f) = \int_{-\infty}^{\infty} \bar{R}_{s_{\ell}}(\tau) e^{-i2\pi f \tau} d\tau
= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} \int_{-\infty}^{\infty} g^{*}(t) \left(\int_{-\infty}^{\infty} g(t+\tau) e^{-i2\pi \left(f - \frac{k}{T}\right)\tau} d\tau \right) dt
= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} \int_{-\infty}^{\infty} g^{*}(t) \left(\int_{-\infty}^{\infty} g(u) e^{-i2\pi \left(f - \frac{k}{T}\right)u} du \right) e^{i2\pi \left(f - \frac{k}{T}\right)t} dt
= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} G\left(f - \frac{k}{T} \right) \left(\int_{-\infty}^{\infty} g(t) e^{-i2\pi \left(f - \frac{k}{T}\right)t} dt \right)^{*}
= \frac{\sigma^{2}}{T} \sum_{k=0}^{Q-1} \left| G\left(f - \frac{k}{T} \right) \right|^{2}$$

(c) Since

$$X_{k,n} = \sum_{\ell=0}^{N-1} x_{\ell,n} e^{-i2\pi \frac{\ell k}{N}} \quad k = 0, 1, \dots, Q-1$$

we obtain

$$s_{\ell}(t) = \sum_{n=-\infty}^{\infty} \left(\sum_{k=0}^{Q-1} X_{k,n} e^{i2\pi \frac{k}{T}t} \right) g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \left(\sum_{k=0}^{N-1} \left[\sum_{\ell=0}^{N-1} x_{\ell,n} e^{-i2\pi \frac{\ell k}{N}} \right] e^{i2\pi \frac{k}{T}t} \right) g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \left(\sum_{k=0}^{N-1} e^{-i2\pi \left(\frac{\ell}{N} - \frac{t}{T} \right) k} \right) g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \left(\sum_{k=0}^{N-1} e^{-i2\pi \left(\ell/N - t/T \right) k} \right) g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \frac{1 - e^{-i2\pi \left(\ell/N - t/T \right) N}}{1 - e^{-i2\pi \left(\ell/N - t/T \right)}} g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \left(\frac{e^{-i\pi tN/T} - e^{i\pi tN/T}}{e^{i\pi \left(\ell/N - t/T \right)}} \right) \left(\frac{e^{i\pi tN/T}}{e^{-i\pi \left(\ell/N - t/T \right)}} \right) g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \left(\frac{-i2 \sin(\pi tN/T)}{i2 \sin(\pi \left(\ell/N - t/T \right))} \right) e^{i\pi tN/T + i\pi \left(\ell/N - i\pi t/T \right)} g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \left(-\frac{\sin(\pi tN/T)}{\sin(\pi \left(\ell/N - t/T \right))} \right) e^{i\pi tN/T + i\pi \ell/N - i\pi t/T} g(t-nT)$$

$$= \sum_{n=-\infty}^{\infty} \sum_{\ell=0}^{N-1} x_{\ell,n} \frac{\sin(\pi tN/T)}{\sin(\pi \left(\ell/N - t/T \right))} e^{i\pi \left(t/N - t/T \right)} g(t-nT)$$

(d) For $0 \le m \le N - 1$,

$$\lim_{t \uparrow \frac{m}{N} T} s_{\ell}(t) = \lim_{t \uparrow \frac{m}{N} T} \sum_{n = -\infty}^{\infty} \sum_{\ell = 0}^{N-1} x_{\ell,n} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - \ell/N))} e^{i\pi (t(N-1)/T + \ell/N)} g(t - nT)$$

$$= \lim_{t \uparrow \frac{m}{N} T} \sum_{\ell = 0}^{N-1} x_{\ell,n} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - \ell/N))} e^{i\pi (t(N-1)/T + \ell/N)}$$

$$= x_{m,n} \lim_{t \uparrow \frac{m}{N} T} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - m/N))} e^{i\pi (t(N-1)/T + m/N)}$$

$$= x_{m,n} e^{i\pi m} \lim_{t \uparrow \frac{m}{N} T} \frac{\sin(\pi t N/T)}{\sin(\pi (t/T - m/N))}$$

$$= x_{m,n} e^{i\pi m} \lim_{t \uparrow \frac{m}{N} T} \frac{(\pi N/T) \cos(\pi t N/T)}{(\pi/T) \cos(\pi (t/T - m/N))}$$

$$= x_{m,n} e^{i\pi m} N \cos(m\pi)$$

$$= N x_{m,n}$$

3. (Chapter 13)

- (a) (6%) Let $c(\tau;t) = \sum_{i=1}^{3} \alpha_i \cdot \delta(\tau \beta_i)$, where $\beta_1 = 0 < \beta_2 < \beta_3$ are constants, and $\{\alpha_i\}_{i=1}^3$ are independent non-negative random variables. Assume that $\beta_i f_c$ is an integer for all i, where f_c is the carrier frequency. Find its low-pass equivalent channel response $c_{\ell}(\tau;t)$. Note: $c_{\ell}(\tau;t)$ should be a function of carrier frequency f_c .
- (b) (6%) Follow (a). Is $c_{\ell}(\tau;t)$ WSS in t.
- (c) (6%) Follow (a). Show that delay power spectrum $R_{c_{\ell}}(\tau; \Delta t = 0)$ of $c_{\ell}(\tau; t)$ is equal to

$$R_{c_{\ell}}(\tau; \Delta t = 0) = \sum_{j=1}^{3} \left(\mu_{j} \left(\sum_{i=1}^{3} \mu_{i} \right) + \sigma_{j}^{2} \right) \delta(\tau - \beta_{j})$$

provided that $\mathbb{E}[\alpha_i] = \mu_i$ and $\mathbb{E}[\alpha_i^2] = \sigma_i^2 + \mu_i^2$.

Hint: Here, we extend the definition of delay power spectrum to be

$$R_{c_{\ell}}(\tau; \Delta t) = \int_{-\infty}^{\infty} R_{c_{\ell}}(\bar{\tau}, \tau; \Delta t) d\bar{\tau}.$$

- (d) (5%) What is the (maximum) delay spread of the channel in (c)?
- (e) (5%) Which category does the channel in (c) belongs to, overspread or underspread? Hint: What is the Doppler spread of a time-invariant channel?

Solutions.

(a) From Slide 13-5,

$$c_{\ell}(\tau;t) = c(\tau;t)e^{-\imath 2\pi f_c \tau}$$

$$= \sum_{i=1}^{3} \alpha_i \cdot \delta(\tau - \beta_i)e^{-\imath 2\pi f_c \tau}$$

$$= \sum_{i=1}^{3} \alpha_i \cdot \delta(\tau - \beta_i)e^{-\imath 2\pi f_c \beta_i}$$

$$= \sum_{i=1}^{3} \alpha_i \cdot \delta(\tau - \beta_i)$$

(b) The answer is YES. In fact, $c_{\ell}(\tau;t) = c_{\ell}(\tau)$ is time-invariant and not a function of t. So its mean and autocorrelation function are of course not a function of t; hence, they certainly only depend on the time difference.

(c)

$$R_{c_{\ell}}(\bar{\tau}, \tau; \Delta t) = \mathbb{E}\left[\sum_{i=1}^{3} \alpha_{i} \cdot \delta(\bar{\tau} - \beta_{i}) \sum_{j=1}^{3} \alpha_{j} \cdot \delta(\tau - \beta_{j})\right]$$

$$= \sum_{i=1}^{3} \sum_{j=1}^{3} \mathbb{E}\left[\alpha_{i}\alpha_{j}\right] \cdot \delta(\bar{\tau} - \beta_{i})\delta(\tau - \beta_{j})$$

$$= \sum_{i=1}^{3} \sum_{j=1}^{3} \mu_{i}\mu_{j}\delta(\bar{\tau} - \beta_{i})\delta(\tau - \beta_{j}) + \sum_{i=1}^{3} \sigma_{j}^{2}\delta(\bar{\tau} - \beta_{j})\delta(\tau - \beta_{j})$$

Hence,

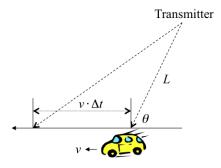
$$R_{c_{\ell}}(\tau; \Delta t = 0) = \int_{-\infty}^{\infty} R_{c_{\ell}}(\bar{\tau}, \tau; \Delta t = 0) d\bar{\tau}$$

$$= \sum_{i=1}^{3} \sum_{j=1}^{3} \mu_{i} \mu_{j} \delta(\tau - \beta_{j}) + \sum_{j=1}^{3} \sigma_{j}^{2} \delta(\tau - \beta_{j})$$

$$= \sum_{j=1}^{3} \left(\mu_{j} \sum_{i=1}^{3} \mu_{i} + \sigma_{j}^{2}\right) \delta(\tau - \beta_{j})$$

- (d) $T_m = \beta_3$.
- (e) The Doppler spread of this channel is $B_d = 0$; hence, $B_d T_m = 0$. The channel is an underspread channel.
- 4. (Chapter 13) (6%) Suppose that the transmitter sends a single tone of 5 GHz to a receiver inside the car as shown in the figure below. What will be the Doppler shift if the light speed is equal to 10⁷ times the car speed?

Hint: Doppler shift is equal to $\lambda_m = \lim_{\Delta t \to 0} \frac{1}{2\pi} \frac{\Delta \phi}{\Delta t} = \lim_{\Delta t \to 0} \frac{1}{2\pi} \frac{\Delta L/\lambda}{\Delta t}$, where λ is the wave length of the single tone.



Solution. From Slides 13-35 and 13-36, the answer is $500\cos(\theta)$ Hz.

5. (Chapter 13) Suppose the channel can be molded as:

$$\boldsymbol{r}_{\ell} = \alpha e^{i\theta} \boldsymbol{s}_{\ell} + \boldsymbol{n}_{\ell},$$

where n_{ℓ} is a zero-mean Gaussian vector with marginal variance σ^2 , α is a non-negative real number, and $\theta \in [0, 2\pi)$. From Chapter 4, we learn that for any binary signaling (denoted by $s_{1,\ell}$ and $s_{2,\ell}$) transmitted over this channel, the error rate is given by

$$Q\left(\sqrt{\frac{d_{12}^2}{4\sigma^2}}\right),\tag{3}$$

where $d_{12} = \|\alpha e^{i\theta} \mathbf{s}_{1,\ell} - \alpha e^{i\theta} \mathbf{s}_{2,\ell}\|$.

- (a) (6%) Denote $\gamma_{12} = \|\mathbf{s}_{1,\ell} \mathbf{s}_{2,\ell}\|$. Let $\Pr[\alpha = 0] = 1 p$ and $\Pr[\alpha = 1] = p$. Assume θ is uniformly distributed over $[0, 2\pi)$. Then, find the error rate under this fading channel.
- (b) (6%) Follow (a). Now suppose θ can be perfectly estimated at the receiver; so it can be removed. One then adopts the maximal-ratio-combining diversity technique to improve the error rate as follows:

$$\boldsymbol{r}_{\ell} = \sum_{k=1}^{L} \alpha_k^2 \boldsymbol{s}_{\ell} + \sum_{k=1}^{L} \alpha_k \boldsymbol{n}_{k,\ell}, \tag{4}$$

where $\{\alpha_k\}$ are i.i.d. with the same distribution defined in (a), and $\{n_{k,\ell}\}$ are i.i.d. Prove that the error rate under this fading channel with maximal-ratio-combining diversity technique is

$$P_e = \sum_{k=0}^{L} Q\left(\sqrt{\frac{k\gamma_{12}^2}{4\sigma^2}}\right) {L \choose k} p^k (1-p)^{L-k}$$

Hint: (4) can be written as $\mathbf{r}_{\ell} = \tilde{\alpha}^2 \mathbf{s}_{\ell} + \tilde{\mathbf{n}}_{\ell}$, where $\tilde{\alpha}^2 = \sum_{k=1}^{L} \alpha_k^2$ and $\tilde{\mathbf{n}}_{\ell} = \sum_{k=1}^{L} \alpha_k \mathbf{n}_{k,\ell}$. Hence, the error rate formula in (3) can be used by replacing σ^2 with the marginal variance of $\tilde{\mathbf{n}}_{\ell}$.

(c) (6%) Use the upper-bound $Q(x) \leq \frac{1}{2}e^{-x^2/2}$ to show that the diversity technique can make the error rate decrease exponentially with respect to L, i.e., P_e can be bounded above by Cq^L for some constant C and q with 0 < q < 1.

Solutions.

(a)

$$d_{12} = \|\alpha e^{i\theta} \mathbf{s}_{1,\ell} - \alpha e^{i\theta} \mathbf{s}_{2,\ell}\| = |\alpha|\gamma_{12}.$$

Hence, the error rate under this fading channel is

$$P_{e} = \sum_{\alpha} \Pr\{\operatorname{error}|\alpha\} \Pr\{\alpha\}$$

$$= \sum_{\alpha} Q\left(\sqrt{\frac{\alpha^{2}\gamma_{12}^{2}}{4\sigma^{2}}}\right) \Pr\{\alpha\}$$

$$= (1-p)Q(0) + pQ\left(\sqrt{\frac{\gamma_{12}^{2}}{4\sigma^{2}}}\right)$$

$$= \frac{1}{2}(1-p) + p \cdot Q\left(\sqrt{\frac{\gamma_{12}^{2}}{4\sigma^{2}}}\right).$$

(b) For given $\{\alpha_k\}$, the marginal variance of $\tilde{\boldsymbol{n}}_{\ell} = \sum_{k=1}^{L} \alpha_k^2 \sigma^2 = \tilde{\alpha}^2 \sigma^2$; hence, the error rate under given $\{\alpha_k\}$ is equal to $Q\left(\sqrt{\frac{d_{12}^2}{4\tilde{\alpha}^2\sigma^2}}\right)$, where with maximal-ratio-combining diversity technique, $d_{12} = \tilde{\alpha}^2 \gamma_{12}$. In other words, the error rate under given $\{\alpha_k\}$ is equal to

$$Q\left(\sqrt{\frac{\tilde{\alpha}^4\gamma_{12}^2}{4\tilde{\alpha}^2\sigma^2}}\right) = Q\left(\sqrt{\frac{\tilde{\alpha}^2\gamma_{12}^2}{4\sigma^2}}\right).$$

Now $\Pr[\tilde{\alpha}^2 = k] = \binom{L}{k} p^k (1-p)^{L-k}$. Hence, the error rate of this fading channel with maximal-ratio-combining diversity technique is

$$P_{e} = \sum_{\tilde{\alpha}^{2}=0}^{L} \Pr\{\text{error}|\tilde{\alpha}^{2}\} \Pr\{\tilde{\alpha}^{2}\}$$
$$= \sum_{k=0}^{L} Q\left(\sqrt{\frac{k\gamma_{12}^{2}}{4\sigma^{2}}}\right) {L \choose k} p^{k} (1-p)^{L-k}$$

(c)

$$P_{e} \leq \sum_{k=0}^{L} \frac{1}{2} e^{-k\frac{\gamma_{12}^{2}}{8\sigma^{2}}} {L \choose k} p^{k} (1-p)^{L-k}$$

$$= \frac{1}{2} \sum_{k=0}^{L} {L \choose k} \left(e^{-\frac{\gamma_{12}^{2}}{8\sigma^{2}}} p \right)^{k} (1-p)^{L-k}$$

$$= \frac{1}{2} \left(e^{-\frac{\gamma_{12}^{2}}{8\sigma^{2}}} p + 1 - p \right)^{L}$$