

SOLUTIONS

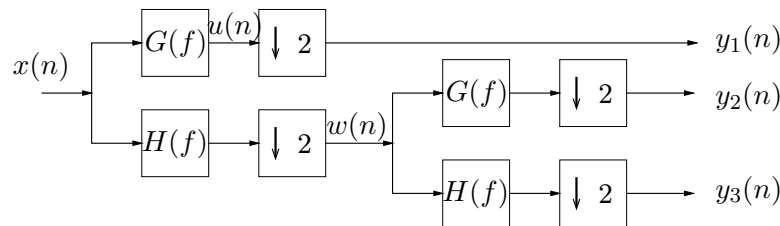
E 82 **Digital Signalbehandling,** 2E1340

Final Examination 2000–09–01, 1400–1800

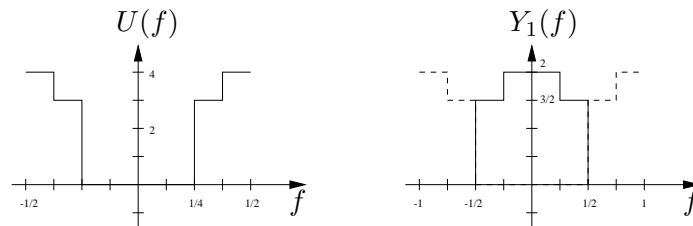
1. Define the vectors $u(n) = [1, 2, 3, 4]$ and $U = \text{DFT}\{u\}$.

- a) Conjugation in the frequency domain corresponds to time reversal and conjugation in the time domain, therefore $x(n) = u^c((-n)_4) = [1, 4, 3, 2]$, so the answer is iii).
- b) Reversing the order in time gives a reversed order also in frequency, thus $x(n) = u((-n)_4) = [1, 4, 3, 2]$, so the answer is iii).
- c) Compared to b), the DFT sequence is circularly shifted one step to the right, which corresponds to $x_c(n) = e^{-j2\pi n/4}x_b(n) = [1, -4j, -3, 2j]$ and the answer is iv).

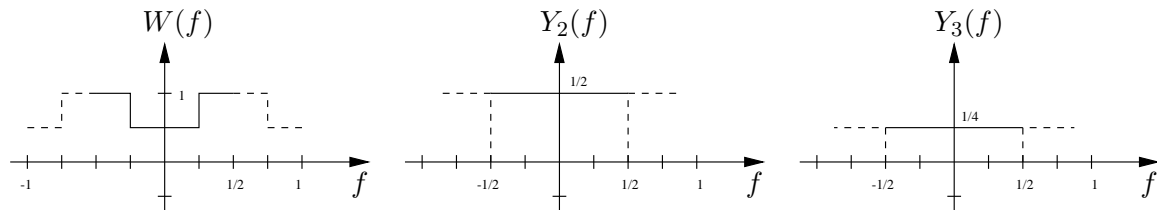
2. Introduce the intermediate signals $u(n)$ and $w(n)$:



Then, $U(f)$ contains the part of $X(f)$ with frequencies higher than $1/4$ and $Y_1(f) = 1/2(U(f/2) + U((f-1)/2))$, which gives:



Likewise, $W(f)$ contain the low-frequency part of $X(f)$ scaled in amplitude and frequency and repeated in frequency. The operation from $W(f)$ to $Y_2(f)$ and $Y_3(f)$ is the same as from $X(f)$ to $Y_1(f)$ and $W(f)$, which gives:



3. a) The plots look different, since we have only 64 sample values and use no zero-padding in the FFT. The DFT of the signal $x(n) = \cos(2\pi fn)$ is

$$\begin{aligned} X(k) &= \sum_{n=0}^{N-1} \frac{1}{2} (e^{j2\pi fn} + e^{-j2\pi fn}) e^{-j2\pi kn/N} = \dots \\ &= e^{j\pi \frac{N-1}{N} (Nf-k)} \frac{\cos(\pi(Nf-k))}{\cos(\pi(f - \frac{k}{N}))} + e^{-j\pi \frac{N-1}{N} (Nf+k)} \frac{\cos(-\pi(Nf+k))}{\cos(-\pi(f + \frac{k}{N}))} \end{aligned}$$

Study the first term (which is the only one that contributes in the region $0 \leq f \leq 1/2$). If Nf is an integer, then the DFT will be zero for all $k \neq Nf$, just as in the plot for $x_1(n)$. If Nf is not an integer, then all DFT values will be non-zero, just as in the plot for $x_2(n)$. For $F = 4\text{kHz}$, $Nf = 64 \cdot 4/16 = 16$ which is an integer, whereas for $F = 4125\text{Hz}$, $Nf = 64 \cdot 4125/16000 = 16.5$. Thus, x_1 has frequency $F = 4\text{kHz}$ and x_2 has frequency $F = 4125\text{Hz}$. If we had used zero-padding, both plots would have shown the side-lobes caused by the short data sample.

- b) The three peaks in the spectrum correspond to signal components of the form $e^{j2\pi ft}$ with normalized frequencies, $f = 0.3, 0.2$ and -0.2 (corresponding to the peak at 0.8). Since the spectrum is not symmetric, the signal is not real valued, which excludes the alternatives x_1 and x_2 . x_4 is impossible since it would give $2+1+1=4$ peaks in the spectrum. The spectrum of the sampled version of x_3 is $X_3(f) = j/2(\delta(f-f_1) - \delta(f+f_1)) + \delta(f-f_2)$ with peaks at $\pm f_1$ and f_2 , thus $f_1 = 0.2$ and $f_2 = 0.3$ and the corresponding continuous time frequencies are $F_1 = f_1 F_s = 2\text{kHz}$ and $F_2 = f_2 F_s = 3\text{kHz}$.
4. The quantization noise for each multiplier is approximately white with power $\sigma_e^2 = \frac{2^{-2b}}{12}$. In the equivalent model this noise is added in each summator following a multiplier. The equivalent quantization noise power at the input is $\sigma_e^2 = (2 + k_2^2)\sigma_e^2 = 2.098\sigma_e^2$. The transfer function for the filter is

$$H(z) = \frac{1}{1 + k_1(1 + k_2)z^{-1} + k_2z^{-2}} = \frac{1}{1 + \frac{1}{8}z^{-1} - \frac{5}{16}z^{-2}} = \frac{\frac{4}{9}}{1 - \frac{1}{2}z^{-1}} + \frac{\frac{5}{9}}{1 + \frac{5}{8}z^{-1}}$$

which gives the impulse response

$$h(n) = \left(\frac{4}{9} \left(\frac{1}{2} \right)^n + \frac{5}{9} \left(-\frac{5}{8} \right)^n \right) u(n)$$

The quantization noise power at the output is then given by

$$\sigma_{\text{output}}^2 = \sigma_e^2 \sum_{n=0}^{\infty} h^2(n) = (2 + k_2^2) \frac{2^{-2b}}{12} \sum_{n=0}^{\infty} h^2(n)$$

where

$$\sum_{n=0}^{\infty} h^2(n) = \sum_{n=0}^{\infty} \left(\frac{4}{9} \left(\frac{1}{2} \right)^n + \frac{5}{9} \left(-\frac{5}{8} \right)^n \right)^2 = \frac{16 \cdot 4}{81 \cdot 3} + \frac{2 \cdot 20 \cdot 16}{81 \cdot 21} + \frac{25 \cdot 64}{81 \cdot 39} = 1.146$$

The SNR is then

$$\text{SNR} = \frac{P_s}{\sigma_{\text{output}}^2} = \frac{0.001}{2.098 \cdot 1.146 \cdot \frac{2^{-2b}}{12}}$$

Sufficient SNR is then obtained when using at least $b = 6$ bits.

5. a) Least squares problem which can be solved by, for example, completing the squares.

$$\begin{aligned}\sum_{t=1}^N (\mathbf{x}(t) - \mathbf{a}s(t))^* (\mathbf{x}(t) - \mathbf{a}s(t)) &= \sum_{t=1}^N (\mathbf{x}^*(t)\mathbf{x}(t) - s^*(t)\mathbf{a}^*\mathbf{x}(t) - \mathbf{x}(t)^*\mathbf{a}s(t) + s^*(t)\mathbf{a}^*\mathbf{a}s(t)) \\ &= \sum_{t=1}^N (\mathbf{x}^*(t)\mathbf{x}(t) - s^*(t)\mathbf{a}^*\mathbf{x}(t) - \mathbf{x}(t)^*\mathbf{a}s(t) + ms^*(t)s(t))\end{aligned}$$

where $\mathbf{a} = \mathbf{a}(\theta_0)$. Minimizing this expression is equivalent to minimizing

$$\sum_{t=1}^N \left(s(t) - \frac{1}{m}\mathbf{a}^*\mathbf{x}(t) \right)^* \left(s(t) - \frac{1}{m}\mathbf{a}^*\mathbf{x}(t) \right)$$

and thus $\hat{s}(t) = \frac{1}{m}\mathbf{a}^*\mathbf{x}(t)$, $t = 1, \dots, N$.

- b) Similarly we have

$$\begin{aligned}\sum_{t=1}^N (\mathbf{x}(t) - \mathbf{A}s(t))^* (\mathbf{x}(t) - \mathbf{A}s(t)) &= \sum_{t=1}^N (\mathbf{x}^*(t)\mathbf{x}(t) - \mathbf{s}^*(t)\mathbf{A}^*\mathbf{x}(t) - \mathbf{x}(t)^*\mathbf{A}s(t) + \mathbf{s}^*(t)\mathbf{A}^*\mathbf{A}s(t)) \\ &= \sum_{t=1}^N \left(\left(\mathbf{s}(t) - (\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*\mathbf{x}(t) \right)^* \mathbf{A}^*\mathbf{A} \left(\mathbf{s}(t) - (\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*\mathbf{x}(t) \right) \right. \\ &\quad \left. + \mathbf{x}^*(t)\mathbf{x}(t) - \mathbf{x}^*(t)\mathbf{A}(\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*\mathbf{x}(t) \right)\end{aligned}$$

Since $\mathbf{A}^*\mathbf{A}$ is positive-semi definite, this is minimized when

$$\hat{\mathbf{s}}(t) = (\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*\mathbf{x}(t), \quad t = 1, \dots, N.$$

- c)

$$\mathbb{E}\{\hat{\mathbf{s}}(t)\} = (\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*(\mathbf{A}\mathbf{s}(t) + \mathbb{E}\{\mathbf{n}(t)\}) = \mathbf{s}(t)$$

The estimator is unbiased.

$$\begin{aligned}\mathbb{E}\{(\hat{\mathbf{s}}(t) - \mathbf{s}(t))(\hat{\mathbf{s}}(t) - \mathbf{s}(t))^*\} &= \mathbb{E}\{\hat{\mathbf{s}}(t)\hat{\mathbf{s}}^*(t)\} - \mathbf{s}(t)\mathbf{s}^*(t) \\ &= (\mathbf{A}^*\mathbf{A})^{-1}\mathbf{A}^*\mathbb{E}\{\mathbf{n}(t)\mathbf{n}^*(t)\}\mathbf{A}(\mathbf{A}^*\mathbf{A})^{-1} \\ &= \sigma^2(\mathbf{A}^*\mathbf{A})^{-1}\end{aligned}$$

Thus, the covariance is proportional to the noise variance and decreases with increasing number of sensors.