

PROBLEM 2. 20 points (Paper and Pencil + MATLAB/Python)

1. By the definition of the IDFT, we have

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{j \frac{2\pi}{N} kn}, \quad n = 0, \dots, N-1.$$

But the symbols $X_k = 1 + j$, for $k = 0, \dots, N-1$, so the previous formula becomes:

$$x_n = \frac{1}{N} (1 + j) \sum_{k=0}^{N-1} e^{j \frac{2\pi}{N} kn}, \quad n = 0, \dots, N-1.$$

For $n = 0$, we obtain $x_0 = 1 + j$. Otherwise, for $n = 1, \dots, N-1$ we have

$$x_n = \frac{1}{N} (1 + j) \sum_{k=0}^{N-1} e^{j \frac{2\pi}{N} kn} = \frac{1}{N} (1 + j) \frac{e^{j \frac{2\pi}{N} Nn} - 1}{e^{j \frac{2\pi}{N} n} - 1} = 0.$$

So the last $L = 20$ values of the training sequence OFDM block are all 0, which means that the CP of this OFDM block contains only zero values.

- 2.

$$y_n = \sum_{i=0}^{P-1} h_i x_{n-i} + z_n, \quad n = 0, \dots, Q + P - 2.$$

- 3.

$$\mathbf{y} = C\mathbf{h} + \mathbf{z},$$

where C is an $(Q + P - 1) \times P$ matrix:

$$C = \begin{pmatrix} x_0 & 0 & \dots & 0 \\ x_1 & x_0 & \dots & 0 \\ \vdots & \vdots & & \vdots \\ x_{Q-1} & x_{Q-2} & \dots & x_{Q-P} \\ 0 & x_{Q-1} & \dots & x_{Q-P+1} \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & x_{Q-1} \end{pmatrix}.$$

4. The values of the CP of the training sequence OFDM block are affecting the entries of the last $P - 1$ rows of C (the lower-left corner consisting of all-zeros). So if they were not 0, we should have taken them into account when writing down the matrix C .
5. We are seeking for the $\hat{\mathbf{h}}$ which minimizes

$$\|\mathbf{y} - C\mathbf{h}\|^2$$

over all \mathbf{h} . $C\hat{\mathbf{h}}$ is an element of the inner-product space spanned by the columns of C . So $\mathcal{V} = \text{span}\{C_1, \dots, C_P\}$ where C_i is the i th column of C , $i = 1, 2, \dots, P$. We are seeking the vector $\hat{\mathbf{y}} \in \mathcal{V}$ which minimizes

$$\|\mathbf{y} - \hat{\mathbf{y}}\|^2.$$

The projection theorem tells us that $\hat{\mathbf{y}}$ is the projection of \mathbf{y} into \mathcal{V} . It has the property that the error vector $\mathbf{y} - \hat{\mathbf{y}}$ is orthogonal to every element of \mathcal{V} . In particular, it is orthogonal to the columns of C . Hence

$$\langle \mathbf{y} - C\hat{\mathbf{h}}, C_i \rangle = 0, \quad i = 1, 2, \dots, P.$$

Hence

$$\langle \mathbf{y}, C_i \rangle = \langle C \hat{\mathbf{h}}, C_i \rangle, \quad i = 1, 2, \dots, P.$$

Equivalently,

$$C_i^\dagger \mathbf{y} = C_i^\dagger C \hat{\mathbf{h}} \quad i = 1, 2, \dots, P.$$

In matrix form

$$C^\dagger \mathbf{y} = C^\dagger C \hat{\mathbf{h}}.$$

Solving for $\hat{\mathbf{h}}$ yields the least-squares approximation of \mathbf{h} :

$$\hat{\mathbf{h}} = (C^\dagger C)^{-1} C^\dagger \mathbf{y}.$$

6. See the provided routines. One can observe a very good agreement between $\hat{\mathbf{h}}$ and \mathbf{h} .