

**Problem 1** (DFT Revisit). (i) Let  $x[n]$  be a real  $N$ -point sequence and  $X[k]$  be its  $N$ -point DFT. Let  $x_1[n]$  be a sequence such that  $X_1[k] = \text{real}\{X[k](-1)^k\}$ . Given that  $N$  is even, find  $x_1[n]$  in terms of  $x[n]$ .

(ii) Let  $x_1[n]$  and  $x_2[n]$  be two real  $N$ -point sequences such that  $x_1[n]$  is symmetric, and  $x_2[n]$  is anti-symmetric. Let  $X_1[k]$  and  $X_2[k]$  denote their corresponding  $N$ -point DFTs. Given  $y[n] = x_1[n] + x_2[n]$  with its DFT denoted as  $Y[k]$ , explain how  $X_1[k]$  and  $X_2[k]$  can be recovered from  $Y[k]$ .

**Problem 2** (Limits of Z-transform). Let  $X(z)$  be z-transform of a causal discrete signal  $x[n]$ , compute the following equations in terms of  $x[n]$ :

(i)  $X(1)$ . What does it show?

(ii)  $\lim_{z \rightarrow \infty} X(z)$ .

(iii)  $\lim_{z \rightarrow \infty} z(X(z) - x[0])$ .

(iv)  $-z \frac{dX(z)}{dz}$ .

(v)  $\lim_{z \rightarrow \infty} -z^2 \frac{dX(z)}{dz}$ .

**Problem 3** (Stochastic Processes). Consider a discrete random process  $X[n] = \sin(\omega n + \theta)$  such that  $\theta$  is a random variable with uniform distribution on  $[0, 2\pi]$  and  $\omega \in \mathbb{R}$ .

(i) Find the mean and autocorrelation function of  $X[n]$ . Is it a wide-sense stationary process?

Define

$$Y[n] = X[n] + \beta X[n-1],$$

where  $\beta \in \mathbb{R}$ .

(ii) Compute the power spectral density  $P_Y(e^{j2\pi f})$ .

Now assume that  $X[n]$  is a zero-mean wide-sense stationary process with autocorrelation function given by

$$R_X[k] = \sigma^2 \alpha^{|k|},$$

for  $|\alpha| < 1$ .

(iii) Compute the power spectral density  $P_Y(e^{j2\pi f})$ .

(iv) For which values of  $\beta$  does  $Y[n]$  corresponds to a white noise?

**Problem 4** (Min. Mean Squared Error Estimator\*). In this problem, we want to approximate random variable  $X$  in terms of a given set of observations  $\{Y_1, \dots, Y_l\}$  such that  $Y_i$ , for  $1 \leq i \leq l$ , is a random variable correlated to  $X$ .

Consider the case that we have only one observation,  $Y$ . Define  $\hat{X} = h(Y)$  as an estimator of  $X$ . Then, we estimate the value of  $X$  by knowing the value of observation  $Y$ . An estimator is called **unbiased** estimator, if  $\mathbb{E}(X) = \mathbb{E}(\hat{X})$ . Assume that  $X$  and  $Y$  are continuous random variables with the joint probability density function (PDF)  $P_{X,Y}(x, y)$ . The marginal PDF of  $X$  and  $Y$  are denoted by  $P_X(x)$  and  $P_Y(y)$ .

Let  $\mathcal{H}$  be a Hilbert space of random variables with an inner product defined by

$$\langle U, V \rangle = \mathbb{E}(UV^*) = \int uv^* P_{X,Y}(x, y) dx dy, \quad (1)$$

where  $U, V \in \mathcal{H}$ . the space  $\mathcal{H}$  contains  $X$  and  $Y$  and all the random variables  $f(X, Y)$  such that  $f(\cdot)$  is a continuous function. Moreover, the subspace of random variable  $Y$  contains random variables  $Y$  and  $f(Y)$  for all continuous function  $f(\cdot)$ .

i) Prove that  $\langle U, V \rangle$  in (1) is an inner product?

Define mean squared error as

$$\langle x - \hat{x}, x - \hat{x} \rangle = \mathbb{E}(|x - \hat{x}|^2) = \int |x - \hat{x}|^2 P_{X,Y}(x, y) dx dy.$$

- ii) Among the linear unbiased estimators, i.e.  $\hat{X} = aY + b$ , find the estimator with the minimum mean squared error.
- iii) Prove that  $\hat{X} = h(Y) = \mathbb{E}(X | Y)$  has the minimum mean squared error among all unbiased estimators.

Hint 1: Use projection theorem.

Hint 2: Due to definition of conditional expectation, if  $Z = \mathbb{E}(X | Y)$  then  $\mathbb{E}((X - Z)f(Y)) = 0$  for all continuous function of  $f(\cdot)$ .

(\*) Just for fun. Such problems are out of focus of this course :-).